Imaging architecture of the Jakarta Basin, Indonesia with transdimensional inversion of seismic noise

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SUMMARY
In order to characterize the subsurface structure of the Jakarta Basin, Indonesia, a dense portable seismic broad-band network was operated by The Australian National University (ANU) and the Indonesian Agency for Meteorology, Climatology and Geophysics (BMKG) between October 2013 and February 2014. Overall 96 locations were sampled through successive deployments of 52 seismic broad-band sensors at different parts of the city. Oceanic and anthropogenic noises were recorded as well as regional and teleseismic earthquakes. We apply regularized deconvolution to the recorded ambient noise of the vertical components of available station pairs, and over 3000 Green’s functions were retrieved in total. Waveforms from interstation deconvolutions show clear arrivals of Rayleigh fundamental and higher order modes. The traveltimes that were extracted from group velocity filtering of fundamental mode Rayleigh wave arrivals, are used in a 2-stage Transdimensional Bayesian method to map shear wave structure of subsurface. The images of S wave speed show very low velocities and a thick basin covering most of the city with depths up to 1.5 km. These low seismic velocities and the thick basin beneath the city potentially cause seismic amplification during a subduction megathrust or other large earthquake close to the city of Jakarta.

Key words: Interferometry; Surface waves and free oscillations; Site effects; Seismic tomography.

INTRODUCTION
Jakarta, Indonesia, is one of the world’s most densely populated cities, with a population exceeding 10 million living in an area of about 600 km² (greater Jakarta has a population of 28 million). Jakarta lies on a sedimentary basin that experiences one of the most rapid rates of subsidence in the world, over 26 cm yr⁻¹, mainly due to groundwater extraction (Abidin et al. 2011; Ng et al. 2012). Although there are no known active faults within the city itself (Harsolumakso 2001), its proximity to the Java Trench 200 km to the south, where the Australian Plate subducts beneath Java, suggests that the seismic hazard is high. In 1985, Mexico City sustained considerable casualties and damage due to the Michoacan earthquake (Mₚ = 8.1) that occurred in the Mexican subduction zone over 300 km away. The shallow sedimentary layers and basin architecture of the Mexico City Valley had a critical influence on amplification and increased duration of seismic waves that contributed to the heavy loss of lives and infrastructure (Anderson et al. 1986; Kawase & Aki 1989; Furumura & Kennett 1998). In urban basins such as Kanto, Los Angeles, Osaka, San Francisco, and Seattle, a variety of data sets and methods are used to constrain 3-D seismic velocity structure, in order to predict the level of strong ground motion and seismic hazard (Kagawa et al. 2004; Brocher 2005; Koketsu et al. 2009; Delorey & Vidale 2011; Lee et al. 2014). These methods typically include borehole, gravity, seismic tomography, seismic refraction, and microtremor studies. In contrast, apart from sparse microtremor observations (Ridwan et al. 2014, 2015) the Jakarta basin has been the subject of very few geophysical or borehole measurements—and to our knowledge few, if any, boreholes in the Jakarta basin have reached bedrock.

In this study, we use data from a temporary seismograph deployment in the Jakarta basin in an attempt to characterize the shallow seismic velocity structure of the basin and surrounding area. In October 2013, 52 broad-band seismometers were installed across Jakarta at public and private high-schools, and recording was conducted continuously until February 2014. During this time, half the stations were maintained at their original locations and half were redeployed in three phases (each with one month duration) to cover the northeastern, northwestern, and southern parts of the city with...
Figure 1. Map of the seismic network operated between October 2013 and February 2014 overlaid on the geological units of Jakarta (Turkandi et al. 1992). The approximate location of the experiment is shown with a red square on the world map (right) with plate boundaries and direction vectors. The administrative boundary of Jakarta is shown with grey lines.

a minimum interstation spacing of 1–5 km. Overall, continuous seismic measurements were conducted at 96 different locations. In Fig. 1, the distribution of the seismic stations is superposed on a map of the surface geology in the Jakarta area.

GEOLOGY AND HISTORICAL EARTHQUAKES

Jakarta is located on the northern coast of the island of Java, Indonesia, which together with Sumatra to the west and Bali, Lombok, and Sumba to the east, comprises the southern edge of the Sunda Block. South of Java, about 200 km from Jakarta, the Australian Plate subducts underneath the Sunda Block at the Java Trench, with a convergence rate of 67 mm yr$^{-1}$ (Simons et al. 2007). Arc volcanism is prevalent in Java, where a number of active volcanoes exist to the south of the city (Hamilton 1979). The Java Trench megathrust, the subducting slab beneath Java, and at least two possibly active crustal faults within 100 km of Jakarta—the Cimandiri Fault to the south and Lembang Fault to the southeast—are all potential sources of earthquakes that might affect Jakarta.

Jakarta has not been subject to strong earthquake ground motion since the explosive growth in population in the late 20th century—the population of greater Jakarta grew from about 0.8 million in 1948 to over 28 million today (see, e.g. Cybriwsky & Ford 2001). It has, however, experienced large earthquakes historically. The most significant of these occurred on 1699 January 5, when Dutch Batavia (the former name of Jakarta) experienced ‘an earthquake so heavy and strong that nothing comparable had ever been known to have occurred here, the movement having lasted with severe shakes and shocks for about three quarters of an hour’ (Coolhaas 1976, translation by Reid (2012)). Another powerful earthquake, with shaking lasting more than 5 min was felt in 1757 and in 1834 an earthquake similar to that in 1699 occurred (Wichmann 1918). The only large, damaging earthquake near Jakarta to have been instrumentally recorded occurred on 1903 February 27, with an $M_w$ of 7.3 (Engdahl & Villaseñor 2002) and a hypocentre in the subducting slab somewhere between northwest Java and southeast Sumatra (Kanamori & Abe 1979).

Jakarta is located on a sedimentary basin with little topographic relief, with elevation gradually increasing from a few metres at the coast to 50 m at a distance 20 km from the coast. The surface geology is comprised of Holocene sand dunes and alluvium from the coast to about 6 km southward to the city centre, whereas farther south it is dominated by Pleistocene alluvial fan deposits with a patch of Tertiary volcanic deposits in the west (Fig. 1, see also Van Bemmelen 1949; Turkandi et al. 1992). Alluvial fan deposits thicken to the north, so that the central part of Jakarta is composed of very thick alluvial fan sediments ($>300$ m) (Patmosukismo & Yahya 1974; Fachri et al. 2003). A recent study by Ridwan et al. (2014, 2015) mapped 1-D basin structure using 11 microtremor measurements, and the results suggest depth to engineering bedrock ($V_S > 750$ m s$^{-1}$) of 600 m to in the north and around 360 m in the central part of the basin.

DATA AND METHODS

Data

We deployed Trillium Compact 20 s, three-component broad-band sensors at every site. Sensors were installed in schools, generally on a concrete slab floor. Data were recorded by dataloggers designed and built by the Australian National University, which are powered by batteries and have a 24-bit dynamic range. Recording was conducted at a 250 Hz sampling rate and instrument drift corrections were applied by the digitizer at every hour based on GPS time. As described above, half of the 52 stations were deployed throughout Jakarta at 3–5 km spacing and left in place for the duration of the 3-month experiment (red circles in Fig. 1). The remaining
Figure 2. Comparison of Green’s functions for two station pairs retrieved with cross-correlation (black traces) and regularized deconvolution (red traces). The map on the right shows the locations of these station pairs. Waveforms are filtered between 0.1 and 2 Hz and normalized to unity.

Instruments were deployed so as to achieve denser spacing first in northeastern Jakarta and then re-deployed after each month to northwestern and southern Jakarta (green, blue, and black triangles, respectively, in Fig. 1). The data were downsampled to 50 Hz and a zero-phase low pass filter was applied prior to down-sampling. We did not carry out instrument response removal, since all of the instruments are identical and deconvolution (see below) cancels out the effect of the identical instrument responses.

Retrieval of Green’s Functions

After resampling the data, we follow Saygin & Kennett (2010, 2012) in the processing of noise recordings. Instead of applying cross-correlation on the noise records, we applied a regularized deconvolution to enable the use of a broader frequency range. The deconvolution is conducted on data of 300 s time interval with a 60 s overlap, and we used 0.01 for the value of the regularization parameter. After the construction of deconvolved traces, stacking is applied on all of the available traces to create the final waveform. In Fig. 2, Green’s functions for two different station pairs are shown from cross-correlation and regularized deconvolution. Waveforms from the regularized approach carry more energetic arrivals with higher signal to noise ratio in the same frequency band.

In Fig. 3, Green’s functions are plotted for a reference station located at the uppermost northeast of the array, where we term the waves propagating away from the reference station as causal, and towards the station as acausal. There is clear propagation of dispersed Rayleigh waves at acausal times, and a faster branch of energy exists at causal times. We identify the faster branch of arrivals as higher order Rayleigh wave modes arriving before the dominant fundamental mode with a much lower signal to noise ratio. We confirm the nature these arrivals by doing simple modelling of the group velocities as in Figures A1 and A2. We identified and picked fundamental mode Rayleigh wave Green’s functions on the dispersed wave trains visible on the vertical components. We verify these picks by comparing them with the arrival time of the Love wave Green’s function that appears on the same receiver pair’s transverse components.

METHODS

Imaging with noise

Seismic noise is generally generated by a combination of ocean-solid earth coupling and human activity, and can propagate over large distances. The simultaneous recording of noise in a seismic network can be utilized by, for example, using the cross-correlation operation to extract the Green’s function between any two stations in the network. This Green’s function will carry information about the subsurface seismic velocity structure between the two stations. Most commonly, the dispersed surface wave components of this Green’s function is used to probe the underlying medium.

Imaging with seismic noise is an emerging technique and often offers much more control on the survey design over traditional
earthquake-based imaging techniques. Review papers by Weaver (2005) and Snieder & Larose (2013) outline the development of the technique since its inception with example studies. Seismic Noise Tomography was first applied by Shapiro & Campillo (2004) and Shapiro et al. (2005), Sabra et al. (2005) to Southern California. Subsequent studies applied the noise tomography technique at a variety of scales, from upper mantle to upper crustal problems associated with 100 to 10 s of km lateral scales, respectively (Gao & Shen 2014; Yang et al. 2007; Mordret et al. 2013; Saygin et al. 2013).

We use over 3000 retrieved Rayleigh waves and measure their group velocities at frequencies between 0.2 and 2 Hz by applying narrowband Gaussian filters. In Fig. 4, the distribution of the total number of ray paths at each frequency and geometry of ray paths at selected frequencies are given. The coverage of the network offers a dense and balanced ray path distribution at the chosen bands of the measurements.

The measured traveltimes are used in a two-step tomographic scheme to image the Earth at different frequencies. In the forward part, we use the Fast Marching Method (FMM; Rawlinson & Sambridge 2004a,b) to trace the wave fronts for a given velocity model. FMM is especially useful to model seismic wave propagation in 2-D where strong velocity anomalies can have a profound effect on ray geometry.

Transdimensional Bayesian seismic tomography

We use a Bayesian framework in the inversion of interstation travel-times at different frequencies to map the Rayleigh wave group velocity perturbation field across Jakarta. In inversion methods which use Bayesian strategies, a probability density is specified a priori to avoid consideration of unrealistic Earth models. Bayes' theorem essentially combines this prior probability density with a likelihood function that expresses the probability of observing the data for a given model, to obtain a posterior probability density distribution for the model given the observed data (Gouveia & Scales 1998). In order to determine an appropriate prior probability distribution, in general information from previous work and knowledge of the expected seismic velocity ranges are used (Scales & Tenorio 2001). In this work, we use uniform priors with wide ranges for the parameters to be searched with a group velocity range between 0.1 and 1.0 km s\(^{-1}\), and a data noise parameter assigned to each cell between 0.1 and 10 s.

One of the key advantages of adopting the Bayesian framework is that it provides a statistically rigorous appraisal of model uncertainty, which can be very important in interpretation of the results. It does this by sampling the posterior probability distribution, so that instead of finding one best model, we obtain a distribution of models from which statistics such as model mean and confidence intervals can be computed.

In this paper, we use the reversible jump Markov chain Monte Carlo (rj-McMC) technique to simultaneously explore model and parameter space in what is termed transdimensional Bayesian inversion. This approach was introduced to the geophysics community by Malinverno (2002), and has since been used for inverting receiver functions and surface wave group and phase velocities (see, e.g. Bodin & Sambridge 2009; Agostinetti & Malinverno 2010; Bodin et al. 2012a,b).

We use the rj-McMC implementation of Bodin et al. (2012a), in which all the Rayleigh wave group velocities observed for a given period are modelled with a parameterization defined by a number...
of constant-velocity Voronoi cells distributed irregularly over the deployment area. Each model is defined by the number of Voronoi cells, their positions, and the values of Rayleigh wave group velocity assigned to the cells. In the sampling of the Bayesian posterior distribution, not only cell group velocities but also the number and positions of cells are varied in different steps of each Markov chain. This allows not only the group velocity but also the level of detail in the model to be determined by the data, thereby avoiding regularization and any arbitrary selection of regularization parameter values. The reversible jump technique automatically adjusts the underlying parametrization of the model to produce solutions with an appropriate level of complexity to fit the data to statistically meaningful levels.

This method has been applied to seismic noise tomography in a number of previous studies: Young et al. (2013) applied it using phase velocity measurements of interstation Green’s functions in Tasmania, and Zulfakriza et al. (2014) used it with group velocity measurements in central Java.

As was done in these previous studies, we accelerate convergence by running a large number (128) of Markov chains in parallel. At each step of each Markov Chain, a velocity model is proposed and then either rejected or accepted to become a member in an ensemble of acceptable solutions. The Markov Chains are run for many iterations producing new models, and eventually converge to a sampling of the posterior distribution that is independent of the initial model. Once this ‘burn-in’ stage has been achieved, we start to extract models to be used in the ensemble averages. At the end, this ensemble can be used to calculate mean Rayleigh wave group velocity models for selected periods through taking a simple arithmetic average over the ensemble values for Rayleigh wave group velocity at that point, and their associated uncertainties.

In Fig. 5, the evolution of ensemble mean Earth models is shown with varying number of chains and burn-in and post burn in steps. With an increasing number of chains, the resulting ensemble averages are much smoother. When the number of chains is low, the averaging process over a relatively short number of runs cannot produce smooth velocity models, so that the sharp edges of Voronoi cells are visible. A degree of convergence is observed even for a lower numbers of steps with higher number of chains. In Fig. 6, the distribution of Voronoi cells for a randomly selected chain is shown for every simulation shown in Fig. 5. It can be seen that the shorter runs have not converged, which is remedied by increasing the number of iterations.

Ray paths were iteratively updated with FMM five times, using the mean velocity models from previous runs to accommodate the effects of velocity changes in wave propagation, and so include ray bending. In Fig. 7, results from iterative updates of ray paths are shown for measurements at 1 Hz. In each panel, the mean velocity model from the previous run was used to calculate the ray path geometry, except in the first panel where straight ray paths were used. Iterative updating of ray paths is important especially in a region such as Jakarta where there is a strong variation of Rayleigh wave group velocities in the measurement band. The effect of the bending of ray paths is reflected in the images, as is particularly notable between Fig. 7(a) and the other parts of Fig. 7. While the ray paths undergo considerable change after the first update, the change in ray path geometry is much smaller in subsequent updates.

The computations were carried out in a parallelized environment, utilizing a total of 128 compute cores. Each core ran a separate chain with 250 000 burn-in steps and 250 000 post burn-in steps at each period. The models generated during the burn-in phase are rejected and not used the ensemble averages. To avoid any dependency during the ensemble averaging, each chain was thinned by taking every 50th model.

RESULTS: GROUP VELOCITY IMAGES

In Fig. 8, we show the results of the Rayleigh wave group velocity maps from 0.2 Hz to 2 Hz. The corresponding uncertainty of the each image is given in Fig. 9.
Because of the low velocity of basin-fill sediments, surface waves in the period range 0.2 to 2 Hz are most sensitive to structure at depths $< 1$ km. In the western and northwestern parts of Jakarta typical velocities of the Rayleigh wave velocities are 200–400 m s$^{-1}$. Towards the east the velocity anomalies exhibit more spatial variability, with a number of small high velocity bodies surrounded by low velocity material. South of latitude 6.3° S, a large block exists with high group velocity across all of the measured period range with velocities up to 0.8 km s$^{-1}$. At around 0.6 Hz, the ray path coverage reaches a maximum, where the low velocity anomalies show similar patterns to those at 2 Hz. This indicates that the extent of the basin does not change over a wide range of depths. The results indicate very low velocities across the region comparable to or even lower than the Kanto Basin (Koketsu & Kikuchi 2000; Denolle et al. 2014) or Taipei Basin (Huang et al. 2010).

**Figure 6.** Randomly selected chains for the same runs with Fig. 5. Curves are coloured with red (first half) for depicting burn-in and blue (second half) post burn-in states.

**TRANSDIMENSIONAL 1-D SHEAR WAVE INVERSIONS**

A common way of inverting the surface wave velocity maps from seismic noise tomography is to conduct pixel by pixel inversion of dispersion curves extracted from these maps. This 2-stage approach has been applied successfully at a number of domains to image depth-shear wave velocity structure. Brenguier et al. (2007) imaged the magma chamber of Piton de la Fournaise volcano from the inversion of dispersion curves extracted from surface velocity tomographic sections. Saygin & Kennett (2012) imaged large scale structures across Australia from the point inversion of dispersion curves. Mordret et al. (2014) applied depth inversion to phase velocity maps constructed from a very dense data set of Valhall Life of Field Seismic network, and recently Pilia et al. (2015) constrained the shear wave velocity in the southeast of Australia from the Trans-dimensional inversion of group velocity measurements of Green’s functions retrieved from noise.

We extracted over 1500 dispersion curves from the group velocity tomograms with an equal spacing of 0.6 km in each direction, for frequencies between 0.2 and 2 Hz. The curves were inverted with a Transdimensional Bayesian scheme to map the variation of the shear wave depth structure across Jakarta. In Bodin et al. (2012b), a detailed description of the method is given. This approach follows the same methodology used in the inversion of traveltimes for creating the group velocity images of this study. The model is parameterized with a variable number of layers defined with Voronoi cells, and thicknesses, all of which are unknowns in the inversions. For the prior that define the search space, we used 0.3–2.7 km s$^{-1}$ for layer velocities, and the number of the layers are allowed to vary between 2 and 30 for characterizing the first 5 km. Each dispersion curve inversion is run for 40 000 steps for the burn-in and another 100 000 steps for the post burn-in. Each resulting velocity model posterior distribution is from an ensemble of 72 chains run in parallel, which is sufficient to explore the parameter space. In general, the misfit between observed and modelled dispersion curves is low. An example of an inverted dispersion curve is given in Fig. 10. The inverted dispersion curves and shear wave velocity-depth models are derived as averages over the respective posterior distributions.

In Figs 11 and 13, shear wave velocity cross-sections are shown which illustrate the structural variation of the basin across Jakarta. The associated uncertainty is presented in Fig. 12. The very low velocity cover ($V_s < 1.2$ km s$^{-1}$) extends to depths over 500 m in northern Jakarta. Another successive unit follows this very low velocity unit extending to depths of 1.5 km. The spatial extent of the basin cover is mainly around northern Jakarta (6.1° S–6.25° S), and the presence of low-velocity material diminishes with increasing depth. Most of the basin fill with velocities less than 1.5 km s$^{-1}$ is in northwest Jakarta. At 2 km, the signature of the low velocity basin has largely disappeared. However, around these depth surface waves are sensitive to a large range of depths.

The inverted shear wave velocities show a high level of similarity to the sedimentary rocks from other domains such as the San Francisco Bay area. A considerable amount of work has been done for this region to produce a compressional and shear wave velocity model varying with depth. Brocher (2005) compiled measurements from number of different methods to create empirical relationships.
Figure 7. Change of earth models with iteratively updated ray paths at 1 Hz. (a) Straight ray paths. (b) Ray paths traced in velocity model (a). (c) Ray paths traced in model from (b). (d) Ray paths updated from panel (c). (e) Updated from panel (d) and (f) updated from panel (e).
Figure 8. Rayleigh wave group velocity tomograms from Transdimensional Bayesian Seismic Noise Tomography between 2 and 0.2 Hz after five updates of ray path geometry: (a) 2 Hz, (b) 1.8 Hz, (c) 1.4 Hz, (d) 1.0 Hz, (e) 0.6 Hz and (f) 0.2 Hz.
Figure 9. Uncertainties of Rayleigh wave tomograms from Transdimensional Bayesian Seismic Noise Tomography between 2 and 0.2 Hz after five updates of ray path geometry: (a) 2 Hz, (b) 1.8 Hz, (c) 1.4 Hz, (d) 1.0 Hz, (e) 0.6 Hz and (f) 0.2 Hz.
between depth, and seismic velocities. As an example for the Great Valley Sequence of sedimentary rocks, typical shear wave velocities are about 1.27 km s\(^{-1}\) at 1 km depth and around 1.8 km s\(^{-1}\) at 2 km depth, which are very similar to results that we obtained from our shear wave inversions.

**DISCUSSION AND CONCLUSION**

For the first time, we developed a high-resolution shear wave velocity model of the Jakarta Basin from a 2-stage Transdimensional Bayesian inversion of Rayleigh wave Green’s functions retrieved from seismic noise. We conducted Rayleigh wave tomography by using Green’s functions retrieved from seismic noise to estimate 2-D Rayleigh wave group velocity maps for different periods. Then, the pixel inversion of dispersion curves across the study area maps the 3-D shear wave velocity variations in the basin. The low-velocity basin covers most of the northern part of Jakarta at shallow depths, where the basin boundaries shrink with the increasing depths. The influence of the basin mostly diminishes at around 1–1.5 km, where the deepest part is below central Jakarta extending to depths of 1.5 km. Even below the basin, shear wave velocities are still relatively low with an average of 1.8 km s\(^{-1}\) at 2.0 km. In the measurement band, surface waves are mostly sensitive to the first 2.5 km. Towards the south, the general trend is toward increasing velocities, however the resolution at the tip of the region is lower compared to the central part of Jakarta due to the coverage of ray paths.

We argue that in the case of a large earthquake, the city of Jakarta will be exposed to enhanced seismic hazard due to amplification and prolonged duration of seismic wave motion. Along with the amplification of seismic waves due to the impedance contrast at the basin-basement contact, the geometry of the basin can increase the duration of strong ground motion by focussing and trapping of seismic waves (Furumura & Kennett 1998). In future work, we hope to consider the influence of the basin on the character of earthquake-generated ground motion.

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Figure 12. The corresponding uncertainty of shear wave velocity slices given in Fig. 11.

Figure 13. Shear wave vertical profiles (1, 2 and 3) for selected three lines shown in the inset map.
Australian Government. Some of calculations were performed on the Terrawulf cluster, a computational facility supported through AuScope and the Australian Geophysical Observing System (AGOS). This work was supported by resources provided by the Pawsey Supercomputing Centre with funding from the Australian Government and the Government of Western Australia. Python packages Matplotlib (Hunter 2007) was used in drafting the figures (except maps), Basemap was used in drafting maps and ObsPy (Beyreuther et al. 2010) was used for the file format conversions, and data management.

REFERENCES


### APPENDIX A: MODELLING GREEN’S FUNCTIONS

We show results of our modelling for two different velocity models to show the effective propagation of first-mode Rayleigh waves as well as fundamental mode (see Fig. A1). This is also clearly visible on the observed section (see Fig. A2) at causal and acausal times. We use the reflectivity method (Kennett 2009) to compute the Green’s function responses for two different Earth models. Vertical dipole force is used as source in the calculations.

### APPENDIX B: REGULARIZED DECONVOLUTION

We use regularized deconvolution as previously employed in Saygin & Kennett (2010, 2012). This approach is implemented in the frequency domain with a water-level type regularization operator (Helmerger & Wiggins 1971). If the velocity fields recorded at stations A and B are given with $v(x_A)$ and $v(x_B)$, respectively then we can denote the deconvolution with

$$
\Phi(\omega) = \frac{v(x_A, \omega) v^*(x_B, \omega)}{\rho(\omega)},
$$

where $*$ is complex conjugation and $\omega$ is angular frequency. The denominator is regularized with a water-level type parameter $c$,

$$
\rho(\omega) = \max[\rho_1, \rho_2],
$$

with

$$
\rho_1 = v(x_B, \omega) v^*(x_B, \omega),
$$

$$
\rho_2 = c \max[v(x_B, \omega) v^*(x_B, \omega)].
$$

The parameter $c$ determines the level of spectral filling in the denominator, which prevents numerical instabilities in the division operation. The resulting signal after transforming back to the time domain is not modulated by the square of the ambient noise spectrum and has a broader response.

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*Figure A1.* Dispersion curves for fundamental and first mode of Rayleigh wave for a fast velocity model (left) and a slower model (right).
Figure A2. Corresponding vertical–vertical component Green’s functions for velocity models given in the Fig. A1. Note the prominent early arrival of first mode of Rayleigh wave computed from faster velocity model. Waveforms are filtered between 0.1 and 0.5 Hz and normalized to their maximum.