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CHALLENGES IN SEISMIC HAZARD ASSESSMENT: INDIAN PERSPECTIVE

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ABSTRACT

Seismic Hazard Assessment (SHA) is a scientific technique used to predict potential ground shaking from earthquakes. It requires state-of-the-art specifications for three key elements: seismic source modeling, ground motion modeling, and uncertainty modeling. SHA is a multidisciplinary science that integrates various fields of study, including geology, tectonics, seismology, geodesy, statistics, and engineering seismology. However, many studies still rely on simplistic seismic source descriptions and basic statistical analyses of historical and incomplete earthquake catalogs, which are subject to various types and degrees of uncertainty. Seismic hazard models generally consist of a probabilistic framework that quantifies uncertainty across a complex system. Most probabilistic seismic hazard analyses use forecasting periods of 30 to 50 years, corresponding to engineering requirements for building codes. To meet the need for more accurate and spatially precise hazard forecasting, science-driven models must integrate all available information, adopt appropriate mathematical frameworks to quantify different types of uncertainty, and establish a robust testing phase to assess the model's consistency and predictive skill. In the Indian context, two main goals should be prioritized: comprehending, quantifying, and reducing uncertainties throughout all phases of the modeling process, and enhancing the targeting of end-user requirements in the development and output of the models.

KEYWORDS: National Seismic Hazard Modelling, Ground Motion, PSHA, Uncertainty, India

INTRODUCTION

Seismic hazard analysis is a scientific method to forecast future ground shaking caused by earthquakes for a specific location or multiple locations. It is widely used in decision-making processes for structural design guidelines for nuclear power plants, bridges, dams, and ordinary structures and risk assessments for insurance and disaster management planning. It is a complex process that requires expertise from various fields, including geology, geophysics, seismology, geotechnical engineering, statistics, and engineering seismology. It involves developing models that simulate the entire earthquake process, from the initial triggering of an earthquake to the propagation of seismic waves through the Earth and the amplification of ground motion at specific sites. Due to inherent uncertainties, seismic hazard analysis typically employs a probabilistic approach which allows incorporating uncertainties in the likelihood or frequency of earthquakes of specific sizes and locations. However, deterministic analysis can also be used when considering a specific earthquake scenario with the primary difference being treatment of earthquake occurrence uncertainties. The deterministic approach focuses solely on ground shaking uncertainties and assumes the occurrence of specific earthquake scenarios, often represented by the maximum expected earthquakes. While the deterministic approach is straightforward but limited by the difficulty of selecting the most appropriate earthquake scenarios, the probabilistic approach determines the likelihood that various ground motion levels will be exceeded at a location or region due to all possible earthquakes of all potential magnitudes and distances from the site(s) of interest. Probabilistic approach eliminates arbitrary scenario selection and provides a more comprehensive seismic hazard assessment and is more widely used in modern seismic hazard analysis. Such an approach is the foundation for most national-level seismic hazard models worldwide. The focus in this paper is on applying Probabilistic Seismic Hazard Analysis (PSHA) to national- and regional-scale assessments, commonly known as National Seismic Hazard Models (NSHMs). Several innovative NSHMs are examined including Australia, Europe, Taiwan, the United States, and India. Finally, a summary of key issues is presented that is fundamental for the future direction of seismic hazard analysis.

SEISMIC HAZARD AND NATIONAL SEISMIC HAZARD MODELS

The fundamental concepts of PSHA were initially introduced by Cornell (1968) and Esteva (1969), with the latter incorporating aleatory variability into the ground-shaking component. PSHA is generally considered a model or algorithm combining multiple component models and their associated uncertainties to assess hazards. They generally fall into three main categories: Seismic Source Modelling (SSM), Ground Motion Modelling (GMM), and Uncertainty Modelling (UM) (Gerstenberger et al. 2020). The SSM forecasts future seismicity, typically expressed as the seismicity rate, taking into account spatial distribution, magnitude, and any additional parameters relevant to the GMM. The GMM is a critical component of PSHA, responsible for estimating the ground shaking intensity at a specific location for a given earthquake scenario, with occurrence parameters defined by the source model. Finally, the UM defines how the component models are combined and what uncertainties are propagated to the final result.

Defining a specific set of seismic hazard using NSHMs or any probabilistic model requires establishing probability thresholds (Gerstenberger et al, 2020). Common building code thresholds are associated with a probability of exceedance (PoE) of 10% and 2% in 50 years. However, the quantitative justification for these thresholds is often unclear (Bommer & Pinho, 2006). Current research efforts aim to develop more appropriate, risk-targeted seismic hazard assessments (Gerstenberger et al. 2017; Silva et al. 2016). An exceedance probability of 10% (or 2%) in 50 years is often referred to as a return period of 475 (or 2,475) years. However, using the term return period is misleading as it implies a regular recurrence of such events, which is inconsistent with the time-memoryless Poisson process commonly used to model seismicity rates. This concept is also inaccurate for any time-dependent model that accounts for earthquake clustering. Therefore, using probabilistic terms that accurately convey hazard information, such as the annual probability of ground motion exceedance, is encouraged in the future.

A PSHA is designed to generate different outputs (e.g., hazard maps, hazard curves, uniform hazard spectrum, and disaggregation etc.). The hazard curve represents the probabilities or rates of exceeding specific ground motion parameters (i.e., expected ground motion with decreasing PoE) for a single site. A uniform hazard spectrum provides the accelerations over various oscillation periods with a uniform PoE. Hazard disaggregation analysis is used to identify the contribution to a specific level of hazard given by components of the SSM and GMM in terms of fundamental variables such as magnitude, distance, and the number of standard deviations by which the ground motion deviates from the mean (Gerstenberger et al, 2020). The selection of specific outputs depends on user requirements and whether it is for a single site or a group of sites. For instance, following IS 1893 (2023), ordinary structures may use 10% PoE in 50 years, important structures may use 5% PoE in 50 years, and lifeline structures may use 2% PoE in 50 years. Moreover, the ground motion intensity measure can be any parameter predicted by the applied GMM. Frequently used intensity measures include Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), Peak Ground Displacement, and 5% damped spectral acceleration with periods ranging from 0.02 s to 10s, depending on analysis requirements. Typically, only the horizontal component of ground motion is taken into account. Additional measures can also be employed, including modified Mercalli intensity cumulative absolute velocity (Wood & Neumann, 1931).

MAIN COMPONENTS OF A SEISMIC HAZARD MODEL

A seismic hazard model comprises two primary components: where and how often earthquakes occur (SSM), how strong the ground will shake (GMM), and their corresponding uncertainties (UM). Together, these components capture the expected earthquakes and the predicted shaking that will result from these earthquakes. While considerable variability exists in the methods to develop these components, the underlying concepts remain consistent across different applications.

1 Seismic Source Modelling (SSM)

The SSM defines earthquake occurrence, containing the locations, sizes, geometries, and frequencies of all observed and anticipated earthquakes affecting the sites of interest. The process of constructing an SSM can be summarized in the steps: (i) Identify all seismic sources capable of producing damaging ground motions within the region of interest, (ii) Characterize the spatial distribution of earthquake sources, assigning each source a geometry and position and (iii) Characterize the magnitude distribution of each earthquake source, assigning each source a magnitude-dependent occurrence rate (Gerstenberger et al. 2020).

Various information and considerations to characterize seismic sources, including recorded seismicity, distribution of observed seismicity, tectonics and geology, and active faults are used assuming that future seismic activity will resemble past occurrences. Therefore, knowledge of past earthquake locations and occurrence rates can be employed to forecast future earthquake occurrences. Depending on the region, different datasets may be available to constrain the behavior of past earthquakes and develop the SSM. Das et al. (2011) developed global regression relationships for converting M_s and mb magnitudes to the unified moment magnitude M_w. Their study analyzed global magnitude data from various sources and recommended using the Orthogonal Standard Regression (OSR) procedure for magnitude conversion. They proposed Inverted Standard Regression (ISR) relationships between mb and Mw for different magnitude ranges.

SSM may consist of several component models based on available data and considered uncertainties. The inherent time-dependent variability of earthquake occurrence is typically modeled using the Poisson distribution, which assumes that earthquakes occur independently in time. The space-magnitude forecast depends on the available data and the assumptions made in the specific model. The two common approaches namely (i) Distributed seismicity model (or areal source model) and (ii) Fault source model are described below.

1.1 Distributed and Areal Source Models

This model describes the occurrence of earthquakes that are not associated with well-identified fault sources. It is typically used when detailed information about fault characteristics is lacking and seismicity is modeled as distributed; a collection of possible sources with less definitive defined geometry. Two main source typologies used are areal sources and smoothed gridded seismicity. Areal sources are typically represented as polygons within which the probability of earthquake occurrence is uniform. They are suitable for modeling seismicity within a boundary that is believed to have consistent characteristics, including occurrence rate but pose challenges when earthquake rates vary spatially (Gerstenberger et al. 2020). In such cases employing numerous areal sources results in a small number of earthquakes within each source, making it difficult to constrain occurrences accurately. Utilizing areal sources also requires defining the boundaries of the zones, which is done using available geological or geophysical knowledge to identify regions where seismicity is expected to be similar. Often, the boundaries are not well-defined which led to smoothed seismicity representations of earthquake rates.

Smoothed seismicity defines regions with internally consistent attributes and treats them as a single source to determine occurrence parameters. Subsequently, the source zones are discretized into a grid of point sources allowing variable occurrence rates across the grid. The smoothed seismicity method captures the variability between the space-time distribution of past and future seismicity and fully depends on the earthquake catalog; therefore, smoothed seismicity models require significantly more earthquake observations to constrain the earthquake rate parameters. Each point source is assigned a fraction of the source zone rate by applying a smoothing kernel to the catalog occurrences. A Gaussian smoothing filter is often employed. Common smoothing methods include those that use a uniform smoothing distance (e.g., Frankel, 1995; Woo, 1996; Lapajne et al. 2003) and those in which the length of the smoothing distance increases as the density of observed earthquakes decreases (e.g., Akinci et al. 2018; Helmstetter et al. 2007). The choice of smoothing method may be based solely on expert judgment or may be determined using statistical optimization of forecast skill using past earthquakes (e.g., Petersen et al. 2015).

1.2 Fault Source Models

When sufficient information is available to characterize the geometry, slip rates, and potential magnitudes of individual faults, a fault source model is employed (Gerstenberger et al. 2020). This model provides a more detailed representation of earthquake occurrence along specific faults. These models utilizes various sources of geological data, including long-term slip rates estimated from geological investigations (e.g., Howarth et al. 2018), paleoseismic studies (e.g., Miyashita, 2018), geodetic observations (e.g., Bird & Kreemer, 2015; Field et al. 2014), and other geological data used to estimate long-term slip rates on faults (e.g., Howarth et al. 2018). Fault-based component models primarily constrain large-magnitude earthquakes, typically $M_w \geq 7.0$, but may also include smaller earthquakes depending on the quality of available earthquake geology data (Sharma and Conrad, 2012). A prevalent assumption is that faults rupture in a repeatable and segmented manner, meaning the rupture length is limited by segment boundaries, and an earthquake is unlikely to rupture multiple segments. This assumption is usually derived from geological observations (Howarth et al. 2018; Sharma and Conrad 2012) and practical considerations for simplifying hazard computations. However, geological studies of certain historical earthquakes (e.g., Wesnousky & Biasi, 2001) have necessitated the increasing allowance for multisegment ruptures in NSHMs (e.g., Stirling et al. 2012)

2 Defining Source Occurrence (Magnitude-Frequency Distributions)

MFDs represent the average frequency at which a source will generate earthquakes of each considered magnitude, typically expressed as annual rate of occurrence calibrated using either observed seismicity over instrumental and historic timescales or slip or strain rates across the seismic sources. Two types of MFDs are developed using Gutenberg-Richter (GR) MFD (Gutenberg and Richter, 1944) (i) Characteristic earthquake model (Schwartz and Coppersmith, 1984, Sharma and Lindholm, 2010 and (ii) Hybrid MFDs (e.g., Youngs and Coppersmith, 1985). Further, two commonly used MFDs are the double truncated Gutenberg-Richter and a G-R with tapering of larger magnitudes (Kagan, 2002). These same MFDs can sometimes be applied for a fault-based SSM, but different MFDs have also been proposed to describe the behavior of a single fault. Notably, the characteristic model suggests that a narrow range of magnitudes is more common than predicted by a G-R MFD. The validity of the characteristic model has long been debated, and statistical tests are still inconclusive about the behavior of individual faults (Page & Felzer, 2015; Stirling & Zuniga, 2017). The Youngs and Coppersmith (1985) MFD offers a compromise, combining a Gutenberg-Richter distribution with a characteristic distribution.

3 Poissonian Assumptions

Mostly the Poisson distribution is deployed to calculate exceedance probabilities of ground shaking, a key objective of PSHA. However, earthquakes cluster in space and time, necessitating the declustering of seismic catalogs (e.g., Gardner & Knopoff, 1974; Reasenberg, 1985) which is a technique used to separate mainshock earthquakes from aftershock events. The resulting mainshock catalog is treated as Poissonian, implying that earthquakes of a given magnitude occur at constant rates over time (Gerstenberger et al. 2020). The underlying assumption is that the ground shaking from the removed earthquakes is negligible for hazard applications. However, recent earthquake sequences in Canterbury, New Zealand (Gerstenberger et al. 2016), central Italy (Marzocchi & Jordan, 2017), and Kumamoto, Japan (Kamaya et al. 2016) have demonstrated that earthquakes typically removed by declustering can be highly relevant for PSHA goals (causing casualties and significant damage). For example, Iervolino et al. (2013) demonstrated that declustering leads to a 30% underestimation of the actual hazard in terms of the annual rate of exceedance of PGA. Similarly, Öncel and Alptekin (1999) showed that the declustering procedure doubles the return period for large seismic events. Furthermore, Teng and Baker (2019) found that the choice of the declustering method significantly impacts the declustered catalog and the hazard assessment. This implies that declustering-based PSHA models may underestimate risk. Furthermore, Gardner & Knopoff (1974) declustering method, the most widely used technique, can introduce inaccuracies in the MFD by eliminating a non-random sample of earthquake magnitudes. While recent research has explored incorporating the contribution of triggered earthquakes (Marzocchi & Taroni, 2014), however, a widely accepted solution remains elusive, and hazard results continue to be affected.

The assumption in the Poisson process that earthquakes occur independently can be relaxed for certain applications to incorporate the debated concept of quasiperiodicity for major faults. Paleoseismological studies have revealed evidence of long-term time clustering on certain faults, indicating that earthquakes may not occur entirely randomly (Taylor-Silva et al. 2019). Additionally, major faults exhibit periodicity in large earthquake occurrences (Nishenko & McCann, 1981) which is often linked to the characteristic earthquake model. The characteristic earthquake model also remains contentious due to unsuccessful statistical validations of the gap hypothesis (Rong et al. 2003). The elastic rebound principle (Reid, 1910) suggests that the stress released during an earthquake requires a repeatable period to recover and trigger another earthquake albeit statistical evidence has not consistently supported it. The primary evidence from paleoseismological observations (Goldfinger et al. 2016) revealing patterns in the timing of large earthquakes on certain faults, suggesting the possibility of quasiperiodic behavior. However, evidence also exists for time variability beyond simple periodic behavior (Wechsler et al. 2014).

4 Time-Dependent Models

Time-dependent earthquake occurrence models determine the likelihood of the next earthquake, where this probability is influenced by the magnitude of the most recent earthquake. Non-Poissonian distributions or Markov chains are employed to incorporate the memory of past events. This approach suggests that seismogenic zones that have recently experienced strong earthquakes become less hazardous than those that have not ruptured in recent history. The time-predictable and slip-predictable models are both based on the observation that seismic activity correlates with earthquake-related coastal uplift in Japan (Shimazaki and Nakata, 1980; Scholz, 1990; Thenhaus and Campbell, 2003). Other time-dependent earthquake occurrence models that result in the stationary Poisson process include log-normal, Gamma, Weibull, doubly exponential, and exponential distributions. These models employ statistical distributions to characterize the intervals between successive earthquakes. Among the various attempts to model earthquake recurrence intervals using statistical distributions, two have gained prominence in PSHA: the log-normal model (Nishenko and Buland, 1987) and the Brownian passage time (BPT) renewal. The BPT distribution, also known as the inverse Gaussian distribution, has gained wider acceptance than the log-normal model in recent years (Matthews et al. 2002). This model is characterized by two parameters, μ, and σ, representing the average time between consecutive earthquakes and the standard deviation, respectively. The aperiodicity of earthquake occurrence, as described by the BPT model, is governed by the variation coefficient $\alpha = \sigma/\mu$. A smaller α indicates lower aperiodicity, resulting in a more symmetrical distribution. Conversely, a larger α leads to a distribution resembling the log-normal model, skewed to the right with a peak at a value lower than the mean. Bajaj and Sharma (2019) have also explored use of stochastic models, namely Weibull, log-normal, gamma, and inverse Gaussian stochastic models in the Himalayas (Harbindu et al. 2012).

GROUND MOTION MODELS

Another important component of PSHA is the ground motion characterization using GMMs to compute the level of ground motion. GMMs make use of earthquake magnitude and source-to-site distance parameters to compute the ground motion at a given site with the associated uncertainty. While sophisticated physics-based ground shaking models (e.g., Graves et al. 2011) hold promise for future but they require detailed source parameters that are not yet readily available through SSMs which partially explains why empirically determined ground motion prediction equations (GMPEs) are the most commonly used ground-shaking models. To improve the predictive capabilities GMPEs have recently incorporated many additional predictor variables (e.g., Gregor et al. 2014). Modern GMPEs have evolved beyond simply fitting equations to observed data; they may incorporate their modeling components using additional constraints from simulated ground-shaking data (e.g., NGA East; Goulet et al. 2018). However, a significant challenge is the limited data availability for large-amplitude ground shaking, particularly in sparse recording networks (Sharma, 1998; Sharma and Bungum, 2006). To address this, global databases of strong ground motion recordings are usually compiled to enhance coverage in key magnitude and distance ranges. However, data for near-source large shaking remains scarce, mainly from a few significant earthquakes.

To complement observational databases, GMMs recently started combining synthetic shaking data from kinematic models (e.g., Frankel et al. 2018). Unlike dynamic models assuming predetermined rupture properties (e.g., Kaneko et al. 2008) they utilize the wave equation and a velocity model derived from geophysical studies to calculate ground motions at specific locations. However, current kinematic methods face limitations in simulating periods shorter than 1 second, requiring additional stochastic approaches for shorter periods. While exploring alternative rupture properties introduces prediction variability, it is computationally expensive. Despite these challenges, kinematic models are expected to become more crucial, especially for estimating large near-source shaking and subduction zone earthquakes, where strong shaking data is limited globally. However, the detailed knowledge required for ground motion simulations, including 3-D geological structure and fault geometry, poses challenges in the hazard model due to limited a priori information and resolution constraints.

GMMs rely on the assumption that ground motion behavior is sufficiently uniform across regions, known as the ergodic hypothesis (Anderson & Brune, 1999). However, global GMMs have been adjusted using local observations to reduce ground motion variability in specific regions (Bradley, 2013; Gregor et al. 2014). Another solution is to explore site-specific corrections to regional or global GMMs (e.g., Sharma et al. 2009; Srinivasan et al. 2012; Al Atik et al. 2010; Sharma & Haribhandhu (2012); Harbindu et al. 2014; Ameri et al. 2017). Similar assumptions are necessary for region-specific models, as all GMMs are axisymmetrical and do not consider azimuthal anisotropy in wave propagation. These assumptions contribute to uncertainty in hazard calculations (e.g., Joshi & Sharma 2010, 2011). However, uncertainty can be reduced by using physics-based GMMs applied to reliable 3-D crustal models (Bradley, 2019) and empirical GMMs that can model the lack of ergodicity using a large dataset of ground motion data over well-sampled broad regions (e.g., Abrahamson et al. 2019). This area of research holds promise for reducing epistemic uncertainty.

For Seismic Hazard Analysis (SHA), the meticulous assessment of ground-motion models stands as a critical component for ensuring the precision and reliability of seismic risk evaluations. The evaluation criteria proposed by Cotton et al. (2006), and Delavaud et al. (2012) offer a comprehensive framework for scrutinizing these models. Bommer et al. (2010) present qualitative criteria that serve as benchmarks for the appropriateness and robustness of seismic ground-motion models.

The accessibility of the dataset used to derive the model is deemed crucial, requiring a presentation in an accessible format. Models that have been superseded by more recent publications raise concerns about their continued applicability and accuracy. Expectations include providing spectral predictions for a sufficient range of response periods, demonstrating functional characteristics like non-linear magnitude dependence or magnitude-dependent decay with distance. Coefficients must be determined with methods accounting for both inter-event and intra-event components of variability. Inappropriate definitions for explanatory variables and limitations in applicability range are also considered drawbacks. Models constrained by insufficiently large datasets are deemed inadequate.

Cotton et al. (2006) focus on the selection and adjustment of ground-motion models tailored for probabilistic seismic hazard analysis in moderately active regions. Their criteria revolve around the quality of selected models, assessing models based on their similarity to the geological and geophysical characteristics of the region, and considering specific path and site properties in the region.

Delavaud et al. (2012) introduce a quantitative measure, the Data Support Index (DSI), to gauge the distance between a model and the data-generating process. They emphasize a quantitative efficacy test over relying solely on likelihood values (LLH). The DSI provides insights into the percentage by which the weight on a model should be adjusted based on data support.

A comprehensive assessment of seismic ground-motion models necessitates a balanced consideration of qualitative and quantitative criteria. Bommer et al. (2010)'s qualitative criteria establish a framework for evaluating the fundamental characteristics and applicability of models, while Cotton et al. (2006). tailor criteria for regions with limited data. Delavaud et al. (2012) quantitative approach adds precision, emphasizing the importance of assessing the distance between models and the actual data-generating process through the DSI. Together, these criteria offer a robust methodology for selecting, adjusting, and scrutinizing seismic ground-motion models for effective use in Seismic Hazard Assessment.

REVIEW OF NSHMS

This section presents a brief description of NSHMs being developed worldwide. Specifically, five NSHMs from Australia, USA, Taiwan, Europe and India are explained in the following section. These NSHMs often reference other countries where data and scientific resources for conducting region-specific seismic hazard analysis are limited.

1 Australia

The NSHA18 (Allen et al. 2018a), a comprehensive seismic hazard assessment for Australia, incorporates a diverse range of 19 seismic-source characterizations to address the inherent uncertainties in understanding the seismic hazard landscape of Australia and its offshore territories (Gerstenberger et al. 2020). This novel approach acknowledges the epistemic uncertainties associated with seismic hazard assessment, recognizing that different interpretations of the available geological and geophysical data can lead to varying seismic hazard estimates (Allen et al. 2020).

Notably, PGA values for the 1/500 Annual Exceedance Probability in Australia dropped by 72% compared to the Australian earthquake loading standard (Standards Australia, 2007). This reduction is attributed to adjustments in earthquake frequency estimates, including corrections to local magnitudes and conversions to moment magnitudes (Allen et al. 2018b). Changes in Gutenberg and Richter ‘b’ values and modern ground-motion attenuation models also contribute to the lowered seismic hazard factors.

2 USA

The seismic hazard models developed by the USGS are used to assess seismic hazards and are used to develop building codes and other safety standards (Gerstenberger et al. 2020). The models have evolved since 1976, with major updates in 1996, 2002, 2008, 2014, 2018, and the latest draft in 2023 incorporating new data and techniques. Over the decades, there has been a shift towards more standardized and analyzed data, embracing open-source computer tools such as Open-SHA (Field et al. 2003) and nshmp-haz (Powers, 2017). The USGS seismic hazard models have two main types: one for public use, guiding hazard assessments for building codes and policies, and another for research purposes, potentially influencing future public models.

The 2018 NSHM includes new GMMs, new estimates of aleatory variability, and new estimates of site amplification factors. Seismic source models include smoothed seismicity, background zones, and fault sources. The 2018 NSHM earthquake catalogs were refined using Mueller (2019) methodology. California has a separate source model which is unique and advanced that explicitly considers time dependence. The most recent version of the California model is UCERF3 (Field et al. 2014). The background-gridded source model employs GR relations with fixed and adaptive-kernel smoothing. Fault source models integrate recurrence rates from geological and geodetic data. Comparing seismic hazard results from two fault slip-rate models, geologic-only and combined geodetic-geologic, shows that combined geodetic-geologic inversions produce larger probabilistic ground motions in some areas. Differences in ground motion between the two slip-rate models are correlated with differences in slip rate, with higher slip rates from the geodetic-informed models resulting in higher ground motions. Increased ground motions from the geodetic-informed models suggest areas where discrepancies between geodetically and geologically observed strain rates may exist (Gerstenberger et al, 2020). Also, adaptive smoothing models focus seismicity rates around earthquake clusters, resulting in higher probable ground motions in areas of high seismicity and lower ground motions in areas far from these clusters.

Compared to previous models, the hazard has been calculated for several additional periods and site classes across the entire WUS. The ground motions are generally higher across the CEUS due to new GMMs with higher sigma and amplification at periods less than 2 seconds. The results indicate an increase in ground shaking intensity in many areas of the CEUS (up to approximately 30%) and in the vicinity of the four major urban areas situated above deep sedimentary basins in the WUS (up to about 50%).

3 Taiwan

Taiwan's seismic hazard assessment, TEM PSHA2020, represents a significant improvement over TEM PSHA2015 with key advancements (Gerstenberger et al. 2020). This includes a more recent database of seismogenic structures, consideration of rupture likelihood across different structures, a predictive model for ruptures over time, updates to the area source model with a recent earthquake catalog, utilization of a smoothing model for background seismic activity depiction, and the introduction of new GMMs (Chan et al. 2020).

The Brownian Passage Time (BPT) model was employed to assess the probability of future earthquakes based on a fault's history. This revealed higher hazards near structures with longer intervals since their last rupture or shorter intervals between ruptures, while structures with recent seismic activity experienced lower probabilities, leading to decreased hazard levels. TEM PSHA2020 provides two versions for different users—one incorporating engineering bedrock data and another considering site amplification effects with a Vs30 map. Areas like the Taipei Basin, Ilan Basin, and Chianan Plain were identified as having high earthquake hazards, with additional risks such as soil liquefaction during strong earthquakes highlighted by the Central Geological Survey (Chan et al. 2020).

4 European Seismic Hazard Model

The 2020 European Seismic Hazard Model (ESHM20) is an updated earthquake risk assessment for the Euro-Mediterranean area, funded by the European Union's Horizon 2020 program (Gerstenberger et al. 2020). Building on its predecessor, ESHM13, it employs the latest procedures consistently across the pan-European region, addressing issues related to country borders. ESHM20 utilizes newly gathered data, including earthquake catalogs, active fault information, and ground shaking records, while incorporating current knowledge about tectonics, geology, and models for seismogenic sources and ground shaking. The model employs a fully probabilistic approach, harmonizing data and inputs across borders (Danciu et al. 2021).

Key features of ESHM20 include a harmonized seismogenic source model, a detailed logic tree with area and hybrid models, and a ground motion characteristic model based on extensive ground-shaking recordings. The model introduces a new method for capturing regional differences in ground shaking and manages uncertainties through a comprehensive logic tree. ESHM20 provides a range of hazard results, including curves, maps, and uniform spectra, considering multiple intensity measures and return periods.

Comparing ESHM13 and ESHM20, while their overall layouts are similar, the newer ESHM20 generally indicates lower hazard levels in most areas. However, specific hazard values vary, with some regions, including parts of Romania, Albania, Greece, Western Turkey, Southern Spain, and Southern Portugal, showing increased hazard levels in ESHM20. Iceland exhibits a significantly lower hazard level in ESHM20 due to updates in earthquake catalogs, active fault data, and calibrated ground motion models. Variations in hazard levels arise from updated seismogenic sources, new GMMs, and changes in earthquake predictions, slip rates, and maximum magnitudes of faults, among other factors.

5 India

The issue of seismic hazard was addressed in India as early as 1956 when a seismic zoning map of India showing three zones was produced by India Meteorology Department (Tandon 1956). These frameworks were based on the maximum expected intensity shaking in terms of MM intensity. Since then, many versions of the seismic zoning map of India has been published by the Bureau of Indian Standard (BIS), the official agency for publishing such maps from time to time, the latest being the seismic zoning map of India showing four zones (I–IV) (BIS code 1893 2002). Following the probabilistic hazard computation approach, Khattri et al. (1984) probabilistic seismic hazard (PSH) model calculated PGA for the Himalayan region of the order of 0.7 g for 10% probability of exceedance in 50 years (Choudhary and Sharma, 2017 & 2018). Under the GSHAP (Global Seismic Hazard Assessment Programme), Bhatia et al. (1999) calculated the PSH using the Joyner and Boore's (1981) attenuation relation for Indian region and produced PGA of the order 0.35–0.4 g for 10% probability of exceedance in 50 years. Kumar et al., (2006) has estimated the conditional probabilities for the whole Indian region by dividing it into 24 seismogenic source regions and found that the conditional probabilities of occurrence of magnitude more than 6.0 were relatively more than the estimates using classical methods of probabilistic seismic hazard. The distributions used in this study were Weibul, normal, Gaussian and Poissonian. The conditional probabilities were estimated for the last occurrence of magnitude 6.0 in the region.

Recently, Anbazhagan et al. (2012) introduced an innovative seismic hazard analysis method called Rupture Based Seismic Hazard Analysis (RBSHA), which considers the likelihood of earthquake occurrence in the regions different from those previously affected by catastrophic earthquakes. The RBSHA method considers the rupture features of local faults and lineaments, offering a means to determine the maximum probable earthquake magnitude. Anbazhagan et al. (2021) conducted the rupture based seismic hazard analysis of Tripura state of North-East India. They have provided the hazard maps of the state developed with this new method. It showed that Tripura state can experience higher PGA values than as mentioned in IS 1893: Part 1 (2016). Recently several researchers/organizations have performed PSHA at National level like NDMA (2010), Nath & Thingbaijam (2012), Sitharam et al. (2015) and Sreejaya et al. (2022). For various cities, the results had a wide range viz., for 10% PoE in 50 years: Delhi (0.08 to 0.27), Mumbai (0.06 to 0.16), Chennai (0.03 to 0.13), Kolkata (0.09 to 0.15), Bangalore (0.02 to 0.13), Guwahati (0.23 to 0.66), and for Ahmedabad (0.07 to 0.11) (Table 1). Figure 1 shows the wide ranges of PGA (g) given by the NDMA (2010), Nath & Thingbaijam (2012), Sitharam et al. (2015) and Sreejaya et al. (2022). Also, Parvez et al. (2003) and Sitharam et al. (2010) have performed the DHSA at National level which differs to a very wide range.

When applying an attenuation relation, validation of parameters such as the number of earthquakes used for regression, tectonic region, site characterization, shear wave velocity, earthquake source parameters (magnitude, depth, stress drop, focal mechanism, fault types, source directivity and radiation pattern, hanging wall and footwall effects, source to site distance) is crucial before assessment.

The Geological Survey of India (GSI) compiled and integrated data on geological, geophysical, and seismological attributes for the entire country, resulting in the Seismotectonic Atlas of India and its Environs (GSI 2000). Khattri et al. (1984) identified 24, Bhatia et al. (1999) - 86, Parvez et al. (2003) - 40, NDMA (2010) - 32. To account for major tectonic and geological features, some studies preferred larger zone selections. Similarly, the Indian shield region was categorized into seven tectonic zones following Seeber et al. (1999), emphasizing the need for incorporating large-scale geological features in identifying source zones when historical data is insufficient. Thingbaijam and Nath (2011) established a layered seismogenic source zonation corresponding to four Hypocentral depth ranges (in km): 0–25, 25–70, 70–180, and 180–300. Smaller seismic source zones yield an unstable estimation of seismicity parameters due to fewer earthquakes per zone. To address this, recent work by Sreejaya et al. (2022) adopted the 32 distributions of NDMA (2010). Among 33 seismogenic zones, the Himalayan zones, North-eastern India region, Andaman region, Chaman fault region, Hindukush-Pamir, and Tibetan Region are active compared to the shield region of India. The Peninsular region encompasses south India, Central India, and Kutch zone. Despite being a stable continental region, the Kutch zone is more active than other peninsular regions. Table 1 provides some of the references of the work carried out at national level.

Previous studies reported hazard estimates in terms of median (or mean) ground-motion values, which are significantly lower, especially at lower annual exceedance rates, according to observations at different cities. Sitharam et al. (2015) used three types of SSMs (linear sources, gridded seismicity model, and areal sources) and different sets of ground motion prediction equations. Hazard estimation at the bedrock level utilized a probabilistic approach, combining results obtained from various methodologies in a logic tree framework. Seismic site characterization of India used a topographic slope proxy map derived from Digital Elevation Model data.

Recently, Sreejaya et al. (2022) developed a new probabilistic seismic hazard map for India and adjoining regions valid at rock type site class B (Vs30 = 760 m/s).

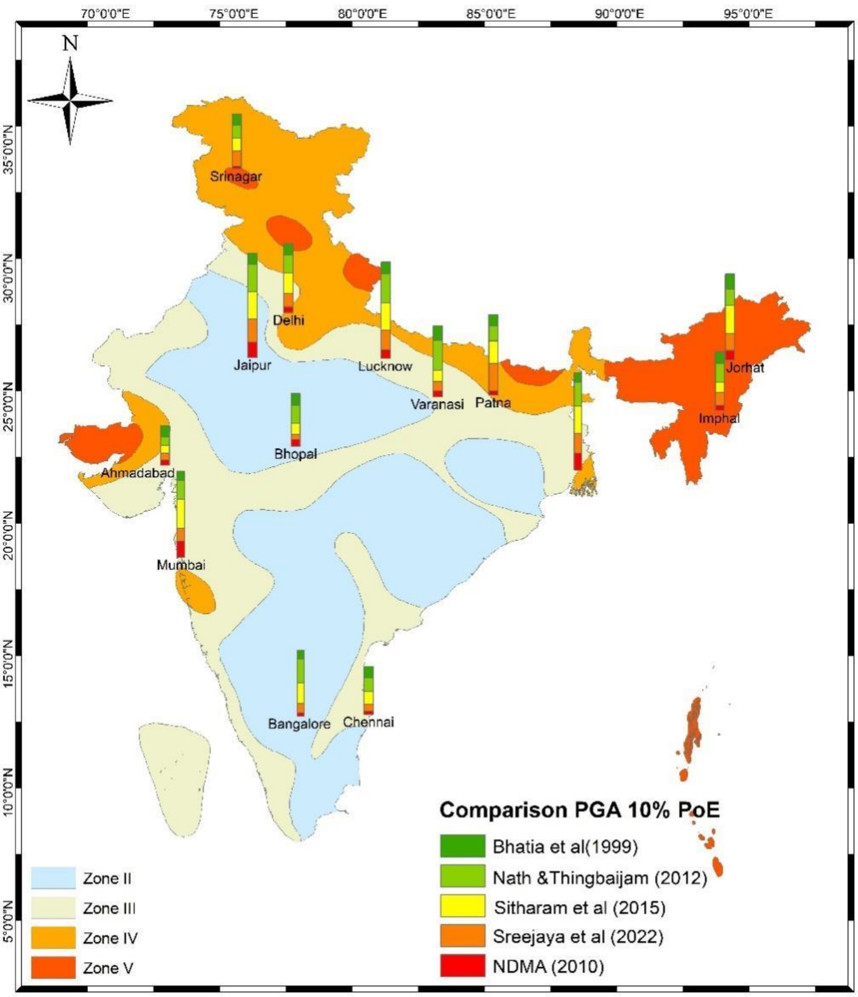

Fig. 1 Comparison of Peak Ground Acceleration (PGA) values for major cities in India as reported by Bhatia et al. (1999), NDMA (2010), Nath & Thingbaijam (2012), Sitharam et al. (2015), and Sreejaya et al. (2023). The length of each color in the candle plot represents the relative values of PGA.

The region is divided into 33 broad seismic source zones following (NDMA 2010). An updated homogeneous catalog since 2600 BC is utilized to derive seismicity parameters. Sreejaya and Raghukanth et al. (2022) produced seismic hazard maps by considering spatially distributed seismicity and fault information. GMPEs were identified for the region and combined in a logic tree to address epistemic uncertainty. Weights for logic tree branches were determined following the ranking schemes of Kale et al. (2019). The work attempts to bridge the gap in establishing suitable logic tree weights for hazard assessment in India. The PGA distribution indicates the highest hazard in the Himalaya and Northeast India, with lower values observed in Central India and the Southern peninsular region. Similar dissimilarities have been observed in the DSHA carried out at regional level of India: Boominathan et al. (2008) for Chennai, Sitharam et al. (2006) and Sitharam & Anbazhagan (2007) for Bangalore, Kataria et al. (2013) for Andaman and Nicobar Islands, Naik and Choudhury (2014) for Goa, Rao and Choudhury (2021) for North-Western part of the Himalaya, Anbazhagan et al. (2021) and Sitharam & Sil et al. (2014) for Tripura region. Kumar et al. (2013), Anbazhagan (2015) and Baro et al. (2018) for Lucknow, Patna and Shillong Plateau respectively, Anbazhagan et al. (2017) for Kanpur, Sitharam and Sil (2014) for Mizoram and Mishra et al. (2023) for Guwahati (Table 2).

PHSA has also produced wide range of results which are not matching with each other for regional level: Das et al. (2016) and Sharma & Malik (2006) for the North-East India, Mishra et al. (2023), Bandyopadhyay et al. (2022), and Ghione et al. (2021) for Guwahati, Bahuguna & Sil (2018) for Assam, Lallawmawma et al. (2023a, 2023b) for the Mizoram, Sitharam & Sil et al. (2014) for Mizoram and Tripura.

Table 1: Seismic hazard assessment performed at national level

City	DSHA		PSHA (10% POE in 50 years)				
	Parvez et al. (2003)	**Sitharam et al. (2010)**	**Bhatia et al. (1999)-**	**NDMA (2010) ‘A’ type Soil**	**Nath & Thingbaijam (2012)-**	**Sitharam et al. (2015)**	**Sreejaya et al. (2022) DBE**
Delhi	0.15-0.3	0.42	0.15	0.08	0.24	0.27	0.176
Mumbai	0.01-0.02	0.45	0.05	0.09	0.16	0.10	0.068
Chennai	0.04-0.08	0.10	0.05-0.10	0.03	0.12	0.13	0.062
Kolkata	0.04-0.08	0.41	0.05	0.09	0.15	0.13	0.107
Lucknow	0.04-0.08	0.25	0.05	0.04	0.13	0.12	0.086
Bangalore	0.0-0.005	0.17	0.05	0.02	0.11	0.13	0.051
Andaman & Nicobar	0.3-0.6	-	0.15-0.30	-	0.71	-	0.45
Patna	0.08-0.15	0.3	0.1	0.04	0.13	0.2	0.057
Srinagar	0.3-0.6	0.6	0.3	0.08	0.33	0.35	0.388
Guwahati	0.6-1.2	0.55	0.35	0.23	0.66	0.4	0.401
Jaipur	0.0-0.005	0.07	0.05	0.07	0.12	0.12	0.101
Ahmedabad	0.08-0.15	0.18	0.15	0.07	0.11	0.10	0.096
Bhopal	0.005-0.010	0.15	0.05	0.03	0.08	0.05	0.023
Varanasi	0.01-0.04	0.2	0.05	0.02	0.04	0.10	0.031
Imphal	0.6-1.325	0.55	0.4	0.2	0.68	0.35	-

Table 2: Deterministic seismic hazard assessment performed at regional level

Author	City	DSHA (PGA in g)
Boominathan et al. (2008)	Chennai	0.004 - 0.106
Sitharam et al. (2006)	Bangalore	0.146
Sitharam & Anbazhagan (2007)		0.146 & 0.159(RLD)
Kataria et al. (2013)	Andaman and Nicobar Islands	0.20-0.58.
Naik & Choudhury (2014)	Goa	0.15-0.62
Rao & Choudhury (2021)	North-Western part of Haryana	0.08-0.15 (considering all scenario)
Anbazhagan et al. (2021)	Tripura (NE India)	0.1-0.22 (conventional DSHA) 0.14-0.20 (Rupture based DSHA)
Sitharam and Sil et al. (2014)		0.29
Kumar et al. (2013)	Lucknow	0.06-0.13

Anbazhagan (2015)	Patna	0.14-0.74
Baro et al. (2018)	Shillong Plateau and adjoining areas	0.27-0.46
Anbazhagan et al. (2017)	Kanpur	0.04-0.36
Sitharam and Sil et al. (2014)	Mizoram	0.24
Mishra et al. (2023)	Guwahati	1.01

Table 3: Probabilistic seismic hazard assessment performed at regional level

Author	City	PSHA (PGA in g)
Das et al. (2016)	North-East India	0.114-0.316
Sharma and Malik 2006		0.05-0.600
Mishra et al. (2023)	Guwahati	0.28
Bandyopadhyay et al. (2022)		0.25
Ghione et al. (2021)		0.35
Bahuguna & Sil. (2018)	Assam	0.27-0.49
Lallawmawma et al. (2023)	Mizoram	0.168- 0.4
Sitharam and Sil et al. (2014)		0.11-0.17
Sitharam and Sil et al. (2014)	Tripura	0.11-0.22
Pallav et al (2012)	Manipur	0.18–0.63
Mohanty & Walling (2008)	Kolkata	0.10-0.34
Agrawal & Chawla (2006)	Delhi	0.12- 0.17
Kumar et al. (2013)	Lucknow	0.04- 0.07
Patil et al. (2014)	Himachal Pradesh	0.092-0.15 (b value varying) 0.09-0.26 (constant b values)
Rout et al. (2015)	North-Western and Central Himalayas	0.06 - 0.36
Anbazhagan et al. (2017)	Kanpur	0.092-0.1525
Mahajan et al. (2010)	North-West Himalaya	0.02-0.75
Anbazhagan (2015)	Patna	0.03-0.165
Huded et al. (2022)	Odisha	0.004 - 0.054
Sana (2019)	Kashmir	0.56 – 0.68
Ashish et al. (2016)	Peninsular India	0.032-0.402
Jaiswal and Sinha (2007)		0.1-0.25
Petersen et al. 2004	North-Western Gujarat	0.2-0.7
Menon et al. (2010)	Chennai	0.090
Sitharam et al. (2007)	Bangalore	0.146
Anbazhagan et al. (2008)		0.17–0.25

Pallav et al. (2012), Mohanty & Walling (2008), Agrawal & Chawla (2006), Kumar et al. (2013) and Patil et al. (2014) for the Manipur, Kolkata, Delhi, Lucknow and Himachal Pradesh respectively. Rout et al. (2015), Anbazhagan et al. (2017), Mahajan et al (2010), Anbazhagan et al. (2015), Huded et al. (2022), Sana (2019), Ashish et al. (2016), Petersen et al. (2004), Menon et al (2010), Sitharam et al. (2007), Anbazhagan et al. (2008), Sharma et al. (2003) and Sharma & Dimri (2003), Joshi & Sharma (2010), and Sharma et al. (2020), Shanker and Sharma, 1997, 1998 & 2001; for the region North-Western and Central Himalayas, Kanpur, North-West Himalaya, Patna, Odisha, Kashmir, Peninsular India, North-Western Gujarat, Chennai, Bangalore, Northern Indian, Delhi and for the Indo-Gangetic Plains region (Table 3).

INTERVENTIONS IN SHA IN INDIA

This section includes some of the exercises carried out in Indian context for using models other than the Poissonian and includes the use of time dependent models (Bajaj and Sharma, 2018, 2019& 2020; Sharma and Bajaj, 2018, 2019 & 2021; Bajaj et al. 2018), use of extreme value statistics, different form of FMD especially the constant seismicity rate and constant moment rate, zone-less SHA, smoothed gridded methods, ANN, Topographic Slope Proxy-Based Vs30 Estimation and scenario developments. It further explores the selection of GMPEs in India context.

The time-dependent seismic hazard assessment for the Himalayas has been carried out by many (Negi et al. 2015, Nishenko & Singh, 1987; Kumar et al. (2006); Sharma & Kumar, 2010; Yadav et al. 2008 & 2010b; Sharma & Shankar, 2001). Utsu (1984) compared different probabilistic models for Japan and observed that the lognormal model gives the best results in some cases but worst in others. Weibull and Gamma models gave the intermediate results. Nishenko and Buland (1987) studied the recurrence interval distribution using Lognormal and Weibull distributions and found the Lognormal to be the best. Rikitake (1991) also used the Weibull and Lognormal models to study earthquake hazard in the Tokyo area of Japan and predicted that the probability of Japan's capital area being hit by a damaging earthquake is too high. Such type of study for Hindukush and the northeast region of India has been carried out by Parvez and Ram (1997) using Weibull, Lognormal and Gamma and latter for the whole Indian subcontinent (Parvez and Ram, 1999). They observed that Gamma and Weibull models are the most suitable models for the Indian sub-continent. Yadav et al. (2010b) and Pasari and Dikshit (2014) applied three stochastic models, namely, Weibull, Gamma, and Lognormal, in the northeast and adjoining region of India and Yadav et al. (2010b) found that the Gamma is the most suitable for this region. Sharma and Kumar (2010) applied Weibull for the whole Indian region. Chingtham et al. (2015) used Weibull and Lognormal distributions for Northwest Indian region and found Lognormal to be the best-suited model for this region. Tripathi (2006) used Weibull, Log-Normal and Gamma distributions for hazard assessment study of the Gujarat region. Along with these models, several modified forms of these have also been used such as generalized Gamma, exponentiated exponential, Inverse-Weibull, etc.

Bajaj and Sharma (2019) focuses on the use of stochastic models, namely Weibull, log-normal, gamma, and inverse Gaussian stochastic models, to estimate non-Poissonian probabilities of exceedance for different seismic source zones (SSZs) in the Himalayas. The study divides the Himalayas into four SSZs and analyzes earthquake data for two magnitude ranges, $M_w \geq 6.0$ and $M_w \geq 7.0$. The best-fitted models for each SSZ are determined using the Kolmogorov-Smirnov (K-S) test. The study finds that the suitability of the models varies across the SSZs, with Gamma, Inverse-Gaussian, Lognormal, and Inverse-Gaussian models being the most suitable for $M_w \geq 6.0$ in SSZ I, II, III and IV, respectively. For $M_w \geq 7.0$, the Lognormal model is most suitable for SSZ I to III, while the Gamma model is best for SSZ IV. The study concludes that various factors, including the region's geometry, interaction between different seismic sources, and the time-dependent occurrence of earthquakes, influence the seismic hazard in the Himalayas.

The frequency-size distribution of earthquakes has attracted interest from many researchers. It was initiated by Ishimoto and Iida (1939) and further followed by Gutenberg and Richter (1944) (GR) which became one of the most common magnitude-frequency relationships used in seismology for estimation of the annual occurrence exceedance rates in an identified seismogenic source zone.

Two of the models became more useful namely the constant seismicity model and constant moment release model. In constant seismicity models, the total number of occurrences greater than equal to minimum magnitude of earthquakes is independent from maximum magnitude. The lower value of maximum magnitude shows lower moment release in the seismogenic source zone and can be overcome by constraining moment release rate. The lowering of maximum magnitude is recompensed by increasing the total number of small to moderate earthquakes. It is thus possible to modify the constant seismicity recurrence models using the geologically determined moment release rate (Shedlock et al. 1980). Constant Moment Release model generally follows some assumptions: (1) If no creep is specified explicitly, the entire slip on a fault or within a seismic source is seismic (2) The mean value of the slip rate for large time interval is applicable to the future time period of interest and the short term fluctuations in the slip rate are not important (3) The slip-rate from surface measurements is representative of the slip rates at seismogenic depths and along the entire fault segment of interest. With these assumptions the long-term average annual occurrence rate is computed by balancing the seismic moment release rate due to average large time period slip rate which can be estimated by geodetic or geological field investigations. For example, Choudhary and Sharma (2018) conducted a seismic hazard assessment in the western to central Himalayas, employing these two models i.e., the constant seismicity model, a statistical approach based on recorded earthquake catalog data, and the constant moment release model, utilizing strain rate data.

The study focuses on three regions within the Himalayas: North-West Himalayan Fold and Thrust Belt, the Garhwal Himalaya, and the Nepal region. The North-West Himalayan fold and thrust belt results show a 55.67% higher total seismicity rate when utilizing the constant moment release model than the constant seismicity model. This difference has been interpreted that the strain accumulated from past earthquakes may not be entirely released, potentially indicating compensatory mechanisms or incomplete earthquake catalog data. In the Garhwal Himalaya region, seismicity rates exhibited significant differences between the constant seismicity model and the constant moment release model implying lower seismicity than in the North-West region. The region demonstrated potential for a significant earthquake ($M_w \geq 8$), and the constant moment release model predicted earthquakes occurring sooner across all magnitude ranges. In Nepal, an observed trend indicated a higher total seismicity (78%) with the constant seismicity model. Given Nepal's history of major earthquakes, notably the Gorkha earthquake 2015, which revealed locked segments of the Main Himalayan Thrust fault, the constant seismicity model predicted an earthquake of magnitude 8 in 700 years. In contrast, the constant moment release model estimated a longer interval of 1100 years for the same magnitude.

Due to our relatively more engineering interests in higher magnitude range, application of extreme value statistics become useful. Nordquist (1945) was the first one to apply the extreme value theory in SHA where Gumbel distribution to estimate probability of occurrence of large earthquakes was used. Subsequently, several investigations (e.g., Srivastava et al. 2013; Bird and Kagan 2004) were conducted in the past for finding a suitable description of the tail of the magnitude frequency distribution. For the large event distribution Pacheco and Sykes (1992) suggested visual inspection, Sornette et al. (1996) pointed out Monte-Carlo simulations, Kagan (1997, 1999) suggested Maximum likelihood estimation of the proposed Pareto distribution tapered by an exponential distribution (Ameer et al. 2002). As one of the example, Choudhary and Sharma (2017) employed statistical methods, specifically utilizing the Pareto, Truncated Pareto, and Tapered Pareto distributions, to assess the probability of earthquake occurrences in the Himalayas. The findings indicated that the Tapered Pareto distribution better describes seismicity for Himalayan seismic source zones. The study concluded that employing different statistical models for fitting individual seismic source zones in the Himalayas is crucial for a comprehensive understanding of seismic activity in the region.

In the absence of clear boundaries for earthquake source zones, the smoothed seismicity approach is also one of the alternatives which can be used to estimate earthquake rates (e.g., Akinci et al. 2018; Frankel, 1995; Helmstetter et al. 2007; Woo, 1996; Lapajne et al. 2003). This approach does not require defining zone boundaries and instead relies on smoothing techniques to represent the spatial distribution of earthquakes. Among the commonly employed techniques are (i) the circular smoothed seismicity approach.

Nath and Thingbaijam, (2012) used a gridded seismicity approach and presented a national seismic hazard map of India. Jaiswal and Sinha, (2007) utilized Kernel estimation techniques for seismic hazard assessment in the Peninsular region. In neighboring regions, Rahman and Bai, (2018) performed for Nepal, while Waseem et al. (2018) conducted a similar analysis for Northern Pakistan. Xu, (2019) used elliptical smoothed seismic approach and performed seismic hazard for China. Comparable studies for other regions, such as Thailand (Ornthammarath et al. 2011), Bangladesh (Carlton et al. 2018), and Afghanistan (Waseem, 2019), are also seen in the literature. Recently (Sreejaya et al. 2022) performed a seismic hazard map of India using elliptical smoothing approach accounting the predominant fault orientations. Illustrating the spatial variation of the smoothed gridded seismicity approach at the regional level, Lallawmawma and Sharma (2023b) performed PSHA for Northeast India considering three source models: (i) the areal source model, (ii) fault zone polygon model, and (iii) smoothed gridded seismicity model using (Frankel, 1995). The comparison between areal source and smoothed gridded seismicity models shows that the PGA ratio ($PGA_{Areal}/PGA_{Gridded}$) ranged between 0.41 and 1.57 on average, and the SA at 0.2 seconds ratio (SA Areal/SA Gridded) ranged between 0.36 and 1.67 on average. Notably, the smoothed gridded model tended to yield higher values for PGA and SA (0.2s) in regions surrounded by large recorded events.

Other examples include use of ANN in seismic hazard assessment (Arora and Sharma, 1998; Sharma and Arora, 2005), use of individual contributions from seismogenic faults (Sharma and Conrad 2012), use of proxy-based techniques such as topography slope, surface geology, site fundamental period and hybrid proxies to determine Vs30 (Srivastava et al. 2022, 2023; Borah et al. 2022, 2023).Topographic variations serve as a primary indicator of near-surface geomorphology and lithology, with steep mountains signifying rock, nearly flat basins indicating soil, and an intermediate slope marking a transition between these extremes. The slope or gradient of the topography is a diagnostic factor for Vs30, as materials with higher velocity tend to maintain steeper slopes, while deep basin sediments are primarily deposited in areas with very low gradients.

CONCLUDING REMARKS

Development of seismic hazard model requires making a series of crucial modeling choices and the decisions made become controversial and lead to justified debates. (e.g., Griffin et al. 2020). Criticisms mainly focus on assumptions made during the modeling process rather than the PSHA framework itself (e.g., Mulargia et al. 2017) which reflects the ongoing challenge that earthquake science is not yet fully understood, and the available data is often insufficient to disprove certain hypotheses about earthquake behavior definitively. As a result, different NSHMs often incorporate assumptions, some of which may be controversial, based on local tectonics, regional understanding, and the scientists' expertise (Gerstenberger et al. 2020). Some fundamental and interrelated assumptions are commonly made when constructing NSHMs which remain controversial and require debates for individual NSHM.

i). The assumption of temporal stationarity of seismicity, which implies that earthquake behavior remains consistent across different time periods and that the available observation period adequately represents long-term earthquake activity. This assumption implies that a 50-year hazard forecast applies to any 50-year time window and not specifically the next 50 years.

ii) The assumption that certain sources only produce earthquakes within a narrow magnitude range (characteristic earthquake sources), limiting hazard contributions to those magnitudes (critiques in Page & Felzer, 2015; Cattania, 2019, Das et al. 2010, 2014 & 2019) and

iii) The assumption that faults rupture with predictable segmentation implies that segment boundaries are predictable and limit possible magnitudes (critiques in Page et al. 2013; Visini et al. 2019), and

iv) Assuming occurrence rates following either constant seismicity model or constant moment release model.

v) The assumption that large earthquakes occur quasiperiodically with a predictable and semiregular recurrence interval within seismic gaps (critiques in Rong et al. 2003;)

vi) The assumption of earthquake occurrence following Poissonian or Non Poissonian distribution, i.e., time independent and time dependent, respectively.

Modern PSHA distinguishes between two types of uncertainty, namely aleatory and epistemic. While aleatory uncertainty is caused by inherent randomness in nature, such as the variability of earthquake sources, paths, and sites, and is unknowable before an earthquake occurs, epistemic uncertainty arises from inadequate knowledge about the model or its parameters. Many scientists argue that the separation is ambiguous and lacks theoretical significance and oppose that as our understanding of the process improves, all uncertainties become epistemic (e.g., Bedford & Cooke, 2001). If an intrinsic aleatory variability of a process exists, we are unlikely to ever fully know it because we will never have complete knowledge of the process; hence, the distinction between aleatory variability and epistemic uncertainty remains slippery, and the utility of the distinction may be both questionable (Budnitz et al. 1997) and a source of misleading debates (Bommer, 2003).

Epistemic uncertainty in seismic hazard analysis arises from various factors, including data scarcity (Musson, 2012), expert disagreement (Abrahamson & Bommer, 2005), and the inherent complexity of seismic processes (Bommer & Scherbaum, 2008). There may be different approaches viz.,

i) Systematically describe epistemic uncertainties using logic trees, consisting of nodes representing decision points and branches representing alternative modeling choices, each assigned a weight based on perceived validity (Marzocchi & Jordan, 2014),

ii) Ensemble modeling (Gerstenberger et al. 2016) which involves considering a collection of independent models rather than relying solely on a logic tree, ultimately representing the PoE for a specific ground-shaking value with a continuous distribution (Edwards et al. 2016) or combining multiple GMMs through logic trees (Atkinson et al. 2014; Douglas, 2018). However, recent developments have led to the creation of specific methods for combining GMMs that aim to reduce the potential bias inherent in traditional logic tree usage (Bommer et al., 2010),

iii) Scaled backbone approach (Douglas, 2018) which typically employs a single GMM to generalize the attenuation and magnitude-scaling behavior for a specific tectonic region type across a range of magnitudes and distances(Gerstenberger et al, 2020). Douglas (2018) proposed a new backbone model for the European hazard model which link uncertainties to the quality and quantity of spatially distributed data, assuming that high uncertainties might be expected in regions with limited data. In contrast, in regions with considerable data, uncertainties might be lower, and

iv) Sammon's mapping techniques (e.g., Goulet et al. 2018) which analyzes the distribution of GMMs and their similarity using two-dimensional representations. Mapping GMMs into a two-dimensional space enables the selection or development of GMMs based on their distance from each other, ensuring an unbiased sampling of the uncertainty space. This method also facilitates the integration of synthetic data from numerical GMM simulations, further refining the selected models.

Further, factors such as directivity effects that are rupture orientation dependent and large uncertainties are also related to the rock/soil de-amplification/amplifications in the GMMs. Amplification models for various soil types use broad proxies such as VS30 or depth to shear-wave velocity horizons (Z1.0 or Z2.5). These indicators are derived from surface geology maps or topographic slopes, serving as useful but uncertain tools for estimating site- and basin response.

Numerical ground motion simulations rely on a precise three-dimensional (3D) model of the Earth's crust to accurately predict ground motion. However, uncertainties in this model are challenging to quantify and significantly impact the accuracy of simulations, especially for short-period shaking near the surface. The intensity and duration of strong ground shaking are closely linked to stress drop. It is currently impossible to accurately measure stress drop before an earthquake occurs. However, ground GMMs may the median ground motion and its variability due to these effects, if built based on a representative sample of earthquakes, further contribute to the complexity of the model. Models depend on expert judgment, a key element in the overall process. It introduces its own set of uncertainties discussed in the following section.

Many PSHAs include some form of expert elicitation to gather subjective input for the model. This often involves informal and unstructured workshops and meetings where experts discuss and decide on the models to use and their relative weights. The workshops often aim to narrow the range of opinions into a single best answer that is assumed to represent a consensus. However, this approach has been criticized for arbitrarily reducing uncertainties and introducing significant biases (Aspinall, 2010; O'Hagan et al. 2006). As a result, more recent hazard models have adopted more formal and structured expert elicitation processes that focus on capturing the full range of uncertainty and avoiding the pursuit of consensus (Gerstenberger et al. 2016; Meletti et al. 2017). These methods, such as rational consensus, allow scientists to agree while maintaining their perspectives.

Structured expert elicitation provides a valuable advantage by mitigating common human biases that can impact the outcome (Gerstenberger et al, 2020). These biases can be broadly classified into three categories: cognitive bias, motivational bias, and group bias (Montibeller & von Winterfeldt, 2015). Cognitive bias is associated with errors in cognitive processes, such as mistaken reasoning, interpretation errors, or incorrect memory recall. Motivational bias comes into play when a desire or assumption regarding the expected hazard result influences a scientist's input. Finally, group bias is related to group dynamics, a desire to conform to the majority opinion or due to a particular dominant or authoritative personality. Unchecked bias in unstructured expert elicitation can significantly impact the final result and is often an unquantified uncertainty.

FUTURE DIRECTIONS

The NSHM has specific objectives and priorities. Two main goals for the NSHM in Indian context should be: (1) comprehending, quantifying, and reducing uncertainties throughout all phases of the modeling process and (2) enhancing the targeting of end-user requirements in the development and output of the models.

Particularly, concentrating on modeling the epistemic uncertainties in earthquake processes is crucial. As of now the Indian NSHMs have not adequately explored the epistemic uncertainties in SSMs. GSI has given detailed information on geology and tectonics in form of Seismotectonic Atlas but proper geodetic and 3D studies have to be carried out for regional seismogenic features. IMD has been the nodal agency for earthquake catalogue. However, no magnitude scales are provided with the catalogue which contain heterogeneous magnitude estimates that undergo numerous changes over time.

As required for GMMs, M_w estimates are often only available for large earthquakes, and catalog completeness typically varies over time. Non-linear bi-variate analysis may be used for homoginisation of the catalogue (Das et al. 2012). Similarly, the completeness and quality of fault catalogs have not yet started at national level suggesting that further research is needed to model the uncertainty in fault data better and to understand how to incorporate it into the NSHM. Models based on geodetic observations have demonstrated forecasting capabilities where traditional SSM methods have and are likely to play a more prominent role in future NSHM. Sincere and serious efforts are required for characterization of seismogenic sources as evident from the published literature on PSHA where a number of seismotectonic models are available which are different from each other and not a single one is complete. Combined efforts from Indian institutes/organisations are required to recommend a detailed SSM for NSHM as this has been carried out in the past through individual/very small groups of scientists /engineers who sometimes lack specific expertise.

The available observational data limit progress in improving SSMs to refine source-modeling techniques. Questions related to fault segmentation's significance for NSHM end-users, optimal MFD selection, and modelling clustering on various time scales requires additional research for inclusion in the NSHM. Future advancements are likely to arise from earthquake simulators generating synthetic earthquake catalogs spanning millions of years, modeling fault interactions, and incorporating detailed aspects of individual ruptures, such as slip distribution and rupture direction (Sharma et al 2023). While simulators have shown potential in NSHMs (Field, 2019), further research is needed to refine the models and assess their utility in improving NSHM forecasts. Proper addressing of the assumptions has to be made which are given in concluding remarks (i to vi) and proper treatment of uncertainties have to be addressed as given in concluding remarks (i to iv).

Knowledge of epistemic uncertainties advances, and there will likely be a growing requirement for an increased number of SSM component models. Ensemble models, which have already demonstrated effectiveness in incorporating multiple models (Allen et al. 2019), are expected to gain broader acceptance in the future. Additionally, there is an increasing recognition of the significance of bias in utilizing expert judgment, leading to a heightened need for employing structured expert elicitation techniques (e.g., Cooke, 1991) to mitigate potential biases in expert opinions.

Simulation techniques currently face challenges in accurately predicting short-period ground motions (e.g., <1 s), a crucial aspect for many NSHM end-users. To overcome this limitation, there is a need to emphasize modeling near-surface velocity structures and develop computationally efficient methods. Moreover, most existing NSHM applications demand probabilistic hazard estimates that consider uncertainty. Simulation methods rely on prior knowledge of geological parameters, which are often unknown, poorly constrained, or lacking in uncertainty assessment (e.g., stress drop, slip distributions, or 3-D velocity structure). Therefore, in the context of NSHM applications, obtaining estimates for the central values and ranges of controlling parameters is essential. Additionally, it is crucial to assess the capability of ground motion simulations to generate a distribution of possible shaking scenarios that incorporates these uncertainties.

Non-ergodic models (e.g., Abrahamson et al. 2019; Al Atik et al. 2010; Ameri et al. 2017) show potential in reducing uncertainty in GMM predictions by adjusting GMMs based on observations at specific locations. However, before these models can be employed in NSHMs, it is essential to demonstrate that the local data used to fit the models are adequate for providing enhanced accuracy in genuinely prospective predictions, as is required for NSHMs. Additionally, whether sufficient data will make these models practical for a national-scale model remains unclear.

An important aspect of hazard uncertainty, often considered separate from NSHM development, is the accurate modeling of site response, which relies on knowledge of the specific site conditions at a particular location. The quality and density of site response databases worldwide vary greatly, and ongoing research is needed to determine the best predictor variables for reducing uncertainty in site response. This information is crucial for adjusting observations to equivalent hard-rock conditions and adjusting the hard-rock hazard value to the actual site conditions.

In Indian context, proper strategic planning is required before building the several inherent modeling's in PSHA through more formal and structured expert elicitation processes that focus on capturing the full range of uncertainty and avoiding the pursuit of consensus.

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