

Value of Information Across Ground Motion Models

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ABSTRACT

Effective seismic emergency management depends on accurate seismic hazard analysis, where selecting a suitable Ground Motion Model (GMM) for the target region is a critical initial step. Although numerous GMMs are available, identifying the one that better captures the intensity measures characteristic of a target region remains non-trivial. This study investigates the effect of GMM selection on the Value of Information (VoI) obtained from ground motion monitoring. A case study is conducted for a bridge, considering multiple potential locations in Central Italy, with seismic demand estimated using two different GMMs applicable to the region. The results reveal that the difference in seismic hazard predictions between the two GMMs significantly affects the identification of the optimal emergency management actions and therefore the VoI. Using Log-Likelihood (LLH) method, to assess the statistical fit of each GMM against observed ground motions, one model is found to provide a better fit and a correspondingly higher VoI. These findings suggest that employing a statistically robust GMM can help avoid unnecessary infrastructure shutdowns and minimize the risk of underestimating seismic damage.

INTRODUCTION

The increasing concentration of urban development in earthquake-prone regions highlights the critical need for accurate prediction of seismic demand and its impact on critical infrastructure. Ground Motion Models (GMMs) are essential for seismic hazard analysis, providing Intensity Measures (IMs) that serve as an input to estimate the structural state of infrastructure following a future potential seismic event. Higher accuracy of the GMM directly translates to higher accuracy of the IM and the probability of damage state estimations, making the selection of an appropriate GMM paramount for reliable damage assessments. However, selecting the GMM that best aligns with a specific study region from the multitude of available models often poses a significant challenge. Cotton et al. [1] proposed seven criteria to eliminate inappropriate GMMs, considering factors such as data quality and quantity and tectonic setting. While

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these criteria aid in narrowing down suitable GMMs, further efforts are necessary to quantitatively assess how well GMM predictions match observed ground motions for more accurate selection. Statistical goodness-of-fit methods based on data, such as those presented in reference [2], can be used for this purpose.

The benefit of incorporating monitoring data, particularly GMMs informed by ground motion data, into emergency management decisions can be quantified using the VoI, which assesses the expected improvement in decision outcomes resulting from the availability of specific information. While numerous studies have explored the VoI derived from Structural Health Monitoring (SHM) systems for various civil engineering applications [3-6], the influence of GMM selection on the VoI obtained from ground motion monitoring for seismic emergency management warrants further attention.

Several studies have investigated VoI from ground motion monitoring, often employing specific GMMs based on area source or fault source assumptions to model seismic demand [5, 7]. These studies highlight the potential of strategically placed ground motion sensors to enhance decision-making. However, the impact of the chosen GMM's accuracy on the calculated VoI has often been overlooked. Recognizing that a more accurate GMM improves IM and damage state estimations, can significantly influence the effectiveness of emergency management actions, understanding how GMM selection affects the VoI derived from ground motion data is crucial.

This paper examines the impact of GMM selection on the VoI obtained from ground motion monitoring and its subsequent utility in supporting emergency management decisions. A case study is presented for a bridge in Central Italy, where the seismic demand is estimated using two different GMMs applicable to the region. The VoI is then computed for each GMM within a seismic emergency management scenario. By comparing the VoI obtained using different GMMs, this analysis aims to demonstrate the importance of GMM selection on the benefits of ground motion monitoring for the selection of effective emergency management strategies. The findings underscore the necessity of considering GMM accuracy when evaluating the potential value of ground motion information in supporting emergency management.

METHODOLOGY

This study quantifies how the choice of GMM influences insights from ground-motion monitoring through two principal stages; (i) modelling the seismic demand and (ii) evaluation of the VoI metric, the details of which are provided in the following subsections.

Seismic Demand Modeling

Seismic-demand modelling based on Monte-Carlo simulation (MCS) adopts an event-based framework in which both the magnitudes and spatial occurrences of potential earthquake scenarios are sampled from the earthquake rupture forecast (ERF) model associated with the region under consideration. For every seismic source surrounding the site, MCS first generates a large ensemble of synthetic earthquake catalogues whose temporal occurrence follows a Poisson process. Each catalogue spans a fixed analysis window (e.g., 100 years) and the number of catalogues is chosen so that the total number of simulated events, S , provides stable estimates of the target annual

exceedance probability (e.g., 1000 catalogues are adequate for an exceedance rate of 10^{-3} yr^{-1} [8]). Within each catalogue the magnitude of scenario earthquakes is randomly drawn from the source-specific magnitude–frequency distribution defined in the ERF. Once a magnitude, m , is sampled, the rupture geometry is determined through a magnitude–scaling relationship that relates m to rupture area and width. The epicenter of the rupture, p , is then assumed to be uniformly distributed over the surface projection of the rupture plane of the scenario earthquake. The distance metrics required by GMMs, such as the Joyner and Boore distance, R_{JB} , are computed for each scenario, (m, p) . Then, the GMM is invoked to predict the intensity measure (IM) at the site. In its functional form the GMM expresses demand as $\ln IM = \ln \overline{IM} + \sigma \varepsilon$. Where, $\ln IM$ is the natural logarithm of the IM of interest, which follows a normal distribution. $\ln \overline{IM}$ is the mean intensity measure, which in general calculated as the function of the magnitude, distance, and site conditions. σ is the total standard deviation of the model and ε is the number of standard deviations. Hereafter the $\ln IM$ will be generically denoted as ‘demand’ D , at a location due to an earthquake scenario, and will be represented as $D \sim N(\mu_D, \sigma_D)$, where μ_D and σ_D stand for the median estimation and the standard deviation of the demand D .

Value of Information

In the aftermath of an earthquake, a bridge can be classified into one of L damage states, DS_l , ranging from negligible, DS_1 , to severe, DS_L , each associated with a diverse failure probability under everyday loads. Site-specific seismic demand, predicted with the chosen GMM and paired with a capacity model, yields the damage-state probabilities and the corresponding expected costs of failure, $c_F(A_n)$, or survival, $c_{\bar{F}}(A_n)$, for each management action A_n . Updating those probabilities with monitoring data (posterior) rather than relying solely on prior estimates reduces expected costs. The resulting difference defines the VoI. If VoI is computed before data collection, based on a probabilistic model of the expected information, the analysis is called pre-posterior.

PRIOR ANALYSIS

Before any monitoring data is available, the bridge manager selects an emergency action, A_n , using prior estimates of seismic demand D and bridge capacity C . Throughout this formulation, both D and C are treated in natural-logarithmic space and the \ln symbol is omitted for brevity. Accordingly, the capacity in the l -th damage state, C_{DS_l} , is modelled as a log-normal variable whose logarithmic mean and standard deviation are $\mu_{C_{DS_l}}$ and $\sigma_{C_{DS_l}}$ respectively (i.e., $C_{DS_l} \sim N(\mu_{C_{DS_l}}, \sigma_{C_{DS_l}})$) [5]. The limit-state function, G_{DS_l} , for the l -th damage state can be expressed as the difference of the D and C_{DS_l} , and noting that the difference of two normal variables remains normal, it becomes $G_{DS_l} \sim N(\mu_{G_{DS_l}}, \sigma_{G_{DS_l}})$ with a logarithmic mean of $\mu_{G_{DS_l}} = \mu_{C_{DS_l}} - \mu_D$ and the standard deviation $\sigma_{G_{DS_l}} = \sqrt{\sigma_{C_{DS_l}}^2 + \sigma_D^2}$. This formulation enables direct computation of the reliability index, $\beta_{DS_l} = \mu_{G_{DS_l}} / \sigma_{G_{DS_l}}$, and the associated probability of the demand D exceeding the capacity C_{DS_l} , $P[D \geq C_{DS_l}] = \Phi(-\beta_{DS_l})$. The prior probability of the damage state, $P(DS_l)$, is given in Eq. (1):

$$P(DS_l) = \begin{cases} P[D \geq C_{DS_l}] - P[D \geq C_{DS_{l+1}}], & \text{if } l \neq L \\ P[D \geq C_{DS_L}], & \text{if } l = L \end{cases} \quad (1)$$

The expected cost of an action A_n given the bridge is in the l -th damage state, is calculated as given in Eq. (2).

$$E[C(A_n)|DS_l] = c_F(A_n)P(F|A_n, DS_l) + c_{\bar{F}}(A_n)P(\bar{F}|A_n, DS_l) \quad (2)$$

where, $P(F|A_n, DS_l)$ and $P(\bar{F}|A_n, DS_l)$ are respectively the probability of failure and the probability of survival of the bridge, given the n -th action, A_n and given the bridge is in the DS_l damage state after the seismic event. Considering all the possible damage states of the bridge, the total expected cost of the action A_n is calculated as given in Eq. (3).

$$E[C(A_n)] = \sum_{l=1}^L E[C(A_n)|DS_l]P(DS_l) \quad (3)$$

The optimal prior action, minimizing expected cost among N alternatives, is given:

$$\hat{A} = \underset{N}{\operatorname{argmin}} E[C(A_n)] \quad (4)$$

The prior expected cost for a single scenario posing a demand D is given in Eq. (5).

$$E[C(\hat{A})] = \sum_{l=1}^L E[C(\hat{A})|DS_l]P(DS_l) \quad (5)$$

PRE-POSTERIOR ANALYSIS

In the pre-posterior analysis, it is assumed that a strong ground motion sensor is deployed at the bridge location and provides additional information on the demand posed by an earthquake scenario. The j -th monitoring information y_j , out of J possible monitoring outcomes, is modeled as, $y_j = D + \epsilon_j$, where, ϵ is the error term in the measurement which is modeled as log-normal variable, $\epsilon \sim N(\mu_\epsilon, \sigma_\epsilon)$. The demand is updated given the monitoring outcome, is modeled as, $D|y_j \sim N(\mu_D|y_j, \sigma_D|y_j)$. The parameters of the distribution of the updated demand are given in Eq. (6).

$$\mu_D|y_j = \mu_D + \frac{\sigma_D^2}{\sigma_D^2 + \sigma_\epsilon^2} (y_j - \mu_y) \quad \sigma_D|y_j = \sqrt{\sigma_D^2 - \frac{\sigma_D^4}{\sigma_D^2 + \sigma_\epsilon^2}} \quad (6)$$

Where, μ_y is the mean of the measurement outcome. Distribution parameters of the limit state functions can be updated using the demand updated given the monitoring outcomes (e.g., $\mu_{G_{DS_l}}|y_j = \mu_{C_{DS_l}} - \mu_D|y_j$ and $\sigma_{G_{DS_l}}|y_j = \sqrt{\sigma_{C_{DS_l}}^2 + \sigma_D^2|y_j}$). Therefore, the reliability index and updated probabilities of the demand $D|y_j$ exceeding the capacity C_{DS_l} can be calculated. The posterior expected cost of the n -th action, given the demand updated based on the j -th monitoring outcome, is calculated as:

$$E[C(A_n)|y_j] = \sum_{l=1}^L E[C(A_n)|DS_l]P(DS_l|y_j) \quad (7)$$

The action with the minimum expected cost is selected as the optimal pre-posterior action for output y_j as given in Eq. (8).

$$\tilde{A}|y_j = \underset{N}{\operatorname{argmin}} E[C(A_n)|y_j] \quad (8)$$

The pre-posterior expected cost, for the considered seismic event is obtained as the expected value of the posterior cost over all the possible J outcomes as given in Eq. (9).

$$E[C(\tilde{A})] = \sum_{j=1}^J E[C(\tilde{A}|y_j)]P(y_j) \quad (9)$$

VALUE OF INFORMATION FROM STRONG GROUND MOTION SENSOR

The VoI from ground motion monitoring is defined as the difference between the prior and pre-posterior expected costs for a given earthquake scenario. For the s -th scenario with magnitude m and epicenter p , the VoI is given by Eq. (10).

$$VoI_s(m, p) = E[C(\hat{A})] - E[C(\tilde{A})] \quad (10)$$

During the reference period T , VoI accounts for all seismic scenarios, weighted by their occurrence probability. Each scenario is defined by magnitude, m , and epicenter, p . Epicentral location follows a uniform distribution f_p , and magnitude follows f_m between m_{min} and m_{max} . The overall VoI is given in Eq. (11).

$$VoI = \int_{m_{min}}^{m_{max}} \int_p VoI_s f_m f_p dm dp \quad (11)$$

CASE STUDY

The decision problem for the VoI analysis for the seismic emergency management of an exemplary bridge with a natural period of 1s, located in Central Italy is presented in this section. Nine possible locations of the bridge are considered, and the seismic demand is derived at these locations considering the scenario earthquakes generated by the area sources given in Figure 1, whose details can be found in reference [9]. To evaluate the seismic demand at the considered locations the GMMs provided by Bindi et al. [10], BND14, and Lanzano et al. [11], ITA18, are selected. As shown in Figure 2, the hazard curves derived from BND14 and ITA18 largely overlap across the full IM range. However, subtle but persistent differences emerge at higher intensity measures, particularly in the range most relevant for structural damage.

The relative performance of the BND14 and ITA18 GMMs in representing seismic hazard in Central Italy is evaluated using the log-likelihood (LLH) method [2], which quantifies the divergence from observed ground motion data based on the Kullback–Leibler information criterion. A lower LLH value indicates better agreement with the recorded data. For spectral acceleration at the fundamental period of the bridge ($T = 1$

s), the BND14 model yields an LLH of 1.8392, while the ITA18 model produces a higher LLH of 2.0506, indicating a better fit for BND14.

In the decision problem, the bridge is assumed to be located at one of the locations given in Figure 2. It is assumed to fall into one of five damage states after an earthquake: no damage, minor (DS₂), moderate (DS₃), major (DS₄), or complete damage (DS₅), with mean spectral acceleration capacities of 0.17 g, 0.24 g, 0.30 g, and 0.44 g respectively, and a lognormal standard deviation of 0.4. Two emergency actions are analyzed: keeping the bridge open (A₁) or closing it (A₂). Associated costs are €10M for failure under A₁, €1M for unnecessary closure under A₂, and zero otherwise. The probability of failure under A₁ increases with damage state, from 1.75×10^{-5} (DS₁) to 0.993 (DS₅), while failure under A₂ is assumed zero across all states. Measurement error is modeled as a lognormal variable with zero mean and a standard deviation of 0.2.

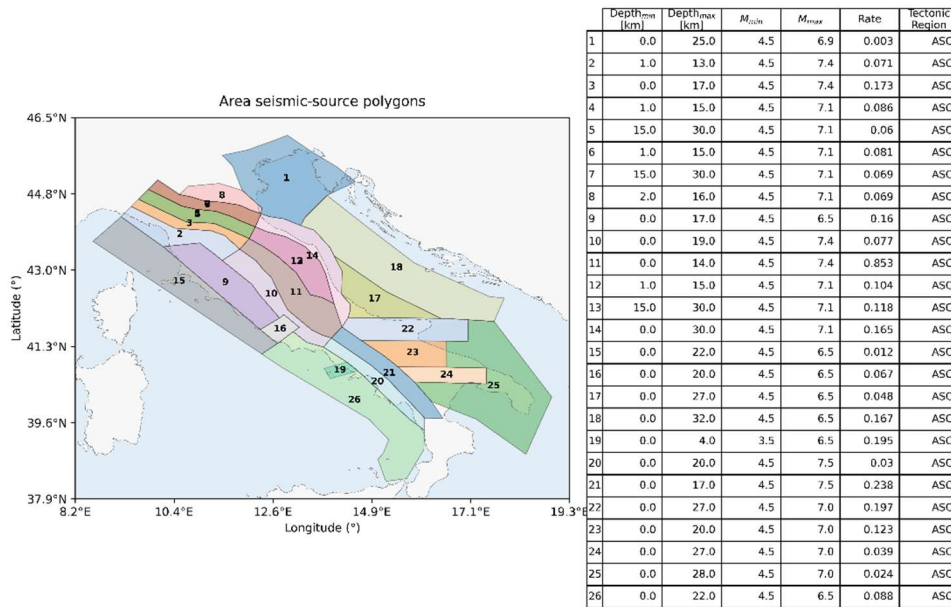


Figure 1. Considered area sources and their properties.

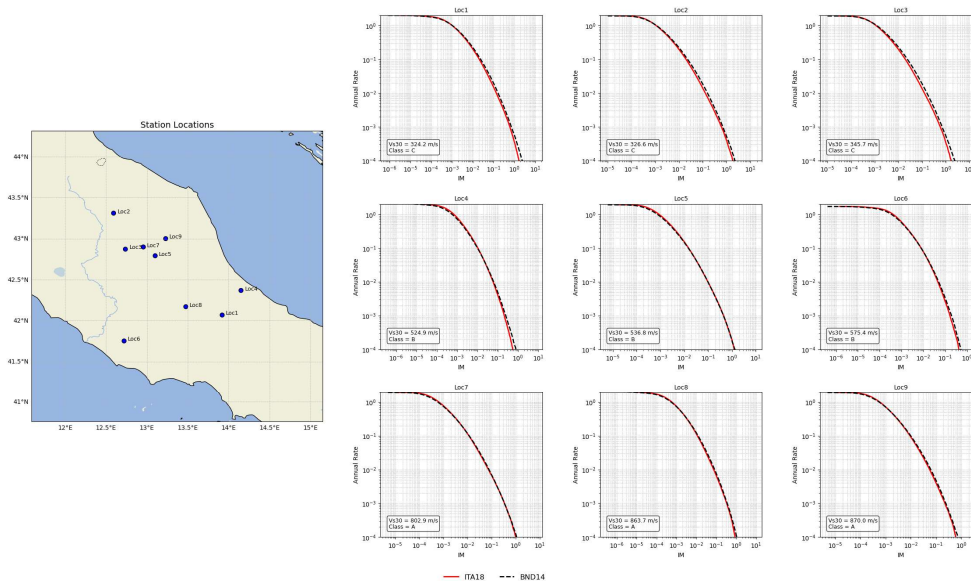


Figure 2. Illustration of the considered locations on map and corresponding hazard curves

RESULTS AND DISCUSSION

This section presents the results of the VoI analysis carried out using BND14 and ITA18 GMMs. The VoI analysis consistently shows an advantage for the BND14 model over ITA18 across all locations. While ITA18 produces VoI estimates ranging from €1122 (Loc6) to €4785 (Loc1), the corresponding values under BND14 are significantly higher, ranging from €2173 (Loc6) to €10014 (Loc1). This pattern holds across all sites, with BND14 yielding nearly double the total VoI (€50438) compared to ITA18 (€25414). The enhanced values under BND14 reflect its tendency to predict higher hazard at higher intensity measures (as shown in Figure 2), which increases the potential benefit of site-specific monitoring data for decision-making. The results emphasize the significant impact the choice of GMM has on the value of monitoring and, consequently, on the justification for instrumentation investments.

TABLE I. VoI analysis results.

	Loc1	Loc2	Loc3	Loc4	Loc5	Loc6	Loc7	Loc8	Loc9	Sum
VoI-ITA18 [€]	4785	4572	4433	1482	3194	1122	2166	2193	1468	25414
VoI-BND14 [€]	10014	9640	9951	2646	5392	2173	3830	4043	2747	50438

To examine the sensitivity of the VoI to GMM selection, VoI estimates were evaluated across a range of earthquake magnitudes for three representative locations: Loc2, Loc5, and Loc8. These sites were chosen to reflect variability in regional hazard and site characteristics. Figure 3 presents the VoI computed using the ITA18 and BND14 models, showing the expected economic benefit of seismic monitoring as a function of magnitude. Across all locations, BND14 consistently yields higher VoI, with the largest differences observed in the 5.5 to 6.5 magnitude range, where emergency response decisions are most critical. This disparity is particularly elevated at Loc2, where BND14 predicts greater seismic hazard, resulting in notably greater VoI, indicating the substantial effect of GMM selection. Equally important is the role of model uncertainty in seismic hazard predictions. The total standard deviation for spectral acceleration at 1 s is 0.9527 for BND14 and 0.7450 for ITA18 (in natural logarithmic units), reflecting differing levels of model uncertainty. Incorporating monitoring data significantly reduces the epistemic uncertainty associated to the parameters of the two models, with preposterior standard deviations decreasing to 0.1957 and 0.1932, respectively. This reduction substantially improves decision confidence and reduces expected costs. Overall, the findings demonstrate that VoI is highly sensitive not only to structural vulnerability, but also to the choice of GMM and its associated uncertainty, reinforcing the critical role of model selection in risk-informed decision-making.

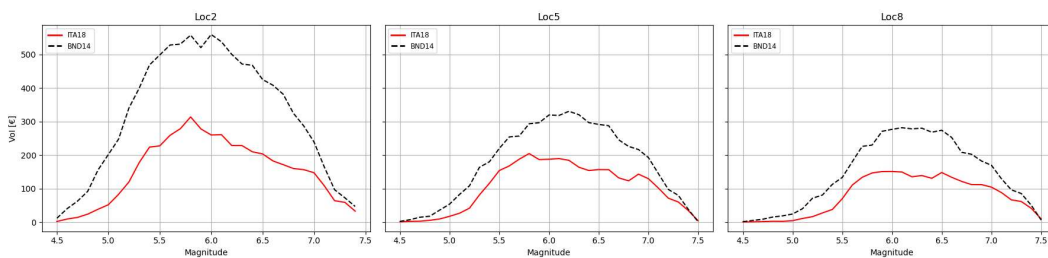


Figure 3. Distribution of the VoI over magnitudes for Loc2, Loc5 and Loc8

CONCLUSION

This study demonstrates that the selection of the GMM significantly influences the Value of Information (VoI) obtained from seismic monitoring. Using a case study involving a bridge in Central Italy, two GMMs - BND14 and ITA18- were compared. The analysis shows that BND14 consistently yields higher VoI, especially at higher intensity measures and magnitudes critical for decision-making. The results highlight that VoI-based justification for seismic instrumentation is not only location-dependent but also highly sensitive to the choice of the hazard model. Therefore, accurate and regionally appropriate GMM selection is essential for effective emergency management.

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