Radial Anisotropy in East Asia From Multimode Surface Wave Tomography

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Abstract We present a model of radial anisotropy in the crust and upper mantle of East Asia from a combination of new group velocity measurements and previously published surface wave dispersion data sets. Our combined data set ranges 5–375 s period and contains dispersion data up to the fifth overtone. We directly relate the data to variations in isotropic and radially anisotropic shear wave crustal anisotropy and find correlations with recent and past tectonics.

Key Points:
- We construct a model of radial anisotropy in East Asia using multimode surface wave dispersion measurements with periods of 5–375 s.
- We find positive radial anisotropy across nearly the entire region with a peak in the lower crust and uppermost mantle.
- We use cluster analysis to quantify regional variations in the radial anisotropy and find correlations with recent and past tectonics.

Supporting Information: Supporting Information may be found in the online version of this article.

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Citation:
Witek, M., Chang, S.-J., Lim, D. Y., Ning, S., & Ning, J. (2021). Radial anisotropy in East Asia from multimode surface wave tomography. Journal of Geophysical Research: Solid Earth, 126, e2020JB021201. https://doi.org/10.1029/2020JB021201

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1. Introduction

The field of seismic tomography has advanced to the point that researchers have been able to determine the isotropic velocity structure of the Earth on a global and regional scale with increasing consistency despite varying methodologies and data sets. Tomographic studies have succeeded in imaging and interpreting large-scale structures such as subducting slabs and upwelling plumes across the globe (e.g., Auer et al., 2014; S.-J. Chang, Ferreira, et al., 2015; Debayle & Ricard, 2012; Ho et al., 2016; Kustowski et al., 2008; Lekić et al., 2012; Ritsema et al., 2011; Shapiro & Ritzwoller, 2002; Simmons et al., 2012). However, tomographic models of isotropic velocity structures are static images and additional constraints, such as from geodynamic modeling and consideration of thermodynamics, mineral physics, and geochemistry, are required to infer the dynamical state of the mantle (e.g., Davaille et al., 2003; Goes & van der Lee, 2002; Khan et al., 2009; McNamara & Zhong, 2005; Trampert et al., 2004; D. Zhao & Ohtani, 2009).
Observations of anisotropy can directly constrain the Earth's internal dynamics. Many materials in the Earth have long been known to be intrinsically anisotropic (e.g., O. L. Anderson et al., 1968; Thomsen, 1986; Verma, 1960), and when large-scale tectonic processes work to deform the Earth these materials can assume a preferred orientation (e.g., Karato et al., 2008), resulting in observable discrepancies in the seismic data when isotropy is assumed. One of the first confirmations of seismic anisotropy was a study of Pn waves propagating along different azimuths in the Pacific, where a fast direction perpendicular to the strike of the spreading ridge was interpreted as being due to the orientation of olivine crystals in the mantle (Hess, 1964). Since then, studies of azimuthal anisotropy have provided valuable insights in our understanding of past deformation episodes and current mantle flow (e.g., Burgos et al., 2014; Marone & Romanowicz, 2007a; Yuan et al., 2011).

Another kind of commonly studied anisotropy in seismology is radial anisotropy (also known as polarization anisotropy or vertically transverse isotropy), which can occur in thinly layered isotropic or anisotropic media or any system displaying hexagonal symmetry with a vertical symmetry axis (e.g., D. L. Anderson, 1961; Backus, 1962). A radially anisotropic medium leads to an apparent discrepancy between Rayleigh and Love wave dispersion due to an insufficiency of isotropic models to simultaneously fit both, and so naturally lends itself to surface wave studies. Increasing amounts of evidence for a Rayleigh-Love discrepancy (Aki & Kaminuma, 1963; Forsyth, 1975; McEvilly, 1964; Schlue & Knopoff, 1977; G.-K. Yu & Mitchell, 1979) led to the introduction of radial anisotropy in the upper mantle of the Preliminary Reference Earth Model (PREM) (Dziewoński & Anderson, 1981), which remains one of the most widely used reference 1-D Earth models. Attempts to constrain the 3-D radial anisotropy of the mantle globally and regionally are now routine (e.g., Auer et al., 2014; Burgos et al., 2014; S.-J. Chang, Ferreira, et al., 2014, 2015; S.-J. Chang, van der Lee, et al., 2010; Kustowski et al., 2008; Sicilia et al., 2008; Yuan et al., 2011).

Models of radial anisotropy have thus far shared little coherency, however, which highlights the difficulty in separating the subtle effects of anisotropy from isotropy in seismic data. For example, A. Levshin and Ratnikova (1984) were able to show that a simple isotropic model where only the crustal thickness varies would create a Rayleigh-Love discrepancy virtually indistinguishable from the effects of anisotropy. As a result, increasingly complex methods have been employed to calculate so-called crustal corrections to dispersion data sets, with the aim of removing the nonlinear effects of crustal variations (e.g., Boschi & Ekström, 2002; Kustowski et al., 2007; Marone & Romanowicz, 2007b). These, however, depend on the prior crustal model used to calculate the corrections, and studies have found substantial differences between anisotropic models depending on the prior crustal model (e.g., Ferreira et al., 2010). There are also indications that the choice of prior model would strongly affect continental regions, at least down to 100 km depth (Xing & Beghein, 2015).

Increasingly, research is showing that the best strategies should allow for crustal properties to vary and to include data sensitive to crust (Bozdağ & Tampert, 2008; S.-J. Chang & Ferreira, 2017).

In this work, we focus on the radial anisotropy of East Asia, an area with a rich tectonic history. Studies have found evidence for the collision and amalgamation of cratonic blocks, various orogenies, lithospheric thinning, and subduction events in the distant past. For example, the North China Craton (NCC) can be divided into distinct western and eastern sub-blocks separated by the Trans-North China orogen (e.g., Kusky & Li, 2003; Y.-F. Zheng et al., 2013). The western portion of the NCC has a thick (>200 km) lithosphere, but this progressively thins toward its eastern margin, and geochemical observations indicate that the thinning of the eastern NCC may have been initiated by the subduction of the Pacific plate (Xu et al., 2012; J.-J. Zhang et al., 2009). To the south of the NCC is the Yangtze craton and the Cathaysia Block. These two terranes are thought to have collided in the Neoerterozoaic along the Jiangnan orogen to form the South China Block (SCB), but the exact timing and mechanism is debated (e.g., G. Zhao & Cawood, 2012; Y.-F. Zheng et al., 2013). The NCC and the SCB converged during the Paleozoic in a series of tectonic episodes including oceanic subduction, terrane accretion, and continental collision, ultimately resulting in the Qingsh-Li-Dabie-Sulu (QDS) orogenic belt (Wu & Zheng, 2013). The Imjingang Belt in the Korean Peninsula may be an extension of the QDS belt (e.g., S. Kwon et al., 2009; Lee et al., 2000; Lee et al., 1996), but whether the entire Korean Peninsula belongs to the NCC, or whether the southern portion belongs to the SCB, is an area of active research (e.g., K.-H. Chang & Zhao, 2012; S.-J. Chang & Baag, 2007; J.-H. Yu et al., 2012). To the west of the NCC and SCB is the largest mountain chain on Earth, the Tibetan-Himalayan orogen, which consists of several terranes and suture zones and is a result of the continuing convergence of the Indian and

10.1029/2020JB021201
Eurasian plates that initially collided c. 50–65 Ma (e.g., Y. Li et al., 2015). Further to the east, the Pacific and Philippine Sea slabs are currently subducting under the Eurasian continent, which c. 32–15 Ma led to intense rifting and the creation of the East Sea (Sea of Japan) back-arc basin (e.g., Jolivet et al., 1994; Kano et al., 2007; Ototfuji et al., 1985; Van Horne et al., 2017). Therefore, with such a storied deformation history, East Asia represents an ideal region well suited to the study of radial anisotropy.

Many regional geophysical studies have been conducted in East Asia that elucidate the nature of its isotropic and anisotropic structures. The earliest studies focused on the structure of Tibet from surface wave dispersion and found a thick crust characterized by low shear wave speeds (e.g., Bird & Toksöz, 1977; W.-P. Chen & Molnar, 1981; Gupta & Narain, 1967; Jobert et al., 1985; Pines et al., 1980; Romanowicz, 1982), and later evidence accumulated for a partially molten crustal layer (e.g., Agius & Lebedev, 2014; Kind et al., 1996; Nelson et al., 1996; Yang et al., 2012). A study of Rayleigh and Love wave group velocity dispersion also found strong radial anisotropy in the mid to lower crust of Tibet, which may be due to mica crystal orientation from crustal flow (Shaprio et al., 2004). East Asia as a whole has been imaged using Rayleigh wave group and phase velocity dispersion (e.g., Feng & An, 2010; Z. Huang et al., 2003; W. Shen et al., 2016; Witek et al., 2018) and waveform inversion techniques (e.g., Lebedev & Nolet, 2003; Legendre et al., 2015) to find thick lithosphere in the western NCC and Yangtze craton and thin lithosphere and low velocities under the eastern NCC and the East Sea. Ambient noise studies of Rayleigh and Love group and phase velocities have been conducted to create high-resolution regional models of the crust and uppermost mantle in Korea (e.g., Cho et al., 2007; Choi et al., 2009; Kang & Shin, 2006), China (e.g., Bao et al., 2015; Guo et al., 2015; H. Li et al., 2009; Xie, Ritzwoller, Shen, & Wang, 2017; Yao et al., 2008), and in Japan (e.g., Nishida et al., 2008; Yoshizawa et al., 2010).

The main contribution of our study is the combination a new data set of short period group velocity Rayleigh and Love wave measurements from both earthquakes and ambient noise with previously published dispersion data sets, which we directly relate to 3-D structure via locally calculated sensitivity kernels using a reference 3-D model consisting of CRUST1.0 (Laske et al., 2013) and AK135 (Kennett et al., 1995). This study is the first to provide a holistic view of the large-scale radially anisotropic structures in East Asia, and our resulting 3-D model shows high radial anisotropy throughout the crust and uppermost mantle. We perform a quantitative regionalization of the radial anisotropy using cluster analysis and find that the region can be separated into areas of recent tectonics such as crustal extension, lithospheric thinning, mantle upwelling, and stable cratons.

2. Data

Three-component continuous broadband waveform data are collected from Chinese regional networks administered by the China Earthquake Administration (CEA) for the period January 2009 through May 2012 (Figure 1). This data set is used to measure Rayleigh and Love group velocity dispersion from both earthquakes and ambient noise. We additionally collected earthquake waveform data from the Korea Meteorological Administration (KMA) and the Korea Institute of Geoscience and Mineral Resources (KIGAM). Dispersion curves from earthquakes were manually measured using the multiple filter technique (also known as frequency-time analysis) (Dziewoński et al., 1969; A. L. Levshin, Pisarenko, & Pogrebinsky, 1972; A. L. Levshin, Ratnikova, & Berger, 1992) and the Computer Programs in Seismology software (Herrmann, 2013). Love wave group velocities were likewise measured; however, rotation of the waveforms to the transverse component is done using the orientation angles estimated in Section 2.1. In total, we measured a new data set of 10,009 Rayleigh group velocity dispersion curves and 9,226 Love group velocity dispersion curves from earthquake waveforms. In addition, we used an automated procedure to process the ambient seismic noise and measure new group velocity dispersion curves for a total of 289,184 Rayleigh group velocity dispersion curves and 106,803 Love wave group velocity dispersion curves. A major aim of this study is to simultaneously invert for crustal and upper mantle structure in order to better resolve radial anisotropy. Since group velocities tend to be sensitive to shallower depths compared to phase velocities at the same period, our short period group velocity measurements should help us resolve shallower structures and mitigate leakage of crustal structure into the mantle (e.g., Figure 4).
The ambient noise processing and measurement techniques are described in Sections 2.1 and 2.2. These new dispersion curves with raypaths inside a rectangular region bound by 15°N, 60°E and 60°N, 165°E were extracted from the global data sets. Details on how the data sets were merged and their errors estimated are provided in Section 2.3.
2.1. Ambient Noise Processing and Station Orientation Angle Estimation

Ambient noise processing proceeded as follows. Continuous waveform data are cut into 24-h time series that have their linear trend and instrument response removed. The data are normalized according to the frequency-time normalization (FTN) method of Y. Shen et al. (2012), who showed that their method produces higher quality cross-correlations compared to other data normalization methods (e.g., Bensen et al., 2007). The FTN method consists of filtering the data through a set of Gaussian bandpass filters, dividing each filtered waveform by its envelope, and linearly stacking the results. Here, we simultaneously normalize all three components by the average envelope to maintain relative amplitudes. While not necessarily important for group velocity measurement, saving the relative amplitudes is important for a potential future study of Rayleigh wave ellipticity, which has been found to provide strong constraints for structures in the uppermost crust (e.g., Lin, Schmandt, & Tsai, 2012; Lin, Tsai, & Schmandt, 2014). The normalized daily waveforms are then cross-correlated and stacked for each of the nine combinations of waveform components (vertical-vertical, vertical-north, etc.). Since the rotation and cross-correlation operations commute, performing cross-correlations first reduces computation time (Lin, Moschetti, & Ritzwoller, 2008).

In order to accurately measure Rayleigh and Love wave dispersion from the horizontal components, station orientation angles must be known. Misorientations of the horizontal components from true north can occur either during station installation or during operation for numerous reasons, so identifying misoriented stations is important for seismic data analysis. For example, Ekström and Busby (2008) used surface wave analysis to find that almost 3% of USArray stations are misoriented by more than 10°. A previous analysis of the CEA network by Niu and Li (2011) found that nearly one third of the stations have misorientation problems. Those stations may have been replaced, removed, added, or variously had maintenance performed on them, so we have opted to perform a new analysis of possible CEA station misorientation.

Station orientations are estimated using the method of Zha et al. (2013), who estimated the orientation angles of ocean bottom seismometers from ambient noise cross-correlations. The cross-correlations are bandpass filtered between 5 and 20 s period to emphasize surface wave signals generated in the primary and secondary microseism bands. We start with a target station A and its cross-correlations with the vertical component of station B, which we denote as

\[ \hat{C}_{zz} = \int C_{zz}^*(t)C_{zz}^B(t + \tau) dt \]

where \( i = e, n, z \) for the east, north, and vertical directions, respectively. The cross-correlations \( C_{ee} \) and \( C_{nz} \) are rotated to the radial component, \( C_{rr} = -\cos(\psi_{AB} - \theta)C_{ee} + \sin(\psi_{AB} - \theta)C_{nz} \), where \( \psi_{AB} \) is the back azimuth from station A to B and \( \theta \) is the orientation angle measured positive clockwise from due north. We then perform a grid search for the orientation angle which maximizes the correlation coefficient

\[ CC = \frac{\int C_{rr} \hat{C}_{rr}^* dt}{\int C_{rr}^2 dt} \]

where \( \hat{C}_{rr} \) is the Hilbert transform of \( C_{rr} \). This procedure is repeated for station A with every other station to retrieve a set of orientation angle estimates. We associate each estimate with two quality control measures. We measure a signal-to-noise ratio (SNR) using the ratio of the maximum amplitude of \( C_{zz} \) to its standard deviation within a signal window of 1 and 5 km/s, and we use the coherence \( \overline{CC} \) between \( C_{rr} \) and \( \hat{C}_{rr} \),

\[ \overline{CC} = \frac{\int C_{rr} \hat{C}_{rr}^* dt}{\sqrt{\int C_{rr}^2 dt \int \hat{C}_{rr}^2 dt}} \]

For our data set, we found useful thresholds to be SNR = 10 and \( \overline{CC} = 0.2 \) (e.g., Figure 2a). We obtain a robust estimate of the orientation angle for station A by using the median angle and we estimate the standard error of the median from a bootstrap procedure. Orientation angle estimates were thus obtained for each station in our data set.

To further determine the robustness of our orientation angle estimates, we followed the method of Stachnik et al. (2012) and estimated orientation angles from Rayleigh wave polarization using earthquakes in the period 2009–2012. This method is roughly the same as that described for the ambient noise, except that instead of cross-correlation functions we use earthquake signals from the radial and vertical components. A similar
analysis of misorientation is performed for CEA stations by Y.-W. Kim et al. (2021). For quality control, we keep the same SNR threshold but increase the coherence threshold to $CC = 0.4$. We find that the majority of stations have consistent orientation angle estimates, but there were stations which were significantly inconsistent with the ambient noise estimates and had large errors. We split the earthquake estimates by year and found that the inconsistent stations had orientation angle estimates that varied with time for unknown reasons. To ensure the quality of our Love wave measurements, we discarded horizontal component cross-correlations from 173 stations that showed a strong time dependence for the orientation angle estimates. We used the ambient noise estimates for rotation as they generally showed smaller error estimates due to better azimuthal coverage.

2.2. Ambient Noise Dispersion Curve Measurement

Due to the large volume of ambient noise cross-correlations, an automated dispersion curve measurement algorithm was implemented. A set of Gaussian bandpass filters are applied to the signal in the form $G(\omega) = \exp \left[-\alpha \left(\frac{\omega - \omega_0}{\omega_0}\right)^2\right]$ in the frequency range 0.007–0.333 Hz to form a spectrogram. Measurement begins at the low frequency end, where we find the group velocity closest to a reference curve from AK135 (Kennett et al., 1995). This step is not necessarily required for group velocity measurement, but it may act as a safeguard against noise that may be present at longer periods. For subsequent measurements, we search for the three largest maxima in the spectrogram and choose the group velocity which minimizes an estimate of the second derivative to ensure a smooth curve. We calculate the SNR for each measurement as the ratio of the maximum amplitude in the signal window to the rms of the noise in a 500 s long noise window 500 s after the end of the signal window (Bensen et al., 2007). The signal window is defined to be that of a surface wave arriving with 1–5 km/s speed. If the SNR is less than 10, we disregard the
measurement. After the curve is measured, we apply energy reassignment corrections so that the frequency of each measurement accurately reflects the energy content of the filtered signal (e.g., Auger & Flandrin, 1995; Pedersen et al., 2003; Shapiro & Singh, 1999; Yanovskaya et al., 1989).

An anisotropic noise source distribution can cause the appearance of spurious, high amplitude signals arriving before the direct wave (e.g., Shapiro et al., 2006; Takagi et al., 2009; Zeng & Ni, 2010; Y. Zheng et al., 2011). Such precursory signals may interfere with the ability to accurately measure group velocities, so to improve resilience to precursory signals we compute time-symmetric cross-correlations \( C_{zz}, C_{SV}, C_{rC}, \) and \( C_n \) (e.g., Haney et al., 2012; van Wijk et al., 2011). A study by Xu and Mikesell (2017) shows that \( C_{zz} \) and \( C_{SV} \) cross-correlations are robust in the presence of non-stationary noise sources, and therefore we calculate an average Rayleigh dispersion curve measured from all four cross-correlations. However, not all stations had usable orientation angle estimates, so for the remaining station-pairs we measure an average Rayleigh dispersion curve using the positive and negative sides of the \( C_{zz} \) cross-correlation. Likewise, for the Love wave dispersion measurements, we used the average of the positive and negative sides of the \( C_n \) cross-correlation. In total, we measured 75,728 Rayleigh wave dispersion curves from a 4-component average, 213,456 Rayleigh wave dispersion curves from \( C_{zz} \), and 106,803 Love group velocity dispersion curves.

### 2.3. Dispersion Data Set Merging and Error Estimation

In order to improve consistency within each data set, and to appropriately balance the different data sets during inversion, we apply a raypath clustering method similar to that used by Ritzwoller and Levshin (1998). For data sets consisting of earthquake measurements, we check every curve and find similar raypaths whose endpoints lie within a radius of 2% of the epicentral distance, and we require more than two raypaths in a cluster. Otherwise, the raypath is considered “unique” and nothing more is done. For ambient noise measurements, we found that despite our quality control methods the dispersion curves display a significant degree of scatter. This may happen during dispersion curve measurement if the cross-correlation stack contains high amplitude noise that interferes with the surface wave signal. Therefore, we apply a minimum search radius of 37 km (1/3°) in order to ensure that more ambient noise data is being averaged. The number of dispersion curves in a cluster is saved and used for weighting purposes during the inversion (see Section 3.5). Dispersion curves within an acceptable cluster are interpolated using piecewise cubic Hermite splines to create smooth curves maintaining local monotonicity, and then an average dispersion curve is measured at an evenly spaced set of periods. Errors are estimated from the standard deviation of velocities at each of these periods. However, if the dispersion curves intersect, then the errors will be severely underestimated at the intersection periods. Therefore, these errors are not applied to the average dispersion curve of the cluster. Instead, the estimated errors from each cluster are collected so that average errors for the entire data set as a whole may be estimated. This is done by binning the log of the errors by period and finding the mean in each period bin. The average errors are then applied to all average and unique dispersion curves in the data set. Estimated mean errors for fundamental mode group and phase velocities are shown in Figure 3. For measurements lying outside of these curves, we extrapolated the error estimates by using the value of the last positive slope to ensure that errors increase outside of the period range where estimates exist.

### 3. Methodology

A radially anisotropic (or transversely isotropic) medium assumed to have a vertical symmetry axis can be defined by the density \( \rho \) and five Love parameters \( C = \rho V_{PP}^2, A = \rho V_{PH}^2, L = \rho V_{SV}^2, N = \rho V_{SH}^2, \) and \( F = \eta \rho (V_{PH}^2 - 2 V_{SV}^2) \) (Love, 1927; Takeuchi & Saito, 1972). The first two parameters, \( C \) and \( A \), are related to vertically and horizontally propagating compressional waves, while the next two parameters, \( L \) and \( N \), give the speeds of vertically and horizontally polarized shear waves traveling in a horizontal direction. The final parameter, \( F \), is related to the speeds of body waves traveling in intermediate directions via the parameter \( \eta \). To reduce the amount of model parameters and thus make the inverse problem tractable, in this study we parameterize our model by defining the isotropic shear wave speed and shear wave anisotropy as follows,

\[
V_s^2 = \frac{1}{2} \left( V_{SV}^2 + V_{SH}^2 \right).
\]
and we couple variations in density and isotropic P-wave velocity to variations in isotropic S-wave velocity via (O. L. Anderson et al., 1968)

\[
\frac{d \ln \rho}{d \ln V_S} = 0.4,
\]

and (Robertson & Woodhouse, 1995)

\[
\frac{d \ln V_P}{d \ln V_S} = 0.5.
\]

The sensitivities of the surface waves to other parameters are ignored, and we also neglect sensitivity to azimuthal anisotropy. When the azimuthal distribution of the data is adequate, variations due to azimuthal anisotropy may be averaged out (Montagner & Nataf, 1988). While the sensitivity kernels and the model parameters are given in terms of \( V_S \) and \( \zeta_S \), in order to make comparisons with other studies we convert our model results to Voigt average \( V_3^2 = \frac{2V_{SH}^2 + V_{SV}^2}{3} \) and anisotropy parameter \( \xi = V_{SH}^2 / V_{SV}^2 \).

### 3.1. Surface Wave Ray Theory

We model the propagation of surface waves by assuming that structural variations in the Earth are laterally smooth, such that the surface wave wavelength is much smaller than the angular sizes of the heterogeneities. Under this assumption, surface waves can be modeled by solving the normal mode problem of the Earth for each 1-D profile along a raypath to obtain so-called local wavenumbers, phase and group velocities, eigenfunctions, and sensitivity kernels (Dahlen & Tromp, 1998). Such an approach was previously applied to find global and regional models of the mantle (e.g., Auer et al., 2014; Boschi & Ekström, 2002; Boschi et al., 2009).

We begin by assuming that the measured travel time of a phase or wave packet is due to perturbations along the raypath,

\[
t = \int \frac{1}{c_0 + \delta c} d\Delta
\]
Figure 4. Example logarithmic local sensitivity kernels used in this study, calculated for a 1-D profile located in the Cathaysia foldbelt extracted from our 3-D reference model. Left two columns show Rayleigh sensitivity kernels, and the right two columns show Love sensitivity kernels. Sensitivity kernel amplitudes are shown in units of km$^{-1} \times 10^3$. (a) Group velocity sensitivity kernels for $V_S$ and $\zeta_S$ at 10 s period. (b) Phase velocity sensitivity kernels for $V_S$ and $\zeta_S$ at 50 s period, up to the fifth overtone. (c) Phase velocity sensitivity kernels for $V_S$ and $\zeta_S$ at 150 s period, up to the second overtone. Also shown in (c) is a comparison of the fundamental mode Rayleigh $\zeta_S$ sensitivity with the conventional S-anisotropy parameter $\xi$. Colors indicate surface wave mode branch, shown at the bottom.
where \( c_0 \) is a position dependent phase or group velocity in the reference model, \( \delta c = c - c_0 \) is a velocity perturbation, and \( \int \cdots \mathrm{d} \Delta \) represents line integration over the raypath. Here and in the following, all variables appearing in an integrand are functions of the integration variable. Assuming \( \delta c/c_0 \ll 1 \), the travel time residual is

\[
\delta t = t - t_0 = \int_{\Delta} \left( \frac{1}{c_0 + \delta c} - \frac{1}{c_0} \right) \mathrm{d} \Delta \approx -\int_{\Delta} \frac{1}{c_0} \frac{\delta c}{c_0} \mathrm{d} \Delta. \tag{9}
\]

In the ray theory approximation, local perturbations to the phase or group velocity can be related to local structural perturbations if they are sufficiently smooth, so that

\[
\frac{\delta c}{c_0} = \sum_{i} K_i \frac{\delta m_i}{m_i} \mathrm{d} r + K_Z \frac{\delta Z}{Z_0}. \tag{10}
\]

where \( i \) indexes the model parameters, the \( K_i \) are the sensitivity kernels, and \( \delta m_i/m_i \) are the model parameters to be solved for. In addition, we include Moho depth perturbations \( \delta Z/Z_0 \) which are related to the velocity perturbations via the Moho depth sensitivity kernel \( K_Z \). Therefore, each phase or group velocity measurement contributes a linear constraint of the form

\[
\frac{\delta t}{t_0} = -\frac{\delta c}{c_0} = -\frac{1}{t_0} \int_{0}^{\Delta} \sum_{i} K_i \frac{\delta m_i}{m_i} \mathrm{d} r + K_Z \frac{\delta Z}{Z_0} \mathrm{d} \Delta. \tag{11}
\]
where \( c_0 \) is the path-averaged phase or group velocity measurement, and we have nondimensionalized the data similar to the model parameters. Proper treatment of surface wave ray theory would require ray tracing through the reference model. However, here we neglect this and approximate raypaths using great circles from the source to the receiver.

### 3.2. Reference 3-D Model

In this study, we construct sensitivity kernels and solve for model variations with respect to a reference 3-D model. We use the CRUST1.0 model for the crust, which is a 1° × 1° block model, each block having a unique eight-layer profile defined by \( V_p, V_S, \) and \( \rho \) (Laske et al., 2013). In order to create a smoother reference model without significant vertical discontinuities, bilinear interpolation is performed inside a 1° × 1° block with corners defined by the 1-D CRUST1.0 profiles that have been assigned to the center of each original CRUST1.0 block. Below the Moho, we use the AK135 model of Kennett et al. (1995). However, the sub-Moho model parameters in CRUST1.0 are taken from a modified version of the LLNL-G3Dv3 model (Simmons et al., 2012), which may cause undesirable “spikes” if the sub-Moho parameter values differ significantly from AK135. Therefore, we linearly interpolate model values from just below the Moho to 120 km depth in AK135.

### 3.3. Model Parameterization

We chose to represent the model parameters using nested shell grids. The grid node locations are derived using the spherical tessellation method of Wang and Dahlen (1995). The center of grid points is placed at 37.5°N, 110.5°E, extending 50° from the center in all directions, with nodes placed approximately 50 km apart on average (Figure 1a). Triangle functions (linear B-splines) are used in the radial direction, with half triangles used for the first and last depth nodes. The depth nodes are located at: 0, 5, 10, 20, 35, 55, 75, 95, 120, 145, 170, 200, 230, 260, 290, 320, 350, 380, 410, 450, 490, 530, 610, 660, 720, 780, and 950 km depth. Topography is included by setting the surface depth node to the local topography at each grid node. Thus, at each grid node, the depth node originally at 0 km will move to a different height or stay at 0 km if there is a water layer. The remaining nodes are unaffected. The model parameters are expanded onto the grid as

\[
\frac{\delta m}{m_i}(r, \theta, \phi) = \sum_{j,k} \gamma_{ijk} f_j(\theta, \phi) h_k(r),
\]

where the summation is done over the grid nodes \( j \) and depths \( k \), \( f_j(\theta, \phi) \) is a weight derived through lateral linear interpolation, \( h_k(r) \) are the vertical basis functions, and \( \gamma_{ijk} \) are the basis function coefficients that are solved for during the inversion. Moho depth perturbations are expanded laterally as

\[
\frac{\delta Z}{Z_0}(\theta, \phi) = \sum_j \gamma_j f_j(\theta, \phi).
\]

In practice, the summation over the grid nodes is made efficient by using an algorithm that quickly finds the surrounding nodes enclosing any arbitrary location, and the linear interpolation ensures that only three nodes are required for the summation.

### 3.4. Sensitivity Kernels

Sample sensitivity kernels are shown in Figure 4 at several different periods and mode branches for various model parameters, and the kernels give a preliminary indication of the depth resolution in our model. In general, Love wave sensitivity tends to be shallower than Rayleigh wave sensitivity and peak group velocity sensitivity is shallower than phase velocity sensitivity at constant period. Surface wave overtone sensitivity displays more complex behavior. The number of peaks in the sensitivity kernels tends to increase with increasing mode number. Rayleigh wave overtone sensitivity may show multiple peaks with similar amplitudes, while Love wave overtone sensitivity generally displays a single prominent peak. In addition, the Rayleigh wave \( V_S \) and \( \zeta_S \) phase kernels and the Love wave \( V_S \) phase kernels are either strictly positive or negative, while the Love wave \( \zeta_S \) phase overtone kernels oscillate between positive and negative values, highlighting the complicated relationship between the dispersion data and S-wave anisotropy.
An interesting consequence of choosing $\zeta$ to parameterize the radial anisotropy is shown in Figure 4c. Compared to the traditional parameterization in terms of $\xi$, $\zeta$ sensitivity kernels may be up three times as large. This may indicate that surface wave data are more sensitive to relative differences in the Love parameters rather than their ratios. However, this should not affect the inversion results, as the sensitivity kernels are derived under the assumption that perturbations in any model parameterization must be equivalent.

### 3.5. Inversion for 3-D Structure

Prior to the structural inversion, we perform an inversion for Moho depth using point constraints from teleseismic receiver functions and seismic studies (S.-J. Chang & Baag, 2007; He et al., 2014; Hetland & Wu, 2001; Hirata et al., 1989; Igarashi et al., 2011; Iwasaki, Hirata, et al., 1990; Iwasaki, Shiobara, et al., 1989; H. J. Kim et al., 1998; Kurashimo et al., 1996; Y. Li et al., 2014; Nakamura, 2014; Nishizawa & Asada, 1999; Ramesh et al., 2005; Sato, Sato, et al., 2006; Sato, Shinohara, et al., 2004; Sato, Takahashi, et al., 2006; Shiomi et al., 2006; Takahashi, Kodaira, Tatsumi, et al., 2009; Takahashi, Kodaira, Tsuru, et al., 2004) in order to reduce the trade-off between crustal thickness and shear wave speeds just above and below the Moho (e.g., Lebedev et al., 2013; Ravenna & Lebedev, 2018). The details of this inversion are given in Text S1 and the results are shown in Figure S1. After the Moho inversion, the new Moho perturbations are used to update the reference model. Then, we calculate linear constraints for every dispersion curve in our data set using Equation 11. If a large number of dispersion curves share similar raypaths, those data will effectively be upweighted relative to other data. Therefore, we keep track of the number of similar raypaths $N_i$ during the raypath cluster analysis to downweight data in clusters (e.g., Section 2.3). Similarly, because the ambient noise data set contains an order of magnitude more dispersion curves, those data may overwhelm other data sets. To balance the contribution from each data set, we split the data sets by surface wave type, dispersion type, and source (i.e., the Author column in Table 1), and separately weight each data set by the number of dispersion curves $N_i$. After combining all linear constraints from Equation 11 into constraint matrices $G$, the misfit equation becomes

$$S(m) = \sum_{i} \frac{1}{N_{ci,i}} (G_m - d_i)^T C_{ci,i}^{-1} (G_m - d_i) + \lambda_D I m I + \lambda_F F m F,$$

where $N_{ci,i}$ is the number of dispersion curves for the $i$th data set $d_i$ and $m$ is the model vector of basis function coefficients. The error covariance matrix $C_{ci,i}$ is a diagonal matrix with entries $\sigma_i^2 (T_i)$, where $\sigma$ is the average error and $N_{ci,i}$ is the number of similar raypaths for datum $d_i$ determined during raypath clustering for the $i$th data set. The matrix $I$ is the identity matrix and $F$ is a discrete horizontal gradient operator, and the factors $\lambda_D$ and $\lambda_F$ control the strength of the model norm damping and horizontal gradient minimization, respectively.

In order to resolve radially anisotropic structure, Rayleigh and Love wave data should cover the region equally. In practice, however, horizontal component data typically has higher noise levels compared to the vertical component, rendering Love waves more difficult to measure (e.g., Wolin et al., 2015). As a result, the amount of Love wave data is often much less than the Rayleigh wave data, and this makes the expected resolution of radially anisotropic structure less than that of the isotropic shear wave speed structure. Likewise, the amount of shorter period fundamental mode data in our data set is an order of magnitude larger than the amount of longer period data or overtone data, which causes the model resolution to degrade with depth. Other studies have rectified these discrepancies by using an adaptive grid approach (Auer et al., 2014), or by varying the grid spacing for each parameter (Marone et al., 2007).

In this study, we use a single grid for all parameters, but we attempt to account for decreased anisotropy resolution by increasing $\lambda_D$ for the anisotropic model parameters to be 1.5 times $\lambda_F$ for the isotropic speed model parameters. To account for decreased data coverage with depth, we create a depth dependent flattening function, where $\lambda_F$ increases by a factor of 1.5 between 120 and 200 km depth, a factor of 2.25 between 200 and 410 km depth, and a factor of 3.375 below 410 km depth. While several such functions were tested in an ad hoc visual analysis of the resolution testing results (Section 4.2), a more rigorous method may be pursued in the future to optimize model resolution.
The damping strength, $\lambda_D$, is kept constant for all parameters. A trade-off analysis is performed to find values for $\lambda_D$ and $\lambda_F$ that balance the model roughness and the fit to the data. Then, outliers are removed from the data set by calculating residuals and removing data that are 2.5σ away from the mean. Roughly 3% of the data are removed this way. After the outliers are removed, a final inversion is performed using the regularization parameters determined during the trade-off analysis.

### 3.6. Computational Aspects

The inversion in Section 3.5 required substantial optimization in order to make this study computationally feasible. The sizes of the matrices were of particular concern, as the LSQR algorithm requires two matrix-vector products per iteration (Paige & Saunders, 1982). If the matrices produced by Equation 11 did not fit in memory, then they would incur significant increases in calculation time due to reading each matrix twice per LSQR iteration. Therefore, we made use of efficient sparse matrix storage techniques to reduce the total size of the matrices down to $\sim 400$ GB, which was just able to fit in memory on our 512 GB system. Read time was significantly reduced through the use of solid state drives and chunked array reading, which achieved speeds of $\sim 2$ GB/s. Furthermore, the use of compressed sparse matrix storage techniques allowed us to partially parallelize one of the matrix-vector products in the LSQR algorithm. Altogether, we are able to perform 50 iterations of LSQR in $\sim 2$ h using 20 Intel Xeon Gold 6152 CPUs. However, by far the largest amount of time spent is on the creation of the sensitivity kernel matrices in Equation 11. Due to the large volume of data, the ambient noise Rayleigh wave group velocity measurements alone required 4 weeks of time running on 20 CPUs.

### 4. Results

#### 4.1. Data Fit

To assess the quality of the data fit to the inversion result, we analyze normalized residuals, defined as

$$r_i = \frac{c_i^{obs} - c_i^{sint}}{\sigma_i \sqrt{N_{i,t}}},$$

where $c_i^{obs}$ is the observed phase or group speed, and $c_i^{sint}$ is the phase or group speed predicted by our inversion result. Figure 5 displays normalized residuals for the fundamental mode data as a function of period. Overtone data residuals are likewise displayed in Figures S2 and S3. Our dispersion data are generally not measured on a common set of periods, and therefore to display the period dependence we binned the residuals in 10-s period bins. Different periods may also have different raypath distributions, and so to help understand the relationship between the spatial distribution of the data and the residuals, we binned the fundamental mode data in 10-s period bins and counted the number of rays passing by each grid node (hit counts) in the model (Figures S4–S7). We find that our reference model tends to predict speeds that are too fast compared to the data. Short period Rayleigh and Love phase and group speeds have distributions strongly shifted toward negative residuals, indicating that the CRUST1.0 model on the continent may be too fast for this region. At longer periods, the Rayleigh data residuals display a strong asymmetry with a majority of the data having a negative residual, while the Love wave data show more symmetric distributions. Longer periods are mostly sensitive to upper mantle structure, so this is an indication that AK135 (our reference mantle model) may also be too fast for this region. The asymmetry of the long period Rayleigh phase and group residual distributions is a result of the division by $\sqrt{N_{i,t}}$ in Equation 15, which tends to concentrate the majority negative residuals toward smaller values, and the lack of positive residuals results in an apparent cutoff in the distributions. Since the long period Love wave phase and group velocities lack this asymmetry, it may be taken as evidence of radial anisotropy in the region since the Rayleigh waves are systematically affected by some structure that is, causing them to propagate slower than Love waves.

This may be also reflected in the variance reduction, shown in Figure 6. Here, we define the variance reduction (VR) as
which can be seen as a measure of how well the data fits the inversion result compared to the reference 3-D model. Here, \( c_{i}^{ref} \) is the phase or group speed predicted by the initial 3-D reference model. We split our data set by surface wave type, dispersion type, and mode number and separately calculate the VR in each 10-s period bin. In addition, we similarly calculate VRs for isotropic velocity variations alone by setting the radial anisotropy perturbations to zero. The resulting patterns in the VRs are complicated and reflect the different sensitivities of the data to different regions in the model. Short period (<10 s) Rayleigh and Love wave group velocities are fit to similar levels with a radially anisotropic model as with an isotropic model. These data have a median path length of \(~840\) km and are concentrated on the continent, which may indicate that the uppermost continental crust has relatively weak or unresolvable radial anisotropy. Group velocity VR decreases with increasing period, but the improvement to the variance reduction with the addition of anisotropy becomes more substantial. The largest improvement to VR for Rayleigh wave group velocities is between \(~30\) and \(~40\) s period, which is sensitive to the lower crust and uppermost mantle. Similarly, the Love group data sees significant improvements around \(~50\) s period where the Love wave sensitivity kernels are strongly peaked in the uppermost mantle.

The most striking features in the VRs are seen in the fundamental mode Rayleigh and Love phase velocity data. Similar to the group velocity data, the VR decreases with increasing period, which can be explained by our neglect of finite frequency effects. Ritzwoller et al. (2002) considered the effects of surface wave scattering theory on Rayleigh wave group velocities and showed that differences between ray theory and scattering theory increase with increasing period and path length. This is consistent with our results, where the median path length increases from \(~2,700\) km at \(20-30\) s period to \(~5,100\) km at \(190-200\) s period for
Past &speriod;240 s period, the Rayleigh wave phase velocity \( VR \) becomes negative, meaning that the inversion result does a worse job fitting the data compared to the initial 3-D model. This is most likely due to a paucity of long period data in combination with neglecting finite frequency effects. Since the majority of our data set is <200 s period, fitting the longer period data only has a minor effect on the data misfit. Compared to an isotropic model, we find that including radial anisotropy significantly improves the Rayleigh phase velocity \( VR \). Perhaps more importantly, we find that the Love wave phase velocity \( VR \) is negative for an isotropic model, which means that it is impossible to fit the Love and Rayleigh wave data simultaneously without including anisotropy. This may be confusing when we consider that the Love wave group data does not show negative \( VR \) for an isotropic model, but there are two factors that may explain the discrepancy. The Love group data has a shorter median path length of &sim;1,400 km and is concentrated on the continent at short periods, but the Love phase data has a longer median path length of &sim;3,700 km and the paths primarily cross the eastern portion of the model. If that region requires stronger radial anisotropy, the longer paths would allow for larger phase anomalies to accumulate, such that an isotropic model would no longer be able to explain both Rayleigh and Love wave dispersion.

The overtones also show interesting \( VR \) patterns. The Rayleigh overtone data appears to have \( VR \) increase with period, while the Love overtone data does not show significant improvement in \( VR \) when anisotropy is included. Both of these features can be explained by considering the overtone sensitivity kernels. While
the first overtone \((n = 1)\) kernel shows a broad peak in the upper mantle, the higher mode kernels become increasingly oscillatory at short periods (e.g., Figure 4b), which increases the nonuniqueness of the inverse problem. However, at longer periods, the kernel oscillations become “stretched” into the lower mantle, leaving a broad peak in the upper mantle (e.g., Figure 4c). Thus, the \(n > 1\) overtones may be better fit at longer periods than at shorter periods. The Love overtone anisotropy kernels, on the other hand, oscillate between negative and positive values. If, for example, the study region has radial anisotropy characterized by a linear function over a large depth range as in PREM (Dziewoński & Anderson, 1981), then Equation 11 implies that the corresponding contributions to perturbations in the Love wave overtone phase velocities would be insignificant. This appears to be what we observe in the Love wave overtone VR.

4.2. Resolution Testing

We carried out checkerboard testing in order to determine the resolution and reliability of our model. While problems with checkerboard tests are well-known (e.g., Lévêque et al., 1993), it remains a widely used and computationally efficient way to estimate model resolution. We created input models with 5\% sinusoidal lateral variations sized 8° × 8°, 4° × 4°, 2° × 2°, and 1° × 1° and constant amplitudes in the vertical direction. In order to check leakage of isotropic \(V_S\) structure into anisotropic structure, we set our input models to only have \(V_S\) perturbations and zero \(\zeta_S\) perturbations. We also performed the converse test to check leakage of anisotropic structure into \(V_S\) structure. For all resolution tests, we added Gaussian noise to the synthetic data. The magnitudes of the synthetic data and observed data vectors, \(|\textbf{d}_i|\) and \(|\textbf{d}_o|\), can differ considerably, so the level of Gaussian noise must be set in proportion to the ratio between the observed data norm and the norm of the estimated errors. If we assume that the synthetic data has errors scaled to the estimated errors by some constant factor, we find that the scaling factor must be \(\lambda = |\textbf{d}_i|/|\textbf{d}_o|\). The noise added to the \(i\)th synthetic data point is then sampled from a Gaussian distribution with standard deviation \(\lambda\sigma_i\), where \(\sigma_i\) is the estimated error for the corresponding observed data point. Resolution test results are presented in Figure 7. We note here that because our checkerboard patterns are not dependent on depth, our estimates of depth resolution only reflect the maximum possible depth of retrieval assuming a perfect forward theory.

The \(V_S\) test results show excellent retrieval of 1° × 1° structures in east Tibet, the NCC, the SCB, the Yellow Sea, the Ryukyu Trench, Northeast China, the Korean Peninsula, the East Sea, and Japan from 5 km depth down to 35 km depth. Below 35 km depth, only the Ryukyu Trench, the East Sea, and Japan are well retrieved down to 120 km depth, with small retrievable regions to the west. For 2° × 2° sized anomalies, the entire region is well retrieved down to 75 km depth, below which point only the easternmost regions of our model are retrieved down to 200 km depth. For 4° × 4° sized anomalies, good resolution is achieved throughout the model region down to 200 km depth, while the easternmost regions are retrieved down to 380 km depth. We achieve good 8° × 8° resolution at all depths, which is similar to most global mantle models. Leakage of \(V_S\) structure into \(\zeta_S\) structure is minimal, staying below 1\% but appearing with sign opposite that of the input anomalies.

The \(\zeta_S\) results show lower resolution compared to \(V_S\), as expected from our discussion in Section 3.5. One-degree resolution is achieved from 5 to 20 km depth in parts of Tibet, the NCC, the SCB, NE China, the Bohai Bay, the southern Korean Peninsula, the eastern margin of the East Sea, and Japan. Two-degree resolution is achieved throughout the entire region in the crust, while the easternmost regions retain resolution down to 95 km depth. Increasing the size of the input anomalies to 4° increases the depth of retrieval down to the uppermost mantle, while the easternmost regions retain resolution down to 200 km depth. For 8°-sized anomalies, we retrieve the input anomalies down to 200 km, but anomaly shapes are retrieved with weak amplitudes down to the MTZ. Leakage of anisotropic structure into \(V_S\) structure is slightly larger than in the converse test. Leaked anomalies also appear with sign opposite of the input models, and reach up to 2\% in regions with poor data coverage.

4.3. Azimuthal Distributions

In addition to checkerboard testing, it is important to show the azimuthal distribution of the data in order to ensure that contributions from azimuthal anisotropy are being minimized. To quantify the degree of azimuthal distribution uniformity, we assess a function proposed by Barmin et al. (2001),
Figure 7. Checkerboard resolution test results. Left two columns show input models, right two columns show the output models corresponding to the models immediately on the left. Depths are displayed at the bottom left corners in each panel.
where $f_i$ is the number of paths falling into the $i$th azimuth bin, and $n$ is the total number of bins. Because we expect the anisotropic part of our model to be smoother than the isotropic portion, we evaluate Equation 17 using $n = 10$ at each node on a grid with spacing 100 km on average, or roughly double the spacing of the model grid. When $\chi \approx 1$, the azimuthal distribution at that point is uniform, but when $\chi \approx 1/n$ the distribution is dominated by a small range of azimuths. We choose an arbitrary threshold value of $\chi_0 = 0.25$ to exclude regions that may be strongly contaminated by azimuthal anisotropy, and we only show regions of the model where both Rayleigh and Love azimuthal distributions have $\chi > \chi_0$. In Figure 8, we see that most of the study region has $\chi > \chi_0$, but higher $\chi$ values are found in eastern China, the Yellow Sea, Taiwan, the Ryukyu Trench, the Korean Peninsula, the southern East Sea, and Japan. A more rigorous treatment would show the period dependence of the azimuthal distributions (e.g., similar to Section 4.1), but our purpose here is mainly to produce a mask that excludes the most poorly resolved regions.

Previous studies have found azimuthal anisotropy in East Asia, which may affect our results in regions of poor azimuthal distribution. W. Shen et al. (2016) conducted a study of Rayleigh wave dispersion in East Asia to create a 3-D $V_{3V}$ model of the region. While their focus was on isotropic velocity structures, they simultaneously inverted for azimuthally anisotropic Rayleigh wave phase velocities. Their results indicate that azimuthal anisotropy may reach 3%–4% at 10 s period, particularly in eastern Tibet, the Bohai Bay, and Songliao basins, and in the boundary between the Yangtze craton and the Cathaysia block. The azimuthal anisotropy weakens to <2% at 30 s period on most East Asia and in the East Sea, but remains relatively strong in Tibet and in Japan. A study of azimuthally anisotropic Rayleigh wave phase velocity by Legendre et al. (2014) in eastern China indicates amplitudes of up to 2% at 20 s period beneath the NCC, but moderate anisotropy (∼1%) in the Yangtze craton. Anisotropy amplitudes decrease from 2% to 1% in the Cathaysia Block at 20–30 s period. Anisotropy appears to remain strong at 50–100 s period beneath the western NCC, but is weak in the eastern NCC. Ekström (2011) conducted a study of global fundamental mode Rayleigh and Love wave phase dispersion but only found that Rayleigh waves showed significant azimuthal anisotropy, and their preferred model shows similar azimuthal anisotropy as Legendre et al. (2014) in East Asia at long periods. On the other hand, Visser et al. (2008) also conducted a global study of Rayleigh and Love wave phase dispersion, and found that both fundamental mode and overtone data require azimuthal anisotropy. However, their results also seem to indicate relatively weak azimuthal anisotropy in our study region, except for Tibet. Our Rayleigh wave raypath azimuthal distributions (Figure 8) tend to show high values of $\chi$ in eastern China, Korea, and the southern East Sea, so those regions might not be heavily affected by azimuthal anisotropy. However, we may expect bias due to azimuthal anisotropy in the uppermost crust and in Tibet.
4.4. Isotropic $V_s$ Structure

The velocity structure of East Asia has been covered extensively in high-resolution using various tomographic techniques by previous studies (e.g., M. Chen et al., 2015; Tao et al., 2018), so here we briefly review several radially anisotropic regional and global models and one regional $V_{st}$ model, explain large-scale features observed in our model, and discuss similarities and differences. In the following, we shall refer to our model as KEA20.

Here we list our selection of regional and global models. This list is not meant to be exhaustive; rather, we made our selections to get a representative sample of the different kinds of surface wave data sets, model parameterizations, and inversion methods that have been used to study East Asia and the globe.

1. FWEA18 (Tao et al., 2018) is a high-resolution model of East Asia based on a full waveform inversion of ~1.35 million body wave windows filtered between 8 and 100 s period and ~72 thousand surface wave windows filtered between 40–100 s period. As the radial anisotropy is mostly constrained by the surface wave data, the depth range of radial anisotropy variations is limited to 220 km depth. Crustal variations for both isotropic $V_s$ and radial anisotropy are included and thus crustal corrections are not used.

2. CU_SDT (Shapiro & Ritzwoller, 2002) is a global 2° × 2° model derived from a two-step inversion process. The first step involves the creation of phase and group velocity dispersion models, including diffraction effects (Ritzwoller et al., 2002), in the period range 16–200 s. The second step involves a Bayesian Monte Carlo inversion that finds an ensemble of physically plausible 1-D models at every point on a 2° × 2° grid. Crustal $V_s$ variations are allowed, but radial anisotropy is only allowed to vary in the uppermost mantle.

3. Savani (Auer et al., 2014) is a global model on a variable grid with 1.25° spacing in well sampled regions and 5° in poorly sampled regions. The same surface wave ray theory as presented in Section 3.1 was used to model surface wave phase velocity data up to the sixth overtone in the period range 20–350 s. Body wave data are also included in the construction of savani. Crustal perturbations are not included, and CRUST2.0 (Bassin et al., 2000) was used to calculate local sensitivity kernels and to calculate crustal corrections for the data.

4. SGLOBE-rani (S.-J. Chang, Ferreira, et al., 2015) is a global model parameterized by spherical harmonics up to order $l = 35$, corresponding to roughly 6°. Phase and group velocity dispersion data are used in the period range 16–375 s, and ~420,000 body wave travel time data are included in a joint inversion for whole mantle structure. Crustal corrections are made using CRUST2.0 (Bassin et al., 2000), and crustal thickness perturbations are included as model parameters to minimize the contamination of mantle structure by nonlinear crustal effects.

5. CAM2016 (Ho et al., 2016) is a global model of the upper mantle derived from a multimode waveform inversion scheme based on the method of “secondary observables” (Cara & Lévéque, 1987). The radially anisotropic portion is based on a simultaneous inversion of ~0.5 million Rayleigh and Love waveforms filtered between 50 and 200 s period along similar raypaths and uses a smoothing length of 600 km. Crustal perturbations are not included, but the reference model uses CRUST1.0 (Laskar et al., 2013) to include crustal effects in the synthetic waveforms.

6. SEMUCB-WM1 (French & Romanowicz, 2014) is a radially anisotropic global mantle model which combines a full waveform modeling approach (French et al., 2013) with efficient sensitivity kernel calculations that incorporate mode coupling in the vertical plane between the source and receiver (X.-D. Li & Romanowicz, 1995). The method carefully constructs a smooth crustal model that can accurately predict long period waveforms, and crustal corrections are employed that mimic the nonlinear response of the crust (Lekić et al., 2010). Over 500 seismic stations and 273 events were used to fit ~447,800 waveform windows, with surface waves filtered between 60–400 s period and body waves filtered between 32 and 300 s period. Additionally, group velocity dispersion data in the range 25–150 s period are used to constrain the crustal model.

7. S16sv (W. Shen et al., 2016) is a regional isotropic $V_{st}$ model compiled from a combination of Rayleigh phase and group velocity measurements from ambient noise in the period range 8–50 s and earthquake derived Rayleigh phase velocity measurements from 30 to 70 s period. Similar to the CU_SDT model, maps of group and phase velocities are first constructed. Ambient noise phase velocity maps are made using the method of eikonal tomography (Lin, Ritzwoller, & Snieder, 2009), while group velocity maps are made using traditional ray theory techniques (Barmin et al., 2001). Earthquake phase velocity maps are constructed using the Helmholtz tomography method, which incorporates finite frequency effects.
(Lin & Ritzwoller, 2011). Then, a Monte Carlo method is used to invert local dispersion curves for 1-D $V_{Sv}$ profiles on a 0.5° grid, which are combined to form a 3-D model.

In order to provide quantitative estimates of the similarity between models, we calculate a correlation coefficient between two models A and B at some depth defined as

$$CC = \frac{\int_C (m^A(r) - \bar{m}) (m^B(r) - \bar{m}) d\sigma}{\sqrt{\int_C (m^A(r) - \bar{m})^2 d\sigma \int_C (m^B(r) - \bar{m})^2 d\sigma}}.$$  \hspace{1cm} (18)

where $m(r)$ is a model parameter value at some position $r$, $\bar{m}$ is the mean model parameter value, and the integration is done over an area $\sigma$ where both models are defined. For example, we mask regions of poor data coverage in KEA20, so the integration region is defined by the area where KEA20 has good data coverage. In order to meaningfully compare models at similar scales, we apply Gaussian bandpass filters with center wavelengths 1°, 2°, 4°, and 8° and a full width at half maximum of 1° to the models before calculating the CC.

Figures 9, 10, and S8 show comparisons of the crustal and mantle Voigt averaged $v_S$ structure of KEA20 with previous models at mutually defined depths. Figure S9 compares our model converted to $V_{Sv}$ with model S16sv. While our resolution testing shows excellent retrieval of structure in the shallowest crust (<10 km depth), it is likely that shallow crustal structures are contaminated by sediment structures, which dispersion data are not able to uniquely constrain, and upper crustal azimuthal anisotropy (e.g., W. Shen et al., 2016). Therefore, we start our comparison of $v_S$ structure at 20 km depth.

Overall, KEA20 shows high agreement with other models in the crust and upper mantle, with CC values >0.5 for the largest scale structures in many cases. Small-scale structures on the order of 1° typically have low CC values, although for global models this is expected since this is below their resolution limits. We find a high correlation with FWEA18, CU_SDTC and S16sv in the mid-crust, where we image similar $v_S$ structures in the western portion of the region. The Sichuan basin and Ordos block are similarly imaged with higher relative $v_S$ compared to the surrounding region, and Tibet is imaged with lower $v_S$ anomalies compared to the east. In the eastern portion of the region, KEA20 matches better with CU_SDTC than FWEA18, where the Yellow Sea, eastern SCB, and eastern NCC show lower $v_S$ anomalies compared to FWEA18, which may be due to the shorter period dispersion data used in the construction of KEA20 and CU_SDTC. KEA20 shows very low $v_S$ anomalies along the Ryukyu Trench, which may be due to CRUST1.0 being inadequate for that region, where Moho depth constraints show a large mismatch with CRUST1.0 Moho depths. The subducting plate may double the thickness of the crust there, so that the dispersion data show much lower speeds than predicted by the reference 3-D model, which would have a shallower Moho and thus faster phase and group velocities at shorter periods.

We show high levels of correlation around 40 km depth with FWEA18, but CU_SDTC and S16sv are highly similar as well. At this depth all four models roughly image the same structures. As the Moho depth increases from east to west, velocities decrease moving from upper mantle structures in the east to thick crust in the west. Sharp lateral discontinuities may be seen in KEA20 and FWEA18 as both models use CRUST1.0 to model the Moho boundary as a sharp discontinuity. In the East Sea, Yellow Sea, and Ryukyu Trench, the small-scale features in KEA20 and FWEA18 appear to match closely, while CU_SDTC images slightly lower $v_S$ anomalies on average, and the small-scale low $v_S$ anomalies in the Ryukyu trench are missed.

We retain high levels of correlation with FWEA18 at 60 and 80 km depth, but we show lower levels of correlation with global models. One particular point of low correlation is around 80 km depth, where CC values drop to 0.27 for 8° structures in savani, which may be due to leakage of Tibetan crustal structure into the uppermost mantle, as it shows large negative velocities where KEA20, FWEA18, CU_SDTC, and SEMUCB-WM1 show moderately low values. At these depths, our resolution testing shows that KEA20 has similar resolution with FWEA18 in the east, while the western portion of the study region shows resolution more similar to CU_SDTC. As a result, KEA20 shows low $v_S$ anomalies in the East Sea, Ryukyu Trench, and Yellow Sea similar to FWEA18, while areas to the west such as the Yangtze craton, Ordos block, and Tibet more closely match CU_SDTC, savani, SGLOBE-rani, and SEMUCB-WM1.
Our similarity with S16sv also weakens at 80 km and below. The Yangtze and Ordos cratons retain higher amplitude $V_{SV}$ anomalies in S16sv similar to FWEA18 and CU_SDT, which may be due to those models incorporating more realistic waveform propagation theories (full waveform inversion for FWEA18, surface wave diffraction for CU_SDT, and Helmholtz tomography for S16sv). However, S16sv appears to show increasingly negative $V_{SV}$ anomalies in Tibet, which could be due to contamination by crustal structure from a lack of long period phase velocity data in that region.

Below 100 km depth, the advantages of the full waveform inversion approach become apparent as FWEA18 retains high amplitudes and sharp boundaries between different structures. At that point, KEA20 becomes more similar in resolution to the global models. At 120 km depth models savani and CAM2016 may be more strongly affected by crustal corrections compared to models that inverted for crustal structure, given the low $v_S$ anomalies beneath Tibet due to the leakage of crustal structure.

**Figure 9.** Horizontal slices through KEA20 showing Voigt average $v_S$ perturbations and comparisons with regional and global radially anisotropic models at 20–80 km depth: FWEA18 (Tao et al., 2018), CU_SDT (Shapiro & Ritzwoller, 2002). Each column shows a different model, with labels shown on top. The rows show different depth slices, with the depth shown at the top left corner of KEA20. Color bars at the right of each row indicate the range of amplitude perturbations in percent. All amplitude perturbations are shown with respect to the mean Voigt $v_S$ value for KEA20, shown in the bottom left corner. Correlation coefficients ($CC$) of each model with KEA20 are shown in the bottom right corners. Subscripts for each $CC$ value indicate the center wavelength in degrees of the Gaussian bandpass filter used before $CC$ calculation. Regions with insufficient data coverage are masked in KEA20.
Our resolution testing shows that smearing affects deep structures more strongly in the west, so that below 160 km depth we lose the ability to resolve the Yangtze and Ordos cratons as in FWEA18. However, similar to the global models we do image the large-scale high $v_S$ anomalies in the west due to the combined influence of the Yangtze and Ordos cratons and the subducting Indian lithosphere. We image the large swath of low $v_S$ anomalies underneath the eastern Chinese coast, Yellow Sea, and Korean Peninsula that are observed in all models compared. Further east, KEA20 images the subducting Pacific and Philippine Sea plates, but these become increasingly smeared and lose amplitude with depth.

4.5. Radial Anisotropy

We present our radial anisotropy model and provide comparisons with other models at similar depths in Figures 11, 12, and S10. Correlations with other models are much lower than for isotropic $v_S$, as has been observed in previous studies (e.g., Auer et al., 2014; S.-J. Chang, Ferreira, et al., 2014, 2015; French & Romanowicz, 2014). A maximum CC value of 0.27 is observed with 4° and 8° structures in SGLOBE-rani at
60 km depth. Other models show relatively little similarity with KEA20 with CC values ∼0.20 or below at all scales, although all models do seem to show decreased levels of $\xi$ around the northern Korean Peninsula.

A study by S.-J. Chang and Ferreira (2017) showed that dispersion data with periods around 20 s or shorter are needed to adequately constrain crustal structure and avoid strongly affecting retrieved upper mantle structures. To check the effects of excluding short period data, we performed a test inversion where we removed all data with period less than 20 s, and we also removed all crustal perturbations above 35 km depth. The results, shown in Figure 13, confirm the findings of S.-J. Chang and Ferreira (2017). The patterns of radial anisotropy in the test inversion are significantly different compared to KEA20, and larger positive anisotropy is projected to deeper regions in the model. These patterns are similar to the radial anisotropy displayed in models FWEA18, CU_SDT, and other global models (Figures 11, 12, and S10), with higher radial anisotropy at 60–80 km than in shallower depths. This suggests that these models may have their upper mantle radial anisotropy strongly contaminated by structures near the Moho discontinuity. Performing crustal corrections may mitigate these effects somewhat (e.g., Panning et al., 2010), but we find that these results are consistent with previous studies of the effects of the crust on radial anisotropy. Bozdağ and Tampert (2008) found that improper crustal corrections can strongly bias upper mantle models of radial anisotropy, and suggested that the best recourse would be to invert for both crustal and mantle perturbations starting from a good 3-D reference model. Ferreira et al. (2010) considered the effects of different reference 3-D crustal models and found substantial differences in radial anisotropy throughout the upper mantle, suggesting that data able to resolve crustal structure should be included. Xing and Beghein (2015) used a Bayesian approach to invert Rayleigh and Love wave phase velocity maps and found that the discrepancies in radial anisotropy between models using different crustal corrections were larger than the model uncertainties down to 250 km depth.

Figure 11. Horizontal slices through KEA20 showing $\xi = (V_{SW} / V_{SV})^2$ and comparisons with regional and global radially anisotropic models between 20 and 60 km depth.
Therefore, we attribute the low CC values to the inclusion of short period ambient noise group velocity data, the inclusion of crustal perturbations, and using local sensitivity kernels calculated for a 3-D reference model with crustal thickness updated using Moho depth constraints in KEA20. For instance, Tao et al. (2018) write that most of the radial anisotropy in FWEA18 is constrained by their surface wave data, but they only attempted to fit surface waves between 40 and 100 s period. Shapiro and Ritzwoller (2002) included group velocity data with periods as short as 16 s, but only allowed radial anisotropy perturbations in the upper mantle. Furthermore, S.-J. Chang, Ferreira, et al. (2015) found that body wave travel time data does not seem to constrain radial anisotropy in shallow depths well, which supports the idea that good coverage by surface wave data is necessary to retrieve robust images of radial anisotropy in the crust and uppermost mantle. Auer et al. (2014) used the same local sensitivity kernel approach as in this study, but did not include crustal perturbations. We find it likely, therefore, that radial anisotropy in the crust and uppermost mantle in these models may be strongly affected by choices in reference crustal structure and crustal corrections or by limitations due to the data sets used.

On the other hand, our model is consistent with recent regional studies of the crust in East Asia. The eastern Tibetan margin is largely characterized by weakly negative radial anisotropy (ξ < 1.0) in the shallow crust, but transitions to positive radial anisotropy (ξ > 1.0) in the mid-crust. In contrast, the nearby Sichuan basin shows little radial anisotropy down to 40 km depth. These patterns are similar to those found in a regional study of eastern Tibet by Xie, Ritzwoller, Shen, and Wang (2017), who performed a Bayesian Monte Carlo inversion of Love and Rayleigh wave phase speeds between 8 and 40 s period for a tilted hexagonally symmetric medium, which removes the constraint of a vertical symmetry axis imposed by radial anisotropy. When they translate their model to the “apparent” radial anisotropy, their model shares similar general features with KEA20. In southeastern Tibet and southwestern China, H. Huang et al. (2010) measured
Figure 13. Comparison of KEA20 (right column) with an inversion that excluded short period (<20 s) data and removed crustal perturbations ≤ 35 km depth (middle column). Rightmost column shows the percent difference between the test inversion and KEA20. Positive differences signify that KEA20 has smaller values of $\xi$ relative to the test inversion, and negative differences signify that KEA20 has larger values.
Rayleigh and Love wave phase velocities in the period range 7–40 s, performed 1-D Monte Carlo inversions of localized phase velocities on a 0.5° × 0.5° grid, and found evidence for strong positive radial anisotropy in the deep crust, similar to what we find.

Elsewhere in the crust, we find positive radial anisotropy in the shallow to mid-crust along the border of the Yangtze craton and the Cathaysia foldbelt, in the QDS orogenic belt, and in the Bohai Bay basin. In the Yellow Sea, we image weak radial anisotropy between China and the Korean Peninsula. We find weak radial anisotropy in the northern Korean Peninsula and in the northern portion of the East Sea. However, the azimuthal distributions of Rayleigh and Love wave raypaths in the northern East Sea may not be uniform enough to avoid contamination by azimuthal anisotropy (Figure 8). In contrast, the southern East Sea appears well resolved, and displays positive radial anisotropy. Further east, the Japan trench is imaged with weakly positive to slightly negative radial anisotropy.

We find the strongest radial anisotropy to be confined to the lower crust and uppermost mantle. At 40 km depth, the eastern region of the model shows positive radial anisotropy which increases near the Bohai Bay and Cathaysia Foldbelt regions as well as under southwestern Japan. At 60 km depth, most of the region underneath China displays positive radial anisotropy, while the Yellow Sea continues weakening in strength. Strong positive radial anisotropy is found under SW Japan, whereas weak radial anisotropy is found in the mantle wedge underneath NE Japan, beginning at 60 km depth and continuing down to 100 km depth. The resolution of deeper radial anisotropy structures weakens with depth, but large-scale features should remain resolvable down to at least 120 km depth. At these depths, we only find evidence for weakly positive radial anisotropy throughout the region, with the exception of slightly elevated amplitudes in the East China Sea.

4.6. Radial Anisotropy Cluster Analysis

To help simplify interpretation of the model results and to identify large-scale patterns in the radial anisotropy, we performed a cluster analysis of 1-D $\xi$ profiles at each node in our model grid lying within the area deemed to have adequate azimuthal distributions and data coverage. Regionalization of tomographic models has been conducted via visual analysis in the past (e.g., Babuška et al., 1998), but recently cluster analysis has been used in a similar fashion to quantitatively identify tectonic regions and compare global models of the upper mantle (Lekić & Romanowicz, 2011) and to identify anomalous $\xi$ in the mantle transition zone (S.-J. Chang & Ferreira, 2019), and a small set of regionalized dispersion curves resulting from cluster analysis of surface wave dispersion maps was shown to predict group speeds just as well as the surface wave tomography results (Witek et al., 2018). Here, we use an hierarchical, agglomerative clustering method where each 1-D profile starts out as its own cluster. Clusters are merged according to Ward’s variance minimization criterion (Ward, Jr., 1963), which minimizes the total in-cluster variance. This method requires that the clusters are compared using a Euclidean distance metric, so we define the “distance” between two 1-D $\xi$ profiles to be

$$d_{ij} = \frac{1}{n_2 - n_1} \int_{r_1}^{r_2} [\xi_i(r) - \xi_j(r)]^2 \, dr,$$

where $d_{ij}$ is the distance between the $i$th and $j$th 1-D $\xi$ profiles and may be understood as a measure of dissimilarity. To meaningfully compare profiles in well resolved regions, we limit the cluster analysis to the region of good data coverage at 120 km depth (Figure 12), and we set the upper and lower depth bounds to be 10 and 120 km depth, respectively. We present several models with different amounts of clusters in Figure 14.

Based on only a set of 1-D $\xi$ profiles and without any prior geographical knowledge, the cluster analysis is able to extract and quantify regions of the model described in Section 4.5. However, despite attempting to limit the cluster analysis to regions of good resolution, some areas of poor resolution may interfere with the results. In particular, we consider the northern East Sea and regions north of Japan to have poor azimuthal data coverage, so we will not include them in the following discussion. Likewise, areas immediately to the east and south of Taiwan also have poor resolution.
The choice of how many clusters to include is guided by the dendrogram in Figure 14f. The dendrogram illustrates cluster composition by drawing U-shaped links between clusters at the distances that they are merged. For example, in Figure 14f, we see that Clusters 1 and 6 are merged at a lower distance than Clusters 4 and 5 (cluster labels referring to Figure 14e). This indicates that Clusters 1 and 6 are more similar to each other than 4 and 5. Likewise, Clusters 1, 4, 5, and 6 are more similar to each other than Clusters 2 and 3. As the model splits into smaller clusters, the differences between successive merging distances decreases. It is possible to check how many clusters are necessary to sufficiently explain the data by replacing the 3-D model perturbations with the cluster results and calculating variance reductions (e.g., Witek et al., 2018).

However, our purpose here is merely to use the cluster models to guide discussion, and the question of cluster model robustness may be the subject of a future study.

The results confirm that overall the region is characterized by positive radial anisotropy, with the strongest amplitudes confined to the lower crust and uppermost mantle. The peak amplitudes of radial anisotropy generally decrease moving away from the Bohai Bay and eastern NCC region. With two clusters, the region separates into an area that has been dominated by lithospheric thinning and crustal extension in the center and an area of thicker crust in the west and trenches in the east. The third cluster to form has the Sichuan basin and oceanic trenches separate as distinct regions of relatively low ξ. Afterward, we observe the large central cluster break up into a back-arc basin region and a continental region. The eastern margin of China appears to show the highest ξ, with values approaching 1.12 in areas of extensive past deformation such as in the Jiangnan Orogen between the Cathaysia block and Yangtze craton, the QDS belt between the NCC and the SCB, and the Bohai Bay basin. Southwestern Japan also appears as a region of relatively high ξ.
Finally, the northern Korean Peninsula, northern Japan, and a portion of the Ordos block form a separate cluster of relatively low $\xi$ compared to their surroundings. In the following discussion, we will refer to the clusters that appear in Figure 14e.

5. Discussion

Typical global models of radial anisotropy show $\xi$ increasing to a maximum in the asthenosphere before decreasing again (e.g., Burgos et al., 2014). Becker et al. (2008) compared a geodynamic model of radial anisotropy with S362WMANI (Kustowski et al., 2008), and they found that radial anisotropy in the asthenosphere can be explained by applying experimentally derived laws for olivine lattice preferred orientation (LPO) formation; however, the largest discrepancies were found in the lithospheric mantle, which they explained as being due to frozen-in anisotropy that is, not explained by asthenospheric mantle flow. Our results show similar levels of radial anisotropy in the asthenosphere, indicating similar mechanisms for the causes of radial anisotropy there. However, we show that by including a large data set of short period dispersion measurements we image strong positive radial anisotropy in the lithospheric mantle.

Strong positive radial anisotropy in the lithospheric mantle has been found in tectonically active regions across the world. Yuan et al. (2011) created a radially and azimuthally anisotropic model of North America and split the continent into cratonic and tectonically active regions. When comparing 1-D average structures in each region, the tectonically active region has its peak $\xi$ at shallower depth, while the cratonic region has a lower peak amplitude at greater depth. Lebedev et al. (2006) conducted a study of asthenospheric flow in the Baikal rift region using dispersion data in the period range 10–300 s and found strong positive radial anisotropy ($\xi \sim 1.1$) at sub-Moho depths in regions of thinner lithosphere (60–70 km).

We propose that the high positive radial anisotropy found in the southern East Sea is due to a combination of LPO and shape preferred orientation (SPO) of horizontally aligned olivine fabrics and melts inside the lithospheric mantle and lowermost crust. If we define a seismic lithosphere-asthenosphere boundary (LAB) as the depth to the maximum negative velocity gradient, we find shallow LAB depths under the southern East Sea of ~50–60 km depth. As seafloor spreading commenced in the Japan basin c. 28 Ma, crustal extension initiated in the Ulleung and Yamato basins via continental rifting (Jolivet & Tamaki, 1992), which was accompanied by fissure-type volcanism (G. Kim et al., 2011; Y. K. Kwon et al., 2009). Melts are expected to rapidly leave the asthenosphere and collect at the bottom of the lithosphere, causing a sharp LAB (Sakamaki et al., 2013). Early studies found large amplitude short period geomagnetic variations in Japan and the surrounding regions, which were interpreted as being due to a highly conductive layer in the upper mantle (Rikitake, 1962, 1966, 1969), and studies also found high heat flows (Honda et al., 1979; Uyeda, 1972). Estimates of heat flow from bottom-simulating reflectors of gas hydrates in the Ulleung basin indicate hotter than normal mantle (Horozal et al., 2009; Yamano et al., 1982). A study by Tesoniero et al. (2015) shows larger than expected $V_p$ and high $V_p/V_S$ ratios under the East Sea, implying large fluid content. Recent seismic constraints on the crustal structure of the Yamato basin find P-wave speeds higher than 7.1 km/s in a thicker than normal lower crust, indicating underplating of anomalously hot mantle material (Sato, No, et al., 2014). Similar results are found along the southeastern margin of the Korean Peninsula and in the Ulleung basin, with a high P-wave velocity (~7.4 km/s) layer with up to 15 km thickness (H.-J. Kim et al., 2003). Thus, rifting must have allowed a way for ponded melt at the shallow LAB to travel vertically upwards to form thicker than normal oceanic type crust under parts of the southern East Sea. As fault zones may extend into the lithospheric mantle (Vauchez et al., 2012), the rifting could have also caused the formation of horizontally deformed volcanic sills in the lithospheric mantle (Menand, 2011).

In the northern portion of Cluster 1 is Cluster 6, a region comprised of the northern Korean Peninsula and NE Japan. It has moderately high positive radial anisotropy in the lower crust, but has the lowest levels of radial anisotropy at depths between than ~70–100 km. Cluster 3, a region of relatively low positive anisotropy also appears in the northern East Sea, but the azimuthal distribution of the data makes it unclear as to whether it is a real feature. Cluster 6 contains some notable intraplate volcanoes, such as Mt. Baekdu (Changbaishan), which was the site of a particularly devastating eruption c. 946 CE (e.g., Zou et al., 2010). The origins of intraplate volcanism in Cluster 6 have been the subject of much debate, but it is clear that upwelling mantle material is responsible for their formation (e.g., J. Huang & Zhao, 2006; Y.-W.
Kim et al., 2021; Lai et al., 2019; Z. Liu et al., 2015; Tang et al., 2014; D. Zhao, Lei, & Tang, 2004; D. Zhao & Ohtani, 2009; D. Zhao, Tian, et al., 2009). There are also some indications from geochemical and electrical conductivity studies that the mantle transition zone under Mt. Baekdu may be particularly hydrated (e.g., Kelbert et al., 2009; Kuritani et al., 2011; Y. Zhang et al., 2020). A hydrated upwelling plume could be composed of C-type olivine fabric, which, under vertical shear, would display weak positive radial anisotropy (Karato et al., 2008). Moho depths under Mt. Baekdu average 30–35 km, where we see a sharp increase in the radial anisotropy. This could be an indication of horizontally aligned melts and/or underplating under Mt. Baekdu. Other upwelling plumes, such as the Afar plume in Africa, have also been imaged with weak positive or negative radial anisotropy relative to their surroundings, supporting this idea (e.g., S.-J. Chang, van der Lee, et al., 2010; Sebai et al., 2006; Sicilia et al., 2008).

NE Japan also belongs to Cluster 6, where we see that the decrease in the strength of radial anisotropy appears in the mantle wedge above the subducting Pacific slab. This is in contrast to a study by Yoshizawa et al. (2010), who conducted a study of the East Sea using Rayleigh (25–140 s period) and Love (30–80 s period) phase velocity measurements and found strong positive radial anisotropy (\(\xi > 1.1\)) in the mantle wedge. The reason for this difference may be twofold. Our study uses much shorter period group velocity measurements in the same region, which are more sensitive to shallower structures. Furthermore, Yoshizawa et al. (2010) used 3SMAC (Nataf & Ricard, 1996) to construct a prior 3-D model, which Xing and Beghein (2015) caution against using due to significant effects on radially anisotropic structure above 100 km depth. Our results are more consistent with a P-wave anisotropy study of Japan by X. Liu and Zhao (2017), who find weak to slightly negative radial anisotropy. By determining the radial anisotropy between vertically propagating P-waves and the fast and slow directions of horizontally propagating P-waves, and by assuming simple relationships between olivine fabrics, their dominant slip systems and mantle flow patterns, X. Liu and Zhao (2017) were able to constrain distributions of likely olivine fabric types. Their results show that E-type olivine fabric under horizontal shear may dominate the region directly underneath NE Japan, with some B-type fabric under vertical shear in a small zone in the forearc mantle wedge. Given that the E-type fabric dominates over a wider volume, it is likely that our results would be more indicative of E-type olivine fabric in support of X. Liu and Zhao (2017). On the other hand, Ishise et al. (2018) also conduct a P-wave radial anisotropy study of NE Japan and find negative radial anisotropy (\(V_{PH} < V_{PV}\)) in the mantle wedge and positive radial anisotropy (\(V_{PH} > V_{PV}\)) in the subducting slab. Instead of invoking different olivine types, Ishise et al. (2018) explain their results by small-scale convection in the mantle wedge assuming an A-type olivine fabric. Numerical simulations by Morishige and Honda (2011) indicated steep downflows and gentle upflows, which would produce strong negative radial anisotropy given an A-type olivine fabric in the mantle wedge. Our resolution test results indicate 4° anisotropy resolution in the NE Japan mantle wedge (e.g., Figure 7), so it may be that our surface wave data average over the small-scale convection cells resulting in weak radial anisotropy.

To the west are Clusters 2, 3, 4, and 5, comprised of eastern Tibet, the Sichuan basin, the NCC, and the SCB. The Moho depth in Clusters 4 and 5 ranges 30–40 km depth, so that the peak radial anisotropy appears in the lower crust and uppermost mantle. Strong positive radial anisotropy of the lower crust in this region has been interpreted as being due to crustal extension by previous studies (e.g., Cheng et al., 2013; Fu et al., 2015; Guo et al., 2016). As amphibolites are considered to be a major constituent of the middle to lower crust (e.g., Christensen & Mooney, 1995; Fountain & Salisbury, 1981), horizontal shear stresses induced in extensional environments are expected to cause Type-I LPO in amphibolites and thus strong positive anisotropy (Ko & Jung, 2015). A marked decrease in the strength of positive radial anisotropy is seen going west from Clusters 4 and 5 to Clusters 2 and 3. Also seen is a small portion of Cluster 6, which contains the core of the Ordos block. Regions of relatively stable tectonics typically display weaker radial anisotropy. Whereas the eastern part of the NCC experienced significant lithospheric thinning, the Ordos block and the Yangtze craton have remained relatively stable and experienced little internal deformation. The radial anisotropy in the Yangtze and Ordos cratons may therefore represent remnant radial anisotropy from the time of formation. Priestley et al. (2020) conduct a global study of the radial anisotropy of crustal roots and find a transition to negative radial anisotropy around 150 km depth. Geochemical and petrological observations of garnet-peridotite nodules (e.g., Bernstein et al., 2007; Canil & Wei, 1992) suggest that their depth of formation must have been much shallower than the current lithospheric thickness, implying horizontal shortening and vertical thickening of cratonic lithosphere. Our observations of weak radial anisotropy in
the Yangtze and Ordos cratons around 120 km depth is consistent with this model of vertical shear caused by cratonic thickening in the distant past.

Clark and Royden (2000) proposed lower crustal flow out of the northeastern Tibetan margin into the Ordos block. However, our results show that radial anisotropy decreases westwards from the NCC to NE Tibet between 20 and 50 km depth. This may be more consistent with the crustal shortening proposed by Pan and Niu (2011), who performed a receiver function analysis at 154 seismic stations in the Ordos block and NE Tibet. Recent geologic results indicate that crustal thickening is enough to account for changes in crustal thickness in NE Tibet without the need for lower crustal flow (Lease et al., 2012). Crustal shortening can produce horizontal shear on dipping faults (Escher & Watterson, 1974), which would align anisotropic minerals in a subhorizontal plane and reduce the strength of radial anisotropy. However, consistent with previous studies, for Cluster 2 in eastern Tibet we observe higher positive radial anisotropy for depths <50 km, which corresponds to the middle to lower crust (e.g., Agius & Lebedev, 2014; Xie, Ritzwoller, Shen, & Wang, 2017; Xie, Ritzwoller, Shen, Yang, et al., 2013). Bai et al. (2010) conducted a magnetotelluric study of the region and found major zones of high electrical conductivity between 20 and 40 km depth, where we observe a sharp increase in radial anisotropy. Xie, Ritzwoller, Shen, and Wang (2017) report strong positive radial anisotropy in the middle to lower crust of eastern Tibet, and remark that this may indicate horizontal ductile deformation. Thus, our results support a weaker lower crust in eastern Tibet due to elevated fluid content and/or partial melt that would have allowed for crustal flow and alignment of lower crustal minerals. However, this flow may encounter resistance from the stable Ordos and Yangtze cratons, which would tend to focus lower crustal flow into the QDS belt and may be connected to the observed higher radial anisotropy in that region.

6. Conclusions

In this study, we create a new data set of Rayleigh and Love wave group velocity measurements from ambient noise and earthquake data recorded at regional and international seismic networks across China, Taiwan, Korea, and Japan in the period range 5–175 s. We combined this data set with several global dispersion data sets containing data up to the fifth overtone, and directly relate the data to changes in isotropic and radially anisotropic structure relative to a prior 3-D reference model. Our isotropic \( v_S \) results show a high degree of correlation with previous studies, including a model derived using a full waveform inversion method. However, we find large differences in the radial anisotropy, which we contribute to our addition of short period data and allowing for crustal variations, rather than calculating crustal corrections. Our results indicate near ubiquitous positive radial anisotropy from the middle crust down to the asthenosphere, and regional differences in the strength of the radial anisotropy are quantified using a cluster analysis of 1-D \( \xi \) profiles. We find hydrated upwelling mantle material underneath Mt Baekdu resulting in the lowest levels of asthenospheric radial anisotropy, possibly due to C-type olivine fabric. This vertical flow then dehydrates near the LAB and transitions to horizontal flow, leading to increased radial anisotropy in the uppermost mantle under Mt. Baekdu and in surrounding areas. High amplitudes of radial anisotropy are found underneath the southern East Sea, where back-arc related crustal extension led to the creation of high velocity lithospheric mantle through the upward migration of melts from a hotter than normal mantle. Low levels of radial anisotropy are found in the mantle wedge beneath NE Japan, which could be due to either E-type olivine fabric or small-scale convection. To the west, we find high levels of radial anisotropy in regions associated with significant lithospheric thinning and rift basin formation such as the Bohai or Songliao basins, and in collisional belts such as the QDS or Jiangnan orogen. This is in contrast to the more stable tectonic regions of the Ordos block and Yangtze craton, where we find low levels of radial anisotropy that may be associated with vertical shear caused by lithospheric thickening at the time of their formation. We find lower levels of radial anisotropy in the upper to middle crust of NE Tibet relative to the surrounding region, which is more consistent with a model of crustal shortening. On the other hand, high levels of radial anisotropy in the lower crust of eastern Tibet may indicate crustal flow that is, constrained by the Ordos and Yangtze cratons.
Data Availability Statement

Waveform data from the CEA is available at the Data Management Center (DMC) of the China Earthquake Network Center of the CEA (http://www.cea-igp.ac.cn, English: http://www.cea-igp.ac.cn/en/). KIGAM data is available at https://www.kigam.re.kr/quake (English: https://www.kigam.re.kr/english). KMA data is available at http://ncis.kma.go.kr (English: http://www.kma.go.kr/eng/weather/kma_service/observation.jsp) The noise cross-correlations used to measure Rayleigh and Love wave dispersion are available at https://doi.org/10.5281/zenodo.4985031. The primary data processing of CEA data was done by S. Ning. The Generic Mapping Tools software (Wessel et al., 2019) was used to plot figures containing maps. Our model is available at https://doi.org/10.17611/dp.emc.2021.kea20.1.

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Acknowledgments

The authors would like to thank the associate editor and two anonymous reviewers for their constructive comments which helped to improve the quality of this manuscript. This work was financially supported by the Korea Meteorological Administration Research and Development Program under Grant KMI 2018-09312, by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (2019R1A2C20850111), by Basic Science Research Program through the NRF funded by the Ministry of Education (No. 2019R1A6A1A0303167), and by the Ministry of the Interior and Safety as Human Resource Development Project in Disaster Management.
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