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VARIABILITY OF KAPPA (κ): A STUDY USING BOREHOLE RECORDS

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ABSTRACT

The site studied is Aegion, located on the south of the Gulf of Corinth, Greece. The CORinth Soft Soil Array (CORSSA) is a downhole array consisting of 5 accelerometers, one at the surface and four at various depths down to bedrock. The data recorded at CORSSA have been used so far mainly for the study of site effects on ground motion. In this paper 180 high-quality records are used to compute kappa (κ), the high-frequency decay of the acceleration amplitude spectrum. We investigate the effect of depth and soil conditions on the estimation of κ . Because there is no agreed protocol for doing this, we chose to focus on the variability of the results depending on the different methods applied and the various decisions that need to be made during the κ computation process; these are not uniform across literature. The variability of κ estimates in this sensitivity study is significant, much larger than the error bars accompanying each estimate, and may have implications on the precision and variability of results derived from GMPEs (for which κ is a basic input parameter) and hence PSHA studies.

INTRODUCTION

Knowledge of the acceleration spectral shape is important for the prediction of ground motion. At high frequencies, the spectral amplitude decreases rapidly with frequency, with high frequencies acting as filters on the acceleration values. Hanks (1982) introduced the notion of f_{\max} to model this observation, while Anderson and Hough (1984) modeled the spectral decay as exponential (Fig. 1) and introduced the spectral decay factor (κ), which – although empirical rather than theoretical – is a basic input parameter in stochastic ground motion prediction some thirty years later (e.g. Boore, 2003; Atkinson and Boore, 2006). In the present study we follow the κ rather than the f_{\max} model to study high-frequency attenuation. As shown in Fig. 1, κ can be simply related to the slope λ of the spectrum when plotted in lin-log_e space, over a certain range of frequencies:

$$\kappa = -\lambda/\pi, \text{ where } \lambda = \Delta(\ln a) / \Delta f \quad (1)$$

Anderson and Hough (1984) also observed a correlation between observed values of κ and the distance of the source from the station where the record was obtained. They suggested a linear relation where the intercept of the κ trend with distance (denoted κ_0) corresponds to the attenuation that S waves encounter when travelling through the subsurface geological structure to the surface, while the slope of the trend corresponds to the incremental attenuation due to predominantly horizontal S-wave propagation through the crust. If the trend is denoted by m then the relation can be written as follows, in units of time:

$$\kappa = \kappa_0 + m \cdot R \quad (s) \quad (2)$$

In more recent years there have been studies to estimate κ and its dependence on various factors and to decipher its origins. Tsai and Cheng (2000) propose an alternative model to the original one of eq. 2, where κ depends primarily on the source, secondarily on the site and only slightly on the distance (Papageorgiou and Aki, 1983, had first considered source effects as responsible, when suggesting that Hanks' f_{\max} was due to fault nonelasticity rather than attenuation). Boore (2003), who refers to κ_0 as path-independent diminution, considers it may be due to source or site effects. Even if κ is estimated according to eq. 2, despite the simplicity of the computation, there is no general agreement as to how it is estimated, because the results depend on various decisions and assumptions made in the process. More than provide a single answer as to the value of κ in the area under study, this paper aims to draw attention to the variability of the estimates based on these decisions.

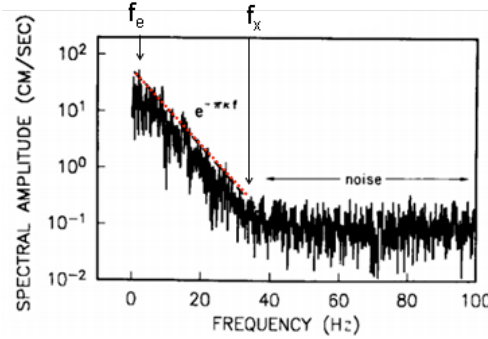


Fig. 1. Linear decay trend of the acceleration spectrum when plotted in lin-log_e space (adapted from Anderson and Hough, 1984).

STUDY AREA AND DATASET USED

The present work follows up on that presented in Ktenidou et al. (2011), so we will only repeat a few details here. The area studied is Aegion, located in the southwest part of the Gulf of Corinth, Greece, one of the most active seismic areas in Europe. The city is crossed by a fault whose escarpment divides it in two levels, while the site is also marked by the edge of a sedimentary basin which extends to the North (Fig. 2). Our dataset comes from the Corinth Soft Soil Array (CORSSA), whose location is shown in Fig. 2 (Pitilakis et al., 2004). The soil profile there is known to consist of soft, loose materials underlain by a stiff conglomerate at 155 m depth, while the seismic bedrock is a limestone at 700 m, according to the cross-section. CORSSA is a vertical array consisting of five broad-band 3D accelerometers, one at the surface and four at depths of 14, 31, 57 and 178 m. The latter is located in the conglomerate while all other instruments lie in soil. The dataset used consists of 180 earthquakes recorded between 2002 and 2008. Figure 3 shows their epicentre and magnitude distribution. Moment magnitudes range from 1.9 to 6.5, epicentral distances from 1 to 255 km and focal depths from 2 to 38 km. The vertical components are not used in this study, so the number of traces examined is 1800: 2 components at 5 stations for 180 events. This dataset is based on the one used earlier in Ktenidou et al. (2011), with the difference that 20 events were excluded from the initial 200 events. These events corresponded to subduction seismicity and the current dataset consists only of crustal earthquakes. Here we continue and refine our previous work for this subset.

PRELIMINARY PROCESSING

Acceleration time-histories were baseline-corrected, P and S wave arrival times were manually picked and S-wave windows were extracted, with durations chosen based on event magnitude and distance. Noise windows were also extracted. S-wave and noise windows were tapered at both edges with a hanning taper (2.5% of the window duration), they were Fourier-transformed and only the amplitudes of the spectra were kept. The raw (unsmoothed) spectra were inspected in lin-log space and frequencies f_e and f_x (following the nomenclature of Douglas et al., 2010, see Fig. 1) were picked. The resulting windows all passed through visual inspection to ensure that the spectral amplitude degradation in each of them was indeed linear. Before proceeding with κ computation we set the requirement that signal-to-noise-ratio (SNR) must be above 3 for all spectra to be used. To compute SNR we smooth the S and noise window spectra with a mild Konno-Ohmachi filter ($b=40$ after Konno and Ohmachi, 1998) and interpolate to a common frequency step and number of points to perform the spectral division. Going back to the raw spectra, only points for which $\text{SNR} > 3$ are used. So the initial frequency range (f_e - f_x) may be decreased to accommodate this requirement, but the final frequency range used is rather wide, between 20-50 Hz for most events. Frequency f_e ranges from 1-20 Hz and f_x is between 10-70 Hz, depending heavily on the magnitude and distance of the event. The sampling rate of the records is 200 Hz and instrument response is practically flat up to

relatively high frequencies (at least 60 Hz). This allows us to use a rather large range of frequencies without including instrument response decay in our κ computations. More details about data processing are given in Ktenidou et al. (2011).

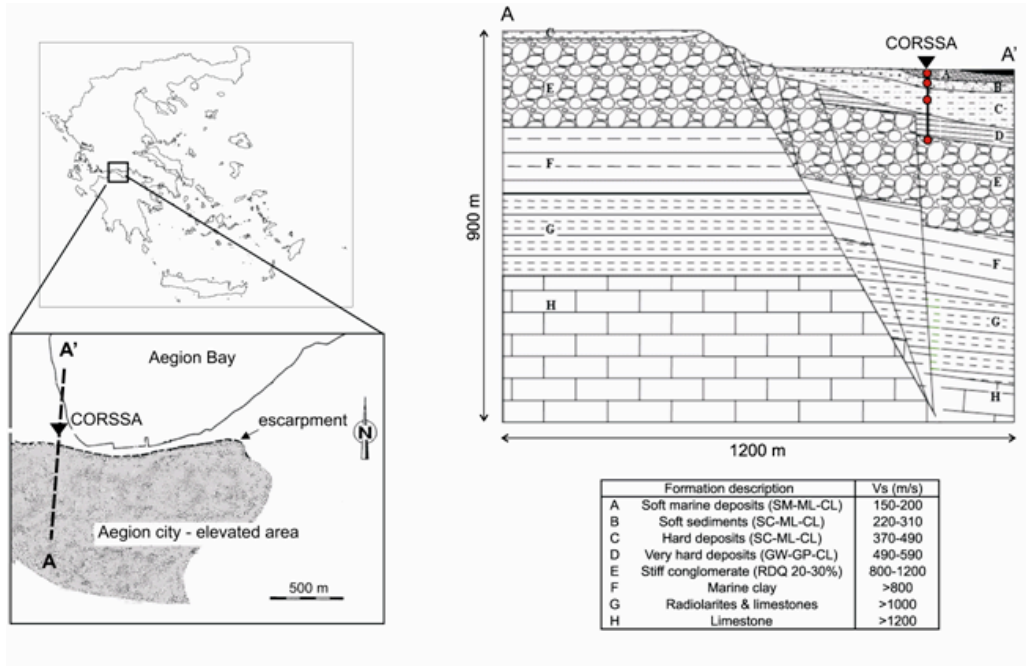


Fig. 2. Left: location of the city of Aegion, Gulf of Corinth (adapted from Athanasopoulos et al., 1999). The locations of the Corinth Soft Soil Array, the fault escarpment and cross-section A-A' are marked. Right: cross-section perpendicular to the slope and table of Vs velocity values for each layer (after Apostolidis et al., 2006).

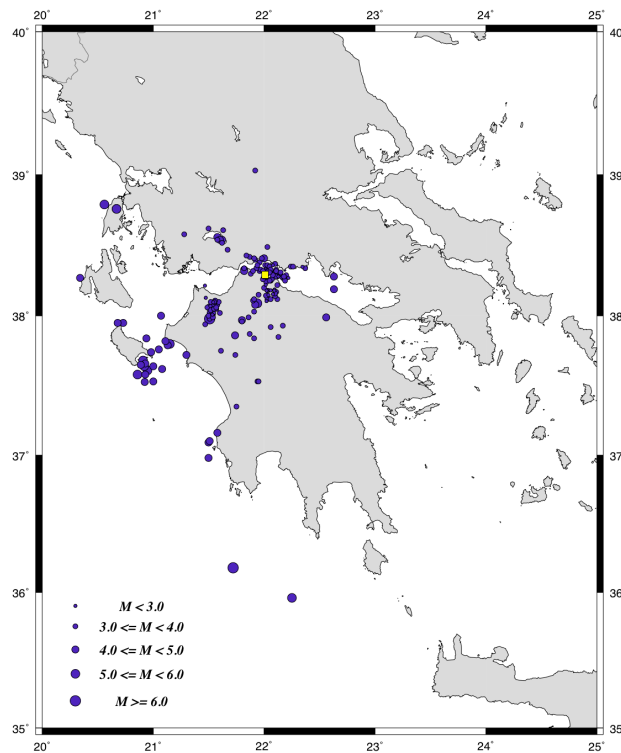


Fig. 3. Epicentre distribution for the 180 events of the dataset. The size of the circle scales with moment magnitude. Location of CORSSA site is marked by a square.

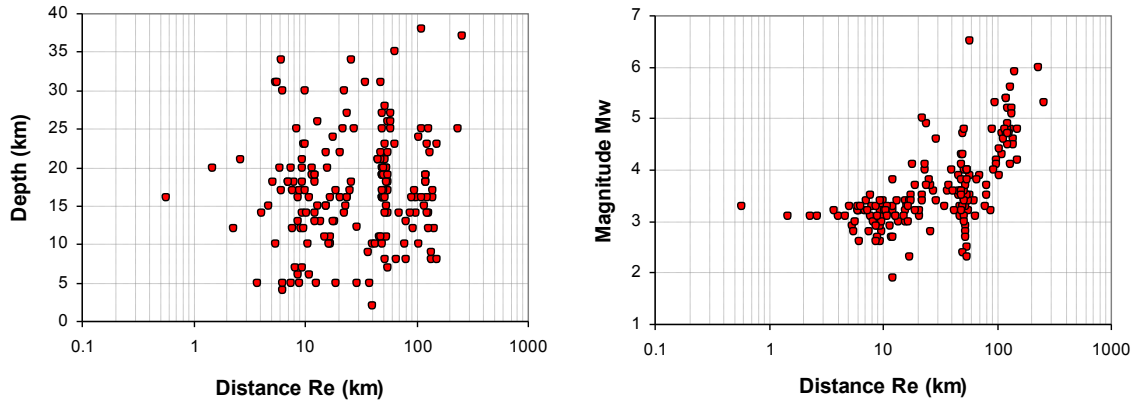


Fig. 4. Magnitude and depth distribution with distance for the dataset.

COMPUTATION OF κ

Dependence on distance

The raw spectra are first used to compute the linear trend of amplitude decay using standard linear regression. The individual values of κ are computed for each event, depth and component, based on the slopes of the spectra according to Eq. 1. Once the individual κ values have been computed, we can investigate their dependence on distance (Eq. 2). At this stage there are various issues to be decided upon, and these decisions may affect the results of the computations. Firstly, there is no consensus as to which definition of distance to use. In the study that first introduced this concept, Anderson and Hough (1984) used epicentral distance. In recent studies, Douglas et al. (2010) use epicentral distances, while Van Houtte et al. (2011) use hypocentral distances. The hypocentral distance seems physically better related to the path followed by the seismic waves from source to site, and thus might seem more fit to describe the regional effect on κ , but its use implies the added uncertainties of focal depth estimation. On the other hand, the main goal of κ computation is to extrapolate the $\kappa(R)$ function to $R=0$ in order to estimate κ at the site under study (κ_0). This has more physical meaning when using epicentral distance, as the hypocentral distance should inevitably leave an offset on the distance axis, unless the source coincided with the station. In this study we present results for both types of distances and investigate the effects of the choice. A second issue to be considered is the type of dependence on distance. Most studies to date assume a linear dependence of κ with distance, though Anderson and Hough (1984) and Hough et al. (1988) mention that there is no reason to assume it other than simplicity, and Tsai and Chan (2000) actually find very little dependence of κ on distance altogether. After inspecting the distribution our data (e.g. Fig. 5), we consider a linear trend adequate at least as a first approximation. A third issue arising concerns the type of linear regression performed on the data. We perform two types of regression: standard linear regression, which minimizes the sum of squared errors of all points from the line, and a robust linear regression where the algorithm uses iteratively reweighted least squares with bisquare weighting. In Ktenidou et al. (2011) we introduced the latter and found that it may help minimize bias from outliers in the data. In the case at hand, this permits us to use the few records we have at large distances without allowing them to bias the results.

First we use the data at each of the five stations independently and perform a single regression per station to get an equation for κ as a function of distance. Figure 5 shows results for the surface (top) and deepest (bottom) station with respect to epicentral (left) and hypocentral (right) distances, for the linear (blue) and weighted robust (red) analysis. It shows the regressed line plus/minus one standard deviation plotted onto the cloud of points. The regression parameters (κ_0 and m of eq. 2), standard deviation and the coefficient of correlation (R^2) are also plotted. Standard deviation, as expected, is smaller when the weighted robust regression is used rather than the standard one. The type of regression also affects both κ_0 and m , particularly the latter. The coefficient of correlation ranges from 0.75-0.85, meaning that the linear assumption can account for around 75%-85% of the scatter in the observed data. R^2 is higher when R_c is used, indicating a better linear fit than with R_h . Naturally, the two types of distance used also yield differences in the values computed for κ_0 but not for m : κ_0 is lower if R_h is used rather than R_c , since R_h includes also the focal depth and hence shifts the computed best-fit line farther away from $R=0$, on which κ_0 is measured. The difference in κ_0 is up to 15% at the surface station and up to 40% at bedrock, which is significant and much larger than the standard deviation of the computed values. For this reason we believe that the definition of distance is important and that when a certain estimate of κ_0 is used (e.g. in GMPes), it may be worth taking into account the type of distance used in its computation, as such variations may have a significant effect on the results.

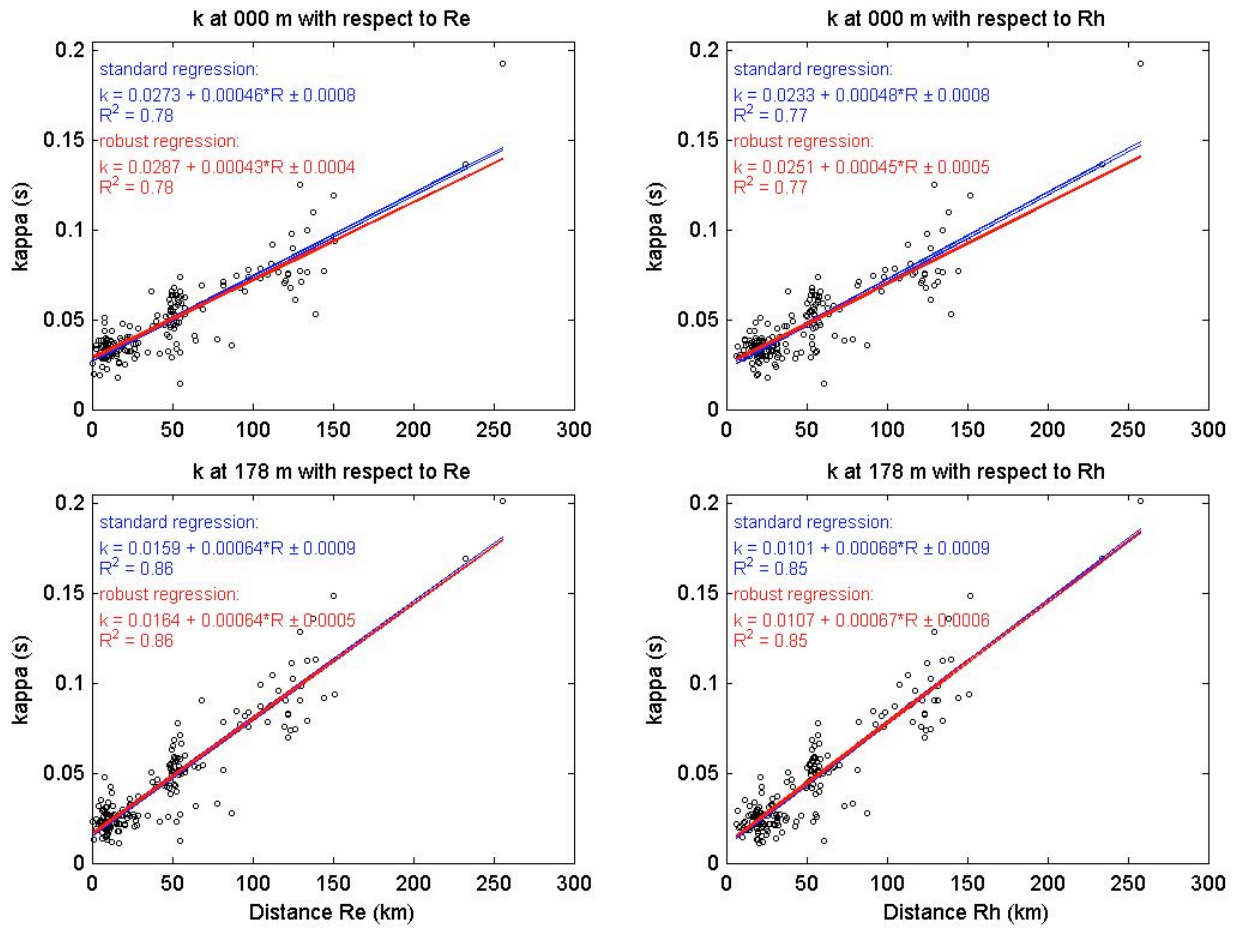


Fig. 5. Distribution of individual κ values computed (180 events, average values for the two horizontal components) at the surface (top) and deepest (bottom) station of CORSSA with epicentral (left) and hypocentral (right) distance. Regressed lines (average ± 1 standard deviation) resulting from standard linear (blue) and weighted robust (red) individual regressions are plotted onto the data points. Formulas show average line equations, standard deviation and coefficient of correlation.

Dependence on station depth / soil Vs

Above we observed and compared results for the topmost and deepest stations. Figure 6 shows results (average regressed lines plus/minus the standard deviation) for all five stations, as yielded by the standard and robust regressions for both types of distance. The regression parameters and standard deviation are noted on the plot. Results are statistically different for the different stations. An interesting observation can be made here, which was found previously in Ktenidou et al. (2011). Both by intuition and based on the literature, it would be expected that κ values be systematically higher at the surface than at depth, correlating with Vs. However, we find that here this only holds for small distances, perhaps up to 50 km, while at larger distances the pattern is reversed. This is reflected in the intercept being larger as the soil gets softer (i.e. stations nearer the surface) and the slope being larger at stations nearer bedrock. This may indicate that there are different mechanisms at work behind κ which become dominant at different distances. We are not aware of many studies that look into κ beneath the surface. Oth et al. (2011) used data from the Japanese K-NET and KiK-net networks and computed individual κ values at the surface and at depth in order to account for attenuation differences in source spectra at different depths. They found that κ values at the surface were on average larger than those at depth. To our knowledge, only Van Houtte et al. (2011) have proposed complete κ models (i.e., as functions of distance) for both surface and downhole stations, using data from KiK-net. At this point it is interesting to note that Van Houtte et al. (2011) used this as a restriction in choosing their dataset: only events which produced larger κ values at the surface with respect to the borehole were used to construct their model. We make the comparison between the surface and the deepest station for our data and investigate what the effect of this criterion would be at our site. Fig. 7 shows the dependence with distance of the quantity: $\kappa_{0m} / \kappa_{178m}$. We find it decreases linearly with distance. We choose a subset of 128 events in our dataset for which this quantity is larger than 1 ($\kappa_{0m} > \kappa_{178m}$) and recompute κ as a function of distance. The results are shown in Fig. 8. Where previously the dataset was relatively complete up to 150 km, this distance is now halved. There is very little data at larger distances, which causes the very low coefficient of correlation in the new regression results and also makes the

results more dependent on this sparse data available at large distances. Comparing Figs. 5 and 8, we see that the computed m values are underestimated and κ_0 values are overestimated when using this criterion to constrain the dataset.

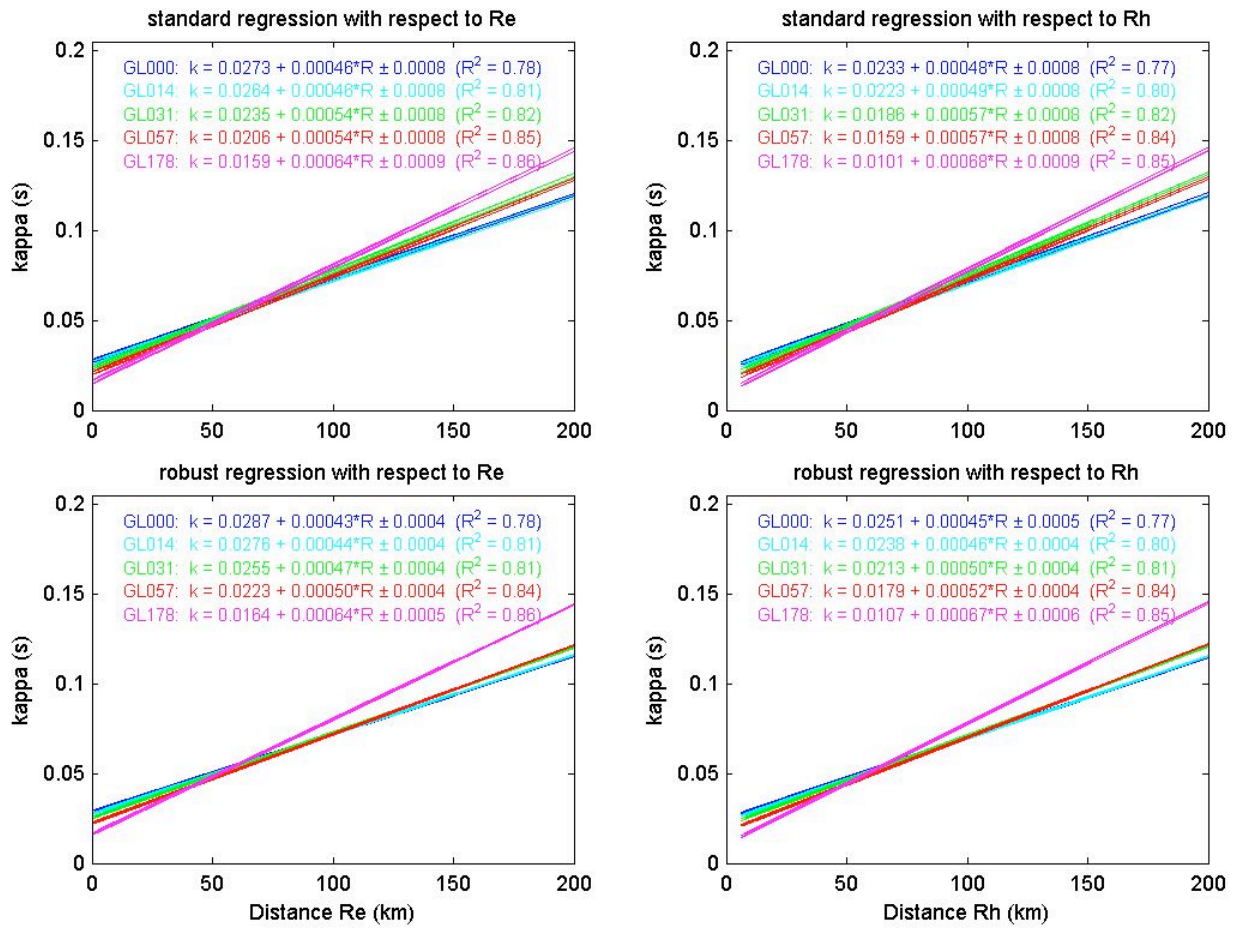


Fig. 6. Regressed lines (average \pm 1 standard deviation) resulting from standard linear (blue) and weighted robust (red) individual regressions at all stations from the surface down to the deepest station with epicentral (left) and hypocentral (right) distance. Formulas show average line equations and standard deviation.

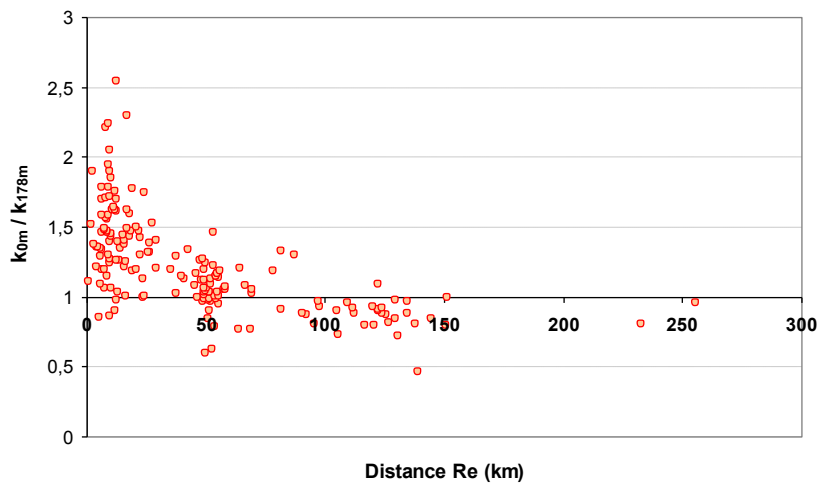


Fig. 7. The dependence on distance of the quantity $\kappa_{0m}/\kappa_{178m}$.

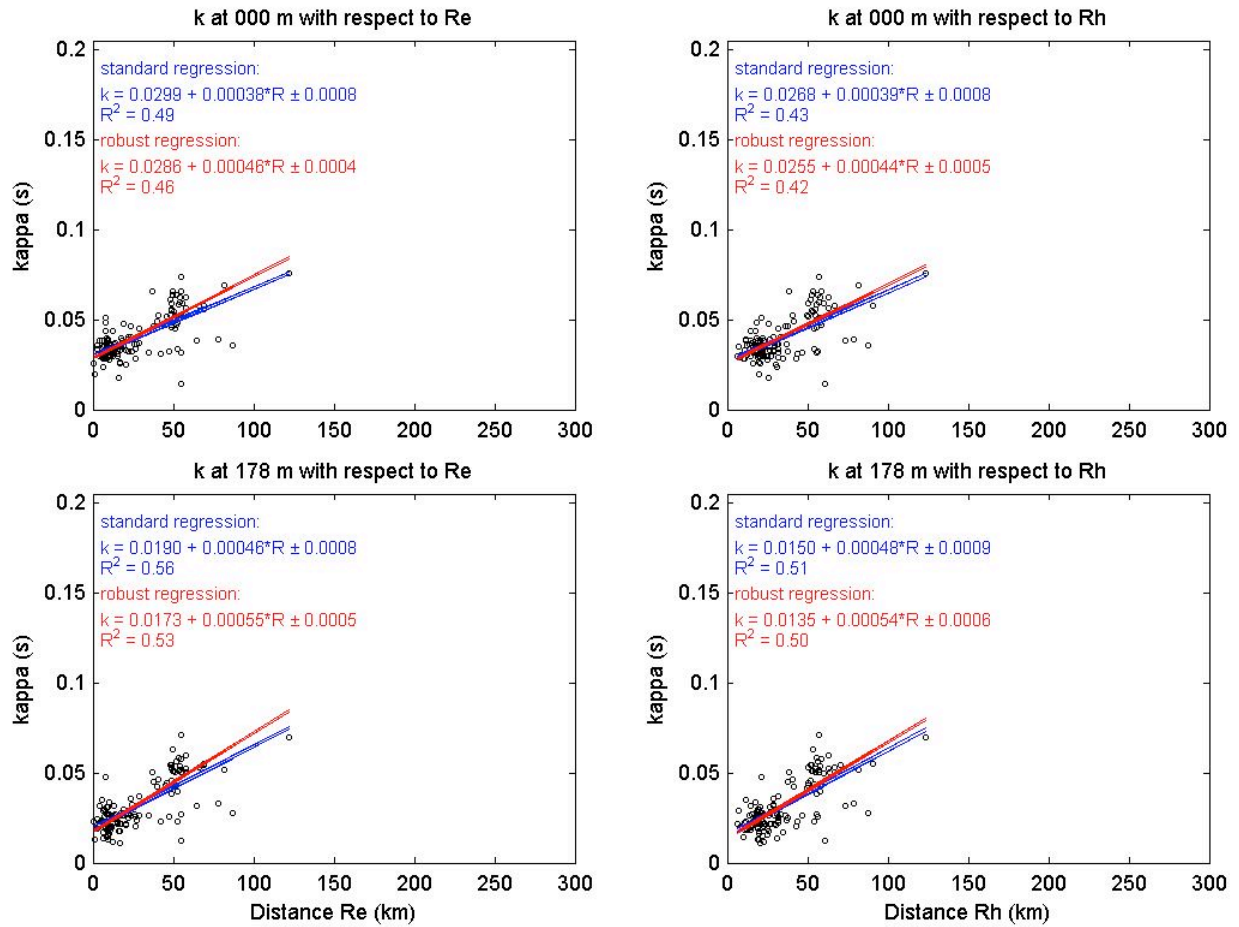


Fig. 8. Distribution of individual κ values for the subset of 128 events for which $\kappa_{0m} > \kappa_{178m}$ at the surface (top) and deepest (bottom) station of CORSSA with epicentral (left) and hypocentral (right) distance. Regressed lines (average ± 1 standard deviation) resulting from standard linear (blue) and weighted robust (red) individual regressions are plotted onto the data points. Formulas show average line equations, standard deviation and coefficient of correlation.

Dependence on constraints imposed and data availability

Another issue that arises when studying κ in a borehole rather than only at the surface is the assumptions and constraints made in computing the value of the slope (m), which –as mentioned when presenting eq. 2– was initially assumed to represent the regional effect. Hough et al. (1988) compared the variation of κ between a deep sediment site and a granite site. They found that although κ_0 values differed greatly between the two sites, the slopes were similar, i.e. the regressed lines seemed to be parallel. Based on this observation, Anderson (1991) suggested κ models whose shape (m) remains constant for different sites and is only moved along the vertical axis so as to give different absolute values (κ_0) depending on local conditions; they considered m a regional characteristic depending on the Q structure at depth and κ_0 a reflection of the local Q structure a few kilometres below the station. Based on this concept, different approaches have been implemented recently in computing κ simultaneously on soil and rock conditions. Douglas et al. (2010) made a multiple regression using data recorded on soil and rock outcrop and constraining the slope to remain constant for both site types. Van Houtte et al. (2011), on the other hand, claim that the slope is best computed based only on downhole bedrock data, so they computed it only at depth and then fixed it for the surface data regression.

We, on the other hand, saw that our independent regressions did not for the most part yield parallel lines and that our data at different depths systematically showed different distribution shapes with distance (despite the dataset being common for all stations, which of course would secure the same regional effects). Thus, following the independent regressions we presented, we recompute κ according to these two strategies of constraining the slope. First we make a multiple regression using data from all stations at the same time and constraining the slope to remain constant at all depths. Then we make individual regressions at each station in soil after fixing m to its value at depth. In Fig. 9 we show results for robust regressions with respect to epicentral distance according to these two assumptions.

Comparing with Fig. 6 we see that the κ_0 values follow the order expected (i.e., decrease with depth) not only at small distances, as seen in the data, but this order is forced upon the κ values at large distances as well. In the first case, the values of κ_0 and m are different but in the same range as those computed independently. In the second case, the slope chosen is very steep with respect to the data, which leads to a significant decrease in κ_0 values.

So we see that the three assumptions we made as to whether and how to constrain the slope (m) affect the results of our regressions. Furthermore, this implies that if only certain of the stations were used in the regressions and not all five, again the results would differ. So it seems that the final estimate depends not only on the decisions made as to the dataset compilation, the definition of distance, the type of regression etc., but also on the data available. The fact that in most studies data is only available at the surface renders computations more straightforward and hence the great variability we have seen here is not visible in most cases, but that does not mean that the uncertainty is decreased.

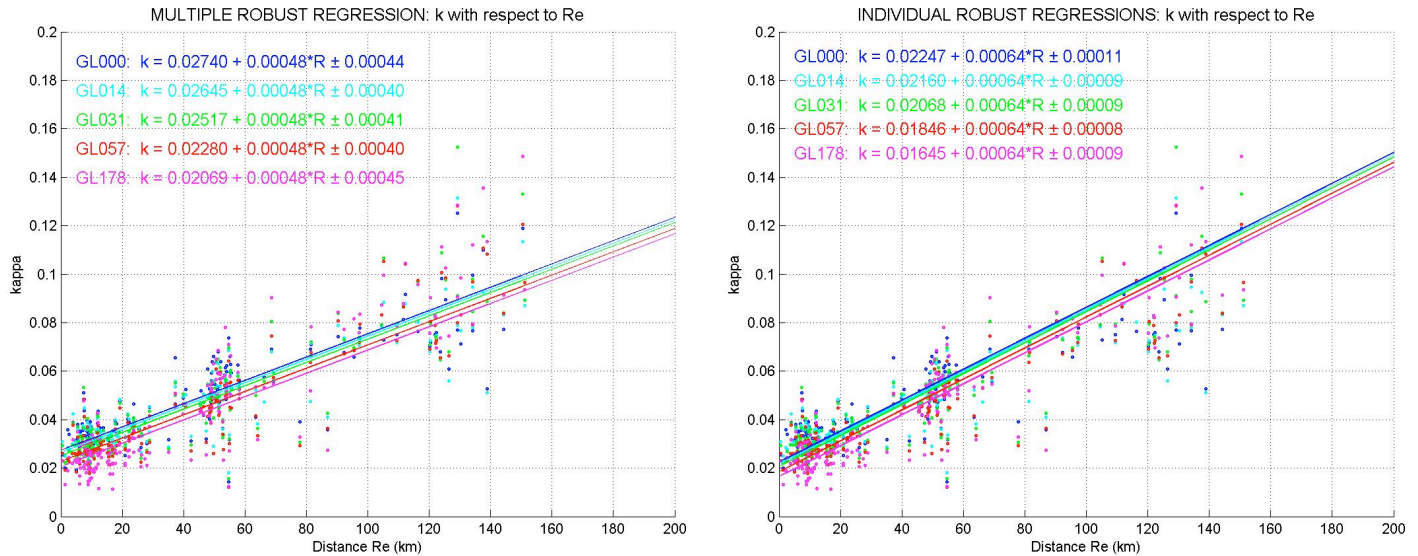


Fig. 9. Regressed lines (average ± 1 standard deviation) resulting from weighted robust multiple regression with epicentral distance at all stations in order to achieve a common slope. Left: simultaneous multiple regression with contribution from all stations. Right: individual regressions with slope fixed at bedrock value. Formulas show average line equations and standard deviation.

Up to now we have not corrected the records for local site effects. Considering that the frequency ranges we used are quite wide and the frequency values themselves are high, as suggested by Parolai and Bindi (2004), site effects should not significantly bias the estimation of κ . However, given the local soil conditions and the geological structures present, site and topographic effects have been studied in this area before (e.g., Ktenidou, 2010) so we will now attempt to account for them in the computation of κ . Using Kennet's (1983) reflectivity method we compute the theoretical 1D transfer function between the surface and the conglomerate bedrock in which the deepest station lies, based on a 1D model extracted from the 2D model of Fig. 1. With this transfer function we deconvolve the surface accelerograms to rock level. Using these corrected accelerograms we repick frequencies f_c and f_x , recompute individual κ values and κ models as functions of distance. The results are shown in Fig. 10. Comparing with Fig. 5 we find that after the correction the slope of the k model remains the same but the values of κ_0 decrease drastically with respect to the uncorrected surface records, and are actually even lower than the κ_0 values of the bedrock records by 20-50%. One possible interpretation for this would be to assume that the station at 178 m is not an adequate reference station and is affected by downgoing waves, hence its response includes site effects. However, in previous studies of site effects (Ktenidou et al., 2011) we found that though there is a reflected wave field at the downhole station, it is not that strong, nor does it extend to such high frequencies. Another explanation would be that the theoretical transfer function may not be dependable at very high frequencies. Though it is comparable to empirical transfer functions previously computed at CORSSA using earthquake data, namely standard and horizontal-to-vertical spectral ratios, this can only be verified at relatively low frequencies, especially since the site is very soft (with a fundamental frequency of only 0.9 Hz) and our 1D model does not account for very fine surface structure. Thus, we view theoretical results at very high frequencies (e.g. between 20 Hz and 50 Hz, which is the range for which κ is picked for most records) with some caution, since we cannot be sure they are free of artifacts. Douglas et al. (2010) did not correct accelerograms for site response in the interest and simplicity and consistency. Van Houtte et al. (2011) attempted correction of surface records but did not implement it in their final results because the transfer function introduced problems at high frequencies. According to them, site effects may cause greater variability in κ values at the surface compared to the

downhole values. Overall, it is not often that κ is computed from any records other than surface records, and those will inevitably contain some soil effects. However, we see here that using the theoretical transfer function to correct them, even in such a case as ours where the profile is well known and the function can be verified through empirical data as well, it is not necessarily an easy task and it may introduce further uncertainty.

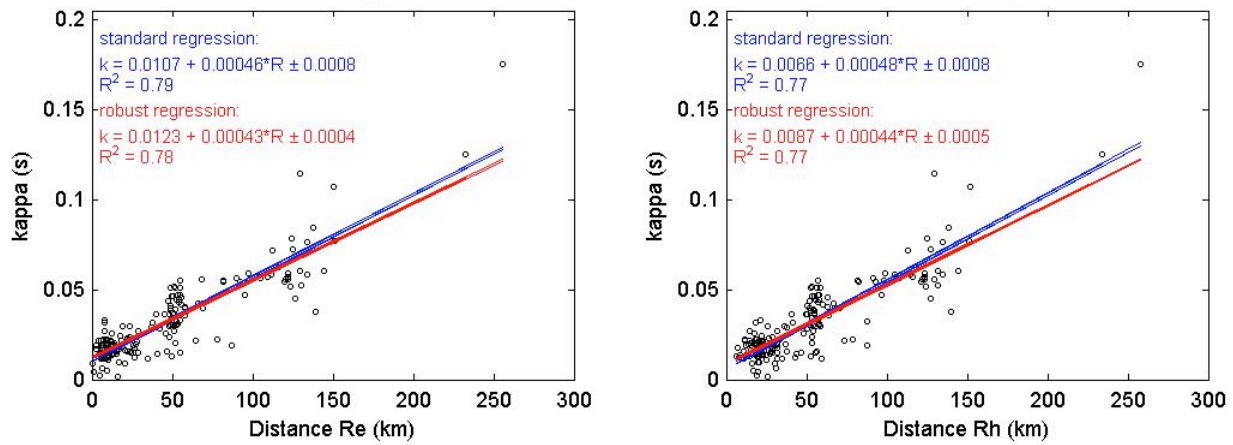


Fig. 10. Distribution of individual κ values with epicentral (left) and hypocentral (right) distance, as computed for the surface spectra after correction using the theoretical transfer function. Regressed lines (average ± 1 standard deviation) resulting from standard linear (blue) and weighted robust (red) individual regressions are plotted onto the data points. Formulas show average line equations, standard deviation and coefficient of correlation.

In order to give a visual inspection of the variability of κ in the computations we have presented here, in Fig. 11 we plot all the κ_0 values at the surface and downhole station according to the different hypotheses and methods implemented. The computation varies according to whether epicentral or hypocentral distance is used and whether the regression is standard linear or weighted robust (these four combinations correspond to the four colors). The five cases shown on the x axis correspond to the following: the initial dataset used here as reference (180 crustal events, uncorrected records, each station dealt with independently), the dataset consisting of the events for which the criterion $\kappa_{0m} > \kappa_{178m}$ holds true, the corrected dataset based on the theoretical transfer function (deconvolved results are only compared to the downhole values), and the two cases where the slope (m) was constrained: the multiple regression taking into account data from all five stations simultaneously, and the individual regressions where the slope was fixed to the bedrock value. It is evident that κ_0 values vary greatly depending on the combination of these assumptions and decisions. The use of hypocentral distance in particular yields systematically lower κ_0 in all cases. If each station is viewed separately, κ_0 varies up to 3 times at bedrock and up to 2 times at the surface. If we compare results at the surface and rock station, we find that κ_0 values are higher at the surface by a factor that varies between 1.2 and 2.3.

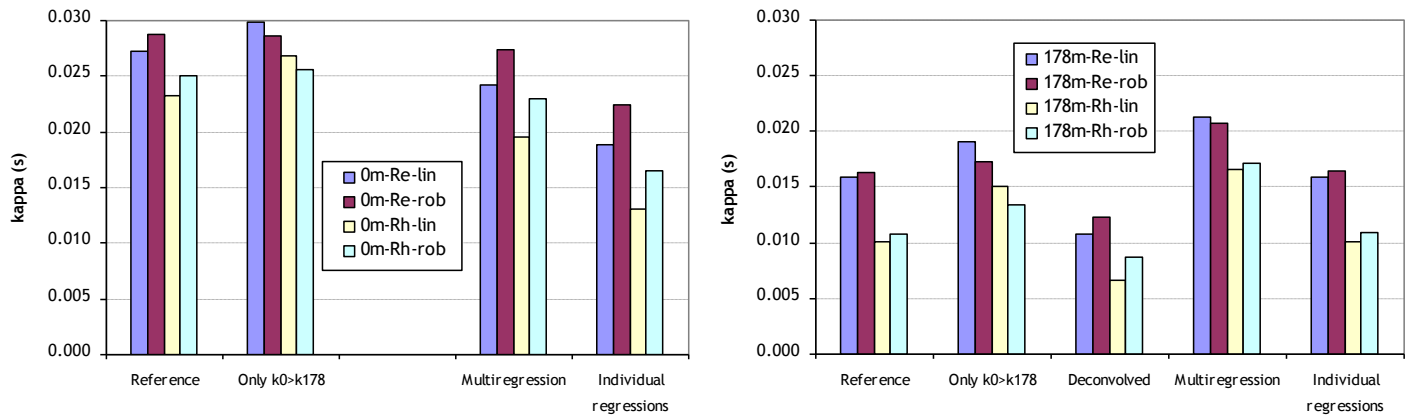


Fig. 11. Variability of κ_0 values computed for the surface (left) and downhole (right) station according to the different assumptions made during the computation process.

CONCLUSIONS

We estimate κ at different stations of a vertical soft soil array. We focus on the variability of the results depending on the soil conditions but also on the different methods applied and the decisions that need to be made during the κ computation process. These decisions include: the definition of distance, the type of linear regression performed on the acceleration spectra, the definition of the dataset (e.g. use of constraints such as $\kappa_{\text{soil}} > \kappa_{\text{rock}}$), and the removal of site effects from surface records. We find that κ_0 values are significantly lower (up to 15% at the surface and up to 40% at bedrock) if hypocentral distance is used rather than epicentral distance. Computing κ independently for each station of the array we find that κ values only correlate to soil V_s up to a certain distance; at larger distances κ is higher for rock than soil, which is contrary to the assumption usually made. When imposing this assumption in the selection of the dataset (i.e., using only records for which it holds true), almost all data corresponding to larger distances are eliminated and the resulting κ_0 is overestimated. Our data also contradicts another common assumption: that the slope of the computed κ models at different stations should be the same, reflecting an identical regional effect. This assumption can be forced upon the results if a common slope is assumed for all array stations and a multiple regression is performed; however, in this case, data availability (e.g. the number of stations used) becomes yet another factor affecting the final results. An alternative way to apply this constraint is to fix the slope based exclusively on the bedrock data (considering they contain fewer site effects). This leads to a slope that is very steep with respect to the data and hence to a significant decrease in κ_0 values. Finally, if we attempt to correct surface records for site effects, e.g. deconvolving them to rock level using the site's theoretical transfer function, we find it is not a straightforward process, but on the contrary may introduce further uncertainty: in our case, κ_0 values are greatly underestimated (up to 20-50% compared to bedrock), which we attribute to possible artifacts in the theoretical computation of site response at very high frequencies, such as those used here. The fact that in most studies data is only available at the surface renders computations more straightforward but that does not mean that the uncertainty is decreased. Overall, in this sensitivity study we find that the final estimate depends not only on decisions such as dataset selection, distance definition, regression type, but also on the data available and the way we choose to relate and constrain it. The variability of κ_0 estimates in this study is significant and much larger than the error bars accompanying each estimate. Since there is no agreed procedure for κ_0 estimation, the results of each study made are dependent on such decisions and they are not uniform across literature. The variability in κ_0 values may have implications on the precision and variability of GMPE results and hence PSHA studies.

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REFERENCES

- Apostolidis, P., D. Raptakis, K. Pandi, M. Manakou, and K. Pitilakis [2006], 'Definition of subsoil structure and preliminary ground response in Aigion city (Greece) using microtremor and earthquakes', *Soil Dyn. Earthq. Eng.*, Vol. 26, pp. 49-67.
- Athanasopoulos, G. A., P. C. Pelekis, and E. A. Leonidou [1999], 'Effects of surface topography on seismic ground response in the Egean (Greece) 15 June 1995 earthquake', *Soil Dyn. Earthq. Eng.*, Vol. 18, 1999, pp. 135-149.
- Anderson, J.G. & Hough, S.E. [1984], 'A model for the shape of the Fourier amplitude spectrum of acceleration at high frequencies', *Bull. Seism. Soc. Am.*, Vol. 74, pp. 1969-1993.
- Atkinson, G.M. and D.M. Boore [2006], 'Earthquake Ground-Motion Prediction Equations for Eastern North America', *Bull. Seism. Soc. Am.*, Vol. 96, pp. 2181-2205.
- Boore, D.M. [2003], 'Simulation of ground motion using the stochastic method', *Pure Appl. Geophys.*, Vol. 160, pp. 635-676.
- Douglas, J., P. Gehl, L. F. Bonilla and C. Gélis [2010], 'A κ Model for Mainland France', *Pure Appl. Geophys.*, Vol. 167, pp. 1303-1315.

Goldstein, P., D. Dodge, M. Firpo, and L. Minner [2003], 'SAC2000: Signal processing and analysis tools for seismologists and engineers', Invited contribution to 'The IASPEI International Handbook of Earthquake and Engineering Seismology', W.H.K. Lee, H. Kanamori, P.C. Jennings, and C. Kisslinger (Editors), Academic Press, London.

Hanks, T. C. [1982], ' f_{\max} ', Bull. Seismol. Soc. Am., Vol. 72, pp. 1867-1879.

Hough, S.E., J.G. Anderson, J. Brune, F. Vernon, J. Berger, J. Fletcher, L. Haar, T. Hanks, and L. Baker [1988], 'Attenuation near Anza, California', Bull. Seism. Soc. Am., Vol. 78, pp. 672-691.

Kennet, B.L.N. [1983]. '*Seismic wave propagation in stratified media*'. Cambridge University Press, New York.

Konno, K. and Ohmachi, T. [1998], 'Ground-motion characteristics estimated from spectral ratio between horizontal and vertical components of microtremor', Bull. Seismol. Soc. Am., Vol. 88, pp. 228-241.

Ktenidou, O.-J. [2010]. '*Theoretical and instrumental study of site and topographic effects on strong ground motion in Aegion*', PhD thesis, Aristotle University Thessaloniki, Greece.

Ktenidou O.-J., F.J. Chávez-García, K. Pitilakis [2011], 'Variance reduction and signal-to-noise ratio: reducing uncertainty in spectral ratios', Bull. Seismol. Soc. Am., 101, pp. 619-634.

Ktenidou O.J., L.F. Bonilla, S. Arnaouti, C. Gelis, K. Pitilakis [2011], 'Preliminary estimation of κ at Aegion (Gulf of Corinth, Greece) using a downhole accelerometric array', *8ème colloque national de l'Association Française du Génie Parasismique (AFPS)*, Ecole des Ponts ParisTech, Champs-sur-Marne, France, 6-8 Sep., accepted.

Oth, A., D. Bindi, S. Parolai, and D. Di Giacomo [2011], 'Spectral Analysis of K-NET and KiK-net Data in Japan, Part II: On Attenuation Characteristics, Source Spectra, and Site Response of Borehole and Surface Stations', Bull. Seismol. Soc. Am., Vol. 101, pp. 667-687.

Papageorgiou, A. S., and K. Aki [1983], 'A specific barrier model for the quantitative description of inhomogeneous faulting and the prediction of strong ground motion. Part I: Description of the model', Bull. Seismol. Soc. Am., Vol. 73, pp. 693-722.

Parolai S. and D Bindi [2004], 'Influence of Soil-Layer Properties on κ Evaluation', Seism. Soc. Am., Vol. 94, pp. 349-356.

Pitilakis K., Makropoulos K., Bernard P., Lemeille F., Lyon-Caen H., Berge-Thierry C., Tika Th., Manakou M., Diagourtas D., Raptakis D., Kallioglou P., Makra K., Pitilakis D., and Bonilla F. [2004] 'The Corinth Gulf Soft Soil Array (CORSSA) to study site effects' C.R. Geoscience, Vol. 336, pp. 353-365.

Tsai, C.-C. P., and K.-C. Chen [2000], 'A model for the high-cut process of strong motion accelerations in terms of distance, magnitude, and site condition: an example from the SMART 1 array, Lotung, Taiwan', Bull. Seism. Soc. Am., Vol. 90, pp. 1535-1542.

Van Houtte C., Drouet C. and F. Cotton [2011], 'Analysis of the origins of κ (Kappa) to compute hard rock to rock adjustment factors for GMPEs', Bull. Seism. Soc. Am., accepted for publication.

Wessel, P., and W. H. F. Smith [1998], 'New, improved version of the Generic Mapping Tools Released', EOS Trans. AGU, Vol. 79, pp. 579.