

1 **Ambient noise tomography of northern Borneo reveals**  
2 **evidence of subduction and post-subduction processes.**

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9 **Key Points:**

- 10 • New 3D shear wave model of crust in northern Borneo from ambient seismic noise  
11 tomography illuminates post subduction setting  
12 • Velocity structure underlying the Crocker Range is consistent with underthrust  
13 continental crust following proto South China sea subduction  
14 • Velocity structure in the southeast consistent with widespread igneous intrusion  
15 and underthrusting of mantle wedge sediments

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## Abstract

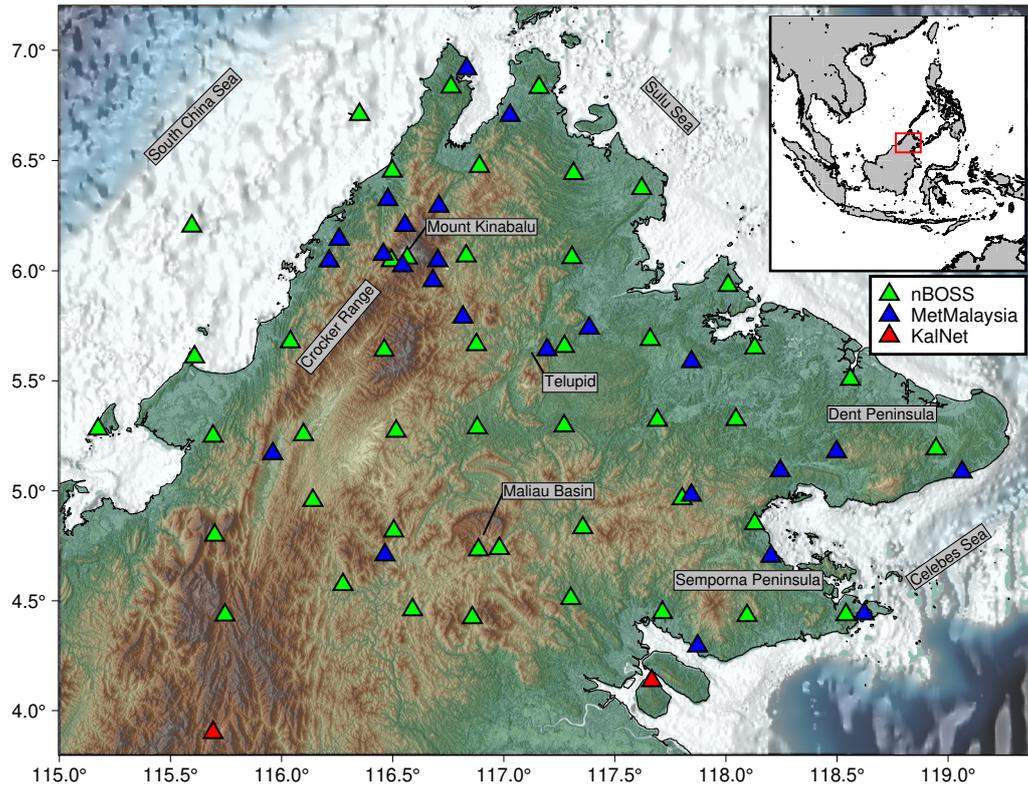
The region of northern Borneo in South East Asia sits within a post-subduction setting formed by the recent termination of two sequential but opposed subduction systems. In this study we use seismic data from a recent temporary array deployment to image the crustal velocity structure beneath northern Borneo using a two-stage Bayesian trans-dimensional tomography scheme, in which period dependent phase velocity maps are first generated, and then used to build a 3-D shear wave model through a series of 1-D inversions. In the second stage, we also apply an Artificial Neural Network to solve the 1D inverse problem, which results in a smoother 3-D model compared to the TransD approach without sacrificing data fit. Our shear wave velocity model reveals a complex crustal structure. Under the Crocker Range, a heterogeneous velocity structure likely represents remnants of early Miocene subduction, including underthrust continental crust from subsequent continent-continent collision. In the east we observe high velocities that are interpreted to be igneous rocks in the crust generated by melting due to mid Miocene Celebes Sea subduction and later decompression melting as well as a low velocity zone that could represent underthrust sediment or duplexes from Celebes Sea subduction. A low velocity zone in the lower crust is present in a region of apparent crustal thinning. Our preferred explanation for this anomaly is remnant thermal upwelling within a failed rift that represents the on-shore continuation of the extension of the Sulu Sea, most likely caused by rollback of the Celebes Sea slab.

## Plain Language Summary

The island of Borneo is located in South East Asia. Although some distance from active plate boundaries, its northern tip has a complex tectonic history over the last ~30 million years, with sequential subduction (one tectonic plate descending into the mantle beneath an adjacent plate) from the north and south that that ceased ~9 million years ago. In this study we use data recorded by seismometers to image the properties of the rocks in the crust underneath northern Borneo. Rather than use earthquake signals, we instead use ambient seismic noise, which is continuous low amplitude ground motion largely produced by ocean waves. This data can be used to produce a 3-D model of shear wave (transverse elastic waves) velocity structure. From this model we observe evidence of continent-continent collision following subduction of the proto-South China Sea. We see evidence of rock that melted during subduction of the Celebes Sea slab that has re-solidified following subduction termination. We also see evidence of a high temperature anomaly at depth in the centre of our model, which supports the idea of crustal extension in central Borneo driven by opening of the Sulu Sea in response to retreat of the subducting Celebes Sea slab.

## 1 Introduction

Northern Borneo encompasses the Malaysian state of Sabah and is located in the intra-plate region of southeast Asia (Figure 1), with the nearest subduction zone lying beneath the Northern Sulawesi trench over 500 km to the south east. Despite its remoteness from plate boundaries, northern Borneo is geologically very complex and exhibits signs of ongoing tectonic activity, likely related to the recent termination of two opposed subduction systems (Hall, 2013). Beneath north-west Borneo, subduction of the Proto-South China Sea terminated in the Early Miocene (~21 Ma) with the onset of continent-continent collision involving the Dangerous Grounds block; this caused much of northern Borneo to uplift and deform as part of the Sabah Orogeny (Hall, 2013; Hutchison et al., 2000; Hall, 1996; Tongkul, 1994). This is believed to have been followed by north-west directed subduction of the Celebes Sea beneath the Sulu Arc to the southeast, which began at ~21 Ma and was followed by rifting of the Sulu Sea due to subduction rollback (Hall, 2013). The subduction of the Celebes Sea is thought to have terminated at ~9



**Figure 1.** Location of seismic stations (coloured triangles) and networks (see key) used in this study. Inset map shows the location of northern Borneo in the greater southeast Asia region.

66 Ma as recorded by the cessation of arc magmatism (Lai et al., 2021). Linang et al. (2022)  
 67 propose that this sequence of events constitutes subduction polarity reversal or SPR in-  
 68 volving continental lithosphere as opposed to oceanic arcs or oceanic plateau that are  
 69 normally invoked to produce a polarity switch (Almeida et al., 2022; Wang et al., 2022).

70 The complicated tectonic history of northern Borneo described above is expressed  
 71 in a variety of different ways in the surface geology and landscape of the region (Figure  
 72 1). Major surface features include the Crocker Range in the northwest, which formed  
 73 during the Sabah Orogeny in the Miocene, as well as Mt Kinabalu, an exposed granitic  
 74 intrusion within the Crocker Range that was emplaced  $\sim 7$  Ma and subsequently uplifted,  
 75 which now sits at the surface with an elevation of 4095 m, much higher than the major-  
 76 ity of the Crocker Range with  $\sim 1500$  m elevation (Cottam et al., 2010). There are also  
 77 large sedimentary basins in the region including unusual elevated circular basins in the  
 78 south, such as the Maliau Basin, which is believed to have formed from deltaic sediments  
 79 in the mid to late-Miocene but was subsequently uplifted in the Pliocene (3-5 Ma) (Balaguru  
 80 et al., 2003). The peak of the surrounding escarpment now sits at 1675 m above sea level  
 81 and the underlying basin sediments are thought to be up to 6000 m thick (Balaguru et  
 82 al., 2003). One of the challenges in trying to unravel the geology and tectonics of north-  
 83 ern Borneo is that much of the surface is masked by thick tropical regolith and dense  
 84 vegetation, which severely limits outcrop. This leaves many basic questions to be answered  
 85 including the extent to which compressional (Morley et al., 2011; Morley & Back, 2008;  
 86 Tongkul, 1997) or extensional (Pilia et al., 2023a, 2023b; Hall, 2013) tectonics control  
 87 the evolution of the lithosphere.

88 There have been a number of previous geophysical studies that have included north-  
 89 ern Borneo, many of which involve the generation of regional velocity models of south-  
 90 east Asia from seismic imaging. Although limited in resolution, they consistently reveal  
 91 a high velocity feature in the upper mantle at around  $\sim 100$ -300 km depth, which is gen-  
 92 erally attributed to remnant slabs (Laat et al., 2023; Wehner et al., 2022; Zenonos et al.,  
 93 2020; Hall & Spakman, 2015; Tang & Zheng, 2013). More recently, targeted seismic stud-  
 94 ies have been performed using data from the northern Borneo Orogeny Seismic Survey  
 95 (nBOSS) experiment (Pilia et al., 2019). Imaging of the mantle using teleseismic P and  
 96 S wave arrival time tomography has been performed by Pilia et al. (2023a), who found  
 97 two distinct anomalies, one of which was attributed to a proto-South China Sea slab rem-  
 98 nant and the other to a lithospheric drip that detached from beneath the Semporna Penin-  
 99 sula. Imaging of the mantle by 2-plane wave surface wave tomography was performed  
 100 by Greenfield et al. (2022), who found thin lithosphere beneath the Semporna Peninsula,  
 101 further supporting the idea that mantle lithosphere has been removed from this region.  
 102 Detachment of lithosphere in this way has been shown, via numerical modelling, to cause  
 103 extension and thinning of the crust, subcrustal melting and exhumation (Pilia et al., 2023b).  
 104 Linang et al. (2022) found evidence for Sulu Sea extension continuing on-shore in north-  
 105 ern Borneo by imaging crustal thickness variations using virtual deep seismic sounding.  
 106 Bacon et al. (2022) measured lithospheric anisotropy using XKS splitting and found that  
 107 orientations of the fast axis of anisotropy were predominantly parallel to the Crocker Range  
 108 in western northern Borneo, suggesting that anisotropy is dominated by recent continen-  
 109 tal collision. Fast axis orientations orthogonal to the opening of the Sulu Sea in central  
 110 northern Borneo further support the idea of Sulu Sea extension propagating on-shore.  
 111 Receiver functions have also been produced for the nBOSS network stations by Gilligan  
 112 et al. (2023) and subsequently inverted for S wave velocity structure, which revealed com-  
 113 plex crustal structure in the western region of northern Borneo, which was interpreted  
 114 to be underthrust Dangerous Grounds crust. Thinner crust likely related to the rollback  
 115 of the Celebes Sea slab and lower velocities beneath the Semporna Peninsula that may  
 116 be attributed to the previously mentioned lithospheric detachment were also delineated.

117 In this study we apply two-step surface-wave Ambient Noise Tomography (ANT)  
 118 to data from the recent temporary nBOSS deployment to produce a new crustal scale  
 119 shear wave velocity model of the region. Our aim is to study how the complex tectonic  
 120 history from the early Neogene has imprinted itself on the velocity structure of the crust,  
 121 thereby enabling a better understanding of its origins and evolution. We aim to use the  
 122 higher lateral resolution inherent in ANT to image new features not recovered in stud-  
 123 ies such as Gilligan et al. (2023) and illuminate shallower structures than were imaged  
 124 in Greenfield et al. (2022). We follow a method similar to Pilia et al. (2020), but also  
 125 apply a new method for improving the two-step inversion process of ANT by using a Neu-  
 126 ral Network in the 1D inversions, which reduces sensitivity to unphysical dispersion curves,  
 127 and enhances the quality of the final model that is produced.

## 128 2 Data and methods

### 129 2.1 Deployment and data

130 Data for this study were collected primarily during the northern Borneo Orogeny  
 131 Seismic Survey (nBOSS), which was a temporary deployment of 46 broadband seismic  
 132 stations throughout northern Borneo between 2018 and 2020 (Pilia et al., 2019). A mix-  
 133 ture of sensors with frequency responses from 30 seconds to 100 Hz (Guralp 6TD) and  
 134 60 seconds to 100 Hz (Guralp 3ESP) were used in the deployment. This was augmented  
 135 by 24 MetMalaysia permanent stations with a frequency response between 120 seconds  
 136 to 50 Hz (STS-2) as well as two stations deployed in northern Kalimantan (Guralp 6TD).  
 137 In total, 72 broadband seismometers with between 20-24 months of continuous record-  
 138 ings were available for surface wave ambient noise tomography. The location of the com-  
 139 plete station network is shown in Figure 1. The data were generally of average to good

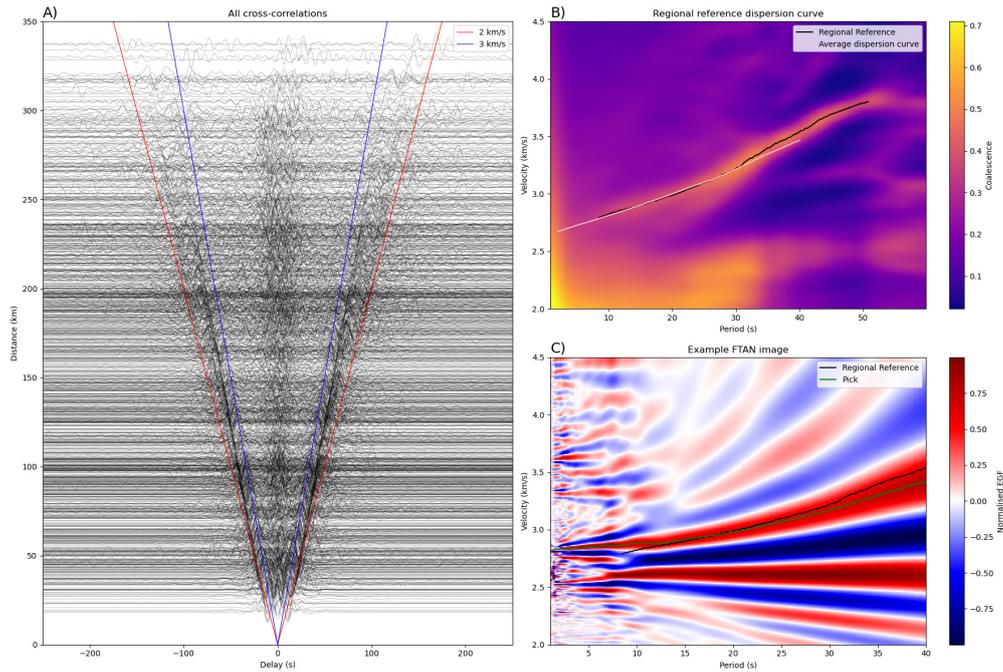
140 quality for surface wave ambient noise due in part to the proximity of the sea on three  
 141 sides, which provided strong signal from oceanic microseisms. The cross correlations that  
 142 were used in picking had a signal to noise ratio (SNR) of 92, as defined by taking the  
 143 ratio of the average power of the cross correlation between 1.5 and 4.5 km/s moveout  
 144 over the average power of the remaining wavetrain. However, the signals were not as clean  
 145 as expected. Many of the stations, especially in the south-east, were deployed in palm  
 146 oil plantations where anthropogenic noise may have overprinted at least parts of the fre-  
 147 quency range of interest. More importantly, a number of deep sedimentary basins exist  
 148 in central Sabah, which may generate ringing effects that manifest as an inhomoge-  
 149 neous noise source within our array. According to Hanasoge (2013) a noise source within  
 150 the array would result in signal occurring at or around zero delay time, which we see very  
 151 strongly in our cross correlations shown in Figure 2.

## 152 2.2 Extracting dispersion curves

153 In order to obtain phase velocity dispersion curves for each station pair we follow  
 154 the Frequency Time Analysis (FTAN) method described in Yao et al. (2006). We first  
 155 use the python package MSNOISE (Lecocq et al., 2014) to compute daily inter-station  
 156 cross-correlations that were subsequently stacked with non-linear phase-weighted stack-  
 157 ing to reduce amplitude sensitivity compared to linear stacking, thus diminishing the ef-  
 158 fect of incoherent noise in the final set of cross-correlations (Pilia et al., 2020; Ventosa  
 159 et al., 2017), which are shown in panel A in Figure 2. The cross-correlations were then  
 160 converted into Empirical Green’s Functions (EGF) using the symmetric component of  
 161 the cross correlations. The EGFs represent an estimate of the impulse response of the  
 162 Earth to a surface wave traveling between two stations. The time domain EGFs were  
 163 then converted into FTAN images that are made by narrow band filtering over a range  
 164 of central periods and a width in each case equal to 0.4 times the central period (Volk  
 165 et al., 2021; Volk, 2020). Each of the FTAN images were then converted pixel by pixel  
 166 to have a value of one at local maxima along the velocity axis and a value of zero every-  
 167 where else, highlighting the peaks representing different possible curves in the given FTAN  
 168 image. These were then summed together for each station pair and smoothed, result-  
 169 ing in the image shown in panel B in Figure 2. This shows a peak in the velocity-period  
 170 domain that represents a regional dispersion curve that can be used to guide the pick-  
 171 ing of each interstation dispersion curve. Panel C in Figure 2 shows an example FTAN  
 172 image that includes the regional curve to help identify the correct peak. We limited the  
 173 maximum period that could be picked by making sure the inter-station distance was greater  
 174 than 2 wavelengths at that period (Luo et al., 2015). This approach was used to obtain  
 175 fundamental mode Rayleigh wave dispersion curves in the period range 2-40 seconds by  
 176 manually picking the correct dispersion curve from each FTAN image. After picking, the  
 177 resultant dataset for use in tomography comprised 1172 dispersion curves.

## 178 2.3 2D tomography

179 Period-dependent phase velocity maps were obtained via inversion of the disper-  
 180 sion data at each period using the 2D trans-dimensional trees tomography method of Hawkins  
 181 and Sambridge (2015). This approach uses a reversible jump Markov Chain Monte Carlo  
 182 (rj-MCMC, Green, 1995) method to sample models over a tree structure that allows for  
 183 varying levels of complexity within the final ensemble. The tree structure works by hav-  
 184 ing the model described by sets of wavelet parameters that can be thought of as nodes  
 185 in the branches of a tree. At each layer up the tree the node splits into a set of finer wavelet  
 186 parameters (with up to 7 hierarchical layers), thus allowing a model to be described as  
 187 a combination of coarse parameters and fine parameters depending on the shape of the  
 188 tree. At each iteration, one or more of the parameters in the tree can be perturbed, new  
 189 nodes can be birthed and existing nodes can die, resulting in the total number of param-  
 190 eters being allowed to change throughout the inversion. The number of parameters and



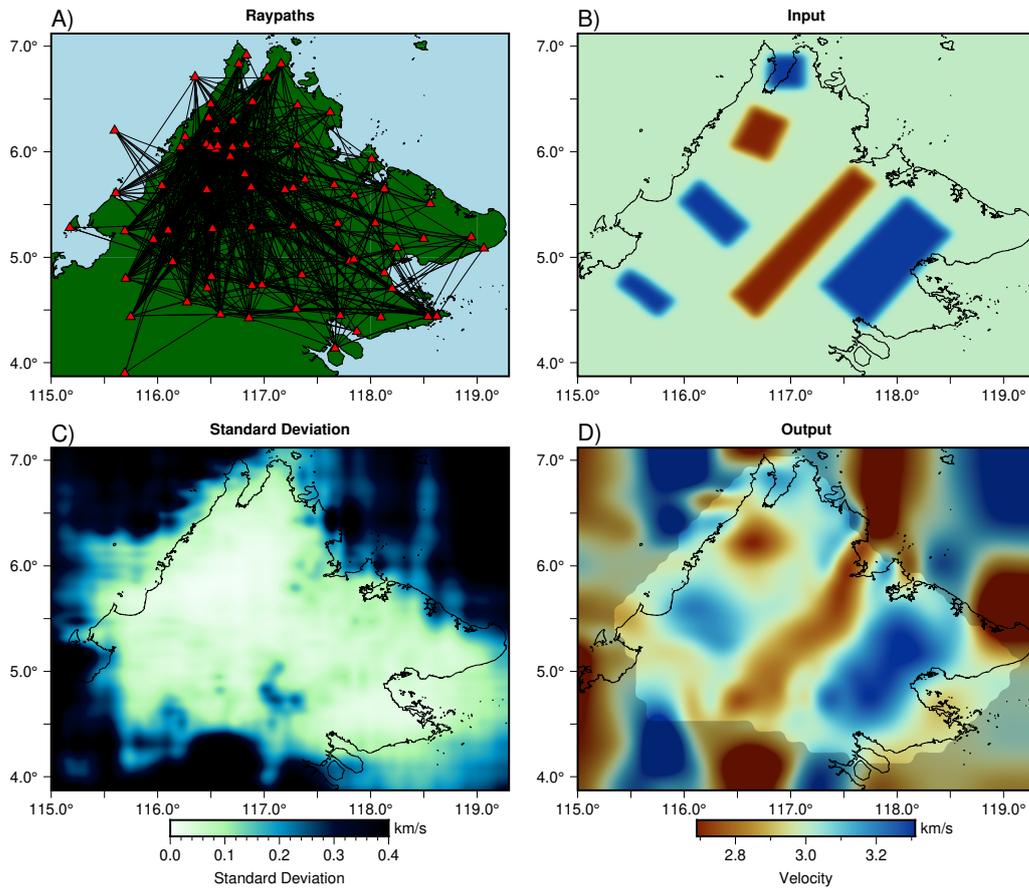
**Figure 2.** (A): All cross correlations from which dispersion curves were extracted plotted as interstation distance vs delay time, filtered with a broadband filter between 8-40s. Red and blue lines show the move-out of 2 km/s and 3 km/s surface waves respectively. (B): Regional reference dispersion curve formed by stacking the peaks of FTAN images and picking the prominent dispersion curve along with the average of all picked dispersion curves from 2-40 seconds to show their similarity to the reference. (C): Example FTAN image with picked phase velocity dispersion curve in green and the regional reference curve in black.

191 shape of the tree is controlled by the data and its associated uncertainty, with the scale  
 192 of the uncertainty being controlled by a hierarchical scaling parameter that is also in-  
 193 verted for; thus the inversion does not require explicit regularization. The maximum num-  
 194 ber of parameters is therefore dictated by the highest level of the tree which, in this case  
 195 is set to 7, a value that worked well in a comparable study by Pilia et al. (2020). For this  
 196 region a maximum level of 7 would result in a minimum horizontal length scale of about  
 197 2 km; however the acceptance rate for parameters at this level is zero, indicating that  
 198 the minimum length scale required by the data is larger and is thus not limited by this  
 199 parameter choice.

200 The convergence of the Markov chain is aided by parallel tempering, where mul-  
 201 tiple chains at higher “temperature” are run in parallel with a primary chain, and ex-  
 202 changes permitted based on a probability calculated using the likelihood value of each  
 203 model (Sambridge, 2014). The chains with higher temperatures will have an adjusted  
 204 exchange probability that allows more variation in the model than the likelihood would  
 205 typically allow, meaning that a wider set of models is sampled. This property, combined  
 206 with exchanges with the primary chain, means that the final Markov Chain will be able  
 207 to jump between local minima more easily and thus more efficiently search parameter  
 208 space compared to a standard Markov Chain. Although this comes at the cost of extra  
 209 computing resources required to run these chains in parallel, the time taken to run the  
 210 same number of iterations remains similar. Using this method, we produced phase ve-  
 211 locity maps for all periods of interest. For each period, we ran 8 parallel chains with 7  
 212 temperatures per chain for 2 million iterations and removed 750,000 iterations that ac-  
 213 commodated a burn-in period. Each map took roughly 2.5 hours to produce on 448 CPUs,  
 214 using 8 CPUs for each chain for each temperature, which we found to be the most com-  
 215 putationally efficient distribution of resources. Once the ensemble of models was calcu-  
 216 lated, the final 2D phase velocity maps were generated from the average at every 20th  
 217 iteration to avoid averaging correlated results. The advantage of using this method over  
 218 other less computationally expensive methods (e.g. FMST, Rawlinson & Sambridge, 2004)  
 219 include variable model resolution in the ensemble and posterior uncertainty estimates  
 220 that can aid with the interpretation of results. Having variable resolution is particularly  
 221 useful with this data set due to spatial variations in data coverage and quality (Figure  
 222 3a). While dispersion curves were extracted across most of the model, there were many  
 223 station pairs for which the quality of the cross-correlations was not sufficient to obtain  
 224 phase dispersion; this was particularly true for stations in the south east of the array.  
 225 The input parameters controlling the inversion were tuned by performing various test  
 226 runs at different periods and monitoring the acceptance rate of models and convergence  
 227 of key parameters (e.g. likelihood, prior, hierarchical scaling, and number of model pa-  
 228 rameters). Monitoring the convergence of the number of model parameters was particu-  
 229 larly useful since a similar distribution of parameters across all chains was a strong in-  
 230 dicator of stability. More information on convergence can be found in the Supplemen-  
 231 tary Material.

## 232 2.4 Synthetic 2D tomography

233 In order to test the ability of our dataset to resolve lateral structure, we invert period-  
 234 dependent inter-station path averaged velocity derived from a synthetic model for phase  
 235 velocity structure. Here we choose the path coverage for 12 seconds period since it is rep-  
 236 resentative across the full period range with an average number of ray paths. We pro-  
 237 duced a simple synthetic model consisting of blocks of different shapes, sizes and orien-  
 238 tations perturbed by 10% from a background velocity of 3 km/s, and computed travel  
 239 times through it by using the fast marching method implemented in the pykonal python  
 240 package (White et al., 2020). This forward calculation takes into account ray bending  
 241 to give more accurate travel times; however, the forward method used in the inversion  
 242 scheme is based on computing path averaged velocity over a great circle. This means that  
 243 the inversion will not be able to fit the synthetic data exactly, thus providing a more re-



**Figure 3.** Results from the synthetic test using the 2D trans-dimensional trees tomographic method. (A): The location of the stations and the associated ray path coverage. (B) The input velocity model for the synthetic test. (C) The standard deviation of the ensemble produced by the rj-MCMC. (D) The recovered mean velocity model with a transparent mask to highlight the region of low uncertainty and hence robust recovery.

244 alistic view of the features that can be resolved. We then used the trans-dimensional trees  
 245 method to reconstruct the model from calculated travel times with Gaussian noise of 0.3  
 246 s standard deviation added. The input model, ray paths and the mean and standard de-  
 247 viation map of the ensemble produced by the inversion are shown in Figure 3. The method  
 248 does a good job of recovering the structure within the array; however, on the margin of  
 249 the array there are many artefacts that could cause problems with any subsequent in-  
 250 terpretation if not appropriately masked. The standard deviation map is very useful since  
 251 it clearly shows that the uncertainty beyond the border of the array is considerably higher  
 252 than within the array, so it is relatively straightforward to identify anomalies that are  
 253 not interpretable. The underlying cause of the artefacts can be attributed to the bisect-  
 254 ing rectangular parameterisation of the trans-dimensional trees method, where a few ray  
 255 paths on the edge of the array are affecting the entire velocity model outside the array.  
 256 In comparison, a trans-dimensional Voronoi cell parameterisation would tend to locate  
 257 nodes within the array and hence the associated cells would be unlikely to span signif-  
 258 icant regions beyond the array boundary (Bodin et al., 2012b).

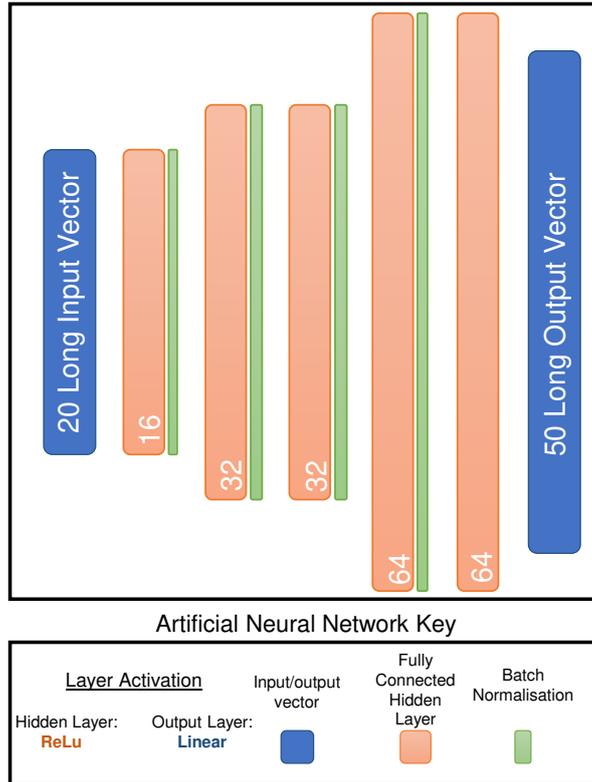
## 259 **2.5 1D Inversion for S-wave velocity ( $V_s$ )**

260 Once the 2D phase velocity maps are generated, the next step is to convert them  
 261 into a 3D shear wave velocity model. This is achieved by sampling the period-dependent  
 262 phase velocity maps on a grid of points to produce a corresponding set of pseudo dis-  
 263 persion curves, which can be separately inverted for 1D  $V_s$  structure. These models can  
 264 then be combined into a single 3D  $V_s$  model. The method we use is described in Bodin  
 265 et al. (2012a), although we did not exploit the capability of joint inversion with receiver  
 266 functions and only inverted for 1D shear wave structure by using Rayleigh wave phase  
 267 dispersion information. The 1D  $V_s$  inversion scheme also uses a rj-MCMC method that  
 268 has hierarchical data error estimation in a data-driven approach for quantifying the ap-  
 269 propriate data fit to the model. We ran this inversion on all 938 pseudo-dispersion curves  
 270 that were sampled evenly in latitude and longitude with a grid spacing of 0.1 degree in  
 271 the region of the mask shown in Figure 3, which was chosen on the basis of the standard  
 272 deviation of the results from the 2D inversion. The grid spacing of 0.1 degree was cho-  
 273 sen because it captured the smallest wavelength structure of the 2D models without adding  
 274 unnecessary computation in the form of additional inversions. The output from this pro-  
 275 cess was a depth dependent posterior distribution of  $V_s$  at each grid point from which  
 276 the average and standard deviation was chosen as the final model and its associated un-  
 277 certainty respectively. These 1D models were then used to construct a 3D shear wave  
 278 velocity model by using 3D linear interpolation.

## 279 **2.6 1D Inversion using an Artificial Neural Network**

280 To help evaluate the robustness of our results, we tested an alternative method for  
 281 inverting the pseudo-dispersion curves by using an Artificial Neural Network (ANN) that  
 282 was applied in Yablokov and Serdyukov (2020) and adapted to suit this data set. To do  
 283 so we created an ANN in the form of a simple vector to vector mapping that inputs a  
 284 vector of phase velocity from a pseudo-dispersion curve and outputs a vector of shear  
 285 wave velocity (Figure 4).

286 The network was first trained on a synthetic data set of 1D models produced by  
 287 sampling 3D shear wave velocity models built from random perturbations to a 1D ref-  
 288 erence model based on the average interstation dispersion curve in our dataset. These  
 289 random perturbations were drawn from a Gaussian distribution with 1 km/s standard  
 290 deviation. The models were then smoothed both laterally by a Gaussian filter of 30 km  
 291 width and in depth by a Gaussian filter of 5 km width to give more realistic models to  
 292 train the network on. Phase velocity dispersion curves were calculated using the Com-  
 293 puter Programs in Seismology (CPS) software (Herrmann, 2013) for each of the 1D mod-  
 294 els in the ensemble. This gave us a set of 5.4 million synthetic 1D shear wave velocity



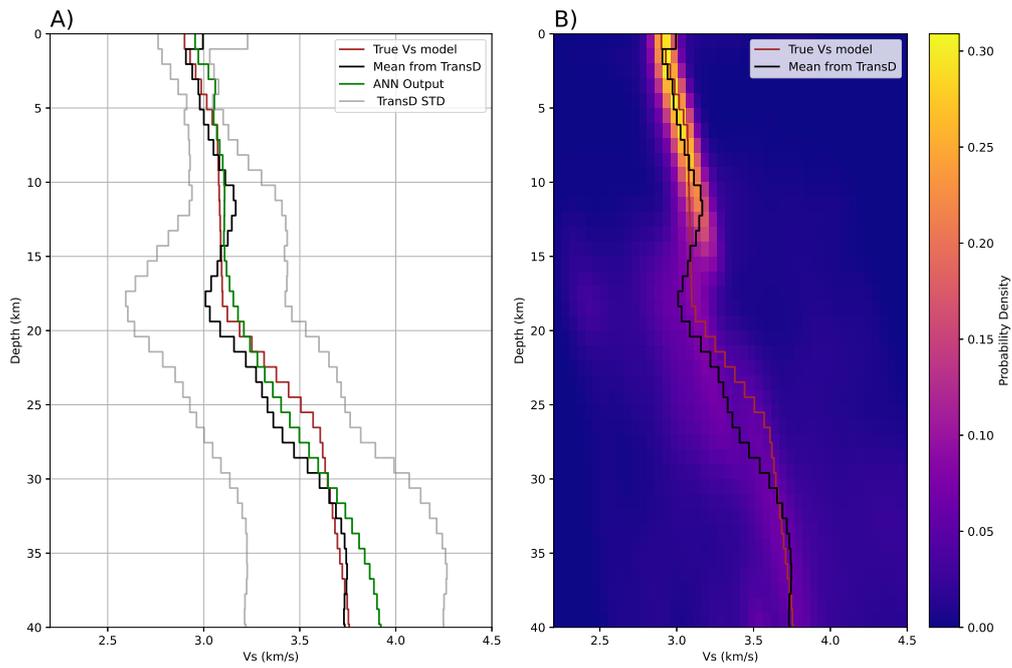
**Figure 4.** The architecture of the Artificial Neural Network used to perform the 1D inversions. The size of each fully connected layer and the input and output vector is written in each box along with the location of batch normalisation layers. The activation on all the hidden layers is a rectified linear unit (ReLu) and the activation on the output layer is linear.

295 models and associated Rayleigh phase velocity dispersion curves. The network was then  
 296 trained on this output with 80% of the curves used to train the network and the remain-  
 297 ing 20% to validate the network and ensure that we were not overfitting the data. The  
 298 training was done with the ADAM optimiser with the learning rate set to the default  
 299 value of 0.001 (Kingma & Ba, 2014) for 2000 epochs. The network was found to converge  
 300 after 950 epochs when the minimum validation loss was found. This is the baseline net-  
 301 work that approximates the inversion of phase velocity dispersion curves based on the  
 302 synthetic data set. We then took the 1D models produced by the trans-dimensional method  
 303 and performed transfer learning on our baseline network in order to update the model  
 304 to include information about our region and the noise characteristics of the pseudo-dispersion  
 305 curves. We again used an 80/20% train and validation split but this time the ADAM  
 306 optimiser had the learning rate set to  $5 \times 10^{-5}$  and was trained for 1200 epochs. By us-  
 307 ing a learning rate 20 times smaller we try to ensure that the information learned by the  
 308 network in the previous step is not forgotten and that any patterns in the noise on the  
 309 real data are not learned by the model. The data set was much smaller for the trans-  
 310 fer learning stage and therefore was very fast to compute making it feasible to run the  
 311 training for 3000 epochs to ensure that even with the low learning rate it could converge  
 312 on a reasonable solution. The test and training losses started to diverge at 2000 epochs  
 313 so the final re-trained model was assumed to be optimum at that point.

314 The result of the above workflow is a network that provides a regionally localised  
 315 approximate solution for the inverse problem as an application of the theorem that neu-  
 316 ral networks are universal approximators (Hornik et al., 1989). The reasoning for this  
 317 is based on Yablokov and Serdyukov (2020), where they found that the neural network  
 318 trained on synthetic data was much less sensitive to noise when performing inversions  
 319 after training. This is a particularly useful feature of the method since many of the pseudo-  
 320 dispersion curves contain unrealistic spikes or troughs in phase velocity due to the 2D  
 321 inversions being performed separately; this means that there is no control on the lateral  
 322 correlation of velocity anomalies between adjacent periods. When the neural network  
 323 is re-trained on the pseudo-dispersion curves from the real data set after training by a  
 324 synthetic data set, it will learn an approximate mapping for that region. When re-doing  
 325 the inversion from pseudo-dispersion curve to 1D shear wave velocity with the re-trained  
 326 ANN the result will be less sensitive to noise and unphysical changes in the dispersion  
 327 curves. Using this method, all pseudo-dispersion curves were run on the final trained net-  
 328 work to produce a new set of 1D velocity models that are used to construct a second 3D  
 329 shear wave velocity model. This model is generally smoother and easier to interpret, al-  
 330 though it is also helpful to consider the rj-McMC model in the interpretation, since many  
 331 of the features are similar.

## 332 2.7 Synthetic 1D inversion results

333 We performed several synthetic tests for the 1D inversion scheme to determine how  
 334 effective both of our methods are at resolving shear velocity from phase velocity disper-  
 335 sion curves. We used a model that extends in depth to 40 km with 1 km thick velocity  
 336 layers that vary smoothly as a function of depth. The top 8 km features a gentle increase  
 337 in velocity gradient with a homogeneous section between 8 and 18 km depth and a sharper  
 338 velocity gradient between 18 and 25 km depth before changing back into a milder ve-  
 339 locity gradient that extends to the base of our model. Although not identical to any model  
 340 used for training the ANN, it is similar enough to expect that a good reconstruction is  
 341 possible. We calculated the dispersion curve from the input model using CPS (Herrmann,  
 342 2013) and then added Gaussian noise with a 0.01 km/s standard deviation, which is a  
 343 similar noise level to that of a good quality pseudo dispersion curve. We then ran it through  
 344 both the TransD 1D inversion method and the ANN inversion method using the re-trained  
 345 model as described above. Both results are shown in Figure 5.



**Figure 5.** Results from a synthetic inversion for 1D structure. (A): 1D Vs models from the synthetic tests; the true model is in red, the average of the ensemble produced by the TransD method is in black with its associated standard deviation in gray and the result from the ANN method is in green. (B): The posterior PDF produced by the TransD method overlain by the TransD average in black and the true model in red.

346 The result from the synthetic TransD inversion include measurements of uncertainty  
 347 and an output probability density map, shown in Figure 5B, representing the posterior  
 348 distribution sampled by the Markov chain, which is used to produce the mean and stan-  
 349 dard deviation which we take to be the final 1D Vs model and its uncertainty. The TransD  
 350 and ANN methods gives a very similar 1D profile to the true model, however, there are  
 351 a few differences. Between 10 and 20 km depth in the model the TransD scheme has a  
 352 tendency to overestimate the changes in velocity; this is most notable in Figure 5A at  
 353 12 and 18 km depth where the recovered TransD model has a positive and negative ve-  
 354 locity anomaly respectively. This is not observed in the ANN model, which better matches  
 355 the true velocity model in this region. For the sharper velocity gradient between 18 and  
 356 25 km depth, both the TransD and the ANN slightly underestimate the gradient but ex-  
 357 tends the feature over a greater depth range, which is typical of surface wave dispersion  
 358 inversion. At 35-40 km the TransD model recovers the velocity quite well but the ANN  
 359 model overestimates the velocity by up to 0.2 km/s. We expect this is likely due to the  
 360 ANN not having seen a model quite like this since we do not see an overshoot at depth  
 361 when comparing the final TransD and ANN models of the region. With the exception  
 362 of the base of the model, the two different methods produce very similar results, which  
 363 is to be expected since the ANN is designed as a preconditioned emulator of the TransD  
 364 method.

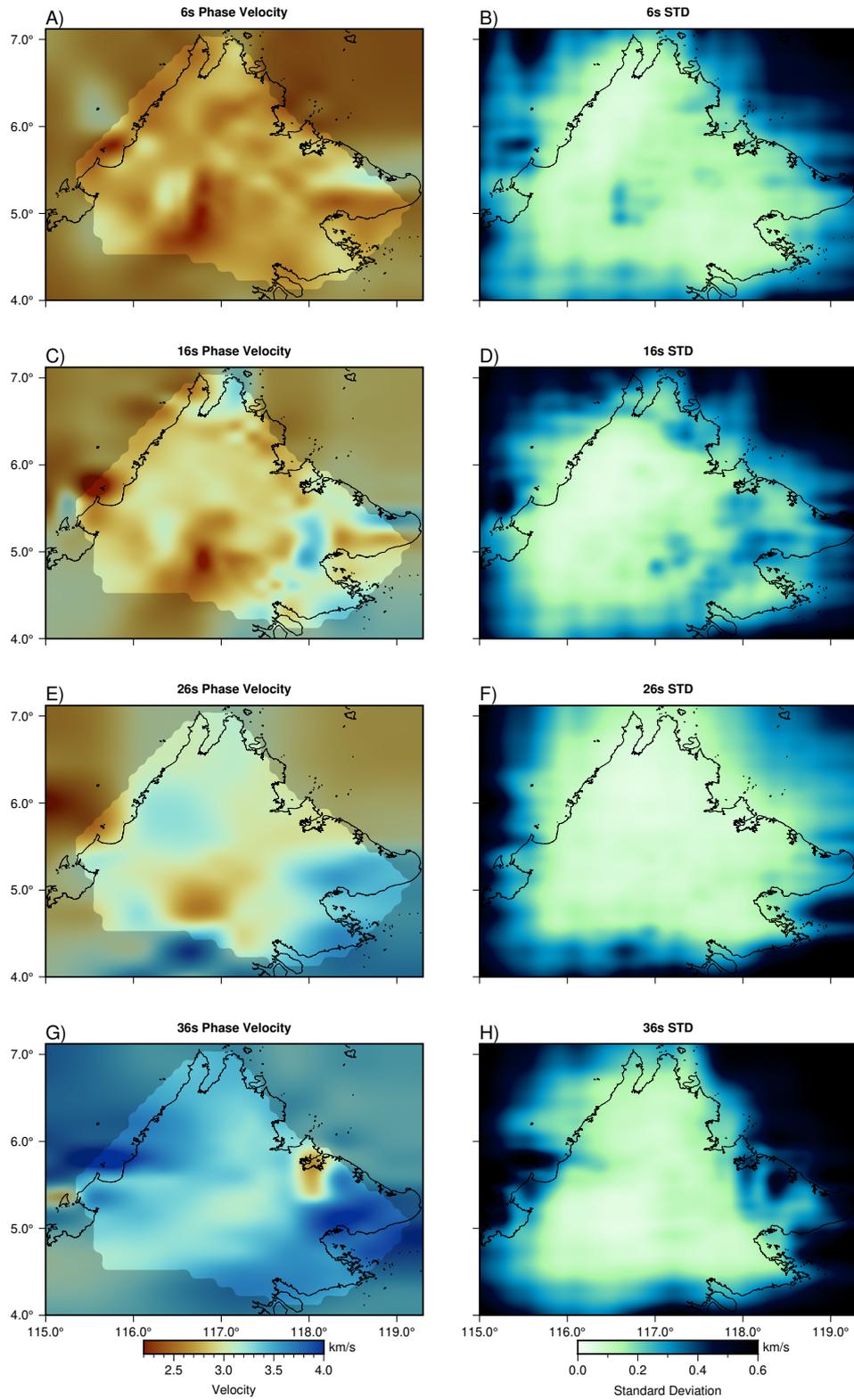
### 365 3 Results

#### 366 3.1 Phase velocity maps

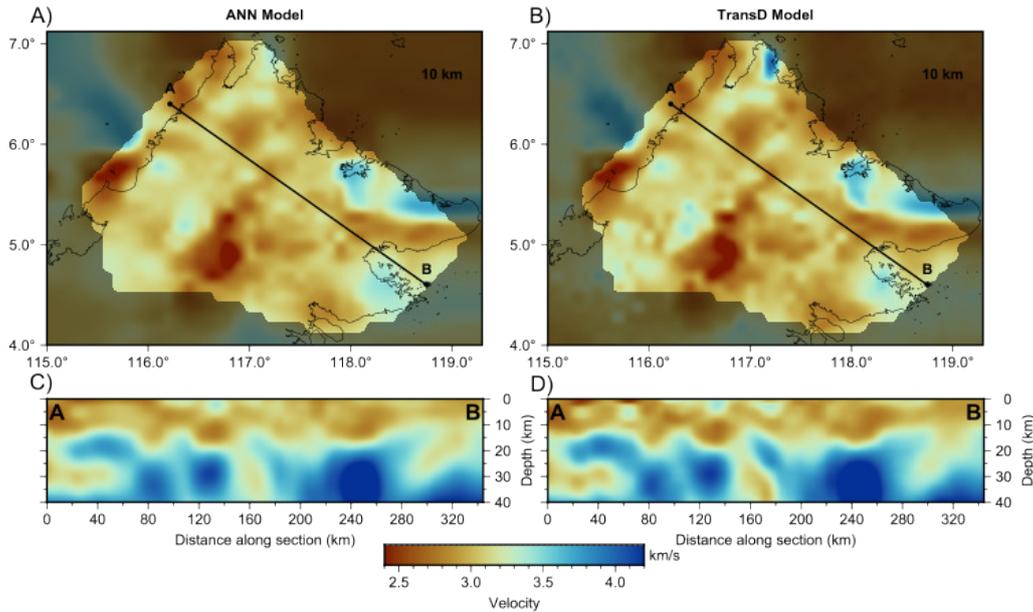
367 Figure 6 shows the period-dependent phase velocity maps and standard deviations  
 368 computed for 6, 16, 26 and 36 seconds. The velocity models adopt the mask that we used  
 369 in the synthetics (Figure 3) due to the presence of similar edge effect issues. The stan-  
 370 dard deviation maps for these models show a consistent story with higher uncertainties  
 371 in the east of the model, especially underneath the Dent peninsula, where there is poorer  
 372 ray path coverage and apparently noisier data. The region of the models under the Crocker  
 373 Range has lower standard deviation that is consistently under 0.1 km/s and as such can  
 374 be more reliably interpreted. There are also higher standard deviations located in the  
 375 neighbourhood of strong lateral velocity contrasts even in regions that have good path  
 376 coverage, such as the low velocity anomaly in the 6 second map in Figure 6A and B where  
 377 the standard deviation rises to 0.3 km/s. This is due to the uncertainty around where  
 378 to place such a contrast since there is a trade-off between the location, size and magni-  
 379 tude of the velocity change (Hawkins & Sambridge, 2015; Pilia et al., 2020), an effect  
 380 perhaps more pronounced when using Voronoi cells (Pilia et al., 2015b).

#### 381 3.2 Comparison of models produced by the two methods

382 To illustrate the difference between the two 1D inversion methods, we show a hori-  
 383 zontal slice through the two final 3D models in Figure 7 with no smoothing applied. For  
 384 long wavelength features, the two models look virtually identical, with low and high ve-  
 385 locity anomalies found in the same place laterally and with depth. This is reassuring since  
 386 it demonstrates that both methods agree that certain key features are required to fit the  
 387 phase velocity maps. The models are more different at shorter scale lengths, with the  
 388 ANN model showing a generally much smoother result both laterally and in depth com-  
 389 pared to the TransD model. This is to be expected given the initial training of the ANN  
 390 model on an ensemble of synthetic models, prior to transfer learning with the TransD  
 391 inversion results. As a consequence, the 1D ANN inversion effectively features a higher  
 392 degree of implicit smoothing regularisation yet is still capable of satisfying the data to  
 393 the same extent. When compared to the picked phase velocity dispersion curves the model  
 394 produced by the ANN has a residual mean of  $-0.057$  km/s and residual standard devi-  
 395 ation of 0.19 km/s whereas the model from the TransD method has a residual mean of



**Figure 6.** Example phase velocity maps and standard deviations produced by the trans-dimensional trees method. The velocity models are partially masked to show regions of lower standard deviation and improved recovery. Panels (A) and (B) show results for 6 s period, (C) and (D) for 16 s, (E) and (F) for 26 s and (G) and (H) for 36 s.



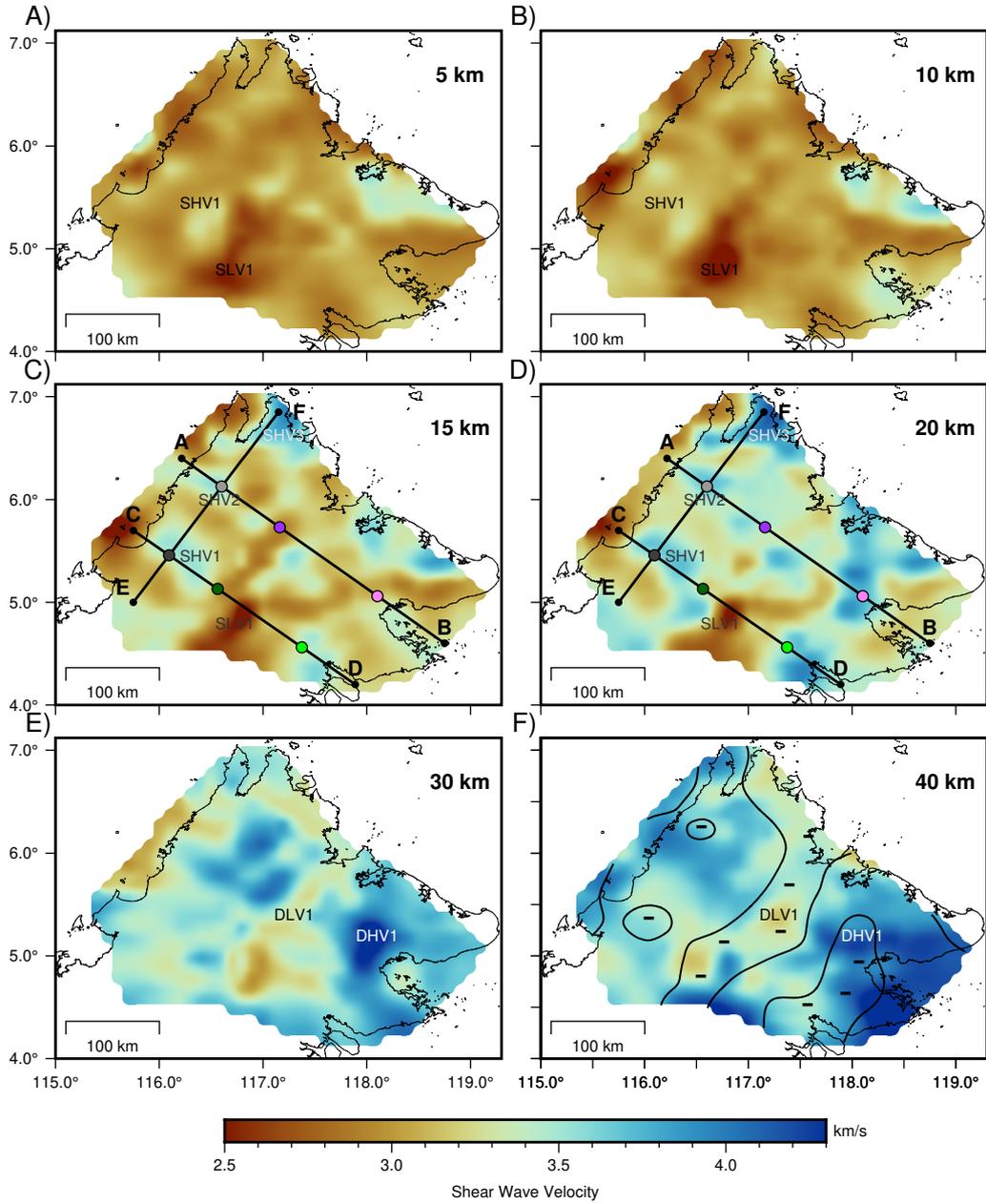
**Figure 7.** Horizontal slice at 10 km depth and cross-section from A to B for the final 3D shear wave velocity model produced by using the ANN method (left) and the TransD method (right).

396  $-0.050$  km/s and a residual standard deviation of  $0.19$  km/s. For this study we decided  
 397 that the ANN model is more useful for interpretation since many of the short wavelength  
 398 features are not resolvable by our level of data coverage and hence should not be con-  
 399 sidered.

### 400 3.3 Shear wave velocity model

401 The final composite 3D shear wave velocity model produced by the re-trained ANN  
 402 1D inversions is presented as a series of horizontal slices in the range 5-40 km depth (Fig-  
 403 ure 8) and cross sections through key sections of the model (Figure 9). Based on the syn-  
 404 thetic inversions and the phase velocity maps, lateral features larger than 50 km are res-  
 405 solvable except in regions on the edge of the model where artefacts of the low coverage  
 406 and trans-dimensional trees parameterisation appear. In some regions lateral resolution  
 407 will be better, particularly in the region of the Crocker range where we have the most  
 408 crossing rays. The lateral resolution will also reduce with increasing depth, since the ray  
 409 path coverage at longer periods reduces, though there are fewer short wavelength struc-  
 410 tures visible below 20 km depth due to the trans-dimensional parameterisation reduc-  
 411 ing the length scale of features in the longer period phase velocity models. From the 1D  
 412 synthetics, uncertainty generally increases with depth, but broadscale anomalies can still  
 413 be reliably interpreted. The synthetics show that we do not resolve vertical contrasts very  
 414 well and so we are unlikely to be able to accurately determine the dimensions of verti-  
 415 cal anomalies. To ease interpretation, the model has been laterally smoothed using a Gaus-  
 416 sian kernel with 10 km standard deviation. The text labels superimposed on Figures 8  
 417 and 9 highlight features that we will interpret in the discussion section.

418 In the upper 20 km of the crust, one of the more obvious features is the large Shal-  
 419 low Low Velocity (SLV) anomaly in the central southern region of the model (SLV1 on  
 420 Figures 8 and 9). Here, velocities are as low as  $2.5$  km/s and the anomaly extends to  $\sim 25$   
 421 km depth. This feature underlies the Maliau Basin and other circular basins of Sabah,



**Figure 8.** Horizontal slices from 5 to 40 km depth (Panels A-F) through the final shear wave velocity model produced by the re-trained ANN inversion. The three lines A-B, C-D and E-F are the locations of cross sections that are plotted in Figure 9. The velocity anomalies interpreted in the discussion section are also marked as SHV1, SHV2 and SLV1 for the shallow anomalies and DLV1 and DLV2 for the deep anomalies. The region of thinner crust found by Linang et al. (2022) is plotted on the 40 km depth slice as a single contour at 34 km depth.

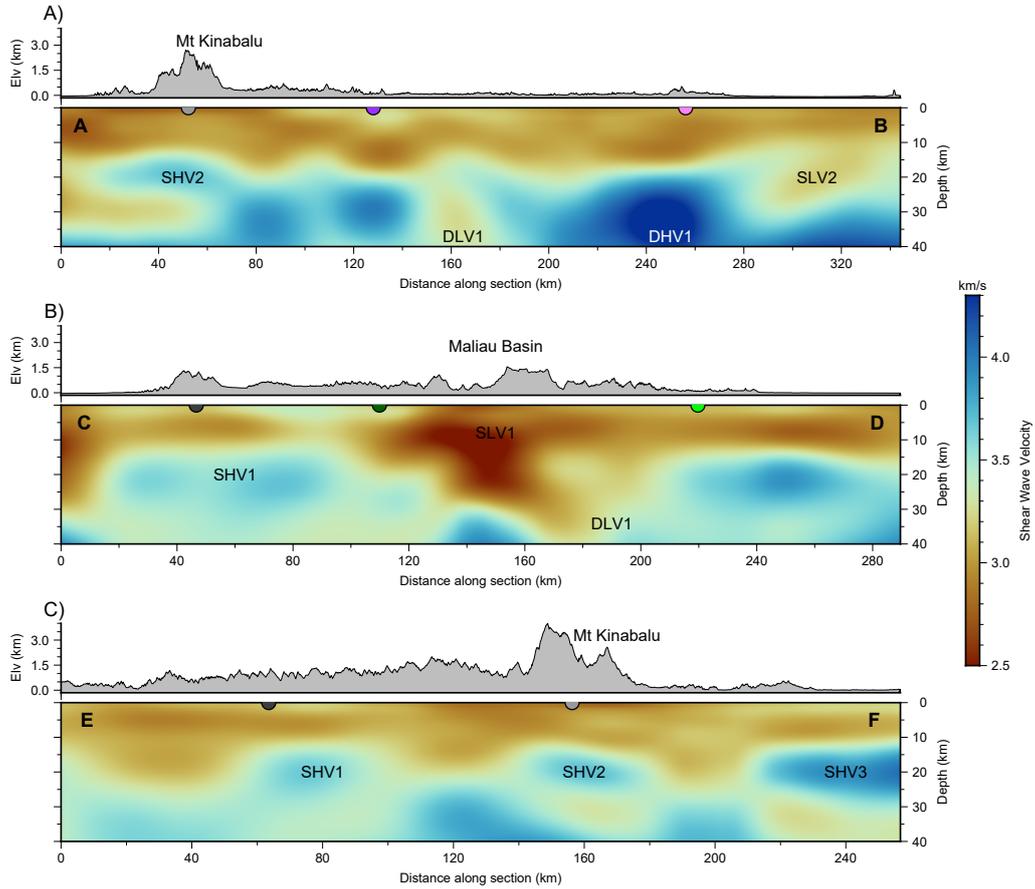
so is likely a signature of low velocity sediments, although they are unlikely to extend that deep, suggesting that vertical smearing – an expected byproduct of surface wave inversion – is at play here. Previous estimates from structural geology, which themselves are not well constrained, have put the thickness of the Neogene sediments in this region at 6-7 km (Balaguru et al., 2003) so we may be seeing the effects of a very low velocity layer being smeared out by the bulk sampling of the surface waves measured in the ambient noise recordings. The upper mid-crust reveals a Shallow High Velocity (SHV) anomaly beneath the Crocker Range (SHV1 on Figures 8 and 9) of about 3.5-3.7 km/s extending from about 10 to 25 km depth. It is approximately 80 km long with a NW-SE strike that aligns with cross section C-D and is also visible in cross section E-F (Figure 9). This anomaly also seems to mark a difference in the topography between the northern and southern parts of the Crocker Range, which is an interesting correlation that will be discussed later. A second smaller high velocity anomaly exists under the Crocker Range beneath Mt Kinabalu (SHV2 on Figures 8 and 9); it is roughly cylindrical with a diameter of  $\sim 40$  km between depths of 15-25 km and has a maximum velocity of about 3.7 km/s, which is similar to SHV1. Finally a third high velocity anomaly labelled SHV3 is located in the north of the region; it extends from around 15 to 30 km depth and has velocities up to 3.8 km/s. SHV3 is the largest of these three shallow high velocity anomalies but is near the edge of the model so is not as well resolved when compared to SHV1 and SHV2.

Deeper in the model between 30-40 km depth, there is an intriguing pattern of NE-SW oriented high velocity anomalies in the southeast, low velocities in the centre and higher velocities in the northwest. This trend is primarily expressed in the long wavelength features of the model and also matches the central region of thin crust found by Linang et al. (2022), which is shown on Figure 8 as a 34 km depth contour from their crustal thickness model. The Deep Low Velocity (DLV) band featuring velocities of 3.2-3.4 km/s in the centre of Sabah and striking NE-SW extends southwest from the northeast coast and is about 200 km long and 40 to 80 km wide. It is most clearly seen in the 40 km depth slice in Figure 8F and cross section AB in Figure 9A where it is marked as DLV1. There is also a Deep High Velocity (DHV) anomaly with values ranging between 4.1-4.2 km/s that covers much of eastern Sabah marked as DHV1 in Figures 8E/F and 9A. The peak velocities of this anomaly are mostly concentrated around Darvel Bay between the Dent and Semporna peninsulas, but it covers most of the eastern part of our region at depth. It is worth noting that the uncertainty in this region is higher than elsewhere, especially on the Dent peninsula (Figure 6), but it is likely that we can still resolve larger scale high velocity anomalies at this depth, especially under the Semporna peninsula where the values of uncertainty are generally lower.

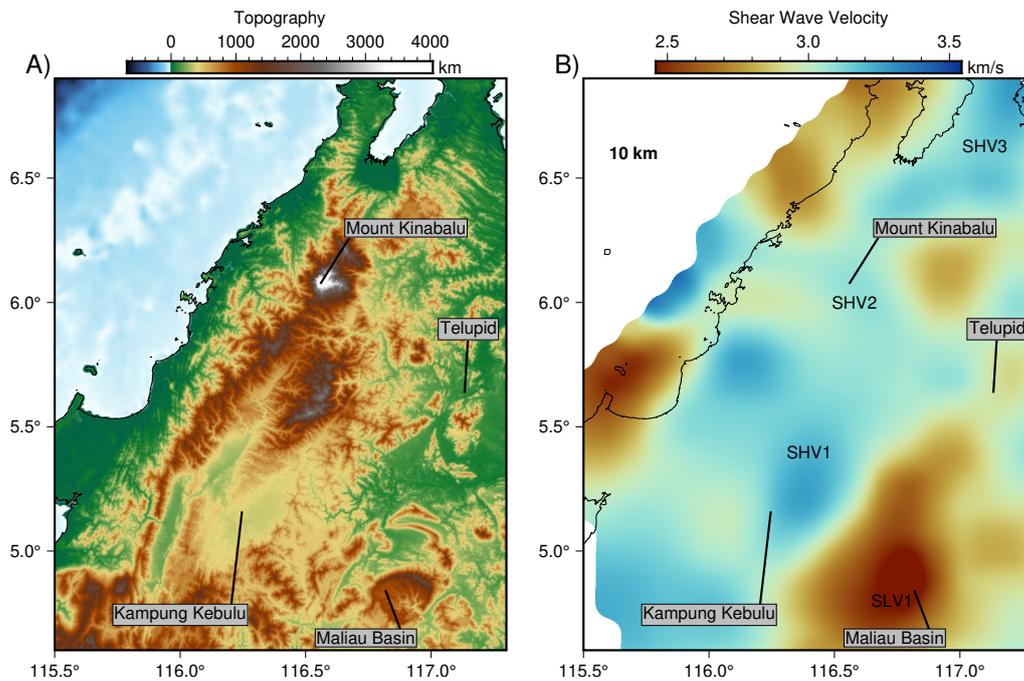
## 4 Discussion

### 4.1 Complex crustal structure in western Sabah

The crust beneath the Crocker Range lies in the most well constrained region of our model according to the standard deviation maps and synthetic inversion results (Figure 3). It also contains several unexpected complexities in a region that has relatively simple mapped surface geology as shown in Hall (2013), with much of the area being covered by Cretaceous-Lower Miocene sediments and more recent Pleistocene sediments. The complexity we see in the 10 to 20 km depth range of the shear-wave velocity model is manifest in the presence of SHV1, SHV2 and SHV3 along with SLV1 located further southeast beneath the Maliau Basin. Figure 10 shows a 10 km depth slice through this section of the model alongside a map of topography with the locations of SHV1, SHV2, SHV3 and SLV1 highlighted. The subduction of the Proto-South China Sea (PSCS) is believed to have occurred in this region (Hall, 2013), as supported by recent evidence of a relict slab that traverses the NW coast in the mid-lower upper mantle from teleseismic travel time tomography (Pilia et al., 2023a, 2023b). The subsequent collision and



**Figure 9.** Cross sections through the final shear wave velocity model produced by the re-trained ANN inversion and the elevation (Elv) of the topography along the section. The locations of the cross sections are shown in Figure 8. Cross section A-B in panel A transects Mt Kinabalu, which can be seen in the elevation, as well as the interpreted anomalies SHV2, DLV1 and DHV1. Cross section C-D in panel B runs through the Maliau Basin, which shows up as the shallow low velocity anomaly SLV1 and also converges on anomalies SHV1 and DLV1. Cross section E-F in panel C runs along strike of the Crocker Range and through the anomalies SHV1, SHV2 and SHV3.



**Figure 10.** Surface topography and a 10 km depth slice from our final shear wave velocity model showing the shallow anomalies in relation to surface features. SHV1 is located under a region of low topography in the Kampung Kebulu area, SHV2 is located underneath Mount Kinabalu and SHV3 is located underneath Telupid. The depth slice is plotted with a different colour scale than Figure 8 and 9 and is centred on the mean shear wave velocity at 10 km depth to better highlight the anomalies we see in this section of the model.

474 underthrusting of the Dangerous Grounds block is believed to be the reason for the ter-  
 475 mination of the subduction of PSCS (Hall, 2013). The three high velocity anomalies and  
 476 the lower velocities that underlay them are, therefore, possible evidence of the under-  
 477 thrusting of heterogeneous continental crust from the collision of the Dangerous Grounds  
 478 block producing along strike variations in velocity structure. This variation was also ob-  
 479 served by Gilligan et al. (2023) who sees similar regions of high and low velocity anom-  
 480 alies in the crust along the Crocker Range from inversion of receiver functions for shear  
 481 wave velocity structure. If these anomalies are associated with underthrusting, it is likely  
 482 that the high velocity structures represent the lower portion of what was the overriding  
 483 crust, and the low velocities beneath represent the upper part of the underthrust Dan-  
 484 gerous Grounds crust.

485 The velocity anomaly at the southern edge of the Crocker Range, SHV1, also co-  
 486 incides with a region of flat topography that marks a clear difference in relief between  
 487 the mountainous regions to the north and south (Figure 10). This topographic low could  
 488 be caused by heavy erosion followed by infill of younger Pliocene/Pleistocene sediment  
 489 (<5 Ma) (Hall, 2013). This would explain the apparent thinning of the low velocity layer  
 490 in the upper crust as seen in Figure 9B. However, another option, supported by the pres-  
 491 ence of SHV1, is the existence of rigid material under this section of the Crocker Range  
 492 that resisted deformation or limited it to the narrow band near the coast as seen in the  
 493 topography. A similar structure is seen in the Iberian Peninsula in the form of the Ebro  
 494 block, which is a continental block within the compressional margin of the Pyrenees that  
 495 shows a region of thin crust and lower relief surrounded to the north and south by thicker  
 496 crust and higher relief (King et al., 2023). This is in a comparable tectonic setting with

497 similar topography to what we see on this segment of the Crocker Range, though the scale  
498 of the Pyrenees is larger.

499 The second high velocity anomaly in western Sabah is located under Mt Kinabalu  
500 (SHV2). This is a much smaller anomaly than SHV1 in both depth and lateral extent  
501 and lies beneath a region of anomalously high topography. This high velocity anomaly  
502 is most clearly seen in cross section A-B (9) and in Figure 10, which show it extending  
503 down to 20 km depth and underlain by a lower velocity zone. Mt Kinabalu is a large gran-  
504 ite pluton that was intruded into Mesozoic igneous and metamorphic rocks and Ceno-  
505 zoic sediments (Cottam et al., 2010) and then extension caused exhumation of a sub-continental  
506 peridotite suite (Tsikouras et al., 2021). It is therefore likely that SHV2 and the smaller  
507 high velocity zone beneath Telupid represents this ultramafic material that is also found  
508 at the surface in this area (Hall, 2013). The third high velocity anomaly in the very north  
509 of our model, SHV3, is much larger and has a higher amplitude than SHV1 and SHV2.  
510 It is in a region of our model that has relatively poor coverage and therefore has the po-  
511 tential to suffer from edge effects. However, a very similar structure has been imaged by  
512 Gilligan et al. (2023), suggesting that it is real, though its exact dimensions are likely  
513 to be poorly constrained. The position of the SHV3 anomaly coincides with a clear shift  
514 in the fabric of the region, with southwest-northeast striking features to the south in the  
515 Crocker Range to more east-west fabric on the northern tip of Borneo, as seen in the to-  
516 pography map in Figure 10A. This change in fabric is interpreted to be the result of col-  
517 lision with the Reed Bank in the north (Tongkul, 1994). The Reed Bank is another con-  
518 tinental block within the South China sea that collided with Palawan to the north. Tongkul  
519 (1994) suggests that this region has undergone uplift as a result of this collision, so the  
520 shallow high velocities could be evidence of uplifted ultramafic material near the surface.

## 521 4.2 Evidence for extensive melting and subduction in Sabah

522 In eastern Sabah between 20-40 km depth, the velocities are higher than anywhere  
523 else in the model region – see anomaly DHV1 in Figures 8 and 9. The Dent and Sem-  
524 porna peninsulas are characterised by Miocene island arc magmatism, with samples dated  
525 between 16-9 Ma (Lai et al., 2021; Bergman et al., 2000), which is thought to be the re-  
526 sult of Celebes Sea subduction that occurred immediately to the southeast. Subsequently,  
527 the Semporna peninsula experienced magmatic episodes from 4-2 Ma that exhibit an ocean  
528 island basalt type signature (Macpherson et al., 2010), which has since been related to  
529 possible lithospheric delamination directly beneath (Pilia et al., 2023b; Greenfield et al.,  
530 2022). It is therefore possible that the high velocities beneath eastern Sabah represent  
531 plutonic mid-lower crust that may have formed due to melting, as first suggested by Hall  
532 (2013). The shallowest point of the DHV1 anomaly is also co-located with the exposed  
533 ultramafic material of the Darvel Bay ophiolite (Hall, 2013). If the higher velocities do  
534 represent a plutonic crustal layer, then it appears to shallow between the Semporna and  
535 Dent peninsulas, though this is hard to quantify given the uncertainty limiting our res-  
536 olution in the east, particularly under the Dent peninsula.

537 A notable feature adjacent to DHV1, which is most visible in cross section AB in  
538 Figure 9A, is a low velocity anomaly (SLV2) that extends down to  $\sim 35$  km depth and  
539 has a slight dip to the northwest. This anomaly is located on the edge of our region of  
540 low standard deviation that ranges from around 0.1 km/s beneath the Semporna penin-  
541 sula to 0.4 km/s beneath the Dent peninsula, thus requiring any interpretation to be made  
542 with a certain degree of caution. However, given its moderate dip and location, it may  
543 be a signature of underthrust sediment or duplexes at the former subduction front of the  
544 Celebes Sea Slab, consistent with what is observed in the study of Zhang and Miller (2021)  
545 in a similar setting. If so, it would represent the first geophysical evidence of Celebes Sea  
546 subduction, though further work is required to support this interpretation, particularly  
547 in light of the limited data coverage in this region of the model.

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### 4.3 Sabah failed rift from Celebes Sea subduction rollback

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Near the base of our model at 40 km depth, the anomaly DLV1 in Figures 8 and 9 shows a band of low velocity stretching from the Sulu Sea to the Maliau Basin. This low velocity anomaly coincides with a region of thin crust found by applying Virtual Deep Seismic Sounding (VDSS) on the same data set as this study (Linang et al., 2022). VDSS resolves the Moho discontinuity (as shallow as  $\sim 20$  km in this part of northern Borneo), whereas ANT using surface waves can only recover smooth velocity variations as a function of depth. As a consequence, the two sets of results are not directly comparable, but one could be expected to see low velocities in rifted crust due to a thermal anomaly (Accardo et al., 2020).

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In Linang et al. (2022), this region of crustal thinning is explained as a continuation of the extension of the opening of the Sulu Sea caused by the rollback of the Celebes Sea Slab, which at the time subducted NW beneath northern Borneo. When the subduction ceased at 9 Ma, the extension stopped leaving a region of thinned crust. The idea of continued extension of the Sulu Sea on land in northern Borneo was first suggested by Hall (2013) and was corroborated by Tsikouras et al. (2021), who found Miocene zircons in the mafic rocks at Telupid and Ranau. In Tsikouras et al. (2021) these were used to suggest that extension led to the exhumation of a sub-continental peridotite suite near Ranau and a rift-related magmatic episode near Telupid. Whether these zircons were magmatic or metasomatic due to their presence in mafic/ultra-mafic rocks was questioned by Cullen and Burton-Johnson (2021). We suggest that the DLV1 anomaly and its very strong correlation with the region of thin crust seen in Linang et al. (2022) supports the idea that late Miocene extension occurred under northern Borneo, thus producing an upwelling of warmer material into the region left by the thinned crust. The anomaly DLV1 is also mildly asymmetrical and dipping towards the southwest, which matches up with numerical simulations of continental rift initiation where asymmetrical features of this type have been observed (Brune et al., 2014). Pilia et al. (2015a) invoked a similar explanation when they discovered a low velocity anomaly beneath the failed rift in Bass Strait, Southeast Australia. This was interpreted as a residual thermal upwelling initiated by thinning during extension. Invoking a similar mechanism here supports the model of late Miocene extension due to rollback of the Celebes Sea slab and is consistent with other evidence of a failed rifting episode (Tsikouras et al., 2021; Linang et al., 2022). As a simple check of the validity of this interpretation, we calculated the characteristic thermal relaxation time of a thermal anomaly at 40 km depth in the Earth's crust using the following calculation (Michaut et al., 2007).

$$\tau = \frac{L^2}{\kappa} \quad (1)$$

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where  $\tau$  is the characteristic thermal relaxation time,  $L$  is the length scale and  $\kappa$  is the thermal diffusivity of the crust. By taking the length scale to be 40 km, which is the depth to the velocity anomaly, and a range of realistic thermal diffusivities, we can calculate a range of characteristic thermal relaxation times. We use thermal diffusivities that span  $7.0 \times 10^{-3}$  -  $15.0 \times 10^{-3} \text{ cm}^2\text{s}^{-1}$  to represent extreme differences in crustal composition found in Seipold and Gutzeit (1982). This gives us a range of relaxation times from 33-72 million years, which means that if extension ceased at approximately 9 Ma, then insufficient time has passed to significantly dissipate the resultant thermal anomaly produced by the extension (Chenin et al., 2020). While compositional variations cannot be ruled out to explain our observations, higher temperatures associated with relatively recent failed rifting appears to be the most likely explanation.

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## 5 Conclusions

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We have imaged the shear wave velocity structure of the crust beneath northern Borneo to a depth of 40 km using ambient noise tomography applied to data from the

597 nBOSS array collected between 2018 and 2020. We apply a two step inversion method  
 598 using Trans-dimensional Trees for the 2D step and a combination of Trans-dimensional  
 599 inversion and a new artificial neural network based inversion for the 1D inversion step.  
 600 The new ANN inversion was shown to be effective at recovering heterogeneous structure  
 601 and produced a smoother model than the transD method while still satisfying the data.  
 602 From this new crustal shear wave velocity model, complex subsurface structure beneath  
 603 the Crocker Range is discovered containing various high velocity anomalies that are in-  
 604 terpreted to be evidence of underthrusting of Dangerous Grounds continental crust that  
 605 feature significant along-strike variations. High velocities in east Sabah reveal evidence  
 606 of significant melting due to the subduction of the Celebes Sea slab and subsequent de-  
 607 compression melting. In the east a low velocity anomaly may indicate the presence of  
 608 underthrust sediments or duplexes that support Celebes Sea subduction, though reso-  
 609 lution is limited. We find evidence of Sulu Sea extension – likely caused by Celebes Sea  
 610 subduction – propagating southwest into northern Borneo to ultimately produce a failed  
 611 continental rift. This is in the form of a low velocity anomaly that may be the signature  
 612 of elevated temperatures that persist following the cessation of failed rifting. Further-  
 613 more, we illuminate the subsurface structure of the Maliau Basin and reveal a thick low  
 614 velocity anomaly that likely represents a thick sedimentary sequence that formed prior  
 615 to the emergence of the eastern part of northern Borneo following Celebes Sea slab break-  
 616 off. Further work on this region could include the extraction and inversion of Love wave  
 617 dispersion data, the joint inversion of receiver functions and surface wave dispersion, and  
 618 the inclusion of longer period dispersion data extracted from teleseismic events.

## 619 Data Availability Statement

620 The nBOSS dataset is accessible through the IRIS Data Management service  
 621 ([https://www.fdsn.org/networks/detail/YC\\_2018/](https://www.fdsn.org/networks/detail/YC_2018/)). Data from the Malaysian national  
 622 seismic network (<https://www.fdsn.org/networks/detail/MY/>) are restricted but may  
 623 be obtained by contacting the Malaysian Meteorological Department. The stacked cross  
 624 correlations produced as part of this study are available at doi:10.6084/m9.figshare.25360090

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 636 al., 2020), obspy (Beyreuther et al., 2010), matplotlib (Hunter, 2007), pytorch (Paszke  
 637 et al., 2019), xarray (Hoyer & Hamman, 2017) and pyGMT (Wessel et al., 2019).

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