Seismic velocity structure of the Jakarta Basin, Indonesia, using trans-dimensional Bayesian inversion of horizontal-to-vertical spectral ratios

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SUMMARY
Characterizing the interior structure of the Jakarta Basin, Indonesia, is important for the improvement of seismic hazard assessment there. A dense-portable seismic broad-band network, comprising 96 stations, has been operated between October 2013 and February 2014 covering the city of Jakarta. The seismic network sampled broad-band seismic noise mostly originating from ocean waves and anthropogenic activity. We used horizontal-to-vertical spectral ratio (HVSR) measurements of the ambient seismic noise to estimate fundamental-mode Rayleigh wave ellipticity curves, which were used to infer the seismic velocity structure of the Jakarta Basin. By mapping and modelling the spatial variation of low-frequency (0.124–0.249 Hz) HVSR peaks, this study reveals variations in the depth to the Miocene basement. These variations include a sudden change of basement depth from 500 to 1000 m along N–S profile through the centre of the city, with an otherwise gentle increase in basin depth from south to north. Higher frequency (2–4 Hz) HVSR peaks appear to reflect complicated structure in the top 100 m of the soil profile, possibly related to the sediment compaction and transitions among different sedimentary sequences. In order to map these velocity profiles of unknown complexity, we employ a trans-dimensional Bayesian framework for the inversion of HVSR curves for 1-D profiles of velocity and density beneath each station. Results show that very low-velocity sediments (<240 m s$^{-1}$) up to 100 m in depth cover the city in the northern to central part, where alluvial fan material is deposited. These low seismic velocities and the very thick sediments in the Jakarta Basin will potentially contribute to seismic amplification and basin resonance, especially during giant megathrust earthquakes or large earthquakes with epicentres close to Jakarta. Results have shown good correlation with previous ambient seismic noise tomography and microtremor studies. We use the 1-D profiles to create a pseudo-3-D model of the basin structure which can be used for earthquake hazard analyses of Jakarta, a megacity in which highly variable construction practices may give rise to high vulnerability. The methodology discussed can be applied to any other populated city situated in a thick sedimentary basin.

Key words: Seismic noise; surface waves; site effects.

1 INTRODUCTION
This study aims to develop a model for the basin structure of Jakarta, the capital city of Indonesia. Jakarta is one of the world’s megacities, with at least 10 million inhabitants in Jakarta itself and over 30 million people living in the greater Jakarta area. Jakarta’s average population density of about 14 000 km$^{-2}$ indicates it is an area of high potential risk, and therefore it is important to carefully
assess its seismic hazard. In terms of geotectonic and demographic conditions, Jakarta is similar to Mexico City, with both cities sitting on deep sedimentary basins and 250–350 km distant from the Java and Mexican subduction zones, respectively. Therefore, it seems reasonable to expect that to first order the cities might experience similar impacts from a major subduction zone earthquake.

The 1985 Mw 8.1 Michoacán earthquake occurred at the Mexican subduction zone more than 300 km away from Mexico City. Despite the relatively large distance, this event resulted in about 10,000 deaths and extensive damage of more than 2000 structures (Esteva 1988; Padilla y Sanchez 1989). Poorly consolidated lake sediments and the geometry of the Mexico City Valley acted to amplify and increase the duration of shaking, the combined effect of which had a critical influence on the extent of damage (Kawase & Aki 1989; Padilla y Sanchez 1989; Furumura & Kennett 1998).

Previous studies in the basins of southern California (Magistrato et al. 2000) and the Lower Rhine Embayment (Ewald et al. 2006) showed the importance of 3D basin geometry in modeling the characteristic of seismic waves propagation in basins. Data from 3D simulations of wave propagation showed the importance of wavefront focusing due to low velocity zones or edge-diffracted waves (Ewald et al. 2006), basin resonance (Castellaro et al. 2014) and local-scale multi-scattering and prolonged ground motion (Olsen et al. 2006; Furumura & Hayakawa 2007; Denolle et al. 2014; Cruz-Atienza et al. 2006; Viens et al. 2016). On the other hand, Roten et al. (2014) found that non-cohesive shallow low-velocity sediments of Los Angeles Basin may reduce seismic shaking due to earthquake rupturing the San Andreas Fault. Accordingly, a rigorous quantification of seismic properties and geometry of the Jakarta Basin is a prerequisite to generating a robust seismic hazard map for the city.

At any given site, the dynamic soil properties and basin geometry are the principal components that account for site amplification and prolonged duration of ground motion. Understanding the seismic shear wave velocity profile is important for reliable forecasts of ground response for earthquake scenarios and seismic hazard evaluation. In Europe, America and Japan, models for sedimentary basins are available such as the Mygdonian Basin in Greece (Manakou et al. 2010), the Lower Rhine Embayment in Germany (Ewald et al. 2006), the Santiago de Chile Basin in Chile (Pilz et al. 2010), the Osaka Basin in Japan (Kagawa et al. 2004; Iwaki & Iwata 2011), the Tagus Basin in Portugal (Borges et al. 2016), the Mexico Valley Basin in Central Mexico (Cruz-Atienza et al. 2016) and the Po Plain in Northern Italy (Berbellini et al. 2017). For the case of the Jakarta Basin, however, very few geophysical studies are available (Ridwan et al. 2016; Saygin et al. 2016, 2017). Furthermore, only a few measured boreholes have reached the geological bedrock deemed to be the Pliocene–Pleistocene boundary (Delifnom et al. 2009).

Jakarta’s sedimentary basin is undergoing rapid subsidence, with a maximum rate of about 26 cm yr$^{-1}$, mainly due to groundwater extraction (Abidin et al. 2011; Ng et al. 2012). From this fact alone it can be deduced that Jakarta Basin is filled with highly saturated poorly consolidated sediments which can accommodate a huge volume of groundwater. This suggests that, in addition to increasing the intensity and duration of seismic wave motion, Jakarta Basin may also be prone to liquefaction if it were to experience earthquake-generated strong ground motion.

Hence, in order to ascertain the extent to which future earthquakes may affect the megacity of Jakarta, it is vital to develop a robust model for the geometry and physical properties of the Jakarta Basin. Since the basin is a densely populated urban area, passive seismic methods are the most viable approach to determining basin structure. Among passive seismic methods, spatial autocorrelation, known as SPAC (Aki 1957; Okada 2003; Asten 2006), ambient seismic noise tomography (ANT; Shapiro & Campillo 2004; Shapiro et al. 2005) and horizontal-to-vertical spectral ratio (HVSR, see below) are the most common techniques applied in urban areas. While SPAC and ANT utilize interstation cross-correlation of ambient seismic noise as estimates of surface wave dispersion curves, HVSR makes use of single-station HVSR as estimates of the Rayleigh wave ellipticity. In this study, a trans-dimensional (trans-D) Bayesian approach is applied for the ellipticity curve inversion to obtain 1-D velocity profiles at each station. Subsequently, a 3-D basin model is constructed by interpolating these 1-D profiles.

## 2 Geotectonic Setting and Historical Earthquakes

Two major tectonic components comprise the Indonesian archipelago: the Sundaland or Sunda block in the west and micro-blocks in the east. The former is composed of Java, Sumatra, Kalimantan, Sulawesi and Nusa Tenggara Islands. Jakarta is located on northwest Java as highlighted in Fig. 1. Estimates of the northward motion of Australia with respect to Java range from 67 mm yr$^{-1}$ (Simons et al. 1997) to 70 mm yr$^{-1}$ (Hall 2009) with direction almost normal to the Java Trench. This megathrust plate boundary located approximately 250 km south of Jakarta and the subducting slab beneath Java pose a high seismic hazard that may seriously affect the city when large earthquakes occur. In addition, crustal faults including the Cimandiri, Lembang and Baribis faults, located within the vicinity of Jakarta, also contribute to the high-hazard level in the city.

Using borehole and geohydrological data, Lubis et al. (2008) described Jakarta Basin as separated from Depok in the south by normal faults and underlain by geological bedrock composed of Tertiary rock. The depth of the bedrock near Depok was estimated at 50 m, undergoing an abrupt change 3 km from the basin’s southern rim, to up a depth of 250 m. The basin depth gradually deepens from that point to central Jakarta to a depth of at least 350 m, and the basin floor was thought to flatten from central Jakarta to Jakarta Bay in the north. However, a recent ANT study suggested a basin depth of more than 1000 m (Saygin et al. 2016) while a microtremor array study estimated a maximum depth to engineering bedrock (where shear wave velocity $V_S \geq 900$ m s$^{-1}$) of 725 m (Ridwan 2016; Ridwan et al. 2016). The surface geology of Jakarta has Quaternary sedimentary units like alluvium, alluvial fan and beach ridge deposits (Turkandi et al. 1992). Alluvium is exposed from the coastline to 6 km southwards in the city centre, which covers 35 per cent of Jakarta. Further southward, the surface geology is dominated by alluvial fan deposits with a patch of Tertiary volcanic material deposited in the west. The alluvial fan sediments are deposited from elevated areas in the south of Jakarta, piling up at the centre with up to 300 m thickness. These Plio–Pleistocene sediments, mostly composed of clayey-sand, unconformably overlie the Miocene formations which are cropping out and encircling the basin in the west, south and east. These uplifted Tertiary formations are known as the Tangerang High in the west, Depok High in the south and Rengasdengklok High in the east (Delifnom 2008).

Throughout Jakarta’s history, at least three large earthquakes have devastated the city. The 1699 earthquake caused 28 casualties (Reid 2012) and triggered a number of landslides within the vicinity of Bogor (Nata & Witsen 1700), a city located about 50 km south of
where Jakarta. The largest earthquake to impact the city had a magnitude of $M_w$ 8.5 and occurred on 1780 January 22 (Albini et al. 1913). Ground shaking caused 27 sheds and houses to collapse in Zandsee and Moorish gracht (canal), located in present-day Central Jakarta where Jakarta Cultural Centre is now standing (Wichmann 1918 translated by Haris & Major 2016). Half a century later, on 1834 October 10, an $M_w$ 7.0 earthquake was associated with seismic intensity considered to be the highest to strike the region (Musson 2012). With 30 million people inhabiting Greater Jakarta, the fatality count could be very high should any of these historical events re-occur today (Nguyen et al. 2015).

3 HVSR MEASUREMENTS

Microtremor survey methods to evaluate the shear wave velocity profile are gaining in popularity because of their applicability in urban areas. These methods are non-invasive, utilizing continuous energy produced by both natural phenomena and human activity. Kanai (1957) observed that the amplitude–frequency relation of earthquake motion exhibited peaks whose period depended on 'each kind of ground'—short period (0.1–0.4 s) on hard ground and longer period (0.4–0.8 s) on softer ground—and noted that the same peak periods were observed in ambient seismic noise (microtremors). Aki (1957), using microtremors recorded at night (6–10 p.m.), also observed that dispersion was site-dependent, and appeared to be characteristic of the underlying medium. Although the HVSR method was first applied for seismic microzonation by Nogoshi & Igarashi (1971), Nakamura (1989) is more widely cited for his promotion of the method and for proposing that the fundamental resonance frequency be defined as the peak of the HVSR curve, defined as

$$\text{HVSR}(\omega) = \frac{\sqrt{H_{EW}(\omega) \times H_{NS}(\omega)}}{V(\omega)},$$

where $H_{EW}(\omega)$ and $H_{NS}(\omega)$ denote Fourier amplitude spectra in east–west and north–south directions, respectively, while $V(\omega)$ is the Fourier amplitude spectrum for the vertical component. The two horizontal components are combined using the geometric average, then divided by $V(\omega)$ to obtain the measured HVSR curve (Harutoonian et al. 2013).

Since this early work, the HVSR technique has been widely used to characterize site response in seismic microzonation studies. The method as proposed by Nakamura (1989) equated both the HVSR peak amplitude and period with those of the S-wave transfer function. Subsequent studies found that, while the period of the HVSR peak coincides with the resonant period of S waves in the sediment column, the amplitude of the peak often does not match that of the S-wave transfer function (Lermo & Chavez-Garcia 1993; Lachet & Bard 1994; Bonilla et al. 1997; Lunedei & Albarello 2010). Several studies have used HVSR to measure this resonant period in the range 0.1–2.0 s to infer site class (Zhao 2010). HVSR measurements of resonant period have also been used to infer depth of sediments when velocity is known from, for example, surface wave dispersion (Ist-von Seht & Wohlenberg 1999; D’Amico et al. 2008) or average velocity when depth is known from geophysical surveys (Bodin et al. 2001).

Other studies have confirmed the original result of Nogoshi & Igarashi (1971) that, although the peak in the HVSR curve coincides with the S-wave resonant period, the HVSR curve itself is closely related to the ellipticity of Rayleigh waves (Konno & Ohmachi 1998; Arai & Tokimitsu 2000). This is true not only when the ambient seismic noise was confirmed to be dominated by Rayleigh waves (Scherbaum et al. 2003) but also in numerical studies that used full wavefield modelling of the ambient seismic noise (Field & Jacob 2003; Arai & Tokimitsu 2004; Scherbaum et al. 2008; Parolai et al. 2005), and this is the approach we adopt in this study.

The Jakarta Basin is thought to have a relatively long resonant period, with the results of (Saygin et al. 2016) indicating an average S-wave velocity of 500 m s$^{-1}$ extending to an average depth of 500 m. This suggests an S-wave resonant period of about 4 $\times$...
$hV_S = 4$ s, with even longer periods possible in the deepest part of the basin beneath northern Jakarta. Although most of the aforementioned studies have involved $S$-wave resonant peak periods in the range of 0.1–1.0 s, typically associated with $S$-wave velocity structure at 100 m depth or less, a few involved situations similar to the Jakarta Basin. Yamanaka et al. (1994) used HVSR measurements with peak periods of 2–8 s to infer basin depths in the Kanto Plain of 1550 m. Bodin et al. (2001) used HVSR measurements with peaks in the range 2–5 s to infer average basin velocities of 600–1000 m s$^{-1}$ in the Mississippi Embayment, for which previous studies had established a maximum depth of about 1000 m.

In order to make HVSR measurements covering long resonant periods, passive seismic measurements have been carried out using three-component Trillium Compact sensors, with sensitivity to velocity flat in the frequency range 0.05–100 Hz. These sensors recorded background noise at 96 sites distributed over the Jakarta Basin (Fig. 2a). Ambient seismic noise was recorded for at least 1 month at each site and processed according to the details given below.

### 3.1 Assumptions

Foremost among our assumptions is that the HVSR curves we estimate are determined by the ellipticity of the fundamental mode Rayleigh wave. It is important to note that in general the ambient seismic noise wavefield consists of body waves ($P$ and $S$) and surface waves (Rayleigh and Love; Bonnefoy-Claudet et al. 2006). Indeed, the original explanation of the HVSR method as proposed by Nakamura (1989) was that it is determined solely by the $SH$-wave resonance. However, subsequent studies showed that the HVSR curve is closely linked with Rayleigh wave ellipticity (Lachet & Bard 1994; Lerme & Chavez-Garcia 1994; Fäh et al. 2001, 2003). Failing to account for other, non-Rayleigh wave components of the ambient seismic noise can lead to an overestimation of the Rayleigh wave ellipticity (Poggi et al. 2012; Hobiger et al. 2013). Following the conclusions of the comprehensive review of the nature of the seismic ambient seismic noise wavefield by Bonnefoy-Claudet et al. (2006), our assumption that the ambient seismic noise wavefield is dominated by the fundamental mode Rayleigh wave is supported by the proximity of the ocean, both the Java Sea to the north and the Indian Ocean to the south. This suggests that the dominant sources of seismic noise will be associated with Rayleigh waves excited by ocean swell (Longuet-Higgins 1950; Yamanaka et al. 1993). The long period, 5–7 s, of the main peak in our HVSR curves (see below), and even the higher frequency peaks at 2–4 Hz are likely associated with this natural source of Rayleigh wave energy, especially since we used measurements made at night and verified their stability.

Our assumption that the fundamental mode is dominant is supported by the ANT study of Saygin et al. (2016), who used this same data set and noted that possible higher order Rayleigh wave modes arriving before the dominant fundamental mode had a much lower signal-to-noise ratio. While several studies that use HVSR to invert for $V_S$ profiles have obtained satisfactory results using only the fundamental mode Rayleigh wave (Yamanaka et al. 1994; Konno & Ohmachi 1998; Scherbaum et al. 2003), other studies have found that higher modes can make an important contribution to the HVSR curve, particularly when low-velocity zones are present (Arari & Tokimatsu 2004; Parolai et al. 2005; Savage et al. 2013; Rivet et al. 2015). The emergent higher mode Rayleigh waves are usually related to peaks above the $S$-wave resonance frequency, hence the secondary and later peaks should be treated carefully because they may be contaminated with higher mode energy (Asten et al. 2004).

Finally, we note that we assume the velocity structure beneath the station can be approximated by a set of horizontal layers, each uniform in seismic velocities and density. Previous studies (Ridwan et al. 2016; Saygin et al. 2016, 2017) assumed a locally 1-D approximation and suggested that the seismic velocity structure in the Jakarta Basin is slowly varying, except for a possible sharp increase in depth from about 300–500 m in central Jakarta along the south–north profile (see fig. 13.1 of Saygin et al. 2016). The influence of 3-D structure on HVSR curves has been studied by Uebayashi et al. (2012a, b) for Osaka Basin and Guéguen (2007) for the Grenoble Basin, who have noted that the 3-D structure can lead to peaks in HVSR curves that are broader than those predicted from the 1-D velocity profile beneath the station, and can also shift the peak HVSR frequencies by 10–20 per cent or more. Thus, care should be taken in interpreting our HVSR curves both at the edges of the Jakarta Basin and at the putative sharp increase in depth near central Jakarta.

### 3.2 Data

Prior to the seismometer deployment whose data are used here, the only previous seismographic study covering the Jakarta Basin was that of Ridwan (2016) and Ridwan et al. (2016), who used shorter period sensors to estimate surface wave dispersion curves in the frequency range 0.2–3.0 Hz using the SPAC method (Aki 1957). The considerable depth to engineering basement (>700 m) and the low velocities of the sediments comprising the basin ($\approx$500 m s$^{-1}$) found by Ridwan (2016) and Ridwan et al. (2016) suggested that the seismic records from broad-band seismometers may be more useful in modelling its interior geometry. To this end, 52 three-component, broad-band sensors were deployed at various sites throughout Jakarta from October 2013 to January 2014 (Saygin et al. 2016). In order to cover the basin at an average interstation spacing of about 2 km, 26 seismometers were re-deployed successively at 44 locations every 3 months. In total, 96 seismic stations were installed, with ambient seismic noise recorded over intervals ranging from 1 to 3 months.

The data from this broad-band experiment were used in an ANT study to image the shear wave velocity structure of the Jakarta Basin (Saygin et al. 2016), as well as in a study of $P$-wave reflectivity from autocorrelation of seismic noise (Saygin et al. 2017). However, both of these studies have limiting resolving power for the basement: the long wavelengths of the ANT study precluded imaging of sharp discontinuities and the $P$-wave reflectivity method lacked an advanced modelling framework. In this study, these same ambient seismic noise recordings are used to compute HVSR curves, and an inversion is applied to these curves to obtain a velocity profile at each station.

Since both the ANT study of Saygin et al. (2016) and the SPAC study of Ridwan et al. (2016) suggest that low shear wave velocities extend to a basin depth of 500–700 m or more, it was important for the data processing to resolve the HVSR at periods of 5 s or longer. While HVSR studies typically use a time window of around 100 s duration (SESAME 2004), we tried to ensure stability of our long-period HVSR curves by using time windows of 1000 s duration (see Figs 2a–f). We note that Langston & Horton (2004) suggested a 600 s window to retrieve fundamental frequencies near 0.1 Hz in the Mississippi Embayment. We used the Geopsy software (Geopsy Team 2004) to compute the HVSR curves in the frequency range...
from 0.1 to 10 Hz as shown in Fig. 2. In general, the observed peak frequencies and amplitudes at each station changed slightly with time, but using measurements at quiet times (i.e. from 10 p.m. to 4 a.m., see Fig. 2) resulted in very stable curves, for peak frequency as well as amplitude. For most stations, a 100 s time-series window resulted in reliable HVSR curves. However, for stations JKA54 and JKA42, a window length of 750 s or higher was needed. Therefore, for consistency, a 1000 s window length was applied for all stations.

Raw spectra often show narrow modulations and spikes that lead to extreme values of HVSR. To mitigate this effect, the smoothing operator proposed by Konno & Ohmachi (1998) was introduced. Also, the ratio between the average level of signal amplitude over a short period of time (STA) and long term average (LTA) is used as a parameter to exclude transient signals. The STA and LTA are set to 1 and 30 s, respectively, and only windows with STA/LTA ratio between 0.2 and 2.5 were used for the HVSR computation.

### 4 HVSR CURVES

HVSR curves show peaks for certain dominant periods that are diagnostic of the impedance contrasts in the underlying velocity structure. Peaks in the HVSR curve are typically associated with zeros in the vertical component Rayleigh wave, at frequencies where the sense of motion switches from prograde to retrograde or vice versa, and the Rayleigh wave is horizontally polarized (Konno &
Such peaks typically coincide with the fundamental resonant frequency $f_0$ of $S$ waves in the sedimentary column, given by period $T = \frac{1}{2\pi} V_S/h$, where $h$ is the depth to a strong impedance contrast and $V_S$ is the shear velocity of basin sediments.

In this study, we found that the HVSR curves were typically characterized by two peaks, one a low-frequency peak in the range $0.1-0.3$ Hz which we denote $f_{L0}$ and a high-frequency peak above $1$ Hz, which we denote $f_{H0}$. We found that our observations could be broadly classified into four groups: (1) the absence of any peak (i.e. a flat HVSR curve or no peak with amplitude >2) which may reflect the absence of a strong impedance contrast due to gradual compaction of the rock during self-loading, as observed at site JKC13 (Fig. 3a); (2) a sharp and high peak at an $f_{H0}$, followed by another sharp and quite high peak at $f_{L0}$ between 1 and 2 Hz, as observed at site JKA49 (Fig. 3b) recorded in the northern basin where the Holocene alluvium overlies older alluvial sand; (3) a sharp and high peak at an $f_{H0}$, followed by a second peak at $f_{L0}$ higher than 2 Hz (Fig. 3c), observed in stations near alluvial fan deposits or along an alluvium boundary where river channel deposits slice through alluvial fan or where beach ridges are deposited over alluvium; and (4) a single peak at $f_{L0}$, as observed at alluvial fan sites such as JKC01 as shown in Fig. 3(d).

Types 2–3 are all characterized by sharp $f_{L0}$ peaks, while Type 4 includes both sharp and broad $f_{L0}$ peaks. We distinguish between these sharp and broad $f_{L0}$ peaks in the following section. Overall, most of the stations having lowest $f_{L0}$ (0.12–0.13 Hz) are located in areas predominantly composed by recent alluvium, however, a less clear correlation between $f_{L0}$ and surface geology is shown in Fig. 3(e).

4.1 Sharp $f_{L0}$ peaks

Almost all the stations recorded sharp HVSR peaks in the frequency range 0.1–0.2 Hz, except for the southernmost stations. These sharp $f_{L0}$ peaks suggest a strong and deep impedance contrast. A high and narrow peak indicates a strong and sharp impedance contrast (Gosar 2010). The greater the magnitude and sharpness of the contrast in lithology, the higher and sharper the peak in the HVSR curve is expected to be (Tarabusi & Caputo 2016).

While observed $f_{L0}$ range from 0.12 to 0.249 Hz, the frequencies of the $f_{L0}$ peaks range between 1 and 6 Hz or are absent. Generally, the stations in the south have $f_{L0}$ that are lower and broader, and centered at higher frequencies than the $f_{L0}$ peaks for stations in the north. The broad peak amplitude may reflect the irregular structure of the basin floor, the stratigraphic complexity at depth or the unconformity between younger volcanic and older marine formations. At JKC18 where the Plio–Pleistocene volcanic rocks and alluvial fan are underlain by Tertiary marine formations, a broad HVSR curve was recorded.

In the north, the absence of Pleistocene volcanic rocks should result in a significant impedance contrast between the Tertiary basement and overlying soft sediment. Near the surface, the broad variability of $f_{L0}$ indicates a corresponding variability of surficial sediment thickness. This also suggests variability in short-period amplification level. On the other hand, the absence of an HVSR peak as shown in Fig. 3(a) may be related to a shallow stratigraphic horizon or compaction that is gradual with depth and results in weak basement impedance contrast (it might also be due to bedrock outcrop, but little or no such outcrop exists in our study area).

This implies that little or no amplification will occur (Castellaro & Mulargia 2009a,b).

Cipta et al. (2018) have used 2-D waveform modelling along an NS cross-section of the Jakarta Basin model developed here to show that very large amplification of ground motion (up to 1500 per cent PGV) can occur for a large scenario earthquake on the Java Trench, with the thicker sediments in the north experiencing the largest amplification. However, the wedged shape of the basin edge as it shallows to the south also plays an important role in amplifying seismic waves (up to 1200 per cent PGV), particularly for the intraslab earthquake scenario considered by Cipta et al. (2018). For both the megathrust and intraslab scenarios, the spectral amplifications were most prominent in the period range 5–7 s, similar to that of the observed $f_{L0}$ HVSR peaks.

4.2 Broad $f_{L0}$ peaks

Lower amplitude and broader peak could reflect a weaker contrast or a more gradual discontinuity. A high variability of surface lithology may also cause a lower peak amplitude. A broad peak is also indicative of irregularity of subsurface structure (Uebayashi 2003) and a broad asymmetric peak indicates variability in rock formation (Gosar 2010).

Broad HVSR peaks at $f_{L0}$ as observed at stations JKA55 and JKC02 (Fig. 4) may be related to steeply dipping bedrock underlying shallow sediments (Ozalaybey et al. 2011) or variability of bedrock formation (Uebayashi 2003; Bonnefoy-Claudet et al. 2009; Gosar 2010). Broad HVSR peaks may also correspond to meaningful 2-D or 3-D variation in the bedrock–sediment interface. In such a situation, diffracted waves including body and surface waves, including Love and higher order Rayleigh waves may be present, so that our interpretation of the HVSR curves in terms of fundamental mode Rayleigh waves in a 1-D structure may not be reliable (Bonnefoy-Claudet et al. 2009). In any case, the study of such small-scale 3-D structure is beyond our scope.

Broad HVSR peaks at $f_{L0}$ are recorded at the southernmost stations where the bedrock depth is expected to be shallow. The slightly bumpy topography decorated by low hills reflects the variation of underlying bedrock structure. In accordance to its proximity to the stream heads, this area is relatively closer to the basin rim, and as a consequence the bedrock depth is shallow. This geographic condition may lead to the emergence of broad $f_{L0}$ peaks at stations JKA55 and JKC02, as shown in Fig. 4. Similarly, broad HVSR curves are observed at stations in elevated areas in southwest Iznit Bay basin where the basin depth is about 200 m based on a gravimetric study (Ozalaybey et al. 2011).

5 HVSR PEAK FREQUENCIES AND AMPLITUDES

The HVSR technique is able to furnish estimates of the frequencies $f_{L0}$ and the corresponding HVSR peak amplitudes at each site. Both of these can potentially be used as proxies to map basement depth, and in Figs 5(a) and (b) we have mapped the interpolated values of $f_{L0}$ and peak amplitudes, respectively. These both suggest a pattern of deepening basement from south to north that is very similar to the results of Saygin et al. (2016). It is important to note that the simple kriging method is used to interpolate data sets and produce those maps. The kriging method considers the distance and the degree of variation between known data points when estimating values.
Figure 3. Ellipticity curves measured in Jakarta: (a) flat, (b) sharp peak at low frequency (<0.25 Hz) and another at a frequency between 1 and 2 Hz, (c) peak at low frequency (<0.25 Hz) and at frequency above 2 Hz and (d) peak only at low frequency (<0.25 Hz). Variability of the second peak (or absence of this high-frequency HVSR peak) roughly reflects surface geology. Panels (e) and (f) show the distribution of low- and high-frequency HVSR peaks, respectively, plotted on a geological map. Thin blue lines indicate Cisadane, Ciliwung and Kali Bekasi faults as mentioned by Moechtar (2003) and Putra et al. (2016). Location of stations is shown in Fig. 2(a).

in unknown areas. However, at the data points themselves it may produce values that are slightly different from the observed data.

Maps of $f_{l0}$ and corresponding peak amplitudes (Figs 5a and b, respectively) show two areas that exhibit both pronounced lows in peak frequency $f_{l0}$ and high-peak amplitude: (1) the deepest part of the basin located in the northeast; and (2) the high-peak amplitude passage crossing the city from the northwest to the southeast. The former coincides with high rates of subsidence (Abidin et al. 2011) while the latter may reflect a fault or anticline axis.

Supplementary to $f_{l0}$, higher frequency peaks at $f_{h0}$ emerge at 33 stations. Stations that exhibit $f_{h0}$ peaks are distributed mostly in northern Jakarta where thin marine and terrestrial sediments overlie the stiffer and older alluvium. Recently deposited and intercalated marine and terrestrial sediments may form a relatively thin sediment layer which may be responsible for the $f_{h0}$ in the frequency ranges 1–2 Hz (Fig. 2f). We surmise that the high amplitude of these $f_{h0}$ peaks indicates a high impedance contrast between relatively young sediments and underlying stiffer alluvium in Figs 3(b)–(f) and 6(a)–(d).

Higher frequency ($f_{h0}$) peaks also emerge at stations in the south-north (SN) cross-section indicated in Fig. 2(a) where alluvial fan deposits dominate the surface geology. In these stations, $f_{h0}$ appears...
Figure 4. Curves showing broad peaks at $f_0$ at stations JKA55 and JKC02, both located in the southernmost of the city where basin depth is shallow. Location of stations is shown in Fig. 2(a).

Figure 5. (a) Map of interpolated $f_0$ frequencies, showing two prominent low-frequency areas (coloured red) in the northeast corner and along a northwest–southeast passage. Coloured circles indicate stations at which the corresponding peak frequencies were observed. (b) Map of interpolated $f_0^h$ amplitudes, with coloured circles indicating the stations where the corresponding amplitudes were observed.

At higher frequency (4–6 Hz) than those that emerge at northern stations. We speculate that self-compaction and near-surface weathering are the cause of the emergence of higher frequency $f_0^h$ peaks. Low amplitude ($\leq 3$) at $f_0^h$ (4–6 Hz) implies this geological phenomenon, where thin degraded alluvial fan is overlying the firmer soil (Figs 4b, 3f, 6a–d).

In Figs 6(a) and (b), 2-D transects have been constructed which show the correlation of $f_0^h$ and $f_0^h$ HVSR peaks between adjacent stations, and illustrate how they vary in SN and west–east (WE) directions. A sudden decrease of $f_0^h$ is clearly visible in the SN transect. In particular, $f_0^h$ decreases from 0.223 Hz (JKC02) to 0.146 Hz (JKA12), indicating an abrupt change in basin depth over a distance of only 2.6 km. At the northernmost stations (e.g. JKA24), $f_0^h$ has increased slightly to 0.154 Hz, over a distance from JKA12 of around 14.6 km. This suggests an abrupt increase in basement depth northward between JKC02 and JKA12, the basement then flattening up to the central part of Jakarta and becoming slightly shallower to the north.

The WE transect shows a complexity of near-surface layering, as reflected by the $f_0^h$ peaks. Sites JKA44 and JKB14, located near and on Plio–Pleistocene tuff deposits, respectively, do not show clear $f_0^h$ (Figs 6c and d). The absence of $f_0^h$ peaks suggests there are no strong impedance contrasts in the near-surface layering. Further to the east, as the surface geology changes from tuff to alluvial fan and alluvium with locally intercalated beach deposits, the $f_0^h$ peaks are more pronounced. These $f_0^h$ peaks appear at a frequency of 4 Hz except for stations JKA32 and JKA07 where they appear near 2 Hz. In addition, a smooth decrease of $f_0^h$ is shown in the WE transect. The $f_0^h$ at the westernmost station decreases towards the centre, fluctuates and then decreases eastward. This pattern indicates a shallower basement in the west, undulating in the centre and deeper in the east (Figs 6c and d).

The peak frequency data from 93 stations covering Jakarta have indicated significantly low $f_0^h$ in the northeast corner of the city, high $f_0^h$ in the west and south and fluctuating values of $f_0^h$ at the centre. A low $f_0^h$ patch along the NW–SE portion of central Jakarta is sandwiched within the three narrow patches of high $f_0^h$ in the west, south and east. This gully-like feature is situated at high-peak HVSR, with surrounding low-peak HVSR within the vicinity. In general, the low $f_0^h$ values in Jakarta corresponds to high-peak HVSR and vice versa as depicted in Fig. 5.

6 INVERSION OF HVSR CURVES

Quantitative estimates of depth profiles of elastic properties such as shear wave velocity $V_S$ can be obtained through HSVR curve
Figure 6. Comparison of HVSR spectra along the SN (a and b) and WE (c and d) transects indicated in Fig. 2(a). The SN transect (a and b) shows that the frequency $f_{l0}$ of the low-frequency HVSR peak abruptly decreases at JKA12, then gradually increases at JKA47. This graph also illustrates the effect of the impedance contrast at shallower depth on the high-frequency peak amplitude in the ellipticity curve. The WE transect (c and d) shows highest $f_{l0}$ at the western end, lowest $f_{l0}$ at the eastern end and variable $f_{l0}$ in the middle. Blue and red dashed lines are the highest and lowest peak frequencies (peak $f_{l0}$), respectively, at corresponding cross-sections. The green solid lines show lineation of peak frequency and blue dots are stations indicated in Fig. 2(a). The x-axis is the relative location of stations in the SN (b) and WE (d) directions, as indicated by blue dots in (a) and (c).
inversion, wherein it is typically assumed that the shape is determined by the Rayleigh wave ellipticity. However, the nonlinear dependence of the HVSR curve on the depth profile of elastic parameters makes the inversion challenging. Scherbaum et al. (2003) used a simple model in which $V_S$ having a power-law dependence on depth overlays a half-space to invert HVSR curves for model parameters using a grid search. Arii & Tokimatsu (2004) developed a nonlinear least-squares approach in inverting HVSR curves using multimodel Rayleigh wave ellipticity to resolve $V_S$ profiles including low-velocity zones. More recently sampling methods, with a fixed number of layers, are becoming widely used (Fäh et al. 2003; Wathelet et al. 2004; Parolai et al. 2005; Hobiger et al. 2013). All of these methods use simplifying assumptions on the model, for example, power-law depth dependence (Scherbaum et al. 2003), fixed number of layers (Fäh et al. 2003; Parolai et al. 2005; Hobiger et al. 2013), fixed $V_S$ and/or density (Scherbaum et al. 2003), restricted Poisson’s ratio (Hobiger et al. 2013) or fixed bedrock velocity (Parolai et al. 2005).

A priori constraints on the complexity of velocity profiles in the Jakarta Basin present a problem because we do not know how complicated they might be. The surface geology is dominated by poorly consolidated, water-saturated sediments with a basement at hundreds of metres depth. Thus, we expect the velocity profile to be complicated in the topmost 100 m of the profile, where water saturation will lead to a high Poisson’s ratio that will decrease rapidly with depth along with an increase in seismic velocity due to compaction. Deeper than 100 m, there may be intervening layers of marine Pliocene and Quaternary sand and deltaic sediments until compaction. Deeper than 100 m, there may be intervening layers of marine Pliocene and Quaternary sand and deltaic sediments until the basement is reached at several hundred metres depth or more. We would like to find the simplest model that can fit the data, but we neither know what minimum complexity is required nor what the uncertainty is in our HVSR curves.

Bayesian inversion provides a framework to combine information on model parameters we have before making an observation with a probabilistic expression of data information to obtain an a posteriori probability density function (PDF) for the model parameters. To define the posterior distribution, Bayes’ theorem (Bayes 1763; Sivia & Skilling 2006) is used, which is expressed as:

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}.$$  

More specifically, if we consider a model space consisting of a fixed number $k$ of horizontal layers, each having a uniform distribution of S-wave velocity $V_S^k$, ratio of P- to S-wave velocity ($V_P/V_S$), and density $\rho$, Bayes’ theorem can be expressed for a data vector $d$ and model vector $m_k$: as:

$$P(m_k|d) = \frac{P(d|m_k)p(m_k)}{\int_{M} P(d|m')dm'},$$  

where $P(m_k|d)$ is the conditional probability of the model given the data (the ‘posterior’), $P(d|m_k)$ is the conditional probability of the data given the model (the ‘likelihood’), $P(m_k)$ is the a priori probability of the model (the ‘prior’) and $\int_{M} P(d|m')dm'$ is the probability of the data (the ‘evidence’). We note that in Bayesian inversion the evidence integral is typically regarded as a normalization constant and ignored, and the numerator of the posterior PDF can be explored using a Markov chain (Mosegaard & Tarantola 1995), which would sample over the space of models with $k$ uniform layers. While it might be possible to perform multiple inversions for different values of $k$, and test the hypothesis that a model with $k'$ layers is more plausible than one with $k$ layers using the ratio of evidence values (Bayes’ Factor), in practice computation of the evidence integral $\int_{M} P(d|m')dk'$ is very time consuming, and this would not address the problem of assessing how our lack of knowledge of an appropriate value for $k$ contributes to model uncertainty.

Green (1998) showed that Bayes’ rule can be written for a Bayesian hierarchical model to include a hyperparameter $k$:

$$P(k, m_k|d) = \frac{P(k)p(d|m_k)p(m_k|k)}{\sum_{k'=0}^{k} \int_{M} P(k')P(d|m'_k)dm'_k},$$  

where $k$ can be interpreted as indexing possible choices of models, in our case models with different numbers of layers. As with eq. (2), the denominator in eq. (3) can be regarded as a normalizing constant and ignored, and the posterior $P(k, m_k|d)$ can be explored by using a Markov chain Monte Carlo approach to sample the numerator, as described in Malinverno (2002), Sambridge et al. (2006), Dettmer et al. (2010) and elsewhere. This ‘trans-D’ approach allows a group of model parametrizations, in our case models with varying number of layers, to be considered simultaneously for analysis. Because all models are considered in the analysis, the trans-D approach allows us to account for how limited knowledge about the number of layers affects the parameter and uncertainty estimates based on the posterior. Inferences obtained in this manner avoid the inherent biases involved in selecting a single fixed number of layers and are hence more realistic and reflective of the state of knowledge about model parameters.

We invert our HVSR curves for depth profiles of elastic parameters using trans-D Bayesian inversion (Malinverno 2002; Sambridge et al. 2006; Dettmer et al. 2010). Since this statistical sampling method requires very rapid forward computations, we make use of the highly optimized forward computations of Wathelet et al. (2004), which parametrize the velocity structure as a stack of homogeneous layers overlying a half space. We invert for the number of layers $k$ as well as for $V_S, V_P/V_S, \rho$ and thickness $h$ in each layer. In addition, we use a hierarchical approach (e.g. Bodin et al. 2012; Dettmer et al. 2012) to estimate the noise (i.e. the value of $\sigma$) as part of the inversion.

Following Dettmer et al. (2012) eq. (6), we use the likelihood function:

$$P(d|m_k) = \frac{1}{(2\pi)^{N/2}C_d^{1/2}} \exp \left( -\frac{1}{2}(d - d(k, m_k))^T C_d^{-1}(d - d(k, m_k)) \right),$$  

where $C_d = \sigma^2 I$, with $I$ the identity matrix and $\sigma$ the noise standard deviation (the magnitude of the noise) and the data vector $d = [\text{HVSR}(\omega_0), \text{HVSR} (\omega_1), ..., \text{HVSR}(\omega_q)]$. The modelled data vector $d(k, m_k)$ is the value of HVSR calculated at frequencies $\omega_0, \omega_1, ..., \omega_q$ for the model having number of layers $k$ and model vector $m_k$ consisting of the layer parameters $h_i, V_S^i, (V_P/V_S)^i$ and $\rho^i$, where $i = 1, ..., k$. These layer parameters, as well as the number of layers $k$ and the standard deviation $\sigma$, are unknowns in the inversion.

As described in more detail by Dettmer et al. (2012), this trans-D approach to model selection lets the data infer its own noise magnitude and model complexity. Although it involves no regularization such as model smoothing, Malinverno (2002) has shown that Bayesian model selection tends to ‘parsimony’ in the sense that models with more complexity than is required to fit the data tend to be assigned low posterior probability.
6.1 Synthetic tests

The importance of model selection using the trans-D method for uncertainty quantification is illustrated with a simulation example in Fig. 7 and Supporting Information Figs S1–S3. Data were simulated by calculating an HVSR curve for a 10-layer model which is representative of the expected complexity in the Jakarta Basin. Gaussian-distributed random noise with $\sigma = 0.07$, in logarithmic scale, was added to the HVSR curve, which appears close to the noise level in the observed data.

In the true model, velocity rapidly increases with depth in the top 100 m due to compaction, after which there is little variation until a basement is reached at 900 m depth (the white curve in Fig. 7). This structure results in two peaks in the fundamental-mode Rayleigh wave ellipticity spectrum at 3.0 and 0.16 Hz, corresponding to the velocity increase in the top 100 m and the 900 m basement depth, respectively. Three inversions were carried out: (1) Fig. 7(a) (see also Supporting Information Fig. S1) shows the results for trans-D inversion, where the number of layers in the model is treated as unknown, with a prior set as uniform between 3 and 20 layers; (2) Fig. 7(b) (see also Supporting Information Fig. S2) shows results for an inversion were the number of layers was fixed at three, which would generally be regarded as a reasonable choice, but represents an underparametrized inversion; (3) Fig. 7(c) (see also Supporting Information Fig. S3) shows results for an inversion where the number of layers was fixed at 20, which represents an over-parametrized inversion and is expected to result in spurious, unconstrained structure.

In all three cases eight Markov chains were run in parallel and more than 100,000 posterior samples were recorded. The total number of steps was much larger, since only every 100th step was recorded and half the initial steps were discarded as ‘burn-in’. The prior was uniform and is given by the plot boundaries in Supporting Information Figs S1–S3. The bounds are wide so that data information predominantly constrains the solution. Convergence for these inversions was judged based on examining the chain history for all eight chains. Since the chains are independent but sample the parameters in highly similar manner, convergence is likely.

The trans-D results in Fig. 7 show excellent agreement with the true model. Importantly, uncertainty estimates appear reasonable and increase substantially with depth, which is commonly observed for diffusive wave fields, such as Rayleigh waves. The data also appear to provide only limited information about selecting the number of layers for this site which results in substantial uncertainty in k and models with 7 to 15 layers all fit the data acceptably well. However, the posterior also shows clearly that the $V_S$ marginal profile is parsimonious in that it captures an appropriate level of complexity without introducing spurious layers. The trans-D result also provides an excellent data fit and the noise standard deviation estimated by the inversion is close to the true value with some uncertainty from 0.06 to 0.10. Importantly, the ability of HVSR curve inversion to resolve multiple $V_S$ layers is encouraging for our application. While the HVSR curve is mostly sensitive to $V_S$, its sensitivity to $V_p/V_S$ and $\rho$ is in general significant (Berbellini et al. 2016). For this reason we included $V_p/V_S$ and $\rho$ as well as $V_S$ in the inversion, but since the resolution of $V_p/V_S$ and $\rho$ was poor we will not interpret them further.

In the three-layer case (Fig. 7b and Supporting Information Fig. S2), an apparently reasonable and well-constrained model is obtained. However, the estimated posterior bears little resemblance to the true model and uncertainties are estimated to be low and increase only slightly with depth. In addition, the estimated noise standard deviation is four times larger than the true value, a known issue for inversions with underparametrized models (Dettmer et al. 2009). The large noise standard deviation is also reflected in the poor data fit (Supporting Information Fig. S2).

In the 20-layer case (Fig. 7c and Supporting Information Fig. S3), the data fit is excellent and the noise standard deviation is estimated close to the true value. Such good data fits commonly boost confidence in the inversion results. However, the posterior estimate does not represent the true model well. Rather, the results are plagued by very large uncertainties and erroneous, unconstrained structure.

In conclusion, the trans-D results are far superior and this parametrization is appropriate for HVSR data. Importantly, the ability of HVSR curve inversion to simultaneously resolve both the fine scale $V_S$ layering in the upper 100 m and the coarser scale layering associated with a basement depth of several 100 m is encouraging for our application.

6.2 Inversion of Jakarta’s HVSR curves

Out of the 96 stations with data, 93 stations were deemed useful in mapping the geometry of the Jakarta Basin. The trans-D inversion is applied to HVSR curves from these stations to obtain estimates of $V_S$ profiles in this deep basin with an irregular bedrock-sediment interface. The HVSR curves are assumed to be a representation of fundamental-mode Rayleigh wave ellipticity over the frequency band of 0.1–10 Hz.

To assign the prior, we choose upper and lower limits for parameter values ($k$ and $V_S$), based on existing geological knowledge (thickness and age of rock formations), boreholes and hydrogeological investigations (depth and thickness of aquifers). The hydrogeological study of Delinom et al. (2009) found that underneath the Jakarta Basin, there are three groundwater aquifers at depths of 0–40, 40–140 and 140–250 m, respectively. This may indicate that there are at least three distinguishable layers in the top 250 m of soil. The series of volcanic products and by-products, such as alluvial fans, that were deposited after the Plio–Pleistocene thrusting (Kloosterman 1989), marked the early Quaternary sedimentation and likely have different density from underlying Late Miocene formations. In addition, an interface due to the Oligocene–Miocene tectonic period (Turkandi et al. 1992) is expected. Therefore, we set a uniform prior on $k$ between 3 and 20 layers, ensuring that the expected structure fits well within this prior specification. The prior for interfaces to occur is chosen to be uniform from 0 to 3000 m depth. The prior on $V_S$ is chosen uniform between 100 and 4000 m s$^{-1}$ to include a wide variety of sediment and rock types. Both density and $V_p/V_S$ are treated as unknown nuisance parameters in the inversion. For density, the prior is set uniform between 1.5 and 4.0. Finally, the $V_p/V_S$ prior is set uniform from $\sqrt{2}$ to 8, to include the potential of poorly consolidated, highly water-saturated sediments.

Fig. 8 shows an example of inverted $V_S$ profiles and observed and computed HVSR curves for station JKB18. Log likelihood, optimum number of layers and standard deviation are also presented. Fig. 9 shows $V_S$ results and HVSR curves for stations JKB20 and JKA12. The slim coloured bands indicate the posterior probability (normalized at each depth level) and show that the prior information was substantially updated with data information which resulted in a narrow range of acceptable velocity-depth profiles. The data fits for these stations are also shown and show good fits to both the low- and high-frequency HVSR peaks.

The inversion procedure was repeated for the remaining 93 stations in identical manner. The maximum a posteriori $V_S$ profiles
Figure 7. $V_S$ results of Bayesian inversion of synthetic data for which random noise has been added to forward calculations of an HVSR curve calculated using the 10-layer model indicated by the white solid curve. Three inversions have been carried out: (a) a trans-dimensional inversion that accounts for models with variable numbers of layers and inversions in which the number of layers is fixed at 3 and 20 (b and c, respectively). The insets at the top right of each panel expand the details of the velocity profile in the top 200 m.

from each station were then gridded with linear interpolation in 3-D space. Since all models featured an abrupt change in $V_S$ from a value of 700–900 to 1500–2100 m s$^{-1}$ at some depth that we interpret as basement, an iso-surface at $V_S = 1500$ m s$^{-1}$ was used to construct a basin depth model. On average, the depth of this iso-surface ranges from 700 to 900 m, although some western and eastern parts of the Jakarta Basin are significantly deeper than 1250 m, while shallower basement depths of $\sim 300$ m or less are estimated in the south. In general, the southern part of the basin is shallower than the northern part.

An SN transect of basin structure constructed by interpolating inversion results along the line indicated in Fig. 2(a) shows the variation in basement geometry (Fig. 11a). A zone of very low velocity (300 m s$^{-1}$ or less) dominates the top $\sim 100$ m, while the shear wave velocity above the basement is less than 900 m s$^{-1}$, abruptly increasing to 1500–2100 m s$^{-1}$ in the basement. Taking this as the basement–sediment boundary, in the southern half of the city it is significantly shallower than the northern, with an abrupt increase in depth at around 6.24° S as depicted in Fig. 11(a). These velocity profiles are in good agreement with the distribution of low-frequency HVSR peaks. The stations in the south, including JKC18, JKC14 and JKC02 recorded higher $f_0$ (0.191–0.224 Hz), while the central stations, such as JKA12, JKC16 and JKC01, recorded significantly lower $f_0$ (0.138–0.146 Hz), the northern stations, including JKA38, JKB16, JKA47, JKB20 and JKA24, recorded higher $f_0$ (0.154 Hz) compared to the stations at the centre, as shown in the same figure.

A shallow basin depth in the south has also been inferred from the surface geological data. At the head of the alluvial fan, the deposits are thinner with coarser grain-sized components. Further from the head, along the gentle slope, thicker and finer grain-sized sediments were deposited. This may explain the basement depth reaching a maximum depth in central Jakarta. The accumulation of younger marine sediments overlies the alluvial fan on the northern part of the city, which together with the alluvial fan and Plioence–Pleistocene tuff fill the basin up to a thickness of 1300 m. The tectonic high known as Thousand Islands High in the north of the bay of Jakarta limits the sedimentation rates along the coastal plain. Consequently, sediment deposits are gradually thinning northwards. Prograde depositions, both from the south and north, caused thick sedimentation in the centre while thinning southwards and northwards as indicated in the basin depth map in Fig. 10.

7 DISCUSSION

Our study has shown that the Jakarta Basin, a Miocene basin filled with Pliocene–Holocene sediments, has thickness ranging from 300 m up to 1350 m. It is located approximately 250 km from the Java subduction zone. The similarity in geology and tectonics suggests that Jakarta may experience significant building damage analogous to Mexico City if a high-magnitude subduction zone or intraslab earthquake occurs. Further complicating the situation for Jakarta are 69 tall buildings (40+ storeys) that are currently in use, ranking Jakarta as 14th among the cities with the greatest number of buildings of at least 150 m height (CTBUH 2017; Emporis 2017). Such high-rise buildings are prone to high shaking at 3 s or longer periods as was observed in Mexico City during the Michoacán Earthquake (Padilla y Sanchez 1989; Flores-Estrella et al. 2007). Previous studies in the basins of southern California (Magistrale et al. 2000) and the Lower Rhine Embayment (Ewald et al. 2006) showed the importance of 3-D basin geometry in modelling the characteristic basin propagation of seismic waves. Data from the 3-D simulations of wave propagation are available including wave front focusing due to low-velocity zones or edge-diffracted waves (Ewald et al. 2006), basin resonance (Castellaro et al. 2014) and local-scale multiscattering and prolonged ground motion (Olsen et al. 2006; Furumura & Hayakawa 2007; Denolle et al. 2014a; Cruz-Atienza et al. 2016; Viens et al. 2016). Interesting research of Roten et al. (2014) found that non-cohesive shallow low-velocity sediments of...
Los Angeles Basin may reduce seismic shaking generated by San Andreas Fault. Accordingly, a rigorous quantification of seismic properties and geometry of the Jakarta Basin is a prerequisite to generating a robust seismic hazard map for the city.

Given the basin model presented in Fig. 10, it is clear that there are some regions flanked by deeper depressions. A ridge-like structure (light green: shallower depth), extending from the central–north coast to the southwest, is sandwiched by two deeper bedrock regions (yellow–red) on its northwest and southeast sides (dashed lines). The southern basin is shallower but also exhibits significant topography, including a shallow ‘bump’ in the basement that is surrounded by deeper sediment. In the case of the Lower Rhine Embayment, prolonged shaking is recorded in an area situated between two deep depressions. The dependence of seismic wave amplitude on basin depth was also observed in the Lower Rhine Embayment (Claperoëd et al. 2012; Gorstein & Ezersky 2015; Pandey et al. 2016). As shown in Fig. 11(a), our direct inversion of the ellipticity curve resulted in a velocity profile that is comparable with the results obtained using ANT conducted by Saygin et al. (2016). The advantage of ANT is its treatment of lateral variability, while in our HVSR analysis we have assumed locally 1-D structure. However, the vertical resolution of our results is higher than the results presented by Saygin et al. (2016).

8 CONCLUSION

We have shown that the HVSR of seismic ambient seismic noise in the Jakarta Basin can be used to make robust estimates of the HVSR peak periods, which has been shown to coincide with the $S$-wave resonant period in many studies (Lermo & Chavez-Garcia 1993; Lachet & Bard 1994; Bonilla et al. 1997; Lunedei & Albarello 2010). In Jakarta, these peak periods are in the range 4–8 s,
Figure 9. Inverted velocity profile at stations JKB20 (a) and JKA12 (b), the relatively thin coloured bands near surface and broader in the deeper part indicate standard deviation broader as depth increasing, as expected. The very thin bar at depth more than 2300 m indicates that inversion cannot resolve the data well (b). Computed ellipticity curves (green) at stations JKB20 (c) and JKA12 (d) fit observed ellipticity curves (blue) well.

with generally shorter periods in the south and longer periods in the north, in agreement with previous studies suggesting very low velocities extending to a basement at several hundred metres depth that deepens northwards (Ridwan 2016; Ridwan et al. 2016; Saygin et al. 2016). S-wave resonant periods in this range are potentially a concern for very tall (40–80 storey) buildings, which are prevalent in Jakarta currently and whose number is expected to increase in the next decade.

Assuming the HVSR curve measured from ambient seismic noise in the Jakarta Basin is dominated by the fundamental mode Rayleigh wave, and is therefore an expression of its ellipticity (Lachet & Bard 1994; Scherbaum et al. 2003; Arai & Tokimatsu 2004) we have also inverted this curve to estimate the S-wave velocity structure of the basin. In order to resolve both shallow velocity structures due to compaction of unconsolidated sediments as well as the deep basin architecture, we used trans-D Bayesian inference, which not only allows the complexity of the model (in our case the number of layers) to adapt to fit the data but also accounts for uncertainty in the model due to the unknown number of layers. At the same time the ‘Bayesian parsimony’ feature of Bayesian model selection (Malinverno 2002) assigns low a posteriori probabilities to models whose complexity is not required by the data. The dense seismic network we deployed in the Jakarta Basin enabled the mapping of basement topography, whose depth varies within the range 300–1400 m in a pattern similar to that obtained in previous studies using ANT (Saygin et al. 2016) and SPAC (Ridwan et al. 2016), respectively.

Previous studies using HVSR to infer basin structure have noted limitations of the type of HVSR analysis presented here. Several have noted the importance of using higher order Rayleigh modes in fitting observed HVSR curves, particularly when low-velocity zones may present (Arai & Tokimatsu 2004; Asten et al. 2004; Parolai et al. 2005; Poggi et al. 2012; Rivet et al. 2015). Others have discussed the importance of also taking into account Love and body wave energy when interpreting the HVSR curve (Arai & Tokimatsu 2004; Sánchez-Sesma et al. 2011; Salinas et al. 2014) as well as the importance of jointly inverting HVSR data with other data sets such as surface wave dispersion curves to avoid some of the strong trade-offs in thickness versus velocity model layers (Scherbaum et al. 2003; Parolai et al. 2005; Hobiger et al. 2013). Finally Guéguen et al. (2007) have discussed the difficulty in applying HVSR to basins with small aspect ratio. We agree that all of these are potential shortcomings of the approach we have taken in this study, and for this reason regard our model of the Jakarta Basin as preliminary pending further investigation of these limitations. However, we believe that we have shown that the trans-D Bayesian approach to inversion of HVSR data is an effective approach to this highly nonlinear inverse problem that is worthy of further study, especially in deep sedimentary basins like Jakarta.
Figure 10. Considering velocity $= 1300 \text{m s}^{-1}$ as the basement, we can map the geometry of the basin. The basin depth ranges from 300 m in the southeast to more than 1300 m in the west and east. Coloured circle is actual data point resulted from inversion of HVSR, while areas surrounded by deeper bedrock-depth is indicated by black dashed lines.

Figure 11. A drastic velocity change is apparent as velocity reaches about $1300 \text{m s}^{-1}$. We consider this boundary to be the basement (white stripe). Considering this white stripe as basement, it can be concluded that in southern Jakarta the sediment thickness reaches 700 m and is the thickest sediment ($1300 \text{m}$) accumulated in the centre of Jakarta. A normal fault-like structure delimits the thinner sediment in the south from the thicker sediment in the north. Comparing between (a) HVSR and (b) ANT, in general, both methods resulted similar patterns, with the southern half of the city having significantly shallower basement than the northern half. An abrupt topographic change in basement depth appears in the centre of the cross-section. ANT and HVSR results were gridded using the simple kriging interpolation method. The location of the cross-section line (and its S–N direction) and measurement points are presented in Fig. 2(a).
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**SUPPORTING INFORMATION**

Supplementary data are available at *GJI* online.

**Figure S1.** Results of a synthetic trans-D inversion in which random noise with standard deviation of 0.07 has been added to forward calculations of an HVSR curve calculated using a 10-layer model (white curve). The top-left panels (a), indicate log likelihood (top), number of layers (middle) and standard deviation (bottom), for individual steps of the Markov chain used to sample the posterior PDF. Each of the eight parallel Markov chains is assigned a distinct colour, so it can be seen that each chain is sampling a consistent distribution. (only every 100th step in each chain was saved, and half the initial steps were discarded as ‘burn-in’, leaving about 7000–10 000 steps in each chain which are displayed). In (b), the synthetic data used as the observed (black curve) HVSR is displayed along with the HVSR curve for the model associated with the maximum sampled posterior PDF (magenta curve). The lower panels display histograms of the sampled models for $V_s$, $V_p/V_s$ and density $\rho$ in (c)–(e), respectively. The inset of (c) shows detail for the shallowestmost
200 m of the $V_S$ profile. The white curve indicates the $V_S$ used to produce the synthetic HVSR curve.

**Figure S2.** As for Fig. S1, but the number of layers in the inversion is fixed to three. This results in velocity profile far from the initial model and the inversion cannot recover the ellipticity curve, hence the noise level is overestimated ($\sim 0.27$ compared with the true value of 0.07).

**Figure S3.** As for Fig. S1, but in contrast to the three-layer model of Fig. S2, a 20-layer model recovers the ellipticity curve well. However, the estimated velocity profile is much more complicated than the true one. The white curve indicates the velocity model used to produce the synthetic HVSR curve.

**Figure S4.** Distribution of stations indicated as black dots while blue dots indicate stations mentioned in the main text to make SN and WE cross-section plots and red diamonds are stations which profiles are shown in Fig. S5.

**Figure S5.** Shear wave velocity profiles to the depth of 40 m obtained from HVSR, NSPT and SPAC techniques. Location of stations is presented in Fig. 2.

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