

Global Long-wavelength Body-wave Catalog (GLoBoCat) for Lower Mantle P and S Wave Travel Times

Jun Su *, Christine Houser , John W. Hernlund ^{2,3}

¹Japan Agency for Marine-Earth Science and Technology (JAMSTEC), ²Earth-Life Science Institute, Institute of Science Tokyo, ³Department of Earth and Planetary Science, Institute of Science Tokyo

Author contributions: *Conceptualization:* Jun Su, Christine Houser, John W. Hernlund. *Methodology:* Jun Su, Christine Houser. *Software:* Jun Su. *Validation:* Jun Su, Christine Houser. *Formal Analysis:* Jun Su, Christine Houser, John W. Hernlund. *Investigation:* Jun Su. *Resources:* Jun Su. *Writing - Original draft:* Jun Su. *Writing - Review & Editing:* Christine Houser, John W. Hernlund. *Visualization:* Jun Su. *Supervision:* Christine Houser, John W. Hernlund. *Project administration:* Christine Houser. *Funding acquisition:* Christine Houser, John W. Hernlund.

Abstract Travel times of long period body waves passing through the lower mantle reveal the deep seismic structure and forces shaping our planet. Manual methods measuring P and S wave arrivals produce travel time catalogs with high internal consistency, but have not kept pace with the rapid growth in waveform records. Here we use attention-based machine learning trained on prior manual datasets to develop a catalog spanning 2010-2023 which is consistent with previous catalogs and straightforward to update. The new catalog exceeds millions of measurements for P and S wave travel times and retains features of the previous datasets while improving coverage in the lower mantle, particularly for raypaths turning beneath the southern hemisphere. Comparing our measurements to short period travel times, we find the correlation is different for early versus late arrivals, and that this difference is larger for P waves than S waves. The change in slope we observe is opposite to that proposed for wave propagation effects and warrants further investigation into the origin of this apparent dispersion in Earth's lower mantle.

Non-technical summary Comparing the time intervals between earthquakes and their arrivals recorded at seismograph stations around the world provides fundamental constraints on Earth's radial structure as well as defining areas where seismic waves are relatively fast or slow. Short period P and S wave arrival times (dominant period ~ 1 s) are hand-picked in real time by station operators for locating earthquakes. In contrast, the task of picking long period arrival times (dominant period ~ 20 s) falls on individual researchers who use the differences in arrival times to map out seismic structure of the Earth's interior. The growth of digital seismic arrays has dramatically increased the volume of available data, however, the laborious task of picking long period data by hand has fallen far behind. To meet this challenge, we use machine-learning trained on established hand-picked long period datasets. We find that the relation between overlapping short and long period measurements changes for early versus late arrival times, revealing an apparent dispersion in the Earth's mantle.

1 Introduction

Global seismology extracts information such as velocity, density, and attenuation from seismic waves that propagate across the planet to survey Earth's deep mantle and core. The rapid expansion of seismic recordings due to the proliferation and continuous operation of seismic stations over the past thirty years necessitates advancements in data analysis tools. Elastic properties and mineralogical characteristics of the lower mantle are inferred through analysis of seismic waveforms for earthquakes recorded at distances greater than 23° . Long period (~ 20 s) travel times for P and S body waves (Su and Dziewonski, 1991; Liu and Dziewonski, 1998; Grand, 2002; Gu et al., 2001; Bolton and Masters, 2001; Ritsema and Van Heijst, 2002; Simmons et al., 2006; Kustowski et al., 2008; Houser et al., 2008; Tesoniero et al., 2016;

Lai et al., 2019) reveal the global distribution of fast and slow seismic velocity regions in the Earth's mantle and form the basis for interpreting the dynamics and evolution of our planet. Nevertheless, concerns regarding the variable coverage of this data underlie a variety of uncertainties in the interpretation of major features of our planet's interior.

The data needed to address lingering questions regarding Earth structure in the deepest mantle potentially exists in current digital seismographic archives; however, the volume of data is too great to tackle using traditional manual or semi-manual techniques. The number of waveforms for each earthquake which are publicly available through the Incorporated Research Institutions for Seismology (IRIS) has ballooned from around 600 in 2005 to over 3000 in 2025 (Trabant et al., 2012) for P and S waves turning in the lower mantle. While purely manual (Bolton and Masters, 2001) or hy-

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*Corresponding author: junsu@jamstec.go.jp

brid manual-automated (Houser et al., 2008; Lai et al., 2019) methods to determine the onset of a P or S wave arrival (commonly referred to as “picking”) produce high-quality arrival time catalogs, the volume of data recorded since the 2010s has rendered manual methods applied consistently for all earthquakes propagating through the lower mantle infeasible (Arrowsmith et al., 2022). At the same time, traditional “rule-based” automated phase picking algorithms (Allen, 1978; Earle and Shearer, 1994; Igarashi et al., 2003; Peng and Zhao, 2009) face two obstacles when applied to real global long period data. First, their picking functions are sensitive to variable noise sources, so that thresholds and filter parameters must be re-tuned for individual stations and events (Zhang et al., 2018). Second, no single set of rules generalizes across the highly heterogeneous global networks and source conditions; for example, onset detectors that rely on first-motion polarity fail when a reflector near the source reverses the apparent polarity. Human experts overcome these obstacles by selecting and adjusting a measurement strategy only after synthesizing the source mechanism, path complexity, and record quality, judgements that are difficult to encode as fixed rules. The semi-automated cluster analysis of Houser et al. (2008) faces a related limitation: it is most effective when the user can visually distinguish waveform shapes to choose the initial clustering window and to evaluate the waveform alignment in the subsequent clusters. Once the number of waveforms per event began to exceed 800 in the late 2000s, following the roll-out of USArray and the general expansion of networks across the globe, evaluating the cluster quality by eye became impractical. In this study we explore the application of machine learning in order to (1) maintain continuity with the travel time picks of Bolton and Masters (2001) and Houser et al. (2008) on which the model is trained, (2) measure onset times and thereby avoid mapping waveform dispersion into the travel time measurement (Hung et al., 2001), and (3) develop the infrastructure and intuition to apply machine learning techniques to measure the arrivals of other phases.

Neural networks were introduced to picking arrivals of seismic phases in the 2000s (Gentili and Michellini, 2006), but it was not until advances in computational power and algorithms in the 2010s enabled the development of deeper models for “close-to-expert” performance (Ross et al., 2018; Zhu and Beroza, 2018; Woolam et al., 2019). Recent studies presented an attention-based machine-learning method (Vaswani et al., 2017) to extract context for seismic phases across the complete time series (Mousavi et al., 2020). This architecture accurately identifies both P and S wave arrivals in seismograms without reliance upon pre-defined velocity models or synthetic waveform calculations. Although the original model is designed for local (short epicentral distance) events and to identify seismicity with small magnitude, it has also proven useful in regional seismic studies (e.g., Nguyen et al., 2022; Bornstein et al., 2024). It was recently applied to massive data volumes from global seismic networks for picking short period arrivals of distant events, producing global catalogs of unprecedented scale (Cole et al., 2023; Ni et al.,

2025). However, this model has not yet been applied to long period P and S waves jointly.

Here we describe an extension of this method for teleseismic data to produce a new Global Long-wavelength Body-wave Catalog (GLoBoCat) consisting of more than 2 million direct P and S arrival times. The algorithm for generating GLoBoCat is trained on prior hand-picked data (Bolton and Masters, 2001; Houser et al., 2008) using the same processing methods to ensure mutual consistency. GLoBoCat reveals many of the same features as older datasets while significantly improving spatial coverage of the deep mantle, achieving similar resolution near the core-mantle boundary for both P and S waves. This larger data volume now provides sufficient overlap with short period arrival times to assess whether these may be robustly combined in tomographic inversions. We find (1) the short-long period correlation changes for late versus early arrivals, (2) the relative slope for late arrivals is greater for P than for S, and (3) the steep slope is opposite the shallower slope predicted by wavefront healing effects. These characteristics are not straightforwardly explained by wave propagation effects, and require further study.

2 Data & methods

In the following, we briefly introduce the machine learning approach in general before explaining our model architecture. To predict P and S arrivals in a seismic waveform, we employ a neural network, defined as layers of interconnected “neurons” that pass weighted sums of their inputs through simple non-linear functions. The first layer receives the digitized samples of the three-component seismogram (the “input”), and the final layer outputs, for every time sample, the probability that a P or S wave arrives at that instant (the “output”). The weights, collectively called parameters, are not prescribed by rules; they are iteratively optimized (“trained”) so that the output reproduces a set of reference measurements, in our case previously curated manual picks of long period P and S arrivals (Bolton and Masters, 2001; Houser et al., 2008). In this way the network encodes the picking behavior of human analysts without requiring explicit picking rules.

Our machine-learning (ML) model for P and S wave onset detection is adapted from the Earthquake Transformer (Mousavi et al., 2020) architecture, which we briefly summarize here in seismological terms. An encoder acts like a bank of filters that scans the seismogram over a range of time scales, producing a set of feature series that highlight characteristics of the record such as changes in amplitude, frequency content, and particle motion. A global attention layer (Vaswani et al., 2017) weighs the extent to which each feature series contributes to identifying an arrival at each point in time, much as an analyst focuses on the segments of a record and the signal characteristics most diagnostic of an onset while disregarding uninformative noise. Because these weights are computed from the whole time series rather than from a short sliding window, the model can use context (e.g., the noise level before the arrival, or the presence of a later phase) to inform each

pick. Finally, two decoders, one for P and one for S, convert this weighted information into the output probability sequences, in which the probability at each sample point represents the likelihood that it is the onset of the phase. The prediction is assessed by comparison to training data, wherein the manually picked arrivals are converted into temporal functions of probabilities, normally distributed with a maximum of 1 at the picked instant and standard deviation of 1.25 s. This 1.25 s standard deviation was chosen to match the empirical uncertainty (set to 1.0–3.0 s in the training dataset) in manual picking for long period data and provides a reasonable balance between precision and recall in the training process. The misfit between this target distribution and the ML prediction is quantified by the binary cross-entropy, a standard measure of the disagreement between two probability sequences that plays the role of a loss (misfit) function. Updating the trainable parameters with the Adam optimizer (Kingma and Ba, 2014), we iteratively minimized this loss, so that the model “learns” to reproduce the manual picks. In order to avoid overtraining (overfitting), we examined the updated parameters with the validation set every epoch and recorded the loss. The new parameters are only accepted when the loss in validation set decreased compared to the last epoch.

Our training data comprise direct P and S wave onset times from Houser et al. (2008) and continued, unpublished work through 2009. Masters et al. (2000) manually compared observed and synthetic waveforms to measure the onset of phase arrivals individually for each station. Houser et al. (2008) measured phase arrival onsets by introducing a clustering technique based on the relative alignment of all the waveforms for each event designed to significantly increase measurement speed while maintaining user-guided quality control compatible with the previous Masters et al. (2000) method. To ensure consistency between the training data and the waveforms, we followed the procedures outlined by Houser et al. (2008) which includes the following steps: 1) We requested digital long period (LH) seismic data from the Data Management Center of the IRIS, EarthScope Consortium (Trabant et al., 2012), for earthquakes of magnitudes ≥ 5.5 according to the Global Centroid Moment Tensor (GCMT) earthquake event catalog (Dziewonski et al., 1981; Ekström et al., 2012). 2) We removed the instrument response from each seismogram and applied the instrument response of the reference GRFO station to low-pass filter the data compatible with early long period networks. 3) The seismograms are rotated into radial, transverse, and vertical component waveforms before being trimmed to 1,500 seconds (see below for starting time) so that P and S arrivals are both present for all training data. 4) The waveforms are resampled at 4 Hz to improve seismogram alignment.

We constructed our model using the original Earthquake Transformer architecture and adapted to handle long periods relevant for lower mantle studies by changing the sampling rate from 100 Hz to 4 Hz and probability width σ for training arrivals from 10 samples (0.1 s) to 5 samples (1.25 s). The 0.25 s sampling interval is a trade-off between timing precision and computa-

tional cost: the size of the model grows roughly quadratically with the length of the input time series, and a finer sampling would demand substantially more training data and computation while contributing only a subtle improvement, given that the picking uncertainty is dominated by the 1.25 s width of the training probability function. We retain all three components as input following the original Earthquake Transformer and most models fine-tuned from it. Restricting the input to the vertical and transverse components would reduce the model size only marginally, because the number of channels expands immediately in the first encoder layer, whereas the radial component preserves particle-motion information that can help the model discriminate P and S energy.

To tailor the learning process for the ML model to handle both P and S arrivals, we used the 65,295 waveforms for which both P and S onset times are available as the training data. These waveforms are randomly divided into a training set (60%), validation set (20%), and test set (20%) to establish and evaluate the ML model. All waveforms randomly start between 150 to 350 seconds before P wave arrival times estimated by PREM (Dziewonski and Anderson, 1981) using TauP (Crotwell et al., 1999) and origin times from the GCMT catalog. Following the work by Mousavi et al. (2020), data augmentation is further applied to the training set, including randomly adding noise, modifying amplitude, flipping polarity, dropping a channel, and removing sample points from the time series.

Five CNN blocks and two LSTM blocks (refer to the original Earthquake Transformer paper for details) are used in the model, resulting in a total of 1,856 non-trainable and 371,639 trainable parameters to learn without using a pre-trained model. This model jointly determines onset times for P and S wave arrivals with the input of all three components from each station. No other *a priori* information, such as the epicentral distance, focal mechanism, or Green's function, is involved in the training process. The process requires 563 CPU hours on a modern laptop without GPU acceleration.

3 Results

The ML model with parameters from the course of training in 80 epochs with a batch size of 20, which we refer to as the ML phase picking model, is applied to waveforms not included in the training data for earthquakes recorded between 2010 and 2023. These waveforms are processed with the same method as the validation and test set, but the starting time is set at 250 seconds before the PREM-estimated arrival times. This new set of waveforms consists of 5,864,311 records from 5,617 stations and 5,880 earthquakes without epicentral distance constraints (Fig. 1a).

The detection threshold is defined by the maximum value of the prediction probability sequence. While a high value culls the volume of data, a low value leads to reduced accuracy. We evaluate the picking uncertainty by calculating the standard deviations among picking errors ($T_{\text{ML}} - T_{\text{Houser}}$) on the 13,060 records from the test

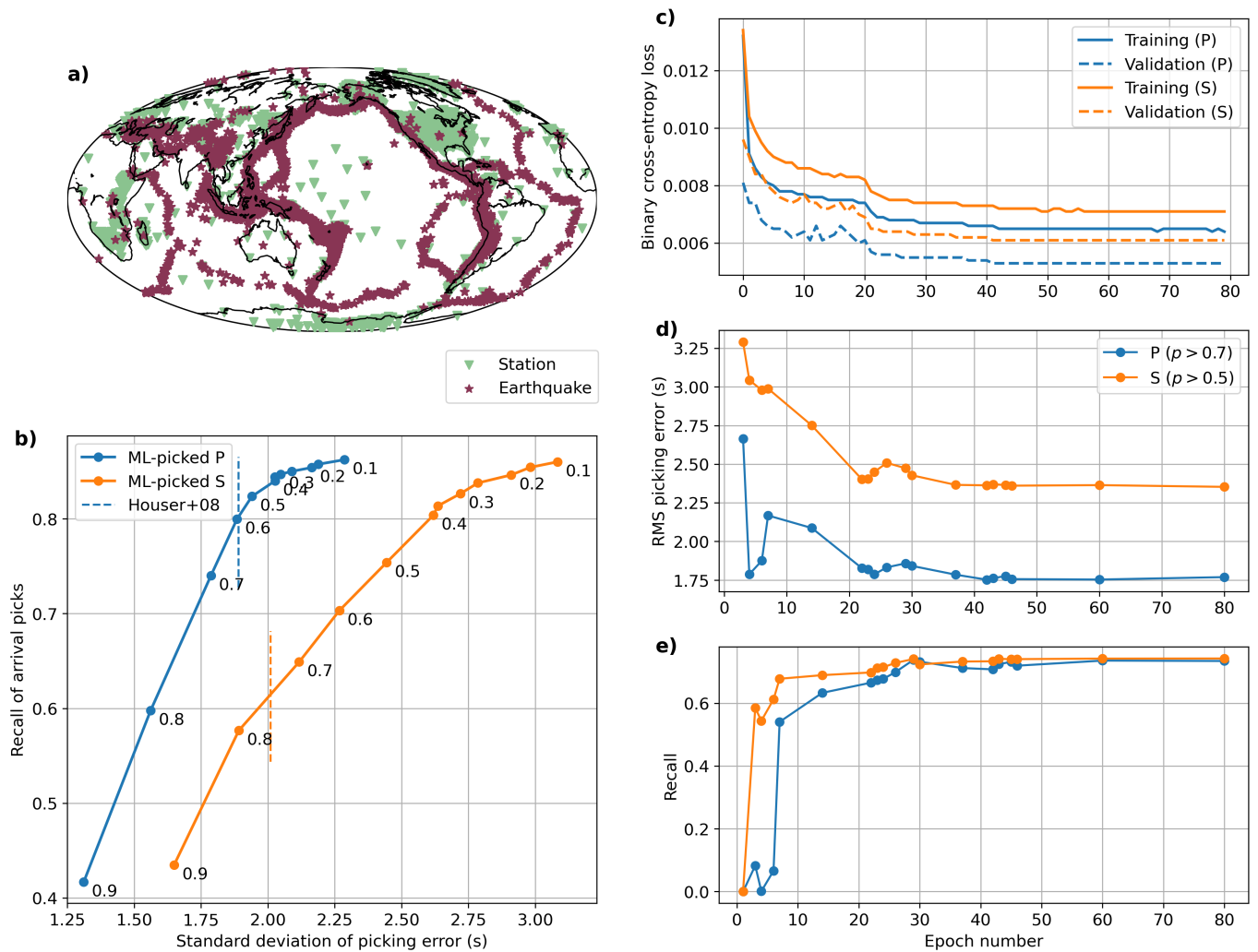


Figure 1 (a) Geographical distribution of the seismic sources and stations used in this study. (b) Trade-off curves between data availability and picking errors for P and S wave arrival times for different probability function thresholds. Dashed lines indicate the estimated picking errors in Houser et al. (2008) demonstrating that human-expert level error can be achieved by selecting the appropriate thresholds. (c) Loss curve of the training set and the validation set. The solid line is the loss in the training set, and the dashed line is the loss in the validation set. (d) RMS picking error of the test set. (e) Recall of the test set.

set for the prediction probability thresholds shown in Fig. 1b. T_{ML} is designated at the point where the prediction probability sequence reaches its maximum value. A total of 11,263 P and 11,233 S arrivals exceed a threshold of 0.1, with a picking error of 2.29 s for P and 3.08 s for S. The number of arrivals decreases to 5,444 for P and 5,678 for S when the threshold is raised to 0.9, likewise the picking error decreases to 1.31 s for P and 1.64 s for S.

For the purposes of investigating the bulk and geographic distributions in GLoBoCat, we seek to maximize the number of data while maintaining similar error values as the manual picked data. The uncertainty among the complete Houser et al. (2008) dataset is 1.89 s for P and 2.01 s for S, estimated by evaluating the internal consistency of the travel times for three user-defined quality levels based on the alignment of the synthetic and summary waveform for each cluster. The GLoBoCat crosses these error thresholds at values of $p = 0.6$ for P and $p = 0.75$ for S arrivals. Thus, it is possible to have a human-expert level performance with the ML phase picking model. We proceed with our analysis us-

ing threshold values of $p = 0.7$ for P and $p = 0.5$ for S arrivals based upon achieving $\sim 75\%$ recall in the test data (9,667 P and 9,846 S arrivals). While the associated error is 1.79 s for P and 2.44 s for S, we find that this threshold maximizes the number of reliable travel times for evaluating geographic patterns and comparing to short period data. In addition, in our approach the Gaussian probability distribution used in the training process with $\sigma = 1.25$ s limits the precision to similar values.

We further examined the quality of the trained models using the test data set to evaluate recall and overfitting. Fig. 1c shows the loss curve of the training set and the validation set. The losses in both sets decrease, dropping from 0.0132 to 0.0064 (P) and 0.0134 to 0.0071 (S) for the training set and from 0.0081 to 0.0053 (P) and 0.0096 to 0.0061 (S) for the validation set indicating that the model is not overfitting. Fig. 1d shows the change in RMS picking error of the test set which generally converges around epoch 40. The initial sharp drop followed by a recovery of error is due to the first few epochs where the model learned to pick only in very few cases,

suggested by the low recall (Fig. 1e). The recall increasing to ~75% over the training process and staying stable after epoch 60 also indicates that the model is not over-fitting. Note that Figs. 1d–e are calculated based on the probability threshold $p = 0.7$ for P and $p = 0.5$ for S, but changing the threshold does not significantly affect the results.

Applying the ML phase picking model to the 5,864,311 seismograms recorded between 2010 and 2023 yields GLoBoCat containing 2,109,961 P and 1,965,807 S arrivals for which the probability threshold exceeds 0.1. The choice of probability threshold depends on the intended application, so we include all data with a threshold exceeding 0.1 for completeness. The prediction probability of each pick is retained in the catalog and serves as a per-measurement quality indicator, analogous to the user-assigned quality levels in earlier interactive datasets (Houser et al., 2008), so that users can select their own trade-off between data volume and precision rather than adopting a single uniform uncertainty. The increase in the volume of arrival picks is significant compared to previous studies on which the training data was based (Bolton and Masters, 2001; Houser et al., 2008) and a recent long period catalog by Lai et al. (2019) in Fig. 2a.

Applying the probability thresholds discussed above results in 1,195,649 P and 1,442,730 S arrivals. We compare these picks with previous studies using the travel time residual defined as

$$\delta t = t_{\text{pick}} - t_{\text{model}} + \epsilon_{\text{corr}}, \quad (1)$$

where the 1D velocity model-derived travel time t_{model} is calculated for every source-receiver pair, ϵ_{corr} represents applicable corrections (such as crustal corrections and ellipticity corrections in Houser et al., 2008), and the picked travel time residual t_{pick} is defined by

$$t_{\text{pick}} = T_{\text{pick}} - T_O, \quad (2)$$

where T_{pick} is the picked arrival time, and T_O is the origin time. The distributions of travel time residuals are similar in the resulting catalog and in previous studies (Fig. 2b–c). The variations in the measured travel time residuals ($\sigma_P = 3.62$ s and $\sigma_S = 5.62$ s) are larger than the picking errors ($\sigma_P = 1.79$ s and $\sigma_S = 2.44$ s) indicating that the catalog is appropriate for studying lower mantle seismic structure. The difference between distributions of travel time residuals from GLoBoCat and previous studies can be explained by the difference in reference velocity models (PREM vs. AK135) and the increased coverage in the southern hemisphere (Supplementary S1). The maximum source-receiver distance for δt is constrained by that of t_{PREM} at 102.7° for S and 98.4° for P.

We take advantage of the larger data volume to apply summary ray analysis (Van Der Hilst et al., 1997; Su and Dziewonski, 1997; Ruan et al., 2019) to remove the outliers that have distinct travel times compared to similar raypaths for further analysis. In our approach, summary rays are dynamically decided by each source-receiver pair and its neighboring pairs with longitude, latitude, and distance difference $\leq 2^\circ$. A global variation at the depth σ_d is measured using all δt whose travel

distances, as a proxy, fall in the same 5° band. When the absolute difference between each travel time and the average of its neighboring pairs exceeds σ_d , it is removed from further analysis (Supplementary S1). The remaining data are then demeaned for every 5° distance range from 30° to 105° .

In Fig. 3 we plot the global distribution for lateral variations in travel time residuals for GLoBoCat data with raypaths turning in the lower mantle (epicentral distance 60° – 100°). Fast and slow velocity structure are suggested by the early and late arrivals. We observe a degree-2 harmonic pattern across different layers dominated by fast structure beneath the western Pacific and Mesoamerica and slow structure beneath Africa and the central Pacific. The GLoBoCat data improve the coverage especially for the southern hemisphere due to seismic network expansion (Fig. 1). Side-by-side maps comparing the geographic distribution of GLoBoCat travel time residuals with those of previous catalogs (Supplementary Figs. 3–4) show where mantle sampling has improved since 2008: raypaths turning beneath the South Atlantic, southern Africa, the Indian Ocean, and the South Pacific, which were sparsely sampled by the Houser et al. (2008) catalog, are now densely covered for both P and S waves, while the coverage of the northern hemisphere is retained.

4 Discussion

4.1 Comparison of long period P and S wave travel time patterns

GLoBoCat is trained by and thus self-consistent with legacy data (Bolton and Masters, 2001; Houser et al., 2008), offering extensive coverage in the lowermost mantle for both P and S waves which is essential for interpreting the processes creating the observed seismic patterns. Late S wave arrivals appear to have relatively larger delay than the P wave arrivals, as suggested by previous studies (e.g., Dziewonski et al., 1977; Masters et al., 1996; Bolton and Masters, 2001; Ritsema and Van Heijst, 2002; Simmons et al., 2012b; Bozdağ et al., 2016; Lei et al., 2020; Su et al., 2023). Comparisons of P and S wave signals are often expressed as $R_{S/P} = \delta \ln V_S / \delta \ln V_P$ and values exceeding a certain threshold indicate non-thermal contributions (composition or mineral phase) to the velocity anomalies (Karato and Karki, 2001). The $R_{S/P}$ values can be solved for by joint inversions (Robertson and Woodhouse, 1996; Su and Dziewonski, 1997; Kennett et al., 1998; Masters et al., 2000; Saltzer et al., 2001; Tesoniero et al., 2016; Koelemeijer et al., 2016), but these methods are subject to velocity model parameterization and variable resolution of the P and S wave data. Although P and S wave coverage at the base of the mantle is generally similar, S wave studies often rely on the addition of ScS-S to increase coverage which is not possible for P wave studies due to the small amplitude and limited distance range for PcP. (Woodward and Masters, 1991; Tkalčić and Romanowicz, 2002). The large volume of P and S wave travel times in GLoBoCat allows us to directly assess their relative behavior with depth across the mantle.

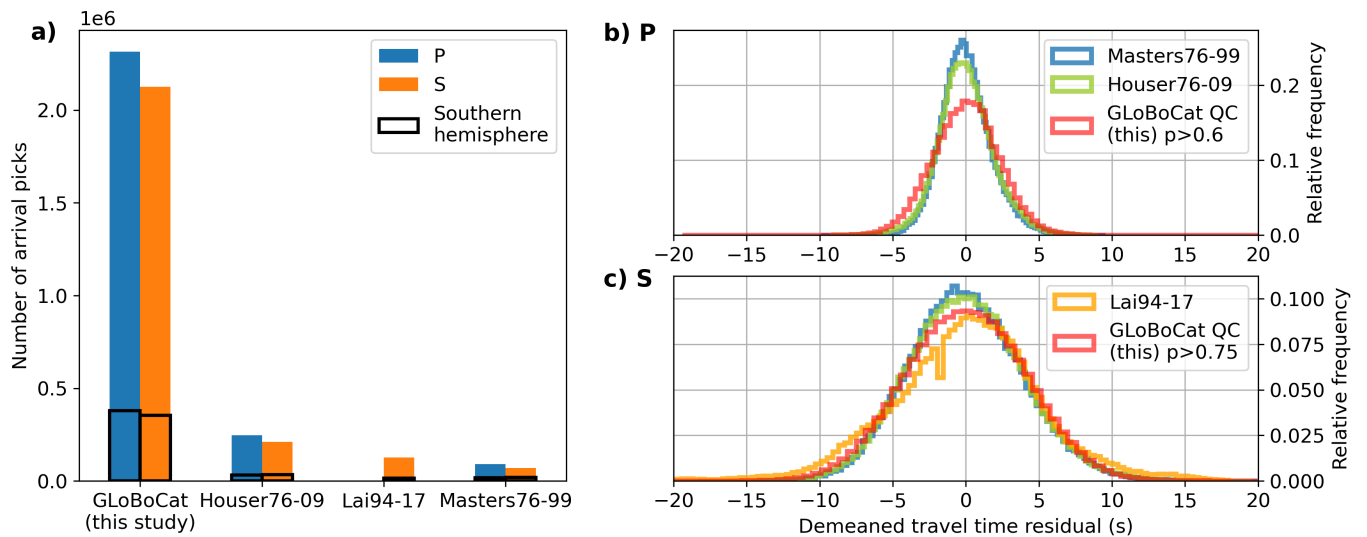


Figure 2 (a) Comparison of measured P and S arrivals between this study and previous datasets used to establish the ML phase picking model. Houser et al. (2008) includes 247,158 P and 210,733 S arrivals on 1976–2009 data, and Bolton and Masters (2001) includes 90,065 P and 69,594 S on 1976–1999 data. Lai et al. (2019) includes 126,488 S arrivals on 1994–2017 but consists of no P data. All P and S picks discussed in this study are direct arrivals and reflection phases are excluded from the original datasets. The black boxes indicate the numbers of records whose bounce points locate in the southern hemisphere. (b, c) Travel time residual distributions for selected GLoBoCat and previous studies. The mean values for individual dataset is removed to account for 1D reference model difference. The standard deviations for GLoBoCat with QC (see below) is 2.30 s for P ($p=0.6$), and 4.16 for S ($p=0.75$). The Houser et al. (2008) has standard deviations of 1.92 s for P and 3.95 s for S. The standard deviations for the Masters et al. (2000) dataset are 1.74 s for P and 3.88 s for S, and for the Lai et al. (2019) dataset is 5.15 s for S. Note that the vertical axis is scaled by the number of data available to allow visual comparison of the P and S travel time residual distributions.

First, we examine depth variations in the travel time residual ratio ($\delta t_S/\delta t_P$) from the GLoBoCat for P picks with $p > 0.7$ and S picks with $p > 0.5$. We grouped residual times by source-receiver distance and analyzed the correlation between δt_P and δt_S by measuring their ratio every 5° ranging from 30° to 100° (Fig. 4a). Here, the distance is used as a proxy for turning point depth which we list as an estimated value based on PREM along the right axis. To obtain a representative value for $\delta t_S/\delta t_P$, we use a stochastic approach to minimize the influence of outliers by separating them from the main batch (Sen, 1968) and fit δt_P given δt_S only for the main batch. The $\delta t_S/\delta t_P$ ratio is obtained by regression from data within each distance interval, and we calculate the Monte-Carlo uncertainty with 90% confidence interval by repeating the measurement 200 times with 5% randomly chosen subsets of the data (Papadopoulos and Yeung, 2001). The $\delta t_S/\delta t_P$ ratio is steady at ~ 3 between 30° and 80° (< 2200 km depth) and doubles to ~ 6 in the lowermost mantle. This increase suggests that the source of uncorrelated V_P and V_S lies in the lowermost mantle, echoing the finding of previous studies (e.g., Bolton and Masters, 2001; Ritsema and Van Heijst, 2002; Della Mora et al., 2011; Su et al., 2023), reflecting contributions from the large low shear wave velocity provinces (LLSVP) beneath Africa and the Pacific (Cottaar and Lekic, 2016, cf., Fig. 3). We emphasize that the epicentral distance is only a proxy for turning point depth, and the travel time residual ratio is an integrated quantity along the raypath rather than a direct estimate of the local velocity anomaly such as the $R_{S/P}$ value. Raypaths at all

distances traverse the strongly heterogeneous crust and upper mantle where velocity structure as well as errors in centroid locations and origin times contribute to the travel time residuals (Chaves et al., 2021). Moreover, the LLSVPs rise hundreds of kilometers above the core-mantle boundary, so that waves from, e.g., southwest Pacific events to North American stations can accumulate delay over the full vertical extent of these structures rather than only near their turning points. Isolating the lower mantle contribution requires a formal inversion that accounts for three-dimensional structure and corrects for the crust and upper mantle, which we defer to a follow-up study built on this catalog.

The agreement of the travel time residual patterns in depth slices and profiles across the lower mantle demonstrates that the ML phase identification is capable of improving lower mantle imaging. Benefits of the ML picking model include that it requires no synthetic waveform, reference velocity model, or source information. This makes it applicable to records for which reliable synthetics are unavailable and potentially to records with lower signal-to-noise ratios than interactive procedures accept. Quantifying the performance for low signal-to-noise records relative to the semi-manual procedures is the subject of ongoing work. We envision future studies will expand the phase picking functionality of our ML to reflected and diffracted phases (e.g., PP, P_{diff} , SS, ScS, and S_{diff}). Not only will these phases improve coverage in the lower mantle, the attention encoder trained with these additional phases may improve the performance of the phase picking

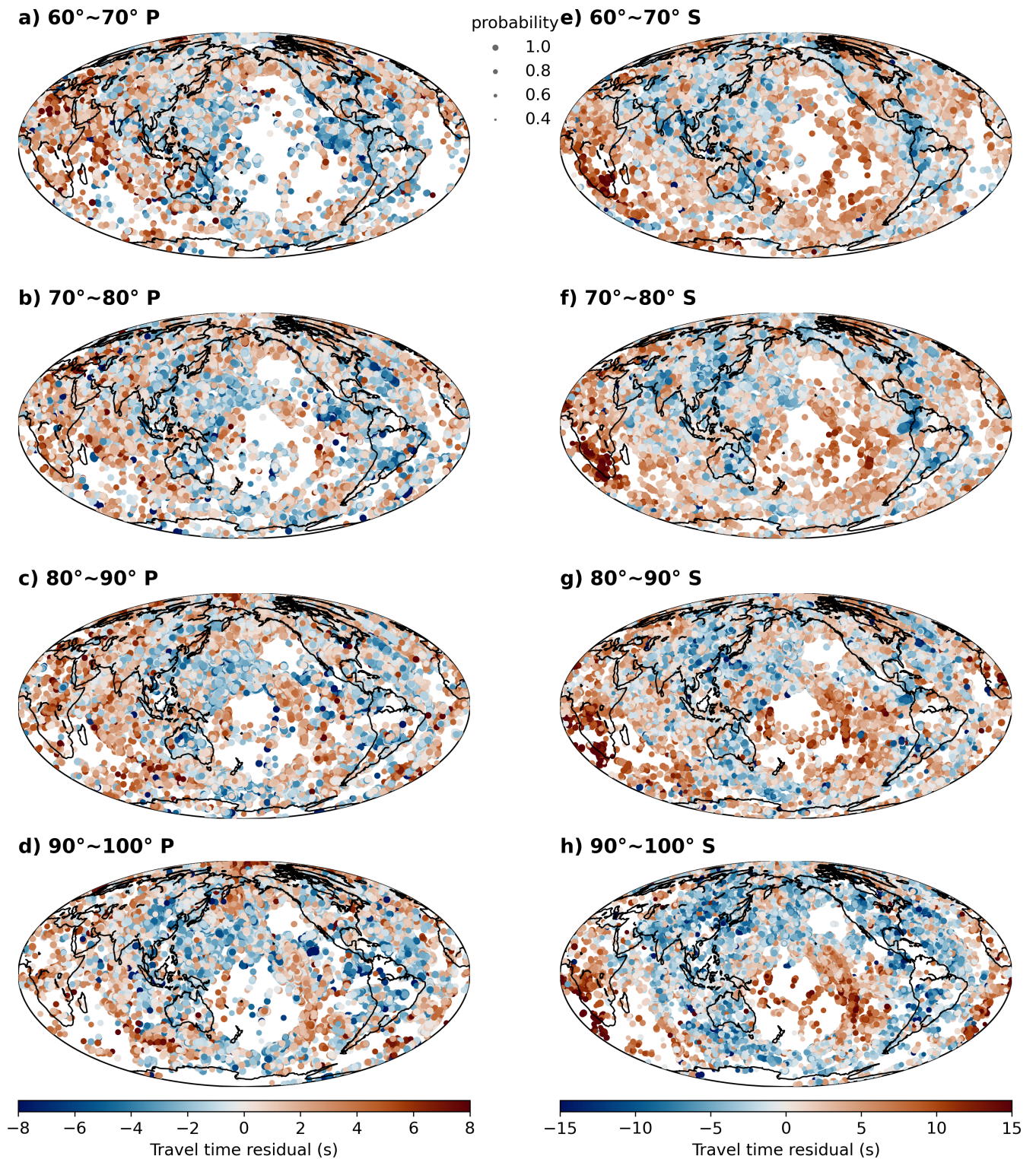


Figure 3 (a–d) The P wave travel time residuals (δt_P), and (e–h) S travel time residuals (δt_S) for the distance ranges 60°–70°, 70°–80°, 80°–90°, and 90°–100°. The full residuals are plotted at the turning point of each raypath. Early arrivals (blue) indicate fast velocity, and late arrivals (red) indicate slow velocity regions.

model for direct S and P waves, increasing the accuracy and recall. Applying the expanded ML model to waveform data will provide more reliable measurements, which can be updated into a newer version of GLoBoCat. Future tomographic models based on GLoBoCat and other ML-based catalogs will be able to improve data coverage and redundancy and thus our ability to discern details regarding the lateral velocity variation in

the lower mantle.

4.2 Comparison of long and short period travel time variations

Next, we compare our results with the International Seismological Centre (ISC) travel time catalog (Bondár and Storchak, 2011; Storchak et al., 2020; International Seismological Centre, 2024) from short period (~ 1 s)

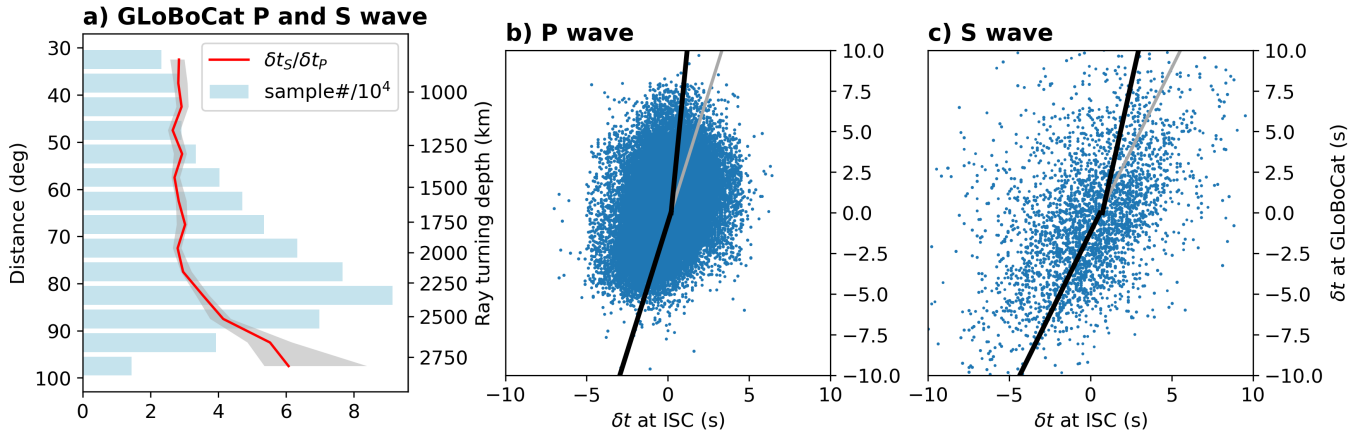


Figure 4 (a) Travel time residual ratio between P and S waves ($\delta t_S/\delta t_P$) and the number of measurements as a function of distance. The gray shade indicates the Monte-Carlo uncertainty. (b, c) Travel time residual ratio for source-receiver pairs common to the long-wavelength GLoBoCat catalog and the short-wavelength ISC catalog. The ratio is divided into two groups for $\delta t_{ISC} < 0$ and $\delta t_{ISC} > 0$, depicted by black lines, for both P wave ($N=101,302$) and S wave ($N=3,363$). The ratio grows from 3.18 to 10.12 in P and from 2.02 to 4.50 for S with the slope for the early arrivals continued to late arrivals as gray lines.

seismograms. To facilitate comparison between the two datasets, we implement the following steps. Based on Equation 1, travel time residuals in GLoBoCat are described as $\delta t_{\text{GLoBoCat}} = t_{\text{GLoBoCat}} - t_{\text{PREM}}$, where the 1D model-derived travel times t_{PREM} are calculated with PREM using the GCMT centroid locations and origin times for all sources in the GLoBoCat table. In the former section, the correction term ϵ_{corr} is not applied to GLoBoCat. Therefore, before we compare the long and short period measurements, we have to tackle the variations in the source times (centroid vs hypocenter), correction method, and selection of reference 1D velocity model. Thus, we modified the travel time residual of the GLoBoCat picks for measurements with common source-receiver pairs in the ISC catalog. Combining Equation 2, the travel time residual aligned with ISC can be represented by

$$\delta t'_{\text{GLoBoCat}} = \delta t_{\text{ISC}} + (T_{\text{GLoBoCat}} - T_{\text{ISC}}) \quad (3)$$

for both P and S waves without needing to apply extra corrections (Fig. 4b–c). Here T_{GLoBoCat} and T_{ISC} are the picked arrival times of the same phase at the same station in absolute (calendar) time, and δt_{ISC} is the residual reported by the ISC relative to its own source parameters and reference model. Because the difference in absolute pick times is simply added to the ISC residual, the influences of the source, raypath, reference velocity model, and any station corrections are common to both terms. Thus, the comparison between the two catalogs rests entirely on the arrival picking itself. We note that for large earthquakes the effective source location and origin time “seen” by long period waves can differ from those seen by short period waves.

We measured 101,617 P and 3,363 S wave travel times and divided the scatter into two groups for $\delta t_{\text{ISC}} < 0$ and $\delta t_{\text{ISC}} > 0$. We find similar slopes for early P arrivals (3.32) as for early S arrivals (2.02). The slopes steepen for late arrivals, but with a significantly higher slope for P (14.58) than for S (4.50). We calculated the 90% confidence intervals for the slope values measured by

Monte-Carlo uncertainty analysis where the slope for P ranges from [9.48–26.49] and the slope for S ranges from [2.08–23.17] for delayed arrivals. Thus, the steep slopes are robust and not an artifact of outliers. The same pattern can also be observed in the original Houser et al. (2008) catalog compared to ISC, where the ratio grows from 4.49 to 21.69 in P ($N=16,440$) and from 2.16 to 4.51 in S ($N=1,251$), although it is less certain due to the smaller number of matching data for comparison.

We examined the pairs of strongly delayed GLoBoCat P residuals ($\delta t'_{\text{GLoBoCat}} > 7.5$ s) associated with near-zero ISC residuals. These extreme points show no coherent geographic concentration in their source or turning point distributions, and visual inspection of representative records shows that most correspond to mispicks on a later swing of the waveform with cycle skipping, amounting to $\sim 0.3\%$ ($N=315$) of the picks in common with the ISC catalog. We removed these records and the change in slope is not significant. The revised P slopes are 3.18 for early ($\delta t_{\text{ISC}} < 0$) and 10.12 [8.62–26.77] for late ($\delta t_{\text{ISC}} > 0$) arrivals, shown in Fig. 4b–c.

A possible contribution to the differences in short and long period arrival picks could be related to differences in their sensitivity to the rupture process. Short period ISC picks are tied to the sharp onset of rupture initiation whereas long period picks respond to the first major asperity, analogous to the difference between NEIC hypocenters and long period GCMT centroids; however, the corresponding offset is only ~ 3 s when comparing origin times of the common events, and cannot explain the varied patterns for early and late arrivals. The ISC S wave data must also be interpreted with caution. ISC S picks are dominantly measured on short period vertical components, where the S arrival is depleted in high frequencies by attenuation and can be contaminated by S-to-P conversions beneath the station and, beyond $\sim 80^\circ$, by interference with SKS. The limited number of common S picks ($N=3,363$) does not allow us to categorize the data by source depth or distance to isolate these ef-

fects. We therefore treat the S wave comparison primarily as a control group for the P wave observations, and the discussion below rests chiefly on the P wave slopes.

This study is the first to relate the short period ISC travel times which are used to construct most lower mantle P wave velocity tomography models (Dziewonski, 1984; Inoue et al., 1990; Van Der Hilst et al., 1997; Vasco and Johnson, 1998; Bijwaard and Spakman, 1999; Boschi and Dziewonski, 1999; Zhao, 2001; Fukao et al., 2003; Zhao, 2004; Li et al., 2008; Simmons et al., 2012a; Zhao et al., 2013; Obayashi et al., 2013; Hosseini et al., 2020) with a mutually consistent long period catalog of P and S arrivals similar to those used to construct lower mantle S wave tomography models (Su et al., 1994; Masters et al., 1996; Grand et al., 1997; Ritsema et al., 1999; Masters et al., 2000; Houser et al., 2008; Ritsema et al., 2007; Simmons et al., 2010; Lu et al., 2019; Simmons et al., 2021). Our null hypothesis is that there should be a simple linear relationship for both P and S waves across early and late arrivals, but instead the slope changes offering an opportunity to relate the observed slopes to wave propagation effects capable of affecting slow and fast material differently for P and S waves. Since short and long period waves have different wavelengths in the lower mantle, 14 km versus 280 km for P and 7 km versus 140 km for S, one possibility is wavefront healing (Hung et al., 2001). Another possibility is dispersion that occurs at the grain scale as seismic waves deform crystals. Dispersion occurs when waves with different periods travel at different velocities, which can occur when variable anelastic deformation mechanisms are activated at different scales which can depend on the size, shape, distribution, and composition of the mineral grains (Karato, 1993). The more energy lost due to anelasticity, the more delayed the wavefront which modifies waveform shape and amplitude.

Wavefront healing (Hung et al., 2000) is a phenomenon that is predicted to occur when waves encounter slow velocity anomalies of a size similar to their wavelength in finite frequency calculations for wave propagation (Hung et al., 2001). When passing through a slow anomaly the wavefront folds in on itself and the distortion to the wavefront is eventually erased after 40 wavelengths past the anomaly. Thus, studies have considered how this could manifest for P waves and S waves in the lower mantle (Schuberth et al., 2012), finding that wavefront healing suppresses P wave arrival time delays compared to S wave delays for wavefronts passing through large slow anomalies. This effect is predicted to manifest in tomography as a regions that are slower for S waves than P waves which is what is observed for slow seismic structures above the core-mantle boundary (Garnero et al., 2016). The wavefront healing hypothesis posits that relatively modest P delays in comparison to S delays are artifacts of finite frequency wave propagation in the mantle, rather than a real difference in P and S wave speed anomalies in slow features. The finite frequency hypothesis predicts that short period delays should be larger than long period delays given the absence of similar diffraction effects in higher frequency wavefronts. However, we observe the opposite effect in our comparison between short and long period

arrivals, depicted by the steep slopes in the delayed arrival times in Fig. 4b–c, instead of hypothesized shallow slopes. This implies that either such finite frequency effects do not affect long period travel time picks, or other factors over-correct for these effects in the opposite direction.

We stress that our reasoning here is comparative: the wavefront healing hypothesis predicts a specific sense of frequency dependence between the short period (~ 1 s) and long period (~ 20 s) picks, and the observed change in slope has the opposite sense. Since our measurements are onset times, a delay of the onset directly records a slowdown of the earliest arriving energy at the measured frequency band rather than a distortion of the waveform shape, making the comparison between the two catalogs ideal for this purpose. We hope to motivate studies that quantify the magnitude of dispersion predicted for the relevant frequency bands and paths, perhaps using full waveform synthetics in three-dimensional models computed at both short and long periods. In addition, other frequency-dependent effects can contribute to short versus long period onset differences and cannot yet be ruled out, including the finiteness of the source time function, focal depth errors that modify the interference of P with the pP and sP depth phases, and crustal reverberations that distort long period P and S waveforms (Ritsema et al., 2009). We expect future studies will test the extent to which these factors influence the observed trends between short and long period arrivals.

If the apparent dispersion persists after the aforementioned factors are taken into account, we should consider the possibility of actual dispersion in the lower mantle due to anelastic effects. Waves propagating through the anelastic mantle are subject to relaxation processes, where the material responds to applied stress through multiple relaxation mechanisms with different characteristic length scales (Karato and Spetzler, 1990; Getting et al., 1997; Flidner and French, 2024). These relaxation mechanisms result in both the absorption (attenuation) and velocity dispersion of seismic waves described by a frequency dependent relaxation spectrum (Liu et al., 1976; Cormier, 2011). This phenomenon is expected to be more pronounced for S waves relative to P waves with similar frequency; however, we observe a larger change in slope for P waves than S waves. Regional variations in anelasticity due to chemical (e.g., enriched (Fe,Mg)O ferropericlase) or mineralogical (e.g., post-perovskite) heterogeneity have been invoked to mutually explain the increase in $\delta t_S / \delta t_P$, sometimes represented by velocity ratio $R_{S/P}$ (Karato and Karki, 2001; Matas and Bukowski, 2007; Li et al., 2015; Deng et al., 2023), and the bimodal statistical distribution of travel time residuals (Hernlund and Houser, 2008; Su et al., 2023), but further investigation is necessary to explore the relationship between dispersion and P–S velocity discrepancy observed in seismic tomography.

Our results highlight a longstanding divide in global seismology between short and long period studies. Due to the high noise levels at intermediate periods (Astiz et al., 1996), the characteristics of the lower mantle fre-

quency dispersion have not been resolved. Currently, the larger uncertainties in the P picks and the smaller number of mutual S picks in the ISC catalog make it difficult to uniquely identify the cause of the apparent dispersion although we are able to rule out some proposed mechanisms (Supplementary S2). We hope this study motivates further work to unveil the nature of the apparent dispersion pattern.

5 Conclusions

In this study, we have successfully developed GLoBoCat, a new Global Long-wavelength Body-wave Catalog containing over 2 million P and S wave travel times, significantly expanding upon previous hand-picked datasets. By applying attention-based machine learning trained on established hand-picked data, we have maintained consistency with traditional methods while dramatically increasing data coverage. Our analysis reveals the following. (1) The ratio of S wave to P wave travel time residuals ($\delta t_S/\delta t_P$) remains steady at approximately 3 between 30° and 80° but increases significantly to ≈ 6 in the lowermost mantle, suggesting uncorrelated V_P and V_S structures in this region. (2) The comparison with short-period ISC data reveals an apparent dispersion that contradicts previously hypothesized wavefront healing effects, particularly for P waves, which we present as an observation whose physical origin remains to be established by quantitative modeling. (3) The expanded catalog confirms known large-scale mantle structures while providing enhanced resolution of southern hemisphere. The massive size and accessibility of GLoBoCat opens new avenues for understanding Earth's deep interior structure and dynamics.

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Data and code availability

All codes are openly available via GitHub (<https://github.com/Jun1453/phasepick>). The trained parameters of the machine learning picking model, the catalog in QuakeML format, along with ~ 4 million new picks between 2010 and 2023 in plain text and pickle format

Pandas table are available via Zenodo (Su et al., 2025, DOI: 10.5281/zenodo.15111545).

The semi-automated picking results used for training the machine learning model are provided by Christine Houser and are available upon request. The waveform data can be obtained by performing the data processing documentation for picker.py.

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The networks used for training and inference are listed below with DOIs available: AS (Albuquerque Seismological Laboratory (ASL)/USGS, 1976), AT (NOAA National Oceanic and Atmospheric Administration (USA), 1967), AZ (Vernon, 1982), BE (Royal Observatory of Belgium, 1985), BK (Northern California Earthquake Data Center, 2014), CD (Albuquerque Seismological Laboratory (ASL)/USGS, 1986), CI (California Institute of Technology and United States Geological Survey Pasadena, 1926), CU (Albuquerque Seismological Laboratory (ASL)/USGS, 2006), CZ (Charles University in Prague et al., 1973), DK (GEUS Geological Survey of Denmark and Greenland, 1976), DW (Albuquerque Seismological Laboratory (ASL)/USGS, 1980), G (Institut de physique du globe de Paris (IPGP) and École et Observatoire des Sciences de la Terre de Strasbourg (EOST), 1982), GE (GEOFON Data Centre, 1993), GT (Albuquerque Seismological Laboratory (ASL)/USGS, 1993), HG (Albuquerque Seismological Laboratory (ASL)/USGS, 1972), IC (Albuquerque Seismological Laboratory (ASL)/USGS, 1992), II (Scripps Institution of Oceanography, 1986), IU (Albuquerque Seismological Laboratory/USGS, 1988), KN (Kyrgyz Institute of Seismology, IVTAN/KIS and University of California, San Diego, 1991), LD (Lamont Doherty Earth Observatory (LDEO), Columbia University, 1970), LI (California Institute of Technology (Caltech), 2000), MN (MedNet Project Partner Institutions, 1990), NR (Utrecht University (UU Netherlands), 1983), PM (Instituto Português do Mar e da Atmosfera, I.P., 2006), RS (Albuquerque Seismological Laboratory (ASL)/USGS, 1982), SR (Albuquerque Seismological Laboratory (ASL)/USGS, 1974), TA (IRIS Transportable Array, 2003), TW (Institute of Earth Sciences, Academia Sinica, Taiwan, 1996), US (Albuquerque Seismological Laboratory (ASL)/USGS, 1990), XE (Ebinger, 2014), XR (Pulliam et al., 2013), YW (Brudzinski and Allen, 2012), Z1 (Wiens et al., 2013), ZA (West, 2010), and ZE (Ebinger, 2012). Below we also acknowledge the networks with DOIs not available: Black Forest Observatory (BF), operated by Universities of Karlsruhe and Stuttgart, Germany, Leo Brady Network (LB), operated by Sandia National Laboratories, United States of America, Singapore Seismological Network (MS), operated by Meteorological Service of Singapore, Malaysian National Seismic Network (MY) operated by Malaysian Meteorological Service, Cooperative New Madrid Seismic Network (NM) operated by CERI

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Competing interests

The authors have no competing interests.

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