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Sreeram Reddy Kotha (✉ sreeram-reddy.kotha@univ-grenoble-alpes.fr)

Institut des Sciences de la Terre <https://orcid.org/0000-0002-4874-3730>

Paola Traversa

Electricite de France, Aix-en-Provence

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A Bayesian Update of Kotha et al. (2020) Ground-Motion Model Using Résif Dataset

Sreeram Reddy KOTHA¹ and Paola TRAVERSA²

Abstract

Recent updates of pan-European seismic hazard and risk maps adopted the partially non-ergodic Kotha et al. (2020) ground-motion model. This model was regressed from the Engineering Strong Motion dataset, containing ground-motion data of $M_W \geq 3$ events mostly from Italy, Turkey, Greece, and in smaller fractions from rest of the active shallow crustal tectonic regions of Europe. Through mixed-effects regressions, the non-ergodic model partially resolved the spatial variability of attenuation characteristics across most of seismically active Europe, but not in France due to the then lack of a regional dataset. With the availability of a manually processed dataset from Résif network, and a computationally viable Bayesian inferencing algorithm, this study extends the non-ergodic applicability of the model to $M_W < 3$ earthquakes, attenuating regions, tectonic localities, and sites located in France. In process, a few important decisions had to be made concerning the updating methodology, and the interpretation of spatial variability of attenuation – specifically, that of the tectonic localities producing earthquakes. The methodology and results are discussed, emphasising the need to revise the current ground-motion regionalisation approach, and to tailor the updating procedure to be application specific. This study anticipates and supports a shift from *frequentist* to *Bayesian* approach of ground-motion modelling, in order to maintain continuity of knowledge regressed from various ground-motion datasets.

Keywords: Ground-motion model, seismic hazard, seismic risk, response spectra, Bayesian regressions

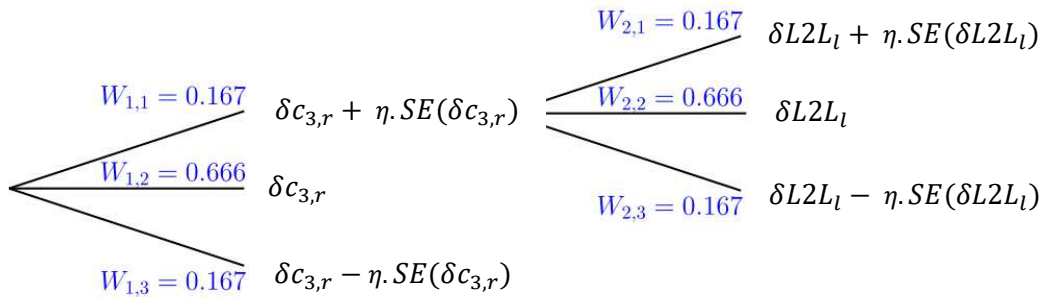
¹Univ. Grenoble Alpes, Univ. Savoie Mont Blanc, CNRS, IRD, Univ. Gustave Eiffel, ISTerre, 38000 Grenoble, France

²Electricité de France - EDF, 13290 Aix-en-Provence, France

30 1 INTRODUCTION

31 The European Seismic Hazard Maps of 2020 (ESHM20) have adopted new strategies in developing
 32 harmonised hazard assessments across the geological and tectonically diverse environments of Euro-
 33 Mediterranean region (Danciu et al. 2021). Among these is the shift towards a more data-driven
 34 representation of ground-motion epistemic uncertainties (Weatherill et al. 2023), as a variation of the
 35 ‘scaled backbone’ ground-motion model (GMM) logic-tree approach of Bommer (2012) and Douglas (2018).
 36 The backbone approach ensures transparency on the level of uncertainty implied by the GMM, a clearer
 37 description of logic-tree branch weights, and the flexibility to make the logic-tree specific for a given region.
 38 One of the main challenges of regionally *scaling* and *adapting* the ESHM20 backbone GMM logic-tree is to
 39 ensure that its calibration captures the appropriate level of ground-motion epistemic uncertainty; which is
 40 particularly difficult for regions with limited ground-motion data, and hence is the interest of this study.

41 The ESHM20 GMM logic-tree for active shallow crustal earthquakes (Weatherill, Kotha and Cotton
 42 2020) is an application driven implementation of the Kotha et al. (2020) and Kotha et al. (2022) GMMs.
 43 Together, these GMMs together will be referred to as K20 from hereon. The K20 models were regressed
 44 from the Engineering Strong Motion (ESM) dataset developed and validated by Lanzano et al. (2018) and
 45 Bindi et al. (2018). The ESM dataset featured ground-motions recorded in several seismically active Euro-
 46 Mediterranean regions hypothesised to exhibit strong spatial variability of attenuation characteristics. To
 47 quantify the spatial (or regional) variability of ground-motion attenuation characteristics, K20 relied on
 48 geology and tectonics based regionalisation models of Basili et al. (2019) and Danciu et al. (2021).



49 **Fig.1: Partially non-ergodic region-specific GMM logic-tree proposed in Kotha et al. (2020)**

50 Fig.1 shows a partially non-ergodic region-specific application of K20 GMM as a logic-tree two
 51 branching levels: level 1 to account for variability and uncertainty in far-source attenuation ($> 80km$)
 52 depending on the receiving site location, and level 2 to account for variability and uncertainty in *at-source*
 53 attenuation ($\sim 1km$) depending on the event location. Note that, at-source attenuation introduced in this
 54 study is an alternative interpretation/hypothesis on the tectonic-locality random-effects group elaborated
 55 in K20 development (see Kotha, Bindi and Cotton 2022), and will be detailed in later sections. The two
 56 branching levels adjust specific coefficients of K20 to predict Gaussian distributions of ground-motions best
 57 representing the site and event location dependent attenuation characteristics in a region. In level 1 of the
 58 logic-tree shown in Fig.1, $\delta c_{3,r}$ is the adjustment to the ‘apparent anelastic attenuation’ coefficient (c_3 in
 59 K20) specific to the region r hosting the site, and $SE(\delta c_{3,r})$ is the uncertainty on $\delta c_{3,r}$. In level 2, $\delta L2L_l$ is
 60 the adjustment to the ‘offset/bias/intercept’ coefficient (e_1 in K20) specific to the tectonic locality l hosting

61 the event, and $SE(\delta L2L_l)$ is the uncertainty on $\delta L2L_l$. To ensure that the resulting ground-motions follow
62 a Gaussian distribution, one may set $\eta = 1.732$ with branch weights $W_{1,j} = 0.167, 0.666, 0.167$ for $j = 1, 2, 3$
63 (Miller III and Rice 1983) – similar to those in ESHM20 GMM logic-tree. The logic-tree is cast as such so that
64 $[\delta c_{3,r}, SE(\delta c_{3,r})]$, $[\delta L2L_l, SE(\delta L2L_l)]$, η , and the branch weights can be modified and adapted to new
65 regions when and where new ground-motion datasets beyond ESM become available.

66 In K20, $\delta c_{3,r}$ and $\delta L2L_l$ were treated as statistical estimates, while Kotha, Bindi and Cotton (2022)
67 evaluated the physical meaning of these random-effects and their spatial variabilities. Subsequently, it was
68 argued that the regionally-adaptable scaled GMM logic-tree reflects, for example, weaker far-source
69 attenuation in Pyrenees compared to French Alps, weaker far-source attenuation in French Alps compared
70 to Apennines in Italy, weaker far-source attenuation towards east of Apennines compared to the west of
71 Apennines in central Italy, etc. However, ESM contained very few ground-motion records from France
72 (~ 300) compared to Italy (~ 10000), while several densely populated regions in France (e.g., Parisian basin)
73 were barely sampled. Since $\delta c_{3,r}$ and $\delta L2L_l$ were inestimable for most regions in France, the ESHM20
74 backbone GMM logic-tree could only use the pan-European *averages* with large uncertainties in these
75 regions; resulting in hazard estimates with large uncertainties as well. This study is a step towards updating
76 the K20 GMM using the Résif ground motion dataset by Traversa et al. (2020) – recently extended to the
77 end of 2021 by Buscetti et al., (in-prep.) – and adapting the Fig.1 backbone logic-tree to France.

78 A modest updating procedure would be to compare the ground-motion distributions from the GMM
79 logic-tree against the new data from a region, and iteratively – and *exclusively* – modify the $\delta c_{3,r}$, $\delta L2L_l$, or
80 other GMM coefficients. There are at least three problems that deter such a simplified approach: 1) GMM
81 fixed-effect coefficients are often correlated – this challenges exclusively adjusting any coefficient while
82 leaving the rest unchanged; 2) the new dataset may have sampled $[M_w, R_{jB}]$ ranges beyond the GMM's
83 applicability – this may require evaluating first and then recalibrating the GMM to extend its usability; 3)
84 the new dataset may have sampled $[M_w, R_{jB}]$ scenarios well within GMM's applicability, but the event-,
85 path-, and site-effects, and their combinations may be rather *peculiar* – this may lead to misattributing, for
86 example, systematically strong site-effects as event- and path-effects. In combination, these three issues
87 may render iterative estimation of physically meaningful $\delta c_{3,r}$ and $\delta L2L_l$ rather challenging, and possibly
88 unreliable. Incidentally, this was the case with the Résif dataset of French ground-motions. It was impossible
89 to *guess* via residual analyses, for example, if the French earthquakes were systematically stronger, if the
90 French site amplifications were stronger, or if the French regional crust attenuated ground-motions rather
91 weakly compared to the pan-European average of K20. Therefore, this study required shifting from classical
92 or *frequentist* mixed-effects regressions to *Bayesian* mixed-effects GMM regressions (Samaniego 2010).

93 Essentially, this study first recasts the K20 GMM in a Bayesian framework. Following an
94 implementation and evaluation of the new regression approach, the K20 model is updated using the French
95 dataset. The changes to K20 GMM, the relevant technical issues in Bayesian updating, and the apparent
96 causes for the most remarkable changes in the GMM are discussed. This study does not propose an
97 *application-ready* update to ESHM20 logic-tree for France, but is intended as a reference to any future
98 attempts to scale and adapt the K20 GMM to new regions.

99 **2 DATASETS**

100 The pan-European dataset (ESM, yellow markers and histograms in Fig.2) was used in conjunction with the
 101 regionalisation model of Basili et al. (2019) and tectonic localisation model of Danciu et al. (2021) in
 102 deriving the K20 GMMs. Details on each of these are available in their respective publications, and will be
 103 skipped here. The data selection procedure for the robust linear mixed-effects regression (RLMM;
 104 *robustlmm* by Koller 2016) of K20 is also described in Kotha et al. (2020). The companion dataset from
 105 France by Traversa et al. (2020) contains ground-motion data recorded by Résif network (Résif, blue
 106 markers and histograms in Fig.2). The key features of the datasets relevant to this study are:

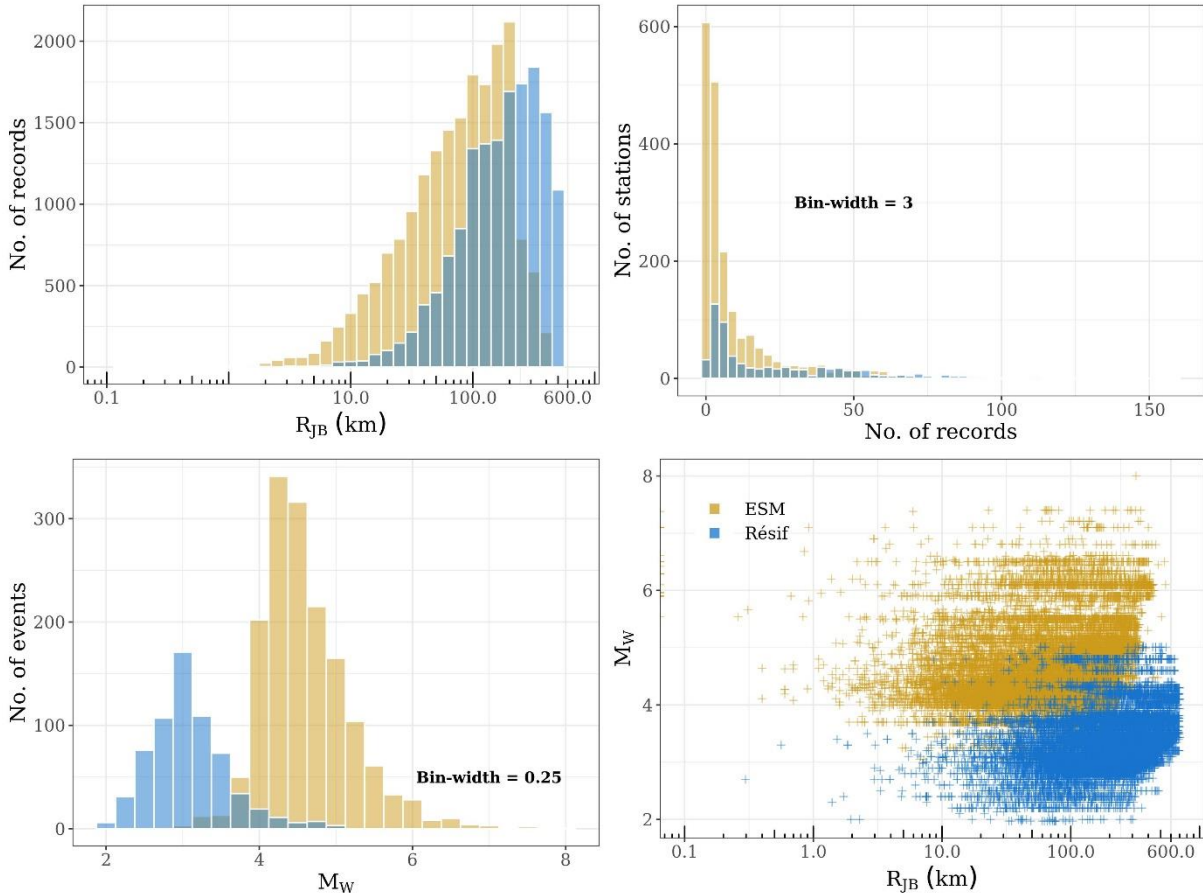


Fig.2: Comparison of ESM (yellow) and Résif (blue) ground-motion datasets

107

- 108 1) Prior to data selection procedure based on usable frequency range with good signal-to-noise ratio,
 109 while ESM contains data from $3 < M_W < 8$ events, Résif dataset contains data from a largely disjoint
 110 range $2 < M_W < 5$. This means that, the new data is well beyond the applicability range of K20,
 111 particularly towards lower M_W .
- 112 2) The preferred M_W of events in ESM dataset are those from the EMEC catalogue (Grünthal and
 113 Wahlström 2012) revised by Weatherill. G. and Lammers. S. (GeoForschungsZentrum, GFZ Potsdam)
 114 during ESHM20 development. The M_W estimates of Résif events are derived predominantly from the
 115 SIHEX-BCSF-RENASS catalogue (Cara et al. 2015) and from conversions from local-magnitude
 116 estimates. In this study, the M_W provided in the Résif dataset are preferred even if EMEC values are
 117 available for some of the events.

118 3) Résif dataset contains data from broadband seismometers, structure-related and borehole sensors as
 119 well. There are 98 stations common to both the datasets. These stations are retained in the analyses,
 120 because many of them have recorded several small M_W events in Résif dataset that were absent in ESM.
 121 Only data from the sea-bottom station “FR.ASEAF” was removed from the analyses.

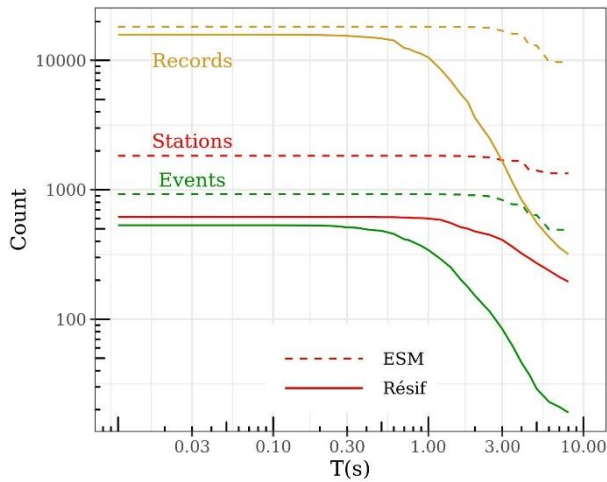


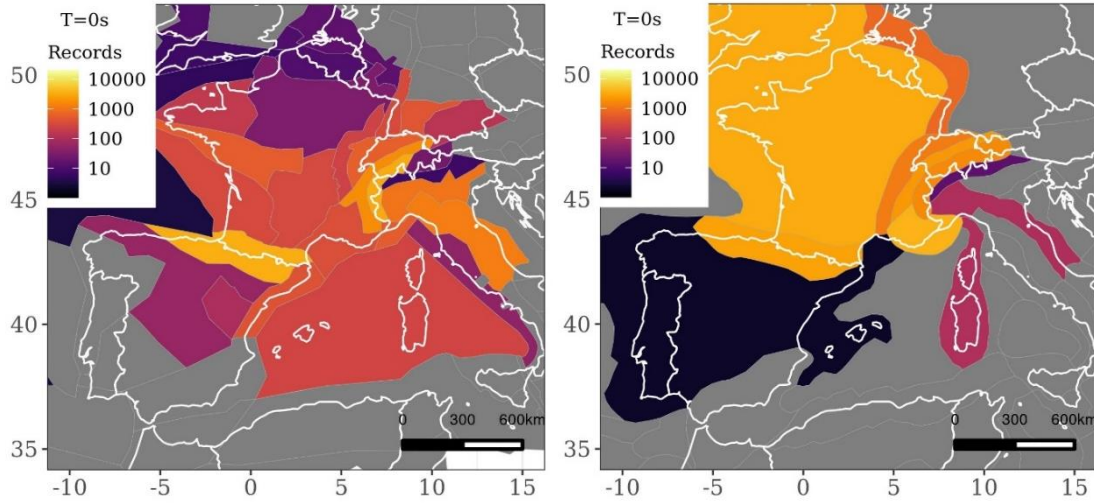
Fig.3: Comparison of number of usable records passing the low-pass and high-pass filter criteria in ESM and Résif datasets

122
 123 4) Laurendeau, Clément and Scotti (2022) identified 11 events common to both ESM and Résif datasets.
 124 Associated to these events, there are 270 records common to both the datasets. Following the data
 125 selection procedure described in Kotha et al. (2020), K20 GMM was derived using 18222 records in
 126 ESM. Following an identical data selection procedure, 15586 Résif records were available for the
 127 Bayesian update in this study. As shown in Fig.3, the number of usable records in Résif dataset
 128 decreases rapidly towards longer periods due to limited usable frequency range with signal-to-ratio
 129 ≥ 3 (details in Traversa et al. 2020). At short periods, the relatively small fraction of common records
 130 did not alter the key outcomes of this study. At long periods, removing these common records further
 131 reduced the available Résif records. Therefore, in this study, the common events, stations, and their
 132 associated ground-motion records are all retained in the analyses.
 133 5) The Résif ground-motion data is regionalised with the same models as the ESM dataset in Kotha et al.
 134 (2020). As in, ground-motion records are assigned into different attenuating regions based on site
 135 locations, and into different tectonic localities based on event locations. Regions that were very poorly
 136 sampled in ESM are now populated with several tens of recordings in a few cases (Fig.4).

137 3 METHOD

138 The published K20 GMM was derived using a robust linear mixed-effects regression (RLMM) algorithm of
 139 the *robustlmm* package in R (R-Core-Team 2000, RStudio-Team 2022). The robust regressions were
 140 necessary to identify and down-weight possible outlier ESM data from biasing the fixed-effects median and
 141 random-effect variances of the mixed-effects K20 GMM. Although RLMM regressions could provide the
 142 maximum-likelihood estimates of GMM fixed-effects coefficients and random-effects variances (and
 143 standard-deviations), they do not inform on uncertainties of these quantities. Uncertainties are joint
 144 distributions of GMM mixed-effects estimates that could allow a modeller understand which components
 145 are relatively better constrained, and which ranges of the dataset may require better sampling. In addition,

146 the customary practice has been to derive a completely new maximum-likelihood based GMM every few
 147 years when new datasets become available; while ignoring the *knowledge* regressed from existing datasets
 148 via GMMs. With ground-motion datasets growing exponentially large every year, this practice could soon
 149 become computationally intense, and the number of GMMs may become too numerous and incongruent to
 150 choose from (see Douglas and Edwards 2016).



151 **Fig.4: Distribution of Résif ground-motion data among the attenuation regions (right panel) of Basili et al. (2019) and tectonic localities (left panel) of Danciu et al. (2021)**

152 Bayesian approach to ground-motion modelling overcomes most of the above issues. A Bayesian
 153 regression yields joint distributions of the mixed-effects parameters of a GMM. These joint distributions
 154 help in assessing the strengths and weaknesses of the GMM; but more importantly, instead of performing a
 155 new regression on a new and extended dataset, these joint distributions of mixed-effects can be used as
 156 *informative priors* in developing a new GMM or updating an existing GMM. Several authors have argued for
 157 the need and advantages of Bayesian approach in ground-motion modelling (e.g. Kowsari et al. 2019,
 158 Stafford 2019, Kuehn and Scherbaum 2016, Arroyo and Ordaz 2010, Wang and Takada 2009). Moreover,
 159 with the recent developments in approximate Bayesian inferencing using Integrated Nested Laplace
 160 Approximation (INLA; Rue, Martino and Chopin 2009), Bayesian GMM regressions have become
 161 computationally much more viable (e.g. Kuehn 2021, Gómez-Rubio 2020). Therefore, in this study, the first
 162 step is to recast the ESM based frequentist K20 GMM in a Bayesian framework (Samaniego 2010), and then
 163 perform a Bayesian update using the Résif dataset using the *R-INLA* package (Lindgren and Rue 2015).

164 **3.1 Bayesian inference of K20 GMM from ESM dataset**

165 The functional form of K20 GMM is shown in equations (1 – 4). The purpose of its fixed-effects
 166 ($e_1, b_1, b_2, b_3, c_1, c_2, c_3$), random-effects ($\Delta c_{3,r}, \Delta L2L_1, \Delta B_{e,l}^0, \Delta S2S_s$), and residuals (E) are explained in Kotha
 167 et al. (2020), Kotha et al. (2022), Kotha, Bindi and Cotton (2022), and will be skipped here.

$$\ln(\mu) = e_1 + f_{R,g}(M_W, R_{JB}) + f_{R,a}(R_{JB}) + f_M(M_W) + \Delta L2L_1 + \Delta B_{e,l}^0 + \Delta S2S_s + E \quad (1)$$

$$f_{R,g} = (c_1 + c_2 \cdot (M_W - M_{ref})) \cdot \ln \sqrt{(R_{JB}^2 + h_D^2) / (R_{ref}^2 + h_D^2)} \quad (2)$$

$$f_{R,a} = \frac{c_3 + \Delta c_{3,r}}{100} \cdot (\sqrt{R_{JB}^2 + h_D^2} - \sqrt{R_{ref}^2 + h_D^2}) \quad (3)$$

$$f_M = \begin{cases} b_1 \cdot (M_W - M_h) + b_2 \cdot (M_W - M_h)^2 & M_W \leq M_h \\ b_3 \cdot (M_W - M_h) & M_h < M_W \end{cases} \quad (4)$$

168 The exact same subset of ESM dataset used in deriving the K20 model is used in this study. The
 169 robust estimates of K20 GMM fixed-effects published in Kotha et al. (2022) are used as means of informative
 170 priors with a precision of 0.1. The robust standard-deviations of random-effect groups $\Delta c_{3,r} = N(0, \tau_{c3})$,
 171 $\Delta L2L_l = N(0, \tau_{L2L})$, $\Delta B_{e,l}^0 = N(0, \tau_0)$, and $\Delta S2S = N(0, \phi_{S2S})$ were published and detailed in Kotha et al.
 172 (2022). The informative priors of these quantities in the Bayesian regression are input as typical log-gamma
 173 distributions with $1/\tau_{L2L}^2$, $1/\tau_0^2$, and $1/\phi_{S2S}^2$ as scale parameters and 1 as the rate parameter. Following a
 174 few trials, the rate parameter of log-gamma distribution with scale parameter $1/\tau_{c3}^2$ is changed to 0.5
 175 (instead of 1) to bring the INLA estimates of τ_{c3} closer to its RLMM counterpart. With these settings, the
 176 GMM is regressed using the *inla* function of *R-INLA* package.

177 Kotha et al. (2020) derived two sets of K20 mixed-effects estimates: robust approach (RLMM)
 178 where random-effects and residuals follow a Huber loss distribution (Huber 1992), and a *classical* approach
 179 (LME) where random-effects and residuals follow a Gaussian distribution (*lme4* by Bates et al. 2015). At the
 180 time of this study, the *inla* function of *R-INLA* package failed to converge for any error distribution (e.g.,
 181 student-t) other than the Gaussian. Consequently, the INLA mixed-effects estimates cannot be expected to
 182 coincide with RLMM estimates, but perhaps be closer to LME estimates.

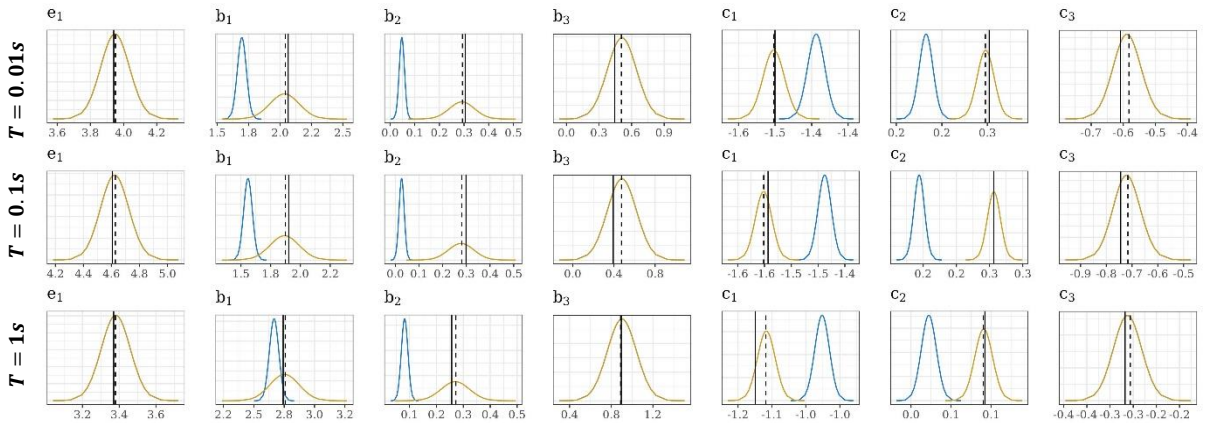


Fig.5: Joint distributions of Kotha et al. (2020) GMM fixed-effects coefficients at $T = 0.01, 0.1, 1s$ (top - to - bottom). The black solid lines are robust (RLMM) estimates, the black dashed lines are classical (LME) estimates, the yellow curves are the joint distributions estimated in the Bayesian (INLA) regression of K20 GMM with ESM, and the blue curves are the joint distributions from the Bayesian (INLA) update of K20 using Résif dataset.

184 Fig.5 shows the fixed-effects ($e_1, b_1, b_2, b_3, c_1, c_2, c_3$) estimates from multiple regressions: the black
 185 solid lines are robust RLMM estimates, the black dashed lines are the ordinary-least square LME estimates,
 186 and the yellow curves are the joint distributions estimated in the Bayesian regression of K20 GMM
 187 (assuming Gaussian errors). The blue curves are those from the Bayesian update of K20 with Résif dataset,
 188 and will be discussed in the [Results](#) section. Fig.5 indicates that the RLMM, LME, INLA fixed-effects estimates
 189 from ESM dataset are in reasonably good agreement, with the maximum likelihood estimates of LME
 190 (dashed lines) falling closer to the medians of INLA joint distributions (yellow curves) than those of RLMM
 191 (solid lines). This confirms that, at least the fixed-effects estimates from INLA can be used as reliable priors
 192 in the subsequent Bayesian update. In addition, although not shown here, the fixed-effects variance-
 193 covariance matrices were almost identical; which means, the within-model epistemic uncertainty (σ_μ , Atik
 194 and Youngs 2014) from RLMM and INLA can be used interchangeably.

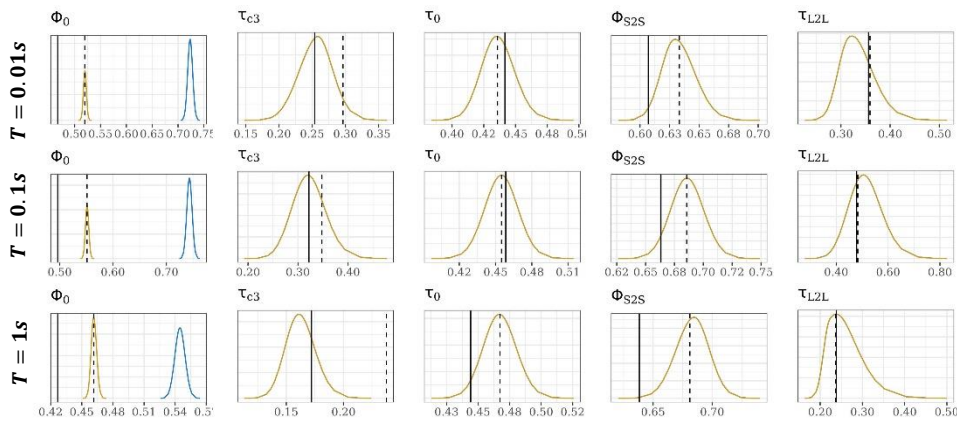


Fig.6: Joint distributions of Kotha et al. (2020) GMM random-effects standard-deviations at $T = 0.01, 0.1, 1s$ (top-to-bottom). The black solid lines are robust (RLMM) estimates, the black dashed lines are classical (LME) estimates, the yellow curves are the joint distributions estimated in the Bayesian (INLA) regression of K20 GMM with ESM, and the blue curves are the joint distributions from the Bayesian (INLA) update of K20 using Résif dataset.

195

196 Fig.6 is similar to Fig.5 but shows instead the residual and random-effects standard-deviations
 197 ($\phi_0, \tau_{c3}, \tau_0, \phi_{s2s}, \tau_{L2L}$) from RLMM (solid black lines), LME (dashed black lines), and INLA (yellow curves)
 198 approaches to inferring K20 from ESM. The difference in RLMM and LME standard-deviations are clearer
 199 in Fig.6, where the former are often smaller than the latter as a consequence of down-weighting outlier data
 200 from their estimations. The INLA estimates of ϕ_0 and ϕ_{s2s} match remarkably well with LME estimates while
 201 being very different from RLMM estimates, indicating possibly a large number of outlier records and sites
 202 in ESM dataset – which the LME is unable to identify. Such differences can be expected between different
 203 regression algorithms due to the various underlying assumptions and approximations (also remarked in
 204 Stafford 2019). For the purpose of this study, however, they are considered reasonably similar and
 205 interchangeable. The INLA mixed-effects joint distributions obtained for ESM dataset will be used as
 206 informative priors in Bayesian update of K20 using Résif dataset.

207 3.2 Bayesian update of K20 GMM with Résif dataset

208 The data selection procedure described in the [Datasets](#) section resulted in 15586 records in Résif dataset
 209 available for the Bayesian update at $T = 0.01s$; which falls to 10450 at $T = 1s$, and 3558 at $T = 2s$. The
 210 marginal distributions of K20 mixed-effects – the yellow curves in Fig.5 and Fig.6 – can be used as
 211 informative priors in the Bayesian update using Résif dataset.

212 Initial attempts with the *inla* function allowed simply updating the K20 mixed-effects with the
 213 natural-log of ground-motion values in Résif dataset as likelihoods. Following the INLA package update
 214 (version 23.04.24) the regressions have become unstable and produced nonsensical GMM coefficients. To
 215 remedy this, the Bayesian update is performed on the *Residuals* obtained by subtracting K20 fixed-effects
 216 (median, equations 2-4) prediction from natural-log of Résif ground-motions ($\ln(GM)$), as in equation (5).
 217 Accordingly, the priors for the fixed-effects are those shown in Fig.5 but instead centred on zero, because
 218 the fixed-effects trends are already removed from the Résif data via equation (5). Therefore, the *Residuals*
 219 regressed in equation (6) produce δ estimates of the fixed-effects. The δ estimates are then added to the
 220 K20 median of priors of fixed-effects to obtain their conjugate posteriors.

$$Residuals = \ln(GM) - \left(e_1 + f_{R,g}(M_W, R_{JB}) + f_{R,a}(R_{JB}) + f_M(M_W) \right) \quad (5)$$

$$Residuals = \delta e_1 + \delta b_1 + \delta b_2 + \delta b_3 + \delta c_1 + \delta c_2 + \delta c_3 + \Delta c_{3,r} + \Delta L2L_l + \Delta B_{e,l}^0 + \Delta S2S_s + \epsilon \quad (6)$$

221 Through several trials it is understood that the Bayesian updates (of GMMs) are rather sensitive to
 222 the priors and the *restrains* placed on them. The effect of restrains, i.e., to allow random-effects parameter
 223 to be updated or to remain fixed, will be shown in the [Discussion](#) section. Only the trial considered to be
 224 producing the most *defensible* GMM update is discussed here. These restrains were placed on specific fixed-
 225 effects; meaning, certain coefficients among $(e_1, b_1, b_2, b_3, c_1, c_2, c_3)$ were restrained from being updated:

- 226 • e_1 is the offset, bias or intercept of the GMM median (equation 1). This fixed-effects coefficient is
 227 indispensable in a GMM regression, but has no strict physical meaning. A positive δe_1 (equation 6)
 228 following the update would shift the GMM median to higher values for all $[M_W, R_{JB}]$ combinations –
 229 both ergodic and non-ergodic predictions. This can be considered *indefensible* because the Résif
 230 dataset does not have the same $[M_W, R_{JB}]$ range as ESM, and the updated coefficients should
 231 (preferably) not effect predictions beyond the $[M_W, R_{JB}]$ range of the new dataset.

232 In addition, the $\delta L2L_l$ values are added to e_1 to obtain partially non-ergodic predictions via
 233 the GMM logic-tree (level 2 in Fig.1). Since, the K20 estimate of e_1 is a pan-European average,
 234 modifying e_1 may render the ESM estimates of $\delta L2L_l$ incompatible with K20. In order to be able to
 235 compare $\delta L2L_l$ of the new Résif tectonic localities (in left panel of Fig.4) to those estimated using ESM,
 236 it was deemed necessary to restrain e_1 from updating. Therefore, e_1 is not updated by fixing $\delta e_1 =$
 237 0 in equation (6).

- 238 • b_1, b_2 fixed-effects coefficients control the scaling of ground-motions with M_W (equation 4) for events
 239 with $M_W \leq M_h = 5.7$. Since Résif dataset contains data from events with $2 < M_W < 5$, it is necessary
 240 to allow b_1, b_2 to be updated. It is important to note that, e_1 is positively correlated to b_1, b_2 (discussed

241 in Kotha et al. 2022). Therefore, constraining $\delta e_1 = 0$ or not strongly effects the update of b_1, b_2 . In this
242 study, $\delta b_1, \delta b_2$ in equation (6) are allowed to take non-zero values.

- 243 • b_3 fixed-effects coefficient controls the scaling of ground-motions with M_W (equation 5) for events
244 with $M_W > M_h = 5.7$. Although b_3 is allowed to be updated, the $[M_W, R_{JB}]$ range of the Résif dataset
245 should not affect it. In this study, δb_3 in equation (6) is allowed to obtain non-zero values.
- 246 • c_1, c_2 fixed-effects coefficients control the linear-decay of ground-motions with R_{JB} and $[M_W, R_{JB}]$,
247 respectively. Equation (2) models the geometric attenuation of ground-motions via weakly correlated
248 c_1, c_2 (discussed in Kotha et al. 2022). Bindi and Kotha (2020) observed that geometric spreading could
249 be region-specific due to regional differences in near-surface crustal structure, and seismogenic
250 depths. Since the hypocentral depth of small events are often poorly constrained, there was no
251 concrete reason to restrict these coefficients from updating. Therefore, $\delta c_1, \delta c_2$ are allowed to obtain
252 non-zero values.
- 253 • c_3 fixed-effects coefficient controls the exponential-decay of ground-motions with R_{JB} . Equation (3)
254 models the so-called ‘apparent anelastic’ attenuation of ground-motions at far-source distances. This
255 parameter is regionalised via $\delta c_{3,r}$ in equation (3). The c_3 estimated from ESM are the pan-European
256 averages, to which region-specific $\delta c_{3,r}$ values can be added (level 1 in Fig.1) to obtain region-specific
257 predictions. $\delta c_{3,r}$ values are estimated for new Résif regions beyond the ESM coverage (Fig.4). In this
258 study, similar to argument made against updating e_1 , in order to main the compatibility of ESM based
259 c_3 and $\delta c_{3,r}$ values, and to evaluate $\delta c_{3,r}$ values of new Résif regions against those from ESM, c_3 is not
260 allowed to change during the Bayesian update by constraining $\delta c_3 = 0$ in equation (6).
- 261 • The marginals of all random-effects groups $\Delta c_{3,r} = N(0, \tau_{c3}), \Delta L2L_l = N(0, \tau_{L2L}), \Delta B_{e,l}^0 = N(0, \tau_0)$,
262 and $\Delta S2S = N(0, \phi_{S2S})$ are restricted from being updated. The random-effect values of the levels
263 within each group – say, the $\delta c_{3,r}$ of a region r in $\Delta c_{3,r} = N(0, \tau_{c3})$ group – are estimated with respect
264 to their group variance. In doing so, for example, the $\delta c_{3,r}$ values of regions common to both datasets
265 are *not updated* but *re-estimated* using the new Résif data; and are compared to their ESM based
266 estimates in Supplementary Figures. This has been decided after several trials, but there is no clear
267 reason as to whether they should be or not. The only justification is that, allowing one or more of these
268 parameters to update led to instabilities in regression across the spectral period range. This study
269 discusses the results of the trial where none of the random-effects are allowed to update, but this issue
270 will be revisited in the [Discussion](#) section.

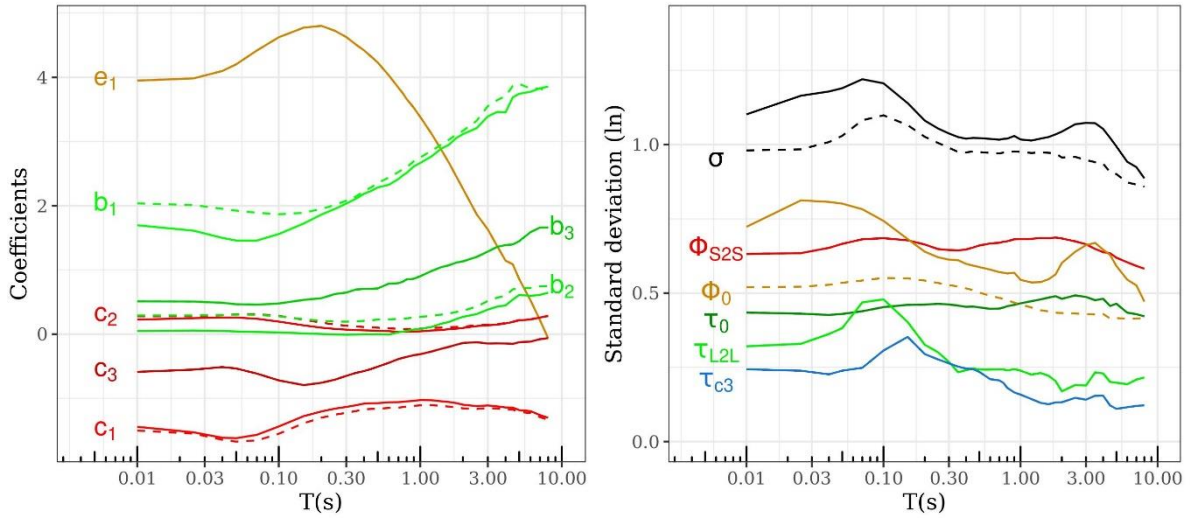


Fig.7: Comparison of ESM (dashed lines) inferred and Résif (solid lines) updated GMM fixed-effects coefficients (left panel), random-effects and residual standard-deviations (right panel)

271

272 4 RESULTS

273 Bayesian inference of K20 from ESM and subsequent update using Résif data were performed for *RotD50*
 274 combination of horizontal spectral accelerations at periods $T = 0.01 - 8s$, *PGA* and *PGV*. Fig.7 compares
 275 the fixed-effects (left panel) and random-effects (right panel) values inferred from ESM (dashed lines) and
 276 updated using Résif (solid lines) datasets.

277 4.1 Fixed-effects

278 Fig.5 and the left panel of Fig.7 show the behaviour of the fixed-effects coefficients following the Bayesian
 279 update. Coefficients e_1 and c_3 are restricted from updating, so there is not much to discuss except for a
 280 remark that: $\delta L2L_l$ and $\delta c_{3,r}$ values estimated from ESM - for regions not present in Résif - will remain
 281 usable even after the update. Regarding the other coefficients:

- 282 • b_1, b_2 fixed-effects coefficients exhibit the largest changes. The blue curves in Fig.5 suggest that both
 283 these coefficients have lower uncertainty following the update, as indicated by the posteriors (blue curves)
 284 narrower than the priors (yellow curves). Fig.7 suggests that at short-periods both coefficients
 285 have updated values (solid lines) smaller than those of K20 (dashed lines), although the changes are
 286 less significant for b_1 . The effect of these changes in GMM median predictions can be observed in Fig.8.
 287 In the lower panels of Fig.8 showing the scaling of spectral accelerations at $T = 0.01, 0.1, 1s$ (left-to-
 288 right) with M_w , the faded lines correspond to ESM based K20 predictions, overlain by solid lines from
 289 updated predictions. The updated predictions are lower than K20 predictions at $M_w \leq 4$ at all distance
 290 ranges. However, the smallest events considered hazard relevant in most PSHA studies, even in low
 291 seismicity regions, are of $M_w \geq 4.5$. Therefore, changes in b_2 shown here do not affect the ESHM20.

292 A more interesting aspect of this update is that b_2 values are now close-to-zero as opposed to
 293 being positive in K20. While discussing the purpose of various fixed-effects coefficients, Kotha et al.
 294 (2022) acknowledged that while empirically b_2 takes positive values in K20, theoretically it should
 295 take non-positive values as proposed by Fukushima (1996) and Douglas and Jousset (2011). Kotha et

al. (2022) argued that the uncertainty on b_2 and K20 predictions at $M_W \leq 4$ is large due to sparse calibration data in ESM, and the errors in M_W of small events. Although errors in M_W of small French events persist in Résif, the 10000+ records from $M_W \leq 4$ have worked in favour of reducing the uncertainty in b_2 values.

- b_3 fixed-effects coefficient controls the scaling of ground-motions at $M_W > 5.7$. Since the $[M_W, R_{JB}]$ range of Résif dataset falls short, b_3 has remained the same.
- c_1, c_2 fixed-effect coefficients controlling the geometric attenuation exhibit only marginal changes in their median values (Fig.5 and left panel of Fig.7) but have lower uncertainties than in K20. The update has mostly unnoticeable impact on predictions at near-source distances (e.g., $\leq 30\text{km}$).

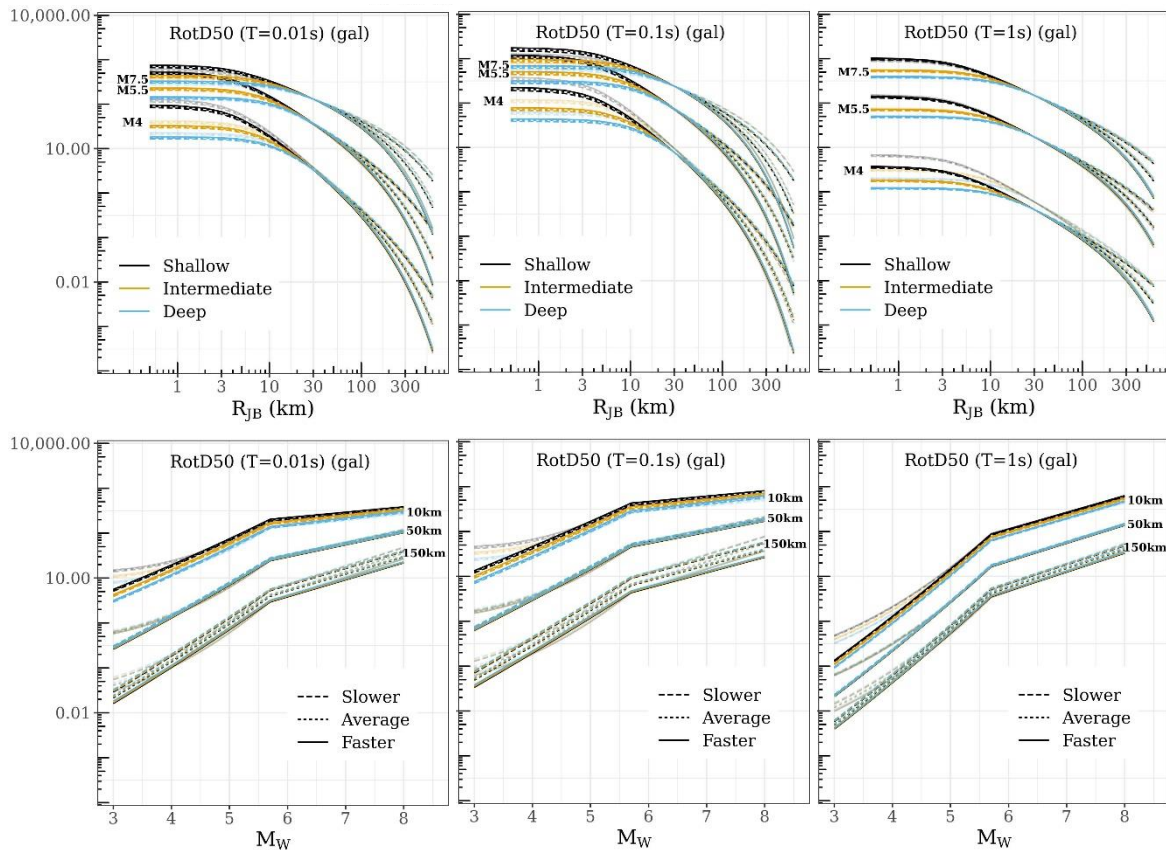


Fig.8: Comparison of ESM inferred (faded lines) and Résif-RAP updated (strong lines) scaling of spectral accelerations at $T = 0.01\text{s}, 0.1\text{s}, 1\text{s}$ (left-to-right columns) with distance metric R_{JB} (top panels) and with M_W (bottom panels). The curves are colour coded according to the hypocentral depth-bin of the event, and the curves' line-type changes with attenuation region - details in Kotha et al. (2020, 2022)

In summary, the only remarkable changes following the update are the lower uncertainties on the fixed-effects coefficients that were allowed to be updated, and b_2 values that better confirm with analytical expectations. The impact on median predictions is largely unnoticeable, and may even be irrelevant to most PSHA studies. However, prospective PSHA studies in low-moderate seismicity regions such as France, Germany, United Kingdom, and regions effected by local induced seismicity composed of small events, this Bayesian update of K20 may be more appropriate with its improved predictions at $M_W \leq 4$.

312 As a side note, a trial regression where e_1 was allowed to update had increased its value ($\delta e_1 > 0$)
 313 at short-periods, which traded-off with a stronger decrease in b_2 on to negative values. This increase in e_1
 314 combined with decrease in b_2 rendered only minor changes in predictions in the range $3.5 < M_W < 4.5$, but
 315 led to an increase in GMM median predictions by up to 50% at $M_W > 5.7$. Since that would be an update
 316 difficult to substantiate, the decision to restrain e_1 from updating was considered more defensible.
 317 Similarly, allowing c_3 to update also increased its values. However, the updated (less negative) c_3 in
 318 combination with ESM based $\delta c_{3,r}$ values would have suggested anelastic *amplification* at far-source
 319 distances in a few ESM regions. Therefore, not allowing c_3 to update was considered appropriate. It is
 320 important to note again that, the restraints chosen in this study are appropriate for this dataset, but may
 321 need revision for other datasets.

322 4.2 Random-effects

323 Fig.6 and the right panel of Fig.7 show the behaviour of the random-effects standard-deviations following
 324 the Bayesian update. Since all the random-effect variances are restricted from updating, neither of these
 325 plots show curves corresponding to the Résif update – except ϕ_0 . The random-effects (variability)
 326 components of a mixed-effects GMM are as important as the fixed-effects (median) component. Higher
 327 random-effects standard-deviations, if treated as aleatory variabilities, contribute to the total ground-
 328 motion aleatory variability (σ in Fig.7) – which in-turn yield *conservative* hazard estimates with extreme
 329 ground-motions becoming more likely (e.g., Bommer and Abrahamson 2006). When instead treated as
 330 epistemic uncertainties, the random-effects standard-deviations can be discounted from the total ground-
 331 motion variability, and used in GMM logic-tree. For example, Weatherill, Kotha and Cotton (2020) used τ_{c3}
 332 and τ_{L2L} to define the attenuation uncertainties in the ESHM20 shallow crustal GMM logic-tree. Since
 333 neither of τ_{c3} and τ_{L2L} is changed in this update, the ESHM20 logic-tree is not impacted.

334 In this study, as important as the random-effects *groups'* standard-deviations ($\tau_{c3}, \tau_0, \phi_{S2S}, \tau_{L2L}$)
 335 themselves are the random-effects values ($\delta c_{3,r}, \delta B_{e,l}^0, \delta S2S_s, \delta L2L_l$) of the *levels* within the groups. For
 336 instance, τ_{c3} is a quantification of spatial variability of far-source attenuation in ESM ground-motion data,
 337 when regionalised using Basili et al. (2019). The group in this case is 'far-source attenuation regions', and
 338 the levels are the 'far-source attenuating regions' within Basili et al. (2019) regionalisation model. When τ_{c3}
 339 is the (group) standard-deviation, $\Delta c_{3,r} = N(0, \tau_{c3})$ is the Gaussian random-variable with unique $\delta c_{3,r}$
 340 values for each (level) region r . Fig.1 is a logic-tree using region-specific $\delta c_{3,r}$ and $\delta L2L_l$ values from Kotha
 341 et al. (2020), and is different from that of Weatherill, Kotha and Cotton (2020) using τ_{c3} and τ_{L2L} values.
 342 Similarly, $\Delta S2S_s = N(0, \phi_{S2S})$ can be used to make site-specific hazard and risk assessments as
 343 demonstrated in, e.g., Kotha, Bindi and Cotton (2017), and Kohrangi, Kotha and Bazzurro (2020),
 344 respectively.

345 It is important to note also that, the random-effects level values ($\delta c_{3,r}, \delta B_{e,l}^0, \delta S2S_s, \delta L2L_l$) are
 346 estimated from the group standard-deviations ($\tau_{c3}, \tau_0, \phi_{S2S}, \tau_{L2L}$), respectively. This means that, the ($\delta c_{3,r},$
 347 $\delta B_{e,l}^0, \delta S2S_s, \delta L2L_l$) and their standard-errors (e.g., the *SE* in Fig.1) are sensitive to ($\tau_{c3}, \tau_0, \phi_{S2S}, \tau_{L2L}$) values

348 being updated or not. The methods to estimate $\delta B_{e,l}^0$ (or δB_e) and δS_2S_s using τ_0 (or τ) and $\phi_{S_2S_s}$,
 349 respectively, were already presented in earlier studies (e.g., Abrahamson and Youngs 1992, Stafford 2014,
 350 Bradley 2015, etc). In this study, $(\tau_{c_3}, \tau_0, \phi_{S_2S_s}, \tau_{L_2L_l})$ are restrained from being updated. The following
 351 subsections discuss the $(\delta c_{3,r}, \delta B_{e,l}^0, \delta S_2S_s, \delta L_2L_l)$ estimated under these restrains.

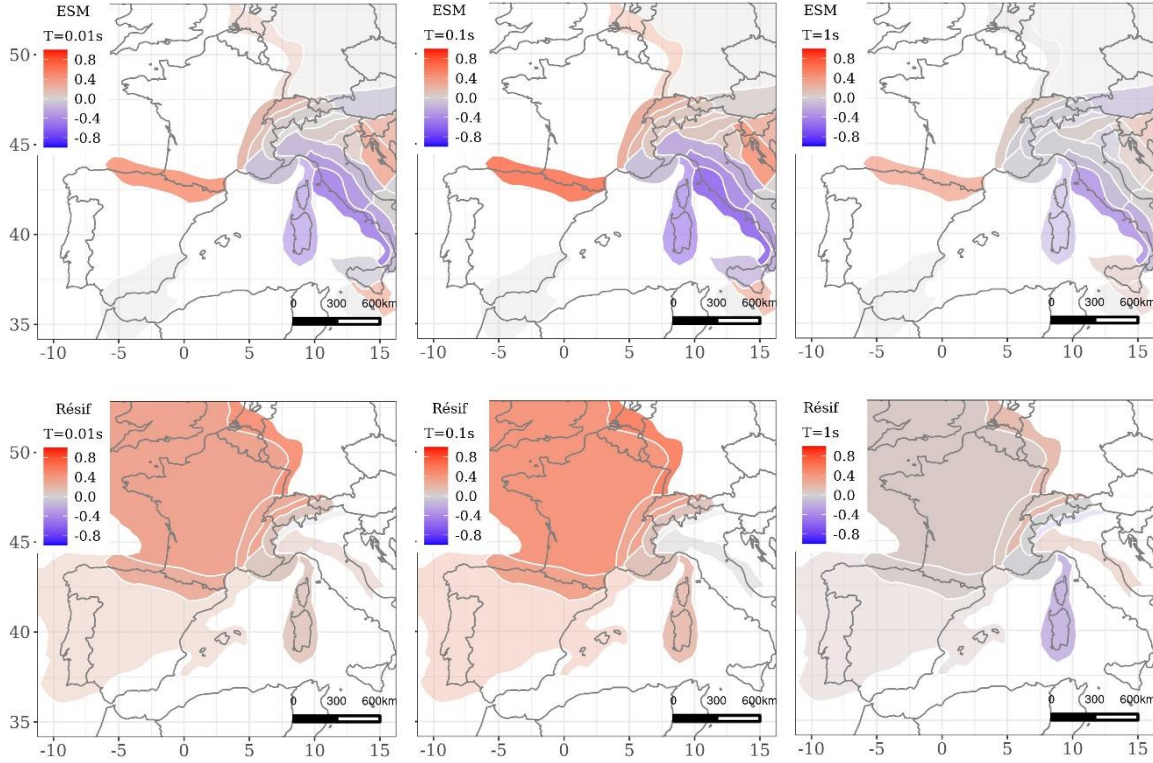


Fig.9: Comparison of ESM inferred (top) and Résif inferred (bottom) region-to-region variability of apparent far-source anelastic attenuation random-effects group $\Delta c_{3,r} = N(0, \tau_{c_3})$

352

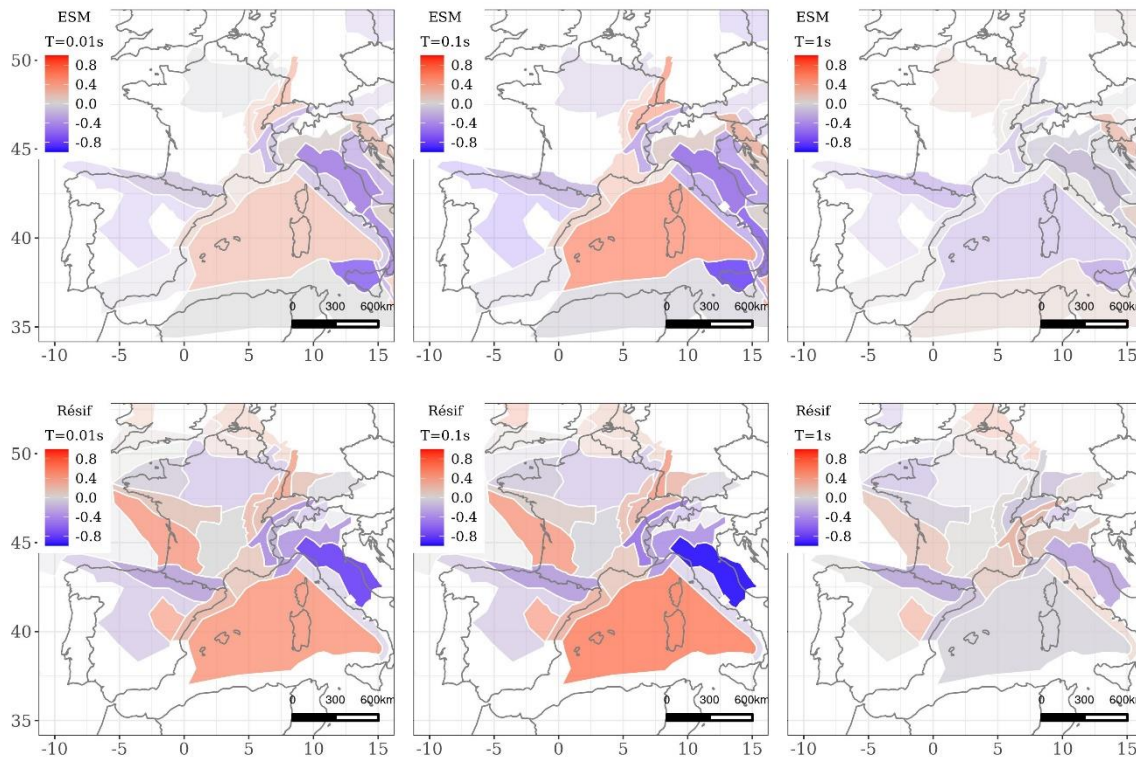
353 4.2.1 Attenuation variability: $\Delta c_{3,r} = N(0, \tau_{c_3})$

354 Fig.9 shows the $\delta c_{3,r}$ values of the various far-source attenuation regions estimated using ESM (top panels)
 355 and Résif (bottom panels) datasets at spectral periods $T = 0.01, 0.1, 1s$ (left-to-right). Clearly, the regions
 356 newly populated with Résif data (right panel of Fig.4) now have region-specific $\delta c_{3,r}$ values; which were to
 357 be otherwise assigned the pan-European average c_3 values with $\delta c_{3,r} = 0$ in equation (3).

358 The ‘red regions’ in Fig.9 are those with $\delta c_{3,r} > 0$ values, and are supposed to exhibit
 359 *weaker/slower* far-source attenuation than the pan-European average with $\delta c_{3,r} = 0$. Partially non-ergodic
 360 region-specific ground-motion predictions (from level 1 of Fig.1) for these red regions would therefore be
 361 larger than those predicted for ‘white/grey’ and ‘blue’ regions, with pan-European average $\delta c_{3,r} = 0$ and
 362 *stronger/faster* attenuation characteristics with $\delta c_{3,r} < 0$, respectively. However, despite the surplus of
 363 Résif data in France, since the regionalisation model itself does not distinguish regions within France, there
 364 is not much to infer from these maps regarding the variability of far-source attenuation. The crustal
 365 tomography maps of Mayor et al. (2018) image France as multiple regions with distinct intrinsic absorption
 366 Q_i/Q_m characteristics in different frequency bands – except the Parisian basin with no data ($0^\circ - 5^\circ$ East and

367 47° - 50°North). The Basili et al. (2019) model did not adopt the Mayor et al. (2018) findings in their
 368 regionalisation of France, because neither were specifically designed for GMM attenuation regionalisation.

369 Supplementing Fig.9, Fig.S1 shows that the $\delta c_{3,r}$ values for some of the regions common to both
 370 ESM and Résif datasets are rather similar, and with lower uncertainty following the update. However, there
 371 are as well regions with very different values estimated from ESM and Résif datasets, e.g., Pyrenees (-5° -
 372 2°East and 42° - 45°North) and Corsica Sardinia (10°E and 38° - 43°N). The latter contains only about a dozen
 373 ground-motion records in Résif dataset and will be ignored for the time being. The Pyrenees region
 374 however, has a few 100s of new Résif records that were absent in ESM, and now is assigned a *less extreme*
 375 positive $\delta c_{3,r}$ value. The tomography maps of Mayor et al. (2018) showed that the Pyrenees region has an
 376 intrinsic absorption Q_i close to the French national average Q_m , and lower than Brittany region to its north-
 377 west (-5° - 0°E and 46° - 50°N) – suggesting that attenuation in Pyrenees could be stronger (less positive
 378 $\delta c_{3,r}$) than in Brittany. However, none of these features could be captured with the current Basili et al.
 379 (2019) regionalisation model used in K20. Therefore, recognising the need for better refinement on
 380 regionalisation of France, this study will be followed-up by an evaluation and redesign of the regionalisation
 381 models used in K20. Meanwhile, this update suggests that far-source attenuation in France is on average
 382 *always* weaker/slower than elsewhere in pan-European region covered by ESM, and especially, in
 383 comparison to the stronger/faster attenuation inferred for the highly active regions of Central Italy.
 384 Consequently, ergodic GMMs developed using ground-motions recorded primarily at stations located in
 385 Italy may severely under-predict far-source ground-motions observable in France.



386 **Fig.10: Comparison of ESM inferred (top) and Résif inferred (bottom) tectonic locality-to-locality variability of at-source attenuation random-effects group $\Delta L2L_l = N(0, \tau_{L2L})$**

387 4.2.2 Tectonic variability: $\Delta L2L_l = N(0, \tau_{L2L})$

388 Fig.10 shows the $\delta L2L_l$ values of the various tectonic localities estimated using ESM (top panels) and Résif
389 (bottom panels) datasets at spectral periods $T = 0.01, 0.1, 1s$ (left-to-right). Similar to Fig.9, the localities
390 newly populated with Résif data (right panel of Fig.4) now have locality-specific $\delta L2L_l$ values; which were
391 to be otherwise assigned average pan-European e_1 values in equation (1).

392 The ‘red regions’ in Fig.10 are those with $\delta L2L_l > 0$ values, and are supposed to exhibit *lower* at-
393 source attenuation than the pan-European average with $\delta L2L_l = 0$. Partially non-ergodic locality-specific
394 ground-motions (from level 2 of Fig.1) for these red localities would therefore be larger than those
395 predicted for ‘white/grey’ and ‘blue’ localities, with pan-European average with $\delta L2L_l = 0$ and *stronger* at-
396 source attenuation characteristics with $\delta L2L_l < 0$, respectively. Unlike the far-source attenuation
397 regionalisation in Fig.9, the at-source attenuation regionalisation in Fig.10 appears to capture a greater
398 spatial variability within France. For instance, tectonic localities in Fig.10 are distinct for the Pyrenees (-5°
399 - 2°E and 42° - 45°N), the Parisian basin (0° - 5°E and 47° - 50°N), and the Brittany regions (-5° - 0°E and 46°
400 - 50°N) – the latter two were merged into one far-source attenuation region in Fig.9. In this study, it is
401 important to reintroduce and clarify the meaning of *at-source* attenuation.

402 Both K20 and Kotha, Bindi and Cotton (2022) adopted the tectonic localities of Danciu et al. (2021)
403 (left panel of Fig.4) to regionalise (or localise) ground-motion data and quantify source related attenuation
404 characteristics in the ESM dataset. In those studies, the τ_{L2L} took larger values – indicating a greater regional
405 variability – at short spectral periods ($T < 1s$) and high frequencies ($f > 1Hz$). However, random-effects
406 and residual analyses showed that the $\Delta L2L_l = N(0, \tau_{L2L})$ were poorly correlated to any available physical
407 parameters at that time. For instance, $\Delta L2L_l$ showed no correlation with Brune (1970) stress-drop
408 estimated by Bindi and Kotha (2020) of events originating the tectonic localities. $\Delta L2L_l$ showed some
409 negative correlation to Activity Index (Aix) of Chen et al. (2018), which in-turn is a fuzzy combination of
410 1Hz coda Q, crustal shear-wave velocity at 175km, and seismic moment rate density parameters. Meaning,
411 tectonic localities with higher Aix had on-average lower $\delta L2L_l$ values (and the other way), but it was
412 inconclusive which of the three Chen et al. (2018) crustal parameters are responsible for the correlation.
413 Essentially, $\delta L2L_l$ was assigned no physical meaning in Kotha, Bindi and Cotton (2022).

414 In this study, upon comparing the crustal tomography maps of Mayor et al. (2018) with the $\Delta L2L_l$
415 spatial variability in Fig.10, it becomes evident that the regions with higher Q_i/Q_m often coincide with
416 tectonic localities with $\delta L2L_l > 0$ (e.g., the Brittany region), and those with lower Q_i/Q_m coincide with
417 tectonic localities with $\delta L2L_l < 0$ (e.g. the Pyrenees region). Note that a higher intrinsic absorption *quality-*
418 *factor* Q_i/Q_m implies lower attenuation. Based on this observation, this study hypothesises that the regional
419 variability of source-effects captured by $\Delta L2L_l = N(0, \tau_{L2L})$ – via the tectonic localities of Danciu et al.
420 (2021) – could in fact be related to intrinsic absorption quality-factor Q_i/Q_m at the earthquake source
421 location and the Earth’s crust immediately around its hypocentre. Therefore, in this study, the tectonic
422 localities random-effects group is hypothesised to be capturing the at-source attenuation characteristics.
423 Based on this hypothesis, evidently, the earthquakes originating in the Brittany region with $\delta L2L_l > 0$
424 suffered weaker at-source attenuation by virtue of the region’s lower intrinsic absorption as indicated by
425 its higher Q_i/Q_m . Supplementary to Fig.10, Fig.S2 shows that the $\delta L2L_l$ values for the tectonic localities

426 common to both ESM and Résif datasets are rather similar at short periods $T < 1s$, and with lower
 427 uncertainty following the update.

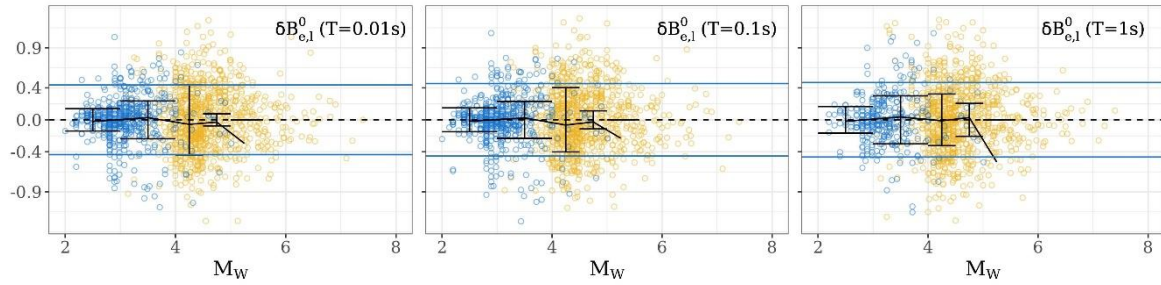


Fig.11: Comparison of $\delta B_{e,l}^0$ trends versus M_W of ESM events (yellow) and Résif-RAP events (blue), at $T = 0.01, 0.1, 1s$ (left-to-right)

428

429 4.2.3 Between-event variability: $\Delta B_{e,l}^0 = \mathcal{N}(0, \tau_0)$

430 Fig.11 shows the trend of $\delta B_{e,l}^0$ with M_W of ESM events (yellow markers) and Résif events (blue markers) at
 431 spectral periods $T = 0.01, 0.1, 1s$ (left-to-right). The $\delta B_{e,l}^0$ versus M_W plots are customarily used to verify if
 432 the M_W -scaling component of GMM (equation 4) is appropriate for the dataset. Absence of any systematic
 433 trends confirm that the Bayesian update efficiently removed M_W -scaling from Résif ground-motion data.
 434 However, it appears that the *scatter* of $\delta B_{e,l}^0$ of $M_W < 4$ Résif events is rather *narrow*, suggesting that the
 435 between-event variability of such small events is in fact lower than that of $4 < M_W < 5.7$ events in ESM
 436 dataset. This observation is counter to the general consensus on heteroskedastic M_W -dependent between-
 437 event variability $\tau_0(M_W)$ (e.g., Youngs et al. 1995).

438 K20 proposed a heteroskedastic model with a large $\tau_0(M_W)$ at $M_W < 5$, decreasing linear with M_W
 439 and reaching about a 20% smaller $\tau_0(M_W)$ at $M_W \geq 6.5$. The heteroskedastic model used in ESHM20 is a
 440 Weatherill, Kotha and Cotton (2020) adoption of the Al Atik (2015) proposal. Fig.11 suggests that either of
 441 the above-mentioned heteroskedastic $\tau_0(M_W)$ models can be used with this Bayesian update. However, it is
 442 important to recall that the Bayesian update trial being discussed here is the one with all random-effects
 443 group variances restrained from changing, and that the $\delta B_{e,l}^0$ are estimated directly from the unchanged τ_0 .
 444 If the between-event variability τ_0 is allowed to change, the consequent $\delta B_{e,l}^0$ of the Résif events will
 445 necessarily change. This issue will be revisited in the [Discussion](#) section.

446 Supplementing Fig.11, Fig.S3 compares $\delta B_{e,l}^0$ of the events identified by Laurendeau, Clément and
 447 Scotti (2022) as common to both datasets. While majority of events have similar $\delta B_{e,l}^0$ values inferred from
 448 the two datasets, the events with largest differences in their M_W sourced from EMEC in ESM and Si-HEX in
 449 Résif datasets also show the largest differences in their $\delta B_{e,l}^0$ values. In addition, there appears also an
 450 inverse relation, wherein ESM inferred $\delta B_{e,l}^0$ values are larger than Résif inferred $\delta B_{e,l}^0$ when ESM assigned
 451 M_W are lower than Résif assigned M_W – although not strictly. Laurendeau and Kotha (2023) analysed in
 452 detail the impact of M_W homogenisation/unification on the between-event variability of Kotha, Bindi and
 453 Cotton (2022) Fourier GMM derived from ESM, and discussed the sources of such M_W and $\delta B_{e,l}^0$
 454 discrepancies. Such analyses have not yet been performed on the K20 response spectra GMMs, and are
 455 among the planned activities to follow-up this study.

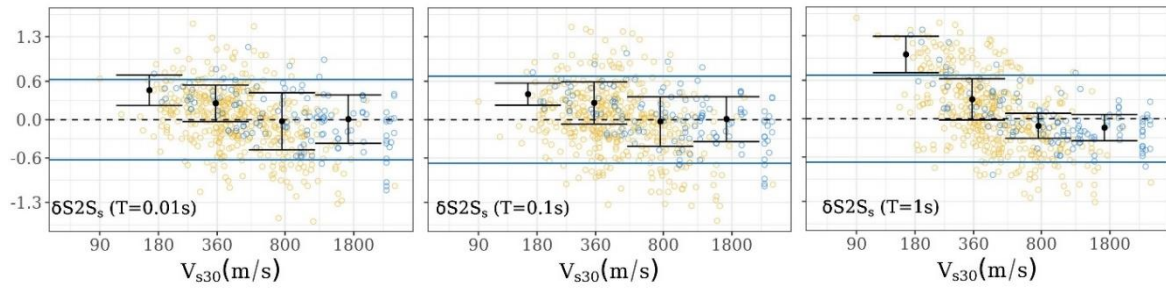


Fig.12: Comparison of $\delta S2S_s$ trends versus measured V_{s30} of ESM stations (yellow) and Résif stations (blue) at $T = 0.01, 0.1, 1s$ (left-to-right)

456

457 **4.2.4 Between-station variability: $\Delta S2S_s = \mathcal{N}(0, \Phi_{S2S})$**

458 Fig.12 shows the trend of $\delta S2S_s$ versus V_{s30} of ESM stations (yellow markers) and Résif stations (blue markers) at spectral periods $T = 0.01, 0.1, 1s$ (left-to-right). The plot offers not much insight except that
 459 the Résif stations with $V_{s30} > 800m/s$ are more numerous. Fig.S4 supplements Fig.12 by comparing the
 460 $\delta S2S_s$ of stations common to both datasets at spectral periods $T = 0.01, 0.1, 1s$ (left-to-right). Most sites
 461 with $\delta S2S_s$ values around the zero-median of $\mathcal{N}(0, \Phi_{S2S})$ distributions appear to have similar values across
 462 datasets, while those at the extremes of the random-distributions are very different. Once again, note that
 463 restraining Φ_{S2S} from updating also effects the $\Delta S2S_s$ estimates. Although not shown here, in trials where
 464 Φ_{S2S} is allowed to update, the between-dataset coherence of $\delta S2S_s$ of common stations noticeably
 465 improves. It is not clear yet whether Φ_{S2S} should be updated or not, but this issue is briefly revisited in the
 466 [Discussion](#) section.
 467

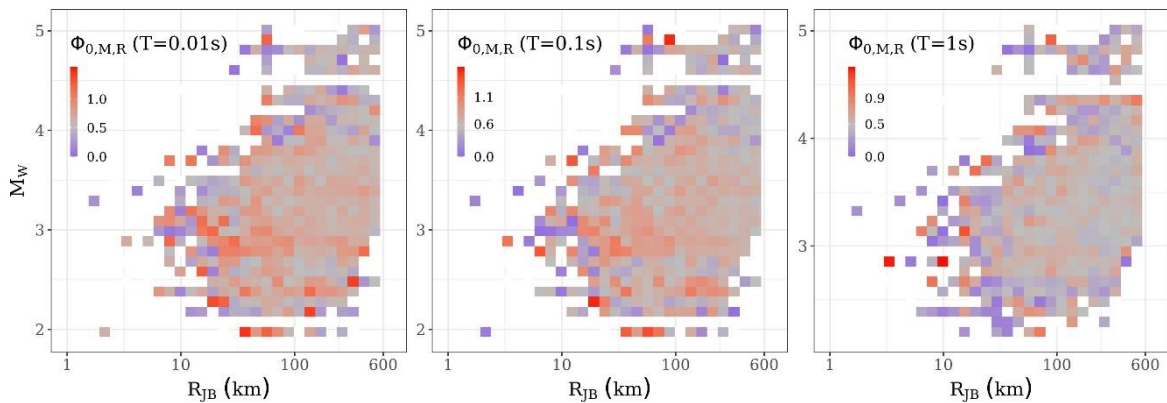


Fig.13: $M_W - R_{JB}$ dependence of residual variability $\phi_{0,M,R}$ at $T = 0.01, 0.1, 1s$ (left-to-right columns).

Note that the colour scale is centred (grey) on the ϕ_0 at that specific period

468

469 **4.3 Residuals: $E = \mathcal{N}(0, \phi_0)$**

470 Fig.6 and Fig.7 compare the standard-deviation of 'left-over' residuals ϕ_0 from ESM and Résif datasets.
 471 Despite all the random-effects and residual standard-deviations being restrained from updating, ϕ_0
 472 becomes larger following the update. This is because, unlike with the random-effects where level-specific
 473 values are estimated from group variances, residual variance is estimated from record-specific residuals
 474 obtained after removing mixed-effects values from the ground-motion observations. The hypothesis in this
 475 study is that the random-effect and residual variances trade-off depending on whether their priors are

476 restrained from updating or not. Here, the *additional* variability of Résif ground-motion data appears to be
 477 absorbed into the residuals and their inflated standard-deviation ϕ_0 .

478 Fig.13 visualises the $M_W - R_{JB}$ dependence of Résif record-to-record variability $\phi_{0,M,R}$ at $T =$
 479 0.01, 0.1, 1s. Here, $\phi_{0,M,R}$ is the standard-deviation of residuals in the 900 evenly spaced $M_W - R_{JB}$ bins
 480 defined solely for visualisation and discussion purpose. The numerous $M_W - R_{JB}$ bins with grey colour are
 481 those where $\phi_{0,M,R}$ is equal to the generic ϕ_0 for that specific period. Moderate deviations of $\phi_{0,M,R}$ from ϕ_0
 482 appear at $30 < R_{JB} < 100km$, where the Résif dataset is densely sampled. Stronger deviations appear at
 483 $0 < R_{JB} < 30km$, where the dataset is poorly sampled. However, at this resolution of $M_W - R_{JB}$ binning, the
 484 deviations are rather irregular between adjacent cells, with steep changes in $\phi_{0,M,R}$; plus, choosing larger
 485 $M_W - R_{JB}$ bins show similar trends with no additional insights. An $M_W - R_{JB}$ dependent heteroskedastic
 486 $\phi_{0,M,R}$ is an option for this update, but perhaps after first evaluating their physical causes. Since both τ_0 and
 487 Φ_{S2S} are restricted from updating, it is likely that the event- and site-dependent variabilities have been
 488 absorbed by the event- and site-specific residuals; which can be captured by period-dependent event-
 489 specific residual standard-deviation $\Phi_{0,e}$ and station-specific residual standard-deviation $\Phi_{0,s}$.

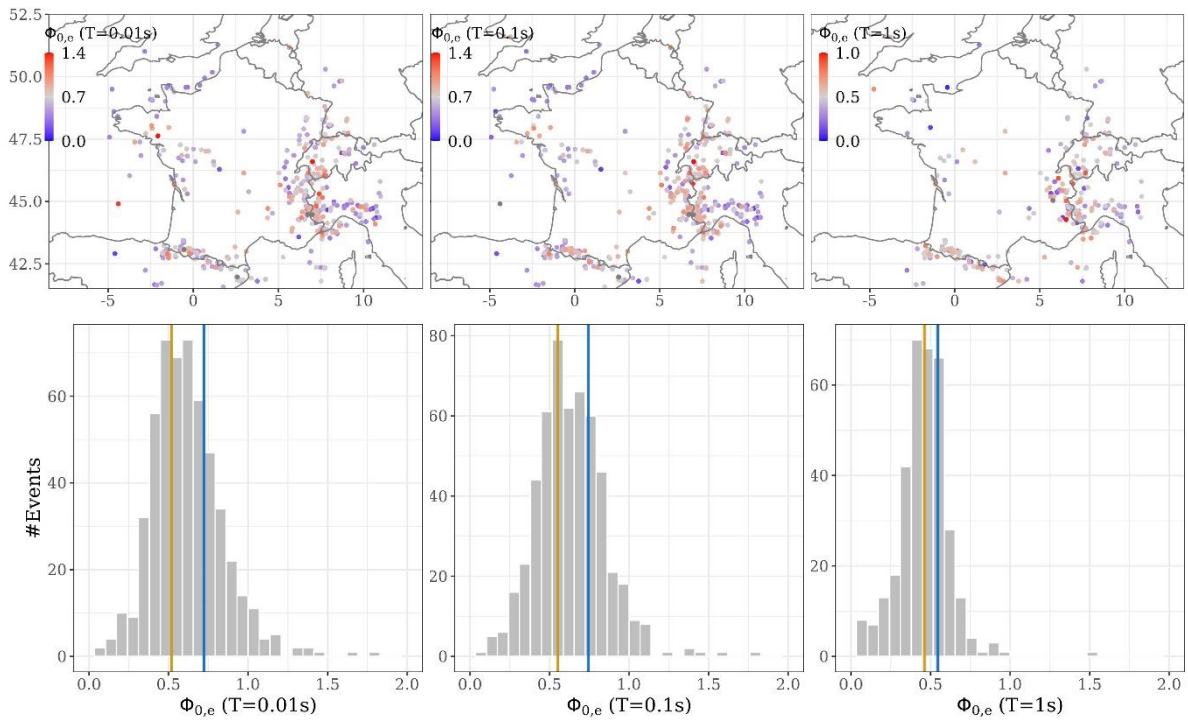


Fig.14: Spatial distribution (top) and histogram (bottom) of event-specific residual variability $\phi_{0,e}$ at $T = 0.01, 0.1, 1s$ (left-to-right). The map colour scales are centred on ϕ_0 (grey) at respective periods, with events of $\phi_{0,e} > \phi_0$ coloured in red, and vice-versa for blue. The histograms are overlain with vertical lines at ϕ_0 of ESM (yellow) and of Résif (blue)

490

491 Fig.14 shows the event-specific residual variabilities $\phi_{0,e}$ at $T = 0.01, 0.1, 1s$; in top panels at event
 492 locations, and in bottom panels as histograms. The histograms suggest that a majority of events have $\phi_{0,e}$
 493 lower than the updated Résif ϕ_0 ; which means, the larger Résif ϕ_0 could have been biased by a few extreme
 494 $\phi_{0,e}$ values. Therefore, it is worth analysing ground-motions of (these few) individual events for an

495 explanation. An immediately noticeable feature in the maps (top panels) is that $\phi_{0,e}$ are systematically
 496 larger (in red) than ϕ_0 for events located at the Italy-France-Switzerland frontier [45°N, 7.5°E] compared
 497 to elsewhere; especially compared to events more eastward in Italy [45°N, 10°E]. The Alpine region on the
 498 Italy-France-Switzerland frontier is geologically a very complex region, which can be hypothesised to have
 499 caused stronger azimuthal variability in propagation effects (e.g., Causse et al. 2021, Laurendeau et al.
 500 2023). It could also be due to the anisotropy in shear-wave radiation pattern of small, point-source
 501 approximal, $M_W < 3$ events in this region (e.g., Dujardin et al. 2018, Kotha, Cotton and Bindi 2019, Trugman,
 502 Chu and Tsai 2021). The deterministic radiation pattern effects can be empirically modelled provided
 503 reliable event hypocentral depth and centroid-moment-tensor solutions are available, and the large $\phi_{0,e}$
 504 can be resolved. However, the crustal heterogeneities around event locations may rapidly render the
 505 radiation patterns stochastic, making it impossible to resolve the large $\phi_{0,e}$ in this region. Another option is
 506 a regionally varying ϕ_0 , but only following an evaluation of its physical meaning. Moreover, such analyses
 507 are more sensible in the Fourier domain than with the response spectra here.

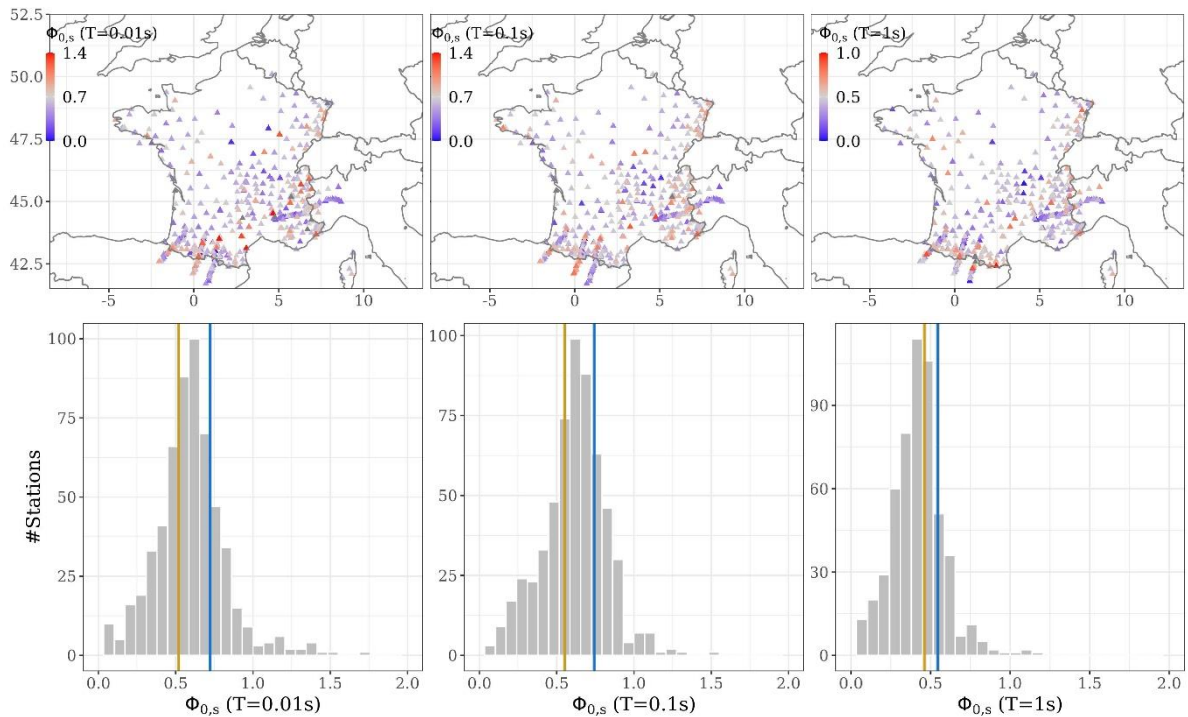


Fig.15: Spatial distribution (top) and histogram (bottom) of station-specific residual variability $\phi_{0,s}$ at $T = 0.01, 0.1, 1s$ (left-to-right). The map colour scales are centred on ϕ_0 (grey) at respective periods, with stations of $\phi_{0,s} > \phi_0$ coloured in red, and vice-versa for blue. The histograms are overlain with vertical lines at ϕ_0 of ESM (yellow) and of Résif (blue)

508

509 Fig.15 shows the station-specific residual variabilities $\phi_{0,s}$ at $T = 0.01, 0.1, 1s$; in top panels at
 510 station locations, and in bottom panels as histograms. The histograms suggest that a majority of stations
 511 have $\phi_{0,s}$ lower than the updated Résif ϕ_0 . As with the events, it is worth analysing ground-motions of
 512 individual stations for an explanation. The maps (top panels) show that a few stations in the Pyrenees region
 513 (-5° - 2°E and 42° - 45°N) show systematically larger $\phi_{0,s}$ (in red) compared to stations elsewhere in France.
 514 Site-responses can become extremely complex, especially at the numerous Résif stations located in basins

515 and valley. Results from this study can help in selecting sites with large $\phi_{0,s}$ for site characterisation
516 missions (e.g., Hollender et al. 2021), to identify reference sites with small $\phi_{0,s}$ (e.g., Pilz, Cotton and Kotha
517 2020, Lanzano et al. 2020, Thompson et al. 2012), and to improve regional site-response maps (e.g.,
518 Weatherill et al. 2023, Parker and Baltay 2022)

519 **5 DISCUSSION**

520 The parametric K20 ground-motion models were developed from the pan-European ESM dataset,
521 quantifying various repeatable physical phenomena as mixed-effects. These models were intended to be
522 evaluated, updated and adapted to new regions as and when new ground-motion datasets become available.
523 Regression of a dataset is essentially a *condensation* of knowledge it provides into an interaction of a few
524 predictable physical parameters. This condensed knowledge can be used as prior information that can be
525 validated and updated with new data as likelihoods. Such an approach to ground-motion prediction is more
526 aptly handled via a Bayesian framework. In this work the first step was to recast the regression of ESM into
527 K20 GMMs in a Bayesian framework; in order to validate the knowledge gained from regression of ESM
528 against Résif ground-motion data, and update as necessary.

529 The Bayesian linear mixed-effects regression of ESM dataset yielded a version of K20 that can be
530 used interchangeably with the published version. While the fixed-effects components of the two versions
531 produce identical median ground-motion predictions, the random-effects and residual components
532 (standard-deviations) are not identical. The published random-effects estimates were from a
533 computationally intense robust regression that iteratively down-weight outlier data, but were not
534 replicable with current capabilities of the INLA algorithm – although this may change in the near future. For
535 the time being, the marginal distributions of mixed-effects inferred from ESM dataset were used as priors
536 to update the K20 with Résif ground-motion data. In process, a few major assumptions had to be made.

537 There are events, stations, and associated ground-motion records common to both datasets. These
538 were few in number, and were retained in the update process. The M_W of events in ESM and Résif datasets
539 are sourced from different catalogues, and based on different selection criteria. It is unreasonable to expect
540 that newer datasets will share the same preferred M_W selection criteria as ESM. Therefore, M_W reported in
541 Résif dataset were used as are. Among the planned activities is a unification/homogenisation of M_W across
542 datasets, and advance this study into Fourier domain as well.

543 ESM dataset regression considered only the surface strong-motion sensors, while all Résif stations
544 were used, irrespective of their installation conditions, to enhance the spatial coverage. The resulting site-
545 specific random-effects can be investigated if this selection criteria can be justified. In this study, there is no
546 such detailed analysis because nothing remarkably peculiar was noticed. However, the outcomes from this
547 study can be used to develop a more application-ready version of the GMM; with revised decisions on which
548 sites should be retained in, for example, developing a companion empirical site-response model for France.

549 Multiple trial regressions were made with various restrains on the mixed-effects, allowing them to
550 be updated or not. Ultimately, a rather *restrained* approach was chosen wherein some of the fixed-effects
551 known to be strongly correlated are locked to their prior values, allowing the others to absorb the possible

552 differences in physical process across the two datasets. The first important outcome, in this approach, is a
553 large correction to the quadratic scaling of ground-motions with M_W . While the model inferred from ESM
554 suggested a counter-intuitive scaling towards small M_W , the Résif update rectified it to a more analytically
555 agreeable scaling. With this update, the K20 model becomes slightly more appropriate for small M_W ground-
556 motion predictions, e.g., those likely to be critical in PSHA of regions with low-moderate tectonic and
557 induced seismicity.

558 The second, equally important outcome, are the regional variabilities of at-source and far-source
559 attenuations connected to event and station locations. The far-source attenuation variability is governed by
560 station location, and can be used to adjust the ‘apparent anelastic’ exponential decay of ground-motions
561 with R_{JB} to be specific to a far-source attenuating region hosting the station. The at-source attenuation
562 variability is governed by the event location. In this study, the at-source attenuation is hypothesised as an
563 intrinsic absorption-scattering process that occurs around the events’ hypocentres, and therefore, effects
564 ground-motion predictions at all distances. ESM dataset had barely enough data to quantify these well-
565 known regional variabilities in attenuation within France. Résif dataset has tremendously increased the
566 capability of K20 to make partially non-ergodic region-specific ground-motions in France; and not-to-
567 mention, site-specific predictions now possible at several dozen new locations all over France.

568 The maps showing spatial variabilities of far-source and at-source attenuation are interesting but
569 offer little insight on the underlying physical processes. Particularly, the attenuation regionalisation model
570 used to quantify far-source attenuation variabilities are in urgent need of refinement. The model used to
571 quantify at-source attenuation variabilities are at-times consistent with crustal tomography maps available
572 for France. This means that, the hypothesis on at-source attenuation may hold– but further investigation is
573 necessary. These crustal tomography models will come handy in refining the regionalisation models.

574 Random-effects quantifying event- and site-specific ground-motion variabilities did not offer much
575 insight into how French events and stations are systematically different from the pan-European sample in
576 ESM. This could be partly because these random-effects priors were restrained from updating, and hence
577 being validated with Résif data. These restrains however appear to have *forced* the ‘left-over’ residuals to
578 accommodate the additional ground-motion variability. This brings to scrutiny the approach of restraining
579 all random-effects variabilities from updating.

580 Fig.16 shows partial results from three distinct Bayesian update trials: Trial 1 is one where all the
581 random-effects group variances were *unrestrained* from updating; Trial 2 is where only the far-source and
582 at-source attenuation random-effects were restrained from updating, leaving the rest unrestrained from
583 updating; Trial 3 is the one presented in this study, with all random-effects variances being restrained to
584 their prior ESM inferred values. The impact of these methodical assumptions is evident in the top panels of
585 Fig.16. Trial 1 suggested that the Résif updated far-source (τ_{c3}) and at-source (τ_{L2L}) attenuation group
586 variabilities coincide with those inferred from ESM, at short periods. At long periods, the updated values
587 become negligibly small and unstable across periods. In turn, the random-effects values for their levels –
588 estimated from their small group variances – were close to zero. Trial 1 outcome was considered
589 unpromising, and needed a remedy – therefore, trial 2.

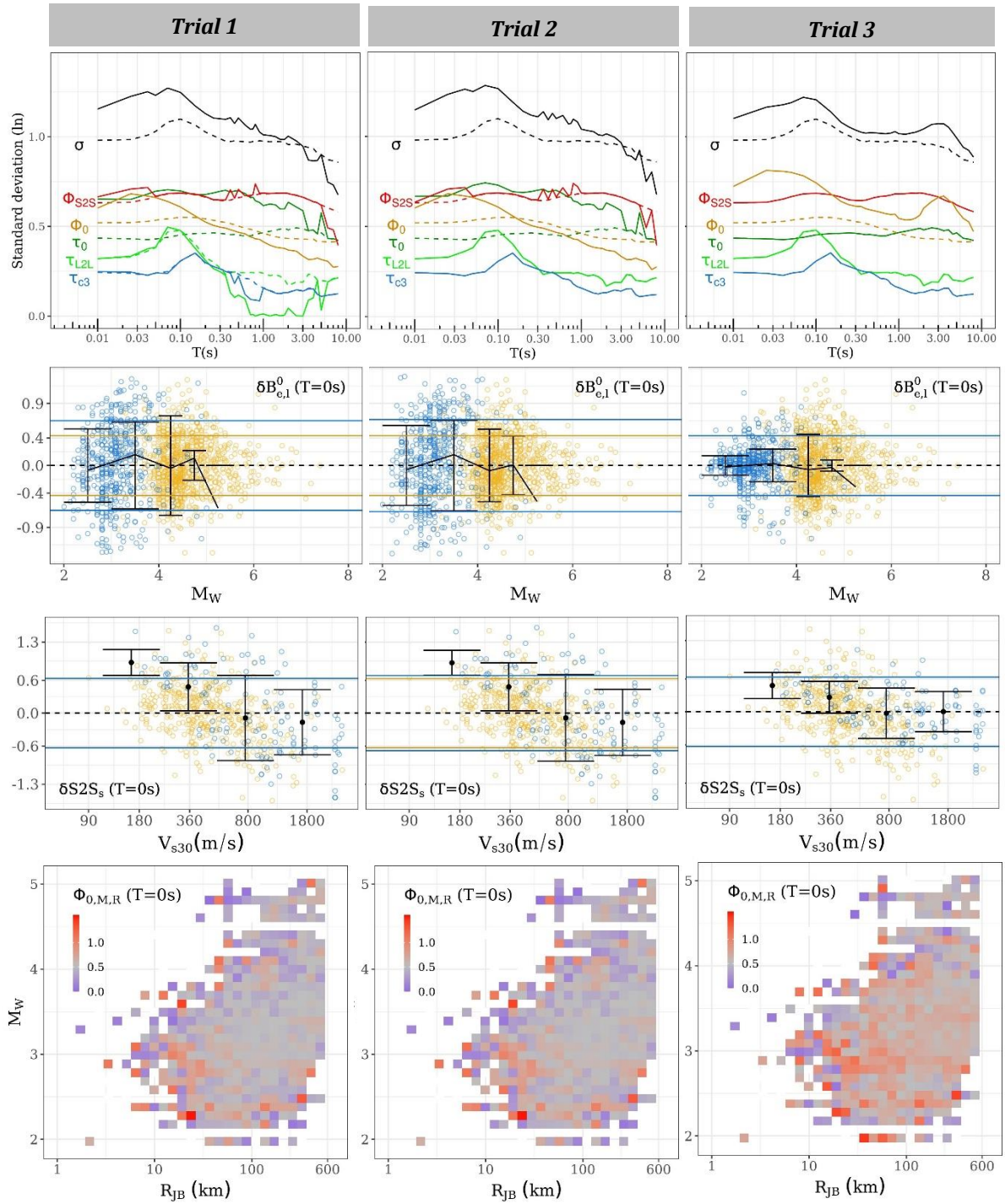


Fig.16: Comparison of three trial regressions with selective restraining of ESM inferred prior random-effects group variances from being updated with Résif data. In the top panel, ESM inferred estimates are in dashed lines, overlain with Résif estimates in solid lines. In the two middle rows, $\delta B_{e,l}^0(T=0s)$ versus M_W and $\delta S2S_s(T=0s)$ versus V_{s30} plots show ESM estimates in yellow and Résif estimates in blue. The bottom panels show 'left-over' residual variabilities estimated for several $M_W - R_{JB}$ bins ($\Phi_{0,M,R}$), with the colour scale centred at Φ_0 (grey). $T = 0s$ in these plots implies *PGA*

590

591 Instead of restraining the priors from updating at specific periods, trial 2 superseded trial 1 by
 592 simply restraining far-source (τ_{c3}) and at-source (τ_{L2L}) attenuation group variabilities from being updated
 593 at all spectral periods. The resulting outcomes on regional variabilities of far- source and at-source

594 attenuations were similar to those from trial 3 presented in Fig.9 and Fig.10. This brings to emphasis the
595 very large between-event group variabilities (τ_0) estimated in trial 2. The $\delta B_{e,l}^0(T = 0s)$ versus M_W plots
596 under trial 1 and trial 2 are quite similar; with the scatter at $M_W < 4$ being as large as at $4 < M_W < 5.5$. The
597 M_W - dependent heteroskedastic models either of K20 or ESHM20 can be used as is with this update. The
598 large $\delta B_{e,l}^0(T = 0s)$ versus M_W in trial 1 and 2 may be indicative of the well-known uncertainties and
599 regional variabilities in M_W estimation procedures of Résif events. At the time of this study, there was no
600 remedy for this issue. A similar analysis in Fourier domain may offer more insights on trial 2.

601 The usable Résif ground-motion data with good signal-to-noise ratio falls rapidly at $T > 0.3s$. The
602 sudden changes in the dataset composition may have caused convergence issues, leading to the *instabilities*
603 in random-effects standard-deviations around $T = 1s$; otherwise, trial 2 would be as acceptable as the
604 preferred trial 3 in this study - if not more. However, it is the $\delta S_2S_s(T = 0s)$ versus V_{s30} plots from trial 2
605 that dissuaded from it being preferred over trial 3. This plot shows that the variability in site-response of
606 Résif stations with $V_{s30} > 1800m/s$ to be rather large. At the time of the study, the inexplicably high
607 variability of high-frequency site-response has already been a key issue in ground-motion analyses - and it
608 was not clear if there is supposed to be an upper or lower limit to site-response variability Φ_{S2S} . Bayesian
609 frameworks are quite convenient in setting up prior constraints, which in this case is to use the ESM inferred
610 knowledge of Φ_{S2S} to be undisputed and thus, not updated. With these assumptions regarding both τ_0 and
611 Φ_{S2S} , and other random-effects groups, trial 3 is presented as the preferred approach. However, it is to be
612 noted that if the Bayesian regression algorithm becomes capable of robust regressions, it is worth repeating
613 the analyses presented in this study.

614 Restraining all the random-effects variances to their ESM inferred priors led to trial 3, which clearly
615 shows the largest 'left-over' residual variabilities Φ_0 at all spectral periods. The running hypothesis, in this
616 study, is that the additional Résif ground-motion variability is absorbed into residual variability Φ_0 ,
617 suggesting a high record-to-record variability for a few events and stations. The bottom panels of Fig.16
618 show $\Phi_{0,M,R}$ across the three trials at $T = 0s$, which is essentially the $M_W - R_{JB}$ dependent residual
619 variability of *PGAs* in Résif dataset. The redistribution of residual ground-motion variability - from trial 1
620 to 3 - appears to have accumulated in $30 < R_{JB} < 100km$ range across the entire M_W range. Further
621 investigation showed that the record-to-record variabilities are systematically larger for events located in
622 the complex tectonic environment of the Alps mountain ranges, and for stations located in the Pyrenees
623 mountain ranges. There are a few options to reduce or *remodel* the residual variability Φ_0 , in order to
624 mitigate its impact as a component of aleatory variability (σ) in PSHA. But these options can be explored in
625 a more application-oriented manner; similar to the implementation of K20 GMMs in ESHM20.

626 This study presents the K20 GMMs in a Bayesian framework, with a more formalised updating
627 procedure. New ground-motion datasets are steadily becoming more available following the demonstration
628 of impact of GMM uncertainties in ESHM20, especially for low-moderate seismicity regions of pan-Europe.
629 These new datasets can serve to extend the non-ergodic application of K20 GMMs to newer regions; but
630 more significantly, in validating existing ground-motion models themselves. It has often been the case that,
631 numerous new GMMs supersede earlier models derived from older, more limited datasets. The newer
632 models also often predict median ground-motions incongruent with their superseded versions, and quite

633 often with larger aleatory variability. Bayesian frameworks may offer a connectivity between various
634 versions of a GMM, and ensure a continuity of knowledge inferred from across various ground-motion
635 datasets. This study concludes with the outlook that: Ground-motion models should benefit from advances
636 in Bayesian regressions, by bringing in more data-driven transparency to their development, and
637 application in seismic hazard and risk assessments.

638 **6 STATEMENTS AND DECLARATIONS**

639 **6.1 Funding**

640 The authors acknowledge the support provided by Direction Générale de la Prévention des Risques (DGPR),
641 and Electricité de France in developing the study, presenting the progress at conferences and meetings, and
642 preparing this manuscript.

643 **6.2 Competing interests**

644 The authors ensure there are no conflict of interests.

645 **6.3 Author contributions**

646 The authors recognise the contribution of Paola Traversa in developing and disseminating the Résif French
647 ground-motion dataset, and the contribution of Sreeram Reddy Kotha in developing the mixed-effects
648 regression analyses. Both authors were involved in interpreting the results and preparing the manuscript.

649 **6.4 Data availability**

650 The pan-European Engineering Strong Motion (ESM) flatfile is available at [https://esm.mi.ingv.it/flatfile-](https://esm.mi.ingv.it/flatfile-2018/)
651 [2018/](https://esm.mi.ingv.it/flatfile-2018/) with persistent identifier PID: 11099/ESM_flatfile_2018. The Résif French Strong Motion flatfile is
652 currently being updated with ground-motion data from 1996 - 2021 and will be soon disseminated by Buscetti et
653 al. (in-prep) – an earlier version covering 1996 – 2016 can be requested from Traversa et al. (2020) . The analyses
654 in this study have been performed in R software Team 2013. In particular, libraries INLA (Lindgren and Rue
655 2015), *dplyr* (Wickham et al. 2019), *ggplot2* (Wickham et al. 2019), *ggmap* (Kahle, Wickham and Kahle 2019),
656 *viridis* (Garnier 2019). All the outputs of the Bayesian linear mixed-effects regressions – including coefficient
657 tables and marginal distributions, non-ergodic adjustments, and full regression summaries – may require revision
658 over time and can be made available for dissemination upon request.

659

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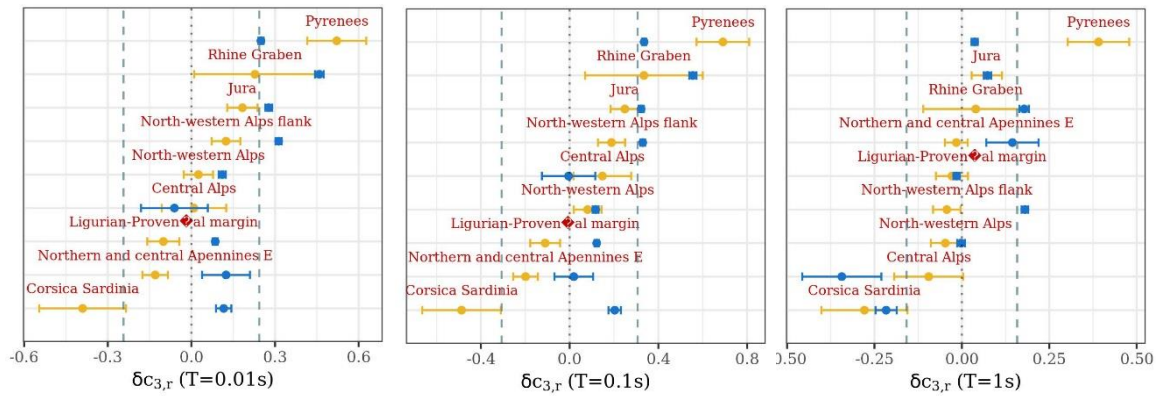


Fig.S1: Comparison of ESM inferred (yellow) and Résif-RAP inferred (blue) region-specific apparent anelastic attenuation random-effect $\delta c_{3,r} \pm SE(\delta c_{3,r})$ of attenuation regions (r) common to both the datasets

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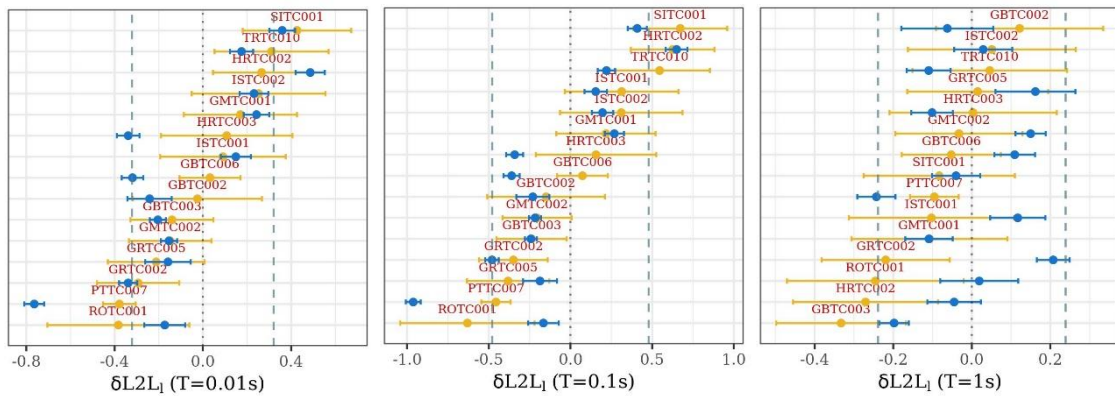


Fig.S2: Comparison of ESM inferred (yellow) and Résif-RAP inferred (blue) tectonic locality-specific random-effect $\delta L2L_l \pm SE(\delta L2L_l)$ of tectonic localities (l) common to both the datasets

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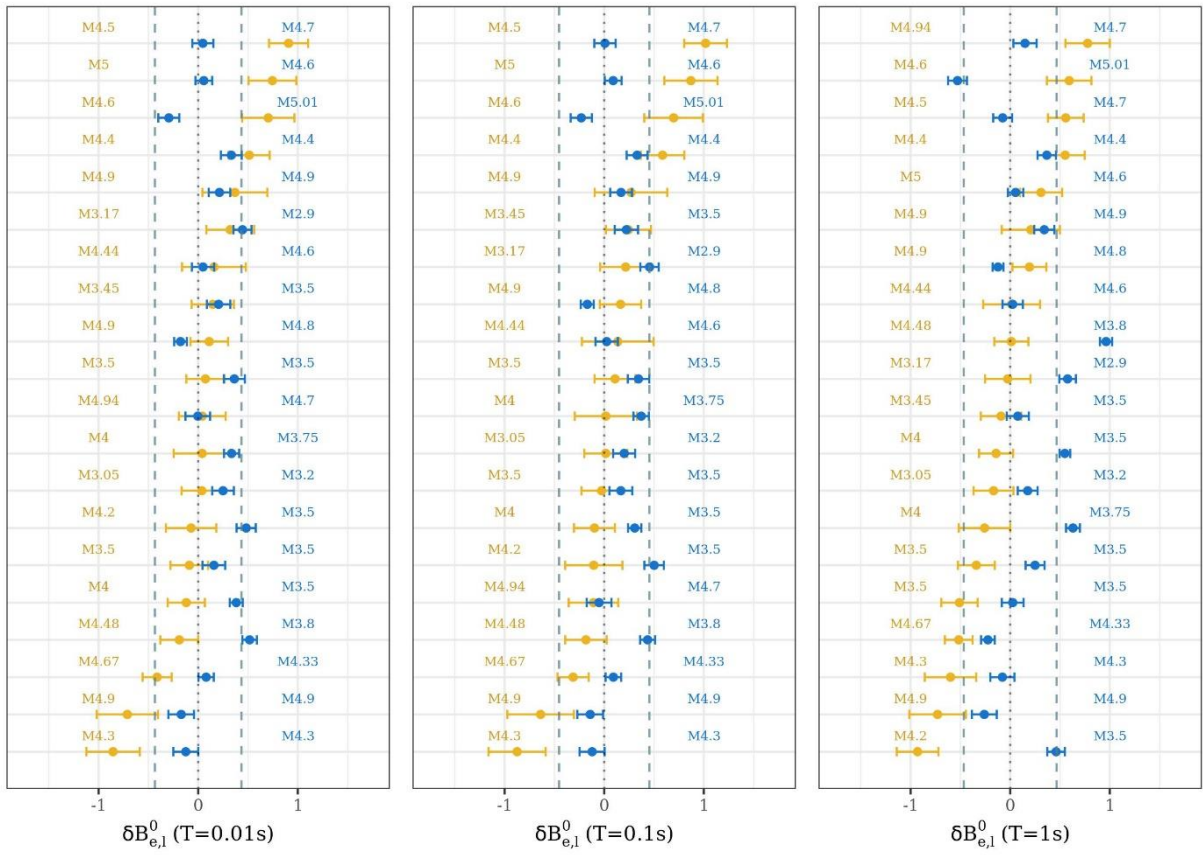


Fig.S3: Comparison of ESM inferred (yellow) and Résif-RAP inferred (blue) $\delta B_{e,l}^0$ of events common to both the datasets, at $T = 0.01, 0.1, 1s$ (left-to-right columns)

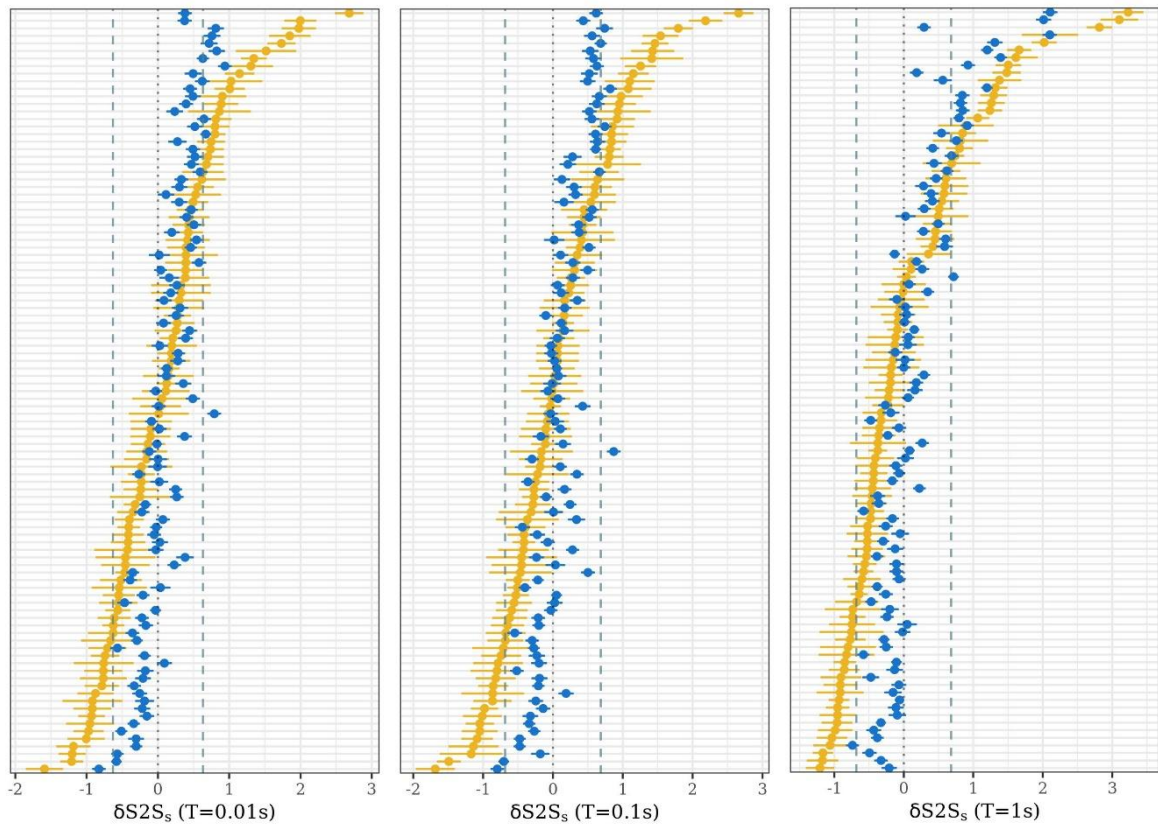


Fig.S4: Comparison of ESM inferred (yellow) and Résif-RAP inferred (blue) $\delta S2S_s$ of stations common to both the datasets, at $T = 0.01, 0.1, 1s$ (left-to-right columns)

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