Closing the Resilience Gap: A Preliminary Study on Establishing the National Fragility Curve Catalog for Multi-Hazard Assessment in Indonesia

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Abstract. This research paper presents a preliminary study aimed at closing the resilience gap in Indonesia through the establishment of a national fragility curve catalog for multi-hazard assessment. Indonesia is located in a high-risk hazard area, yet it currently lacks a comprehensive fragility curve catalog, which hinders effective risk assessment and mitigation strategies. By developing this database, the study aims to improve the understanding of structural vulnerability and enhance resilience planning across various hazards, such as earthquake, tsunami, wind, and flood. The research methodology involves collecting and analyzing data on the performance of different building types, exposed to multiple hazards. This includes considering various factors such as construction materials, design standards, and geographical characteristics. Statistical techniques and analytical modeling will be utilized to derive fragility curves that depict the probability of exceeding different damage levels or performance states given a specific hazard intensity. The findings of this study will provide valuable insights into the vulnerability of infrastructure and communities in Indonesia, enabling more informed decision-making for disaster risk reduction and resilience planning. The fragility curve database will facilitate quantitative risk assessments, support the development of appropriate building codes and standards, and inform the prioritization of mitigation measures. Ultimately, the establishment of a national fragility curve database will contribute to enhancing Indonesia's resilience to multi-hazard events and improving disaster preparedness at various scales.

Keywords. Fragility curve, Hazard and risk assessment, Indonesia

1 Introduction

Indonesia is ranked 12th out of 35 nations facing a relatively high mortality risk from multiple natural hazard [1]. Another source mentions that Indonesia is ranked the third position globally, in terms of disaster risk [2]. It is worth noting that the geographical location of Indonesia in the Pacific Ring of Fire exposes the nation to substantial threats from natural hazards, including earthquakes, tsunamis, and volcanic eruptions. Moreover, some studies indicate that Tsunami pose a particularly a high threat to Indonesia, secondly at risk after Japan [3], and [4]. Meanwhile, Indonesia falls within the top-third of countries affected by climate risk [1], resulting in recurrent floods that ravage various regions, leading to economic losses and serving as a catalyst for other natural hazards, such as landslides. In light of these challenges, it is crucial for Indonesia to prioritize comprehensive disaster mitigation strategies and climate resilience initiatives to reduce the risk posed by natural hazards through hazard and risk mapping.

This work is part of a larger, holistic study aimed at establishing a national-scale framework for loss estimation, incorporating multi-hazard risk assessment. In the context of risk assessment, vulnerability functions play a crucial role in determining the potential economic loss resulting from exposure to natural hazards, specifically buildings and infrastructure. These functions also serve to demonstrate the subtle correlation between the intensity of a particular hazard and the probable loss or damage experienced by the exposed assets. By utilizing vulnerability functions, a comprehensive understanding of the susceptibility of exposure to harm can be obtained.

Furthermore, fragility functions are required as a component to establish vulnerability. Fragility functions focus specifically on quantifying the probability of damage or failure of an asset under the influence of a hazard. They provide essential input to the overall vulnerability assessment, complementing the broader perspective that vulnerability encompasses. While fragility and vulnerability are terms that are sometimes used interchangeably, their distinct definitions and roles have been broadly clarified [5].

Fragility functions are often presented graphically as curves, illustrating the probability of damage in relation to hazard intensity. Extensive research has produced numerous earthquake fragility curves. With the field's maturity, a global database of seismic fragility curves has developed, incorporating distinct classifications based on building taxonomy [6]. This standardized framework enhances our understanding of building vulnerability, facilitating risk comparisons and assessments, while promoting global knowledge sharing and collaboration.

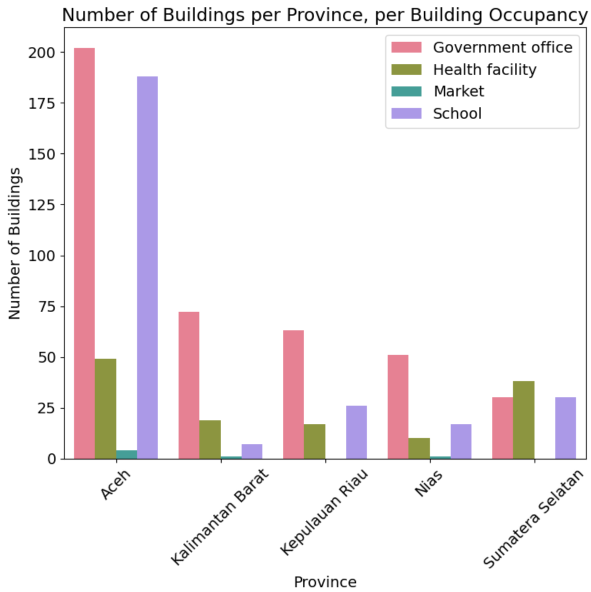
Besides earthquake fragility functions, there is a notable emergence of studies aiming to develop fragility functions for various other hazards. For instance, in the literature, researchers have explored different approaches to establish tsunami fragility curves, including empirical-based [7,8] and analytical-based methods [9]. Similarly, there are also analytical-based wind fragility curves available in selected sources, specifically for assessing building exposure [10,11]. However, in contrast to these hazards, there is a relative scarcity of fragility curves with limited variations pertaining to flood [12], landslides [13], and volcano [14] hazards.

Unlike building assessment, which involves detailed inspection and structural analysis to assess the performance of an existing building for countermeasure actions (such as targeted retrofitting or maintenance efforts), fragility analysis provides a probabilistic framework to quantify the risk and potential damage for a building stock with a similar taxonomy. While building assessment practices are reasonably effective in evaluating individual buildings, fragility analysis is particularly efficient in evaluating large exposure databases of buildings with a consistent taxonomy. Therefore, utilizing a suitable fragility curve and properly identifying building taxonomy is crucial in the computation of loss estimation, by virtue of the unique characteristic of building taxonomy and its response to the specific hazards that serve as the applied loading on the structure.

This study aims to assess a range of fragility functions for various natural hazards found in existing literature, with a specific focus on their compatibility with Indonesia's building taxonomy. The six natural hazards considered include earthquakes, tsunamis, floods, and winds. By conducting a comprehensive evaluation of these fragility functions, the research aims to determine their suitability in quantifying the vulnerability and risk of Indonesia's diverse building stock, providing valuable insights for future efforts in conducting risk assessment and developing mitigation strategies, particularly in estimating economic losses resulting from multiple natural hazards.

2 Building taxonomy

The first step involves creating Indonesia's building taxonomy, which is crucial for assessing the compatibility of fragility functions. Field surveys are conducted in multiple cities across Indonesia, including Aceh, West Kalimantan, Riau Islands, Nias, and South Sumatera. These surveys collect data on different building typologies, materials used, and construction practices prevalent in different regions of Indonesia. This compiled information serves as the foundation for creating building taxonomy specific to Indonesia. The surveyed building data, comprised of 825 entries and aggregated to illustrate trends in Indonesia's building taxonomy, are depicted in Fig. 1.



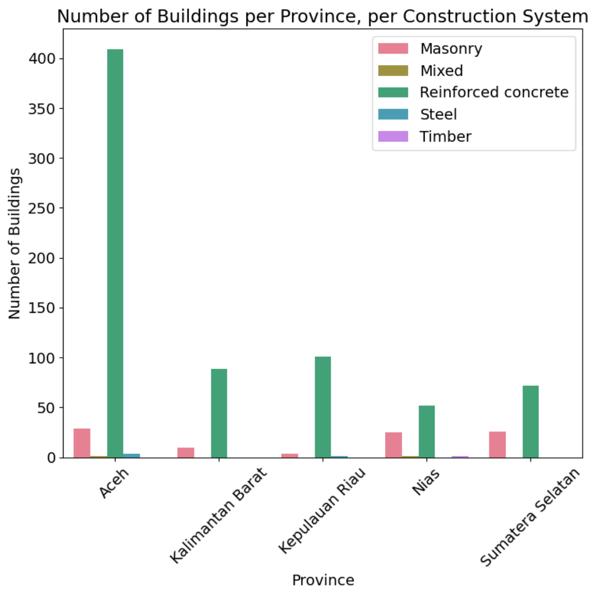


Fig. 1 Compiled surveyed data of Indonesia's building taxonomy trends

3 Introduction to Fragility Functions

3.1 Key concepts in fragility function

A fragility function addresses the damage probability of a building subjected to an extreme event set, typically natural hazards. Graphically, it is presented on an x-y diagram. The y-axis refers to the damage probability (represented as a percentage or a value bounded between 0 and 1), while the x-axis refers to the Intensity Measure (IM). The IM denotes the severity of a hazard event, measuring the correlation between the event's intensity and the degree of structural damage. Another fundamental element of the fragility function is known as 'damage states'. These classify specific ranges of damage, such as slight, moderate, extensive, and complete damage or collapse of the structure.

Generally, the fragility function can be expressed as a lognormal Cumulative Distribution Function (CDF), which can be written as per Eq. 1. It is worth mentioning that this lognormal CDF model is widely employed in existing fragility studies [15–18].

$$P(DS \geq ds_i | IM = x) = \Phi\left(\frac{ln\left(\frac{x}{\mu}\right)}{\beta}\right) \qquad \textit{Eq. 1}$$

In the equation above, $P(DS \geq ds_i | IM = x)$ represents the probability of a building reaching or exceeding a specific damage state (ds_i) when subjected to an intensity measure (IM) of value x. Φ symbolizes the cumulative standard normal distribution function. μ is the median IM value at which the building is expected to reach or exceed the damage state ds_i, and β represents the logarithmic standard deviation, indicating the dispersion or uncertainty in the IM at a given damage state. The parameters μ and β define the shape and location of the fragility curve.

To date, there are three critical features in a fragility function: Damage States (DS), Intensity Measures (IM), and Probability. Firstly, DS represent various potential degrees of damage that a system or structure may experience under a specific hazard event. Each DS classifies the damage, distinguishing the probability most likely associated with each category of damage. Secondly, the IM serves as an indicator of the hazard intensity. For instance, in seismic events, it could be Peak Ground Acceleration (PGA) or Spectral Acceleration (Sa); in floods and tsunamis, it could be water depth or flow velocity; and in hurricanes, it can be wind speed. These factors are critical in determining the force exerted on the structure or system. Lastly, Probability quantifies the likelihood of a system or building reaching or exceeding a specific damage state given a certain level of IM. This probability can be determined using statistical techniques based on observed damage data or results from structural analysis.

3.2 Derivation method of fragility function

Several techniques can be adopted to derive the fragility function. There are four approaches that are available in the literatures, include the empirical-based, analytical-based, heuristic-based, and hybrid-based [19,20].

Empirical-based is an approach of fragility function to observe damage data from past disaster events. It involves collecting detailed data about the damage states of structures after an event, as well as the intensity of the event at each location. This data is then statistically analysed to derive the fragility function. This approach is highly reliable as it is based on actual observations, but it requires a robust and demanding taskforce to collect the observational data upon the assessment from post-disaster event. Two example studies for the derivation of empirical-based fragility curve can be referring to the 2009 L'Aquila earthquake [16] and the 2011 great east Japan tsunami [8].

The analytical-based relies on structural analysis to estimate the response of a structure to a hazard event. This approach is particularly useful when sufficient empirical damage data is not available, or for predicting the behavior of new structures or designs that have not yet been exposed to hazard events. In the context of structural engineering, the implementation of analytical-based of fragility function is often referred to as Probabilistic Performance Based Design, which represents the next generation of Performance Based Design. Since the analytical-based relies on structural analysis, it requires Engineering Demand Parameters (EDPs) to formulate the interpretation of fragility functions. These parameters are computed through robust numerical simulations, and generally prefer measures like maximum inter-story drift [21,22] or base shear [9], or any pertinent measures, depending on the hazard type and the specific structural system of building under consideration.

Beside empirical and analytical approach, the fragility functions can also be derived through expert judgment. It is often employed when there is a lack of sufficient analytical models or empirical data. Experts with substantial experience and knowledge on the performance of structures under different hazard levels provide estimates, which are then used to construct the fragility function. Although this approach may have drawbacks that could result in bias or subjective outcomes, it remains one of the most commonly employed methods [23].

The last approach is called hybrid-based. This method combines the other three approaches to leverage their advantages and mitigate their drawbacks. For instance, it may involve using a heuristic approach to initially define the fragility function, followed by an empirical approach to calibrate it based on observed data, and an analytical approach to fine-tune it based on numerical simulations. Some of research works can be found in literatures, adopting hybrid approach [24,25].

3.3 Statistical procedures for fitting fragility

One of the dubious issues in developing fragility curve is in how to generate the continuous fragility function from the observed data by using suitable statistical approaches. Although the fragility function relationship can be presented as damage probability matrices, the most typical representation is in form of continuous curve, particularly the lognormal CDF fragility curve, which is illustrated in Fig. 2. A study [26] suggested that this form offers mathematical convenience by maintaining the lognormal distribution when a lognormally distributed random variable is multiplied or divided by uncertain and lognormally distributed factors, such as safety factors.

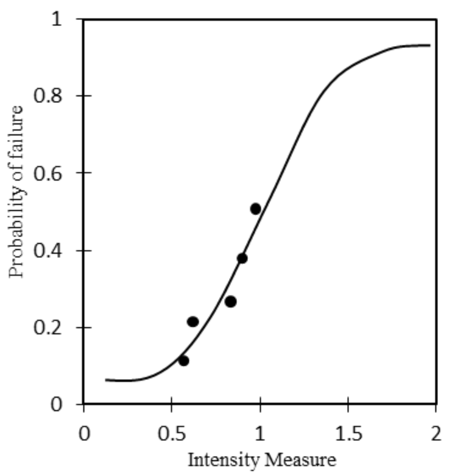


Fig. 2 Lognormal CDF fragility curve

In addition, data points are crucial for generating a reliable fragility function, particularly when using empirical-based methods. Some studies [27] suggest that a minimum of at least 200 data points of observed damage is needed, along with a minimum of 20 observations per intensity measure (IM) bin, for at least 10 bins.

3.3.1 Moment Method

The MM is often used to derive fragility curve by adopting analytical-based approach, by performing Incremental Dynamic Analysis (IDA) [28]. By modifying Eq. 1 into Eq. 2, the resulting collapse fragility curve can be obtained by solving both mean, and standard deviation with Eq. 3 and Eq. 4. However, it is important to acknowledge that the MM approach has limitations [20], particularly when it comes to handling empirical data and scenarios with limited intensity measures (truncated IDA).

$$P(C|IM = IM_i) = \Phi\left(\frac{ln(IM_i - \bar{\mu})}{\bar{\beta}}\right) \qquad Eq.\ 2$$

$$\bar{\mu} = E\left[ln\left(IM_{collapse}\right)\right] \qquad Eq.\ 3$$

$$\bar{\beta} = \sqrt{Var\left(ln\left(IM_{collapse}\right)\right)} \qquad Eq.\ 4$$

3.3.2 Least Square Regression to minimize Weighted Sum of Squared Error (SSE)

Another prevalent method is by using the least square regression technique to minimize the weighted sum squared error (SSE). The method of least squares is employed to calculate the values of $\bar{\mu}$ and $\bar{\beta}$ parameters, which aim to minimize the sum of squared errors (SSE) between the predicted probabilities derived from the fragility function and the observed fractions obtained from the dataset. The errors can further be weighted by the number of observed data at each IM. Furthermore, the SSE can measure the discrepancy between the data and estimation model, finding the best fit of the fragility curve to the observed data. As such, in the context of fragility function, the SSE parameters can be expressed such as Eq. 5.

$$\{\bar{\mu}, \bar{\beta}\} = \underset{\mu, \beta}{argmin} \sum_{i=1} N_i \left(\frac{n_i}{N_i} - \Phi\left(\frac{ln(IM_i - \mu)}{\beta}\right)\right)^2 \qquad Eq.\ 5$$

Please note that n_i/N_i is the ratio of observed data at the corresponding intensity measure (IM).

It must be underscored that while some studies suggest the SSE (Sum of Squared Errors) approach often yields results nearly comparable to the MLE (Maximum Likelihood Estimation), there are, however, inherent limitations that make MLE generally more favorable [16,20,29]. This preference is primarily due to the SSE method's inherent inability to account for the non-constant variance observed in the fraction of collapsed data. To illustrate this point, consider a scenario where no collapses are observed at a specific Intensity Measure (IM) level, and the fitted collapse probability is 0.1. The resulting error in this situation is significantly larger compared to when a collapse probability of 0.6 is fitted at an IM level where 50% of motions result in collapse. This discrepancy stems from the fact that the least squares method treats all errors uniformly and assumes constant variance, a practice which fails to accurately capture the varying magnitudes of error associated with different observed collapse fractions.

3.3.3 Maximum Likelihood Estimation (MLE)

To date, the maximum likelihood estimation (MLE) method is widely used and applicable for both analytical and empirical fitting approaches of the lognormal cumulative distribution function (CDF) in fragility curve analysis. The key principle of the MLE is that it estimates the parameters that extent the probability of occurrence of the observed collapsed data. Unlike the Sum of Squared Errors (SSE) method that aims for the most accurate data description, MLE seeks the parameters most likely to have yielded the data [16]. In this context, for the creation of an analytical-based fragility curve using Incremental Dynamic Analysis (IDA), to a certain extent (i.e., when adopting multiple stripe analyses), MLE does not require high Intensity Measure (IM) amplitudes where ground motion causes a building to collapse in a numerical simulation [29].

Processing the post-event damage data for instance, it can give the probability of observing damaged buildings, n_i out of the total buildings, N_i at the IM of interest, which can be represented by the binomial distribution as Eq. 6.

$$P(n_i \; in \; N_i \,|IM = IM_i) = \binom{N_i}{n_i} \, {p_i}^{n_i}(1-p_i)^{N_i-n_i} \qquad \textit{Eq. 6}$$

In Eq. 6, p_i is the probability that an event with IM of interest will cause damage to the building. To date, the MLE method is used to identify the highest probability of observed damage data at each IM level to get the likelihood of the whole dataset. This idea can be expressed in Eq. 7.

$$Likelihood = \prod_{i=1}^{m} \binom{N_i}{n_i} \, {p_i}^{n_i}(1-p_i)^{N_i-n_i} \qquad \textit{Eq. 7}$$

In the context of applying the MLE into the lognormal CDF, the MLE can be pretty useful to estimate the statistical parameters of μ useful β. These values can be computed accordingly as in Eq. 8.

$$\{\bar{\mu}, \bar{\beta}\} = \underset{\mu, \beta}{\arg max} \sum_{i=1} [A + B]$$
$$A = n_i \ln\left(\Phi\left(\frac{ln(IM_i - \mu)}{\beta}\right)\right) \qquad \textit{Eq. 8}$$
$$B = (N_i - n_i)\ln\left(1 - \Phi\left(\frac{ln(IM_i - \mu)}{\beta}\right)\right)$$

Referring to Eq. 8, the parameters of $\bar{\mu}$ and $\bar{\beta}$ are the estimates of μ, β, so thus it will maximize the likelihood function. This equation is written as a summation over all IM levels. Simply put, for each IM level, this equation enables the computation of log-likelihood for the observed damage fraction one by one, and then summing all of it, to obtain the total likelihood for the entire dataset.

3.3.4 Other fitting strategies

Many research studies have referenced the notable works of Shinozuka [18] to develop fragility functions. Over time, numerous variants of fitting approaches have been proposed for constructing these fragility functions.

Rossetto et al. [30] suggested the use of Generalized Additive Models (GAM) to develop empirical-based fragility curves, particularly when the relationship between the IM and the damage probability is not well understood or known to be linear. Conversely, Rossetto et al. [21] utilized Generalized Linear Model (GLM) with the probit link to develop the analytical-based fragility curve. Giordano et al. [31] highlighted the benefits of Bayesian updating, given its flexibility in handling inhomogeneous data and enabling ease of updating existing datasets. In addition, some researcher pointed out the premise of neural networks (machine learning) to estimate the vulnerability function with limited datasets [32].

4 Fragility Curve of buildings for Natural Hazards

4.1 Seismic fragility

There is abundance of literature on the seismic fragility of buildings, with this function being the most established globally compared to other hazards. Numerous empirical seismic fragility functions have been developed based on past earthquake events. For instance, the fragility function for Nepali residential building stock was established from data collected during severe earthquakes, including the 2015 Gorkha earthquake [33], The fragility function for Nepalese school buildings also leverages data from the 2015 Gorkha earthquake [31], Other examples include fragility functions for Reinforced Concrete (RC) buildings based on the 2009 L'Aquila earthquake [16], RC residential buildings based on the 2017 Iran earthquake [34], churches following the 2016 Central Italy earthquake [35], and both engineered and non-engineered buildings based on the 2014 Thailand earthquake [36].

In addition, tools for crafting analytical-based fragility curves are also enumerated. For example, Rossetto et al. [21] proposed a fragility curve via the capacity spectrum method integrating record-to-record variability, known as FRACAS. Baltzopoulos et al. [22] expanded the applicability of static pushover results to Incremental Dynamic Analysis (IDA) for fragility curve creation, termed SPO2FRAG. Meanwhile, Martins et al. [37] created the Vulnerability Modeller's ToolKit (VMTK), which encapsulates not only the fragility function but also the vulnerability function.

Large-scale building taxonomies, along with fragility and vulnerability function databases, have been developed by the Global Earthquake Model (GEM) [38]. The aim of these resources is to create an established yet collaborative platform for conducting earthquake risk assessments. Other successful initiatives include the Global Program for Safer Schools (GPSS) [39], which focuses on school buildings globally. In addition, HAZUS 5.1 framework [40] also provides a comprehensive library of structural fragilities for various types of buildings, infrastructure, and utilities, thereby offering a robust tool for estimating earthquake losses.

4.2 Tsunami fragility curve

In the pursuit of understanding the impact of tsunamis on structures, various studies have been conducted to develop fragility curves. These curves, which represent the probability of exceeding a certain damage state given a hazard intensity measure, are derived either empirically or analytically.

Empirical-based fragility curves are derived from observed damage data. For instances, Koshimura et al. [41] followed a semi-empirical approach, developing fragility functions for tsunami damage estimation via numerical simulation of tsunami inundation model and post-tsunami data from Banda Aceh, Indonesia. Valencia et al. [42] developed tsunami damage functions for European-Mediterranean coasts based on empirical dataset from December 2004 tsunami. Subsequently, Suppasri et al. [8] utilized data from the 2011 Great East Japan tsunami to derive fragility functions for over 250,000 surveyed structures. Later, Charvet et al. [43] adopted generalized linear models to assess the potential tsunami damage to buildings, using empirical data from the same event. Furthermore, De Risi et al. [44] investigating the importance of incorporating flow velocity in the tsunami, multi-variate empirical fragility modelling and highlighted its significant contribution, particularly for severe structural damage states.

On the other hand, analytical-based fragility curves are derived from theoretical models and simulations. A novel study by Petrone et al. [9] assessed the fragility of a reinforced concrete structure under tsunami actions using nonlinear static and nonlinear dynamic analyses by linking inundation depth variance. Later, Petrone [45] extended the study to examine the sequential event of an earthquake and tsunami. Another example of analytical fragility curve is based on the study of Medina et al. [46], which combined rigorous nonlinear structural analysis with the Monte Carlo statistical algorithm to develop theoretical probability fragility curves in the building context of the Colombian Pacific coast. These studies highlight the importance of analytical models in understanding and predicting the impact of tsunamis on structures.

4.3 Wind fragility curve

The vulnerability of structures to wind damage is a significant concern in the field of structural engineering. This vulnerability is influenced by a variety of factors, including roof design, construction quality, and geographic location. However, currently, wind fragility function is limited to analytical-based fragility curve. Moreover, only wind fragility curve in the context of building will be discussed herein.

A series of studies by Stewart and colleagues have made significant contributions to our understanding of these factors. For instance, Stewart et al. [47] conducted a fragility analysis of roof damage to industrial buildings subject to extreme wind loading in non-cyclonic regions. In another study, Stewart et al. [48] developed a new fragility function for roof sheeting failure under extreme wind conditions, highlighting the potential impact of climate change on housing vulnerability, particularly in coastal regions. Furthermore, Qin and Stewart [49] demonstrated that construction defects significantly increase the vulnerability of metal roofs to wind damage.

A particularly noteworthy contribution to this field is the work of Pandolfi et al. [50] who introduced a tool, termed ERMESS, a new method for assessing the risk of extreme wind damage to building portfolios. This method combines building-specific fragility curves with regional wind hazard maps to estimate the risk of wind damage to a portfolio of buildings. The authors demonstrated the effectiveness of ERMESS by applying it to a case study in Italy. This approach allows for a more comprehensive assessment of wind risk, considering both the vulnerability of individual structures and the spatial distribution of wind hazards. This innovative approach represents a significant advancement in the field and provides a solid foundation for future research.

In summary, it is essential to note that wind hazards predominantly might significantly affect a specific set of structures. It seems that the effects are most substantial on flexible structures such as cold-formed or light structures, timber structures, transmission towers, structural poles, and roof structures. This specificity indicates a need for targeted research and mitigation strategies for these types of structures that could significantly reduce their vulnerability to wind hazards.

4.4 Flood fragility curve

Floods are a recurrent hazard globally, affecting not only emerging regions but also developed areas. The impact of climate change has further complicated the understanding of flood hazards, necessitating the development of effective mitigation strategies to address this challenge.

The flood fragility function uses inundation depth as the Intensity Measure (IM), similar to the approach used for characterizing tsunami hazards. Tsunamis are distinguished by high water flow velocities and the potential to carry debris, resulting in significant impact forces on buildings. In contrast, typical types of floods, such as river floods, urban floods, and pluvial floods, are triggered by heavy rainfall, leading to a gradual increase in water levels until surrounding buildings or infrastructure are submerged. Conversely, flash floods can occur suddenly, inundating neighboring buildings rapidly. Accurate classification of the flood type is crucial for developing an appropriate fragility function to effectively estimate and mitigate risks.

Flood fragility curves have been extensively studied and applied in various contexts, as evidenced by the diverse range of literature available on the subject. The development of these curves often involves the use of empirical or analytical methods, each with its unique advantages and limitations. For instance, the JRC Tech Report [51] presents a global analysis of flood depth-damage functions, proposing a new approach that incorporates a wider range of factors, including building characteristics, flood characteristics, and socio-economic factors. Similarly, Thapa et al. [52] present a methodology for mapping flood hazards and analyzing the vulnerability of residential buildings at the catchment scale, using a combination of Digital Elevation Model (DEM), HEC-geoRAS preprocessing, spatial analysis, and empirical damage data collected after the 2017 flood in eastern Nepal.

The vulnerability of buildings to flood hazards, particularly traditional and residential structures, is a recurring theme in the literature. D'ayala et al. [53] discuss the vulnerability and risk assessment of traditional buildings in a heritage district of Kuala Lumpur, Malaysia, proposing a novel physical-based approach that combines hydraulic modeling, building surveys, and vulnerability curves to assess flood loss estimation. Torres et al. [54] focus on the vulnerability of Florida residential structures to hurricane-induced coastal flooding, providing valuable insights into the specific risks associated with coastal regions. Interestingly, this study incorporated the 2011 Great East Japan tsunami as a benchmark to produce coastal flood vulnerability function. In addition, insurance claims data and expert-based models are used to validate the model, resulting a comprehensive hybrid approach.

The literature also highlights the importance of using multi-variate approaches to estimating flood fragility and loss for buildings. Nofal et al. [55] proposing a general method without requiring direct empirical (field) data. This study also emphasize that the multi-variate approach provides a more accurate and comprehensive assessment of flood risk, particularly for buildings with complex characteristics. This is further supported by Lazzarin et al. [56], who propose a new flood damage function based on the impact parameter (W) that combines both physical and data-based aspects, arguing that this provides a more accurate estimate of flood damage than traditional methods that rely solely on water depth, where flow velocity is unconsidered.

The development and application of models for flood fragility and vulnerability assessment are also well-documented in the literature. Galasso et al. [57] present a taxonomy for models used in the assessment of building fragility and vulnerability to flooding, providing a framework for selecting appropriate models for flood risk assessment.

4.5 Other fragility curve

In addition to seismic, tsunami, wind, and flood fragility functions, other types of fragility functions are also crucial in assessing the vulnerability of structures to various hazards. Alberico et al. [58] developed a fragility function to assess building damage probability due to pyroclastic currents from small-size explosive eruptions at Campi Flegrei, Italy. This function provides a quantitative tool, which can be used for loss estimation of volcanic hazard event. Szagri and Szalay [59] proposed a novel approach to assess heat vulnerability of residential buildings using theoretical fragility curves. This approach considers the impact of extreme weather events, such as heatwaves, on building overheating, thereby providing a more objective measure of heat vulnerability.

5 Discussion

5.1 Catalog of selected studies of worldwide fragility functions

The dataset presented in Table 1 represents a comprehensive compilation of fragility functions sourced from a literature review of selected studies. The data encompasses a range of hazard types including, but not limited to, seismic, tsunami, wind, and flood hazards.

The building characteristics impacted by these hazards are diverse. This diversity underscores the broad applicability of the dataset across different building typologies. Factors such as the uniqueness of the building archetype, vernacular aspects, local materials availability, construction technology, and prescribed building codes impact these variabilities. This diversity emphasizes the need for a similarly diverse set of fragility functions to accurately represent the vulnerability of different types of buildings to various hazard types.

In conclusion, the presented dataset is an extensive collection of fragility functions derived from a thorough review of existing literature. It spans a range of hazard types, derivation methods, building types, and intensity measures. This broad scope makes it a valuable resource as a starting point to develop a robust catalog of Indonesian fragility functions, which are incredibly beneficial in providing insights to estimate potential national hazard loss.

5.2 Formulating Indonesian fragility functions

This chapter will focus on the development of Indonesian-specific fragility functions. One could argue whether those fragility functions in Table 1 could be used for Indonesia's structural fragility, given the known constraints, where those studies could or might not reflect Indonesia's building characteristic or taxonomy. The need for these fragility functions arises from the unique architectural styles, building materials, and construction methods common in Indonesia.

5.2.1 Seismic fragility model

Seismic fragility functions are frequently studied in the literature. When empirically derived for a specific event, these functions can portray building losses via statistical estimation of observed datasets. If the empirical data on damaged buildings are meticulously surveyed, detailed insights into building characteristics such as construction type and material, the number of stories, and structural systems can be obtained. Conversely, the distribution of intensity, such as Peak Ground Acceleration (PGA), is estimated based on the Ground Motion Prediction Equation (GMPE), which can vary depending on the computational model and parameter assumptions. However, a noteworthy issue with post-damage surveys is the quality of the collected data, as the varying decisions made by surveyors when filling out assessment forms could introduce bias. Another concern when using seismic empirical-based fragility functions is that structural systems can differ significantly from one country to another. From this standpoint, the existing empirical data often do not align with the Indonesian building taxonomy.

An analytical-based approach can be employed to create seismic fragility functions for any building taxonomy. For instance, by constructing an analytical model based on the Indonesian building taxonomy (outlined in Chapter 2), an analytical-based seismic fragility can be generated using the framework of Rossetto et al. [21] or Baltzopoulos et al. [22]. The spectral acceleration, Sa, represents the most suitable Intensity Measure (IM) from an engineering perspective due to the structural system nature to excite at its fundamental mode [28]. Consequently, a seismic fragility function representing the Indonesian building taxonomy can be constructed. However, this approach raises a question about the number of structural models that should be built to conduct the numerical simulation, ensuring a probabilistic consideration of unique building characteristics in Indonesia.

To cope up with this limitation, an in-depth building classification strategy can be implemented in this case. For instance, the selection of fragility functions can be categorized based on occupancy type, structural system (e.g., RC, Steel, masonry), and the number of building stories. Perhaps the most efficient method is to incorporate some of the fragility function from existing world-wide databases like the Global Earthquake Model [38] and the Global School Infrastructure (GLOSI) [39]. It is important to note that most fragility functions from these databases are derived analytically. By utilizing these databases along with the framework of FRACAS [21] or SPO2FRAG [22], it is possible to supplement the specific building taxonomies where necessary.

5.2.2 Tsunami fragility model

Perhaps, compared to other hazards, a tsunami is the most destructive event, which is most likely to cause damage or lead to building collapses. This is reflected in the notorious events of the 2004 Indian Ocean tsunami and the 2011 Great East Japan tsunami. In the context of Indonesian building regulation, except for tsunami evacuation buildings, engineers are not required to consider tsunami loading for building permits, even in coastal regions with a history of tsunamis. Consequently, buildings can be highly vulnerable if exposed to a tsunami event.

The use of an analytical fragility framework for tsunami hazards can be facilitated by applying the proposed framework of Petrone et al. [9]. However, the selected IM (i.e., base shear force, which preferrable from an engineering perspective) can be problematic to use, since Probabilistic Tsunami Hazard Analysis (PTHA) or scenario-based computations generally derive the hazard intensity in terms of tsunami inundation depth. This *IM* appears to be the most appropriate measure of intensity for non-engineers.

Both the studies of Koshimura et al. [41] and Valencia et al. [42] could potentially align with the regional characteristics of Indonesian building taxonomy. However, these studies lack detail in defining the building taxonomy and do not sufficiently elaborate the damage state of fragility functions. In contrast, the works of Suppasri et al. [8] and Charvet et al. [43], based on empirical-driven fragility functions from the 2011 Great East Japan tsunami, have done an excellent job in classifying the building classes. Considering the devastating effect of tsunami impact on buildings, it is reasonable to assume that the work of Suppasri et al. [8] can be used for Indonesia's tsunami fragility function, offering a more various building taxonomy.

5.2.3 Wind fragility model

Generally speaking, rigid structures, such as those using an RC structural system, have very low susceptibility to wind impact. If there is any damage, it's most likely to occur on components such as the façade, door, window, or roof structure. During an extreme wind event, the roof of a building might endure the most pressure from both wind and rain. Therefore, the vulnerability of the roof should be governed more thoroughly, especially when developing a wind fragility function.

In addition to the ERMESS [50], which is currently not publicly accessible, most references from Table 1 are inferred from the works of Stewart et al. [47] [48] [49]. These studies are derived from an analytically-based fragility curve for residential house typology in Australia. The characteristics of the structural system mentioned in these studies have a weak relation to Indonesia's roof typologies. However, these studies provide an insightful framework to develop a unique wind fragility function for Indonesian typology.

This study reports some development progress of the wind fragility function. A triple fink truss composed of cold-formed members is considered as a case example. The probabilistic aspect of generating a fragility function can be achieved by varying the slope degree of the roof, from 20 to 45 degrees. The wind loading procedures follow SNI 1727 2020, which are equivalent to ASCE 7-16. Due to the absence of an Indonesian wind speed map, the wind gust is assumed to range from 0 to 40 m/s. The EDPs are in terms of the ratio of demand per capacity of structural members, and the deflection limit. Furthermore, the Open Application Program Interface (OAPI) script is introduced to ease the modelling process, such as enabling a communication interface between Python and SAP2000. The resulting structural analysis output is then processed as an input for a random seed to generate the Monte-Carlo simulation. Finally, the optimized Monte-Carlo results of observed collapsed datasets are processed to generate the wind fragility function.

5.2.4 Flood fragility model

Currently, the flood fragility model is the least explored reference in this study, but it will be reserved for valuable discussions in future work.

Flood inundation insignificantly damages or affects the structural systems of buildings, except in the case of flash floods which, along with relatively high flow velocity water and debris, can likely affect vulnerable structural systems (e.g., such as poorly constructed or temporary dwellings [52]). The empirical flood vulnerability model is particularly effective in estimating economic losses due to flood hazards [53]. To date, for RC building taxonomy, flood fragility functions are typically used in estimating the probability of loss in terms of component or asset losses, rather than building failure.

The most direct use of a flood vulnerability model (e.g., damage to water depth function) can be inferred from the JRC Technical Report and Hazus Flood Technical Manual. The single curve of the vulnerability model can be used to estimate the percentage of damage loss for buildings exposed to flood hazards.

6 Conclusion

This paper has presented (1) a general overview of techniques used to derive fragility functions; (2) a statistical trend of Indonesia's building taxonomy; (3) a multi-hazard catalog of fragility functions; and (4) a pilot model to generate unique fragility functions for multi-hazard events. To offer an intuitive overview, Fig. 3 presents an illustration of the multi-hazard assessment framework by highlighting several important key terms.

This study is part of a larger project aimed at developing a national-scale framework for loss estimation, incorporating multi-hazard risk assessments. The findings and results of this study will be set aside and are anticipated to make a significant contribution to further work.

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Table 1 Database of references of fragility functions

Derivation	Hazard event	Building characteristics	Intensity Measure (IM)	References /Remarks
Seismic hazard				
Empirical	2009 L'Aquila earthquake	RC building	PGA	Del Gaudio et al. [16]
	2015 Gorkha earthquake	Masonry, RC frame, and timber of school buildings	PGA	Giordano et al. [31]
	2015 Gorkha earthquake	RC, brick, and stone masonry residential buildings	Sa & PGA	Gautam et al. [31]
	2017 Iran earthquake	Steel and RC residentials	EMS-98 & PGA	Biglari et al. [34]
	2016 Italy earthquake	Italian churches: masonry	PGA	Hofer et al. [35]
	2014 Thailand earthquake	RC engineered, non-engineered	PGA	Foytong and Ornthammarath [36]
Analytical	-	Applicable to any structures	Sa, PGA	Rossetto et al. [21]
Analytical	-	Applicable to any structures	Sa	Baltzopoulos et al. [22]
Various	Various	Various	Sa, PGA, PGV, MMI	GEM [38]
Analytical	-	Various (School building)	Sa, PGA	(GLOSI) [39]
Analytical	-	Various	PGA, Sd	HAZUS 5.1 framework [40]
Tsunami hazard				
Semi-empirical	2004 Indian ocean tsunami	Generalized	Inundation depth	Koshimura et al. [40]
Semi-empirical	2004 Indian ocean tsunami	Generalized into specified building classes	Inundation depth	Valencia et al. [41]
Empirical	2011 Great East Japan tsunami	RC, steel, wood, masonry	Inundation depth	Suppasri et al. [8]
Empirical	2011 Great East Japan tsunami	RC, steel, wood	Inundation depth	Charvet et al. [42]
Empirical	2011 Great East Japan tsunami	RC, steel, wood, masonry	Multi-variate Inundation depth with flow velocity	De Risi et al. [43]
Analytical	2011 Great East Japan tsunami	Example model (Can be applicable to any structure)	Shear force	Petrone et al. [9]
Analytical	-		Multi-variate Sa & shear force	Petrone [44]
Analytical	-		Inundation depth	Medina et al. [45]
Wind hazard				
Analytical	Extreme wind (non-cyclonic) in Australia	Roof cover typology for industrial steel building	Gust wind speed	Stewart et al. [47]
Analytical		Contemporary housing roof in Australia	Gust wind speed	Stewart et al. [48]
Analytical		Contemporary housing roof in Australia	Gust wind speed	Qin and Stewart [49]
Various	Various	Various	Gust wind speed	Pandolfi et al. [50]
Flood hazard				
Empirical	Various	Various	Inundation depth	JRC Tech Report [51]
Empirical	2017 Khando river, eastern Nepal	Wattle, daub, masonry, RC Residential	Inundation depth	Thapa et al. [52]
Physical	Kuala Lumpur, Malaysia	Urban traditional & heritage buildings	Inundation depth	D'ayala et al. [53]
Hybrid (empirical-analytical-heuristic)	Florida, USA	Timber & Reinforced masonry structures	Inundation depth	Torres et al. [54]
Hybrid (physical-probabilistic)	USA	USA buildings (Can be applicable to any structure)	Multi-variate Inundation depth with flood duration	Nofal et al. [55]
Hybrid (heuristic-empirical)	Italy	Various	Multi-variate Inundation depth with flow velocity	Lazzarin et al. [56]
Various	Various	Various	Various	Galasso et al. [57]

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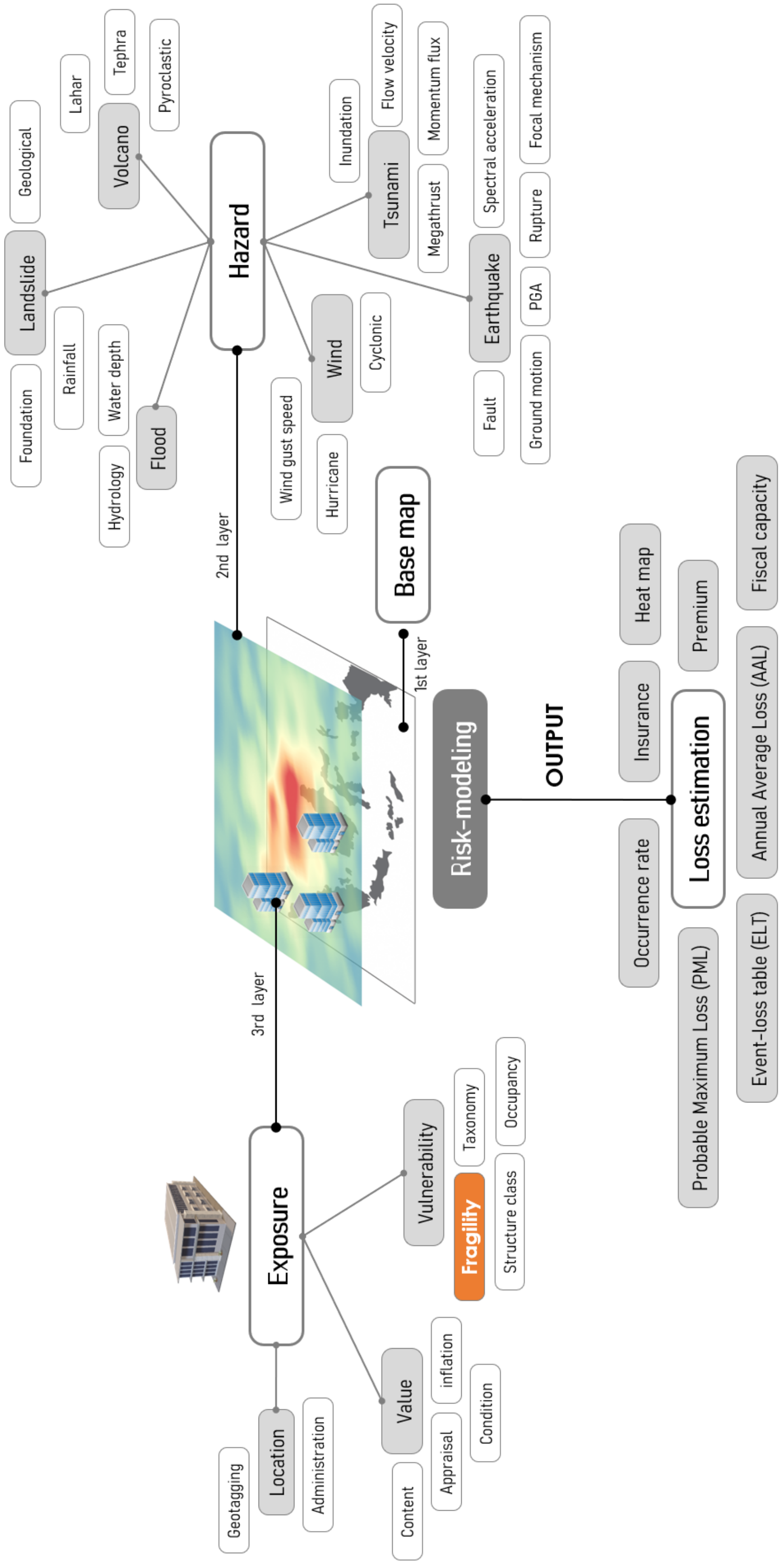

Fig. 3 Illustrative Framework of Multi-Hazard Assessment

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