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**MASTER'S DEGREE THESIS IN
ENGINEERING FOR
NATURAL RISK MANAGEMENT**

**PROBABILISTIC SEISMIC HAZARD ANALYSIS USING
NONERGODIC GROUND MOTION MODEL IN CENTRAL
ITALY**

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LIST OF ACRONYMS

ASCR: Active Shallow Crustal Region

BLUP: Best Linear Unbiased Predictor

CDF: Cumulative Distribution Function

CPTI15: Catalogo Parametrico dei Terremoti Italiani (2015 edition, v3.0)

DISS: Database of Individual Seismogenic Sources

DITEN: Dipartimento di Ingegneria Navale, Elettrica, Elettronica e delle Telecomunicazioni

DSHA: Deterministic Seismic Hazard Analysis

EC8: Eurocode 8

ERF: Earthquake Rupture Forecast

ESM: Engineering Strong-Motion Database

FNE: Fully nonergodic

GEM: Global Earthquake Model

GMC: Ground Motion Characterization

GMM / GMMs: Ground Motion Model(s)

GMPE / GMPEs: Ground Motion Prediction Equation(s)

GPS: Global Positioning System

IM / IMs: Intensity Measure(s)

INGV: Istituto Nazionale di Geofisica e Vulcanologia

ITACA: Archivio Accelerometrico Italiano

MCS: Mercalli–Cancani–Sieberg Intensity Scale

MPS19: Modello di Pericolosità Sismica 2019

ONT: Osservatorio Nazionale Terremoti

PDF: Probability Density Function

PGA: Peak Ground Acceleration

PGV: Peak Ground Velocity

PNE: Partially nonergodic

PoE / POE: Probability of Exceedance

PSHA: Probabilistic Seismic Hazard Analysis

RSN: Rete Sismica Nazionale

SDOF: Single-Degree-of-Freedom

SEA20: Nonergodic Ground Motion Model for Central Italy (Sgobba et al., 2021)

SSC: Seismic Source Characterization

UHS: Uniform Hazard Spectra

LIST OF ABBREVIATIONS

G-R:	Gutenberg–Richter recurrence relation
M_w :	Moment magnitude
M_L :	Local magnitude
M_s :	Surface-wave magnitude
m_b :	Body-wave magnitude
Sa:	Spectral acceleration
V_{S30} :	Time-averaged shear-wave velocity in the upper 30 m
$Z_{1.0}$:	Depth to the shear-wave velocity of 1.0 km/s
$Z_{2.5}$:	Depth to the shear-wave velocity of 2.5 km/s
Z_{hyp} :	Hypocentral depth
Z_{TOR} :	Depth to the top of rupture
R_{JB} :	Joyner–Boore distance
R_{rup} :	Rupture distance
R_{hyp} :	Hypocentral distance
R_{epi} :	Epicentral distance
T_R :	Return period
δB_e :	Between-event residual
δW_{es} :	Within-event residual
$\delta S2S_s$:	Site-to-site residual
$\delta P2P_p$:	Path-to-path residual
$\delta L2L_{source}$:	Location-to-location source residual
$\delta W_{0,esi}$:	Remaining within-event residual

ABSTRACT

Conventional Probabilistic Seismic Hazard Analysis (PSHA) relies on Ground Motion Models (GMMs) based on the ergodic assumption, whereby spatial variability observed in regional or global datasets is considered representative of temporal variability at a single site. Consequently, systematic source-, path-, and site-specific effects may be incorporated into aleatory variability, increasing predictive uncertainty and hiding the location-specific hazard.

This thesis investigates the transition effects from ergodic to partially and fully nonergodic GMMs in Central Italy. Using the OpenQuake Engine and the GMM of Sgobba et al., (2021), seismic hazard was evaluated at four accelerometric stations with contrasting site conditions and observational coverage: IT.LSS (Leonessa), IV. NRCA (Norcia), IV. LNSS (Leonessa local network), and IT.SBT (Subiaco). The epistemic uncertainties in median predictions, location-specific adjustments, and aleatory variability were propagated through a logic-tree framework.

The results show that modeling repeatable source, path, and site effects reduces aleatory variance by approximately 61.8-69.5%, producing narrower conditional ground motion distributions, steeper hazard curves, and generally lower exceedance probabilities at high ground motion levels. At the 2,475-year return period, ergodic Uniform Hazard Spectra (UHS) show a pronounced peak near a response period $T = 0.5$ s, associated with higher ergodic aleatory variability, whereas nonergodic UHS shift the peak response toward $T = 0.2$ s at IV. NRCA, highlighting short-period amplification associated with the shallow sedimentary basin.

The seismic source-area definition also affects site-specific hazard. I compared the effects of two source areas (assuming the same parameterizations): the Umbria-Abruzzo zone from the ZS16 zonation (Visini et al., 2022) and a newly developed small-clustered area densely covered by accelerometric stations with enough local observations and well-sampled ray paths associated with active earthquake sequences (specifically Clusters 1, 4, and 5) as reported in Sgobba et al. (2021). The small-clustered area increases hazard at nearby sites, while its contribution decreases progressively with distance. Epistemic uncertainty is strongly controlled by the density of spatial observations: IV.NRCA shows relatively narrow bounds due to extensive local observation coverage, whereas IT.LSS, IV.LNSS, and IT.SBT exhibit wider bounds because their records are predominantly associated with regional observations. Thus, local sampling quality, rather than record count alone, is critical for constraining epistemic uncertainty. Overall, the results demonstrate that nonergodic PSHA provides a more physically consistent and transparent

representation of site-specific seismic hazard by separating repeatable spatial effects from aleatory variability while explicitly accounting for epistemic uncertainty.

Keywords: PSHA; GMMs; nonergodic modeling; ergodic assumption; aleatory variability; epistemic uncertainty; seismic hazard.

1. INTRODUCTION

Seismic hazard is a type of natural hazard that is caused by seismic events. A seismic event is an event caused by any sudden release of energy in Earth's crust that produces seismic wave vibrations that travel through the ground (Stein & Wyssession, 2009). Usually, the term seismic event refers to earthquakes, but it can also include other ground-shaking phenomena such as volcanic or induced seismicity (Kramer, 1996). So, these ground-shaking phenomena need to be quantified to estimate and determine the hazard that is caused by a seismic event. Usually, ground motion is primarily used to quantify the ground shaking at a particular site (Kramer, 1996; Wang, 2020). This is because in most significant seismic hazards, ground motion acts as the trigger for consequent or secondary hazards such as liquefaction, landslides, and structural collapse (Baker, 2008; Kramer, 1996). Identification, communication, and mitigation of these hazards are central to the practice of seismic risk management and earthquake engineering.

Probabilistic Seismic Hazard Analysis (PSHA) is a well-recognized framework for quantifying seismic hazard. It provides the basis for a wide range of earthquake engineering applications, including seismic design, risk assessment, and performance-based engineering. The fundamental goal of earthquake engineering is to ensure that structures, ranging from residential buildings to complex systems such as pipelines and bridges, can withstand ground shaking while maintaining a specific level of performance (Baker, 2008). This objective is made significantly challenging by the inherent uncertainty regarding the location, size, and resulting intensity of future seismic events (McGuire, 2004). PSHA addresses these uncertainties through the integration of two principal components: seismic source characterization (SSC), which describes the potential occurrence and characteristics of future earthquakes, and ground motion characterization (GMC), which employs Ground Motion Models (GMMs) to estimate the intensity and variability of ground shaking at a site (Cornell, 1968; Meletti et al., 2021).

A fundamental component of conventional PSHA is the use of GMMs developed under the ergodic assumption, which can be viewed as a conceptual approach that “trades space for time.” Under this assumption, the variability observed across a regional or global database comprising multiple earthquakes, sources, propagation paths, and recording sites is considered representative of the variability that would be observed at a single site over a sufficiently long period of time. This assumption has historically been essential for developing statistically robust GMMs, particularly in regions where dense local observations are unavailable. However, it also implies

that systematic and repeatable differences associated with individual sources, propagation paths, and recording sites are incorporated into the aleatory variability of the model. As a result, variability that may be predictable or repeatable at a specific location is treated as random, which can lead to an inflated estimate of aleatory variability (Al Atik et al., 2010).

The limitations of this assumption become particularly important when seismic hazard is evaluated at the level of an individual site. Earthquake ground motions exhibit substantial spatial variability due to the heterogeneous nature of both earthquake sources and the geological medium through which seismic waves propagate. Recording sites and propagation paths are therefore not statistically equivalent; instead, they can exhibit characteristics that are persistent and repeatable across multiple earthquakes. Recognizing and explicitly modeling these characteristics has motivated a broader transition in seismic hazard science from regional-average predictions toward models capable of representing location-specific effects (Liou & Abrahamson, 2025). Within this framework, nonergodic GMMs seek to separate repeatable source, path, and site effects from the remaining event-to-event and record-to-record variability, thereby providing a more physically informed representation of ground motion behavior (Sgobba et al., 2021). As effects that were previously embedded within aleatory variability are explicitly modeled, part of the uncertainty is instead represented as epistemic uncertainty associated with the estimation of location-specific parameters. This creates the potential for a reduction in total predictive uncertainty, provided that the relevant effects can be adequately constrained by the available data (Liou & Abrahamson, 2025; Paredes & De Risi, 2025).

The transition toward nonergodic modeling, however, does not necessarily imply that greater model complexity will always result in improved seismic hazard estimates. Explicitly representing source, path, and site-specific effects requires sufficient observations to distinguish these effects from one another and to constrain their associated parameters. In regions with limited distributed data, the additional parameters introduced by nonergodic models may themselves be associated with substantial epistemic uncertainty. Consequently, the potential reduction in aleatory variability must be considered together with the uncertainty introduced through parameter estimation and model formulation. The key issue is therefore not simply whether a nonergodic model reduces aleatory variability, but whether the resulting reduction leads to a meaningful decrease in total predictive uncertainty and an improved representation of site-specific seismic hazard. This raises an important practical question regarding the level of nonergodicity that is justified by the available

data and whether the additional complexity of partially or fully nonergodic models provides sufficient benefit over conventional ergodic approaches.

These questions are particularly relevant in Central Italy, which provides an appropriate natural setting for investigating the implications of nonergodic ground motion models. The region is characterized by significant seismic potential, complex geological conditions, and pronounced spatial variability in earthquake ground motion characteristics (Bindi et al., 2011; Meletti et al., 2021; Sgobba et al., 2021). Furthermore, the availability of extensive strong-motion observations provides an opportunity to investigate repeatable source, path, and site effects and to assess the extent to which these effects can be reliably constrained. Central Italy therefore offers a valuable setting in which to examine not only the potential benefits of nonergodic modeling, but also the data requirements and epistemic uncertainties associated with progressively increasing model complexity.

Building on these considerations, this study systematically evaluates conventional ergodic, partially nonergodic, and fully nonergodic GMMs within a PSHA framework under two different source area zones. It investigates how progressively accounting for repeatable source, path, and site effects influences ground motion predictions, the partitioning of aleatory and epistemic uncertainties, and the resulting site-specific hazard estimates. Particular emphasis is placed on the trade-off between reduced aleatory variability and the additional epistemic uncertainty associated with estimating location-specific effects, and on how this balance is influenced by the quantity and spatial distribution of available data. By evaluating the three modeling approaches under varying levels of data availability, the study assesses whether increasing model complexity leads to more physically representative and better-constrained hazard estimates. A logic-tree framework is used to propagate epistemic uncertainty associated with alternative model formulations and parameter estimates into the final hazard results, providing an integrated basis for identifying the conditions under which nonergodic modeling offers a meaningful improvement over the conventional ergodic approach.

2. SEISMOTECTONIC BACKGROUND FOR CENTRAL ITALY

The seismotectonic characterization of Central Italy provides the essential physical framework for understanding the complex patterns of ground shaking that govern seismic hazard in the region. Italy is situated within the Mediterranean–Transasiatic seismic belt, one of the world's major seismically active zones, where the Italian Peninsula and the adjacent Adriatic domain form a northern promontory of the African Plate (Lowrie, 2007). Paleomagnetic and tectonic evidence indicates that the present-day geological framework is the result of the long-term convergence between the African and European plates, a process that began during the Early Tertiary and progressively shaped the Apennine mountain chain through subduction, continental collision, and subsequent crustal deformation (Lowrie, 2007; Meletti et al., 2021).

This tectonic evolution has established a highly complex seismotectonic setting in Central Italy, where the transition from compressional to extensional tectonics has generated an active fault system capable of producing frequent shallow earthquakes. Combined with the region's diverse lithological environments and pronounced geological heterogeneity (Bindi et al., 2011), these tectonic processes contribute to its high seismic potential and strongly influence the spatial distribution and amplification of ground motion. Consequently, the interplay between active extensional faulting, shallow seismic sources, and complex geological conditions makes Central Italy one of the most seismically hazardous regions in Europe. This geodynamic framework forms the fundamental basis for the recurrent occurrence of destructive earthquake sequences and constitutes the foundation for seismic hazard assessment within the study area.

2.1 TECTONIC REGIME AND FAULTING MECHANISMS

The current tectonic regime of the Central Apennines is characterized by active crustal extension as shown in Figure 2.1, which governs the majority of seismic activity throughout the region (Bindi et al., 2011; Sgobba et al., 2021). This extensional deformation is accommodated by a network of predominantly NW-SE striking normal faults that constitute the principal active tectonic structures of the Apennine belt (Lanzano et al., 2019; Sgobba et al., 2021). These fault systems developed following the transition from the earlier compressional phase responsible for the formation of the Apennine chain and continue to accommodate ongoing crustal stretching.

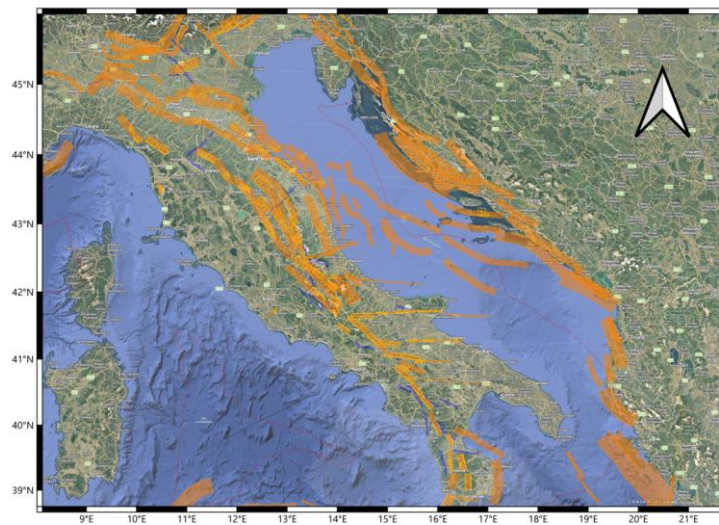


Figure 2.1: Distribution of seismogenic sources in the study area based on the Database of Individual Seismogenic Sources (DISS)

Normal faulting is a type of geological fault formed under extensional tectonic within Central Italy and reflects the current regional stress field as shown by the beachball in Figure 2.2. This tectonic setting has generated numerous destructive earthquakes during both historical and instrumental periods, with systematic instrumental observations available since approximately 1980. Representative examples include the 1997 Mw 6.0 Umbria-Marche sequence, and the 2009 Mw 6.3 L'Aquila earthquake. More recently, the 2016-2017 Central Italy seismic sequence, comprising the Mw 6.0 Amatrice and Mw 6.5 Norcia mainshocks, provided further evidence of the dominant role of extensional faulting in controlling large-magnitude seismic events in the region (Lanzano et al., 2019; Sgobba et al., 2021).

Seismicity associated with these active fault systems is predominantly confined to the upper crust, with hypocentral, depths generally shallower than 20 km (Bindi et al., 2011; Sgobba et al., 2021). Instrumental observations indicate that earthquake hypocentres are concentrated at relatively shallow depth, with a mean focal depth of about 9.3 km (Sgobba et al., 2021). Such shallow seismic source are characteristic of Active Shallow Crustal Regions (ASCRs), where earthquake rupture occurs within the brittle upper crust and can produce strong near source ground motions with significant implications for seismic hazard and engineering design (Meletti et al., 2021). Therefore, understanding the geometry and behavior of these fault systems is fundamental for accurately characterizing regional seismic hazard and developing reliable ground motion models.

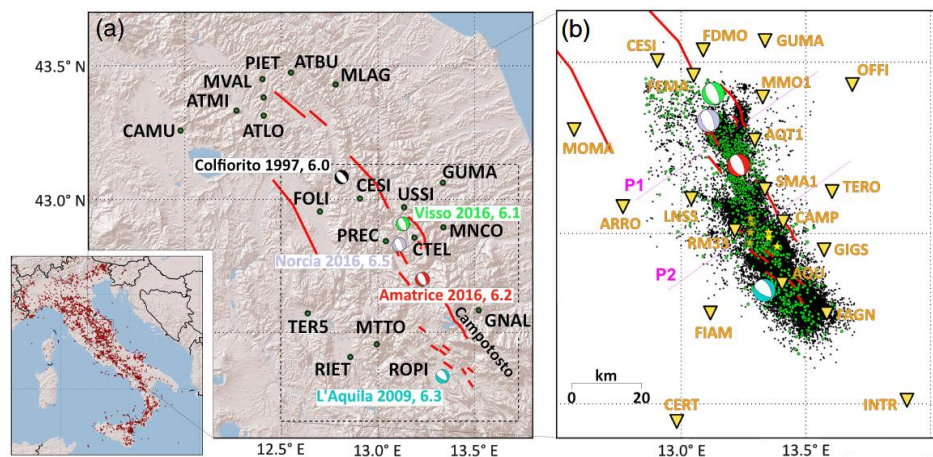


Figure 2.2: Study area. (a) Destructive earthquakes since 1997 along with their beach balls: red lines indicate the traces of the causative faults; green circles are continuous GPS stations. (b) Seismicity associated with the 2009 and 2016–2017 Central Italy sequences (Vičić et al., 2020). Yellow triangles indicate seismic stations (triangles).

2.2 HISTORICAL AND INSTRUMENTAL SEISMICITY

Central Italy is one of the most seismically active and well documented regions in Europe. Its seismic history spans more than a millennium and is supported by a combination of historical macroseismic documentation and modern instrumental observations, providing comprehensive earthquake datasets available worldwide (Rovida et al., 2021). This exceptional record has played a fundamental role in improving the understanding of regional tectonics, earthquake recurrence and seismic hazard.

The primary reference for earthquake parameters in Italy is the Catalogo Parametrico dei Terremoti Italiani (CPTI15). Version 3.0 of the catalogue includes parametric information for 4860 earthquakes that occurred between AD 1000 and 2019 (Rovida et al., 2021). The catalogue combines historical macroseismic observations with instrumental measurements to produce a homogeneous and internally consistent earthquake database. Owing to its completeness and uniformity, CPTI15 constitutes the reference dataset for seismic hazard assessment, earthquake recurrence studies, and seismotectonic investigations throughout Italy (Meletti et al., 2021; Rovida et al., 2021).

Instrumental seismicity is routinely monitored by the Italian National Institution of Geophysics and Volcanology (INGV) through the National Seismic Network (Rete Sismica Nazionale, RSN). Earthquake locations, magnitudes, depths, and focal parameters are published through INGV

seismic monitoring portal (Osservatorio Nazionale Terremoti, ONT), which provides instrumental bulletins for ongoing seismic activity and forms the basis for modern seismological analysis.

Maps of historical and instrumental seismicity based on the previously mentioned catalogs are presented in Figure 2.3 and Figure 2.4.

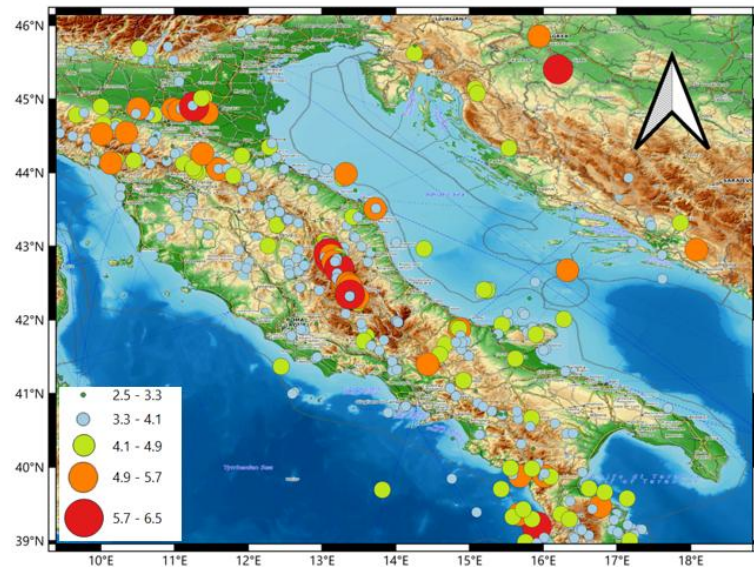


Figure 2.3: Maps of instrumental epicenters in the study area and surrounding (Osservatorio Nazionale Terremoti, ONT).

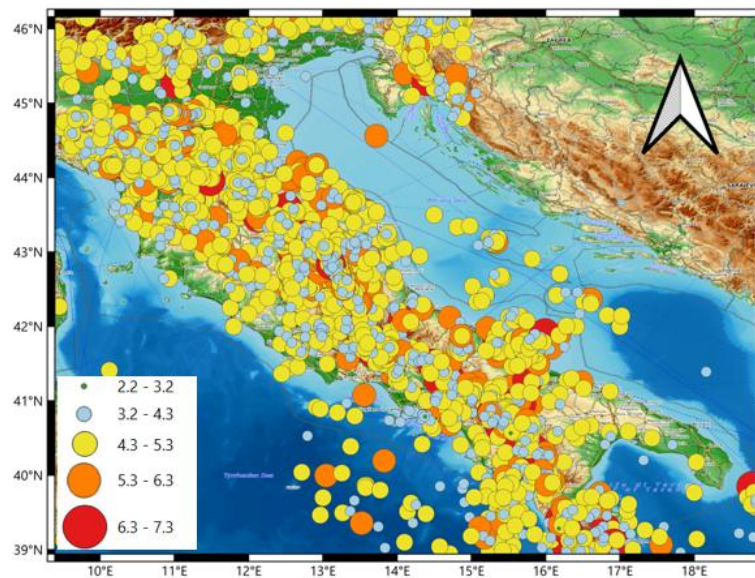


Figure 2.4: Historical and Instrumental seismicity in the study area and surrounding (Catalogo Parametrico dei Terremoti Italiani, CPTI15).

As illustrated in the above figures, the region has experienced several destructive earthquakes over the past millennium. These major earthquakes are summarized in Table 2-1.

Table 2-1: Major earthquakes in Central Italy. Magnitudes for historical events (pre-1900s) are derived as macroseismic equivalent moment magnitudes by applying conversion equations (Galli et al., 2017; Visini et al., 2024).

Date	Earthquake	Imax (MCS)	Mw
1328-12-01	Valnerina	X	-
1349-09-09	Central Italy (Lazio Abruzzi)	IX–XI	-
1456-12-05	Central Southern Apennine	XI	-
1639-10-07	Monti della Laga (Amatrice)	IX–X	6.0–6.2
1703-01-14	Valnerina	XI	6.9
1703-02-02	Aquilano	X	6.7
1706-11-03	Maiella	X–XI	-
1832-01-13	Valle Umbra	X	-
1915-01-13	Marsica (Avezzano)	>X	7.0
1979-09-19	Valnerina	-	5.8
1997-09-26	Umbria–Marche (Colfiorito)	IX	6.0
2009-04-06	L'Aquila	IX	6.3
2016-08-24	Amatrice	X–XI	6.2
2016-10-26	Visso	-	5.9–6.1
2016-10-30	Norcia	XI	6.5

2.3 GEOLOGICAL, GEOMORPHOLOGY AND SITE RESPONSE FEATURES

Within the Central Apennines, the geological framework is strongly influenced by the Sibillini thrust system, a major structural discontinuity that divides the region into two distinct tectono-stratigraphic domains. To the west, the geological succession is dominated by Mesozoic carbonate formations, consisting predominantly of competent limestone and dolomite sequences. In contrast, the eastern sector is underlain by younger post-Messinian foredeep deposits composed of mechanically weaker sedimentary units. This pronounced lithological contrast plays a fundamental role in controlling local seismic site response, as differences in rock stiffness, sediment thickness, and material properties influence the propagation, attenuation, and amplification of seismic waves. Consequently, ground-motion characteristics exhibit considerable spatial variability across the Central Apennines, reflecting the heterogeneous geological framework of the region (Sgobba et al., 2021).

Beyond lithological variability, the geomorphological setting of the Central Apennines further contributes to the spatial variability of earthquake ground motion. The region is characterized by a complex topography comprising mountain ridges, narrow valleys, and sediment-filled intramontane basins, all of which modify seismic wave propagation and generate significant local variations in ground-motion intensity and frequency content (Barani et al., 2014; Sgobba et al., 2021). Consequently, both geological and geomorphological characteristics must be considered when evaluating seismic hazard and developing reliable ground-motion models.

One of the most important sources of site amplification is the presence of sediment-filled intramontane basins, particularly the Fucino and Sulmona basins (Sgobba et al., 2021). These basins are filled with relatively soft marine and continental sedimentary deposits that overlie the underlying carbonate bedrock. The strong impedance contrast between the sediments and the bedrock enhances the trapping and reverberation of seismic waves, producing significant amplification of ground motion, especially at longer vibration periods (≥ 1.0 s). Geospatial analyses have demonstrated that the site-specific amplification within these basins exhibit systematic patterns that cannot be adequately represented by using simplified soil classifications adopted in conventional building codes and ergodic ground motion models (Sgobba et al., 2021). These findings highlight the importance of incorporating nonergodic, site-specific correlations to accurately capture local amplification effects.

In addition to basin effects, topographic amplification represents another important source of ground motion variability throughout the Central Apennines. Mountain ridges, crests, and steep slopes can substantially modify seismic wave propagation, often resulting in stronger shaking at elevated locations than at adjacent valley floors (Kramer, 1996). Experimental observations and numerical simulations consistently demonstrate the ridge crests experience greater amplification than their bases. A notable example is the Narni ridge, where probabilistic seismic hazard analyses indicate that the peak ground acceleration (PGA) at the crest may be approximately 42% higher than that at the base. Neglecting topographic effects may therefore lead to a significant underestimation of local seismic hazard (Barani et al., 2014).

3. BASICS OF SEISMIC HAZARD ANALYSIS

Seismic hazard is commonly quantified using two approaches: Deterministic Seismic Hazard Analysis (DSHA) and Probabilistic Seismic Hazard Analysis (PSHA) (Cornell, 1968; McGuire, 2004). The fundamental difference between deterministic and probabilistic seismic hazard analysis is the use of earthquake hazard information when estimating the level of ground shaking expected at site. DSHA relies on defining a single, physically convincing scenario to represent the maximum credible event, whereas PSHA incorporates the full range of possible earthquakes and their recurrence characteristics to quantify shaking levels in probabilistic terms (Reiter, 1990).

3.1 DETERMINISTIC SEISMIC HAZARD ANALYSIS (DSHA)

Deterministic Seismic Hazard Analysis (DSHA) is a scenario-based methodology used to estimate the maximum level of ground shaking a site may experience from credible earthquake sources. It focuses on defining physically plausible earthquake scenarios specified in terms of magnitude, rupture geometry, and source-to-site distance, rather than quantifying their probability of occurrence. DSHA has been used in engineering seismology, particularly for critical facilities, where extreme events with low probability but high consequences must be considered.

Deterministic seismic hazard analysis can be carried out in the following four sequential steps: identify all nearby earthquake sources, select the appropriate source-to-site distance (R) for each source, and determine which magnitude–distance combination produces the strongest shaking at the site (controlling scenario). The earthquake that yields the highest ground motion level, as evaluated by GMPEs in the controlling scenario, is then used, and its predicted ground motion (Y) serves as a foundation for critical infrastructure design.

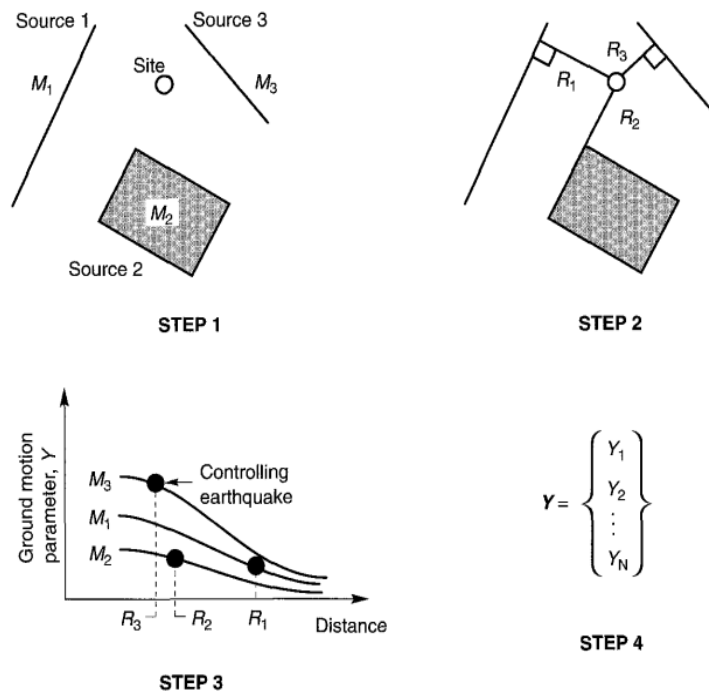


Figure 3.1: The four sequential steps of deterministic seismic hazard analysis (DSHA) (Kramer, 1996)

3.2 PROBABILISTIC SEISMIC HAZARD ANALYSIS (PSHA)

While Deterministic Seismic Hazard Analysis (DSHA) provides a straightforward, conservative method for evaluating seismic hazard, it has inherent limitations because it ignores the full range of possible earthquake events and the probability of their occurrence. As a result, DSHA may underrepresent the likelihood of less extreme but frequent events, which can still contribute significantly to structural damage over time.

Probabilistic Seismic Hazard Analysis (PSHA) is a method that evaluates seismic hazard by explicitly considering uncertainties in earthquake occurrence and ground motion estimates. It combines data from all potential seismic sources, magnitudes, and source-to-site distances to deliver a comprehensive probabilistic assessment of ground shaking risk. This approach accounts for rare, extreme events as well as more common moderate earthquakes.

The PSHA procedure comprises four main steps. First, it locates and characterizes seismic sources that could cause significant ground shaking at a site, including their geometry, rupture mechanisms, and spatial distribution. Next, it assesses each source's seismic potential using magnitude-frequency recurrence relationships that determine their annual earthquake occurrence rates across different magnitudes. Then, ground motion prediction equations (GMPEs) are employed to estimate the probability that earthquakes of various sizes and locations will generate

ground motions exceeding certain levels at the site. Finally, uncertainties related to source-to-site distance, earthquake magnitude, and ground motion are integrated through the total probability theorem to compute the annual probability of surpassing specific ground motion thresholds. Results are often expressed as return periods or exceedance probabilities over a set period (e.g., assuming a Poisson process). This probabilistic method forms the foundation of modern seismic hazard assessment and design codes worldwide (Cornell, 1968; Kramer, 1996; McGuire, 2004). Each step is explained in detail in the following sections.

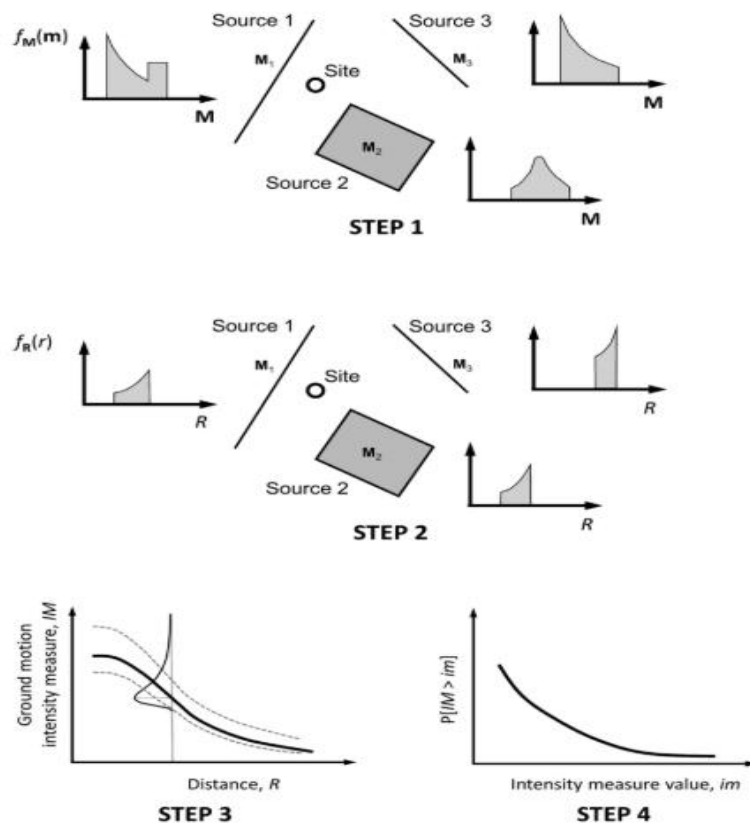


Figure 3.2: The four sequential steps of probabilistic seismic hazard analysis (PSHA) (Kramer, 1996)

3.2.1 IDENTIFICATION AND CHARACTERIZATION OF EARTHQUAKE SOURCES

The first step of Probabilistic Seismic Hazard Analysis (PSHA) is to identify and characterize the earthquake sources that may contribute to seismic hazard at the site. This requires defining the relevant source zones and describing their key characteristics, including geometry, spatial distribution, and rupture mechanisms. This step is fundamental to PSHA because earthquakes can occur at different locations within a fault system or seismogenic region. Therefore, the hazard

model must account for the spatial variability of potential earthquake occurrence and quantify each source's contribution to the overall seismic hazard at the site.

As emphasized in classical references such as, the geometry of a seismic source is a simplified representation of the underlying tectonic structure, chosen to make the analysis manageable while still reflecting the physical processes that control earthquake occurrence. Seismic sources can be represented as one-dimensional (1D), two-dimensional (2D), or three-dimensional (3D), depending on the seismogenic features and the level of spatial uncertainty. Small-scale features, such as volcanic conduits or localized clusters of shallow seismicity, are typically modeled as point sources. In such cases, the distance is deterministic, and the source-to-site distance probability is defined as 1 (i.e., 100%). Faults that are well modeled as 2D or 3D representations (e.g., line sources) introduce spatial variability in the distance from the site. In regions where faults are diffuse, poorly mapped, or where seismicity is broadly distributed, the source is modeled as an area or volumetric source, often referred to as a seismogenic zone, which accounts for a uniform distribution of earthquakes throughout the defined area (Cornell, 1968).

For non-point sources, the exact rupture location is uncertain, and PSHA incorporates this uncertainty by constructing a probability density function (PDF) for the source-to-site distance. To do this, the source is discretized into many small elements of equal length or area, and the distance from each element to the site is computed. These distances are then grouped into bins to form a histogram that approximates the PDF, representing the likelihood that an earthquake occurs at a given distance from the site. This treatment of spatial uncertainty is essential because ground motion amplitude (intensity) depends strongly on the site-to-source distance. PSHA accounts for spatial uncertainties over all possible rupture locations to compute the total hazard (Cornell, 1968; Kramer, 1996).

For non-point sources, the exact rupture location is uncertain, and PSHA incorporates this uncertainty by constructing a probability density function (PDF) for the source-to-site distance, $f_R(r)$. To do this, the source is discretized into many small elements of equal length or area, and the distance from each element to the site is computed. These distances are then grouped into bins to form a histogram that approximates the PDF $f_R(r)$, representing the likelihood that an earthquake occurs at a given distance from the site. This treatment of spatial uncertainty is essential because ground motion amplitude (intensity) depends strongly on source-to-site distance. Thus, PSHA accounts for spatial uncertainties over all possible rupture locations to compute the total hazard (Cornell, 1968; Kramer, 1996).

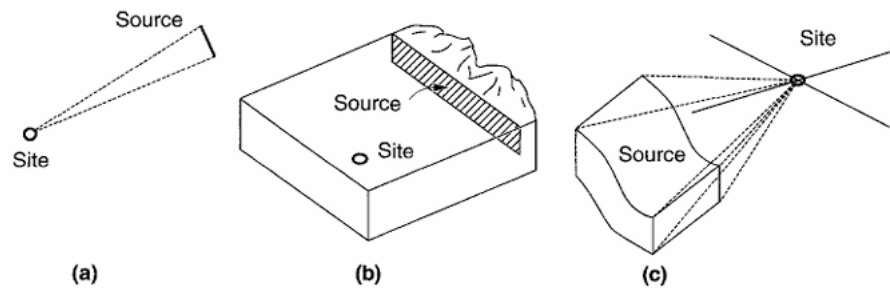


Figure 3.3: (a) Short fault represented as a point source, (b) Shallow fault modeled as a line source, (c) three dimensional (3D) source region. (Kramer, 1996)

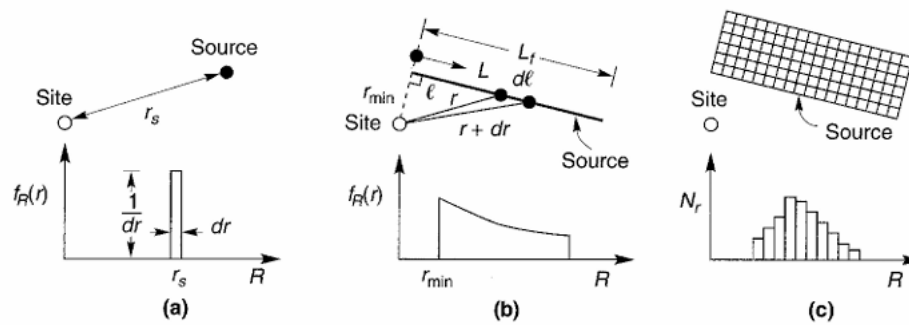


Figure 3.4: (a) Point source with a single fixed source-to-site distance; (b) line source, for which the source-to-site distance varies continuously along the source and is described by a probability density function; and (c) area source, for which the source-to-site distance is represented by a statistical distribution based on the spatial discretization of the source area. (Kramer, 1996)

3.2.2 FREQUENCY-MAGNITUDE DISTRIBUTION

The other fundamental component of probabilistic seismic hazard analysis (PSHA) is the characterization of the frequency-magnitude distribution. This step describes how often earthquakes of different magnitudes occur within a seismic source. Since earthquake occurrence is inherently stochastic, the frequency-magnitude relationship provides the statistical framework for integrating magnitude uncertainty into hazard calculations. Generally, two methods are used to model the frequency-magnitude relationship: the Gutenberg-Richter (G-R) law and characteristic earthquake recurrence on Individual Faults. The most widely used formulation is the Gutenberg-Richter (G-R) law (Gutenberg & Richter, 1944), which expresses an exponential decay in earthquake frequency with increasing magnitude. Applying this law in PSHA requires careful treatment of catalog completeness, physical constraints on maximum magnitude, and the behavior of individual faults that may deviate from the regional G-R trend. These considerations give rise to bounded and characteristic recurrence models that complement the classical G-R formulation.

3.2.2.1 The Gutenberg-Richter (G-R) Relationship

The classical G-R law is expressed as:

$$\log_{10} \lambda_m = a - bm \quad \text{or} \quad \ln \lambda_m = \alpha - \beta \quad \text{Equation 3.1}$$

Where λ_m is the mean annual rate of earthquakes with magnitude greater than or equal to " m ", " a " ($a = \alpha/2.303$) is a coefficient which quantifies the overall seismic productivity of the region, and " b " ($b = \beta/2.303$) is a coefficient that describes the relative portion of small to large earthquakes. The values of a and b can be obtained through regression analysis on data. A typical global value is $b \simeq 1$, although regional variation between 0.7 and 1.3 is common (Kramer, 1996). These variations in " b " value can result from stress conditions (the higher the stress, the lower the " b " value), faulting style (smaller " b " value for reverse faults, higher " b " value for normal faults), and data incompleteness.

Earthquake catalogs used to estimate Gutenberg–Richter parameters often combine instrumental and historical records, which may require conversions between different magnitude scales and can introduce inconsistencies (Kramer, 1996). They may also contain dependent events such as aftershocks and foreshocks, which misrepresent the long-term rate of independent seismicity and therefore must be removed before analysis (Merz, & Cornell, 1973). After declustering, it is essential to assess catalog completeness. Smaller earthquakes are reliably recorded only after improvements in seismic monitoring systems. Therefore, incomplete catalogs tend to miss many small events, which leads to an underestimation of small earthquake occurrence rates and a relative overestimation of large earthquake rates. Different methods can be applied to correct the incomplete recording periods and obtain unbiased long-term seismicity parameters, as proposed by (Stepp, 1972) and (Weichert, 1980).

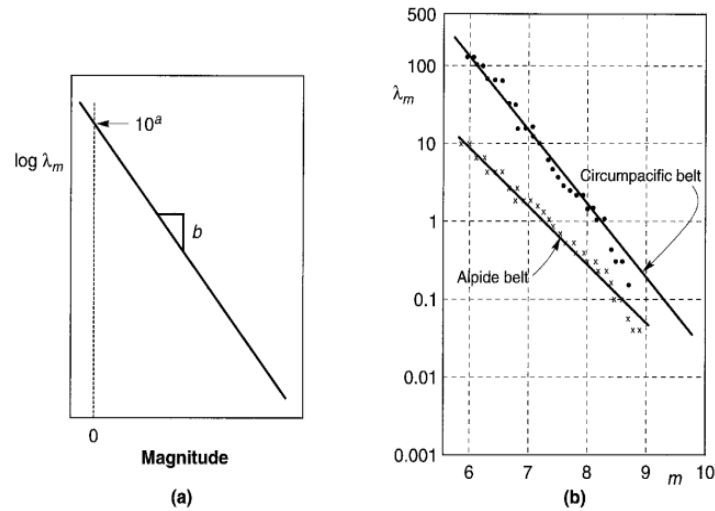


Figure 3.5: (a) Gutenberg-Richter recurrence law; (b) Application of Gutenberg-Richter to worldwide seismicity data. (Kramer, 1996)

3.2.2.2 Bounded (Truncated) Gutenberg-Richter Distribution

The Gutenberg-Richter (G-R) law assumes an infinite range of earthquake magnitudes, which is physically unrealistic. In practice, earthquakes below a certain magnitude (usually 4 or 5) do not contribute significantly to engineering hazard and are therefore bounded by a minimum magnitude $m_{\min}$. Likewise, faults cannot generate earthquakes exceeding their geometric and mechanical limits of faults, which depend on geological and seismological factors such as fault length, slip rate, and paleoseismic evidence (Wells & Coppersmith, 1994). These factors determine the possible maximum magnitude, $m_{\max}$. To account for these physical constraints, the magnitude-frequency relationship is commonly expressed in bounded form. This bounded representation ensures physically meaningful seismic hazard estimates consistent with finite fault dimensions.

The bounded (truncated) form of the magnitude-frequency distribution, as introduced by, is given as:

$$\lambda_m = v \frac{e^{[-\beta(m-m_{\min})]} - e^{[-\beta(m_{\max}-m_{\min})]}}{1 - e^{[-\beta(m_{\max}-m_{\min})]}} \quad \text{Equation 3.2}$$

where v is the mean annual rate of earthquake occurrence above the minimum magnitude ($m_{\min}$).

$$v = e^{[\alpha - \beta m_{\min}]} \quad \text{Equation 3.3}$$

The comparison between the unbounded and bounded (truncated) Gutenberg-Richter (G-R) laws shows that introducing a maximum magnitude $m_{\max}$ limits the occurrence of very large

earthquakes. While the unbounded model allows earthquakes of any size, the bounded formulation accounts for the physical constraints of faults, causing the mean annual rate of exceedance to decrease rapidly as magnitude approaches $m_{\max}$. As a result, the probability of extremely large earthquakes becomes negligible, and the exceedance rate gradually approaches zero as it nears this upper magnitude limit (Baker, 2008). This behaviour provides a more realistic representation of seismicity, as shown in the figure below.

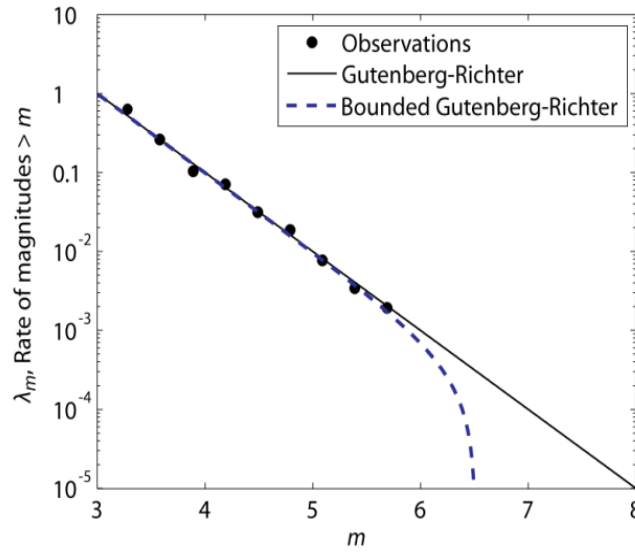


Figure 3.6: Comparison between unbounded and bounded Gutenberg-Richter laws (Baker, 2008)

Based on previous this formulation (see Equation XX), the probability density function (PDF) $f_M(m)$ and the cumulative distribution function (CDF) $F_M(m)$ of earthquake magnitude are expressed as (Cornell & Vanmarcke, 1969):

$$f_M(m) = \frac{\beta e^{[-\beta(m-m_{\min})]}}{1 - e^{[-\beta(m-m_{\min})]}} \quad \text{Equation 3.4}$$

$$F_M(m) = P(M < m \mid m_{\min} \leq m \leq m_{\max}) = \frac{1 - e^{[-\beta(m-m_{\min})]}}{1 - e^{[-\beta(m_{\max}-m_{\min})]}} \quad \text{Equation 3.5}$$

3.2.2.3 Characteristics Earthquake Recurrence on Individual Faults

For well-defined faults that rupture repeatedly in near-maximum events, applying a Gutenberg-Richter (G-R) model may lead to overestimation of the frequency of small earthquakes and underestimation of the frequency of large earthquakes. In such cases, the characteristic earthquake model provides a more realistic description of recurrence. This model reflects paleoseismological evidence showing that some faults tend to repeatedly produce earthquakes within narrow

magnitude range (typically close to $m_{\max}$) associated with full segment ruptures (Schwartz & Coppersmith, 1984; Wesnousky, 1994). As illustrated in Figure 3.7, the hybrid model maps exponential G-R behavior for minor events up to a threshold, where a linear extrapolation (dashed line) would severely underestimate hazard. Instead, the curve transitions into a distinct, elevated plateau between $m_{\max} - 0.5$ and $m_{\max}$ to properly account for repeating, full-segment characteristic ruptures.

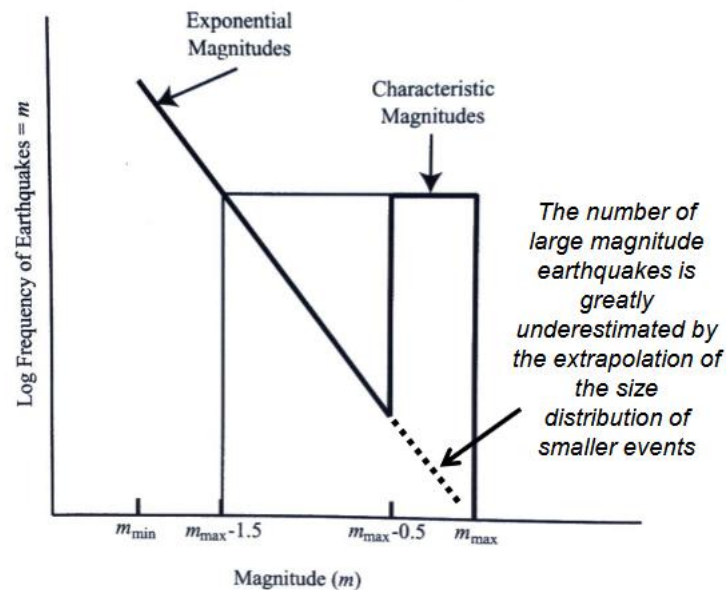


Figure 3.7: The characteristic earthquake recurrence model

3.2.3 GROUND MOTION PREDICTION EQUATION (GMPE)

Ground motion prediction equations (GMPEs) form the core of ground motion computation in probabilistic seismic hazard analysis (PSHA). These empirical models quantify how strongly the ground is expected to shake at a site during an earthquake, expressed through an intensity measure, such as peak ground acceleration (PGA) or spectral acceleration (SA) (e.g., Atik et al., 2010; Baker, 2008). GMPEs relate shaking intensity to key seismological and site parameters, primarily earthquake magnitude M , source-to-site distance R , faulting mechanism, and local site conditions. Moreover, since they are derived from large databases of recorded ground motions, GMPEs capture the statistical variability inherent in earthquake shaking and provide a probabilistic description of possible ground motion levels (e.g., Atik et al., 2010; Liou & Abrahamson, 2025; Paredes et al., 2025).

A general functional form of GMPE expresses the natural logarithm of ground motion as a function of magnitude scaling, distance attenuation, and adjustment terms for source and site effects:

$$\ln Y = C_1 + C_2 M + C_3 M^{C_4} + C_5 \ln[R + C_6 \exp(C_7 M)] + C_8 R + f(\text{source}) + f(\text{site}) + \xi_{\ln Y} \quad \text{Equation 3.6}$$

Where, $C_1 - C_8$ are empirically derived regression coefficients, $f(\text{source})$ accounts for faulting style (e.g., strike-slip, normal, reverse), $f(\text{site})$ incorporates site amplification factors (e.g., rock vs soil), and $\xi_{\ln Y}$ represents the uncertainty in predicted ground motion that couldn't be captured by the GMPE (Kramer, 1996).

As mentioned above, GMPEs can provide a probabilistic description of earthquake-induced shaking by defining the full probability distribution of ground motion intensity at a site, conditioned on earthquake parameters such as magnitude, source-to-site distance, faulting style, and site conditions (Baker, 2008; Liou & Abrahamson, 2025). This means that, beyond supplying a single median prediction, GMPEs quantify the range of possible shaking levels that may occur for a given scenario. For a target ground motion level y^* , GMPEs allow the computation of the conditional exceedance probability $P(Y > y^* | m, r)$, which expresses the likelihood that the ground-shaking from an earthquake of magnitude m at distance r will exceed a certain threshold y^* . This probabilistic formulation is fundamental in PSHA, where seismic hazard is defined as the annual probability that ground motion exceeds a given level over a certain time period.

Specifically, as the logarithm of ground motion is drawn from a normal distribution with mean $\mu_{\ln Y(m,r)}$ and standard deviation $\sigma_{\ln Y}$, the exceedance probability can be written explicitly as :

$$P(Y > y^* | m, r) = 1 - \Phi\left(\frac{\ln y^* - \mu_{\ln Y(m,r)}}{\sigma_{\ln Y}}\right) \quad \text{Equation 3.7}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

Graphically (see Figure 3.8), we can observe that GMPEs produce curves showing how predicted shaking decays with distance. The mean prediction corresponds to the mean value ($\ln y$). The median ground motion level in the original scale is obtained by taking the exponential of the predicted mean logarithmic value, i.e., $\exp(\ln y)$, while the curves corresponding to one standard deviation above and below the mean illustrate the uncertainty captured by $\xi_{\ln Y}$ (Baker, 2008). At any given distance, the distribution of possible shaking levels is represented by a probability density function, and the shaded areas under these curves correspond to the probability of

exceedance decrease, reflecting attenuation of seismic waves with distance (Baker, 2008; Paredes & De Risi, 2025).

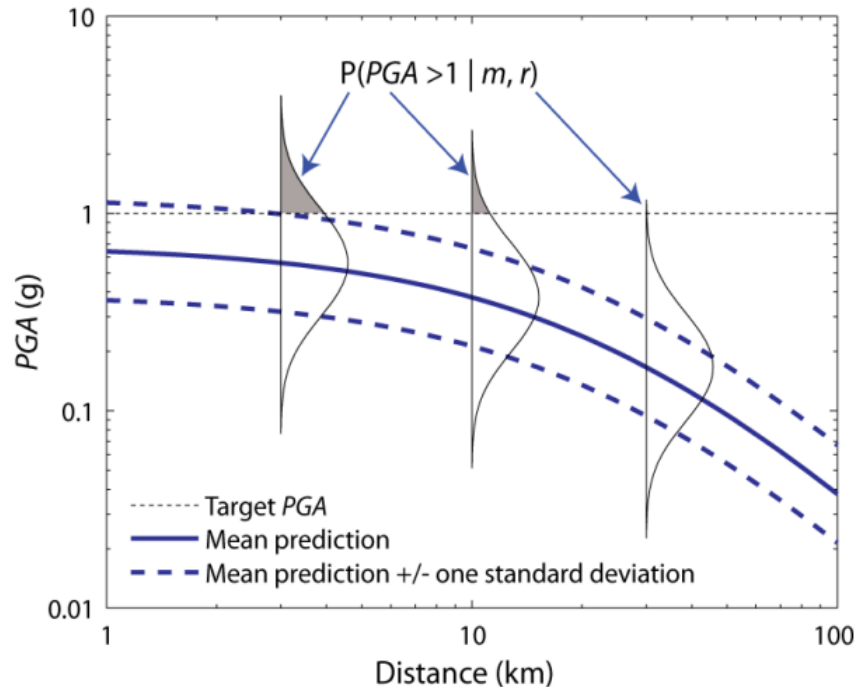


Figure 3.8: Ground motion prediction for a magnitude 6.5 event, illustrating the probability of exceeding $PGA = 1g$ as a function of source-to-site distance. (Baker, 2008)

Given the scope of the thesis, Chapter Four examines the ground motion attenuation model in depth, with particular attention to the representation of ground motion variability and its implications for interpreting PSHA results. In this context, the treatment of aleatory variability and epistemic uncertainty within the ground motion model, as well as their contributions to the overall uncertainty in PSHA, are discussed in detail in the following sections.

3.2.4 HAZARD COMPUTATION

Hazard computation essentially combines variabilities associated with earthquake magnitudes, location, occurrence frequency, and ground motion (Baker, 2008; Kramer, 1996). By aggregating these elements using the total probability theorem into a unified probabilistic framework, PSHA provides a complete assessment of seismic hazard by accounting for the entire range of possible earthquakes that could impact a site. This step transforms the physical understanding of earthquake processes into a quantitative assessment of seismic hazard.

Each seismic source can generate earthquakes of different sizes and at different distances from the site, and each scenario contributes differently to the hazard. Therefore, hazard computation

requires evaluating the exceedance probability of ground motion for a certain threshold $P(Y > y^* | m, r)$ across the full range of magnitudes and distances that characterize the source (Baker, 2008; Kramer, 1996; Liou & Abrahamson, 2025). These probabilities are weighted by the likelihood of each magnitude $f_M(m)$ and source-to-site distance $f_R(r)$, represented by their respective probability density functions (Baker, 2008; Liou & Abrahamson, 2025). The integration (in continuous condition) over magnitude and distance expresses the idea that seismic hazard is not governed by a single characteristic event but by the cumulative effect of many possible earthquakes, each with its own probability of occurrence and shaking potential (Baker, 2008; Kramer, 1996). To convert these scenario-based probabilities into a measure that reflects how often exceedance occurs in time, PSHA incorporates the annual rate of earthquake occurrence on each source. Multiplying the integrated exceedance probability by the sources' occurrence rate produces the annual rate of exceeding the ground motion level y^* . This annual exceedance rate, denoted λ_{y^*} , is the central output of PSHA. It quantifies the expected frequency of exceedance in a single year and forms the basis for constructing hazard curves (Baker, 2008; Kramer, 1996). Mathematically, this is summarized by the following equation:

$$\lambda_{y^*} = \lambda(Y > y^*) = \sum_{i=1}^{n_{source}} v_i \int_{m_{min}}^{m_{max}} \int_0^{r_{max}} P(Y > y^* | m, r) f_M(m) f_R(r) dr dm \quad \text{Equation 3.8}$$

In practical PSHA implementations, the evaluation of hazard is carried out numerically, which requires converting the continuous magnitude $f_M(m)$ and source-to-site distance $f_R(r)$ distributions into discrete forms of magnitude $P(M_i = m_j)$ and source-to-site distance $P(R_i = r_k)$ (Baker, 2008; Kramer, 1996). Because all computations are performed on a computer, it is more efficient to replace the continuous integrals with discrete summations over predefined magnitude and distance intervals. This discretization allows the hazard contribution from each magnitude-distance pair to be calculated explicitly and then combined to obtain the total exceedance rate for the ground motion level of interest:

$$\lambda_{y^*} = \lambda(Y > y^*) = \sum_{i=1}^{n_{source}} v_i \sum_{j=1}^{n_M} \sum_{k=1}^{n_R} P(Y > y^* | m_j, r_k) P(M_i = m_j) P(R_i = r_k) \quad \text{Equation 3.9}$$

Where the ranges of possible magnitude M_i and distance R_i are discretized into n_M and n_R intervals, respectively. If, for a given site, computations are repeated for many target ground motion values (i.e., different y^*), we can display the results in the form of a hazard curve as illustrated in the Figure 3.9 below (Baker, 2008; Kramer, 1996).

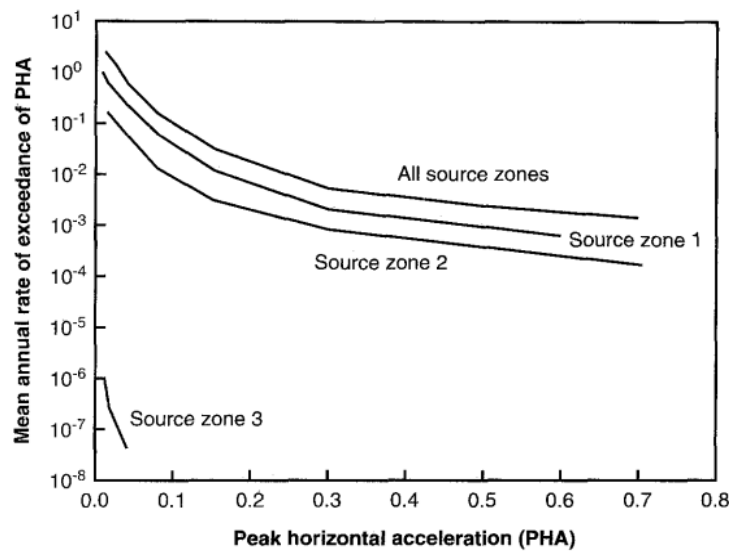


Figure 3.9: Hazard curve for different source zones and all combined source zones (Kramer, 1996)

PSHA results can be also formulated in terms of return period of exceedance. The return period is expressed as a reciprocal of the rate of exceedance ($\frac{1}{\lambda_{y^*}}$). Even if there are various models to compute the probability of exceedance within a finite time window, PSHA typically assumes that earthquakes follow a Poisson process for its mathematical simplicity, which implies independence of events, stationarity of seismicity, and a negligible probability of multiple events in very short intervals (Baker, 2008; Kramer, 1996). Under this assumption, the probability of observing at least one event in a period of time t is given as:

$$P(Y > y^* \text{ in } t \text{ years}) = 1 - e^{(-\lambda_{y^*} t)} \quad \text{Equation 3.10}$$

The Poisson model could be poorly accurate when the hazard is dominated by a single major fault, when the time since the last large event greatly exceeds the average recurrence interval, or when the source exhibits strong characteristic-time behaviour (Baker, 2008; Cornell & Winterstein, 1988; Kramer, 1996). In such cases, time-dependent models may offer a more realistic representation of earthquake occurrence. Nevertheless, for most regional and multi-source applications, the Poisson assumption remains appropriate and computationally efficient, making it the standard choice in PSHA (Baker, 2008; Kramer, 1996).

3.2.5 UNIFORM HAZARD SPECTRA

A Uniform Hazard Spectrum (UHS) is a response spectrum derived probabilistically, where the spectral acceleration values at all vibration periods correspond to the same probability of exceedance or return period at a particular site. It is obtained by first calculating seismic hazard

curves for various spectral periods and then selecting, for each period, the ground motion level associated with a common hazard level (Figure 3.10). Consequently, the resulting spectrum shows ground motion intensities that have an equal likelihood of being exceeded over a specified time frame (Kramer, 1996; McGuire, 2004).

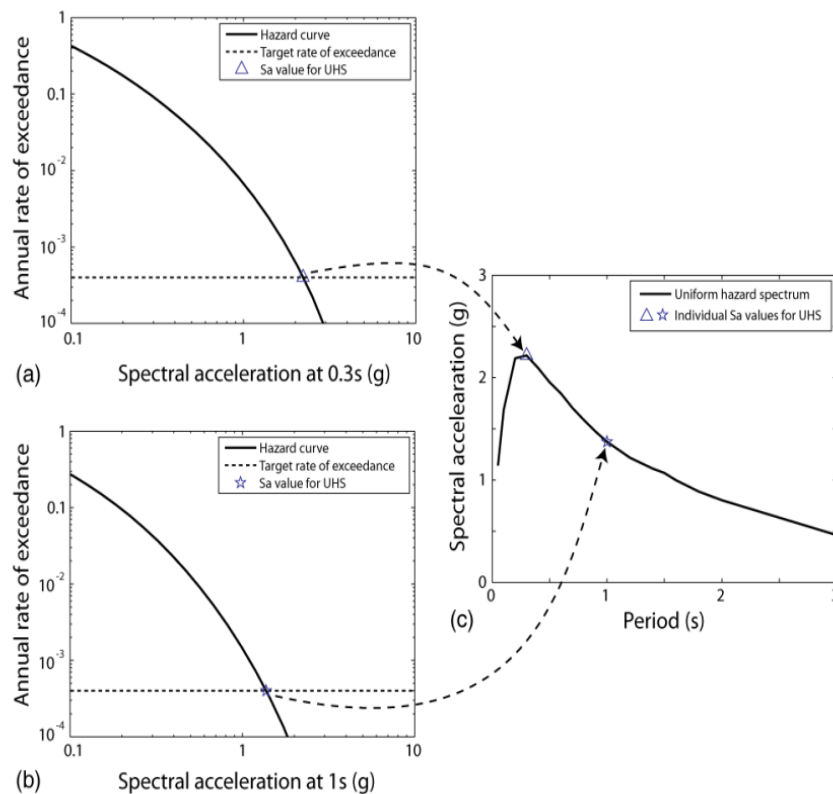


Figure 3.10: Construction of a uniform hazard spectrum (UHS) with an annual exceedance rate of 4×10^{-4} for a site in Los Angeles (Baker, 2008). (a) Hazard curve for SA (0.3s), (b) Hazard curve for SA (1s), and (c) resulting UHS.

Unlike response spectra derived from individual earthquake records or deterministic scenarios, an UHS integrates the contributions from many possible earthquakes affecting the site, including different magnitudes, source distances, faulting mechanisms, and seismic sources. Consequently, different portions of the spectrum may be controlled by different earthquakes. The UHS therefore represents a statistical envelope of the seismic demand rather than the ground motion from a single physical earthquake. Because it provides hazard-consistent spectral ordinates across the entire period range, UHSs are widely used in seismic design codes, site-specific hazard studies, and performance-based earthquake engineering as a standardized representation of the expected ground shaking corresponding to a chosen level of seismic risk (Baker, 2008; Kramer, 1996; McGuire, 2004).

4. GROUND MOTION MODELS (GMM)

4.1 THE ROLE OF GROUND MOTION MODELS IN SEISMIC HAZARD ASSESSMENT

Ground motion models (GMMs) provide one of the essential predictive components required in Probabilistic Seismic Hazard Analysis (PSHA) (Cornell, 1968; McGuire, 2004). A GMM can be expressed in empirical, semi-empirical, and physics-based forms. In the present study, I will focus on empirical models, also referred to as ground motion prediction equations (GMPEs). A GMPE is a mathematical formulation used to predict the ground shaking intensity at a specific site for a given earthquake scenario, defined by measurable earthquake parameters, such as magnitude, source-to-site distance, faulting mechanism, and local site conditions. The ground shaking can be expressed in terms of several intensity measures (IMs), including Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), and spectral acceleration (SA). More precisely, a GMPE allows defining the probability distribution of ground motion by means of two primary statistical parameters: the mean and standard deviation (σ) of the logarithmic ground motion. The latter represents the aleatory variability (or randomness) of the (logarithmic) shaking about its mean (Liou & Abrahamson, 2025; Abrahamson et al., 2019; Al Atik et al., 2010).

The main challenge in ground motion prediction arises from the complex and variable nature of earthquake process. The characteristics of seismic shaking (e.g., amplitude, duration, frequency content) depend on different factors, such as the physical properties of the fault rupture, seismic-wave propagation through heterogeneous geological structures, and local site effects. The complexity and variability of earthquake processes make ground motion prediction inherently uncertain. Since these processes cannot be fully characterized with complete accuracy, GMMs use empirical observations and statistical regression to estimate the median ground motion while accounting for epistemic and aleatory uncertainties (Bozorgnia et al., 2014; Kramer, 1996).

Indeed, the predictive capability of GMMs is limited by both the inherent randomness of earthquake rupture and wave propagation processes (aleatory variability), together with incomplete knowledge of earthquake physics and regional conditions (epistemic uncertainty). Consequently, recent GMM development focuses not only on improving median prediction but also on accurately quantifying and separating different sources of uncertainty to provide more reliable ground motion predictions and seismic hazard estimations (Al Atik et al., 2010; Abrahamson et al., 2019; Liou & Abrahamson, 2025).

4.2 FUNDAMENTAL COMPONENTS OF GMM PARAMETRIZATION

As we discussed earlier (Chapter 3), ground motion prediction is governed by the complex interaction among earthquake source characteristics, seismic wave propagation through the Earth's crust, and local geological conditions at the recording site. Ground motion models (GMMs) are developed to capture these physical processes by establishing empirical or semi-empirical relationships between observed ground motion intensity measures and the parameters controlling their variability (Lanzano et al., 2019; Paredes & De Risi, 2025; Sgobba et al., 2021). Therefore, in this section, we discuss the three fundamental physical components that govern ground motion: earthquake source effects, propagation path effects, and local site effects.

1. Earthquake Source Characterization

The source terms describe the physical characteristics of the earthquake rupture and the amount of seismic energy released during faulting. These parameters control the generation of seismic waves and strongly influence the amplitude, frequency content, and duration of ground motion (Heaton et al., 1986; Kramer, 1996).

- **Magnitude (M):** The primary measure of earthquake size. Although several magnitude scales exist, such as local magnitude (M_L), surface wave magnitude (M_s), body wave magnitude (M_b), and moment magnitude (M_w), M_w is the most widely used in modern GMMs because it is directly related to seismic moment and does not saturate in case of large earthquakes (Heaton et al., 1986; Paredes & De Risi, 2025).

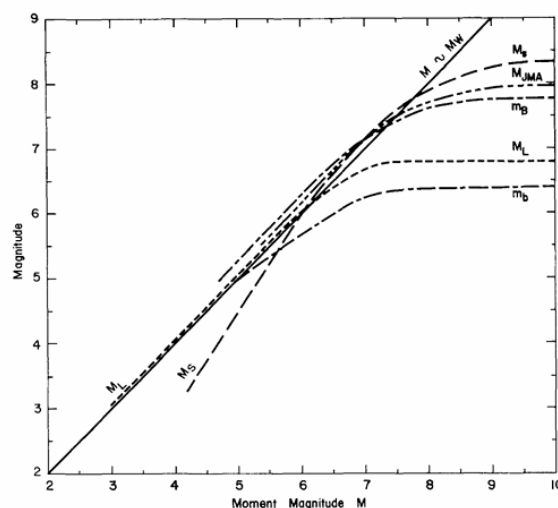


Figure 4.1: Saturation characteristics of various traditional earthquake magnitude metrics contrasted against the moment magnitude scale (Heaton et al., 1986).

- **Style of Faulting:** The faulting mechanism strongly influences the characteristics of seismic radiation and resulting ground motion. Depending on the relative movement of the fault blocks, earthquakes are generally classified as reverse, strike-slip, or normal faulting events (Figure 4.2). Reverse-fault earthquakes generally produce stronger shaking than strike-slip events, whereas normal-faulting earthquakes tend to generate lower-amplitude ground motion for comparable magnitudes and distances (Campbell, 1981; Bommer et al., 2003; Bindi et al., 2011; Paredes & De Risi, 2025).

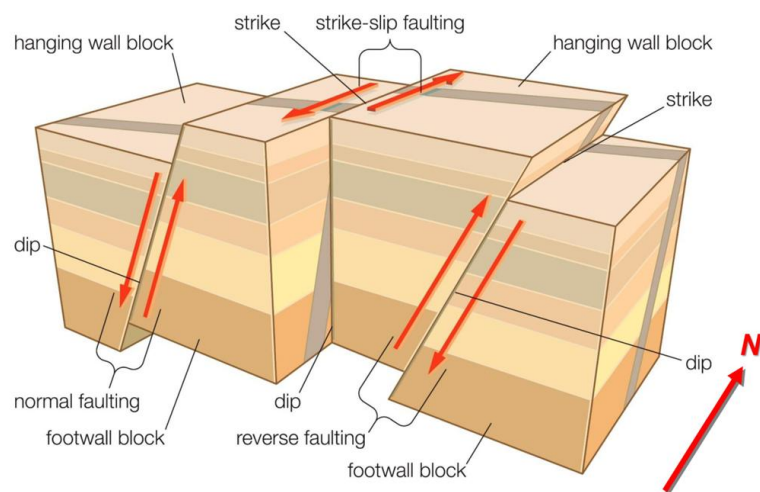


Figure 4.2: Types of faulting in tectonic earthquakes (Encyclopedia Britannica, 2015)

- **Source Depth:** Parameters such as hypocentral depth (Z_{hyp}) and depth to the top of the rupture (Z_{TOR}) influence the propagation path of seismic waves. These variables are particularly important for distinguishing between shallow crustal and deeper seismic events (Lanzano et al., 2019; Paredes & De Risi, 2025).
- **Stress Drop ($\Delta\sigma$):** Stress drop is the difference in fault stress before and after rupture and is closely related to the frequency content of seismic radiation. Higher stress-drop events generally produce larger high-frequency ground motions. (Heaton et al., 1986; Kramer, 1996).
- **Rupture Geometry and Dimensions:** The geometric characteristics of the fault rupture also significantly influence near-fault ground motion behavior. Parameters such as rupture length (L), fault width (W), rake angle (λ), strike angle (Φ), and dip angle (δ) are used to define fault effects (Tavakoli et al., 2018 as cited in Paredes & De Risi, 2025). These variables describe the spatial extent and direction of rupture propagation and are essential for capturing phenomena such as rupture directivity, spatial variations in seismic energy

radiation, and the hanging-wall effect (Campbell & Bozorgnia, 2013 as cited Paredes & De Risi, 2025). Such effects can produce significant differences in ground motion amplitude, duration, and spectral characteristics, particularly for sites located close to the fault rupture (Kramer, 1996).

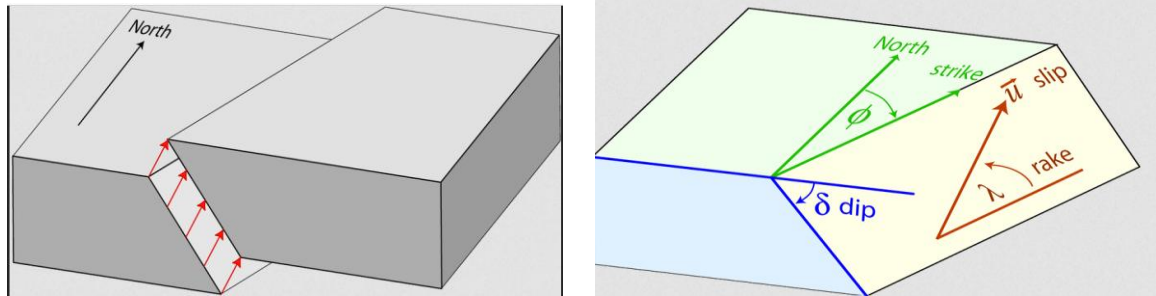


Figure 4.3: Orientation of a fault plane through strike, dip, and rake angles (INGVterremoti (2012), *ingvterremoti.com.*, 2012).

2. Wave Propagation Path Effects

Path effects describe how seismic waves are modified as they propagate from the earthquake source to the recording site. These effects govern the reduction in ground motion amplitude with increasing source-to-site distance and depend on the physical properties of the crust, seismic wave propagation characteristics, and regional attenuation behavior. In Empirical GMMs, path effects are commonly represented by distance-dependent functions that account for both geometric spreading and anelastic attenuation (Bindi et al., 2011; Kramer, 1996; Paredes & De Risi, 2025).

- **Geometric Spreading:** Geometric spreading is the redistribution of seismic energy as wavefronts expand away from the source. As propagation distance increases, the amplitude of seismic waves decreases because the energy is distributed over a larger area. This effect is commonly described by an inverse power-law relationship, where the rate of amplitude decay depends on wave type, distance range, and geological conditions (Liou & Abrahamson, 2025; Lowrie, 2007).

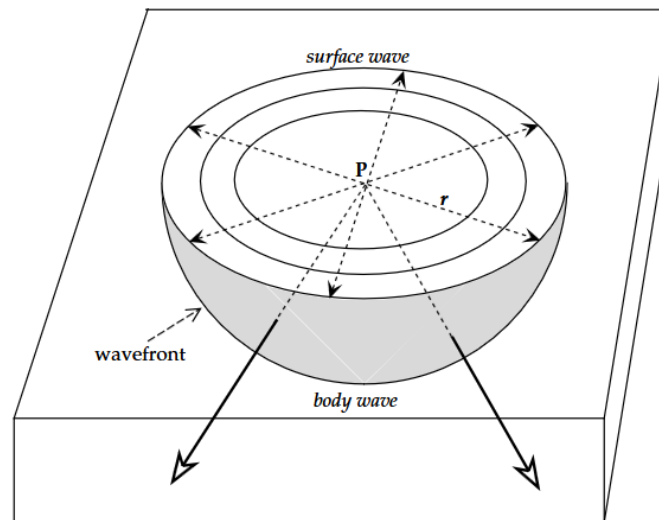


Figure 4.4: Expansion of a seismic body wave from a shallow source. Energy radiates deep into the ground as body waves, and along the open surface as surface waves (Lowrie, 2007).

- **Anelastic Attenuation:** Anelastic attenuation represents the loss of seismic energy caused by internal friction and inelastic deformation within the Earth's crust due to the imperfect elastic properties of Earth materials. Unlike geometric spreading, which describes energy redistribution, anelastic attenuation represents energy dissipation (e.g., it reappears in the form of frictional heat) and is commonly modeled using exponential decay terms related to the quality factor ($Q(f)$), which describes the frequency-dependent attenuation properties of the medium (Kramer, 1996; Paredes & De Risi, 2025).
- **Distance Metrics:** Accurate characterization of the source-to-site distance is essential for capturing attenuation behavior, particularly in near-source regions where fault effects become important. Different distance measures are used in GMMs depending on the earthquake source representation, including rupture distance ($R_{rup} = R4$), Joyer-Boore distance ($R_{JB} = R5$), hypocentral distance ($R_{hyp} = R1$), and epicentral distance ($R_{epi} = R2$). These parameters allow models to account for variations in shaking intensity caused by the relative position of the site with respect to the rupture plane and seismic source (Gregor et al., 2014; Kramer, 1996; Paredes & De Risi, 2025).

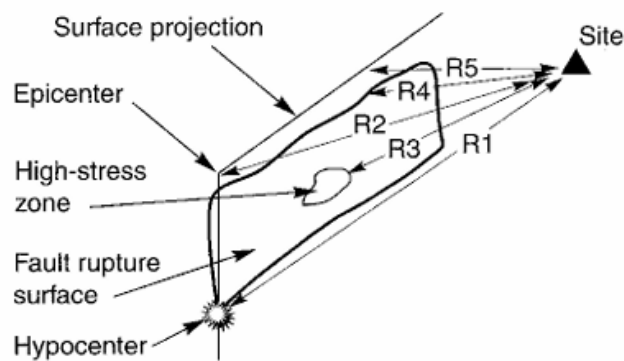


Figure 4.5: Different distance metrics applied within ground motion prediction equations (Shakal and Bernreuter, 1981 as cited in Kramer, 1996)).

3. Local Site Conditions

Site effects represent the modification of seismic waves caused by local geological and geotechnical conditions between the underlying rock and ground surface. Even when two sites experience the same earthquake at similar source-to-site distances, the recorded ground motions may differ significantly due to variations in soil stiffness, sediment thickness, geological structure, and possible nonlinear soil behavior (Kramer, 1996; Paredes & De Risi, 2025). Site effects conditions are typically described by the following parameters.

- **Shear-Wave Velocity (VS_{30}):** The time-averaged shear-wave velocity in the upper 30 m of the soil profile (VS_{30}) is the most widely used indicator of near-surface site stiffness in contemporary GMMs. It provides a practical classification of site conditions, where lower VS_{30} values generally correspond to softer soils and stronger amplification effects, while higher VS_{30} values represent stiffer soil or rock sites with reduced amplification. Due to its availability and correlation with site response, VS_{30} has become a standard predictor variable in many global GMMs (Al Atik et al., 2010; Kotha et al., 2017; Lanzano et al., 2019; Paredes & De Risi, 2025).
- **Basin Depth Parameters ($Z1.0$, $Z2.5$):** Deep sedimentary basins can significantly influence ground motion characteristics, particularly at long vibration periods relevant to tall buildings and large infrastructure. Basin depth parameters, such as the depth to the subsurface layer where shear wave velocity reaches 1.0 km/s ($Z1.0$) and 2.5 km/s ($Z2.5$), are used to represent the effects of sediment thickness and deep geological structures on seismic wave amplification and resonance phenomena (Gregor et al., 2014).

- **Nonlinear Site Response:** Under strong earthquake shaking, soil behavior becomes nonlinear, causing changes in stiffness and damping characteristics. With increasing ground shaking intensity, higher shear strains reduce the soil's shear modulus (G) and shear wave velocity (V_s), leading to a shift of the fundamental resonant frequency toward lower frequencies. Simultaneously, increased damping associated with nonlinear soil behavior dissipates more seismic energy, resulting in lower amplification of ground motion (Barani et al., 2014; Kramer, 1996; Paredes & De Risi, 2025).

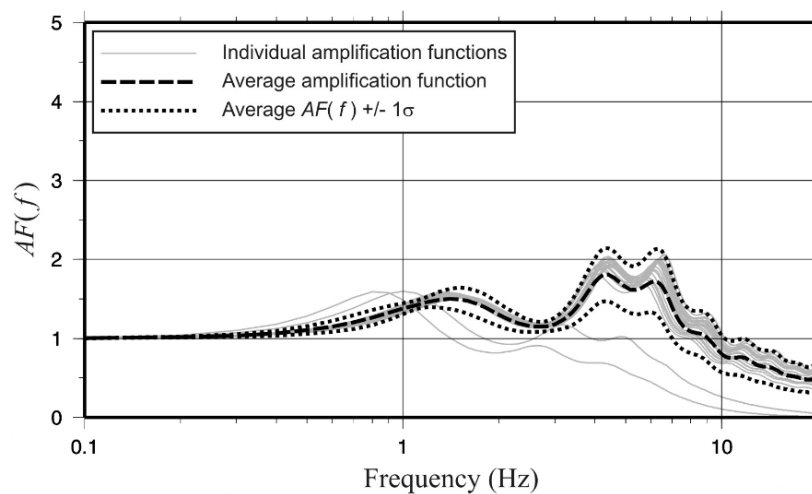


Figure 4.6: Amplification functions that account for the variability of the input ground motion and soil nonlinearity effects (Barani et al., 2014).

- **Additional Site Effects:** Detailed 2D or 3D advanced GMMs also consider other site-related factors, including topographic amplification and local/regional variation in site response. These parameters are more important where local geological structures cannot be adequately represented by (VS30) alone (Gregor et al., 2014; Kramer, 1996; Wang, 2020).

4.3 EVOLUTION FROM ERGODIC TO NONERGODIC GROUND MOTION MODEL

The historical development of GMMs has evolved from the conventional ergodic approach, in which large datasets collected from multiple regions and recording stations are assumed to represent the statistical behavior of ground motions at any individual site, towards a more advanced nonergodic approach that accounts for site-specific effects. The ergodic assumption enables the development of empirical models by allowing limited observations from different earthquakes and regions to be combined into a generalized predictive relationship. However, the ergodic assumption treats systematic variations associated with specific sites, propagation paths, and

regional characteristics as random variability, often resulting in an increase in the estimate of the “true” aleatory variability (σ_{al}) (Al Atik et al., 2010).

The development of nonergodic GMMs represents a fundamental paradigm shift toward identifying and modeling repeatable and physically interpretable components of ground motion variability.

As illustrated in Figure 4.6, GMMs can be broadly classified as ergodic, partially nonergodic, or fully nonergodic depending on the extent to which spatially varying effects are explicitly modeled. Partially nonergodic GMMs provide an initial step toward addressing the limitation associated with the ergodic assumption for the site term. In these models, site-specific effects, which are systematic and repeatable at any given location, are separated from the aleatory variability, while the source and path terms are still generally treated as random terms. In contrast, instead of assuming (and treating) that all recording sites and seismic-wave propagation paths are statistically equivalent, fully nonergodic models acknowledge and introduce location-dependent adjustments associated with site effects, source characteristics, and path-specific variations. By separating these systematic effects from the natural randomness (aleatory uncertainty σ_{al} minus systematic effects), the nonergodic approach reduces the apparent aleatory variability and provides improved site-specific ground motion prediction, particularly in regions with enough observational datasets (Al Atik et al., 2010; Abrahamson et al., 2019; Sgobba et al., 2021). Indeed, the increased predictive capability of nonergodic models strongly depends on the availability of sufficient strong-motion observations, reliable geological information, and appropriate statistical characterization of spatial correlations. In regions with limited data availability, the estimation of site-specific adjustment terms becomes more uncertain, resulting in increased epistemic uncertainty associated with model assumptions and parameter estimation (Abrahamson et al., 2019; Al Atik & Youngs, 2014).

Within this context, this thesis adopts the nonergodic methodological framework proposed by Sgobba et al. (2021) for PSHA in Central Italy. The framework is particularly suitable for the study area as it accounts for spatially varying source, path, and site effects, together with their associated uncertainties. This model is supported by a rich strong-motion database, comprising more than 30,000 records, including data from the 2009 L’Aquila and 2016–2017 Central Italy earthquake sequences, which provide sufficient observations to characterize these spatially varying effects (Sgobba et al., 2021).

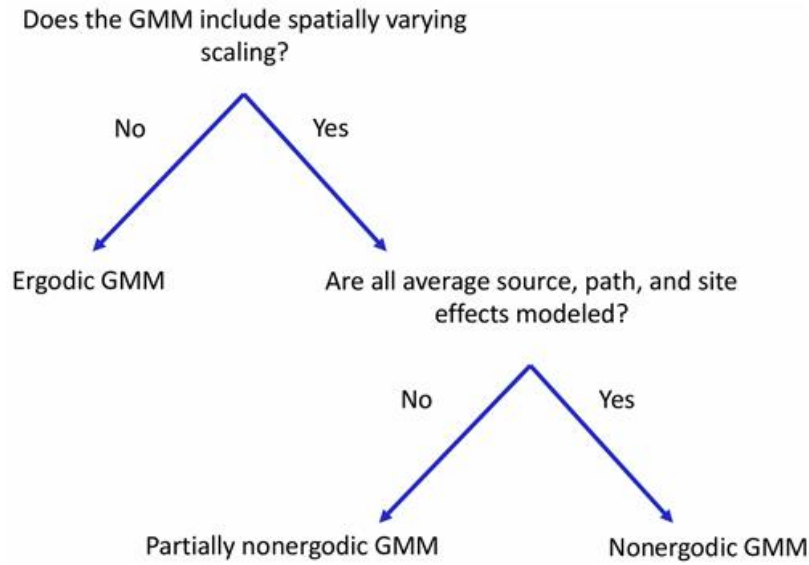


Figure 4.7: Scheme showing the simplification levels of ergodic, partially nonergodic, and nonergodic ground motion models (Liou & Abrahamson, 2025).

4.4 RESIDUAL DECOMPOSITION

As stated above, the decomposition of ground motion residuals plays a crucial role in identifying and characterizing repeatable, systematic effects, thereby improving our understanding and estimation of ground motion variability. This process enables the differentiation of various sources of uncertainty: specifically, aleatory variability, which represents inherent randomness, from epistemic uncertainty, which reflects imperfect knowledge. This decomposition can potentially reduce the standard deviation (sigma) used in hazard calculations by isolating systematic, repeatable sources of variability from the truly random component of ground motion residuals (Abrahamson et al., 2019; Al Atik et al., 2010; Liou & Abrahamson, 2025).

Ground motion residuals quantify the discrepancy between an observed ground motion parameter and the corresponding value predicted by a GMPE. Since ground motion parameters are assumed to follow a lognormal distribution, residuals are evaluated in logarithmic space (Abrahamson et al., 2019; Al Atik et al., 2010). The total residual is expressed as:

$$R_{ij} = \ln(Y_{ij})_o - \ln(Y_{ij})_p \quad \text{Equation 4.1}$$

Where;

R_{ij} = Total residual for earthquake i recorded at station j ;

$(Y_{ij})_o$ = Observed ground motion parameter (IM)

$(Y_{ij})_p$ = Median ground motion predicted by the selected GMPE

A positive residual indicates that the recorded ground motion exceeds the predicted value, whereas a negative residual indicates that the observed motion is smaller than predicted. Since ground motion observations contain contributions from multiple physical processes, the total residual does not represent purely random error. Instead, it includes systematic effects associated with earthquake source characteristics, propagation path properties, and local site conditions. Therefore, to partition and separate the total residual into specific residual component categories, residual decomposition should be conducted.

4.4.1 FIRST- LEVEL RESIDUAL DECOMPOSITION

The first stage of residual decomposition separates the total residual " R_{ij} " (Equation 4.1) into between-event and Within-event components.

$$R_{ij} = \delta B_e + \delta W_{es} \quad \text{Equation 4.2}$$

The between-event residual (δB_e) is the residual component that captures the variability between different earthquakes e . In other words, it is the average shift of observations for a specific earthquake from the median. These differences arise from variations in source characteristics such as stress drop, rupture velocity, focal mechanism, fault geometry, and rupture complexity (Al Atik et al., 2010; Lanzano et al., 2019).

The within-event residual (δW_{es}) represents the remaining station-to-station variability after removing the earthquake-specific effects. In other words, it captures the variability within the single earthquake e , due to the difference in recording sites s (Al Atik et al., 2010; Lanzano et al., 2019).

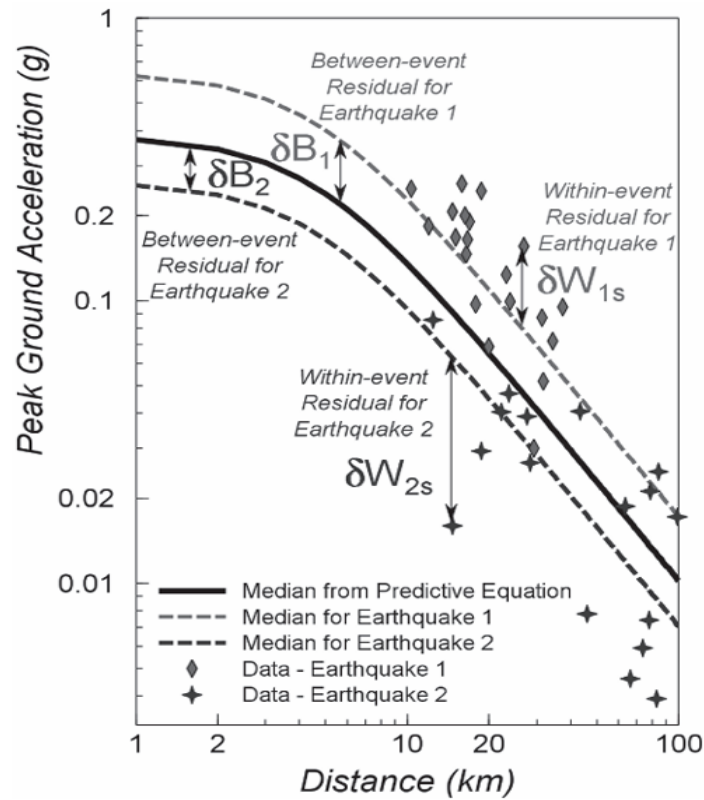


Figure 4.8: Between-event and within-event components of ground motion variability (Strasser et al. 2009, as cited in Al Atik et al. 2010).

4.4.2 DECOMPOSITION OF WITHIN-EVENT (δW_{es}) RESIDUAL

Since the within-event residual (δW_{es}) represents the variability in ground motion observed at different recording stations s for a given earthquake e , these variations are not entirely random, as they contain both systematic and random components associated with local site conditions, seismic wave propagation paths, in addition to the remaining uncaptured residual. To better understand the physical origins of this variability, the within-event residual is further decomposed into repeatable site effects ($\delta S2S_s$), repeatable path effects ($\delta P2P_p$) and a remaining random component ($\delta W0, esl$) (Abrahamson et al., 2019; Al Atik et al., 2010; Sgobba et al., 2021).

Therefore, the decomposition is expressed as:

$$\delta W_{es} = \delta S2S_s + \delta P2P_p + \delta W0, esl \quad \text{Equation 4.3}$$

4.4.2.1 SITE-TO-SITE RESIDUAL ($\delta S2S_s$)

The site-to-site residual ($\delta S2S_s$) represents the systematic deviation of the observed ground motion amplification at a recording station from the median amplification predicted by a ground motion prediction equation (GMPE). It is one of the principal components of the within-event

variability and plays a central role in the development of nonergodic ground motion models. Unlike purely random variability, the site-to-site residual reflects persistent local geological conditions that remain essentially unchanged over engineering timescales. Therefore, this behavior represents a systematic property associated with local geology instead of an inherent source of aleatory uncertainty (Al Atik et al., 2010; Rodriguez-Marek et al., 2014; Sgobba et al., 2021).

Generally, the observed logarithmic site amplification ($\ln A_{mpes}$) can be partitioned into three distinct parts to better characterize ground motion behavior at a specific location (Al Atik et al., 2010).

- **Median Site Amplification** (μ_{Amp}): Median site amplification is an average amplification predicted by a GMPE (Al Atik et al., 2010). It is typically based on broad site classification, such as conventional classifications based on the time-averaged shear-wave velocity in the upper 30 meters, VS_{30} (Al Atik et al., 2010). In an ergodic model, all sites with the same VS_{30} are assumed to have the same median amplification (Abrahamson et al., 2019).
- **Site-to-Site Residual** ($\delta S_2 S_s$): the site-to-site residual term represents the systematic deviation of a specific site's response from the global median predicted by the GMM at hand (GMM) (Al Atik et al., 2010; Kotha et al., 2017). It accounts for local characteristics, such as unique soil profiles or 2D/3D subsurface structures that are not captured by VS_{30} alone (Al Atik et al., 2010; Kotha et al., 2017; Lacour & Abrahamson, 2025). Since the site-to-site term is repeatable across multiple earthquake recordings at the same station, it is considered a deterministic component in nonergodic frameworks (Al Atik et al., 2010).
- **Record-to-Record Residual** (δA_{mpes}): record-to-record residual is the remaining random component that accounts for unexplained, aleatory variability for a specific record. It captures variation due to factors like wave incident angle, complex 3D wave propagation, and measurement uncertainty (Al Atik et al., 2010).

4.4.2.2 *PATH-TO-PATH RESIDUAL* ($\delta P_2 P_p$)

The path-to-path residual ($\delta P_2 P_p$) represents the systematic deviation of observed ground motion caused by the repeatable characteristics of the travel path between a specific source and recording station (Al Atik et al., 2010; Sgobba et al., 2021). While conventional distance measures such as rupture distance (R_{RUP}) or Joyner-Boore distance (R_{JB}) are effective for modeling geometric spreading, they represent a significant simplification that fails to account for the physical complexity of wave propagation through the Earth's heterogeneous crust (Baker, 2008).

The physical drivers of path variabilities include crustal heterogeneity and scattering, seismic anisotropy, and regional variations in anelastic attenuation.

- **Crustal Heterogeneity and Scattering:** within-event residuals capture variation due to crustal heterogeneity and deeper geological structures not represented by simple distance metrics (Al Atik et al., 2010). Structural heterogeneity is a dominant influence on ground motion residuals, particularly for propagation distances exceeding 100 km relative to the source, whereas local site effects are dominant at shorter distances relative to the source (Paredes & De Risi, 2025; Sahakian et al., 2019).
- **Seismic Anisotropy:** repeatable deviations in ground motion can arise from anisotropy in crustal velocity, density, or the attenuation function along the specific ray path (Sgobba et al., 2021). Anisotropy arises when tectonic deformation, stress, or flow causes minerals within the Earth's interior to become preferentially aligned, producing a directional fabric. This fabric causes the rock's physical properties, and consequently seismic-wave propagation, to vary with direction. As a result, shear waves can split into two orthogonally polarized components that propagate at different velocities depending on their polarization relative to the anisotropic structure. These components are commonly referred to as the fast and slow shear waves, with their relative velocities determined by the orientation and characteristics of the underlying anisotropy. (Lowrie, 2007; Heaton et al., 1986; Kotha et al., 2019, as cited in Paredes & De Risi, 2025)
- **Regional Variations in Anelastic Attenuation (Q):** the inelastic attenuation accounts for intrinsic energy loss (absorption) and scattering due to the nonhomogeneous medium. Because different regions have different Quality Factor (Q), waves traveling through low-Q regions, such as regions characterized by active volcanism or highly fractured rock, attenuate much faster than predicted by global average models, while waves in high-Q regions, such as areas presenting deep solid bedrocks or cold subduction slabs, preserve energy over greater distances (Paredes & De Risi, 2025).

4.4.2.3 *REMAINING WITHIN-EVENT RESIDUAL ($\delta W0, esl$)*

The remaining within-event residual ($\delta W0, esl$), is a component of ground motion variability that remains after all systematic (repeatable) site-specific and path-specific effects have been removed from the total within-event residual (Liou & Abrahamson, 2025; Sgobba et al., 2021). The physical conceptual interpretation of the remaining within-event residual is mainly categorized into two unmodeled effects (refer to section 4.5.2):

- **Practically Irreducible:** effects that are theoretically predictable but currently impractical to model due to data limitations or computational costs, such as unresolved small-scale geological heterogeneity, complex 3D velocity structure, or nonlinear wave interaction.
- **Inherent Randomness:** fundamentally, unpredictable processes arising from the intrinsic stochastic nature of earthquake rupture (e.g., chaotic slip distributions).

4.4.3 DECOMPOSITION OF BETWEEN-EVENT (δB_e) RESIDUAL

The between-event residual (δB_e) represents the average deviation of the observed ground motion of an individual earthquake from the median ground motion prediction. It is further decomposed to distinguish between systematic, repeatable effects associated with location-to-location residual ($\delta L2L_{source}$) and remaining between-event residuals ($\delta B_{e,0}$) from random source variability (Abrahamson et al., 2019; Al Atik et al., 2010; Liou & Abrahamson, 2025; Sgobba et al., 2021).

This decomposition is expressed mathematically as:

$$\delta B_e = \delta L2L_{source} + \delta B_{e,0} \quad \text{Equation 4.4}$$

4.4.3.1 Location-to-Location Residual ($\delta L2L_{source}$)

The location-to-location residual ($\delta L2L_{source}$) term is an epistemic, location-specific source term used in GMMs to capture repeatable source effects for a particular geographical region. The location-to-location residual ($\delta L2L_{source}$) term represents the systematic (repeatable) source-specific adjustment to the median ground motion. It is the average difference in source effects for a specific source region relative to the global median predicted by an ergodic GMM (Abrahamson et al., 2019; Liou & Abrahamson, 2025). These systematic shifts are often caused by variations in regional source characteristics that differ from the global average, such as a systematically higher or lower average stress drop ($\Delta\sigma$) compared to the global average (Al Atik et al., 2010; Ameri et al., 2017, as cited in Paredes & De Risi, 2025).

4.4.3.2 Remaining Between-Event Residual ($\delta B_{e,0}$)

The remaining between-event residuals term ($\delta B_{e,0}$) represents the portion of source variability that remains after removing systematic location-specific effects (Al Atik et al., 2010). It is the record-to-record misfit in source properties that cannot currently be predicted through deterministic source-location adjustments (Liou & Abrahamson, 2025).

The physical interpretation of remaining between-event residual reflects the intrinsic nature of earthquake rupture, including random heterogeneity of fault slip variations in rupture velocity, and fluctuating stress drop from one event to the next (Paredes & De Risi, 2025). This is classified as practically irreducible aleatory variability, meaning it is theoretically predictable but currently impractical to model for future events because the specific rupture realization is unknown (Class 2 Aleatory) (Liou & Abrahamson, 2025).

4.5 UNCERTAINTY REPRESENTATION AND TRADE-OFF PRINCIPLE

In modern probabilistic seismic hazard analysis (PSHA), the representation of uncertainty fundamentally accounts for the degree of model simplification. The trade-off principle states that increasing the physical realism of the ground motion model (GMM) reduces the amount of variability treated as aleatory randomness, while simplified models account for a large portion of the variability to be represented as random variability (Liou & Abrahamson, 2025). This principle provides the foundation for distinguishing different sources of uncertainty in ground motion characterization.

4.5.1 ALEATORY VARIABILITY AND EPISTEMIC UNCERTAINTY

Uncertainty in ground motion characterization is generally represented by two complementary components, aleatory variability and epistemic uncertainty (Liou & Abrahamson, 2025). Their relative contributions depend on the level of model simplification/complexity, consistent with the trade-off principle (Liou & Abrahamson, 2025; Paredes & De Risi, 2025).

Aleatory variability represents the residual difference between predicted and observed ground motions that arise from physical processes not captured by the GMM for a given level of model complexity, and it is treated as random (Liou & Abrahamson, 2025; Paredes & De Risi, 2025). Generally according to Liou & Abrahamson (2025), the aleatory variability is classified into three categories:

- Class 1: Apparent randomness arising from physical processes that are practical to model but are not explicitly included in the GMM due to the modeler's choice.
- Class 2: Apparent randomness associated with physical processes that are theoretically explainable but currently impractical to model because of limited data, computational constraints, or insufficient scientific understanding.
- Class 3: Inherent randomness resulting from inherently unpredictable or chaotic aspects of earthquake rupture and wave propagation that can not be deterministically modeled.

Epistemic uncertainty represents the uncertainty associated with incomplete scientific knowledge regarding the correct representation of the earthquake source process, wave propagation, site response, and other physical mechanisms included in the GMM (Liou & Abrahamson, 2025; Paredes & De Risi, 2025). In PSHA, epistemic uncertainty is commonly represented by using the logic tree, in which alternative models and parameter values are assigned weights according to their credibility. The resulting ensemble of hazard estimates is summarized by fractile hazard curves, which quantify the range of hazard levels associated with current knowledge uncertainty (Lacour & Abrahamson, 2025; Liou & Abrahamson, 2025).

4.5.2 THE TRADE-OFF PRINCIPLE

The trade-off principle states that the partitioning of uncertainty between aleatory variability and epistemic uncertainty depends on the level of physical detail incorporated into the GMM (Liou & Abrahamson, 2025; Paredes & De Risi, 2025). As additional physical processes are explicitly represented, the residual variability attributed to aleatory randomness decreases. However, with the addition of model components, the complexity of the model will increase, and this increment leads to an increase in epistemic uncertainty. Thus, the total uncertainty is redistributed rather than eliminated.

Conventional ergodic GMMs employ simplified representations of earthquake source, wave propagation, and site effects by assuming that observations from different regions can be treated as statistically equivalent. Consequently, many systematic physical effects, including site-specific amplification and path-dependent attenuation, are accounted for in the aleatory variability, resulting in relatively large residual variability. Because the global median ground motion model is calibrated using extensive datasets from multiple regions, its median predictions are generally well constrained, leading to comparatively smaller epistemic uncertainty (Al Atik et al., 2010; Liou & Abrahamson, 2025; Paredes & De Risi, 2025).

In contrast, nonergodic GMMs explicitly account for systematic source, path, and site effects that are treated as random in ergodic models. By modeling these repeatable physical processes directly, the aleatory variability can be substantially reduced, with reported reductions commonly ranging from 30% to 40% or more, depending on the availability of high-quality local data (Abrahamson et al., 2019). However, because these model components require estimation from regional datasets, the associated epistemic uncertainty generally increases, particularly where observational local data are sparse (Abrahamson et al., 2019; Liou & Abrahamson, 2025; Paredes & De Risi, 2025; Sgobba et al., 2021).

4.5.3 FRAMEWORK CATEGORIES OF UNCERTAINTY: METHOD AND PARAMETRIC UNCERTAINTIES

Liou & Abrahamson (2025) classifies uncertainty in ground motion characterization into two complementary categories: Method uncertainty, which arises from the selection of modeling approaches and analytical procedures, and Parametric uncertainty, which results from the uncertainty in the values of the model input parameters.

Precisely, Method uncertainty is the uncertainty that arises from the computational methodology and physical formulation that is used to predict earthquake ground motion. It accounts for the assumptions, considerations, and simplifications adopted in the GMM. Within this category, there are different types of uncertainties:

- **Method Aleatory Variability** ($\sigma_{al-Method}$): this represents the standard deviation that results from unmodeled effects due to method simplifications in the GMM. Even with the best possible inputs, there will be a difference (misfit) between predicted and observed ground motions since the GMM is unable to perfectly capture the Earth's physics. For instance, a simplified 1D simulation method will naturally have a larger $\sigma_{al-Method}$ than a complex 3D simulation because it ignores more physical behaviors (Liou & Abrahamson, 2025).
- **Method Epistemic Uncertainty of the Median** ($\sigma_{epi-\mu,Method}$): this represents the scientific uncertainty (due to lack of knowledge) regarding whether the method remains unbiased given optimal inputs. It results from the limited data availability to constrain the median ground motion for a specific earthquake scenario (Liou & Abrahamson, 2025). Therefore, this uncertainty systematically decreases as more recordings are collected, as the estimated median behavior of the model becomes increasingly well constrained and converges towards the true median response (Abrahamson et al., 2019; Liou & Abrahamson, 2025). It is expressed in simple statistical form; it is the standard error of the mean of the residuals, calculated as the method aleatory variability divided by the square root of the number of observations (N):

$$\sigma_{epi-\mu,Method} = \frac{\sigma_{al-Method}}{\sqrt{N}} \quad \text{Equation 4.5}$$

- **Method Epistemic Uncertainty of the Aleatory Variability** ($\sigma_{epi-\sigma,Method}$): This is the scientific uncertainty regarding the size or spread of the randomness for the method. It accounts for the fact that we might not only have the “wrong” median but also an inaccurate estimate of how much the ground motion varies, or the standard deviation (the

“sigma”). Additionally, different calibrations (e.g., global vs. region-specific databases) may produce different estimates of the standard deviation due to regional differences in source, path, and site characteristics. (Liou & Abrahamson, 2025). Likewise, alternative statistical estimation procedures, such as different methods for partitioning between-event and within-event variability, can produce different values for the standard deviation. Method epistemic uncertainty of the aleatory variability ($\sigma_{epi-\sigma, Method}$) can be expressed as:

$$\sigma_{epi-\sigma, Method} = \frac{\sigma_{al-Method}}{\sqrt{2(N-1)}} \quad \text{Equation 4.6}$$

The Parametric category accounts for uncertainty in input parameters that influence ground motion predictions but are not explicitly represented in the seismic source model or hazard integral. Examples include stress drop, rupture velocity, slip distribution, hypocentral location, and other random source characteristics. These parameters are particularly important in physics-based and simulation-based GMMs, where rupture realizations are generated to represent future earthquake scenarios (Liou & Abrahamson, 2025).

- **Parametric Aleatory Variability ($\sigma_{al-Param}$)** : it represents the explainable variability in ground motion that results from the natural randomness of input parameters not included in the hazard integral (Liou & Abrahamson, 2025). Due to the uncertainty in parameter values, such as a future earthquake’s stress drop or slip distribution, we should generate multiple “rupture realizations”. “As an example of $\sigma_{al-Param}$, consider a GMM based on the point-source stochastic model (Boore, 2009) in which stress drop is an input parameter to the GMM; however, the source model or the PSHA software only uses the earthquake magnitude to describe the source. In this case, the simplification is in the source model or used in the PSHA calculation and not in the GMM” (Liou & Abrahamson, 2025).
- **Parametric Epistemic Uncertainty of the Median ($\sigma_{epi-\mu, Param}$)**: it refers to the scientific uncertainty in the median ground motion due to our limited knowledge of the distribution of these input parameters. For example, for a parameter like stress drop, this term quantifies how well we know the true median value of stress drop for a given region. Unlike aleatory variability, this can be reduced by collecting more data to better constrain the “best version” of the input model (Liou & Abrahamson, 2025).

- **Parametric Epistemic Uncertainty of the Aleatory Variability** ($\sigma_{epi-\sigma,Param}$): this refers to the scientific uncertainty regarding the size (or spread) of the randomness for these parameters. It addresses how well we know the standard deviation of the input parameters (e.g., how much stress drop varies event to event). In simulation-based GMMs, this might involve using alternative rupture generators or different source-scaling rules to see how the resulting aleatory spread changes (Liou & Abrahamson, 2025).

This thesis focuses exclusively on the Method uncertainty, as this constitutes the primary source of uncertainty in PSHA applications. Conventional empirical GMMs generally do not require a separate parametric uncertainty framework since their principal predictor variables, such as earthquake magnitude and source-to-site distance, are already incorporated into the PSHA hazard integral. In contrast, simulation-based GMMs require explicit treatment of parametric uncertainty because they randomize additional physical parameters, such as slip distributions and rupture realizations, to simulate future earthquakes (Liou & Abrahamson, 2025).

4.6 UNCERTAINTY QUANTIFICATION IN GROUND MOTION MODELS

As we discussed earlier, the representation of aleatory variability and epistemic uncertainty is fundamentally tied to the selected level of model simplification/complexity. As GMMs evolve from simple ergodic to complex nonergodic formulations, components of ground motion originally treated as random (aleatory) are moved to the systematic (epistemic) category as more physical behaviours such as site, source, and path repeatable terms are explicitly modelled (Liou & Abrahamson, 2025).

In the ergodic formulation, the total residual is decomposed into between-events (δB_e) and within-event residuals (δW_{es}). These two residual components are assumed to be statistically independent, so that the total standard deviation of the ground motion model, σ , is equal to the sum of the standard deviation associated with the between-event (τ) and within-event (ϕ) components. Precisely, the total standard deviation can be written as (Al Atik et al., 2010):

$$\sigma_{Er} = \sigma = \sqrt{\tau^2 + \phi^2} = \sqrt{\tau_{L2L}^2 + \tau_0^2 + \phi_{S2S}^2 + \phi_{P2P}^2 + \phi_0^2} \quad \text{Equation 4.7}$$

where

σ : Total standard deviation (total variability) of the GMM;

τ : Between-event (inter-event) standard deviation, representing variability due to earthquake source characteristics;

ϕ : Within-event (intra-event) standard deviation, representing variability associated with site conditions, wave propagation paths, and other station-specific effects.

τ_0 : standard deviation of $\delta B_{e,0}$ (remaining Between-event residuals)

τ_{L2L} : standard deviation of $\delta L2L_{source}$ (location-to-location term)

ϕ_{S2S} : standard deviation of $\delta S2S_s$ (site-to-site term)

ϕ_{P2P} : standard deviation of $\delta P2P_p$ (path-to-path term)

ϕ_0 standard deviation of $\delta W0, esl$ (remaining within-event residual)

Unlike the ergodic formulation, the partially nonergodic approach recognizes the systematic nature of site effects and removes the repeatable site-specific term ($\delta S2S_s$) from the aleatory variability (Abrahamson et al., 2019; Kotha et al., 2017). This term is then added to the median (logarithmic) ground motion to account for the systematic deviation from the global average (Abrahamson et al., 2019; Kotha et al., 2017; Lacour & Abrahamson, 2025). The reduction in aleatory variability, which ranges between 10% to 30% (Lacour & Abrahamson, 2025; Liou & Abrahamson 2025; Paredes & De Risi 2025), is traded for increasing epistemic uncertainty in estimated site-specific adjustment terms (Kotha et al., 2017; Lacour & Abrahamson, 2025). Therefore, the total residual (R_{ij}) can be expressed as (Kotha et al., 2017):

$$R_{ij} = \delta B_e + \delta W0, esl \quad \text{Equation 4.8}$$

where $\delta W0, esl$ is the site-corrected remaining within-event residual.

According to Equation 4.8, only the between-event residual δB_e and the site-corrected remaining within-event residual $\delta W0, esl$ contribute to the aleatory variability. Again, assuming these two residual components as statistically independent, the total standard deviation of the partially nonergodic ground motion model, commonly referred to as the single-station sigma (σ_{ss}), can be obtained by combining the between-event standard deviation (τ) and the corrected within-event standard deviation (ϕ_0) as:

$$\sigma_{PNE} = \sigma_{SS} = \sqrt{\tau^2 + \phi_{0s}^2} = \sqrt{\tau_{L2L}^2 + \tau_0^2 + \phi_{P2P}^2 + \phi_{0s}^2} \quad \text{Equation 4.9}$$

where ϕ_{0s} is the site-corrected remaining within-event standard deviation (single-station within-event variability), representing the remaining record-to-record aleatory variability after removing the repeatable site-specific effects.

In the fully nonergodic approach, the repeatable effects related to earthquake source location ($\delta L2L_{source}$), specific wave propagation path ($\delta P2P_p$), and site behavior ($\delta S2S_s$) are identified

(Abrahamson et al., 2019; Liou & Abrahamson, 2025; Sgobba et al., 2021) and the relative standard deviations removed from the global sigma. These repeatable terms (i.e., $\delta L2L_{source}$, $\delta P2P_p$, $\delta S2S_s$) are then added to the median ground motion to account for systematic deviations from the global average (Abrahamson et al., 2019; Lacour & Abrahamson, 2025; Paredes & De Risi, 2025). The substantial reduction in aleatory variability, which can reach 60%-70% compared to ergodic models, is traded for increasing epistemic uncertainty in estimated nonergodic adjustment terms (Abrahamson et al., 2019).

Following the previous observations, the total residual is decomposed into the remaining random between-event residual ($\delta B_{e,0}$) and remaining unexplained within-event residual ($\delta W0, esl$) (Abrahamson et al., 2019; Al Atik et al., 2010; Liou & Abrahamson, 2025; Sgobba et al., 2021):

$$R_{ij} = \delta B_{e,0} + \delta W0, esl \quad \text{Equation 4.10}$$

Since all repeatable effects are modeled as epistemic uncertainties, only the random source variability, which is the remaining random between-event ($\delta B_{e,0}$) and the unexplained within-event residual ($\delta W0, esl$) contribute to the aleatory variability (Liou & Abrahamson, 2025). Assuming $\delta B_{e,0}$ and $\delta W0, esl$ statistically independent, the total standard deviation of the fully nonergodic ground motion model (σ_{NE}) becomes (Liou & Abrahamson, 2025):

$$\sigma_{NE} = \sigma_0 = \sqrt{\tau_0^2 + \phi_{0s,p}^2} \quad \text{Equation 4.11}$$

where τ_0 is the remaining random between-event (inter-event) standard deviation, representing variability due to earthquake source characteristics, and $\phi_{0s,p}$ is the site- and path-corrected remaining within-event (intra-event) standard deviation, representing the remaining record-to-record aleatory variability after removing the repeatable site and path effects.

Table 4-1: Components of Ground Motion Model (GMM) Aleatory variability for different GMM approaches

Unmodeled Earthquake Effect	Notion	Class	Ergodic	Partially Nonergodic	Fully Nonergodic
Median Site term	$\delta S2S_s$	1	✓		
Median Path term	$\delta P2P_p$	1	✓	✓	
Median Source term	$\delta L2L_{source}$	1	✓	✓	
Variation of the Source term	$\delta B_{e,0}$	2	✓	✓	✓
Chaotic/quantum effects	$\delta W0, esl$	3	✓	✓	✓

To illustrate the discussion above, and following the technical framework proposed by Sgobba et al., (2021) , which serves as the methodological basis for this study, Table 4-2 and Figure 4.9 present a comparative analysis of the aleatory variability components associated with peak ground acceleration (PGA) across three distinct seismic regions: Taiwan, Japan, and Central Italy.

Table 4-2: Comparison of Ground Motion Variability Component (PGA)

Unmodeled Earthquake Effect	Notion		Class	Standard deviation σ in (ln units)			σ in (log 10 units)
	(Sung et al., 2024)	(Sgobba et al., 2021)		Tiwan	Japan	Central Italy	Central Italy
Median site term	ϕ_{S2S}	ϕ_{S2S}	1	0.259	0.316	0.612	0.2656
Median Path term	ϕ_{P2P}	ϕ_{P2P}	1	0.401	0.355	0.223	0.0970
Median Source term	τ_{L2L}	τ_{L2L}	1	0.254	0.568	0.136	0.0592
Variability of source term	τ_0	τ_0	2	0.247	0.220	0.352	0.1527
Ergodic GMM	σ_{al-Erg}	σ or σ_{tot}	1 and 2	0.637	0.850	0.783-0.875	0.34-0.38
Partially Nonergodic GMM	σ_{al-SS}	σ_{SS}	1 and 2	0.449	0.498	0.488 -0.502	0.212-0.218
Fully Nonergodic GMM	σ_{al-NE}	σ_0		0.337	0.380	0.484	0.210

In Taiwan, the path-specific term is the largest contributor to aleatory variability, indicating that complex crustal heterogeneity and regional variations in wave propagation strongly influence ground motion characteristics (Sung et al., 2024). In Japan, the source term shows a larger contribution compared to other regions. However, this large value is possibly caused by “an artifact of poor azimuthal sampling of offshore events, potentially mapping path variability into the source term” (Sung et al., 2024). For Central Italy, the site-specific term represents the most significant repeatable component, reflecting the strong influence of local geological conditions and basin effects, such as those associated with the Fucino and Sulmona basins (Sgobba et al., 2021). These regional differences are also illustrated graphically in Figure 4.9, which provides a visual comparison of the variability components reported in Table 4-2. The figure clearly highlights the

dominant path, source, and site contributions for Taiwan, Japan, and Central Italy, respectively, as well as the differences in overall variability between the ergodic and nonergodic models.

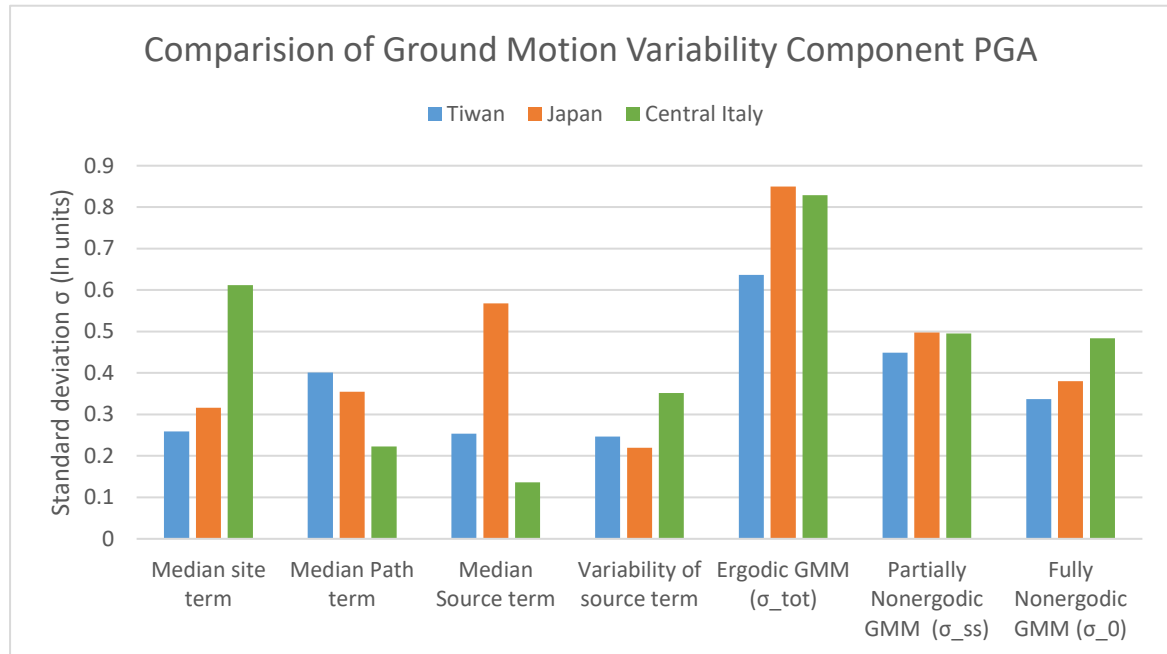


Figure 4.9: Grouped bar chart comparing the standard deviations (σ in ln units) of the unmodeled ground-motion components for Taiwan (blue), Japan (orange), and Central Italy (green).

5. DATA

5.1 SEISMOGENIC SOURCE CHARACTERIZATION

Seismic hazard assessment and earthquake rupture forecasting in Italy rely on standardized seismogenic zonations that define regions with similar seismotectonic characteristics. ZS16 provides a seismogenic input to the MA4 Earthquake Rupture Forecast (ERF) within the Italian national seismic hazard model, MPS19 (Meletti et al., 2021; Visini et al., 2022). The spatial distribution of the ZS16 tectonic regions and associated area sources is shown in Figure 6.1.

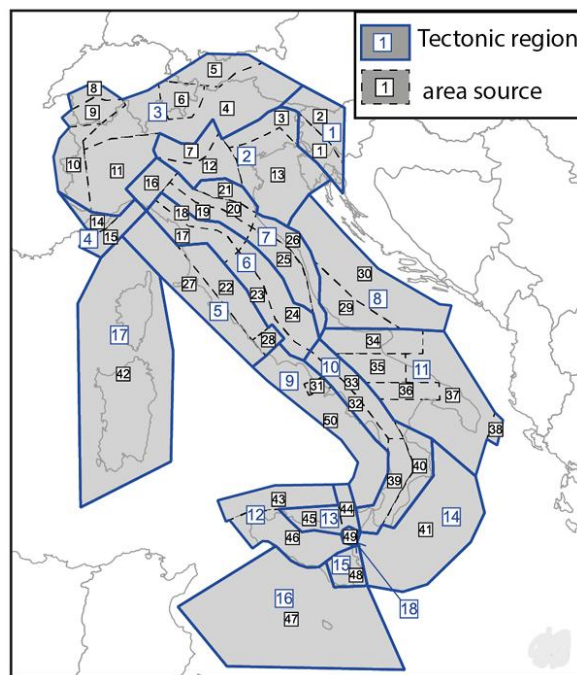


Figure 5.1 Spatial distribution of the tectonic domains, shown in blue, adopted for the estimation of β , together with the ZS16 seismic source areas delineated by dashed black boundaries (Visini et al., 2022)

As shown in the above Figure 5.1, the ZS16 framework divides Italy into 50 active shallow-crustal area sources. Each zone is characterized by a defined geographical extent and associated earthquake occurrence and seismotectonic parameters. Zone Umbria-Abruzzo with ID number 24 from ZS16 tectonic region is located in the Central Apennines, as shown in Figure 5.1 or the polygon with black color in Figure 5.2, and represents an important seismogenic source area for this study. Moreover, as shown in Figure 5.2, the Small clustered source zone (the smaller polygon with red color) is therefore defined based on the observational coverage of Clusters 1, 4, and 5, as stated in Sgobba et al. (2021). The target Small clustered zone encompasses the region supported by sufficient strong-motion observations and a dense network of intersecting source-to-station ray paths. This observational coverage provides the empirical foundation required to resolve

systematic, repeatable variations in ground motion associated with specific earthquake sources and wave-propagation paths. Within this well-sampled region, the recorded dataset enables the better estimation of source-specific ($\delta L2L_{\text{source}}$) and path-specific ($\delta P2P_p$) corrective terms, which represent key components of the nonergodic ground motion framework.(Sgobba et al., 2021).

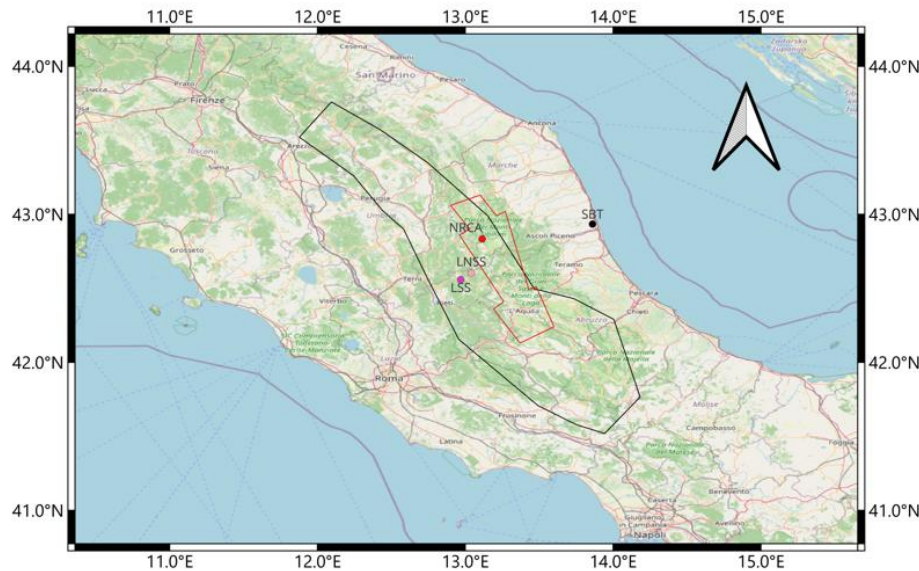


Figure 5.2 Spatial extent of Zone Umbria-Abruzzo (black polygon) and the Small clustered area (red polygon), with the locations of the selected accelerometric stations.

5.2 ACCELEROMETRIC STATIONS

Four stations with station codes IT.LSS (Leonessa), IV. NRCA (Norcia), IV. LNSS (Leonessa local network), and IT.SBT (Subiaco) are selected for this study.

IT.LSS: Leonessa (Italian Strong Motion Network)

Station LSS (Leonessa) is a permanent free-field accelerometric station operated within the national strong-motion network (ITACA/ESM), located at 42.5582°N latitude and 12.9689°E longitude. Under Eurocode 8, LSS is classified as a Class A site, representing a verified reference-rock station situated on competent Mesozoic limestone outcrops. In-situ geophysical testing yields a measured time-averaged shear-wave velocity in the upper 30 m of $V_{S30} = 1091$ m/s (Lanzano et al., 2022).

IV.NRCA: Norcia (Italian National Seismic Network)

Station NRCA (Norcia) is a primary accelerometric station of the Italian Strong Motion Network, with its recordings available through the ITACA database. Located at 42.8335°N latitude and

13.1142°E longitude, the station lies within the active normal-faulting belt of the Central Apennines. NRCA is situated on shallow Quaternary alluvial and lacustrine deposits of the Norcia intramontane basin and is classified as a soft-soil site (Eurocode 8, Class D) in the ITACA/EC8 site classification. The station provided important near-source recordings during the M_w 6.5 2016 Norcia earthquake sequence, making it particularly relevant for the analysis of site-specific and nonergodic ground motion effects (Bindi et al., 2011; Sgobba et al., 2021).

IV.LNSS: Leonessa (Italian National Seismic Network)

Station LNSS (Leonessa local network) is an accelerometric station belonging to the local and regional seismic monitoring networks operating across the Central Apennines normal-faulting belt. Located at 42.60286°N latitude and 13.04032°E longitude, the station lies near the western margin of the areas affected by the 2009 L'Aquila and 2016–2017 Central Italy seismic sequences (Falcucci et al., 2018). The site is characterized using regional surface-geology mapping and topographic-slope proxies, resulting in an Eurocode 8 Class B transition classification, representative of stiff-rock to stiff-soil conditions, with an estimated V_{S30} of approximately 700–800 m/s. LNSS provides localized strong-motion observations in close proximity to the national reference-rock station LSS (Bindi et al., 2011; Lanzano et al., 2022).

IT.SBT: Subiaco (Italian Strong Motion Network)

Station SBT (Subiaco) is a permanent accelerometric station operated within the Italian national strong-motion networks (ITACA / ESM). Positioned along the western margin of the Central Apennines fold-and-thrust belt at geographic coordinates 42.934°N latitude and 13.86°E longitude, the station is situated on competent Mesozoic carbonate platform rock outcrops. Under Eurocode 8 (EC8), SBT is categorized as a Class B site based on local surface lithology and topographical terrain slope. Operating along the Tyrrhenian flank of the central Apennines, the station provides essential accelerometric recordings for calibrating regional ground motion prediction equations and evaluating site and path residual variations (Bindi et al., 2011; Sgobba et al., 2021).

6. METHOD

This section presents the methodology adopted in this thesis to investigate the influence of nonergodic ground motion models (GMMs) on probabilistic seismic hazard analysis (PSHA) by using the computational tool OpenQuake Engine (GEM Foundation, 2026). The objective is to develop a consistent framework for comparing the conventional ergodic approach with partially and fully nonergodic formulations while quantifying their effects on seismic hazard estimates.

The adopted methodology combines theoretical developments from the literature with a practical implementation in a PSHA framework. First, the ergodic ground motion model is reformulated by introducing location-specific source, path, and site correction terms following the nonergodic framework proposed by Sgobba et al. (2021). The methodology then implements a logic tree framework to represent epistemic uncertainty.

6.1 FULLY NONERGODIC GROUND MOTION MODEL (SGOBBA ET AL., 2021)

Sgobba et al., (2021) developed a fully nonergodic GMM for Central Italy to improve the prediction of earthquake-induced ground motions by explicitly accounting for systematic source, path, and site effects.

The predictive equation of the model is expressed as:

$$\hat{\mu}_{es} = \log_{10}(IM_{es}) = a + F_M(M) + F_R(M, R) + C_{es} + \delta W_0 \quad \text{Equation 6.1}$$

where $\hat{\mu}_{es}$ represents the predicted logarithm (base 10) of the intensity measure (IM) for a specific earthquake event “e” at site “s”. The parameter “a” is a regression constant representing the baseline level of ground motion. The first three terms, “ $a + F_M(M) + F_R(M, R)$ ”, constitute the fixed term of the ergodic reference model. Specifically, the magnitude scaling function $F_M(M)$ describes the dependence of ground motion on earthquake magnitude and is formulated as a piecewise linear relationship to account for changes in scaling behaviour above and below a hinge magnitude M_h :

$$F_M(M) = \begin{cases} b_1(M_w - M_h), & \text{for } M_w \leq M_h \\ b_2(M_w - M_h), & \text{for } M_w > M_h \end{cases} \quad \text{Equation 6.2}$$

The distance scaling function “ $F_R(M, R)$ ” represents the attenuation of seismic waves with increasing source-to-site distance and incorporates both geometric spreading and anelastic attenuation effects. Ground motion distance attenuation is parameterized using the Joyner–Boore distance (R_{JB}), defined as the shortest horizontal distance from the site to the surface projection of

the fault rupture plane. To account for finite-fault geometrical effects and prevent singular or excessively high ground motion predictions at extremely short distances ($R_{JB} \rightarrow 0$), GMM functional forms incorporate an additive pseudo-depth parameter (h) to define an effective distance $R = \sqrt{R_{JB}^2 + h^2}$. This fictitious depth term h captures near-source ground motion saturation and reflects the depth-dependent scaling of seismic wave propagation from the effective centroid of rupture to the site.

$$F_R(M, R) = [c_1(M_w - M_{ref}) + c_2] \log \frac{\sqrt{R_{JB}^2 + h^2}}{R_{ref}} + c_3 \left(\sqrt{R_{JB}^2 + h^2} - R_{ref} \right) \quad \text{Equation 6.3}$$

where $[c_1(M_w - M_{ref}) + c_2] \log_{10} \left(\frac{\sqrt{R_{JB}^2 + h^2}}{R_{ref}} \right)$ defines the magnitude-dependent geometric spreading. Here, c_2 is the base geometric spreading coefficient, c_1 is the magnitude-dependent decay parameter that adjusts the logarithmic spreading according to moment magnitude (M_w) relative to the reference magnitude (M_{ref}), and R_{ref} is the normalization reference distance. Furthermore, the linear distance term $c_3 \left(\sqrt{R_{JB}^2 + h^2} - R_{ref} \right)$ accounts for apparent anelastic attenuation, where the coefficient c_3 controls the energy loss associated with intrinsic material absorption and wave scattering along the seismic wave path.

$$C_{es} = \delta B_e + \delta S_2 S_s + \delta L_2 L_{source} + \delta P_2 P_p \quad \text{Equation 6.4}$$

In the framework used by Sgobba et al. (2021) the GMM is calibrated using mixed-effects regression, which treats events, sites, source regions, and paths as separate random effects. When a regression model simultaneously includes a random effect for the “Source Region” ($\delta L_2 L_{source}$) and a random effect for the “Event term” δB_e , the process automatically partitions the variance into independent pieces. Consequently, the “event term” δB_e extracted from such a regression is already independent of the “source region term” $\delta L_2 L_{source}$. Within the C_{es} sum Equation 5.4, δB_e serves as the random event-specific misfit. Similarly, the site term ($\delta S_2 S_s$) captures repeatable local site amplification relative to reference rock, while the path term ($\delta P_2 P_p$) models persistent wave attenuation and scattering anomalies along specific source-to-site ray paths. Because all terms are inverted simultaneously, the systematic site and path corrections are

extracted independently of source misfits, leaving only the unmodeled, purely aleatory intra-event residual δW_0 .

6.1.1 GEOSPATIAL ANALYSIS FOR UNSAMPLED AREA

Under the nonergodic framework adopted in this study, repeatable station- and path-specific corrective terms are incorporated into the median ground motion model. However, PSHA should be performed at both instrumented and uninstrumented locations. Therefore, these corrective terms must be spatially extended to sites without direct accelerometric observations while accounting for their spatial correlation and uncertainty.

The spatial behaviour of the residuals was investigated using an empirical semivariogram, which describes how the difference between residual values changes with increasing separation distance between observation points (Sgobba et al., 2021). As reported by Sgobba et al. (2021), an exponential semivariogram model was fitted to characterize the magnitude and spatial correlation length of the residual field.

As reported in Sgobba et al. (2021), the calibrated spatial models are used in Kriging to interpolate the site and path corrections over a computational grid. By applying geostatistical Kriging interpolation to the decomposed residuals, continuous spatial fields of site-specific adjustments ($\delta S2S_s$, the *S*-model) and path-specific adjustments ($\delta P2P_p$, the *P*-model) were derived (see Figure 6.1 and Figure 6.2). These spatially correlated corrective terms can be incorporated into the median predictions of the ergodic reference ground motion model (μ_{Er}), enabling nonergodic ground motion predictions at locations without direct ground-motion observations. At these locations, Kriging provided both the interpolated corrective terms and the associated prediction variances, which quantify the uncertainty of the spatial interpolation. The resulting variances, $\beta_{S\text{-model}}^2$ and $\beta_{P\text{-model}}^2$, are generally smaller in areas well constrained by observations and increase where station or path coverage is limited (Sgobba et al., 2021). According to Liou & Abrahamson, 2025, the resulting epistemic uncertainties are subsequently propagated through the nonergodic PSHA logic tree.

This thesis focuses on the corrective terms estimated at the accelerometric stations. Therefore, in this study, the values of $\beta_{S\text{-model}}^2$ and $\beta_{P\text{-model}}^2$ remain zero since the computation is at the seismic station. The continuous spatial fields of the adjustment terms shown in Figures 6.1 and 6.2 are demonstrating how the estimated site term variance and path -specific adjustments could be spatially extended to unsampled locations.

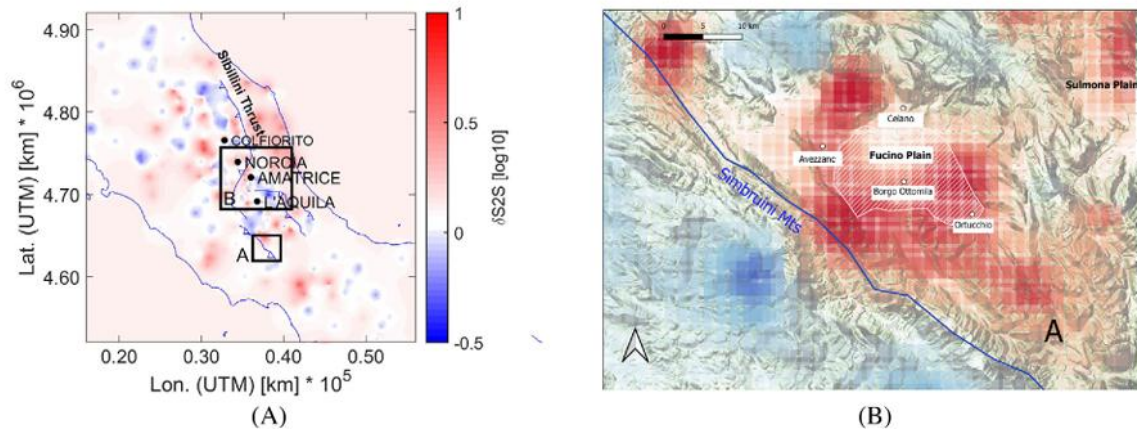


Figure 6.1 Spatially correlated $\delta S2Ss$ site-term variations, expressed in $\log_{10}$ units for SA ($T = 1$ s). (A) provides a detailed view of the Fucino Basin, whereas (B) focuses on the Amatrice region (Sgobba et al., 2021)

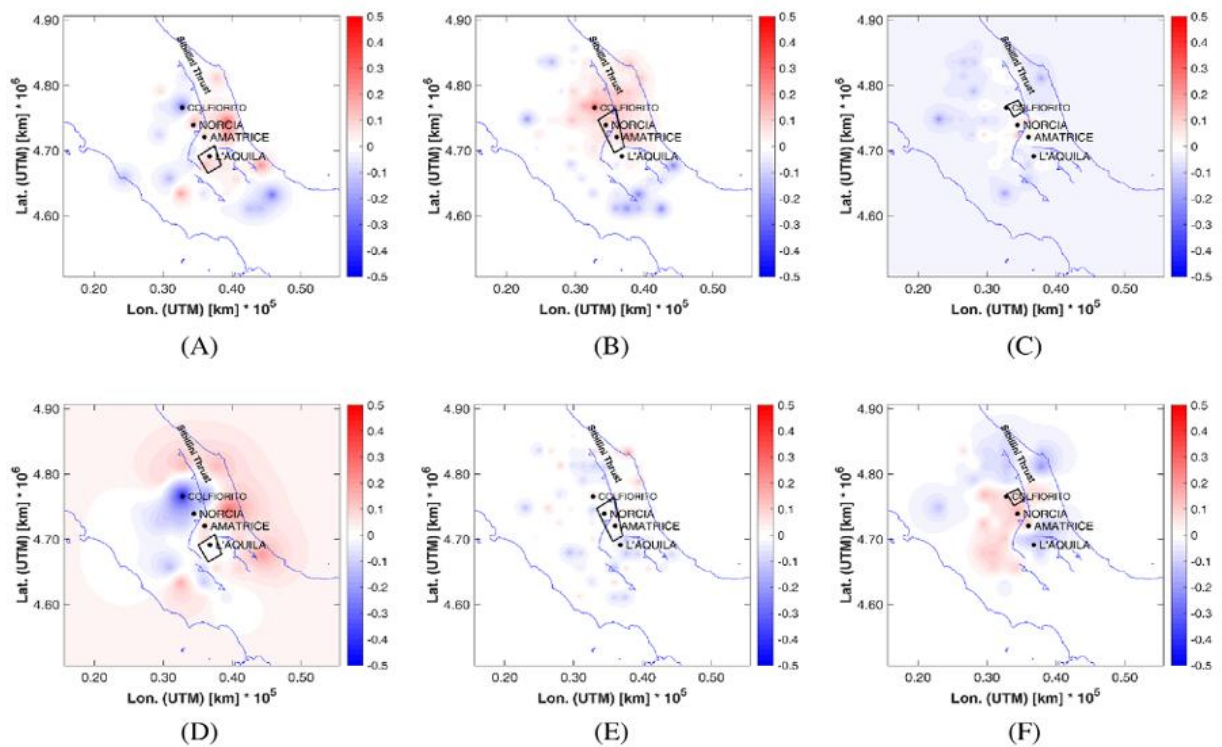


Figure 6.2 Spatial patterns of the correlated P-model fields across three study regions: L'Aquila (Cluster #1), Amatrice–Norcia (Cluster #4), and Colfiorito–Muccia (Cluster #5). The results are presented for PGA and SA($T = 1$ s), corresponding to panels (A–C) and (D–F), respectively. The cluster boundaries are marked by black polygons, while the lines identify the principal thrust systems within the study area. (Sgobba et al., 2021)

6.2 NONERGODIC GMM IMPLEMENTATION IN PROBABILISTIC SEISMIC HAZARD ANALYSIS

The implementation of nonergodic GMMs within probabilistic seismic hazard analysis (PSHA) preserves the classical hazard integration framework (Equation 3.8) while modifying the ground motion characterization. Nonergodic ground motion models account for repeatable source, path, and site-specific effects. These systematic effects are incorporated into the median ground motion prediction, thereby reducing the portion of variability treated as aleatory variability and improving the physical realism of site-specific hazard estimation (Abrahamson et al., 2019; Liou & Abrahamson, 2025).

6.2.1 PSHA FORMULATION WITH NONERGODIC GMMs

As stated above, the overall structure of the hazard integral remains consistent with the classical formulation. However, the conventional formulation given by Equation 3.7 is subsequently Small clustered to incorporate source, path, and site effects into the ground motion prediction (Abrahamson et al., 2019). In PSHA, ground motion is commonly modeled in logarithmic space, where the intensity measure is assumed to follow a normal distribution (Abrahamson et al., 2019; Baker, 2008; Liou & Abrahamson, 2025). This assumption is consistent with empirical observations of strong-motion data and leads to the widely adopted lognormal model for ground motion intensity: $\ln(IM) \sim N(\mu, \sigma^2)$ (or $\log_{10}(IM) \sim N(\mu, \sigma^2)$) where μ represents the mean prediction of the logarithm of the intensity measure, and σ represents the total aleatory variability of ground motion (Abrahamson et al., 2019; Baker, 2008).

As discussed earlier, the ergodic GMM assumes that the spatial distribution of the random variable is identical to its distribution at a single point when sampled over time (Lacour & Abrahamson, 2025; Liou & Abrahamson, 2025). This ergodic assumption trades space for time, using ground motion records pooled from many different earthquakes and recording sites globally to predict the ground motion intensity at a single, specific site (Barani et al., 2014; Lacour & Abrahamson, 2025). Statistically, the logarithm of a ground motion observation (intensity measure, or IM) is expressed as the sum of a median prediction and two independent residual terms (Al Atik et al., 2010; Liou & Abrahamson, 2025):

$$\log(IM) = \log(y^*) + \delta B_e + \delta W_{es} \quad \text{Equation 6.5}$$

where $\log(y^*) = \mu_{Er}$ represents the logarithm of the median ground motion prediction, which is a function of the earthquake source characteristics and propagation path, as equivalently expressed in Sgobba et al., (2021) " $a + F_M(M) + F_R(M, R)$ ". The residual terms δB_e and δW_{es} , represent

the between-event residual and the within-event residual (Al Atik et al., 2010; Liou & Abrahamson, 2025; Sgobba et al., 2021). The between-event and within-event residuals are assumed to be statistically independent, so the total standard deviation of the ground motion model, σ , is equal to the sum of the standard deviation associated with the between-event (τ) and within-event (ϕ) components; accordingly, $\delta B_e \sim N(0, \tau^2)$ and $\delta W_{es} \sim N(0, \phi^2)$. These two components together describe the aleatory component of ground motion prediction. Therefore, the total standard deviation (σ) of the ground motion prediction equation can be written as Equation 4.7.

This representation implies that all spatial and source-dependent variability not explicitly modeled in the median prediction is treated as random variability (Al Atik et al., 2010; Kotha et al., 2017; Liou & Abrahamson, 2025; Paredes & De Risi, 2025). While this approach enables model development using global datasets, it also leads to an overestimation of aleatory variability when systematic source, path, and site effects exist but are not explicitly resolved (Abrahamson et al., 2019; Sgobba et al., 2021; Kotha et al., 2017; Lacour & Abrahamson, 2025).

Given the lognormal assumption, the conditional probability of exceeding a specified ground motion level is obtained by standardizing the logarithm of the intensity measure. As defined in Equation 3.7, the exceedance probability is determined as a function of the mean ground motion prediction, μ , and its corresponding standard deviation, σ . The same probabilistic formulation applies to the different GMM formulations; however, the mean and standard deviation differ depending on which systematic repeatable spatial effects are explicitly modeled.

As discussed earlier in Chapter 4, the progression from the ergodic to the partially nonergodic and fully nonergodic formulations accounts for spatial effects, with repeatable site, source, and path effects progressively separated from the aleatory variability. In the partially nonergodic formulation, the mean prediction accounts for the repeatable site-specific effect, while the remaining source- and path-related variability is represented by the aleatory standard deviation σ_{ss} (see Equation 4.9). In the fully nonergodic formulation, repeatable site, source, and path effects are incorporated into the mean prediction, leaving the irreducible aleatory variability represented by σ_o (see Equation 4.11). Consequently, σ_{ss} and σ_o are generally lower than the total ergodic standard deviation, resulting in a narrower conditional ground motion distribution around the location-specific mean. This reduction in standard deviation narrows the conditional lognormal ground motion distribution centered around the location-specific median ground motion. In PSHA,

reducing the standard deviation directly affects the conditional exceedance probability, given by $P(IM > z) = 1 - \Phi(\epsilon)$, where $\epsilon = \frac{(\ln z - \mu_{NE})}{\sigma}$. For ground motion levels above the location-specific median ($\ln z > \mu_{NE}$), a higher σ , leads to increases the probability of exceedance. This reduction in variability results in steeper hazard curves compared with the ergodic case. Ultimately, the net impact on the PSHA hazard curve depends on three factors: the shift in the location-specific median prediction, the steepening caused by reduced aleatory variability, and the epistemic uncertainty in the nonergodic adjustment terms (Al Atik et al., 2010; Abrahamson et al., 2019; Liou and Abrahamson, 2024). This uncertainty is then propagated through the PSHA logic-tree framework by considering alternative model assumptions and parameter values. The logic tree adopted in the present study is described in the following section.

6.2.2 LOGIC TREE IMPLEMENTATION

Logic trees are the standard tool for representing the range of technically defensible interpretations regarding earthquake source and ground motion process (Liou & Abrahamson, 2025). In PSHA, it is also a structured framework used to represent and manage epistemic uncertainty arising from limited knowledge of earthquake processes and modeling choices (Kramer, 1996; Liou & Abrahamson, 2025). Rather than relying on a single deterministic model, the logic tree approach allows multiple alternative models or parameter values to be considered simultaneously (Kramer, 1996; Liou & Abrahamson, 2025). These alternatives are organized into branches, and each branch is assigned a weight that reflects its relative credibility based on available evidence and expert judgment. The overall hazard is then evaluated by running all possible combinations of branches and aggregating the results through a weighted average (Kramer, 1996; Lacour & Abrahamson, 2025; Liou & Abrahamson, 2025). In this way, the logic tree provides a systematic and transparent method for incorporating model uncertainty into seismic hazard assessments (Kramer, 1996).

Figure 6.3 illustrates how this study framework treats epistemic uncertainties within a logic tree. The logic tree for this study is structured based on the Liou & Abrahamson, (2025).

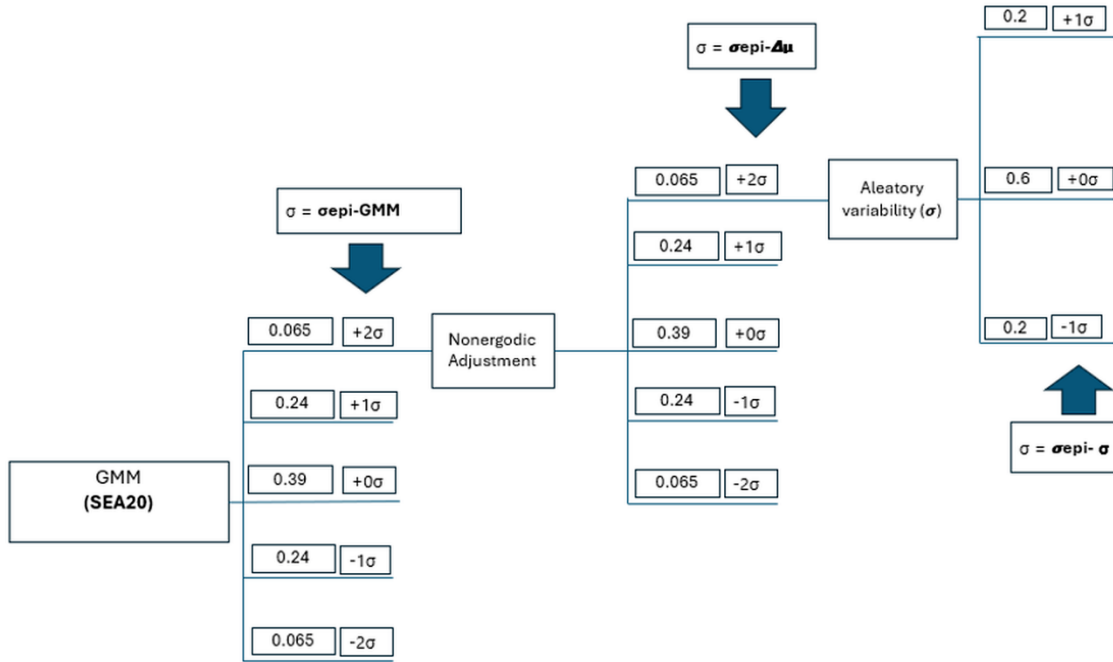


Figure 6.3: Logic tree framework for Ergodic and Nonergodic GMM approach

Node 1 of the logic tree accounts for epistemic uncertainty associated with the median prediction of the GMM. To account for this uncertainty, a 5-point discrete approximation of a normal distribution is adopted. The median ground-motion prediction is shifted by -2σ , $-\sigma$, 0σ , $+\sigma$, and $+2\sigma$ around the nominal (0σ) prediction, with the corresponding branch probability weights of 0.065, 0.24, 0.39, 0.24, and 0.065, respectively, as shown in Figure 6.3. The magnitude of epistemic uncertainty depends on the level of simplification adopted in the ground motion model (i.e. functional form). The epistemic standard deviation of the GMM, denoted by $\sigma_{epi-GMM}$, is given as follows:

$$\sigma_{epi-GMM} = \sqrt{\sigma_{epi-\mu, Method}^2 + \sigma_{\mu}^2} \quad \text{Equation 6.6}$$

where $\sigma_{epi-\mu, Method}$ represents the scientific uncertainty associated with the modeling methodology (i.e., that the GMM is unbiased) and can be computed by Equation 4.5, and σ_{μ} accounts for the statistical uncertainty in the median ground motion prediction; we assume a value of $\sigma_{\mu} = 0.096$ in $\ln$ units by referring to Al Atik & Youngs, 2014.

Node 2 in Figure 6.3 represents the epistemic uncertainty associated with the adjustment $\Delta\mu$ applied to the median ground motion prediction. The adjusted median can be expressed as

$$\mu_{adj} = \mu_{GMM} + \Delta\mu \quad \text{Equation 6.7}$$

where μ_{GMM} is the median prediction of the ground motion model and $\Delta\mu$ represents the corrective terms introduced to account for systematic source, path, and site effects. Since these corrective terms are estimated from finite observational datasets, their values are affected by statistical uncertainty. This uncertainty is represented by

$$\sigma_{\text{epi}-\Delta\mu}^2 = \text{Var}(\Delta\mu) \quad \text{Equation 6.8}$$

where $\sigma_{\text{epi}-\Delta\mu}$ denotes the standard deviation associated with the epistemic uncertainty of the adjustment.

The uncertainty represented by this node is therefore an estimate of uncertainty in the corrective terms, rather than the variability of the corrective terms themselves: τ_{L2L} , ϕ_{S2S} , and ϕ_{P2P} describes the variability of the true corrective terms across sites and paths, whereas the epistemic uncertainty of an estimated corrective term is captured by its standard error (refer to section 6.2.2.1).

The expression of $\sigma_{\text{epi}-\Delta\mu}$ depends on the level (at bedrock or at site) at which the ground motion is evaluated and on the degree of nonergodicity represented in the model. In the present implementation, four configurations are considered: ergodic at bedrock, nonergodic at bedrock, partially nonergodic at the site, and fully nonergodic at the site. The corresponding formulations are described below.

Ergodic formulation at bedrock

For the ergodic formulation at bedrock, the model does not explicitly introduce source- or path-specific nonergodic corrections. Indeed, the GMM of Sgobba et al. (2021) is calibrated on a subset of reference rock sites with slightly different ground response. Accordingly,

$$\sigma_{\text{epi}-\Delta\mu}^2 = SE(\delta S2S, \text{Ref})^2 \quad \text{Equation 6.9}$$

where $SE(\delta S2S, \text{Ref})$ is the standard error associated with the estimation of the site-to-site correction at the reference sites. Therefore, the term $SE(\delta S2S, \text{Ref})$ represents the epistemic uncertainty in the estimated average ground motion level at a reference rock site. This uncertainty is retained even though the formulation is considered ergodic (more specifically for bedrock conditions).

Nonergodic formulation at bedrock

When the model is evaluated at bedrock using the nonergodic formulation, additional source- and path-related systematic effects are represented explicitly. The epistemic variance associated with the adjustment becomes:

$$\sigma_{epi-\Delta\mu}^2 = SE(\delta SLS, Ref)^2 + \beta_{P-model}^2 + SE(\delta P2P)^2 + SE(\delta L2L)^2 \quad \text{Equation 6.10}$$

The first term represents uncertainty in the average ground motion level at a reference site; $\beta_{P-model}$ corresponds to a spatially varying kriging standard deviation that quantifies the uncertainty in interpolating repeatable path-to-path residuals $\delta P2P_p$ (the path model uncertainty approaches zero when it is near a well-sampled path and increases with distance according to an exponential semivariogram, see section 6.1.1); $SE(\delta P2P)$ represents the uncertainty in estimating the path-to-path correction; $SE(\delta L2L)$ represents the uncertainty associated with the location-to-location event-related correction.

Partially nonergodic formulation at the site

When the ground motion is evaluated at a specific site using the partially nonergodic formulation, the site-to-site correction at the target site is explicitly taken into account in addition to the correction associated with the reference sites. The epistemic variance is therefore

$$\sigma_{epi-\Delta\mu}^2 = \beta_{S-model}^2 + SE(\delta S2S, Ref)^2 + SE(\delta S2S)^2 \quad \text{Equation 6.11}$$

Here, $SE(\delta S2S)$ describes the uncertainty in the estimated site-to-site correction at the target site. The term $\beta_{S-model}$ accounts for spatially varying kriging standard deviation that quantifies the uncertainty in interpolating repeatable site-to-site residuals. This term is zero at seismic stations used for calibrating the SEA20 model (see section 6.1.1).

The site-specific standard error depends on the amount of information available at the target station. This is important because the recordings at a station provide repeated observations of the same underlying site; they are not independent realizations of the between-site variability. Thus, the uncertainty in the estimated site correction decreases with increasing local observations, whereas the intrinsic between-site variability ϕ_{S2S} does not.

Fully nonergodic formulation at the site

For the fully nonergodic formulation at the target site, both the site-specific and source/path-dependent corrective terms are represented. The epistemic variance is consequently:

$$\sigma_{epi-\Delta\mu}^2 = \beta_{S-model}^2 + SE(\delta S2S, Ref)^2 + SE(\delta S2S)^2 + \beta_{P-model}^2 + SE(\delta P2P)^2 + SE(\delta L2L)^2 \quad \text{Equation 6.12}$$

This formulation combines the uncertainties associated with the reference-site level, the target-site correction, and the explicitly modelled source and path-related corrections. It therefore contains all the epistemic components introduced when moving from the partially nonergodic site formulation to the fully nonergodic formulation.

Once the $\sigma_{\text{epi}-\Delta\mu}$ has been evaluated for the selected formulation, Node 2 represents the associated epistemic uncertainty by branching the median adjustment. The logic tree considers the nominal adjustment at 0σ , together with alternative realizations at $\pm 1\sigma$ and $\pm 2\sigma$ around the nominal prediction. Again, assuming a five-point discrete distribution, the corresponding weights are 0.39 for the 0σ branch, 0.24 for each of the $\pm 1\sigma$ branches, and 0.065 for each of the $\pm 2\sigma$ branches.

Node focuses on the aleatory variability of the ground motion model, which accounts for natural randomness in earthquake ground motion. Unlike Node1, which modifies the median prediction to account for epistemic uncertainty, Node 3 captures the epistemic uncertainty affecting the standard deviation (σ) of the GMM. This uncertainty ($\sigma_{\text{epi}-\sigma}^2$) is defined by Equation 4.6. To capture the epistemic uncertainty associated with estimating the aleatory variability, a three-point discrete Gaussian distribution is considered, leading to the three weighted branches in Figure 6.3.

6.2.2.1 Standard Error of the Corrective Terms

In the complex tectonic environment of Central Italy, the quantification of standard errors (SEs) associated with corrective terms is a critical step to predict the uncertainty in the final hazard. The standard deviations ϕ_{S2S} , τ_{L2L} , and ϕ_{P2P} describe the regional variability of site, source, and path effects, respectively. Whereas the corresponding standard errors help to quantify the epistemic uncertainty associated with the corrective terms for a given site, source, or path (Kotha et al., 2017; Lanzano et al., 2022). As more observational data become available, epistemic uncertainty generally decreases.

The foundation of site-specific hazard analysis lies in the mathematical decomposition of the ground motion residual (recall Section 4.4.2). For a given recording e , associated with station s , source l , and propagation path p , the total residual can be expressed within a mixed-effects framework as:

$$r_{es} = \delta S2S_s + \delta L2L_l + \delta P2P_p + \epsilon_{0,es} \quad \text{Equation 6.13}$$

When regional prior information is ignored, and the corrective terms are estimated exclusively from local observations, their uncertainty can initially be described using the standard error of a sample mean (Kotha et al., 2017). For the site term, suppose that n_s independent recordings are available at station s , such that:

$$r_{is} = \delta S2S_s + \epsilon_{is}, \quad i=1, 2, \dots, n_s \quad \text{Equation 6.14}$$

Where r_{is} represents the site residual for recording i at site s , it can be decomposed into a systematic site term, $\delta S2S_s$, representing the repeatable local site amplification or deamplification, and a remaining aleatory residual, ϵ_{is} (equivalently denoted as $\delta W_{0,esi}$ or $\epsilon_{0,es}$), representing the random record-to-record variability at the site.

Therefore, for a given station, the mean ($\bar{r}_s$) of its recordings is:

$$\bar{r}_s = \delta S2S_s + \bar{\epsilon}_s \quad \text{Equation 6.15}$$

Conditional on the site-specific effect, the site term $\delta S2S_s$ is constant across all recordings. Consequently, the variance of the estimator is determined only by the independent record-to-record residuals (Kotha et al., 2017):

$$\text{Var}(\bar{r}_s | \delta S2S_s) = \frac{\sigma_0^2}{n_s} \quad \text{Equation 6.16}$$

Therefore, the conditional standard error of the estimated site correction is:

$$SE(\widehat{\delta S2S_s}) = \frac{\sigma_0}{\sqrt{n_s}} \quad \text{Equation 6.17}$$

An analogous expression can be obtained for a path correction when n_p independent observations are available for the corresponding path:

$$SE(\widehat{\delta P2P_p}) = \frac{\sigma_0}{\sqrt{n_p}} \quad \text{Equation 6.18}$$

These expressions demonstrate the reduction in the estimated uncertainty obtained by increasing the number of independent observations, n_s and n_p .

The distinction between physical variability and estimation uncertainty becomes particularly important when observations are clustered. Multiple recordings associated with the same station share the same underlying site correction, and recordings from the same earthquake may additionally share common event-related variability. Consequently, the observations cannot always be treated as independent realizations of the total residual.

If two observations (i and j) are considered independent, the covariance between two distinct observations from the same station is given by (Al Atik & Youngs, 2014; Casella & Berger, 2002):

$$\text{Cov}(r_{is}, r_{js}) = \phi_{S2S}^2, \quad i \neq j \quad \text{Equation 6.19}$$

This covariance is a consequence of the fact that the same systematic site effect contributes to every observation at station s .

To illustrate the distinction between the variability of the observations and the uncertainty in estimating the site effect, consider the unconditional variance of the sample mean,

$$\bar{r}_s = \frac{1}{n_s} \sum_{i=1}^{n_s} r_{is} \quad \text{Equation 6.20}$$

The variance of $\bar{r}_s$ is given by (Casella & Berger, 2002):

$$\text{Var}(\bar{r}_s) = E[(\bar{r}_s - E[\bar{r}_s])^2] \quad \text{Equation 6.21}$$

Substituting $\bar{r}_s$ in Equation 6.20 into Equation 6.21 gives

$$\text{Var}(\bar{r}_s) = E \left[\left(\frac{1}{n_s} \sum_{i=1}^{n_s} r_{is} - E \left[\frac{1}{n_s} \sum_{i=1}^{n_s} r_{is} \right] \right)^2 \right]$$

Using the linearity of expectation, the terms can be grouped within a single summation as follows:

$E \left[\frac{1}{n_s} \sum_{i=1}^{n_s} r_{is} \right] = \frac{1}{n_s} \sum_{i=1}^{n_s} E[r_{is}]$. Therefore, it can be simplified as follows:

$$\text{Var}(\bar{r}_s) = \frac{1}{n_s^2} E \left[\left(\sum_{i=1}^{n_s} [r_{is} - E[r_{is}]] \right)^2 \right] \quad \text{Equation 6.22}$$

From basic algebra, we can expand $(a_1 + \dots + a_n)^2 = \sum_i a_i^2 + 2 \sum_{i < j} a_i \cdot a_j$, yielding:

$$\text{Var}(\bar{r}_s) = \frac{1}{n_s^2} \left[\left(\sum_{i=1}^{n_s} E[r_{is} - E[r_{is}]]^2 \right) + 2 \sum_{i < j} E[(r_{is} - E[r_{is}])(r_{js} - E[r_{js}])] \right] \quad \text{Equation 6.23}$$

Since the variance and covariance are given by $\text{Var}(r_{is}) = E[(r_{is} - E[r_{is}])^2]$ and $\text{Cov}(r_{is}, r_{js}) = E[(r_{is} - E[r_{is}])(r_{js} - E[r_{js}])]$ respectively, the variance can be rewritten as (Fahmy, 2023):

$$\text{Var}(\bar{r}_s) = \frac{1}{n_s^2} \left[\sum_{i=1}^{n_s} \text{Var}(r_{is}) + \sum_{i \neq j} \text{Cov}(r_{is}, r_{js}) \right] \quad \text{Equation 6.24}$$

For an individual recording, the residual r_{is} contains both a systematic site effect and a remaining record-to-record random component. Therefore, $\text{Var}(r_{is}) = \phi_{S2S}^2 + \sigma_0^2$, where ϕ_{S2S}^2 represents the variance of the systematic site effect, while σ_0^2 represents the remaining random variance associated with individual recordings. Because two recordings i and j from the same site share the same systematic site effect, their residuals are not independent. For $i \neq j$, their covariance is therefore given as Equation 6.19. This covariance term reflects the fact that all recordings from the same site are affected by the same underlying site-specific effect. Consequently, when calculating the variance of the site average, both the individual-record variability and the correlation induced by the common site effect must be considered. Since the first summation contains n_s individual variance terms, while the second summation contains $n_s(n_s - 1)$ covariance terms between different observations (see Equation 6.24), Equation 6.23 can be rewritten as:

$$\text{Var}(\bar{r}_s) = \frac{1}{n_s^2} [n_s(\phi_{S2S}^2 + \sigma_0^2) + n_s(n_s - 1)\phi_{S2S}^2] \quad \text{Equation 6.25}$$

Thus, the first term accounts for the variability of the individual recordings, whereas the second term accounts for the covariance between recordings arising from their shared site effect.

Thus, it can be simplified and written as:

$$\text{Var}(\bar{r}_s) = \phi_{S2S}^2 + \frac{\sigma_0^2}{n_s} \quad \text{Equation 6.26}$$

Finally, since the standard deviation of the sample mean, is the square root of the variance,

$$\text{SD}(\bar{r}_s) = \sqrt{\phi_{S2S}^2 + \frac{\sigma_0^2}{n_s}} \quad \text{Equation 6.27}$$

The first term (ϕ_{S2S}^2) in this expression does not decrease with the number of recordings at a specific single station because it represents the underlying systematic site-to-site variability itself. In contrast, the second term decreases as $\frac{1}{n_s}$ and represents the epistemic uncertainty associated with the number of observations. Therefore, conditional on the site-specific effect, the site term $\delta S2S_s$ is constant across all recordings; the standard error reflects only the uncertainty associated with estimating the site-specific correction. $\frac{\sigma_0}{\sqrt{n_s}}$, whereas the unconditional variance of the sample mean additionally contains the regional variance ϕ_{S2S}^2 .

When local observations are sparse, purely data-driven estimators can be unstable. A more statistically efficient approach is therefore to combine the regional distribution of the corrective term with the available local observations using a Best Linear Unbiased Predictor (BLUP), equivalently interpretable within a Gaussian Bayesian framework (Abrahamson et al., 2019; Kotha et al., 2017; Paredes & De Risi, 2025).

For the site term, the posterior standard error is:

$$\text{SE}_{post}(\delta S2S_s) = \left(\frac{1}{\phi_{S2S}^2} + \frac{n_s}{\sigma_0^2} \right)^{-\frac{1}{2}} \quad \text{Equation 6.28}$$

Similarly, for the path term,

$$\text{SE}_{post}(\delta P2P_p) = \left(\frac{1}{\phi_{P2P}^2} + \frac{n_p}{\sigma_0^2} \right)^{-\frac{1}{2}} \quad \text{Equation 6.29}$$

These expressions explicitly demonstrate the trade-off between regional prior information and local observations. In the limit of very sparse data, the posterior uncertainty approaches the

regional standard deviation, whereas with an increasing number of independent observations, the posterior standard error decreases and approaches zero under the assumed model.

Concerning the source term, it ($SE_{post}(\delta L2L_l)$) requires special treatment because multiple recordings from the same earthquake are correlated through common event-related variability. Consequently, the effective amount of information for estimating $\delta L2L_l$ is determined primarily by the number of independent earthquakes contributing to the site rather than by the total number of recordings.

Let $N_{e,l}$ denote the number of independent events associated with source l , and n_e represent the average number of recordings from each event that contribute information to the estimation at the site. The effective variance associated with an individual event can be approximated as $\tau_e^2 + \frac{\sigma_0^2}{n_e}$, where τ_e represents the between-event variability and σ_0 represents the remaining record-to-record variability (Kotha et al., 2017; Paredes & De Risi, 2025). The corresponding approximate posterior standard error of the source correction can therefore be expressed as

$$SE_{post}(\delta L2L_l) = \left[\frac{1}{\tau_{L2L}^2} + \frac{N_{e,l}}{\tau_e^2 + \frac{\sigma_0^2}{n_e}} \right]^{-\frac{1}{2}} \quad \text{Equation 6.30}$$

This expression highlights an important characteristic of source estimation. Increasing the number of recordings from a single earthquake reduces the record-level component $\frac{\sigma_0^2}{n_e}$, but it does not eliminate the between-event variability represented by τ_e^2 . Consequently, once the number of recordings per event is sufficiently large, the number of independent earthquakes increasingly controls the uncertainty in the source term $\delta L2L_l$.

Since the precision of the site-specific correction depends on the stability of the regional reference level, against which the site-specific terms are estimated, it is also influenced by the amount and spatial distribution of observations available in the regional database. In particular, the regional reference level is determined from the ground motion observations across the region and therefore becomes more stable as the number of independent events and recordings increases. Consequently, the uncertainty associated with estimating the regional mean ground motion level can be approximated as (Kotha et al., 2017):

$$SE_{regional,S2S} = \frac{\phi_{S2S}}{\sqrt{N_S}} \quad \text{and} \quad SE_{regional,S2S,ref} = \frac{\phi_{S2S,ref}}{\sqrt{N_{S,ref}}} \quad \text{Equation 6.31}$$

$$SE_{regional,L2L} = \frac{\tau_{S2S}}{\sqrt{N_L}} \quad \text{Equation 6.32}$$

and

$$SE_{regional,P2P} = \frac{\phi_{P2P}}{\sqrt{N_P}} \quad \text{Equation 6.33}$$

where, $N_{S,ref}$, N_S , N_L and N_P denote the numbers of independent sites, earthquake sources, and propagation paths, respectively, in the region.

In PSHA, epistemic uncertainty in the median regional reference level directly governs the dispersion of alternative hazard curves across logic-tree branches. Because the regional baseline anchors all localized site ($\delta S2S_s$), path ($\delta P2P_p$), and source ($\delta L2L_l$) adjustments, statistical estimation uncertainty in this reference level introduces additional variance into the median ground motion prediction. In a logic-tree framework, this baseline uncertainty widens the epistemic confidence band, expanding the separation between lower (e.g., 16th) and upper (e.g., 84th) hazard fractiles, without altering the underlying physical aleatory variability of the earthquake process (Al Atik et al., 2010; Liou & Abrahamson, 2025). When regional ground motion data are sparse, the regional reference level exhibits higher standard errors, thereby increasing the total epistemic variance $\sigma_{epi-total}^2$ (see Equation 6.33), and broadening the spread of exceedance probabilities at target spectral accelerations (Abrahamson et al., 2019; Kotha et al., 2017).

Furthermore, uncertainty in the regional mean prediction propagates non-linearly into the annual exceedance rate calculation. Because hazard curves decay steeply in log-ground-motion space, integrating over logic-tree branches with higher median regional baseline levels produces a larger increase in exceedance frequency than the corresponding decrease associated with lower branches. Incorporating this baseline epistemic uncertainty yields an upward shift in the mean hazard curve at low annual exceedance probabilities (e.g., 10^{-4} to 10^{-6}), typically increasing predicted mean annual frequencies of exceedance by 20% to 25% at high intensity thresholds (Al Atik & Youngs, 2014).

Crucially, unlike site-specific estimation errors that remain localized to individual recording stations, uncertainty in the regional reference level acts as a spatially correlated systematic parameter shift across the entire regional domain, uniformly raising or lowering baseline hazard levels across all interconnected sites evaluated against that regional model (Abrahamson et al., 2019; Lacour & Abrahamson, 2025; Paredes & De Risi, 2025).

As shown in Table 5-1, transitioning from ergodic to partially or fully nonergodic ground-motion models reduces the aleatory variability, σ , by incorporating repeatable source-, path-, and site-specific effects into the location-specific median ground-motion prediction (Abrahamson et al., 2019; Al Atik et al., 2010; Sgobba et al., 2021). This process isolates the irreducible aleatory variability, σ_o , thereby narrowing the conditional ground-motion distribution and reducing the aleatory variability in seismic hazard assessment. The Sgobba et al. (2021) analysis (SEA20 model) considers 424 recording sites ($N_S = 424$), 36 reference rock stations ($N_{S,ref} = 36$), 288 propagation paths ($N_P = 288$), and 456 earthquake source clusters ($N_L = 456$). The corresponding corrective-term values are reported in Table 4.2, except for the reference-site variability, $\phi_{S2S,ref} = 0.2011$ (Sgobba et al., 2021).

Table 6-1: Aleatory Variability and Epistemic Uncertainty on station locations and well-sampled path for the Central Branches of the Logic Tree Shown above in Figure 5.1 (in log10 units)

Term	Ergodic	Partially Nonergodic	Fully Nonergodic
$\sigma_{al-Method}$	0.34-0.38	0.212 - 0.218	0.210
$\sigma_{epi-GMM}$	0.0417	0.0417	0.0417
$\sigma_{epi-\Delta\mu}$	0.0335	0.0464	0.0549
$\sigma_{epi-total}$	0.0535	0.0624	0.0689
Combined $\sigma_{al-Method}$ and $\sigma_{epi-total}$	0.3442 – 0.3837	0.2210 – 0.2268	0.2210
Var_{al}	0.1156 – 0.1444	0.0449 – 0.0475	0.0441
$Var_{epi-total}$	0.1185 – 0.1472	0.0488 – 0.0514	0.0488

The total epistemic uncertainty is obtained from the combined effect of $\sigma_{epi-GMM}$ and $\sigma_{epi-\Delta\mu}$, as presented in Table 6-1, and mathematically it is expressed (Liou & Abrahamson, 2025):

$$\sigma_{epi-total} = \sqrt{\sigma_{epi,GMM}^2 + \sigma_{epi-\Delta\mu}^2} \quad \text{Equation 6.34}$$

Subsequently, the overall predictive uncertainty is calculated by combining the aleatory variability $\sigma_{al} = \sigma_{al-Method}$ and the total epistemic uncertainty $\sigma_{epi-total}$ using (Liou & Abrahamson, 2025):

$$\sigma_{Combined} = \sqrt{\sigma_{al}^2 + \sigma_{epi-total}^2} \quad \text{Equation 6.35}$$

Therefore, to calculate the variance of aleatory variability (Var_{al}) and total epistemic uncertainty ($\text{Var}_{epi-total}$), by simply squared the value of aleatory variability $\sigma_{al} = \sigma_{al-Method}$ and the value of total epistemic uncertainty $\sigma_{epi-total}$, respectively.

This transition represents a fundamental trade-off where repeatable physical processes are transferred from the random aleatory component to the explained epistemic component (Abrahamson et al., 2019; Liou & Abrahamson, 2025). The combined predictive uncertainty (the total used in hazard calculations) demonstrates the genuine improvement achieved through nonergodicity when data is available. For this dataset, the total uncertainty is reduced from a range of 0.3425 to 0.3823 down to 0.2210 in log10 units. This net reduction occurs because the variance removed from the aleatory component (a 61.8% - 69.5% reduction in Var_{al} , from 0.1156 – 0.1444 to 0.0441) significantly outweighs the uncertainty added by estimating the nonergodic adjustments (Abrahamson et al., 2019).

7. RESULTS AND DISCUSSION

This chapter presents the results of the Probabilistic Seismic Hazard Analysis (PSHA) for Central Italy at four representative accelerometric stations with contrasting site conditions and record densities. All hazard calculations are performed using the OpenQuake engine (GEM Foundation, 2026). For each site, results are presented in terms of seismic hazard curves for different response periods and Uniform Hazard Spectra (UHSs).

The selected stations for the seismic hazard assessment are IT.LSS (Leonessa), IV. NRCA (Norcia), IV. LNSS (Leonessa local network), and IT.SBT (Subiaco), see Figure 5.2, which are considered in the following discussion and analysis. These stations provide contrasting site conditions and different levels of observational coverage (in terms of availability of data used to calibrate the GMM selected). IT.LSS, IV. NRCA, IV. LNSS, and IT.SBT have 333, 279, 330, and 24 observations (n_s), respectively. These total numbers of observations do not directly reflect the strength of the local constraints. Many of the IT.LSS, IV. LNSS, and IT.SBT recordings are regional observations located outside the small-clustered source area (out-cluster), whereas IV.NRCA has a larger proportion of local observations because it is located within that area (in-cluster).

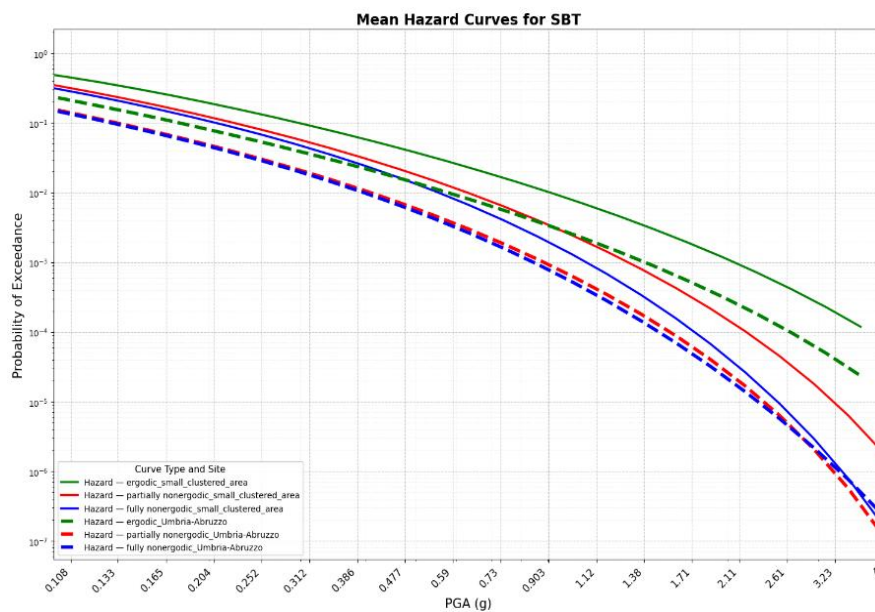
Table 7-1 Summary of Selected Stations and Their Site Properties

Station	Spatial r/ship to small-clustered source	No. Of Records	Site Conditions	Source-to-site distance	Expected effect on hazard
IV.NRCA	In-cluster	279 (most of them are local observations)	Class D (Soft soil; relatively strong site amplification)	Found in small-clustered area	Strongest hazard increase
IV.LNSS	Out-cluster	330 (most of them are regional observations)	Class B (Stiff soil; generally lower site amplification than soft soil)	Close to a small-clustered area	Moderate hazard increase
IT.SBT	Out-cluster	24 (most of them are regional observations)	Class B (Stiff soil; generally lower site amplification than soft soil)	Far from a small-clustered area	Moderate/Smaller hazard increase
IT.LSS	Out-cluster	333 (most of them are regional observations)	Class A (Bedrock; minimal site amplification relative to soil sites)	Close to a small-clustered area	No hazard increase

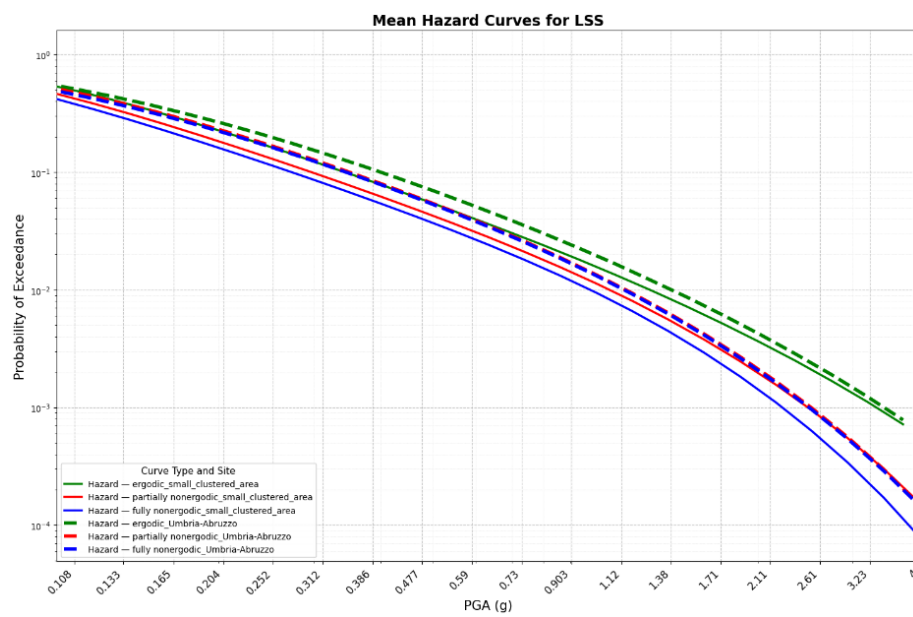
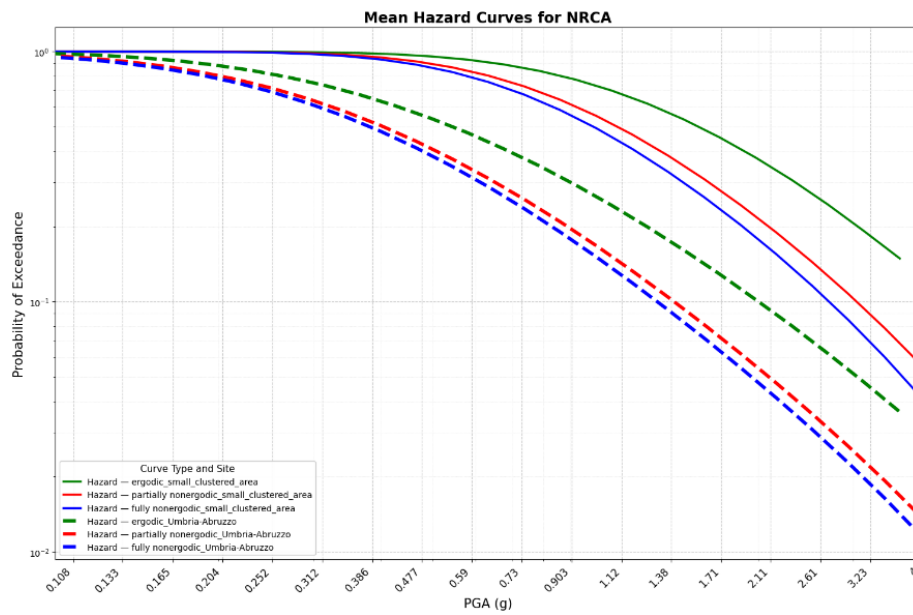
7.1 IMPACT OF SEISMIC SOURCE ON THE HAZARD

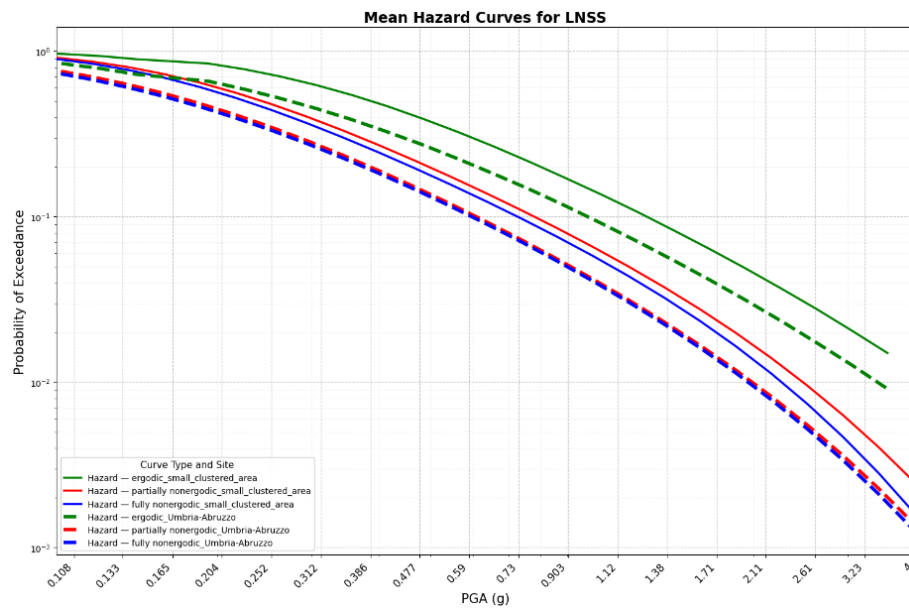
In this study, the impact of the seismic source is evaluated considering two distinct zones (see Figure 5.2): (1) the broad Umbria-Abruzzo source area and (2) the small-clustered source area, both shown in Figure 5.2. The latter encompasses the area densely covered by accelerometric stations with enough local observations and well-sampled ray paths associated with active earthquake sequences (specifically Clusters 1, 4, and 5) as reported in Sgobba et al. (2021). Thus, this zone allows for fully nonergodic computations.

The comparative analysis of the mean hazard curves for the four target accelerometric stations IT.SBT (Subiaco), IV. NRCA (Norcia), IT.LSS (Leonessa, reference rock), and IV. LNSS (Leonessa, local network) are presented in Figure 7.1 (a-d), respectively. The hazard curves represent the probability of exceedance of specified ground motion levels (PGA) in a 50-year period at each station. In each figure, solid lines represent the mean hazard curves obtained using the small-clustered source zone, whereas dashed lines are hazard curves associated with the Umbria-Abruzzo area source. The results are further distinguished according to the three ground motion model formulations: ergodic (green), partially nonergodic (red), and fully nonergodic (blue).



(a)





(d)

Figure 7.1. Mean hazard comparison at target accelerometric stations using the Umbria-Abruzzo and Small clustered Source Area Zone: (a) IT.SBT, (b) IV. NRCA, (c) IT.LSS, and (d) IV.LNSS

Across the four target stations, restricting the seismogenic source boundary from the broad Umbria-Abruzzo polygon to the small-clustered source zone (i.e. concentrating seismicity within that area) alters the probability of exceedance (PoE) and, consequently, the resulting mean hazard curves. However, whether the nonergodic adjustment increases or decreases the hazard, and the extent of this change, depends strongly on the spatial relationship between each station and the seismicity concentrated within the source area. The Umbria-Abruzzo source area distributes the regional seismicity over a larger domain, resulting in a more spatially dispersed earthquake-rate distribution. In contrast, the small-clustered source area concentrates seismicity within the identified active clusters (note that the same activity parameters are assumed) and leads to a different (narrower) source-to-site distance distribution. Thus, for stations located close to the small-clustered source, the contribution of nearby earthquakes increases, thus leading to a higher hazard (Cornell, 1968; Sgobba et al., 2021; Visini et al., 2022). The strongest increase is observed at IV.NRCA (Figure 7.1(b)), located within Cluster 4 (in-cluster) near the 2016 M_w 6.5 Norcia earthquake sequence; see Figure 5.2 (Sgobba et al., 2021). The small-clustered source area concentrates seismicity around the Norcia basin, shifts the source-to-site distance distribution toward shorter distances, and consequently increases the hazard. This effect is further influenced by the soft-soil conditions at IV.NRCA and the associated site and path effects. Similarly, the hazard curves for IV.LNSS (Figure 7.1(d)) and IT.SBT (Figure 7.1(a)) follow a trend similar to

that associated with IV.NRCA, but showing a smaller hazard because of their greater distance from the seismicity clusters (Small clustered zone) and their stiff-soil conditions, which generally produce lower site amplification than the soft-soil conditions at IV.NRCA.

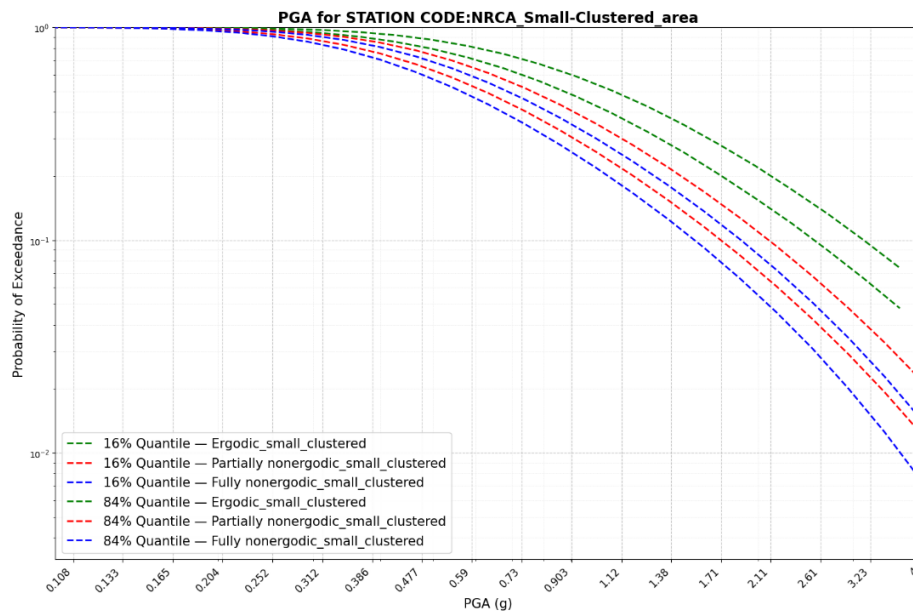
At IT.LSS (Figure 7.1(c)), the hazard curves for the two source-area definitions remain relatively close for both the partially nonergodic and ergodic models. This similarity is partly attributed to the hard reference-rock conditions at IT.LSS, which imply limited site amplification. Although the source- and path-specific effects are also relatively mild, their influence becomes more apparent in the absence of significant site amplification, resulting in comparable hazard estimates for the two source-area definitions. In contrast, the fully nonergodic model produces lower hazard for the Small clustered source-area zone. This is because the fully nonergodic model explicitly accounts for both source- and path-specific terms. The Small clustered area provides a better-constrained path ray than the broader Umbria-Abruzzo source area, leading to more stable and lower path-related contributions.

7.1 ANALYSIS OF EPISTEMIC UNCERTAINTY

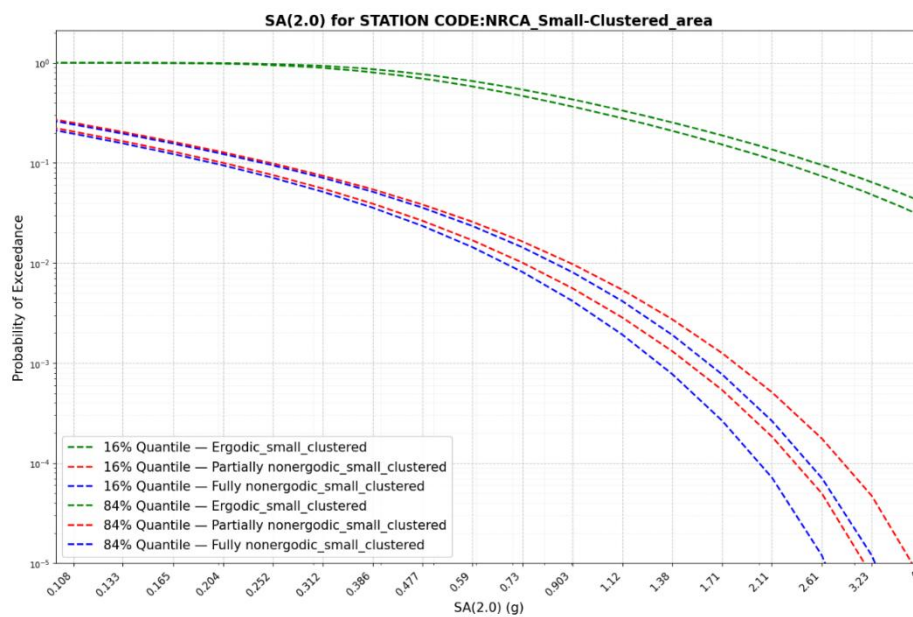
To investigate the influence of nonergodic ground motion models on site-specific seismic hazard and its associated epistemic uncertainty, hazard curves were evaluated for Peak Ground Acceleration (PGA) and Spectral Acceleration at 2.0 s ($S_a(2.0s)$) at the selected stations under both the Small-clustered and Umbria-Abruzzo source zone configurations. Comparing these source-area zones further highlights the influence of the nonergodic spatial parametrization on epistemic uncertainty.

Small-clustered source-area zone

Considering the small-clustered source-area zone, station IV.NRCA exhibits relatively small epistemic uncertainty compared with the out-cluster stations IT.LSS, IT.SBT, and IV.LNSS. This is primarily attributed to its location within the in-cluster region and its substantial observational coverage ($n_s = 279$), most of which corresponds to local observations. The dense local sampling provides strong constraints on the partially nonergodic parameters, and reduces the epistemic uncertainty associated with the estimated site-, path-, and source-specific adjustments for the fully nonergodic model. As shown in Figure 7.2 (a and b), the epistemic fractile range remains relatively narrow for both PGA and SA (2.0 s).



(a)

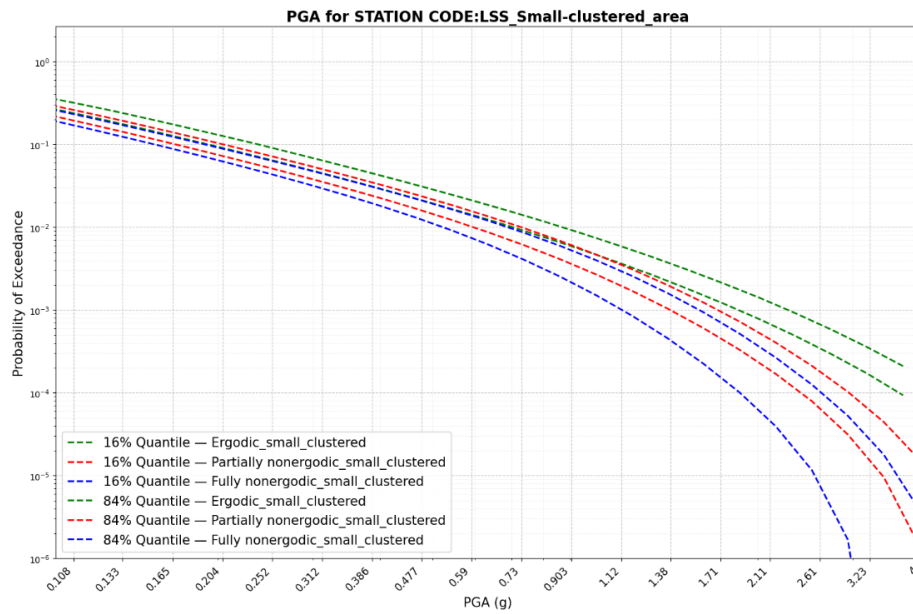


(b)

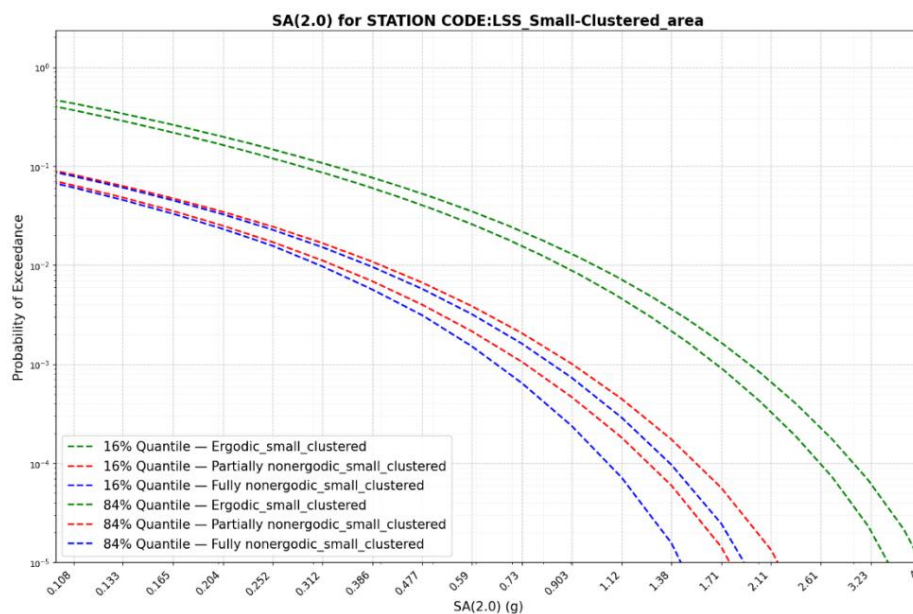
Figure 7.2 Uncertainties in PGA and SA (2.0s) hazard curves (measured by the spread of epistemic fractiles) obtained using the Small clustered source-area zonation schemes for station IV.NRCA: (a) PGA-Small clustered, and (b) SA-Small clustered

The out-cluster stations exhibit comparatively greater epistemic uncertainty. Although both IT.LSS ($n_s = 333$) and IV.LNSS ($n_s = 330$) have relatively large numbers of records, a substantial proportion sample regional rather than local source-station paths, thereby providing limited local observational constraints. Thus, the total number of records alone does not necessarily provide strong constraints on the spatially varying nonergodic parameters. The limited

availability of local observations results in larger posterior standard errors for the site-, path-, and source-specific terms, which in turn leads to wider epistemic uncertainty in the PGA and SA (2.0 s) hazard. This effect is evident in Figures 7.3 and 7.4, where the fully nonergodic hazard curves at IT.LSS and IV.LNSS exhibit wider epistemic fractile ranges than those at IV.NRCA, which benefits from denser local source-station sampling.

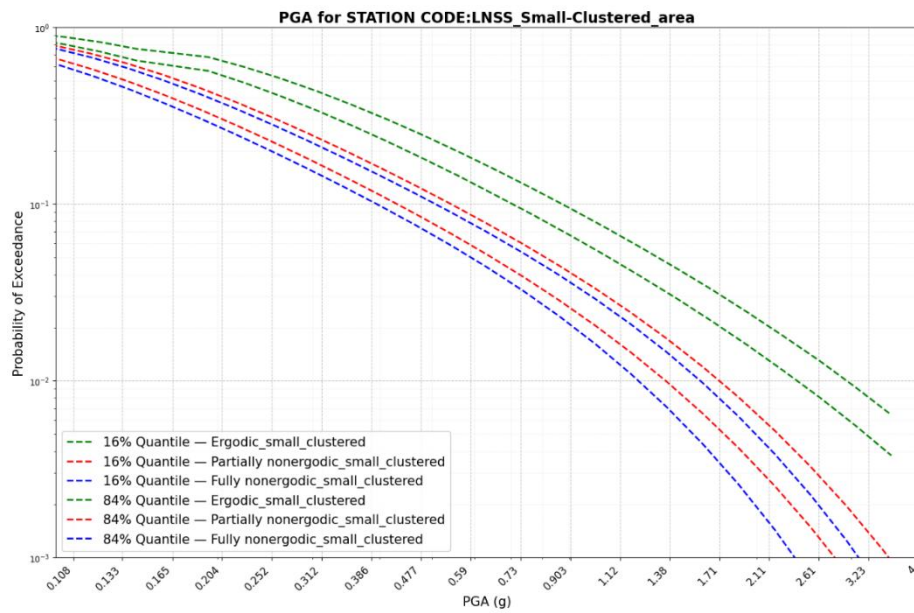


(a)

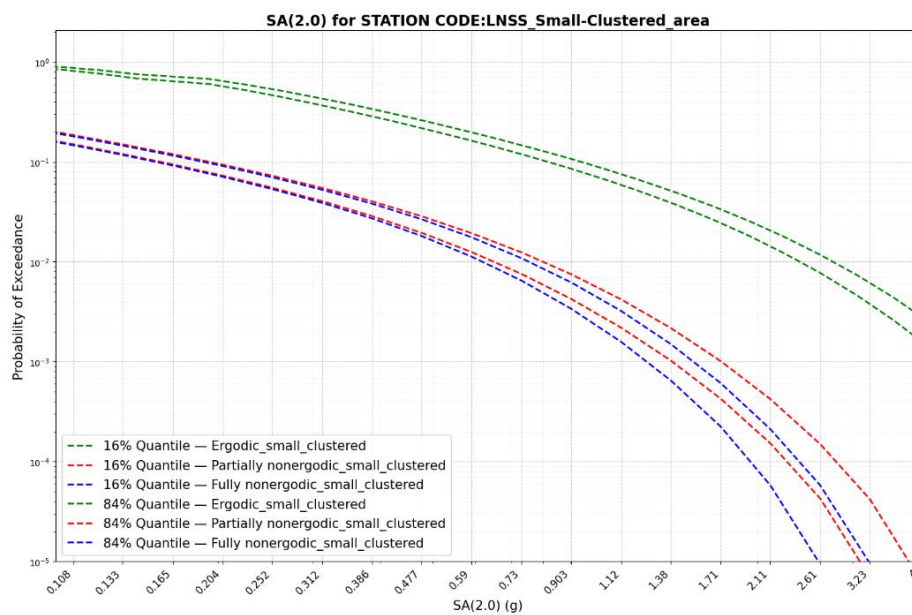


(b)

Figure 7.3 Uncertainties in PGA and SA (2.0s) hazard curves (measured by the spread of epistemic fractiles) obtained using the Small clustered source-area zonation schemes for station IT.LSS: (a) PGA-Small clustered, and (b) SA-Small clustered



(a)



(b)

Figure 7.4 Uncertainties in PGA and SA (2.0s) hazard curves (measured by the spread of epistemic fractiles) obtained using the Small clustered source-area zonation schemes for station IV.LNSS: (a) PGA-Small clustered, and (b) SA-Small clustered

A similar pattern is observed at IT.SBT, where the observational dataset is comparatively smaller ($n_s = 24$) to other station and only a few local observations are available. The resulting weak local constraints produce a wider epistemic fractile range (16%-84%) than that of IV.NRCA for both PGA and SA(2.0 s) (Figure 7.5). This indicates that increasing the total number of

observations alone does not necessarily reduce epistemic uncertainty; rather, sufficient local observations are required to adequately constrain the spatially varying model parameters. This behaviour is consistent with the framework described by Liou & Abrahamson (2025).

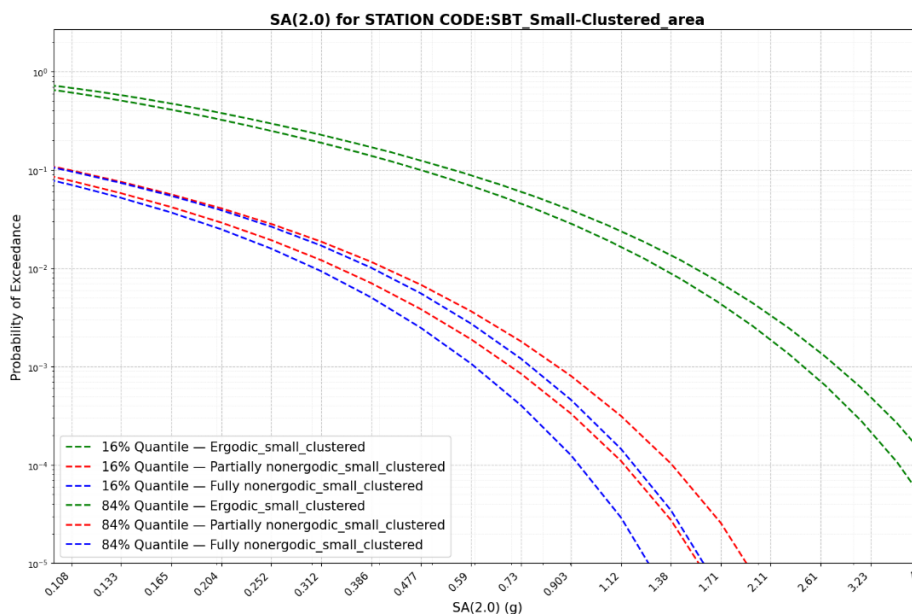
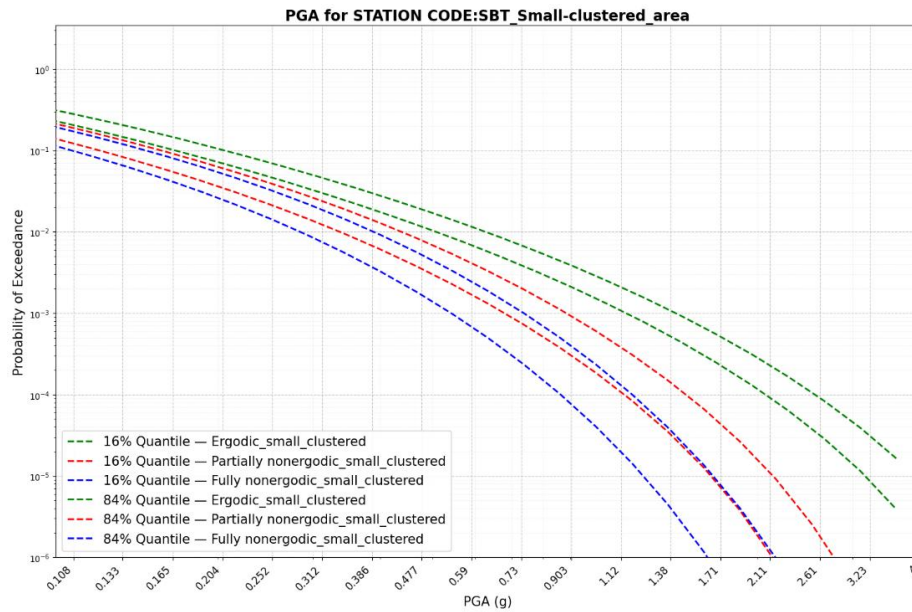
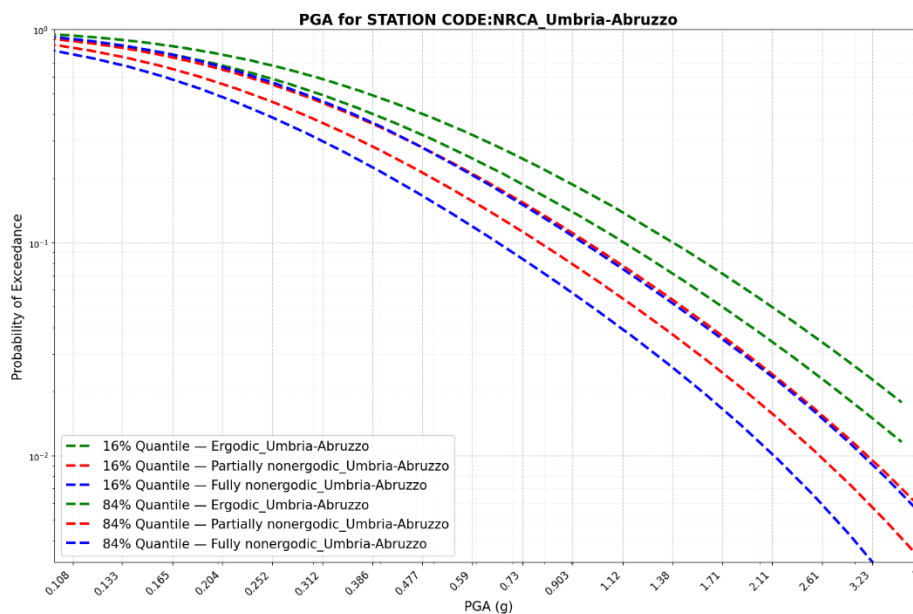


Figure 7.5 Uncertainties in PGA and SA (2.0s) hazard curves (measured by the spread of epistemic fractiles) obtained using the Small clustered source-area zonation schemes for station IT.SBT: (a) PGA-Small clustered, and (b) SA-Small clustered

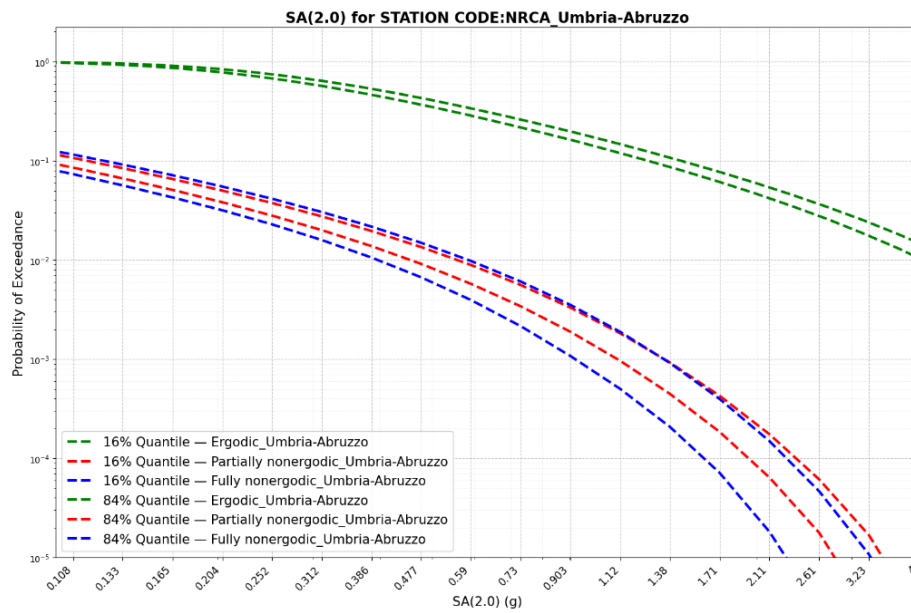
Umbria-Abruzzo source-area zone

Unsing the Umbria-Abruzzo source-area zonation provides the same general pattern; however, the broader source distribution generally results in greater epistemic uncertainty than the small-clustered configuration. The Umbria-Abruzzo source area includes earthquake sources extending beyond the spatially concentrated region represented by the small-clustered area, introducing additional source-station combinations that are less well constrained by local observations. Across all stations, this broader source distribution results in larger posterior standard errors for the path-specific and source-specific terms compared with the small-clustered configuration. These increased parameter uncertainties lead to greater total epistemic uncertainty, ($\sigma_{\text{epi, total}}$), in the fully nonergodic model and, consequently, to wider epistemic fractile.

At station IV.NRCA, which is located within the in-cluster region, the increase in epistemic uncertainty is nevertheless relatively limited compared with the out-cluster stations because of its comparatively dense local observational coverage. However, the inclusion of earthquake sources outside the small-clustered area reduces the local constraint on the out-cluster source-station paths. As a result, the epistemic fractile for both PGA and SA (2.0 s) is wider than those obtained under the small-clustered configuration, as shown by the comparison between Figure 7.6 (Umbria-Abruzzo) and Figure 7.2 (small-clustered area).



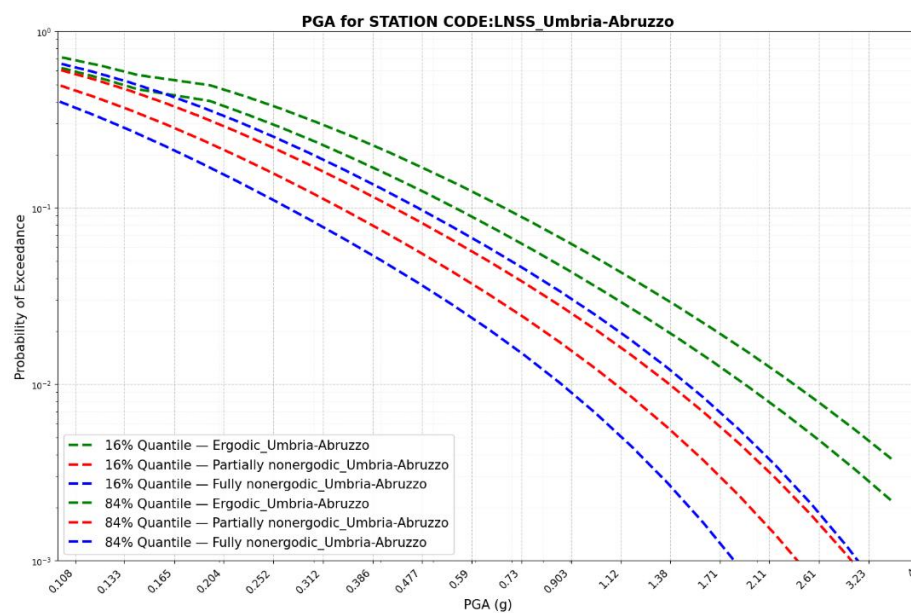
(a)



(b)

Figure 7.6 Uncertainties in PGA and SA (2.0s) hazard curves (measured by the spread of epistemic fractiles) obtained using the Umbria-Abruzzo source-area zonation schemes for station IV. NRCA: (a) PGA-Small clustered, and (b) SA-Small clustered

The effect is more pronounced at the out-cluster stations IT.LSS, IV.LNSS, and IT.SBT. Despite the large number of records, they do not necessarily provide strong constraints on the local source-station-specific terms. These differences in local observational coverage contribute to the larger posterior uncertainties and wider 16%-84% epistemic fractile range for both PGA and SA (2.0 s), as shown in Figures 7.7, 7.8, and 7.9.



(a)

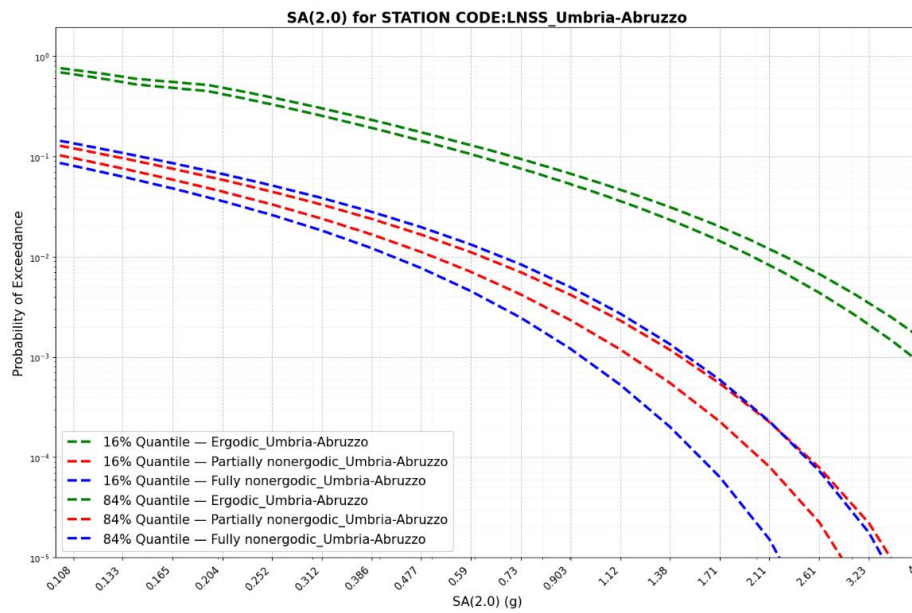
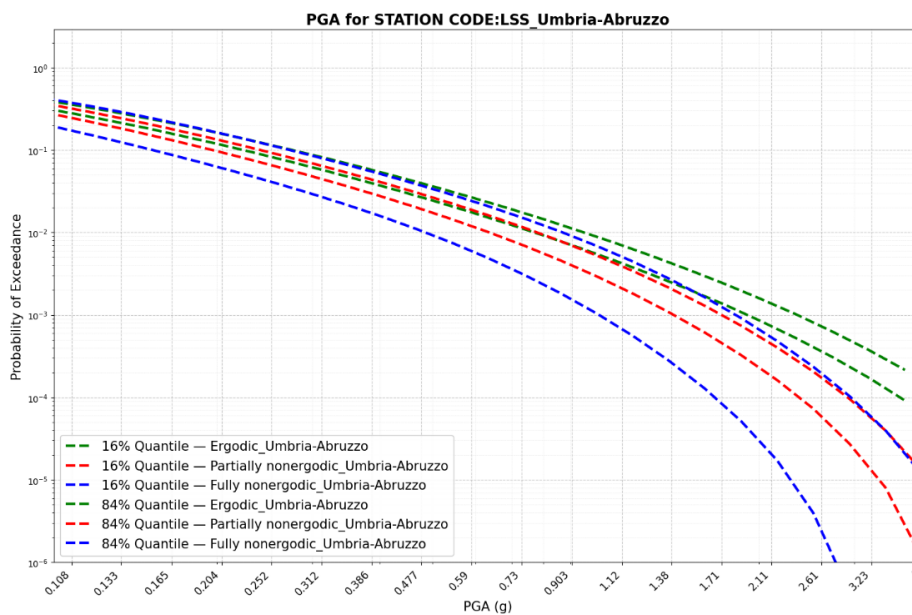


Figure 7.7 Uncertainties in PGA and SA (2.0s) hazard curves (measured by the spread of epistemic fractiles) obtained using the Umbria-Abruzzo source-area zonation schemes for station IV.LNSS: (a) PGA-Small clustered, and (b) SA-Small clustered



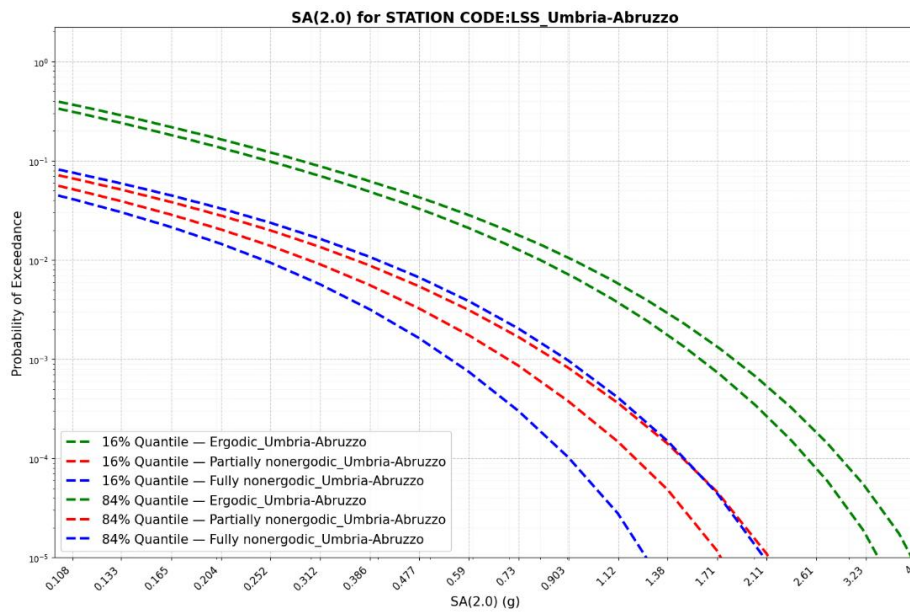
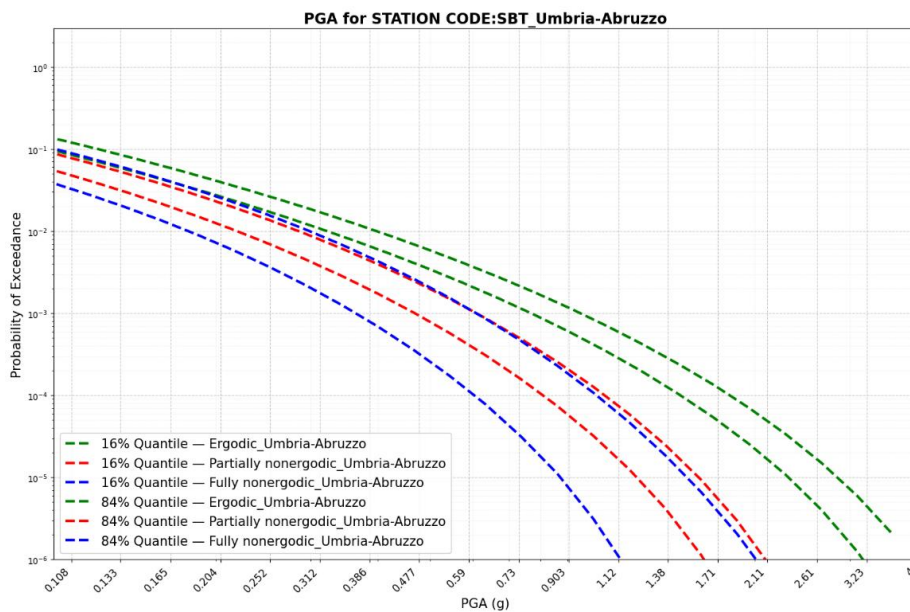


Figure 7.8 Uncertainties in PGA and SA (2.0s) hazard curves (measured by the spread of epistemic fractiles) obtained using the Umbria-Abruzzo source-area zonation schemes for station IV.LSS: (a) PGA-Small clustered, and (b) SA-Small clustered



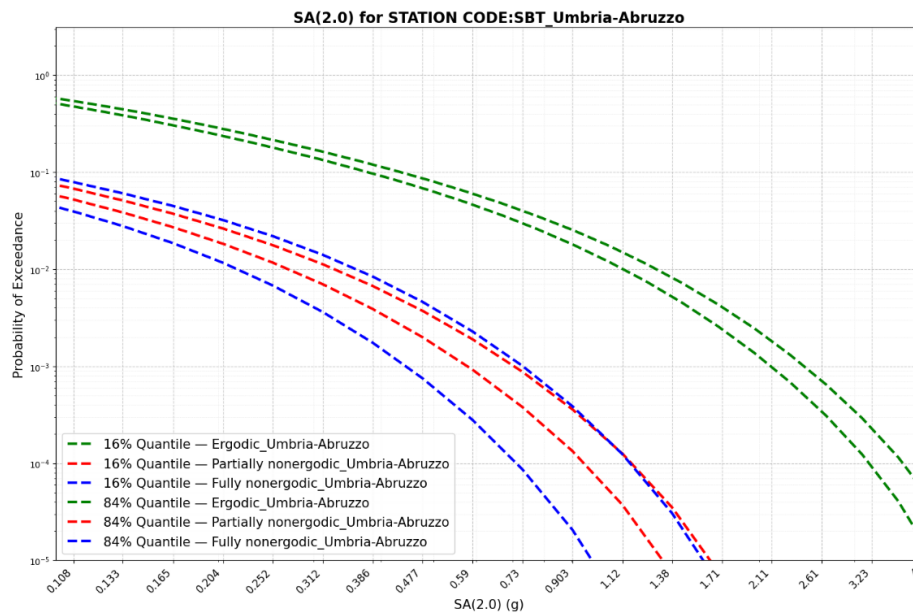


Figure 7.9 Uncertainties in PGA and SA (2.0s) hazard curves (measured by the spread of epistemic fractiles) obtained using the Umbria-Abruzzo source-area zonation schemes for station IT.SBT: (a) PGA-Small clustered, and (b) SA-Small clustered

Hazard Curve Slope Characteristics of Ergodic and Nonergodic PSHA

The transition from the ergodic to the partially nonergodic and fully nonergodic models produces two principal changes in the hazard curves: a shift in the mean hazard level and a change in the slope of the curves. As discussed in Chapter 4, the aleatory standard deviation decreases from approximately $\sigma_{Er} \approx 0.34\text{-}0.38$ in log10 units for the ergodic model, to approximately $\sigma_{SS} \approx 0.212\text{-}0.218$ for the single-station partially nonergodic model and $\sigma_0 \approx 0.210$ for the fully nonergodic model. This reduction in residual variability narrows the conditional ground motion distribution and consequently modifies the exceedance probability (see Equation 3.7), especially at higher ground motion levels. As shown in Figures 7.2 - 7.9, the ergodic formulation generally produces higher exceedance probabilities at all four selected stations and for both PGA and $S_a(2.0s)$ intensity measures, whereas the partially and fully nonergodic formulations progressively modify the hazard by explicitly accounting for spatially persistent source-, path-, and site-specific effects and, consequently, reduce the residual aleatory variability (see discussion in Section 6.2.1). The larger residual variability in the ergodic formulation produces a broader ground motion distribution and a greater contribution from its upper tail, leading to higher exceedance probabilities and generally flatter hazard curves, while the reduced variability in the nonergodic formulations causes the exceedance probability to decrease more rapidly with

increasing PGA or $S_a(2.0s)$, resulting in steeper curves. This effect becomes particularly evident at low exceedance probabilities, where the hazard estimates are more sensitive to the reduction in residual variability and to the source, path, and site effects.

Overall, these results demonstrate that the “true” hazard (“true” hazard is representative of the earth’s behavior without any simplification) is not necessarily captured within the epistemic fractiles of simplified ergodic models, as unmodeled spatial effects are treated as random variability, resulting in flatter hazard curves and insufficient epistemic uncertainty. In contrast, nonergodic GMMs explicitly account for systematic spatial variability, affecting both the level and shape of site-specific hazard through reduced aleatory variability and providing wider epistemic bounds that better represent uncertainty in the true hazard. These findings support the use of nonergodic GMMs for seismic hazard assessment at a site with well-recorded and local data-limited sites (see Figures 7.2-7.9).

7.1 COMPARATIVE ANALYSIS OF ERGODIC AND NONERGODIC UHS

The Uniform Hazard Spectra (UHS) computed the Umbria-Abruzzo source area were evaluated at PGA ($T = 0$ s), 0.2, 0.5, 1.0, and 2.0 s for return periods of 475 and 2,475 years, corresponding to 10% and 2% probabilities of exceedance in 50 years, respectively. The comparison considers the ergodic, partially nonergodic, and fully nonergodic formulations. The results show that the principal differences between the formulations occur at short and intermediate periods, where station-specific site response, source- and path-dependent effects exert a stronger influence on the predicted hazard. Similar trends also appear for the small-clustered source areas, although this case generally produces higher spectral amplitudes because of the concentrated seismicity in these small clusters. The UHS figures obtained for the small clustered source areas are presented in the Appendix.

At the 2,475-year return period, the ergodic UHS shows a pronounced maximum around $T = 0.5$ s at all selected stations, with the highest amplitudes at IV.NRCA (9.03 g) and IV.LNSS (3.95 g). In contrast, at the 475-year return period, the spectral maximum occurs at the shorter period of $T = 0.2$ s, except at IT.SBT, reaching 3.11 g at IV.NRCA and 1.32 g at IV.LNSS, as shown in Figure 7.10. This shift toward longer periods at the higher return period reflects a change in the earthquake scenarios contributing to the hazard at different exceedance probabilities (Baker, 2008). At the 475-year return period, the hazard is predominantly associated with moderate-magnitude, relatively nearby earthquakes, which contribute more strongly to the short-period

response and consequently produce greater spectral amplitudes in the $T \approx 0.1\text{--}0.2$ s range. In contrast, at the 2475-year return period, an increasing contribution from larger-magnitude earthquake scenarios, which contribute more significantly to the upper tail of the ground-motion distribution (Baker, 2008; Barani et al., 2009; Kramer, 1996).

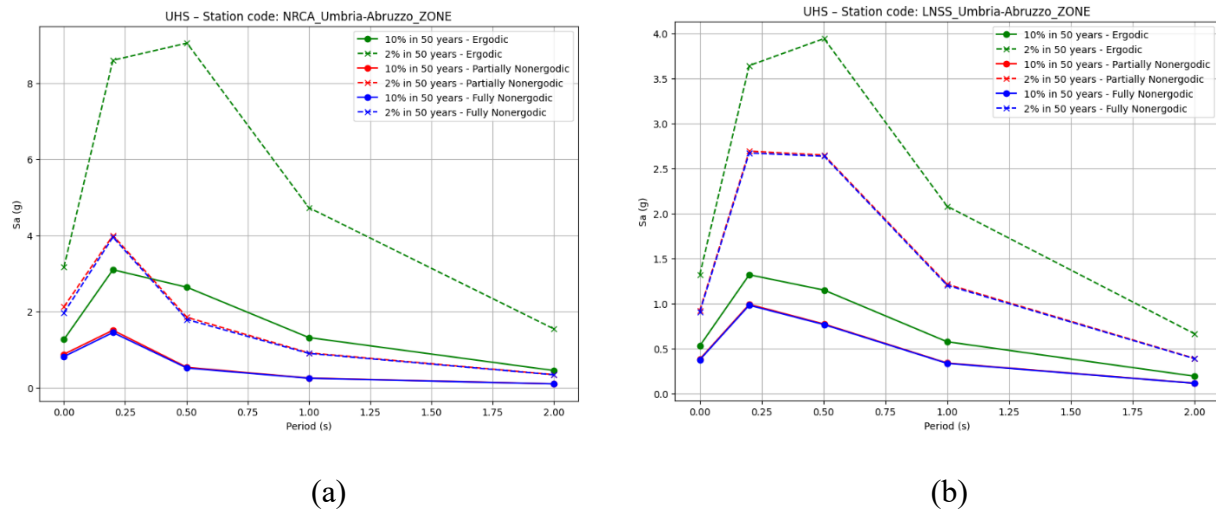


Figure 7.10 Comparison of Ergodic, Partially Nonergodic, and Fully Nonergodic Uniform Hazard Spectra for the Umbria-Abruzzo Source Area at (a) IV.NRCA (b) IV.LNSS

As shown in Figure 7.10 for a 2475-year return period, at station IV.NRCA, the nonergodic spectrum shifts the peak response to $T = 0.2$ s, where S_a reaches approximately 3.99 g , before decreasing to about 1.89 g at $T = 0.5$ s. This pronounced short-period response is consistent with the positive site residual ($\delta S2S = 0.7624 \log_{10}$ units), which reflects the strong frequency-dependent site effects associated with the shallow sedimentary basin conditions at Norcia. These local geological conditions can produce localized short-period amplification, providing a plausible explanation for the enhanced observed ground motion response. In contrast, IV.LNSS exhibits a broader nonergodic response, with spectral accelerations of approximately 2.67 g at $T = 0.2$ s and 2.64 g at $T = 0.5$ s. Its positive site residual ($\delta S2SS = 0.3498 \log_{10}$ units) and stiff-soil site (Eurocode 8, Class B with an estimated V_{S30} of approximately $700\text{--}800$ m/s) is consistent with a more distributed short- to intermediate-period amplification rather than the pronounced localized peak observed at IV.NRCA.

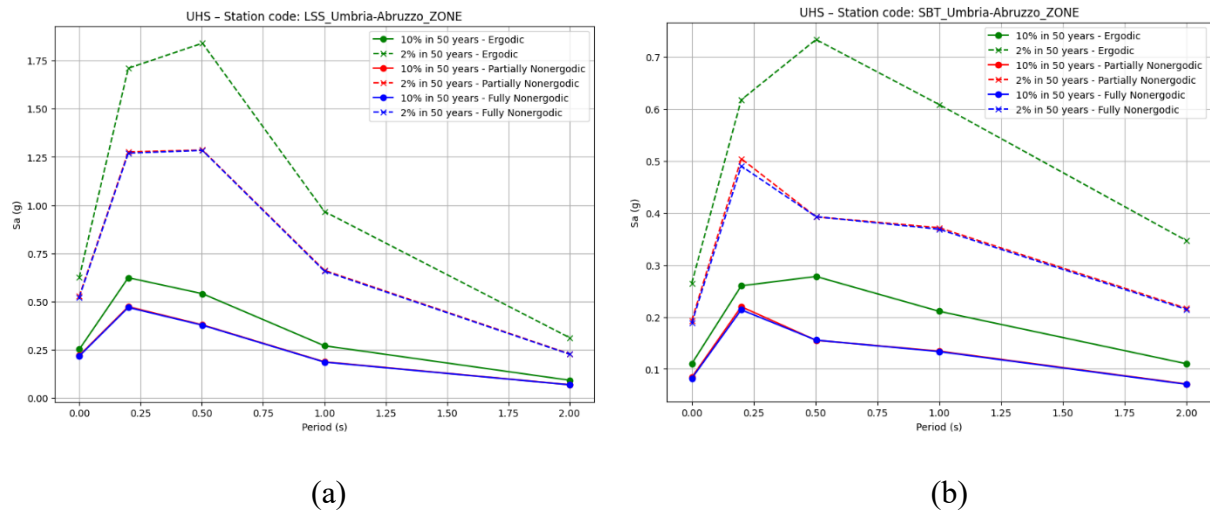


Figure 7.11 Comparison of Ergodic, Partially Nonergodic, and Fully Nonergodic Uniform Hazard Spectra for the Umbria-Abruzzo Source Area at (a) IT.LSS and (b) IT.SBT

Similar to stations IV.NRCA and IV.LNSS, the ergodic UHS at IT.LSS exhibits a shift in its spectral maximum with increasing return period ($T = 0.5$ s). At the 2,475-year return period, the spectrum peaks near $T = 0.5$ s, reaching 1.84 g, whereas at the 475-year return period, the spectral maximum occurs at the shorter period of $T = 0.2$ s, with an amplitude of 0.62 g, as shown in Figure 7.11(a). In contrast, IT.SBT retains its ergodic spectral maximum near $T = 0.5$ s across both return periods, as shown in Figure 7.11(b). This behavior can be interpreted in terms of distance-dependent frequency filtering along the regional crustal path. IT.SBT is located to the far east (Adriatic coast) of the main Apennine seismogenic sources (see Figure 5.2), so it is affected by anelastic attenuation and scattering during propagation toward the Adriatic coast (Kotha et al., 2020; Sgobba et al., 2021). These propagation effects preferentially reduce the high-frequency content of ground motions, resulting in stronger attenuation of the short-period response around $T = 0.2$ s relative to longer periods such as $T = 0.5$ s (Kotha et al., 2020; Paredes & De Risi, 2025). Consequently, the relative persistence of the $T = 0.5$ s ordinate at IT.SBT is consistent with the attenuation of high-frequency components along the source-to-site path (Baker, 2008; Sgobba et al., 2021).

When transitioning to nonergodic formulations, at IT.LSS, despite its competent limestone bedrock ($V_{S30} = 1091$ m/s), the UHS maintains relatively high spectral amplitudes over the short-to-intermediate period range ($T = 0.2$ - 0.5 s). This is consistent with its weak, near-zero site-to-site residual ($\delta S2Ss \approx 0.0356 \log_{10}$ units), indicating that the spectral shape is governed primarily by source scaling and regional propagation rather than localized site amplification. In contrast,

IT.SBT exhibits a pronounced short-period amplification around $T = 0.2$ s, associated with a strong positive site-specific residual ($\delta S2Ss = 0.4902 \log_{10}$ units), followed by a rapid decrease toward longer periods.

The degree of agreement between the partially and fully nonergodic formulations is also related to the amount of observational data available. IV.NRCA, IV.LNSS, IT.LSS, and IT.SBT have 279, 330, 333, and 24 recordings, respectively. Although IT.SBT seems to have fewer observations than the other stations; however, its dataset exceeds the recommended minimum of 5-10 recordings for stable linear site-response estimation (Kotha et al., 2017; Sgobba et al., 2021). This provides adequate constraints on the site-response term, consistent with the generally close agreement between the partially and fully nonergodic spectra at all four stations. The remaining differences, with the fully nonergodic estimates generally lower than the partially nonergodic estimates, reflect the additional source- and path-specific adjustments.

Overall, the comparison demonstrates that the nonergodic formulations provide a more station-specific representation of the hazard than the conventional ergodic model. The most substantial differences occur at short and intermediate periods, where local site response and path effects can strongly modify both the amplitude and shape of the UHS. The magnitude and character of these modifications vary among stations, reflecting differences in site conditions, observational constraints, and earthquake source and propagation characteristics. Moreover, at the 2% probability of exceedance (POE), the ergodic UHS exhibits a pronounced peak around $T = 0.5$ s, as shown in Figures 7.10 and 7.11. This behavior is related to the period-dependent nature of the ergodic standard deviation, $\sigma_{\text{Erg}}(T)$, which is relatively high around this period; this is because of the unmodeled physical heterogeneity incorporated into ergodic GMMs (Al Atik et al., 2010; Kotha et al., 2020; Paredes & De Risi, 2025). Moreover, for all selected stations' UHS curves, the systematic decay of Uniform hazard spectrum ordinates at longer structural periods reflects the combined effects of single-degree-of-freedom (SDOF) oscillator dynamics and earthquake source physics. For a standard 5% damped SDOF oscillator ($\zeta = 0.05$), pseudo-spectral acceleration is related to pseudo-spectral displacement through the natural angular frequency, $\omega = 2\pi/T$, such that $S_a(T, \zeta) = (2\pi/T)^2 S_d(T, \zeta)$. Thus, for finite spectral displacements, spectral acceleration decreases with increasing period (Baker, 2015). In addition, propagation and site effects modify the frequency content of seismic waves; high-frequency motions are particularly influenced by near-surface attenuation and amplification effects, including the high-frequency parameter κ_0

(Kotha et al., 2017; Paredes & De Risi, 2025). These combined effects contribute to the observed reduction in S_a , toward longer periods in the UHS curves.

Moreover, because all the above ergodic hazard is evaluated under bedrock conditions, the resulting ergodic UHS and hazard curves were subsequently converted into site-equivalent ergodic hazard curves using station-specific empirical site-adjustment factors, $e^{\delta S_2 S_s}$, following the two-step approach proposed by Kotha et al., (2017). This procedure provides a consistent basis for comparing ergodic and nonergodic hazard predictions at each station.

8. CONCLUSION

The comparative evaluation of ergodic, partially nonergodic, and fully nonergodic PSHA across Central Italy demonstrates that relaxing the ergodic assumption fundamentally restructures seismic hazard variability. By explicitly modeling location-specific source, path, and site adjustment terms, repeatable physical processes are transferred from aleatory variability into epistemic uncertainty. In Central Italy, this transition yields a 61.8% to 69.5% reduction in aleatory variance (Var_{al}), decreasing the aleatory standard deviation from $\sigma_{\text{Er}} \approx 0.34\text{--}0.38$ (in log10 units) for the ergodic model to $\sigma_{\text{SS}} \approx 0.212\text{--}0.218$ for the partially nonergodic model and to $\sigma_0 \approx 0.210$ for the fully nonergodic model. This reduction in aleatory sigma narrows the conditional ground motion distribution, producing steeper hazard curves and lower exceedance probabilities at high ground motion intensity levels compared to ergodic forecasts.

The seismic source zone plays a governing role in defining site-specific hazard levels across the study area. Restricting the active source domain from the broad Umbria-Abruzzo polygon to the cluster-bounded source zone (Figure 5.2) concentrates earthquake occurrence rates within active fault systems; because of this it changes the distribution of source-to-site distances contributing to the hazard integral, thereby altering their relative contribution to the overall hazard. At the in-cluster station IV.NRCA (Norcia), the concentration of earthquake occurrence rate shifts the hazard contribution towards shorter distances and substantially increases the mean hazard, which is further “amplified” by the local sedimentary basin response ($\delta S_2 S_s = +0.762$ in log10 units), resulting in a peak short-period (0.2s) spectral acceleration. For the out-cluster stations IV. LNSS and IT.SBT, the cluster-bounded zone also increases the mean hazard, although to a lesser extent because of their greater distance from the zone and their site conditions. In contrast, IT.LSS exhibits lower fully nonergodic hazard under the newly defined small-clustered source model. This reduction is primarily attributed to the improved constraint of source- and path-specific effects within the smaller clustered source region. Because site amplification at IT.LSS is relatively limited, the resulting hazard is more strongly controlled by source- and path-specific effects.

The spatial sampling density and local quality of accelerometric records directly dictate the magnitude of posterior standard errors used to model epistemic uncertainties in the logic tree and, consequently, the resulting dispersion between the 16th and 84th fractile hazard. Station IV.NRCA displays a tight 16%-84% epistemic fractile spread because of its substantial number of observations at station ($n_s = 279$) and many of its records represent local in-cluster ray paths that

provide strong empirical constraints on site and path parameters. Conversely, out-cluster stations IT.LSS ($n_s = 333$), IV. LNSS ($n_s = 330$), and IT.SBT ($n_s = 24$) exhibit wider epistemic fractile bounds. Although IT.LSS and IV. LNSS present a large total record counts, most of their recordings correspond to regional rather than local ray paths, demonstrating that the sample size alone cannot substitute for dense local path coverage. Furthermore, under the broad Umbria-Abruzzo zone, out-of-cluster earthquake sources with limited local ray-path coverage introduce higher posterior standard errors in the estimated path-to-path ($SE(\delta P2P)$) and location-to-location ($SE(\delta L2L)$) adjustment terms. These poorly constrained location- and path-specific parameters inflate the median epistemic variance ($\sigma_{\text{epi}-\Delta\mu}$) and the total epistemic uncertainty ($\sigma_{\text{epi-total}}$), significantly widening the spread between the 16th and 84th epistemic fractile hazard compared to the Small clustered area configuration.

Based on these findings, nonergodic PSHA provides a more physically consistent framework for seismic hazard assessment, including at sites where local data are limited. Limited local records provide insufficient information to determine whether spatial variations in ground motion are negligible or systematically variable. However, this lack of observation does not justify the ergodic assumption or imply that an ergodic model adequately represents the true hazard (Liou & Abrahamson, 2025). In ergodic GMMs, unmodeled spatial effects are absorbed into aleatory uncertainty (σ_{Er}), which can result in flatter hazard curves and epistemic bounds that are too narrow to capture the true hazard. In contrast, nonergodic GMMs explicitly represent systematic spatial effects and reflect poorly constrained parameters through wider epistemic bounds, providing a more transparent and robust representation of uncertainty in the true seismic hazard (Liou & Abrahamson, 2025). However, the benefits of nonergodic modeling depend strongly on the availability and spatial distribution of local data. When observations are concentrated within a small portion of the spatial domain, for example, when a large zonation extending up to 200 km from the site is constrained by data from only a limited local region, the spatially varying terms may be poorly constrained outside the data-rich area. In such cases, the advantage of nonergodic modeling may be reduced, and the resulting spatial corrections and epistemic uncertainty may remain highly uncertain.

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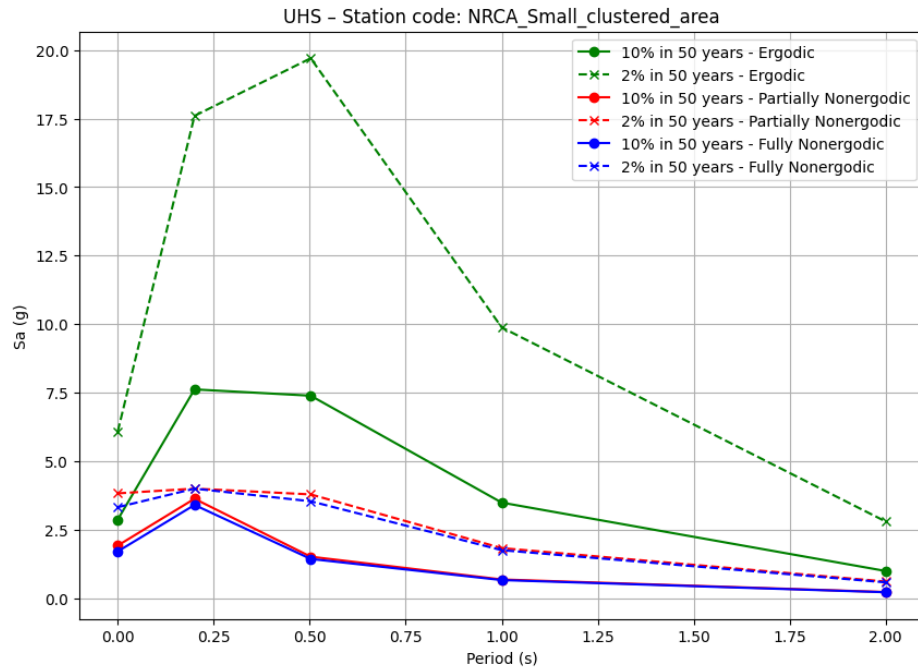
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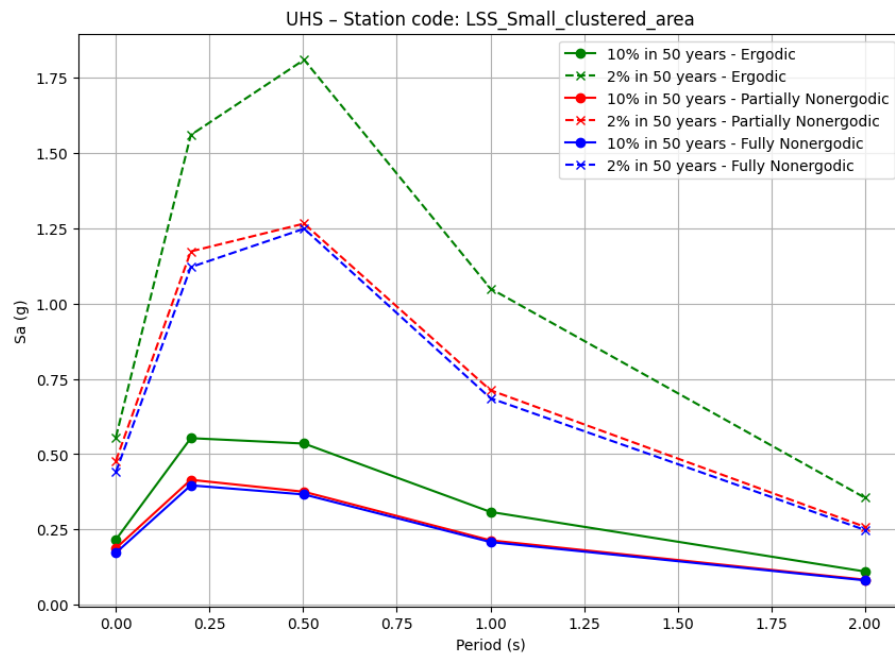
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APPENDIX

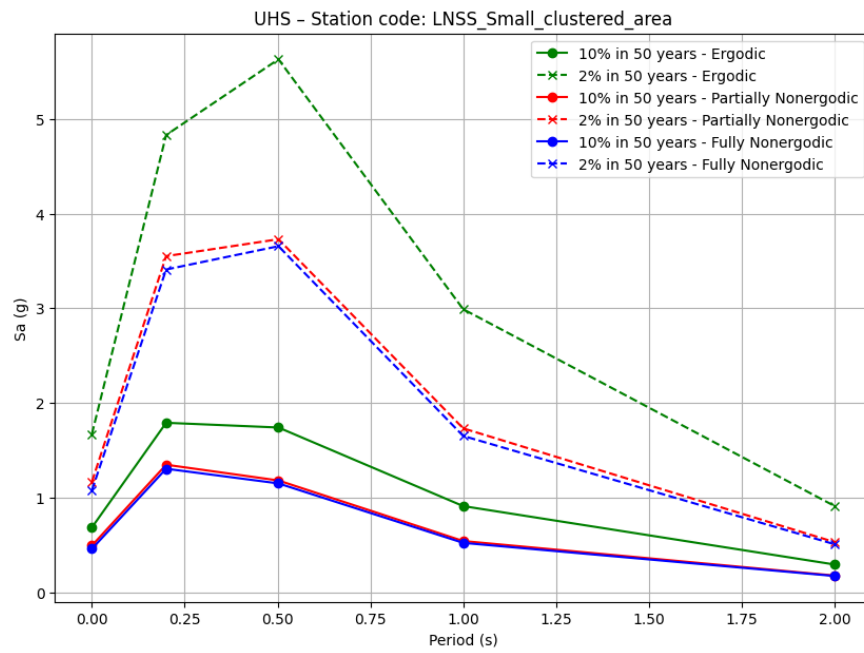
UHS FIGURES FOR SMALL CLUSTERED AREA



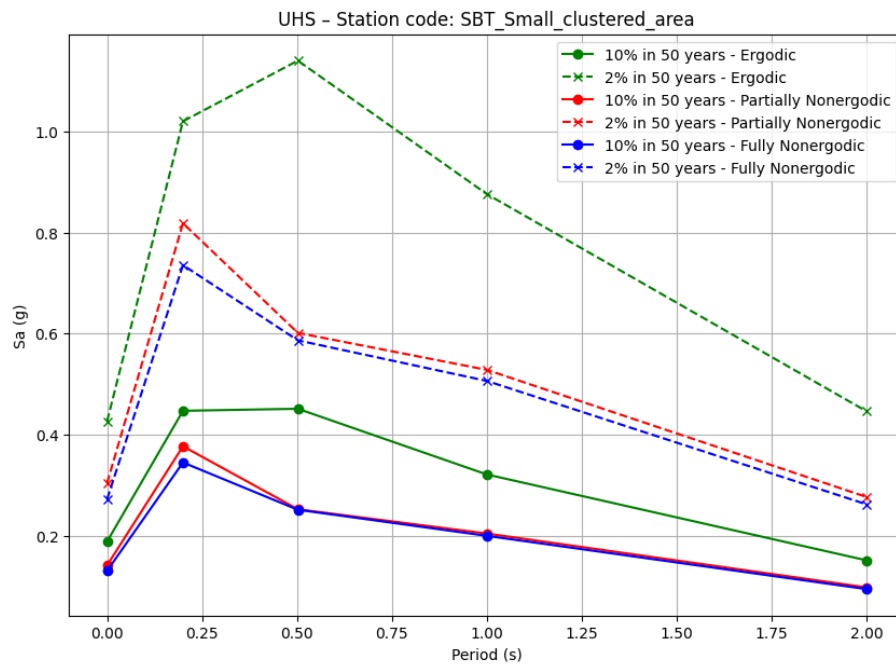
(a)



(b)



(c)



(d)