Approaches and challenges in estimating economic loss from tsunami damage models

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Approaches and challenges in estimating economic loss from tsunami damage models

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Abstract

Tsunami damage assessment as a field has been steadily gaining momentum in the scientific community, and one of the most common ways in which damage has been quantified is by fragility functions. However, how tsunami damage models can be applied to practical disaster risk management is still relatively underexplored. An important aspect of disaster risk management is loss estimations. Loss estimations do not only assist the development of risk maps, risk reduction policies and measures, they also inform decisions on loss compensations from public and private institutions such as the insurance and reinsurance sectors. Tsunami loss estimations usually require the definition of a relation between damage and loss. Different approaches of relating damage to loss and computing losses result in varied loss models. Moreover, most damage and loss models are developed for buildings, with few to no models being developed for non-building structures along the coast. The heterogeneous nature of coastal infrastructure also introduces additional layer of complexity in translating damage to loss. This chapter aims to review the current approaches taken to quantify tsunami damage and loss as well as the challenges in developing loss estimation models. We identify 22 existing tsunami loss modelling studies and propose a structured taxonomy of vulnerability approaches, showing that tsunami loss modelling remains far less developed than for other perils. Our review highlights major sources of uncertainty across hazard, exposure, fragility and loss modules. We find substantial gaps in modelling non-building coastal infrastructure and in accounting for indirect losses such as business interruption and supply-chain impacts. We underscore the need for probabilistic, multi-hazard and time-dependent methods to enhance the reliability of tsunami loss estimation and support the development of tsunami-specific risk financing tools.

Keywords: tsunami, economic loss, damage, risk

Introduction

Tsunami events pose an extreme but often underestimated financial risk to coastal communities. Damage from the 2004 Indian Ocean tsunami was pegged at US$ 2,920 million for Indonesia and US$1,144 million for Sri Lanka (Telford & Cosgrove, 2006). Meanwhile, the 2011 Great East Japan (Tohoku) earthquake and tsunami was estimated to cost US$211 billion in direct damages (Kajitani et al., 2013), US$ 235 billion in total losses and of which only US$ 65 billion was insured (Aon Benfield, 2023). It was a single event with the highest insured losses in the decade between 2010 – 2019 (Aon Benfield, 2023). While these events have spurred investments in disaster risk reduction measures such as early warning systems and hazard modelling, disaster risk financing for tsunami events remains in its infancy.

Unlike primary perils such as earthquakes and tropical cyclones, few ex-ante disaster risk financial instruments are in place to manage and mitigate the impacts of tsunamis. National insurance schemes such as the Japan Earthquake Reinsurance (JER) program and New Zealand's Natural Hazards Commission (Toka Tū Ake) provide indemnity-based protection to households and businesses, with tsunamis usually covered as a secondary peril following earthquakes. In the United States, the National Flood Insurance Program (NFIP) offers partial coverage for tsunami-induced flooding (Federal Emergency Management Agency, 2023). Sovereign risk pools, on the other hand, pool capital from multiple countries to share the risk. Sovereign risk pools such as the Caribbean Catastrophe Risk Insurance Facility Segregated Portfolio Company (CCRIF SPC) and the Pacific Catastrophe Risk Insurance Company (PCRIC) offer parametric insurance to participating governments, by providing rapid payouts triggered by modelled hazard thresholds. However, these national insurance schemes and sovereign risk pools currently do not explicitly model tsunami impacts. Instead, potential tsunami-related losses may be captured indirectly through earthquake-triggered mechanisms, highlighting a critical gap in tsunami-specific risk financing.

This gap is in part due to the limited availability and maturity of tsunami loss models. Loss models play crucial roles in the securitisation of catastrophic losses as they provide the estimates of potential damage and financial impact that underpin the design, pricing and triggering of financial products such as catastrophe bonds, sovereign risk pools and insurance schemes (Cummins, et al., 2004). Regardless of the financial products they support, loss models estimate expected losses by integrating hazard, exposure and vulnerability (Figure 1). The hazard module represents the characteristics of the hazard itself, for instance, tsunami heights for tsunamis and windspeeds for hurricanes. It can include information such as the intensity and probability of hazard occurrence. The exposure module captures the assets at risk, detailing factors such as the construction type, function, occupancy, and asset value, and may also account for building contents, non-structural components such as business interruption and emergency costs (Figure 2). The vulnerability module expresses how susceptible these assets are to damage from the hazard, using tools such as fragility models, damage ratios or vulnerability functions. There are inherent uncertainties in each of these components which challenges the development of tsunami loss models. In the development of catastrophic risk models, the outputs from the hazard, exposure, and vulnerability modules are integrated into a financial module that translates physical damage into economic loss. The financial module typically estimates total or "ground-up" losses before applying insurance or financial adjustments.

There are several approaches to deriving tsunami loss estimates. However, due to the scarcity of historical loss data such as claims and loss databases, tsunami loss estimates are more commonly derived by relating physical damage to economic loss (e.g. Goda et al., 2019; Goda, 2020), in what are known as engineering-based approaches. In these approaches, damage models such as fragility functions or component-level assessments are translated into vulnerability functions (Figure 3), which then inform estimates of potential economic losses. This translation from damage to economic loss is not straightforward, as it must account for uncertainties in the loss development process, such as uncertainties in the hazard estimates, exposure data, and vulnerability models. Moreover, most tsunami damage and vulnerability models have been developed primarily for buildings, with few models addressing non-building structures along the coast. The heterogeneous nature of coastal infrastructure further complicates this process as critical and industrial facilities are exposed to secondary impacts such as business interruption and content loss.

These challenges in translating physical damage into economic losses underscore the need for a critical examination of tsunami loss estimation approaches. The objective of this chapter is therefore two-fold – to (i) review the current methodologies used to quantify tsunami losses from damage estimates and (ii) examine the key challenges inherent in developing reliable tsunami loss models.

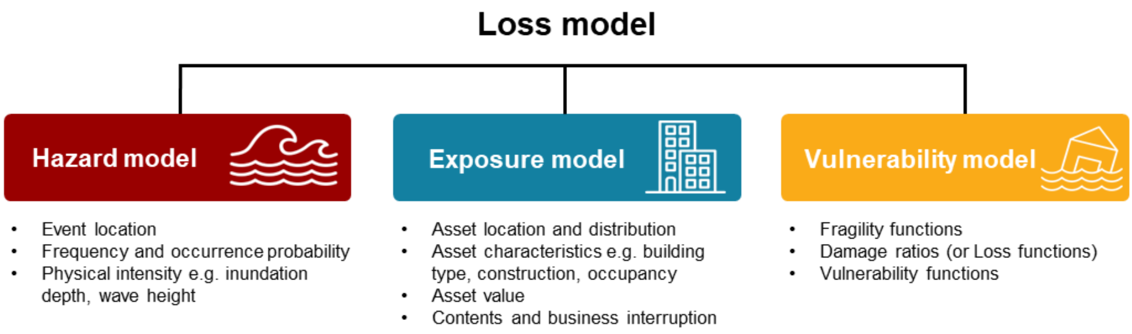


Figure 1. Components of loss modelling for tsunamis.

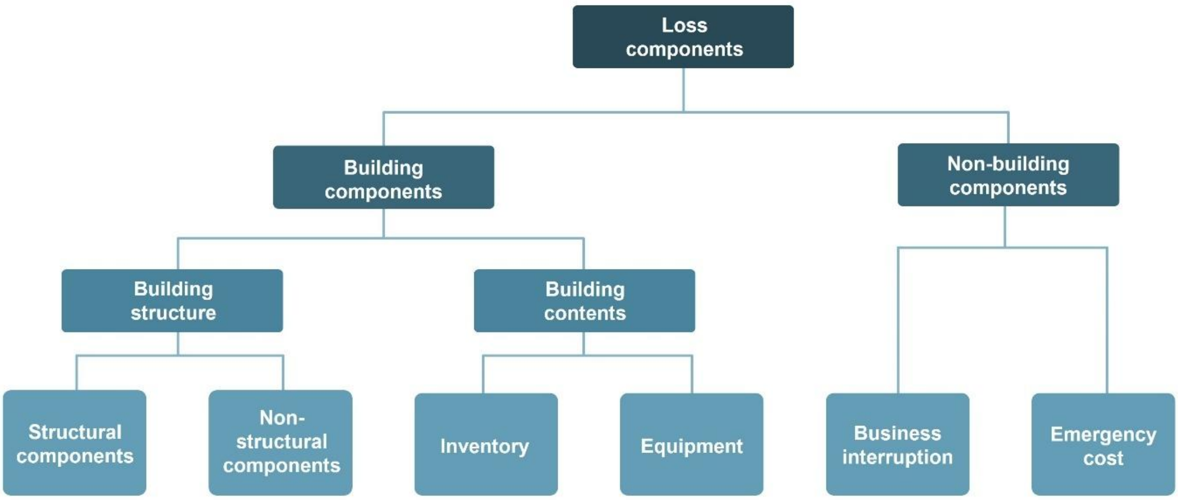


Figure 2. Typical loss components when assessing losses to buildings

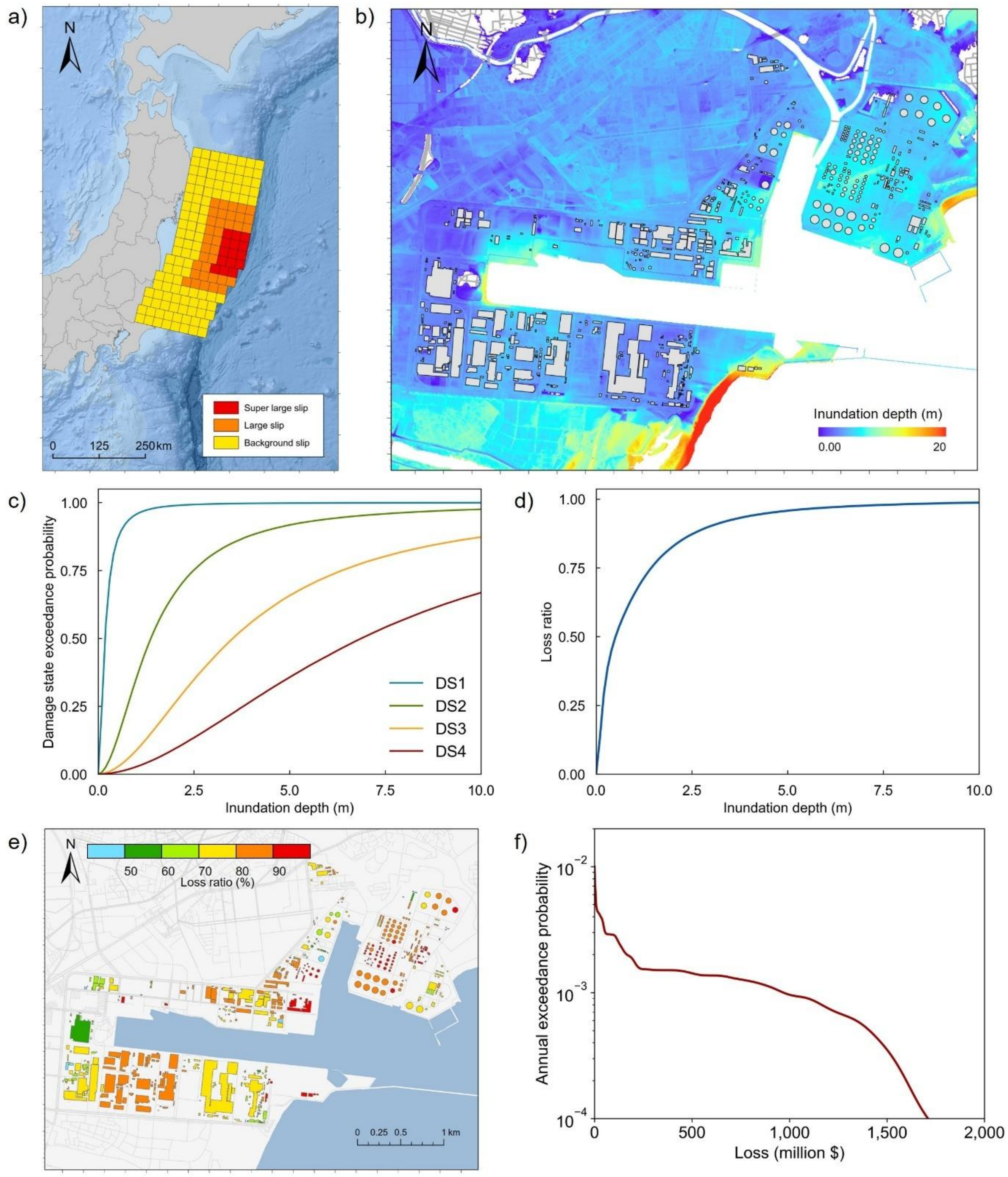


Figure 3. Modules used to develop engineering-based vulnerability models. (a) Potential rupture source for tsunami in the Tohoku region, Japan. (b) Estimated maximum inundation depth in Sendai Port, Japan. (c) Fragility functions for a cargo handling facility, showing four damage states (DS), with DS1 and DS4 representing the lowest and highest levels of damage, respectively. (d) Corresponding vulnerability function for the same facility. Fragility functions relate a tsunami intensity measure (e.g., inundation depth) to the probability of exceeding each damage state, while vulnerability functions translate the intensity measure into a loss ratio, defined as the repair cost expressed as a percentage of the replacement cost. (e) Estimated loss ratio at structure level. (f) Aggregate loss in Sendai Port (Risk curve). Figures adapted from Chua et al. (2021) and Miki et al. (2025), licensed under CC BY 4.0.

Tsunami vulnerability models

Literature reviewing natural catastrophe loss models is scarce and mostly limited to primary perils such as hurricanes and earthquakes (e.g. Pita et al., 2015; Porter, 2021; Hamburger et al., 2025). Pita et al. (2015) provided a comprehensive overview of hurricane vulnerability models developed over the past seven decades, identifying five main typologies: (i) models using only post-disaster building loss data, (ii) models combining damage data with engineering and scientific knowledge, (iii) models based solely on expert opinion, (iv) models estimating physical damage to key structural components with expert input, and (v) simulation-based models capturing the interaction between wind and building loads. Because of the long history of hurricane loss modelling, these classifications often overlap and include hybrid approaches. Porter (2021) reviewed vulnerability models for seismic events and proposed a simpler classification into three types: (i) empirical models using past damage and loss observations such as historical claims, (ii) analytical (or engineering-based) models based on engineering principles, and (iii) expert-judgement models which rely on expert opinion to elicit vulnerability functions for different structure types in terms of their losses from damage, downtime losses and etc. Behrens et al. (2021) provided a comprehensive review of the research gaps in probabilistic tsunami hazard and risk analysis and identified some of the challenges in assessing tsunami vulnerabilities. However, at the time of writing, Behrens et al. (2021) noted the scarcity of tsunami-specific vulnerability models in the literature but did not provide a classification for tsunami vulnerability approaches. For the remainder of this chapter, we adopt Porter's (2021) threefold classification of vulnerability models: (i) empirical models, (ii) expert-judgement models and (iii) engineering-based models.

Across current literature, we have identified 22 studies that explicitly developed or applied loss models (Appendix). To our knowledge, empirical or claims-based tsunami vulnerability models are essentially non-existent, largely due to the very limited insurance coverage and scarcity of historical claims data for tsunami events. For example, in the 2004 Indian Ocean tsunami, only about 5–7% of total economic losses were insured, reflecting the low insurance penetration in the affected countries (King, 2006). Similarly, during the 2011 Great East Japan earthquake and tsunami, approximately 85% of losses were borne by affected communities and businesses due to underinsurance in the commercial sector, even in a country with high-insurance uptake like Japan (Henderson, 2018). The low insurance penetration rates and lack of available data from past events limit the development of statistically robust claims-based vulnerability models for tsunamis.

Only a handful of expert-judgement tsunami vulnerability models were developed in literature. One of the most representative expert-judgement models is the Papathoma Tsunami Vulnerability Assessment model (Papathoma & Dominey-Howes, 2003, Papathoma et al., 2003), and its subsequent enhanced versions PTVA-2 (Dominey-Howes & Papathoma, 2007), PTVA-3 (Dall'Osso et al., 2009a) and PTVA-4 (Dall'Osso et al., 2016). The PTVA models assign vulnerability scores (*VS*) to buildings based on their structural characteristics, construction materials, number of stories, and proximity to the coastline. Vulnerability scores of the original PTVA and the PTVA-2 models were derived solely through expert judgement. On the other hand, vulnerability scores in the PTVA-3 and PTVA-4 were adjusted to reflect observed damage patterns from historical events such as the 2004 Indian Ocean and 2011 Great East Japan tsunamis, which makes them closer to empirical validation while relying primarily on expert judgement. The PTVA models were primarily developed in the 2000s, during a period when robust empirical and engineering-based tsunami vulnerability models were largely absent. This has made PTVA a widely referenced tool in regions with limited historical loss data or where rapid vulnerability assessment is required (e.g., Dall'Osso et al., 2009b; Madani et al., 2017). For example, Dominey-Howes et al. (2010) applied the PTVA model to evaluate the vulnerability of commercial and residential buildings in Seaside, Oregon, USA, for a 1-in-500-year Cascadia Subduction

Zone tsunami, and estimated the probable maximum loss based on the replacement cost of each building (Appendix). Few other expert-judgement models (e.g. Leone et al., 2011; Ismail et al., 2012) exist in literature, reflecting both the challenges in formalising expert opinion into quantitative frameworks and, at the time of their development, the limited empirical knowledge of structural response to tsunami impacts.

The 2011 Great East Japan tsunami and subsequent events provided a wealth of post-event data, improving model calibration and advancing our understanding of structural response to tsunamis, which contributed to the rise of engineering-based vulnerability models (e.g. HAZUS-MH Tsunami model, FEMA, 2017; Goda et al., 2019; Goda, 2020). Engineering-based models use physical principles and structural analysis to estimate damage and loss to buildings and infrastructure under varying hazard intensities. They comprise of two modules – (i) a tsunami-to-damage fragility function and (ii) a damage-to-loss model (Behrens et al., 2021; Galasso et al., 2021). At the core, these models follow a sequential process that links hazard to economic loss through a series of probabilistic relationships:

Hazard assessment → Fragility models → Damage ratios → Vulnerability models → Aggregate risk or losses

Typically, engineering-based models begin with fragility functions, which describe the probability of a structure exceeding specific damage states, given a hazard intensity measure such as inundation depth or flow velocity (Figure 3; Chua et al., 2021). The probability of damage exceedance can simply be expressed as:

$$PDS = P(ds \geq DS|IM)$$

, where ds is the observed damage state of a structure, DS is the classification provided by the damage scale and IM is the intensity measure. Each damage state (DS) describes the degree of damage at a component level, e.g. structural elements, non-structural elements, sub-systems. Buildings or assets are classified into these damage states, which are typically defined as mutually exclusive and sequential, ranging from minor damage to complete destruction. Figure 4 here provides an example of how damage states are being expressed in Chua et al. (2021) for port structures. Fragility functions may be derived empirically, based on expert judgement, or through analytical modelling, and have been extensively reviewed in Tarbotton et al. (2015) and Charvet et al. (2017). Once the damage states are determined, they can be translated into economic loss through multiple approaches.

The most common methods of translating damage into economic loss include the use of damage ratios or vulnerability functions. Damage ratios (DR) quantify the expected loss of a structure or asset as a proportion of replacement cost, e.g. a repair cost of 20% of the replacement cost would correspond to a damage ratio of 0.2. Typically, a mean or a range of damage ratios would be assigned to each damage state, otherwise referred to as a loss scale (Table 1). A loss scale provides repair or replacement cost ratios corresponding to different levels of structural damage. In tsunami loss modelling, several studies (e.g. Song et al., 2017; Goda et al., 2019; Goda et al., 2021) have adopted loss scales developed by the Japanese Ministry of Land, Infrastructure, Transport and Tourism (MLIT). In contrast, Sanderson et al. (2021) employed the loss scales in Bai et al. (2009) which were originally derived from the Applied Technology Council’s ATC-13 framework. More recently, Suppasri et al. (2019) and Miki et al. (2025) developed their own loss scales tailored to Japanese buildings and industrial facilities, respectively, based on component-level analyses (Table 1). The HAZUS-MH Tsunami model defines distinct damage ratios for different damage states, building types, and loss categories (structural, non-structural, and contents). These ratios were informed by post-event data from past tsunamis, including the 2004 Indian Ocean and 2011 Great East Japan events, but are calibrated specifically for U.S. building stock.

These state-specific damage ratios can then be combined with fragility functions to derive a continuous relationship between the hazard intensity and the expected damage ratios (loss ratios). This relationship forms the vulnerability curve, which directly relates hazard intensity to economic loss. The expected damage ratio can be calculated as follows:

$$E[DR] = \sum_i DR_i \times P(DS = ds_i)$$

, where DR_i is the damage ratio when $DS = ds_i$ and $P(DS = ds_i)$ is the probability of damage state exceeding predefined ds_i.

Loss can also be estimated through direct replacement costs, which involve tabulating the repair or replacement costs of damaged assets based on standard unit costs for construction materials or equipment, such as those provided in Spon's Construction Costs Guide (e.g., AECOM, 2024), or using estimated land use or tax lot values (e.g., Marfai et al., 2019; Tanaka et al., 2022). Indirect losses, including business interruption and downtime, are largely absent from tsunami loss models in the literature, despite representing significant economic impacts. Incorporating these indirect losses in future studies would enable more comprehensive risk assessments.

Some studies (e.g., Goda & De Risi, 2018; Goda, 2020) extend loss estimations to a portfolio level by simulating damage across all buildings under multiple stochastic hazard scenarios. The resulting loss samples are then aggregated to derive probabilistic estimates of losses at a portfolio level, capturing the combined uncertainty from hazard, exposure, and vulnerability.

Engineering-based vulnerability models typically employ a hybrid of the methods described above. The approaches used in existing vulnerability models are summarised in the Appendix. The relative scarcity of such models in the literature underscores the challenges involved—such as uncertainties in hazard characterisation and in linking physical damage to economic losses—which are explored in the following section.

Table 1. Loss scale proposed in Suppasri et al. (2019) for residential buildings in Japan

Damage State	Description	Condition	Replacement Ratio
1 (Minor damage)	No significant structural or non-structural damage, possibly only minor flooding	Possible to be use immediately after minor floor and wall clean up	18%
2 (Moderate damage)	Slight damages to non-structural components	Possible to be use after moderate repair	36%
3 (Major damage)	Heavy damages to some walls but no damages in columns	Possible to be use after major repair	54%

4 (Complete damage)	Heavy damages to several walls and some columns	Possible to be use after a complete repair and retrofitting	76%
5 (Destroyed or collapsed)	Destructive damage to walls (more than half of wall density) and several columns (bend or destroyed)	Loss of functionality (system collapse). Non-repairable or great cost for retrofitting	100%
6 (Washed away)	Washed away, only foundation remained, total overturned	Non-repairable, requires total reconstruction	100%

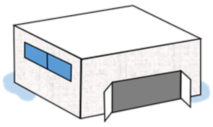
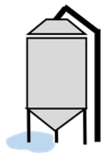
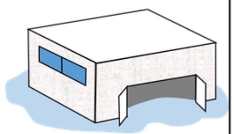
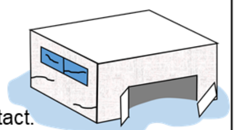
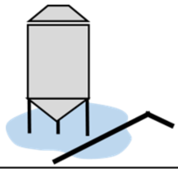
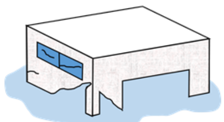
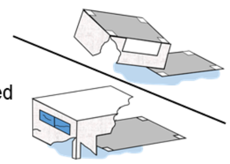
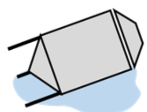
Damage State	Damage Description	
	Buildings (B)	**Infrastructure (I)**
DS 0	• Little to no water penetration. • Non-structural components (windows and door) and roof remain intact.  *Serviceability:* Ready for immediate use	• No floodwater impacts on infrastructure.  *Serviceability:* Ready for immediate use
DS 1	• Water penetration. • Non-structural components and roof remain intact.  *Serviceability:* Ready for immediate use but requires interior restoration, such as drying of floors and walls, repainting, repairs to plumbing and electric systems.	• No visible damage from outside of infrastructure.  *Serviceability:* Ready for immediate use. No obvious repair to infrastructure in the intermediate period after the tsunami.
DS 2	• Non-structural components and/or roof have sustained damage. • Structural components are intact.  *Serviceability:* Obvious repair works in the intermediate period after the tsunami. Operational only after repairs.	• Some damage to infrastructure, while foundation or base remains intact.  *Serviceability:* Some form of repair to infrastructure in the intermediate period after the tsunami. Operational only after repairs.
DS 3	• Structural components (columns and beams) have sustained damage, or rackings have buckled and folded. Buildings may have collapsed as a result.  *Serviceability:* Not repairable. Replacement or removal of building in the intermediate period after the tsunami.	• Foundation or base of infrastructure has folded or buckled. Infrastructure may have collapsed as a result.  *Serviceability:* Not repairable. Removal or replacement of infrastructure in the intermediate period after the tsunami.
DS 4	• Total structural failure. • Building has either overturned or slid from original position.  *Serviceability:* Not operational.	• Infrastructure has overturned or slid from original position.  *Serviceability:* Not operational.

Figure 4. Tsunami damage scale for port structures (buildings and infrastructure). Adapted from Chua et al. (2021), licensed under CC-BY 4.0.

Challenges in developing engineering-based vulnerability models

Current knowledge on tsunami loss modelling remains uneven. In this chapter, we have identified 22 studies on tsunami loss modelling, yet several key challenges extend beyond the scope of these existing works. While approaches to tsunami hazard assessment are relatively well developed, other components of loss modelling—such as fragility and vulnerability modelling, and the quantification of exposure—remain less mature. Moreover, most tsunami loss models focus on earthquake-generated tsunamis, reflecting the relative maturity of seismic hazard characterisation. Addressing these broader challenges is essential for the development of robust and generalizable tsunami loss models. In the following subsections, we systematically review the challenges associated with each component of loss model development.

Challenges in hazard assessment

Tsunami hazard assessment involves the modelling of tsunami source, wave propagation, and onshore run-up characteristics. Each of these stages introduces uncertainties that can propagate through the overall risk assessment. Probabilistic methods have been introduced to quantify uncertainties in hazard modelling, in what is known as probabilistic tsunami hazard analysis (PTHA). In PTHA, the hazard is expressed as the probability that a selected tsunami intensity measure (TIM), such as wave height or inundation depth, will exceed a given threshold within a specified time interval (e.g. 100-, 500-, 1000-year events). The basic outcome of PTHA is a hazard curve. PTHA accounts for both aleatoric and epistemic uncertainties. Aleatoric uncertainty reflects the inherent randomness in the tsunami-generation processes, such as earthquake rupture and landslide characteristics, and is overcome by simulating a wide range of possible scenarios. Epistemic uncertainty arises from the lack of scientific understanding of tsunami sources or model parameters and can be addressed to some degree through the use of multiple models, expert judgement and parameter distributions. A few studies (e.g. Behrens et al., 2021; De Risi et al., 2024; Mori & Miyashita, 2024) have provided extensive reviews of probabilistic tsunami hazard analyses and the current state-of-the-art. In this section, we summarise key challenges in hazard assessment and discuss some gaps that have not been fully addressed in previous reviews.

Tsunamis can be generated by a few sources including earthquakes, submarine landslides, volcanic eruptions and meteorological sources. Each source type introduces distinct uncertainties into the hazard assessment process. For earthquake-generated tsunamis, which account for most historical tsunamis (~80%), the main sources of uncertainty include fault geometry, rupture area, slip distribution and amount of coseismic displacement (Li et al., 2016). Additionally, the variability in the rise time (the amount of time it takes for slip on a fault patch to reach its peak value after rupture begins) and how the slip is distributed along the fault plane significantly influences the tsunami amplitude and arrival times (Suppasri et al., 2010; Satake et al., 2022). Due to the limited availability of tsunami observation data, PTHA for seismic tsunamis typically relies on earthquake source characteristics to numerically simulate seafloor displacement, wave propagation and finally, coastal inundation. Uncertainties arising from the incomplete knowledge of potential rupture zones and fault segmentation are typically overcome by logic tree frameworks, ensemble modelling and Bayesian techniques (e.g. Selva et al. 2016; Grezio et al., 2017; Miyashita et al., 2020). The most commonly adopted approach – logic trees, incorporates epistemic uncertainty by branching into alternative hypothesis or model parameters (e.g. source zones, fault models and earthquake magnitudes). Each branch is assigned a weight based on expert judgment or historical data, and hazard curves from all branches are combined to produce a probabilistic distribution of tsunami hazard (Annaka et al., 2007). However, these methods remain limited by the scarcity and incompleteness of observational data, which in turn limits judgement. For instance, in regions where event catalogues are too short, earthquake events with larger average return periods may be overlooked (Behrens et al., 2021). Moreover, most event catalogues focus on subduction zone earthquakes, leaving atypical tsunami sources such as smaller crustal faults poorly constrained and limiting the accurate representation of all potential hazards in the logic tree (Selva et al., 2021).

Aleatoric uncertainties due to the natural randomness (inherent variability in the fault slip) can be addressed through Monte Carlo simulations or stochastic sampling of the input parameters (e.g. Li et al., 2016; Davies et al., 2022). This approach involves the numerical modelling of a large number of possible events which can be in orders of thousands of scenarios to estimate the exceedance rate of the hazard, which is computationally expensive (Sepúlveda et al., 2022). Moreover, when using Monte Carlo sampling, only a handful of parameters are considered, which also leaves out potentially critical sources of variability (Lorito et al., 2015).

For other non-seismic sources, the uncertainty is even greater due to limited observational data and understanding on the generational mechanisms. Unlike earthquake-generated tsunamis, tsunamis induced by landslides and volcanoes account for approximately 12% and 4% of global tsunamis respectively (Reid & Mooney, 2023). Landslide tsunamis may originate from fully submarine sources (e.g. submarine canyons or volcanic edifices), partially submerged failures, terrestrial slope collapses, or volcanic flank instabilities (Roger et al., 2024; Al Farizi et al., 2025). The initiation and size of a landslide are influenced by sediment properties, slope stability, triggering mechanisms (e.g. earthquakes or submarine slope failures), and the potential failure volume (Pan et al., 2022; Du et al., 2025). The dynamic behaviour of the slide such as acceleration, runout distance and mass deformation influences the generated wave characteristics (Løvholt et al., 2015). The main sources of epistemic uncertainty for landslide tsunamis lie in the probability and location of slope failure, the potential failure volume, and the poorly constrained landslide dynamics—including whether the slide behaves as a viscous, granular, or viscoplastic mass (Grezio et al., 2017). While logic trees are commonly used to represent epistemic uncertainties in earthquake-induced landslide hazards (e.g., Wang & Rathje, 2015; Rodríguez-Peces et al., 2020), they are rarely adapted for landslide-tsunami hazard because tsunami genesis depends on more complex dynamics such as slide-water interaction and slide volume (Løvholt et al., 2020). On the other hand, aleatoric uncertainties in landslide tsunamis arise from inherent natural variability in triggering conditions (e.g. groundshaking, rainfall), timing and geometry of slope failure, slide-water interaction (Yavari-Ramshe & Ataie-Ashtiani, 2016; Grezio et al., 2017). Probabilistic analyses of landslide tsunamis therefore require assumed probability distributions for key geotechnical and kinematic parameters, such as slide density, friction angle, rheology and initial acceleration (Yavari-Ramshe & Ataie-Ashtiani, 2016). However, due to the limited records of landslide events and insufficient empirical data on slide properties, the recurrence frequency and parameter distributions remain poorly constrained, limiting the reliability of probabilistic assessments.

Volcanic tsunamis can be generated by several mechanisms, including pyroclastic flows, lahar, flank collapses, slope failures, submarine explosions and shock waves from large explosions (Paris, 2015). Volcanic tsunami events are controlled by mass-movement processes similar to those governing landslide tsunamis. Consequently, volcanic PTHA shares many of the same challenges as landslide PTHA, particularly regarding source characterisation, parameter uncertainty and slide-water interactions (Grezio et al., 2017). Additional uncertainties stem from the natural variability of eruptive behaviour and limited constraints on failure volume, geometry, and flow kinematics (Schindelé et al., 2024). Compared with submarine landslides, PTHA models for volcano-generated tsunamis remain less mature and less systematically validated (Behrens et al., 2021). It is also important to recognise that existing numerical models for either landslide- or volcano-generated tsunamis have yet to fully capture the complex, multiphase, and scale-dependent dynamics of slide mechanics, volcanic flows, and their coupling with seawater (Yavari-Ramshe & Ataie-Ashtiani, 2016; Schindelé et al., 2024).

In practice, most PTHA studies adopt a time-independent Poisson formulation, assuming a constant probability of event occurrence and statistical independence between events. However, this assumption neglects the temporal evolution of the underlying physical systems, including processes such as stress accumulation along faults, magma recharge, viscoelastic relaxation, fluid migration and pore pressure changes in soil, which alter the occurrence rate of events through time. Recent studies have increasingly implemented time-dependent PTHA for seismic-source tsunamis (e.g. Goda, 2019; 2020; Fukutani et al., 2021). To our best knowledge, existing studies have yet to incorporate time-dependent approaches for non-seismic tsunamis. Nevertheless, time-dependence has been investigated in the context of volcanic eruption and landslide initiation (Garcia-Aristizabal et al., 2012; Jones et al., 2021; Sandri et al., 2021). Several probabilistic models have been applied to capture evolving likelihoods and temporal clustering in hazard assessment, including lognormal distributions (Bebbington & Lai, 1996), Brownian Passage Time models (Matthews et al., 2002), and Gaussian mixture formulations (Goda & De Risi, 2024). Time-dependent occurrence rates derived from such renewal models can be integrated into PTHA logic trees as alternative model branches and parameter sets, which enables the treatment of epistemic uncertainty in source behaviour.The effects of tides have been neglected in most studies, perhaps due to their negligible effects relative to the large amplitudes of tsunami – especially for near-field tsunamis (Sepúlveda & Mosqueda, 2025; Xie et al., 2025). However, for far-field tsunamis such as the 2011 Great East Japan tsunami to the western coasts of United States, Ayca & Lynett (2016) found that tsunami-tide interaction can change event-maximum tsunami current speeds by ± 25% in their study areas, i.e. selected harbours in San Diego Bay. To account for tidal effects, PTHA can incorporate the tidal stage as an aleatoric variable by simulating tsunamis at multiple tidal levels or by statistically sampling tidal distributions across tsunami arrival times (Adams et al., 2015; González et al., 2021). This allows the hazard curves to reflect the compounded variability of tsunami intensity and tidal stage. Nonetheless, the inclusion of tidal variability could be computationally expensive and requires high-resolution tidal data that may be limited in availability (Gao & Niu, 2022).

While tide-related uncertainty is primarily aleatoric, uncertainty due to sea level rise is largely epistemic due to incomplete knowledge of future climate change, ice sheet dynamics and local land subsidence or uplift. Like tides, SLR effectively raises baseline water levels which can amplify tsunami, inundation. Incorporating sea level rise into PTHA requires scenario-based approaches, such as probabilistic projections of future sea levels to assess the potential changes in hazard over long timescales (e.g. Sepúlveda et al., 2021; 2022).

The propagation and inundation mechanisms are almost similar for the different tsunami generation sources; therefore, most tsunami propagation and inundation models are suitable for modelling non-seismic tsunami propagation and inundation. It is, however, important to note that since landslide and volcanic tsunamis usually involve shorter wavelengths, dispersive effects should be considered during the propagation phase (Glimsdal et al., 2013; Baba et al., 2019; Schindelé et al, 2024). Dispersion has also been observed in far-field tsunamis and in nonlinear nearshore dynamics and neglecting it can introduce uncertainty in the waveform evolution, arrival times and hydrodynamic loadings (Watada et al., 2014; Baba et al., 2015). A key limitation in modelling tsunami inundation is the availability of high-resolution coastal topography and bathymetry data, as inaccuracies in these datasets can misrepresent local amplification and inundation patterns. Other sources of uncertainty include frictional resistance, wave breaking and run-up approximations, and numerical discretisation errors, all of which can propagate through probabilistic tsunami hazard analyses and affect predicted hazard curves.

Challenges in fragility modelling

Fragility functions relate structural response – i.e. types and extent of damage – to tsunami intensity. Four main types of fragility functions have been proposed in literature, classified according to the type of damage data used to derive them:

(i) *Empirical-based methods* where structural fragility is quantified through statistical analysis of observed damage data collected from post-event field surveys or physical experiments,

(ii) *Hybrid techniques* which combine damage data collected from remote sensing techniques and inundation characteristics calculated from numerical simulations,

(iii) *Judgement-based methods* which are based on experts' opinions to estimate structural fragility and,

(iv) *Analytical-based methods* which rely on physics-based assumptions of tsunami loading characteristics and structural response to numerically model structural fragility

It should be noted that this classification pertains specifically to fragility functions and is distinct from the typologies used for loss models. Regardless of the type, the key components required to derive fragility functions include the explanatory variable (i.e. tsunami intensity measure or TIM), the response variable (damage) and a statistical linking model (Charvet et al., 2017). Uncertainties in tsunami fragility functions typically arise from each of these components.

Tsunami intensity measures (TIM) provide a quantifiable measure of damage potential in a tsunami (Charvet et al., 2017). Tsunami damage is a result of tsunami loads acting on a structure, including hydrostatic, buoyancy, hydrodynamic and debris impact forces. The intensities of these loads are influenced primarily by inundation depth, flow velocity, duration of inundation, structural geometry and debris. The use of an appropriate TIM is imperative to deriving models with as much accuracy as possible. An optimal TIM should embody characteristics such as efficiency, which is the ability of the TIM to stand on its own as a measure of damage independent of other variables (Bradley et al., 2010; Sousa et al., 2016). Maximum inundation depth is one of the most commonly applied TIMs, especially for empirical fragility functions, due to its ease of observation and validation for tsunami numerical simulation. However, some studies (e.g. Charvet et al., 2014; Park et al., 2017) have pointed out that inundation depth on its own does not sufficiently explain the damage observed and recommended the use of other flow parameters in tsunami fragility modelling.

A handful of studies have attempted to evaluate the appropriateness of TIMs as indicators of structural vulnerability, with each study arriving at different conclusions. For instance, Charvet et al. (2015) considered depth, velocity and debris impact in their fragility models, and depth was found to perform weakly on their own. De Risi et al. (2017a) and Song et al. (2017) found that by including velocity, both fragility and loss models tend to perform better and they recommended the use of bivariate models that include both depth and velocity terms. Macabuag et al. (2016) provided a more comprehensive evaluation of seven tsunami flow parameters for empirical fragility models, and found that indicators of hydrodynamic force (i.e. quasi-steady force and momentum flux) showed more reasonable estimates than other TIMs. Petrone et al. (2017) developed analytical fragility models and found maximum force to be a more efficient TIM than depth and velocity. Attary et al. (2017) similarly developed analytical models and proposed a new TIM, kinematic momentum flux. They found that kinematic momentum flux provided better estimates of damage than depth and velocity. In general, there is little consensus as to which TIM provide the best damage estimates. Additionally, most empirical fragility studies rely on maximum values derived from numerical simulations (e.g., maximum inundation depth, velocity, or force). However, structural damage may occur before these maximum values are reached (Suppasri et al., 2015; Suppasri et al., 2019). Moreover, some studies assume that maximum force can be represented as the product of maximum depth and maximum velocity, though this is physically unrealistic since the two maxima seldom occur simultaneously at the same location.

In fragility modelling, damage states are values assigned to represent the response of a structure to tsunami impacts. Damage classification should as accurately as possible reflect the degree of damage sustained by a structure (Tarbotton et al., 2015). Several damage scales were proposed or adopted in past studies, particularly amongst empirical-based fragility assessments (e.g. Reese et al., 2011;

Suppasri et al., 2013; Paulik et al., 2019). Among these, the classification developed by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) is one of the most widely applied for tsunami damage assessment. However, it has been noted for several shortcomings, including overlapping categories that are not mutually exclusive (Leelawat et al., 2014; Charvet et al., 2015). Charvet et al. (2017) emphasized that the development of damage scales should follow some fundamental rules, which are summarised in Table 2 and advocated for a more systematic and consistent damage scale for future studies. To address inconsistencies across existing scales, some studies attempt to harmonise various damage scales by proposing a reclassified and unified damage scale (e.g. Nanayakkara & Dias, 2016; Mas et al., 2020). More recently, efforts have expanded beyond residential and commercial buildings to include critical infrastructure such as roads, bridges, and port facilities (e.g. Williams et al., 2020a, b; Chua et al., 2021), beyond those for residential and commercial buildings.

Early work in the development of tsunami fragility functions (Koshimura et al., 2009; Suppasri et al., 2013) have adopted the use of ordinary least square methods, assuming either a normal or lognormal distribution. In recent years, a number of studies were carried out to evaluate the suitability of various statistical models in representing tsunami damage to structures (Charvet et al., 2014; Macabuag et al., 2016; Charvet et al., 2017). Parametric (ordinary least square regression, generalised linear model or ordinal logistic regression models), semi-parametric (generalized additive model), and non-parametric (kernel smoother) statistical model types are amongst the most commonly used in literature. These statistical models are extensively reviewed in Rossetto et al. (2014), Lallemant et al. (2015), Macabuag et al. (2016) and Charvet et al. (2017). A general consensus amongst these studies is that fragility functions using ordinary least square methods are unsuitable for use due to limitations such as the inability of these models to consider the probabilities of 0 and 1, and the assumption that the data fitted to these models follow normal or lognormal distributions. On the other hand, while semi-parametric and non-parametric models introduce flexibility to the development of fragility functions by relaxing many of the assumptions used in parametric models, care has to be taken to avoid an overfitting of data to the models (Lallemant et al, 2015; Macabuag et al, 2016).

Statistical variations in the observed damage and tsunami intensity measures (TIMs) introduce uncertainties into the derived fragility functions. Because post-event datasets represent only a sample estimate of the population values, the fragility functions would only capture the expected mean response of all possible structural responses. Statistical variations can be accounted for using methods that quantify uncertainty in the fragility functions. For instance, confidence intervals can be estimated around the median fragility function using resampling techniques such as the bootstrap method (Chua et al., 2021). Alternatively, a more probabilistic approach such as the Bayesian regression approach used in De Risi et al. (2017b) can be applied to propagate uncertainty in the input hazard parameters through the fragility functions, thereby quantifying both data and model uncertainty. The confidence interval in De Risi et al. (2017b) was effectively reduced by 50% by employing this method.

Table 2. Principles of damage scale development (adapted from Charvet et al., 2017)

Principle	Description
Mutual exclusivity	Levels of response (i.e. the damage states) are mutually exclusive
Damage progression	Each new damage state corresponds to an increase in intensity (i.e. an increase in the TIM)

Ease of measurement	Damage states are clearly distinguishable and can be easily applied to populations of the structure
Coverage	Descriptions capture the full range of damage to the building type, including non-structural, local structural and global structural damage

Challenges in vulnerability modelling

Physical damage to structures, as represented by fragility functions, can be translated into economic losses by assigning damage ratios to damage states and deriving vulnerability functions. Uncertainty arises from two key sources. The first is the probabilistic width of each damage state (DS) in the fragility curves. Each damage state (e.g. slight, moderate and extensive) does not occur at a single level of hazard intensity – instead, there is a probability distribution around it. For instance, a building may have a 50% chance of being “extensively” damaged at a certain inundation depth, but it could also be “slightly” or “moderately” damaged. Thus, even for the same tsunami intensity, multiple DS outcomes may be possible. The second is variability in the assigned damage ratio within each DS. For instance, the MLIT loss scale used in several studies (e.g. Goda et al., 2021; Li & Goda, 2023) defines DR in each damage state as 0.0 – 0.1 (minor damage), 0.1 – 0.3 (moderate damage), 0.3 – 0.5 (extensive damage), 0.5 – 1.0 (complete damage) and 1.0 (collapse of structure). The damage ratio corresponding to a given DS is thus not a single deterministic value but a range or distribution, further contributing to uncertainty in the loss estimation. To account for such uncertainties, some studies (e.g. Goda & De Risi, 2017; Goda et al., 2021; Li & Goda, 2023) determine damage ratios probabilistically by random sampling from the distribution of damage ratios associated with each damage state. Applying Monte Carlo simulations to this process derives vulnerability functions that incorporate the combined uncertainty from both the probability of exceeding each damage state (from fragility functions) and the range of damage ratios within each state, providing a more robust estimate of expected losses for buildings with specific attributes.

Damage ratios vary substantially across building types due to differences in structural configuration, material strength, occupancy and function. Because building types differ in construction cost, material strength, and repair complexity, their loss ratios for similar levels of physical damage are not uniform. For example, moderate level of damage for reinforced concrete and wooden buildings may differ in their damage ratios. Similarly, industrial and port facilities may incur disproportionately higher losses due to damage to specialised equipment, non-structural components and contents. Most existing studies adopt generalised loss scales, such as those developed by the Japanese MLIT. The HAZUS-MH Tsunami model (FEMA, 2024) is among the few frameworks that provide building- and occupancy-specific loss ratios, with separate estimates for structural, non-structural, and content damages across multiple construction and use types. However, these ratios are calibrated for U.S. building stock and may not directly represent construction practices in other regions. The lack of tailored damage ratio data constrains the accuracy of economic loss estimations for diverse building inventories.

As highlighted in the preceding sections, tsunamis triggered by seismic sources may produce damage not only from inundation but also from ground-motion effects occurring prior to the arrival of the tsunami. Losses can result primarily from one hazard or from the combined effects of both, for instance, when a structure is weakened by ground shaking and subsequently suffers additional damage from the tsunami impact. Several studies have proposed methods for multi-hazard loss estimation. Goda and De Risi (2018) and Goda et al. (2021), for example, computed damage ratios separately for ground-shaking and tsunamis using hazard-specific fragility functions, and adopted the larger of the two values in the loss estimate, assuming that the dominant hazard determines the total loss. In contrast, Sanderson et al. (2021) and Sanderson and Cox (2023) treat ground shaking and tsunami damage as statistically independent, and determine the final damage state as the union of the two hazards using a Boolean logic rule, as follows:

$$DS_{EQ\cup T} = \max(DS_{EQ}, DS_T)$$

$$DS_{EQ\cup T} = \text{Extensive}, \qquad \text{if } DS_{EQ} = \text{moderate and } DS_T = \text{moderate}$$

$$DS_{EQ\cup T} = \text{Complete}, \qquad \text{if } DS_{EQ} = \text{extensive and } DS_T = \text{extensive}$$

, where DS_{EQ} represents the damage state from shaking, DS_T is the damage state from tsunamis and $DS_{EQ\cup T}$ is the final damage state caused by shaking and tsunamis. This Boolean-logic formulation treats earthquake and tsunami damages as statistically independent events and determines the final damage state based on a predefined combination rule. However, it does not explicitly capture the sequential weakening effect—where structural capacity is first reduced by shaking and subsequently, further degraded by tsunami loading. Thus, while this approach provides a practical means of combining multi-hazard impacts, it may underestimate losses in cases where the cascading interaction between hazards significantly amplifies structural damage.

Quantifying exposure

Tsunamis are relatively infrequent events, particularly at local scales. As a result, tsunami risk assessments are often conducted for extreme scenarios (e.g., 1-in-100-year or rarer events) that fall outside the typical design lifetime of most building stocks. Most tsunami risk assessments assume that the structural capacity of buildings remains static over time. In reality, however, structures evolve dynamically – deteriorating due to corrosion, aging or reduced capacity due to prior hazard exposure, and strengthening through retrofitting or maintenance interventions (Rabonza & Lallemant, 2019). The physical condition of a structure also informs its economic values at the time of damage, meaning that identical hazard intensities could result in different loss outcomes depending on the structure's state of degradation or improvement. In the seismic field, Rabonza & Lallemant (2019) presented a stochastic framework to account for the time- and state-dependent changes in a building's structural capacity, using Markov Chains to represent transitions between discrete states over time. To our knowledge, time- and state-dependent changes in structural vulnerability for tsunami damage have only been explicitly modelled in Del Zoppo et al. (2025). Del Zoppo et al. (2025) use Monte Carlo sampling to generate synthetic building portfolios, where each random realisation considers building characteristics and deterioration parameters including geometric, mechanical and corrosion properties, as well as tsunami load variability. These parameters were treated as aleatory uncertainties. The resulting fragility functions thus capture both the inherent variability and the progressive deterioration of the building stock over time.

A challenge which remains in tsunami loss assessment is characterising the structural fragility of coastal infrastructure. We collectively refer to coastal infrastructure as structures, systems and facilities built along coastlines (Figure 5). Coastal infrastructure usually comprises of large scale, artificial and interdependent systems (Zio et al., 2016). Coastal infrastructure includes but is not limited to (i) harbour facilities, (ii) transportation networks, (iii) electrical supply and communication networks, (iv) water supply, (v) sanitation and wastewater treatment and (iv) port industries. Damage to any one structure could result in the disruption of its functions and the impacts could reverberate throughout the economy and society. As a key example, the damage to electricity transmission facilities and electrical power equipment during the 2011 Tohoku tsunami resulted in power outages in 4.4 million households (Kazama & Noda, 2012).

There has been increasing literature on the quantification of vulnerability to coastal infrastructure. For instance, Maruyama & Itagaki (2017) developed fragility functions for roads using damage data from the 2011 Tohoku tsunami, covering ground-level roads across the Tohoku region. Shoji & Moriyama (2007) developed empirical fragility models for bridges using damage data (87 data points) from Sri Lanka and Sumatra, Indonesia during the 2004 Indian Ocean tsunami, whereas Williams et al. (2020a) developed fragility functions for bridges in the Tohoku region, Japan and Coquimbo, Chile by considering damage from the 2011 Tohoku and the 2015 Illapel tsunami respectively. Imai et al. (2019) developed tsunami fragility functions for fisheries port facilities impacted by the 2011 Tohoku tsunami, while Chua et al. (2021) developed fragility functions for other industries, including cargo handling facilities and manufacturing industries, in the port area from the same event. In our review, we were only able to find existing literature on transportation networks, water, electrical supply and communication networks, and port industries. This is because several aspects limit a systematic approach towards quantitative assessment of them, including:

1. Each facility has varied design and configurations of the components. Unlike buildings, each of these components requires expert knowledge of its functions and resisting capacity. The assignment of damage values or damage states to each of these components would be difficult without expert opinions. Further, given the heterogeneous nature of the components found within each coastal facility, a common damage scale to describe damage to these components is hard to achieve.
2. Coastal infrastructure systems are interrelated and complex. Components may originate from different technological domains, e.g. electrical components and communication technologies. Damage observed to one component or structure may not be a result of a direct impact from tsunami waves. Rather, it may be a secondary effect from a breakdown of a component along the system. While analytical models are more precise in their modelling of structural vulnerability, sophisticated structural models and a deeper understanding of the interaction between tsunami loads and these complex components are needed to accurately model structural response.
3. Tsunami events are infrequent events, which results in a lack of quantitative observational data. Different coastlines imply that different coastal infrastructure are built along the coastlines, therefore in each event, the types of infrastructure which would be impacted would differ. Insufficient information can be collected for a single infrastructure type – a major limitation for empirical-based fragilities.

Direct losses due to structural damage have been the focus of most studies, while non-structural damage and content losses are often neglected in tsunami loss models. It has been estimated that structural damage accounts for only 17% of total building replacement value, whereas non-structural systems and contents represent 50% and 33%, respectively (FEMA, 2024). Likewise, indirect losses such as business interruption and supply chain disruption are also largely missing from tsunami loss models in the literature. Among the few studies that attempt to quantify these effects, Suppasri et al. (2021) assessed the vulnerability of industrial facilities in terms of production capacity loss as a function of tsunami intensity and recovery period. Similarly, Chua et al. (2024) quantified supply chain disruption in port facilities by relating cargo volume losses to the duration of operational downtime. Indirect losses often account for a substantial portion of disaster impacts. Therefore, incorporating them into future tsunami risk assessments would allow for a more holistic evaluation of societal and economic consequences.

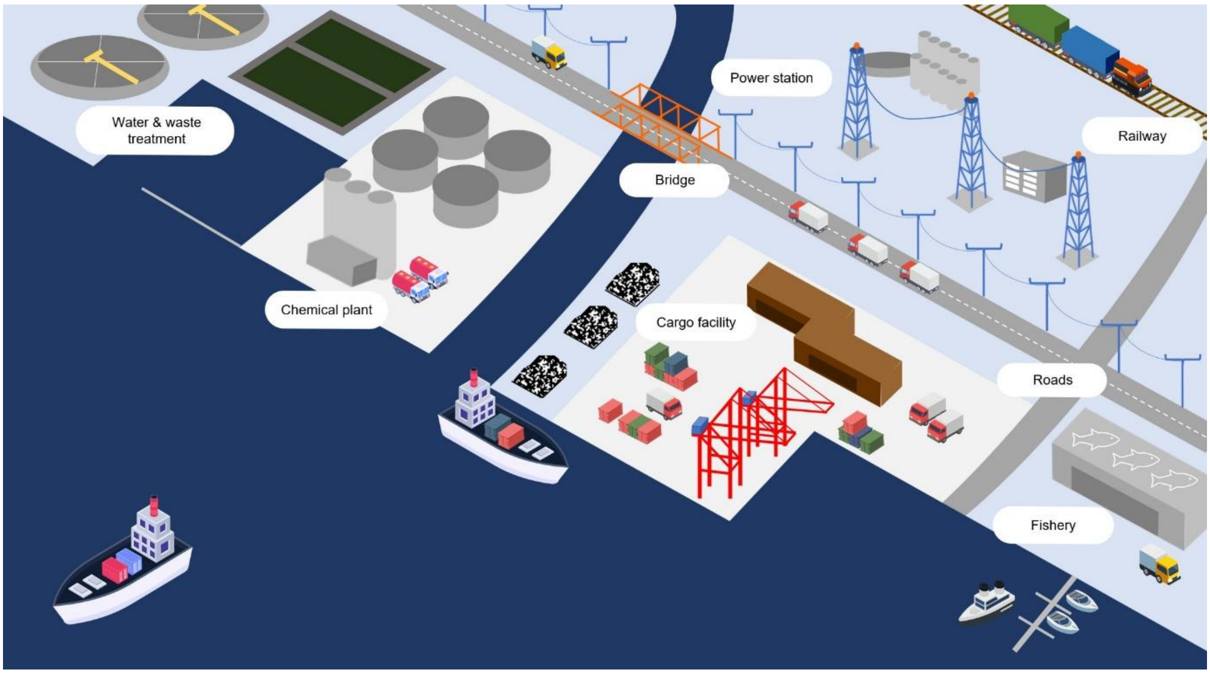


Figure 5. Varied types of non-building infrastructure (e.g. crane and silos), critical infrastructure (e.g. railway and bridge) and facilities (e.g. chemical plant; water treatment plant) built along coastlines.

Conclusions

This chapter provides a systematic review of tsunami loss models (22 existing studies) and proposes a taxonomy for tsunami vulnerability models (Appendix). Because formal tsunami insurance markets are largely absent, historical claims data offer only a limited basis for developing catastrophe loss models used in insurance and risk industries. To bridge this gap, engineering-based approaches have gained traction over the past decade, linking physical damage to economic loss through hazard, exposure, and vulnerability components.

While tsunami hazard modelling is relatively mature—particularly for earthquake-generated tsunamis—significant gaps remain in integrating these components into robust economic loss estimates. Existing loss models overwhelmingly focus on building damage from seismic tsunamis, leaving non-seismic sources, non-building structures, and indirect or cascading losses insufficiently represented. The scarcity of validated tsunami loss data, combined with the heterogeneous nature of coastal infrastructure, further complicates the reliability and transferability of current models.

It is evident throughout this chapter that the development of tsunami loss models is very much in its infancy, with most studies still based on single-peril assumptions. However, different tsunami generation mechanisms may overlap, cascade or interact with other coastal hazards such as tides and sea level rise. Critically, current models often treat hazard occurrence and asset vulnerability as static, when in fact, both evolve over time. Time-dependent processes e.g. earthquake stress accumulation and slope weakening, as well as changes in exposure due to ageing infrastructure and land-use shifts, alter loss potential in which static models may fail to capture.

The challenges highlighted in this review provide direction for advancing the field. Future research should (i) broaden model applicability to include non-seismic tsunami sources, (ii) incorporate indirect and cascading losses, particularly for critical coastal infrastructure and industrial facilities, and (iii) strengthen probabilistic, multi-hazard and time-dependent frameworks that explicitly quantify uncertainties across all stages of the modelling process.Continued development of improved vulnerability quantification methodologies will enhance the accuracy of loss projections and support both risk-informed planning and effective mitigation strategies for both risk managers and the insurance industry.

References

Adams, L. M., LeVeque, R. J., & González, F. I. (2015). The pattern method for incorporating tidal uncertainty into probabilistic tsunami hazard assessment (PTHA). *Natural Hazards*, *76*(1), 19-39.

AECOM, (Ed.). (2024). *Spon's Architects' and Builders' Price Book 2025* (150th ed.). CRC Press. https://doi.org/10.1201/9781003504696

Al Farizi, M. D., Suppasri, A., Nagasawa, T., Mabuchi, Y., Nogami, T., Masuda, H., ... & Imamura, F. (2025). Submarine landslide induced tsunami modeling using 3D slope stability analysis Method: The 2024 Noto Peninsula earthquake and tsunami in Toyama Bay, Japan. *Ocean Engineering*, *340*, 122240.

Alhamid, A. K., Akiyama, M., Koshimura, S., Frangopol, D. M., & So, H. (2024). Tsunami insurance portfolio optimization for coastal residential buildings under non-stationary sea level rise effects based on sample average approximation. *Stochastic Environmental Research and Risk Assessment*, *38*(3), 817-841.

Aon Benfield (2023) *Weather, Climate and Catastrophe Insight – 2023 Annual Report.* Retrieved May 16, 2025 from https://www.aon.com/getmedia/f34ec133-3175-406c-9e0b-25cea768c5cf/20230125-weather-climate-catastrophe-insight.pdf

Annaka, T., Satake, K., Sakakiyama, T., Yanagisawa, K., & Shuto, N. (2007). Logic-tree approach for probabilistic tsunami hazard analysis and its applications to the Japanese coasts. *Pure and Applied Geophysics*, *164*(2), 577-592.

Attary, N., van de Lindt, J. W., Unnikrishnan, V. U., Barbosa, A. R., & Cox, D. T. (2017). Methodology for development of physics-based tsunami fragilities. *Journal of Structural Engineering*, 143(5), 04016223.

Ayca, A., & Lynett, P. J. (2016). Effect of tides and source location on nearshore tsunami-induced currents. *Journal of Geophysical Research: Oceans*, *121*(12), 8807-8820.

Baba, T., Takahashi, N., Kaneda, Y., Ando, K., Matsuoka, D., & Kato, T. (2015). Parallel implementation of dispersive tsunami wave modeling with a nesting algorithm for the 2011 Tohoku tsunami. *Pure and Applied Geophysics*, *172*(12), 3455-3472.

Baba, T., Gon, Y., Imai, K., Yamashita, K., Matsuno, T., Hayashi, M., & Ichihara, H. (2019). Modeling of a dispersive tsunami caused by a submarine landslide based on detailed bathymetry of the continental slope in the Nankai trough, southwest Japan. *Tectonophysics*, *768*, 228182.

Bai, J. W., Hueste, M. B. D., & Gardoni, P. (2009). Probabilistic assessment of structural damage due to earthquakes for buildings in Mid-America. *Journal of structural engineering*, *135*(10), 1155-1163.

Bebbington, M. S., & Lai, C. D. (1996). On nonhomogeneous models for volcanic eruptions. *Mathematical Geology*, *28*(5), 585-600.

Behrens J, Løvholt F, Jalayer F, Lorito S, Salgado-Gálvez MA, Sørensen M, Abadie S, Aguirre-Ayerbe I, Aniel-Quiroga I, Babeyko A, Baiguera M, Basili R, Belliazzi S, Grezio A, Johnson K, Murphy S, Paris R, Rafliana I, De Risi R, Rossetto T, Selva J, Taroni M, Del Zoppo M, Armigliato A, Bureš V, Cech P, Cecioni C, Christodoulides P, Davies G, Dias F, Bayraktar HB, González M, Gritsevich M, Guillas S, Harbitz CB, Kânoğlu U, Macías J, Papadopoulos GA, Polet J, Romano F, Salamon A, Scala A, Stepinac M, Tappin DR, Thio HK, Tonini R, Triantafyllou I, Ulrich T, Varini E, Volpe M and Vyhmeister E (2021) Probabilistic Tsunami Hazard and Risk Analysis: A Review of Research Gaps. *Frontiers in Earth Science*, 9, 628772.

Bradley, B. A., Dhakal, R. P., MacRae, G. A., & Cubrinovski, M. (2010). Prediction of spatially distributed seismic demands in specific structures: Ground motion and structural response. *Earthquake engineering & structural dynamics*, *39*(5), 501-520.

Cummins, J. D., Lalonde, D., & Phillips, R. D. (2004). The basis risk of catastrophic-loss index securities. *Journal of Financial Economics*, *71*(1), 77-111.

Charvet, I., Ioannou, I., Rossetto, T., Suppasri, A., & Imamura, F. (2014). Empirical fragility assessment of buildings affected by the 2011 Great East Japan tsunami using improved statistical models. Natural Hazards, 73(2), 951-973.

Charvet, I., Suppasri, A., Kimura, H., Sugawara, D., & Imamura, F. (2015). A multivariate generalized linear tsunami fragility model for Kesennuma City based on maximum flow depths, velocities and debris impact, with evaluation of predictive accuracy. Natural Hazards, 79(3), 2073-2099.

Charvet, I., Macabuag, J., & Rossetto, T. (2017). Estimating tsunami-induced building damage through fragility functions: critical review and research needs. *Frontiers in Built Environment*, *3*, 36.

Chua, C. T., Switzer, A. D., Suppasri, A., Li, L., Pakoksung, K., Lallemant, D., Jenkins, S.F., Charvet, I., Chua, T., Cheong, A. & Winspear, N. (2021). Tsunami damage to ports: cataloguing damage to create fragility functions from the 2011 Tohoku event. *Natural Hazards and Earth System Sciences*, *21*(6), 1887-1908.

Chua, C. T., Otake, T., Li, T., Cheng, A. C., Qiu, Q., Li, L., ... & Switzer, A. D. (2024). An approach to assessing tsunami risk to the global port network under rising sea levels. *npj Natural Hazards*, *1*(1), 38.

Cousins, W. J., Power, W. L., Destegul, U. Z., King, A. B., Trevethick, R., Blong, R., Weir, B. & Miliauskas, B. (2009, April). Earthquake and tsunami losses from major earthquakes affecting the Wellington Region. In *Proceedings, Conference of the New Zealand Society for Earthquake Engineering* (pp. 3-5).

Dall'Osso, F., Gonella, M., Gabbianelli, G., Withycombe, G., & Dominey-Howes, D. (2009a). A revised (PTVA) model for assessing the vulnerability of buildings to tsunami damage. *Natural Hazards and Earth System Sciences*, *9*(5), 1557-1565.

Dall'Osso, F., Gonella, M., Gabbianelli, G., Withycombe, G., & Dominey-Howes, D. (2009b). Assessing the vulnerability of buildings to tsunami in Sydney. *Natural Hazards and Earth System Sciences*, *9*(6), 2015-2026.

Dall’Osso, F., Dominey-Howes, D., Tarbotton, C., Summerhayes, S., & Withycombe, G. (2016). Revision and improvement of the PTVA-3 model for assessing tsunami building vulnerability using “international expert judgment”: introducing the PTVA-4 model. *Natural Hazards*, *83*(2), 1229-1256.

Davies, G., Weber, R., Wilson, K., & Cummins, P. (2022). From offshore to onshore probabilistic tsunami hazard assessment via efficient Monte Carlo sampling. *Geophysical journal international*, *230*(3), 1630-1651.

Del Zoppo, M., Di Ludovico, M., Lignola, G. P., & Prota, A. (2025). Time-dependent tsunami fragility analysis for reinforced concrete building stock. *Engineering Structures*, 330, 119931.

De Risi, R., Goda, K., Yasuda, T., & Mori, N. (2017a). Is flow velocity important in tsunami empirical fragility modeling?. *Earth-science reviews*, *166*, 64-82.

De Risi, R., Goda, K., Mori, N., & Yasuda, T. (2017b). Bayesian tsunami fragility modeling considering input data uncertainty. *Stochastic environmental research and risk assessment*, *31*(5), 1253-1269.

De Risi, R., Goda, K., Nistor, I., & Gusman, A. (2024). Probabilistic tsunami hazard and risk assessments. In *Probabilistic Tsunami Hazard and Risk Analysis* (pp. 157-190). Elsevier.

Dominey-Howes, D., & Papathoma, M. (2007). Validating a tsunami vulnerability assessment model (the PTVA model) using field data from the 2004 Indian Ocean tsunami. *Natural Hazards*, *40*(1), 113-136.

Dominey-Howes, D., Dunbar, P., Varner, J., & Papathoma-Köhle, M. (2010). Estimating probable maximum loss from a Cascadia tsunami. *Natural hazards*, *53*(1), 43-61.

Du, P., Li, L., Kopf, A., Wang, D., Chen, K., Shi, H., ... & Zhang, P. (2025). Earthquake-induced submarine landslides (EQISLs) and a comparison with their terrestrial counterparts: insights from a new database. *Earth-Science Reviews*, *261*, 105021.

Federal Emergency Management Agency. (2023). *Understanding Tsunamis and the NFIP Fact Sheet*. Retrieved May 16, 2025 from https://www.fema.gov/fact-sheet/understanding-tsunamis

Federal Emergency Management Agency. (2017). *HAZUS tsunami model technical guidance*.

Federal Emergency Management Agency. (2024). *HAZUS tsunami model technical manual. HAZUS 6.1.*

Fukutani, Y., Moriguchi, S., Terada, K., & Otake, Y. (2021). Time-dependent probabilistic tsunami inundation assessment using mode decomposition to assess uncertainty for an earthquake scenario. *Journal of Geophysical Research: Oceans*, *126*(7), e2021JC017250.

Galasso, Carmine, Maria Pregnolato, and Fulvio Parisi. "A model taxonomy for flood fragility and vulnerability assessment of buildings." *International Journal of Disaster Risk Reduction* 53 (2021): 101985.

Gao, X., & Niu, X. (2022). Influence of tidal level on quantifying the probability of nearshore tsunami hazard. *Ocean Engineering*, *266*, 112986.

Garcia-Aristizabal, A., Marzocchi, W., & Fujita, E. (2012). A Brownian model for recurrent volcanic eruptions: an application to Miyakejima volcano (Japan). *Bulletin of volcanology*, *74*(2), 545-558.

Glimsdal, S., Pedersen, G. K., Harbitz, C. B., & Løvholt, F. (2013). Dispersion of tsunamis: does it really matter?. *Natural hazards and earth system sciences*, *13*(6), 1507-1526.

Goda, K., & Abilova, K. (2016). Tsunami hazard warning and risk prediction based on inaccurate earthquake source parameters. Natural Hazards and Earth System Sciences, 16(2), 577-593.

Goda, K., & De Risi, R. (2017). Probabilistic tsunami loss estimation methodology: stochastic earthquake scenario approach. *Earthquake spectra*, *33*(4), 1301-1323.

Goda, K., & De Risi, R. (2018). Multi-hazard loss estimation for shaking and tsunami using stochastic rupture sources. *International journal of disaster risk reduction*, *28*, 539-554.

Goda, K. (2019). Time-dependent probabilistic tsunami hazard analysis using stochastic rupture sources. *Stochastic Environmental Research and Risk Assessment*, *33*(2), 341-358.

Goda, K., Mori, N., & Yasuda, T. (2019). Rapid tsunami loss estimation using regional inundation hazard metrics derived from stochastic tsunami simulation. *International Journal of Disaster Risk Reduction*, *40*, 101152.

Goda, K. (2020). Multi-hazard portfolio loss estimation for time-dependent shaking and tsunami hazards. *Frontiers in Earth Science*, *8*, 592444.

Goda, K., De Risi, R., De Luca, F., Muhammad, A., Yasuda, T., & Mori, N. (2021). Multi-hazard earthquake-tsunami loss estimation of Kuroshio Town, Kochi Prefecture, Japan considering the Nankai-Tonankai megathrust rupture scenarios. *International Journal of Disaster Risk Reduction*, *54*, 102050.

Goda, K., & De Risi, R. (2024). Time-dependent probabilistic tsunami risk assessment: application to Tofino, British Columbia, Canada, subjected to Cascadia subduction earthquakes. *npj Natural Hazards*, *1*(1), 7.

González, M., Álvarez-Gómez, J. A., Aniel-Quiroga, Í., Otero, L., Olabarrieta, M., Omira, R., ... & Aguirre-Ayerbe, I. (2021). Probabilistic tsunami hazard assessment in meso and macro tidal areas. Application to the Cádiz Bay, Spain. *Frontiers in Earth Science*, *9*, 591383.

Grezio, A., Babeyko, A., Baptista, M. A., Behrens, J., Costa, A., Davies, G., ... & Thio, H. K. (2017). Probabilistic tsunami hazard analysis: multiple sources and global applications. Reviews of Geophysics, 55(4), 1158-1198.

Hamburger, R., Zsarnóczay, A., Otu Tackie-Otoo, N., Kijewski-Correa, T., Davidson, R. A., & Spence, S. M. (2025). Unifying the Current State of the Art in Hurricane Wind Risk Simulations: A Systematic Review. *Journal of Structural Engineering*, *151*(8), 03125001.

Henderson, L. (2018, September 11). *De-risking cities & countries: Protection gap*. Aon. https://www.aon.com/reinsurance/gimo/20180911-gimo-protection-gap

Imai, K., Inazumi, T., Emoto, K., Horie, T., Suzuki, A., Kudo, K., ... & Sasaki, T. (2019). Tsunami vulnerability criteria for fishery port facilities in Japan. *Geosciences*, 9(10), 410.

Ismail, H., Abd Wahab, A. K., Mohd Amin, M. F., Mohd Yunus, M. Z., Jaffar Sidek, F., & Esfandier J, B. (2012). A 3-tier tsunami vulnerability assessment technique for the north-west coast of Peninsular Malaysia. *Natural hazards*, 63(2), 549-573.

Jones, J. N., Boulton, S. J., Bennett, G. L., Stokes, M., & Whitworth, M. R. (2021). Temporal variations in landslide distributions following extreme events: Implications for landslide susceptibility modeling. *Journal of Geophysical Research: Earth Surface*, *126*(7), e2021JF006067.

Kajitani, Y., Chang, S. E., & Tatano, H. (2013). Economic impacts of the 2011 Tohoku-Oki earthquake and tsunami. *Earthquake Spectra*, *29*(1_suppl), 457-478.

Kazama, M., & Noda, T. (2012). Damage statistics (Summary of the 2011 off the Pacific Coast of Tohoku Earthquake damage). *Soils and Foundations*, 52(5), 780-792.

King, R. O. (2006). *Tsunamis and earthquakes: is federal disaster insurance in our future?*. Library of Congress. Congressional Research Service.

Koshimura, S., Namegaya, Y., & Yanagisawa, H. (2009). Tsunami fragility: A new measure to identify tsunami damage. *Journal of Disaster Research*, *4*(6), 479-488.

Lallemant, D., Kiremidjian, A., & Burton, H. (2015). Statistical procedures for developing earthquake damage fragility curves. *Earthquake Engineering & Structural Dynamics*, *44*(9), 1373-1389.

Leelawat, N., Suppasri, A., Charvet, I., & Imamura, F. (2014). Building damage from the 2011 Great East Japan tsunami: quantitative assessment of influential factors. *Natural Hazards*, 73(2), 449-471.

Leone, F., Lavigne, F., Paris, R., Denain, J. C., & Vinet, F. (2011). A spatial analysis of the December 26th, 2004 tsunami-induced damages: Lessons learned for a better risk assessment integrating buildings vulnerability. Applied Geography, 31(1), 363-375.

Li, L., Switzer, A. D., Chan, C. H., Wang, Y., Weiss, R., & Qiu, Q. (2016). How heterogeneous coseismic slip affects regional probabilistic tsunami hazard assessment: A case study in the South China Sea. *Journal of Geophysical Research: Solid Earth*, *121*(8), 6250-6272.

Li, Y., & Goda, K. (2023). Random forest-based multi-hazard loss estimation using hypothetical data at seismic and tsunami monitoring networks. *Geomatics, Natural Hazards and Risk*, *14*(1), 2275538.

Lorito, S., Selva, J., Basili, R., Romano, F., Tiberti, M. M., & Piatanesi, A. (2015). Probabilistic hazard for seismically induced tsunamis: accuracy and feasibility of inundation maps. *Geophysical Journal International, 200*(1), 574-588.

Løvholt, F., Pedersen, G., Harbitz, C. B., Glimsdal, S., & Kim, J. (2015). On the characteristics of landslide tsunamis. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *373*(2053), 20140376.

Løvholt, F., Glimsdal, S., & Harbitz, C. B. (2020). On the landslide tsunami uncertainty and hazard. Landslides, 17(10), 2301-2315.

Macabuag, J., Rossetto, T., Ioannou, I., Suppasri, A., Sugawara, D., Adriano, B., ... & Koshimura, S. (2016). A proposed methodology for deriving tsunami fragility functions for buildings using optimum intensity measures. *Natural Hazards*, 84(2), 1257-1285.

Madani, S., Khaleghi, S., & Jannat, M. R. A. (2017). Assessing building vulnerability to tsunami using the PTVA-3 model: A case study of Chabahar Bay, Iran. *Natural Hazards*, *85*(1), 349-359.

Marfai, M. A., Khakim, N., Fatchurohman, H., Cahyadi, A., Wibowo, Y. A., & Rosaji, F. S. C. (2019). Tsunami hazard mapping and loss estimation using geographic information system in Drini Beach, Gunungkidul Coastal Area, Yogyakarta, Indonesia. In *E3S Web of Conferences* (Vol. 76, p. 03010). EDP Sciences.

Mas, E., Paulik, R., Pakoksung, K., Adriano, B., Moya, L., Suppasri, A., ... & Koshimura, S. (2020). Characteristics of Tsunami Fragility Functions Developed Using Different Sources of Damage Data from the 2018 Sulawesi Earthquake and Tsunami. *Pure and Applied Geophysics*, 177(6), 2437-2455.

Matthews, M. V., Ellsworth, W. L., & Reasenberg, P. A. (2002). A Brownian model for recurrent earthquakes. *Bulletin of the Seismological Society of America*, *92*(6), 2233-2250.

Miki, Y., Chua, C. T., Suppasri, A., Cheng, A. C., Iwasaki, T., Shinozuka, Y., Ogawa, T., & Imamura, F. (2025). A proposed approach towards minimizing basis risk in tsunami parametric insurance scheme. *npj Natural Hazards*, *2*(1), 67.

Ministry of Land Infrastructure and Transportation (MLIT). *Survey of Tsunami Damage Condition*, 2014. 〈http://www.mlit.go.jp/toshi/toshi-hukkou-arkaibu.html〉

Miyashita, T., Mori, N., & Goda, K. (2020). Uncertainty of probabilistic tsunami hazard assessment of Zihuatanejo (Mexico) due to the representation of tsunami variability. *Coastal Engineering Journal*, *62*(3), 413-428.

Mori, N. & Miyashita, T. (2024). Modeling and uncertainty in probabilistic tsunami hazard and risk assessment. In *Probabilistic Tsunami Hazard and Risk Analysis* (pp. 465-478). Elsevier.

Maruyama, Y., & Itagaki, O. (2017). Development of tsunami fragility functions for ground-level roads. *Journal of Disaster Research*, 12(1), 131-136.

Nanayakkara, K. I. U., & Dias, W. P. S. (2016). Fragility curves for structures under tsunami loading. *Natural Hazards*, 80(1), 471-486.

Pan, X., Li, L., Nguyễn, H. P., Wang, D., & Switzer, A. D. (2022). Submarine landslides in the west continental slope of the South China Sea and their tsunamigenic potential. *Frontiers in Earth Science*, *10*, 843173.

Papathoma, M., Dominey-Howes, D., Zong, Y., & Smith, D. (2003). Assessing tsunami vulnerability, an example from Herakleio, Crete. *Natural Hazards and Earth System Sciences*, *3*(5), 377-389.

Papathoma, M., & Dominey-Howes, D. (2003). Tsunami vulnerability assessment and its implications for coastal hazard analysis and disaster management planning, Gulf of Corinth, Greece. *Natural Hazards and Earth System Sciences*, *3*(6), 733-747.

Paris, Raphaël. "Source mechanisms of volcanic tsunamis." *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 373.2053 (2015): 20140380.

Park, H., Cox, D. T., & Barbosa, A. R. (2017). Comparison of inundation depth and momentum flux based fragilities for probabilistic tsunami damage assessment and uncertainty analysis. *Coastal Engineering*, 122, 10-26.

Paulik, R., Gusman, A., Williams, J. H., Pratama, G. M., Lin, S. L., Prawirabhakti, A., ... & Suwarni, N. W. I. (2019). Tsunami hazard and built environment damage observations from Palu City after the September 28 2018 Sulawesi earthquake and tsunami. *Pure and Applied Geophysics*, 176(8), 3305-3321.

Petrone, C., Rossetto, T., & Goda, K. (2017). Fragility assessment of a RC structure under tsunami actions via nonlinear static and dynamic analyses. *Engineering Structures*, *136*, 36-53.

Pita, G., Pinelli, J. P., Gurley, K., & Mitrani-Reiser, J. (2015). State of the art of hurricane vulnerability estimation methods: A review. *Natural Hazards Review*, 16(2), 04014022.

Porter, K. (2021). A Beginner's Guide to Fragility, Vulnerability, and Risk. University of Colorado Boulder, 139 pp., https://www.sparisk.com/pubs/Porter-beginnersguide.pdf

Rabonza, M. L. & Lallemant, D. (2019) Accounting for time and state-dependent vulnerability of structural systems. In *13th International Conference on Applications of Statistics and Probability in Civil Engineering,* 2298–2305.

Reese, S., Cousins, W. J., Power, W. L., Palmer, N. G., Tejakusuma, I. G., & Nugrahadi, S. (2007). Tsunami vulnerability of buildings and people in South Java–field observations after the July 2006 Java tsunami. *Natural Hazards and Earth System Sciences*, *7*(5), 573-589.

Reese, S., Bradley, B. A., Bind, J., Smart, G., Power, W., & Sturman, J. (2011). Empirical building fragilities from observed damage in the 2009 South Pacific tsunami. *Earth-Science Reviews*, 107(1-2), 156-173.

Reid, J. A., & Mooney, W. D. (2023). Tsunami occurrence 1900–2020: A global review, with examples from Indonesia. *Pure and Applied Geophysics*, *180*(5), 1549-1571.

Rodríguez-Peces, M. J., Román-Herrera, J. C., Peláez, J. A., Delgado, J., Tsigé, M., Missori, C., ... & Garrido, J. (2020). Obtaining suitable logic-tree weights for probabilistic earthquake-induced landslide hazard analyses. *Engineering Geology*, *275*, 105743.

Roger, J. H., Bull, S., Watson, S. J., Mueller, C., Hillman, J. I., Wolter, A., ... & Davidson, S. (2024). A review of approaches for submarine landslide-tsunami hazard identification and assessment. *Marine and Petroleum Geology*, *162*, 106729.

Sanderson, D., Kameshwar, S., Rosenheim, N., & Cox, D. (2021). Deaggregation of multi-hazard damages, losses, risks, and connectivity: An application to the joint seismic-tsunami hazard at Seaside, Oregon. *Natural Hazards*, *109*(2), 1821-1847.

Sanderson, Dylan, and Daniel Cox. "Comparison of national and local building inventories for damage and loss modeling of seismic and tsunami hazards: From parcel-to city-scale." *International journal of disaster risk reduction* 93 (2023): 103755.

Sandri, L., Garcia, A., Costa, A., Guerrero Lopez, A., & Cordoba, G. (2021). Stochastic modeling of explosive eruptive events at Galeras Volcano, Colombia. *Frontiers in Earth Science*, *8*, 583703.

Schindelé, F., Kong, L., Lane, E. M., Paris, R., Ripepe, M., Titov, V., & Bailey, R. (2024). A review of tsunamis generated by volcanoes (TGV) source mechanism, modelling, monitoring and warning systems. *Pure and Applied Geophysics*, *181*(6), 1745-1792.

Selva, J., Tonini, R., Molinari, I., Tiberti, M. M., Romano, F., Grezio, A., ... & Lorito, S. (2016). Quantification of source uncertainties in seismic probabilistic tsunami hazard analysis (SPTHA). *Geophysical Journal International*, *205*(3), 1780-1803.

Selva, J., Amato, A., Armigliato, A., Basili, R., Bernardi, F., Brizuela, B., ... & Zaniboni, F. (2021). Tsunami risk management for crustal earthquakes and non-seismic sources in Italy. *La Rivista del Nuovo Cimento*, *44*(2), 69-144.

Sepúlveda, I., Haase, J. S., Liu, P. L. F., Grigoriu, M., & Winckler, P. (2021). Non-stationary probabilistic tsunami hazard assessments incorporating climate-change-driven sea level rise. *Earth's Future*, *9*(6), e2021EF002007.

Sepúlveda, I., Liu, P. L. F., Grigoriu, M., Haase, J. S., & Winckler, P. (2022). Non-stationary probabilistic tsunami hazard assessments compounding tides and sea level rise. *Earth's Future, 10(11)*, e2022EF002965.

Sepúlveda, I., & Mosqueda, A. (2025). Climate-driven sea level rise exacerbates Alaskan and Cascadian tsunami hazards in Southern California: Implications to design parameters. *Earth's Future*, 13(3), e2024EF005435.

Shoji, G., & Moriyama, T. (2007). Evaluation of the structural fragility of a bridge structure subjected to a tsunami wave load. *Journal of Natural Disaster Science*, 29(2), 73-81.

Song, J., De Risi, R., & Goda, K. (2017). Influence of flow velocity on tsunami loss estimation. *Geosciences*, *7*(4), 114.

Sousa, L., Silva, V., Marques, M., & Crowley, H. (2016). On the treatment of uncertainties in the development of fragility functions for earthquake loss estimation of building portfolios. *Earthquake Engineering & Structural Dynamics*, *45*(12), 1955-1976.

Suppasri, A., Imamura, F., & Koshimura, S. (2010). Effects of the rupture velocity of fault motion, ocean current and initial sea level on the transoceanic propagation of tsunami. *Coastal Engineering Journal*, *52*(2), 107-132.

Suppasri, A., Mas, E., Charvet, I., Gunasekera, R., Imai, K., Fukutani, Y., ... & Imamura, F. (2013). Building damage characteristics based on surveyed data and fragility curves of the 2011 Great East Japan tsunami. *Natural Hazards*, 66(2), 319-341.

Suppasri, A., Charvet, I., Imai, K., & Imamura, F. (2015). Fragility curves based on data from the 2011 Tohoku-oki tsunami in Ishinomaki city, with discussion of parameters influencing building damage. *Earthquake Spectra*, *31*(2), 841-868.

Suppasri, A., Pakoksung, K., Charvet, I., Chua, C. T., Takahashi, N., Ornthammarath, T., ... & Imamura, F. (2019). Load-resistance analysis: an alternative approach to tsunami damage assessment applied to the 2011 Great East Japan tsunami. *Natural Hazards and Earth System Sciences*, *19*(8), 1807-1822.

Suppasri, A., Nishida, T., Pakoksung, K., Cheng, A. C., Chua, C. T., Iwasaki, T., Pescaroli, G. & Imamura, F. (2022). Quantifying tsunami impact on industrial facilities and production capacity in ports: An application to Sendai Port, Japan. *International Journal of Disaster Risk Reduction*, 78, 103141.

Tada, N. (2014) *A study on the advancement of flood damage estimation methods*. Ph.D. thesis, The University of Tokyo, Japan.

Tanaka H, Yasuda T, Yamanaka R, Fukutani Y, Taniguchi J, Ushiki K, Kitano T (2022) Assessment of coastal levee height using probabilistic tsunami hazard assessment and economic verification. Coastal Engineering Journal of JSCE 78(2): I_283–I_288

Tarbotton, C., Dall'Osso, F., Dominey-Howes, D., & Goff, J. (2015). The use of empirical vulnerability functions to assess the response of buildings to tsunami impact: Comparative review and summary of best practice. *Earth-Science Reviews*, *142*, 120-134.

Telford, J., & Cosgrave, J. (2006). *Joint evaluation of the international response to the Indian Ocean tsunami: Synthesis report*. Tsunami Evaluation Coalition (TEC).

Xie, X., Li, L., Ren, Z., & Chen, C. (2025). The role of narrow fringing reefs in tsunami mitigation: a numerical modelling study along the Sanya coastline. *Engineering Applications of Computational Fluid Mechanics*, *19*(1), 2583301.

Yavari-Ramshe, S., & Ataie-Ashtiani, B. (2016). Numerical modeling of subaerial and submarine landslide-generated tsunami waves—recent advances and future challenges. *Landslides*, *13*(6), 1325-1368.

Wang, Y., & Rathje, E. M. (2015). Probabilistic seismic landslide hazard maps including epistemic uncertainty. *Engineering Geology*, *196*, 313-324.

Watada, S., Kusumoto, S., & Satake, K. (2014). Traveltime delay and initial phase reversal of distant tsunamis coupled with the self-gravitating elastic Earth. *Journal of Geophysical Research: Solid Earth*, *119*(5), 4287-4310.

Williams, J. H., Wilson, T. M., Horspool, N., Paulik, R., Wotherspoon, L., Lane, E. M., & Hughes, M. W. (2020a). Assessing transportation vulnerability to tsunamis: utilising post-event field data from the 2011 Tōhoku tsunami, Japan, and the 2015 Illapel tsunami, Chile. *Natural Hazards and Earth System Sciences*, 20, 451–470.

Williams, J. H., Paulik, R., Wilson, T. M., Wotherspoon, L., Rusdin, A., & Pratama, G. M. (2020b). Tsunami fragility functions for road and utility pole assets using field survey and remotely sensed data from the 2018 Sulawesi tsunami, Palu, Indonesia. *Pure and Applied Geophysics*, 177(8), 3545-3562.

Zio, E. (2016). Challenges in the vulnerability and risk analysis of critical infrastructures. *Reliability Engineering & System Safety*, *152*, 137-150.

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Appendix

Existing studies that developed or applied tsunami loss models.

Reference	**Structure type**	**Case-study event(s)**	**Loss model (Origin event)**	**Study area**	**Fragility model type [#1]**	**Loss variable [#2]**	**Loss scale**	**Vulnerability model type [#3]**	**IM [#4]**	**Application scale**
Alhamid et al. (2024)	Building (residential)	Nankai Trough Earthquake	2011 Tohoku	Kochi city, Konan city and Susaki city, Kochi, Japan	E	DR	MLIT	E	d	Building
Cousins et al. (2009)	Building (timber and concrete)	Wellington Fault, Wairapa Fault, Booboo Fault earthquakes	2006 Java	Wellington, New Zealand	J	DR	NA	J	d	Building
Dominey-Howes and Papathoma-Köhle (2007)	Building	2004 Indian Ocean Tsunami	NA	Heraklion, Crete, Greece	NA	VS	NA	J	d	Building
Dominey-Howes et al. (2010)	Building (residential and commercial)	Cascadia Subduction Zone Earthquake	NA	Oregon, USA	NA	VS	NA	J	d	Building
Goda and Abilova (2016)	Building (houses and offices)	Japan Trench Earthquake	2011 Tohoku	Miyagi, Japan	E	DR	MLIT	E	d	Building
Goda and De Risi (2017)	Building (houses and offices)	Japan Trench Earthquake	2011 Tohoku	Sendai Plain, Japan	E	DR	MLIT	E	d	Building
Goda and De Risi (2018)	Building (wooden)	Japan Trench Earthquake	2011 Tohoku / 1995 Kobe	Ishinomaki, Iwanuma, Onagawa and Shizugawa, Miyagi, Japan	E	DR	MLIT / Damage scale for earthquake insurance in Japan	E	d / PGV	Building

Goda et al. (2019)	Building	Japan Trench Earthquake	2011 Tohoku	Ishinomaki, Iwanuma, Onagawa and Shizugawa, Miyagi, Japan	E	DR	MLIT	E	*d*	Building
Goda (2020)	Building (wooden)	Japan Trench Earthquake	2011 Tohoku / 1995 Kobe	Iwanuma and Onagawa, Miyagi, Japan	E	DR	MLIT / Damage scale for earthquake insurance in Japan	E	*d* / *PGV*	Building
Goda et al. (2021)	Building (wooden)	Nankai Trough Earthquake	2011 Tohoku / 1995 Kobe	Kuroshio town, Kochi, Japan	E	DR	MLIT / Damage scale for earthquake insurance in Japan	E	*d* / *PGV*	Building
Goda and De Risi (2024)	Building	Cascadia Subduction Zone Earthquake	2011 Tohoku	Tofino, British Columbia, Canada	E	DR	MLIT	E	*d*	Building
Li and Goda (2023)	Building (wooden)	Japan Trench Earthquake	2011 Tohoku / 1995 Kobe	Onagawa and Iwanuma, Miyagi, Japan	E	DR	MLIT	E	*d* / *PGV*	Building
Marfai et al. (2019)	Agricultural land, Trading center, Fish pond, Bareland and Shack	NA	NA	Gunungkidul Regency, Yogyakarta, Indonesia	NA	Tax lot value	NA	E	*A*	Tax lot
Miki et al. (2025)	Building and infrastructure	Japan Trench Earthquake	2011 Tohoku	Sendai Port, Miyagi, Japan	E	DR	Tada (2014)	E	*d*	Building
Papathoma-Köhle and Dominey-Howes (2003)	Building (residential/business)	1963 Gulf of Corinth earthquake and tsunami	NA	Gulf of Corinth, Greece	NA	VS	NA	J	*d*	Building

Reese et al. (2007)	Building (timber, brick and RC)		2006 Java	South Java, Indonesia	E	DR	NA	J	*d*	Building
Sanderson et al. (2021)	Building, Transportation network, electric power network and water supply network	Cascadia Subduction Zone Earthquake	NA	Seaside, Oregon, USA	E, A, J	DR	Bai et al. (2009)	E	*d* / *Sd*	Building
Song et al. (2017)	Building	Japan Trench Earthquake	2011 Tohoku	Onagawa and Sendai, Miyagi, Japan	E	DR	MLIT	E	*d* / *v*	Building
Song and Goda (2017)	Building	Japan Trench Earthquake	2011 Tohoku	Onagawa and Sendai, Miyagi, Japan	E	DR	MLIT	E	*d*	Building
Suppasri et al. (2022)	Mechanical structures within an industrial facility	Japan Trench Earthquake	2011 Tohoku	Sendai Port, Miyagi, Japan	NA	DR	NA	E	*d*	Building
Tada (2014)	Building, inventory, equipment and emergency measures cost	NA	2011 Tohoku	NA	NA	DR / Labour cost	NA	E, J	*d*	Building
Tanaka et al. (2022)	Building, infrastructure	Nankai Trough Earthquake	NA	Kochi, Japan	NA	DR * Tax lot value	NA	E, J	*d*	Tax lot

#1 E refers to empirical fragility models, A refers to analytical fragility models, and J refers to expert-judgement fragility models.

#2 DR denotes damage ratio and VS denotes vulnerability score

#3 E refers to engineering-based vulnerability models, and J refers to expert-judgement vulnerability models.

#4 IM (Intensity measure): d refers to inundation depth, v refers to flow velocity, A refers to inundation area, PGV refers to peak ground acceleration and Sd refers to spectral displacement.