Love and Rayleigh phase-velocity maps, 5–40 s, of the western and central USA from USArray data

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Abstract

Continuous data recorded on more than 1600 USArray seismic stations operating in the western and central US between 2006 and 2012 are used to map phase velocities of Love and Rayleigh waves at short periods (5–40 s) using a noise-correlation technique. Vertical and transverse records for all station pairs separated by less than 600 km are cross correlated in 4-hour-long segments, and the resulting spectra are stacked for the time period of station operation. Dispersion curves are determined from the locations of zeros in the real component of the correlation spectra using a method based on that of Aki (1957). Phase-velocity maps expanded on a 0.25°-by-0.25° pixel grid are estimated by inversion of the phase-velocity measurements. Comparison with predicted phase-velocity maps based on the crustal model CRUST2.0 combined with the mantle model ND08 shows good agreement at the longer periods. Strong slow anomalies (>25%) in the short-period maps are geographically correlated with basins and regions of thick sedimentary cover. The strength of these anomalies is not well predicted by existing crustal-velocity models.

Keywords: Surface-wave dispersion, Noise tomography, Earth’s crust

1. Introduction

One of the unexpected, useful applications of the data recorded by the Transportable Array (TA) of USArray is the mapping of crustal structure using surface-wave signals extracted from seismic noise. It is worth noting that none of the three community articles that formulated the case for constructing USArray (Ekström et al., 1998; Levander et al., 1999; Meltzer et al., 1999) mentions continent-scale crustal mapping as a goal, much less achieving this goal by analyzing noise. Because of the relatively large station spacing (~ 70 km), the TA was, at the beginning, mainly viewed as useful for constraining mantle lithospheric and deep Earth structure. This perception gradually changed in the early 2000s when several studies demonstrated the practical possibility of extracting robust structural signals from cross-correlations of seismic noise recorded at two stations. Pioneering papers include those by Shapiro and Campillo (2004), who showed the presence of wavetrains with Rayleigh wave dispersion in noise cross-correlation functions for stations separated by tens and several hundreds of kilometers, and by Shapiro et al. (2005) and Sabra et al. (2005), who demonstrated the possibility of using dispersion measurements obtained from cross-correlation functions for tomographic imaging of phase velocity across southern California. With its regular 2-D-grid geometry and 18- to 24-month-long sliding deployments, the TA turns out to be ideal for surface-wave mapping with noise cross-correlation functions. The last several years have seen rapid growth in research testing and exploiting this capability.

It is apparent from numerous tomographic-mapping experiments that both Love and Rayleigh wave signals over a broad range of relatively short

26 periods (a few seconds to tens of seconds) can be extracted from cross-
 27 correlation functions from station pairs at TA offsets (≥ 70 km) (e.g., Shapiro
 28 et al., 2005; Sabra et al., 2005; Yao et al., 2006; Lin et al., 2008). Mapping of
 29 phase velocities at these periods provides new constraints on P and S veloci-
 30 ties in the crust, as well as on anisotropy. In combination with other seismic
 31 measurements, such as those provided by receiver-function analysis, knowl-
 32 edge of surface-wave dispersion properties allows better-constrained mapping
 33 of crustal velocity structure and depths of horizontal interfaces such as the
 34 Moho and the top of the crystalline basement.

35 Most recent studies that have used noise cross correlation to extract dis-
 36 persion information for tomographic inversion start from the premise that,
 37 for a sufficiently diffuse background-noise wavefield, the cross-correlation
 38 function should approach the inter-station Green function (e.g., Lobkis and
 39 Weaver, 2001; Snieder, 2004; Sánchez-Sesma and Campillo, 2006). This
 40 motivates and justifies the use of standard analysis methods for extracting
 41 surface-wave group- and phase-velocity measurements from the time-domain
 42 cross-correlation function; in essence treating it as a point-source seismo-
 43 gram. In an earlier paper (Ekström et al., 2009), we took an alternative
 44 approach, and returned to the treatment by Aki (1957) of the properties of
 45 the noise cross-correlation spectrum. In Aki’s approach, the underlying as-
 46 sumption is that the cross-correlation function is dominated by contributions
 47 from fundamental-mode surface waves. With this assumption, dispersion
 48 properties can be directly inferred from the cross-correlation spectrum us-
 49 ing algorithms that are straightforward to automate. In our 2009 study, we
 50 demonstrated the performance of this spectral approach, and documented

51 high similarity of our tomographic results with other early results derived
52 from USArray data.

53 In this paper, we extend the method of Ekström et al. (2009) and apply it
54 systematically to the seismic data recorded on USArray. The first objective
55 is the development and presentation of a large data set of inter-station phase-
56 velocity measurements derived from analysis of cross-correlation spectra. The
57 second and main objective is the determination of baseline Love and Rayleigh
58 phase-velocity maps over the period range 5–40 s for the western two thirds
59 of the conterminous US. The third objective is an evaluation of the maps
60 by qualitative and quantitative comparison with an existing continent-scale
61 crustal model and maps of sediment thickness.

62 We assess the uncertainties and the internal consistency of the data set
63 by comparisons of measurements of similar paths, and by the ability of the
64 phase-velocity models to predict the observations. We do not, in this contri-
65 bution, explore the potential effects on measurements or on derived maps of
66 the non-uniform distribution of noise sources, or other uncertainties associ-
67 ated with the noise cross-correlation method. We also limit the tomographic
68 analysis to a standard ray-theory treatment. By publishing the data used
69 in the inversions, we hope to facilitate other uses of these observations. The
70 phase-velocity maps presented here, and the similarities and differences that
71 we document between the maps and predictions from existing crustal models,
72 identify directions for future work. In particular, we expect the models and
73 data presented here to be useful for developing better models of the elastic
74 structure of deep sedimentary basins.

2. Theory and Methods

Theoretically, the cross correlation of a diffuse and equipartitioned elastic wavefield sampled in two locations takes the form of the elastic Green function between the two locations (e.g., Snieder, 2004; Sánchez-Sesma and Campillo, 2006). Over the last decade, this property has been explained theoretically and explored in a number of papers. The phenomenon has also been exploited in many practical applications, leading to the establishment of the new discipline of Ambient Noise Tomography (ANT) (e.g., Bensen et al., 2007). The extent to which the conditions for recovering the true Green function are present in any given real experiment or data set is generally unknown, but from a wealth of studies it is clear that, at a minimum, the cross-correlation function calculated for two seismic stations contains the dispersive properties of fundamental-mode surface waves traveling from one station to the other. This property was first used in seismology by Aki (1957).

Aki (1957) considered the correlation of stochastic, horizontally propagating waves recorded at two stations and derived expressions for the azimuthally averaged cross spectra for dispersive and polarized waves. A key result is his equation 42,

$$\bar{\rho}(r, \omega_0) = J_0 \left(\frac{\omega_0}{c(\omega_0)} r \right), \quad (1)$$

which states that the azimuthally averaged normalized cross spectrum $\bar{\rho}(r, \omega_0)$ for a receiver separation r and frequency ω_0 varies as J_0 , the Bessel function of the first kind, where $c(\omega_0)$ is the phase velocity between the receivers at frequency ω_0 . Aki correlated observed zero crossings in $\bar{\rho}(r, \omega_0)$ with zeros of J_0 to determine the dispersion. In Part 3 of his 1957 paper Aki also

98 argued, on the basis of similarities in the observed correlation functions de-
 99 rived from station pairs oriented at different azimuths, that the azimuthally
 100 averaged cross spectrum $\bar{\rho}(r, \omega_0)$ could be replaced in the analysis by the
 101 cross-correlation spectrum $\rho_{ij}(\omega)$ obtained between two individual stations i
 102 and j . This argument is also the basis for most modern implementations of
 103 ANT, including ours.

104 Our measurement method follows the general approach of Aki (1957) and
 105 builds on our earlier implementation of the spectral method (Ekström et al.,
 106 2009). In the first step of the data processing, we collect long-period (LH-
 107 channel) continuous data from all stations of the USArray TA, the USArray
 108 Reference Network, and a few additional stations. The data are processed in
 109 4.5-hour-long, half-hour overlapping, tapered time windows, with offsets of 4
 110 hours, so that 6 records result for each component and each day. The instru-
 111 ment responses are deconvolved from the original records, and the data are
 112 stored as 4–500 s band-pass-filtered displacement spectra $u(\omega)$. We construct
 113 cross-correlation spectra for the pair of stations i and j as

$$\rho_{ijk}(\omega) = \frac{u_{ik}(\omega)u_{jk}^*(\omega)}{\sqrt{u_{ik}(\omega)u_{ik}^*(\omega)}\sqrt{u_{jk}(\omega)u_{jk}^*(\omega)}}, \quad (2)$$

114 for each 4-hour data window k that is common to the two stations. We calcu-
 115 late vertical cross correlations by cross correlation of the vertical-component
 116 records, and transverse cross correlations by first constructing the component
 117 transverse to the interstation great-circle direction using the two horizontal
 118 components of each seismometer, and then cross correlating the resulting
 119 transverse records.

120 The individual spectra are summed to create stacked spectra,

$$\rho_{ij}^S(\omega) = \sum_{k=1}^{N_{ij}} \rho_{ijk}(\omega), \quad (3)$$

121 where N_{ij} is the total number of 4-hour-long records available for a station
 122 pair, and $\rho_{ij}^S(\omega)$ is the stack. We do not apply whitening or other non-linear
 123 filtering to the data, and do not exclude time windows with earthquake sig-
 124 nals. Strong earthquake signals do not dominate the stacked spectra because
 125 the contributions are normalized at the level of the 4-hour-long records, and
 126 the typical stack is built from more than 2500 records. This approach to sig-
 127 nal conditioning and data selection is different from that typically employed
 128 (e.g., Bensen et al., 2007) and from our earlier work (Ekström et al., 2009),
 129 and was selected based on the outcome of experiments showing minimal dif-
 130 ferences in spectral dispersion measurements or final phase-velocity models
 131 using the different signal-conditioning schemes.

132 In the second step of the processing, the stacked cross-correlation spectra
 133 $\rho_{ij}^S(\omega)$ are analyzed to determine the locations of zero crossings in the real part
 134 of the correlation spectrum. Figure 1 shows the real and imaginary parts of
 135 the transverse correlation spectrum for stations ISA-CI and 109C-TA and the
 136 time-domain representation of the spectrum. The non-zero imaginary part of
 137 the spectrum is a manifestation of the asymmetry present in the time domain.
 138 The focus on the real part of the spectrum in our analysis is equivalent
 139 to considering only the part of the time-domain signal that is symmetric
 140 with respect to the zero-offset time. To reduce the number of spurious zero
 141 crossings when the amplitude of the spectrum is small, we smooth the raw
 142 spectrum by applying a running average with a width of approximately one

143 third of the separation of zero crossings in the real part of the spectrum. The
 144 zero crossings are identified by the running index n and denoted ω_n^Z , with odd
 145 n corresponding to crossings from positive to negative spectral amplitude,
 146 and even n corresponding to crossings from negative to positive amplitude.
 147 The zeros are stored together with information concerning the amplitude of
 148 the local spectral extrema adjacent to each zero. These amplitudes are used
 149 in subsequent processing as indicators of the quality of the zero identification
 150 and its frequency.

151 In the third step of the processing, the zero crossings are analyzed to
 152 construct continuous dispersion curves. Figure 2 illustrates this step. Asso-
 153 ciation of each observed zero crossing ω_n^Z with zeros of J_0 leads to estimates
 154 of phase velocity

$$c_m(\omega_n^Z) = \frac{\omega_n^Z r}{z_{n+2m}}, \quad (4)$$

155 where m takes the values $0, \pm 1, \pm 2, \dots$, indicating the number of missed or
 156 extra zero crossings in the observed spectrum. At long periods ($T \geq 25$ s),
 157 the correct m is inferred by requiring that the phase velocity fall in a real-
 158 istic range. Dispersion curves are constructed separately for odd and even
 159 n by connecting the identified zeros with line segments. At shorter periods,
 160 the appropriate m for each zero is selected on the basis of the range and
 161 smoothness of the dispersion curve defined by the values $c_m(\omega_n^Z)$ across fre-
 162 quencies ω_n^Z . An automated search algorithm is used to track the dispersion
 163 curve from long periods to short periods, extending it by one zero at a time.
 164 When the choice of which Bessel function zero (which m) to associate with
 165 the next observed zero becomes ambiguous, or no smooth dispersion curve
 166 can be constructed, the extension of the dispersion curve to shorter periods

167 is abandoned. The two dispersion curves (odd and even) are then sampled
 168 at discrete periods between 5 s and 40 s, and the average of the two values
 169 is stored as the path-specific phase-velocity observation c_{ij} between stations
 170 i and j .

171 In the fourth step of the analysis, we determine maps of isotropic phase
 172 slowness across the footprint of USArray using a standard least-squares tomo-
 173 graphic method. We parameterize the slowness maps in terms of N latitude-
 174 longitude pixels and denote the slowness in each pixel n by p_n . The distance
 175 along the great-circle path between stations i and j is written X_{ij} , and the
 176 fractional path length in each pixel is X_{ij}^n . We rewrite the observed phase ve-
 177 locity as an observed travel time, $\tau_{ij} = \frac{X_{ij}}{c_{ij}}$, and construct the corresponding
 178 model travel time as

$$\tau_{ij}^P = \sum_n^N X_{ij}^n p_n, \quad (5)$$

179 where only those X_{ij}^n that lie along the inter-station path will be non-zero.
 180 We form the misfit function

$$\chi^2 = \sum_{ij}^K \left(\frac{\tau_{ij} - \tau_{ij}^P}{\sigma_{ij}} \right)^2 \quad (6)$$

181 where the summation is over the K station pairs ij for which an observation
 182 is included at a particular period, and σ_{ij} is an estimate of the observational
 183 uncertainty. We then determine p_n by solving the damped least-squares
 184 problem

$$\min(\chi^2 + \nu R^2), \quad (7)$$

185 where ν is a smoothing coefficient and R^2 is the roughness of the slowness

186 variations. We calculate R^2 as

$$R^2 = \sum_n^N \left[\sum_m^4 \left(\frac{p_n - p_m}{d_{nm}} \right)^2 \right], \quad (8)$$

187 where the index m refers to the pixels north, south, east, and west of the n th
 188 pixel, and d_{nm} is the distance between pixel centers.

189 **3. Analysis and Results**

190 We apply the measurement technique to USArray station data recorded
 191 between January 2006 and December 2012, corresponding to 1630 different
 192 stations. We stack data for all station pairs separated by less than 600 km,
 193 leading to approximately 300,000 station pairs, with each stacked spectrum
 194 corresponding to, on average, ~ 3000 four-hour-long correlation windows, or
 195 approximately 17 months of continuous data. Love and Rayleigh dispersion
 196 curves are extracted from the transverse and vertical stacks, respectively,
 197 and the dispersion curves are sampled at eleven discrete periods: 5, 6, 8, 10,
 198 12, 15, 20, 25, 30, 35, and 40 s. Automatic selection based on the quality
 199 of the derived dispersion curves leads to an initial data set of approximately
 200 three million phase-velocity measurements for the two wave types and eleven
 201 periods.

202 The initial data set is trimmed by considering the wave period and inter-
 203 station distance. Competing effects must be balanced in the data selection.
 204 On the one hand, it is desirable to include short paths in the inversion because
 205 they provide the best constraints on small-scale structure. On the other hand,
 206 measurements of short paths have greater relative errors, and the perfor-
 207 mance of the spectral method for station offsets on the order of a wavelength

208 is not well known. Similarly, long paths provide useful extra path coverage
 209 and integral constraints on the slowness model, but may be more strongly af-
 210 fected by non-ray-like behavior. Uncertainties in the measurements at short
 211 periods for long paths are also larger as a result of difficulties in tracking the
 212 zero crossings that define the dispersion curve. Given these considerations,
 213 and the abundance of available data, we make a conservative selection based
 214 on distance such that $X_{\min} = 2\lambda$ and $X_{\max} = \max(5\lambda, 200 \text{ km})$, where $X_{\min}$
 215 and $X_{\max}$ are the minimum and maximum inter-station distances and λ is the
 216 wavelength, calculated using the period and a velocity of 4 km s^{-1} . At the
 217 shortest periods, $X_{\max}$ is set to 200 km in order to ensure that a sufficient
 218 number of observations are included. At the longest periods $X_{\max}$ is also
 219 limited by the 600-km overall maximum distance of the correlation-function
 220 data set. The resulting data set is summarized in Table 1.

221 Before inversion, we investigate the internal consistency of the selected
 222 data by comparing phase-velocity measurements on long paths with the cor-
 223 responding measurement constructed by combining two shorter paths. Con-
 224 sider stations a , b , and c with inter-station distances X_{ab} , X_{bc} , X_{ac} and
 225 phase-velocity measurements c_{ab} , c_{bc} , and c_{ac} . With ac the longest distance,
 226 we denote the phase velocity predicted from c_{ab} and c_{bc} as c'_{ac} , which we
 227 calculate as

$$c'_{ac} = \frac{X_{ab} + X_{bc}}{X_{ab}/c_{ab} + X_{bc}/c_{bc}}. \quad (9)$$

228 To ensure rough great-circle alignment of the stations we apply the geomet-
 229 rical selection criteria $X_{ab} + X_{bc} < X_{ac} < 1.1(X_{ab} + X_{bc})$, $X_{ab} > X_{ac}/4$, and
 230 $X_{bc} > X_{ac}/4$. Figure 3 shows the resulting scatter plot of c_{ac} *versus* c'_{ac} for
 231 85,620 path combinations that satisfy these criteria for Rayleigh waves at

10 s period. The correlation coefficient is 0.94 and the standard deviation of the distribution of differences $c_{ac} - c'_{ac}$ is 0.05 km s^{-1} , reflecting good agreement. No systematic offset between the two phase velocities is observed, nor is there a detectable deviation from a slope of 1.0 in the correlations. The standard deviations at other periods fall in the range $0.03\text{--}0.14 \text{ km s}^{-1}$, with the largest value found for Love waves at 5 s.

As is evident from Figure 3, the data set contains outliers. To suppress the influence of these outliers on the final models, we adopt a two-step inversion scheme with additional data weighting applied in the second step. In the first step, all of the data are included in the inversion with travel-time uncertainties σ_{ij} corresponding to a uniform phase-velocity uncertainty in the raw measurement c_{ij} . The model is parameterized on a relatively coarse $0.5^\circ\text{-by-}0.5^\circ$ grid. This ensures that each pixel is sampled by a large number of rays, and that the small number of outliers have limited influence on the resulting model.

The misfit of the data to the predictions from the coarser model is then used to identify the outliers, and to adjust their associated uncertainty. Specifically, with δc_{ij} denoting the data misfit following the inversion and σ_c denoting the standard deviation of the misfit, we multiply uncertainties for observations that deviate by more than two standard deviations by the factor $(1 + 2(\frac{\delta c_{ij}}{\sigma_c} - 2))$. This effectively gives those data that were not well fit in the initial inversion less influence on the model derived in the second inversion.

In the second step of the inversion, the model is parameterized on a finer $0.25^\circ\text{-by-}0.25^\circ$ pixel grid. The Love and Rayleigh slowness models are

257 derived by inversion as in equation (7). The damping factor ν is selected
 258 based on a combination of objective and subjective criteria. In general, less
 259 damping is required at short periods, for which the signal strength is high
 260 compared with the data uncertainties. At long periods, the damping results
 261 in relatively smooth models. The differences between the initial models and
 262 the second-iteration models are small: at all periods the correlations are
 263 > 0.97 . However, the two-step process effectively eliminates very-small-scale
 264 (single pixel) anomalies that can result from isolated erroneous measurements
 265 for short paths.

266 The slowness models that result from the second inversion are the main
 267 results of this study. In the presentation and discussion of the models, we
 268 convert phase slowness to phase velocity. Table 1 summarizes the number of
 269 data, average velocities, and the reduction in data variance provided by the
 270 maps.

271 4. Discussion

272 Figures 4 and 5 show our results for Love and Rayleigh waves in terms
 273 of phase-velocity variations at 5 s, 10 s, 20 s and 40 s. At long periods
 274 (≥ 20 s) the most prominent characteristic is the large-scale division of the
 275 continent into a slow western half and a faster eastern half, well documented
 276 in numerous earlier seismological studies (e.g., Romanowicz, 1979; Godey
 277 et al., 2004; Nettles and Dziewoński, 2008) and generally associated with the
 278 contrast between the stable cratonic plate interior in the east and the recently
 279 tectonically deformed boundary of the North America plate in the west. At
 280 short periods (< 20 s), the velocity variations are strong and typically very

281 localized. The velocity distributions around the areal means (the zero values
282 in the maps) are not symmetric: very strong and concentrated slow anomalies
283 are common while fast anomalies tend to be broad and less strong.

284 Most of the dramatic features seen in the short-period maps can be asso-
285 ciated with specific, well-known geologic features. For example, in the state
286 of Wyoming alone, distinct slow anomalies can be associated with the Powder
287 River, Big Horn, Gros Ventre, River, Sand Wash, Hanna, and Denver Basins;
288 and fast anomalies with the Bighorn Uplift, Wind River Mountains, Laramie
289 Range, and Sierra Madre Mountains (e.g., Peterson and Smith, 1986). A
290 more subtle and complex feature extending from Lake Superior to Kansas in
291 both the Love and Rayleigh wave maps can be associated with the surface
292 expression of the mid-continent rift. The largest-scale slow anomaly seen
293 coherently in all maps at periods shorter than 20 s is located along the Gulf
294 Coast, extending from the border with Mexico to the panhandle of Florida,
295 with the most extreme slow velocities located in southern Texas, Louisiana
296 and Mississippi.

297 To investigate the extent to which the phase-velocity maps are consistent
298 with knowledge of the elastic structure of North America, we make compar-
299 isons with predictions based on a three-dimensional seismic-velocity model of
300 the crust and mantle. It is evident that the short-period maps reflect short-
301 wavelength variations in seismic velocities of the shallow crust that have not
302 yet been mapped uniformly across the area of interest. We choose to make
303 our predictions using the global model of the crust CRUST2.0 (Bassin et al.,
304 2000) because it provides a consistent representation of the thicknesses and
305 intrinsic properties of the crust across the area. A drawback of this model is

306 its two-degree spatial parameterization, which does not allow the represen-
307 tation of some of the smaller features observed in the maps. We therefore do
308 not focus on agreement between individual features, but rather summarize
309 the overall correlation and discuss the ranges of anomalies that are observed
310 and predicted.

311 To account also for large-scale mantle heterogeneity, we calculate the
312 predictions for the combination of CRUST2.0 and mantle model ND08 (Net-
313 tles and Dziewoński, 2008), a radially anisotropic shear-velocity model of the
314 mantle beneath North America embedded in a lower-resolution global model.
315 The mantle model ND08 was derived using corrections for CRUST2.0. We
316 also calculate the predictions for a simpler model with CRUST2.0 on top of
317 the 1-D PREM mantle (Dziewonski and Anderson, 1981).

318 For the crust-and-mantle model, the correlations are positive at all pe-
319 riods (Figure 6), and high (> 0.7) at the longest periods. For neither Love
320 nor Rayleigh waves does the crust-only model predict the long-period maps
321 well, reflecting the fact that the long-wavelength patterns seen in Figures 4
322 and 5 result mainly from mantle heterogeneity. At short periods, the two
323 models make very similar predictions, and are moderately well (~ 0.5) cor-
324 related with the observed maps, consistent with the shallow sensitivity of
325 short-period surface waves and the accuracy of CRUST2.0.

326 To investigate the nature of the misfit, we compare the range of predicted
327 dispersion curves for the crust-mantle model with the observed dispersion.
328 Figure 7 shows the dispersion curves predicted for the study area calculated
329 on a one-degree grid. To represent the corresponding observations, we calcu-
330 late the median phase velocity for the study area at each period and identify

331 the full range of values; we plot these together with the predicted dispersion
 332 curves. We observe consistency between the observed ranges and the mod-
 333 els at faster velocities and at the longest periods. However, for both Love
 334 and Rayleigh waves, we observe many phase velocities that are significantly
 335 slower than predicted by CRUST2.0, most likely reflecting much lower shear
 336 velocities in some sedimentary basins. To illustrate this further, we show
 337 in Figure 8 dispersion observations and predictions for two locations: one
 338 in northern Minnesota (47°N, 95°W) and one in southern Mississippi (31°N,
 339 91°W). The agreement is very good for the Minnesota location, with both
 340 Love and Rayleigh waves well predicted even at short periods. Here, the
 341 phase velocities at 5 sec essentially reflect the intrinsic v_P and v_S of the crys-
 342 talline basement exposed at the surface. The Mississippi location displays
 343 extremely slow phase velocities at short periods, and very large disagreement
 344 with the predictions. The disagreement here cannot easily be attributed to
 345 the scale of the mapped anomalies, since similarly slow velocities extend
 346 inland from the coast at least 200 km, and along the coast for several hun-
 347 dred km. To bring the predicted dispersion closer to the observations, lower
 348 shear velocities and a thicker sedimentary layer are likely to be needed, as
 349 the anomalies are severely underpredicted for both Love and Rayleigh waves
 350 between 5 s and 15 s.

351 We assess the relationship between short-period phase velocities and the
 352 sedimentary cover by comparing our phase-velocity maps with maps of sed-
 353 iment thickness provided by Mooney and Kaban (2010). We calculate the
 354 median phase velocity, and the range of the central quartiles, for pixels cor-
 355 responding to different sediment thicknesses. Figure 9 shows the results for

356 Love and Rayleigh waves at 5-s period. Love and Rayleigh phase velocities
 357 slower than 2.0 km s^{-1} are the norm for sediment thicknesses in excess of
 358 10 km, and for Love waves the median speed corresponding to these thick-
 359 nesses is close to 1.5 km s^{-1} . Such slow speeds are clearly not commonly
 360 predicted using existing models of the crust (Figure 7). It should be noted
 361 that the extreme slow velocities imaged at 5-s period in deeply sedimented
 362 areas may challenge assumptions in the analysis, such as the single-mode
 363 assumption inherent in the measurement technique, and the ray-theoretical
 364 formulation used in the imaging. The degree to which this may bias the
 365 imaged velocities is unclear. However, both overtone interference and non-
 366 straight ray paths are likely to lead to overestimates of the velocity using
 367 our assumptions; true velocities may therefore be even slower than we have
 368 imaged here.

369 **5. Conclusions**

370 We have developed a method for cross correlating continuous long-period
 371 seismograms and extracting Love and Rayleigh wave phase-velocity infor-
 372 mation from the stacked cross-correlation spectra. The method is largely
 373 automated, allowing the collection of large data sets of uniform quality.

374 As in many automated measurement procedures, the greatest challenges
 375 are associated with automating choices in the analysis and quality selection.
 376 The construction of dispersion curves by connection of zero crossings in the
 377 spectra is well suited for a computer algorithm because each connection alter-
 378 native can be evaluated based on a combination of quantitative merits, such
 379 as dispersion-curve smoothness or the plausibility, based on prior informa-

tion, of a particular phase-velocity measurement. Though not explored here, a possible extension of the algorithm would involve iterating on the association of the zeros and the construction of dispersion curves using successively updated predictions from the derived phase-velocity models.

The automated measurement method generates a small number of bad observations, and we have chosen to suppress these outliers rather than applying more complicated data-selection criteria. The initial use of a slightly coarser model grid leads to oversampling of most pixels and corresponding dilution of the influence of outlying observations, which can then be down-weighted in subsequent inversion with a finer grid. The dense and nearly uniform coverage provided by USArray inter-station paths makes this approach straightforward to implement, and we were easily able to verify that the downweighting of outliers had the anticipated effect. In applications with more variable spatial coverage, this simple two-step approach may be less effective.

The derived phase-velocity maps explain the new dispersion data well. At the longest periods, the large-scale anomaly patterns are consistent with previously mapped mantle heterogeneity. At short periods, the qualitative agreement between localized velocity anomalies and surface-geologic features is striking, but significant misfit is apparent between the observed velocities and corresponding predictions based on CRUST2.0. In particular, both Rayleigh and Love waves exhibit extremely slow velocities across deep sedimentary basins and along the heavily sedimented Gulf Coast, with the observations lying well outside the range of the predictions. Additional work is needed to reconcile these surface-wave velocities with other relevant ob-

405 servations, such as depth to crystalline basement and measured sediment
406 velocities. We speculate that while the v_P structure of many of these regions
407 is known, v_S may not be as well determined, and may be overestimated. The
408 slow surface-wave phase velocities could therefore be a manifestation of high
409 v_P/v_S ratios in the sediments to great depth.

410 Incorporation of phase-velocity constraints derived from noise tomogra-
411 phy in models of the crust will not only improve understanding of shallow
412 structures, but is also important for purposes of mantle imaging. While
413 the sensitivity of long-period surface waves is small at shallow depths, the
414 heterogeneities are strong, and may therefore still impart a significant signal.

415 The cross-correlation-function stacks ($\rho_{ij}^S(\omega)$), the phase-velocity mea-
416 surements (c_{ij}), and the final slowness maps (p_n) described here are made
417 available at the IRIS DMC in conjunction with this publication, as well as
418 at www.ldeo.columbia.edu/~ekstrom.

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Period	$X_{\min}$	$X_{\max}$	Love waves			Rayleigh waves		
			N	c	ζ	N	c	ζ
	sec	km		km s ⁻¹			km s ⁻¹	
5	40	200	23,240	3.02	0.95	22,324	2.93	0.93
6	48	200	25,461	3.18	0.95	25,530	3.01	0.93
8	64	200	25,999	3.38	0.95	26,616	3.12	0.94
10	80	200	23,833	3.49	0.93	24,054	3.19	0.92
12	96	240	35,975	3.58	0.92	36,214	3.25	0.91
15	120	300	53,322	3.68	0.90	56,998	3.35	0.87
20	160	400	47,522	3.82	0.83	73,979	3.51	0.90
25	200	500	62,340	3.95	0.76	111,948	3.65	0.88
30	240	600	74,425	4.05	0.73	164,872	3.75	0.87
35	280	600	62,328	4.14	0.67	150,445	3.83	0.84
40	320	600	48,596	4.21	0.60	128,754	3.88	0.81

Table 1: Data set and inversion results. The distance range used at each period ($X_{\min}$ and $X_{\max}$); the number of observations (N) used in the inversion, the average phase velocity (c) and the variance reduction (ζ) at each period and for each wave type. The variance-reduction calculation refers to phase-velocity misfit with respect to the best-fitting uniform-velocity model, and includes outliers.

Figure 1: Transverse cross-correlation spectrum for stations ISA-CI and 109C-TA. The top panel shows the real (dark blue) and imaginary (light blue) components of the spectrum. Bottom panel shows the equivalent time-domain signal in the 300-s window centered on 0 s offset.

Figure 2: Diagram illustrating the construction of a Love wave dispersion curve from zero crossings of the cross-correlation spectrum for two stations in southern Texas. Triangles show frequency and phase speed corresponding to different branches m in equation 4. The thin lines show the acceptable range of phase velocities at low frequencies; only the red triangles fall in this range at 25-s period, and this branch can be traced to 5-sec period, defining the dispersion curve. Red squares show group velocities corresponding to this dispersion curve.

Figure 3: Scatter plot showing the comparison of phase-velocity observations for the path between stations a and c . Horizontal axis gives the direct measurement c_{ac} . Vertical axis gives the measurement c'_{ac} obtained by combining two measurements: a to b and b to c .

Figure 4: Maps of Love wave phase velocities at different periods: top left, 5 s; top right, 10 s; bottom left, 20 s; and bottom right, 40 s. The maps are parameterized using 0.25°-by-0.25° pixels, and deviations are shown with respect to the mean (Table 1). Note the different scales at different periods, and the skewed distribution of deviations at short periods.

Figure 5: Maps of Rayleigh wave phase velocities at different periods: top left, 5 s; top right, 10 s; bottom left, 20 s; and bottom right, 40 s. The maps are parameterized using 0.25° -by- 0.25° pixels, and deviations are shown with respect to the mean (Table 1). Note the different scales at different periods, and the weaker expression of some short-period anomalies, as compared with the Love wave maps (Figure 4).

Figure 6: Correlation of observed and predicted phase-velocity maps. Open squares show correlation with predicted maps based on CRUST2.0 and the PREM mantle. Filled hexagons show correlations with predicted maps based on CRUST2.0 and the 3-D mantle model ND08. (top) Love waves. (bottom) Rayleigh waves.

Figure 7: Comparison of observed phase-velocity ranges and those predicted by CRUST2.0 and ND08. (top) Median observed Love wave phase velocity (hexagons) at eleven different periods and the range of observed values (bars) at each period. (bottom) Same as top, but for Rayleigh waves.

Figure 8: Comparison of observed (symbols) and predicted (lines) phase velocities. (top) Love (red) and Rayleigh (green) wave dispersion at 47°N, 95°W (northern Minnesota), showing good agreement. (bottom) Same as top, but for location 31°N, 91°W (southern Mississippi), showing large differences for periods shorter than 20 s.

Figure 9: Phase velocities at 5-s period shown as a function of the thickness of the sedimentary cover. Symbols show the median value for all map pixels that correspond to a specific two-kilometer range of thicknesses, based on Mooney and Kaban (2010). The vertical bars show the range of the central two quartiles of the distribution of phase velocities for these pixels. (top) Love waves. (bottom) Rayleigh waves.