



University of Brasília
Institute of Geosciences
Graduate Program in Applied Geosciences and Geodynamics

**Inversion of Rayleigh and Love wave dispersion
curves: new constraints on the shear-wave
velocity and radial anisotropy structure of the
South American lithosphere**

**Inversão de curvas de dispersão de ondas
Rayleigh e Love: novos vínculos sobre a estrutura
de velocidade de onda de cisalhamento e de
anisotropia radial da litosfera Sul-americana**

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André Vinícius de Sousa Nascimento

Thesis submitted to the Institute of Geosciences of the University of Brasília in partial fulfillment of the requirements for the degree of Doctor of Science.

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Abstract

The scientific advances reported in the present thesis are the result of efforts to measure and invert surface wave dispersion data to image the seismic structure of the lithosphere beneath South America. Our findings are presented in three separate studies. In the first one, we derive a shear-wave velocity model by inverting 26,984 fundamental mode Rayleigh wave group velocity dispersion curves, at periods of 9-180 s. The interpretation of this model focuses on cratonic structure beneath South America. For the Amazonian craton, we find a general correlation between seismic velocity at 150 km depth and geochronological province ages, except at the Maroni-Itacaiúnas province, where we hypothesize that Mesoproterozoic K'Mudku intraplate tectono-thermal events and/or voluminous magmatism of the Central Atlantic Magmatic Province (following the breakup of Pangea) are candidates for decreasing the velocity and thus disrupting the velocity/age correlation. Our model is also consistent with a São Francisco paleocontinent encompassing the current São Francisco craton and parts of the Brasília and Araçuaí belts. Some authors argue whether this extension is also valid for parts of the Borborema province; the slow velocities mapped by our model beneath it from 70 km depth downward are, however, indicative of lithospheric thinning, which is also supported by other geophysical and geological evidence. Thus, we argue that a possible cratonic root of the São Francisco paleocontinent beneath the Borborema province has likely been eroded away. Finally, we also image a fast shear-wave velocity structure in the region of the Río de la Plata craton, consistent with magnetotelluric studies. As manual measurement of dispersion curves is a very demanding and time consuming procedure, we would like an automated tool to carry out more dispersion measurements to improve our models. Bearing this in mind, we develop and present DisperPy in our second study, an open-source Python library based on machine learning algorithms developed to automatically extract group velocity dispersion curves from earthquake data. The analysis framework of DisperPy aims to solve two primary tasks: (1) to assess waveform quality and determine if dispersion extraction is feasible, and (2) to measure group velocity dispersion from good quality waveforms. To address the first task, DisperPy uses a convolutional neural network based on the ResNet-34 archi-

texture. For the second task, DisperPy relies on a combination of different unsupervised machine learning algorithms. We carry out a surface wave tomography experiment across the contiguous United States to further test DisperPy, resulting in a total of 194,325 group velocity dispersion curves extracted from broadband vertical component waveforms. Consistent with previous studies, our maps reveal a prominent velocity dichotomy, with low velocities in the tectonically active western US and high velocities in the stable central and eastern US. In our third study, we turn our attention back to South America and explore an important and yet overlooked property of the lithosphere: anisotropy. Radial anisotropy studies are complementary to isotropic seismic velocity studies, and can provide additional insights into past and present deformation and flow. Using DisperPy, we build a data set consisting of 255,292 Rayleigh and 75,843 Love wave group velocity dispersion curves from both earthquakes and cross-correlations of ambient noise between pairs of sensors. The usage of ambient noise curves allows us to better constrain shallower structure. We invert this data set to construct independent vertically and horizontally polarized shear-wave velocity models, and the difference between them gives us access to radial anisotropy. Our model reveals a very anisotropic crust (and especially shallow upper crust) and a more homogeneous upper mantle, mostly characterized by positive radial anisotropy. We suggest that a large component of the shallow radial anisotropy might be related to shape preferred orientation caused by alignment of heterogeneous material related to the Paraná and Central Atlantic Magmatic Provinces.

Keywords: Surface waves; Cratons; Group velocity; Shear-wave velocity; South America; Machine learning; Python; Radial anisotropy; Earthquakes; Ambient noise; Lithosphere.

Resumo

Os avanços científicos apresentados nesta tese são resultado de esforços para medir e inverter dados de dispersão de ondas de superfície para imagear a estrutura sísmica da litosfera sob a América do Sul. Nossas descobertas são apresentadas em três estudos distintos. O primeiro deles apresenta um modelo de velocidade de ondas de cisalhamento obtido pela inversão de 26.984 curvas de velocidade de grupo de ondas Rayleigh do modo fundamental, com períodos entre 9 e 180 s. A interpretação desse modelo é focada na estrutura cratônica abaixo da América do Sul. Para o cráton Amazônico, o corte de velocidade em 150 km de profundidade apresenta uma correlação geral com idades geocronológicas de províncias, exceto na província Maroni-Itacaiúnas, onde é levantada a hipótese que os eventos intraplaca tectono-termiais K'Mudku do Mesoproterozoico e/ou o magmatismo volumoso da Província Magmática do Atlântico Central (após a ruptura da Pangeia) são candidatos para explicar a diminuição de velocidade e consequentemente a quebra na correlação entre velocidades e idades. O modelo também é consistente com um paleocontinente São Francisco que engloba tanto o atual cráton do São Francisco quanto partes dos cinturões Brasília e Araçuaí. Alguns autores sugerem que essa extensão é válida também para a província da Borborema; entretanto, as baixas velocidades mostradas pelo modelo para profundidades maiores que 70 km sugerem afinamento litosférico, algo que também é corroborado por outras evidências geofísicas e geológicas. Logo, uma possível raiz cratônica do paleocontinente São Francisco sob a província da Borborema provavelmente foi erodida. Finalmente, nosso modelo também mostra uma estrutura de alta velocidade sísmica na região do cráton Río de la Plata, consistente com estudos magnetotelúricos. Como medidas manuais de curvas de dispersão demandam muito e consomem bastante tempo, uma ferramenta para obter automaticamente mais medidas de dispersão para melhorar os modelos é fundamental. Com isso em mente, nós desenvolvemos e apresentamos a ferramenta DisperPy no nosso segundo estudo, uma biblioteca escrita em Python e baseada em algoritmos de aprendizado de máquina desenvolvida para extrair curvas de dispersão de velocidade de grupo de terremotos automaticamente. O arcabouço de análise do DisperPy visa resolver dois problemas principais: (1) avaliar a qualidade da

forma de onda e determinar se é possível extrair a sua respectiva curva de dispersão e (2) medir a curva de dispersão de velocidade de grupo de formas de onda com boa qualidade. Para lidar com o primeiro problema, o DisperPy usa uma rede neural convolucional baseada na arquitetura ResNet-34. Para o segundo problema, o DisperPy depende de uma combinação de diferentes algoritmos de aprendizagem de máquina não supervisionada. Um experimento de tomografia de ondas de superfície é realizado nos Estados Unidos contíguos para testar o DisperPy, resultando em um total de 194.325 curvas de dispersão de velocidade de grupo extraídas a partir de formas de onda de banda larga da componente vertical de sismogramas. Consistente com estudos prévios, os mapas mostram uma dicotomia de velocidade proeminente, com baixas velocidades na parte oeste tectonicamente ativa dos EUA e velocidades altas na parte estável central e leste dos EUA. No terceiro estudo, voltamos a atenção novamente para a América do Sul e exploramos uma importante, embora negligenciada, propriedade da litosfera: a anisotropia. Estudos de anisotropia radial são complementares aos estudos de velocidade sísmica isotrópica, e podem fornecer informações adicionais acerca de deformações atuais e passadas, além de fluxo. Usando o DisperPy, construímos um conjunto de dados de 255.292 e 75.843 curvas de dispersão de velocidade de grupo de ondas Rayleigh e Love, respectivamente, tanto de terremotos como de correlações cruzadas de ruído sísmico entre pares de sensores. O uso de curvas de ruído sísmico nos fornece vínculos mais fortes sobre a estrutura mais rasa. Invertemos esse conjunto de dados para construir de forma independente modelos de velocidade de onda cisalhante polarizados vertical e horizontalmente, e a diferença entre eles nos fornece a anisotropia radial. Nosso modelo revela uma crosta muito anisotrópica (e especialmente a crosta superior rasa) e um manto superior mais homogêneo, caracterizado principalmente por anisotropia radial positiva. Sugerimos que uma grande parte da anisotropia radial rasa possa estar relacionada à orientação preferencial causada pelo alinhamento de material heterogêneo relacionado às Províncias Magmáticas do Paraná e do Atlântico Central.

Palavras-chave: Ondas de superfície; Crátons; Velocidade de grupo; Velocidade de onda cisalhante; América do Sul; Aprendizado de máquina; Python; Anisotropia radial; Terremotos; Ruído sísmico; Litosfera.

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Chapter 1

Introduction

1.1 Motivation

Several Wilsonian orogenic cycles that occurred over billions of years shaped the present-day tectonic elements of South America, leading to a complex setting composed by cratons, mobile belts, intracratonic basins, exotic terranes, an active margin (the Andean chain), and large igneous provinces. Inferring the physical properties and spatial extension of such tectonic entities is essential to understand their origin and evolution. Seismic tomography is currently the main tool to probe the deep Earth by imaging distributions of seismic wave speeds from the crust to the lower mantle. However, determining the origin and evolution of large-scale geologic entities is no longer only a matter of pure research. For instance, [Hoggard et al. \(2020\)](#) have found the transition between thin and thick lithospheres to be a first order control on the location of deposits of sediment-based metals, and around 85% of deposits are located within 200 km of this transition. This implies that near-surface ore deposits are linked to processes that occur deep in the Earth, and thus determining physical properties from the deep Earth might aid to better choose targets for mineral exploration ([Hoggard et al., 2020](#)).

Surface waves have several intrinsic characteristics that make them well suited to investigate crustal and uppermost mantle structure: (i) they travel across the surface of the Earth, providing a good sampling with special importance in areas with scarce station and/or earthquake coverage ([Romanowicz, 2002](#)); (ii) they are usually the largest ampli-

tudes in seismograms because they are less affected by geometric spreading than body waves (Stein & Wysession, 2009); (iii) they present better vertical resolution in seismic tomography than body waves because they do not require nearly vertical upcoming rays to cross beneath the study volume, but instead have frequency-dependent speeds that are a nonlinear function of S-wave structure (Simons et al., 1999); (iv) they are dispersive signals in a seismogram, meaning that waves with distinct periods travel with different propagation speeds depending on Earth structure, and therefore surface waves in a single seismogram bring information related to several depths.

In fact, the first continental-scale tomography studies in South America and neighboring oceans relied on inversion of dispersion curves of surface waves (Silveira et al., 1998; Vdovin et al., 1999; Feng et al., 2004, 2007; Heintz et al., 2005). If we do not consider global studies, these studies provided the first long wavelength images of the distribution of shear-wave velocities of the lithosphere beneath South America, where high-velocity anomalies in northern and central South America correlate with the positions of cratonic material, while a low-velocity anomaly belt correlates with the Andean belt in western South America. Despite their importance as pioneer seismic studies in South America, all these models were calculated prior to deployment of several stations of the Brazilian Seismographic Network (RSBR, Bianchi et al., 2018) and lack resolution, making it difficult to distinguish among all geological features in the onshore area of South America. However, this situation is now changing since 2020 with the advent of a new generation of continental tomography models (Celli et al., 2020; Ciardelli et al., 2022; Nascimento et al., 2024; Melo et al., 2025; Quadros et al., 2025). Even though these models were retrieved using different methodologies and datasets, they tend to agree on long and intermediate wavelength structure.

In addition to conventional surface wave tomography using data excited by earthquakes, since the pioneer studies in California by Shapiro et al. (2005) and Sabra et al. (2005), ambient noise tomography has established itself as one of the most important passive seismic methods for imaging distributions of velocities within the crust and upper mantle, with several papers published all around the world, including the United States (Bensen et al., 2008; Shen & Ritzwoller, 2016; Zhao et al., 2017), Europe (Yang et al., 2007;

Magrini et al., 2022a; Petrescu et al., 2024), Australia (Saygin & Kennett, 2010; Magrini et al., 2023) and China (Zheng et al., 2011; Shen et al., 2016; Peng et al., 2020), among others. In South America, studies that employ ambient noise as a source for imaging have been limited to specific study areas, including the Paraná basin (Shirzad et al., 2019, 2024; Moura et al., 2024), the Borborema province (Dias et al., 2015; Silva et al., 2021), and the Central Andes (Ward et al., 2013), so that a more comprehensive work across the whole continent is still lacking.

Ambient noise tomography relies on the cross-correlation of long “continuous” time series recorded by several pairs of receivers in order to reconstruct the empirical Green’s function (EGF) between them (e.g., Bensen et al., 2007), such that a dispersion curve can be extracted from the EGF relative to each pair of receivers; as a matter of fact, one can consider that one receiver acts as a virtual source (Curtis et al., 2006). Some of the advantages of virtual surface wave data derived from EGFs over typical earthquake data include: (i) retrieval of shorter periods (3 - 8 s), which provide better constraints on upper crust shallower structure; and (ii) improved azimuthal coverage, as the coverage is not attached to unevenly distributed earthquakes along plate boundaries, which can lead to improvements in resolution (Petrescu et al., 2024). However, earthquakes also have advantages over ambient noise, including an ease to cut and store data, a potential for retrieving dispersion curves from more source-receiver paths and most importantly, the sampling of longer periods, which probe deeper structure. Therefore, I argue that dispersion curves from EGFs and earthquakes are complementary and that by combining them, velocity models with better resolution can be achieved from the upper crust to the upper mantle.

Most of the previous tomographic studies performed in South America at large scale focused on retrieving and interpreting seismic velocities, which bring information on the thermal and chemical state of the Earth’s interior (e.g., Karato & Karki, 2001; Kaban et al., 2003), and less attention has been given to anisotropy. Seismic anisotropy refers to a directional change in seismic velocity as a function of propagation direction (azimuthal anisotropy) or polarization orientation (polarization anisotropy, only for shear waves) (Karato, 2008). Although more difficult to interpret compared with isotropic seismic

velocity, the computation of anisotropy can provide valuable additional constraints on past and present geodynamic processes within the Earth, especially information on flow and deformation.

Anisotropy arises from several physical mechanisms. Under a finite strain regime, plastic deformation mainly by dislocation creep can align the crystallographic axes of anisotropic minerals in a specific direction, leading to what is called lattice-preferred orientation (LPO) (Karato, 2008). This is the most significant cause of anisotropy in the upper mantle, as its main constituent minerals, such as olivine, orthopyroxene and clinopyroxene, are very anisotropic, showing P-wave velocity differences between the fast and slow axes larger than 10% (Montagner & Guillot, 2002). The lattice-preferred orientation of micas (Nishizawa & Yoshino, 2001) and amphiboles (Barberini et al., 2007; Tatham et al., 2008) is also thought to be the main factor for anisotropy in the mid and lower crust, respectively. Another class of anisotropy source, named shape preferred orientation (SPO), is associated with a preferential alignment of heterogeneous (isotropic or anisotropic) materials such as fractures, dykes, sills, and sedimentary layers (Crampin, 1981; Luo et al., 2013).

In South America, most of the information on the deep Earth's anisotropic character comes from shear-wave splitting studies. For instance, Assumpção et al. (2006, 2011) and Melo & Assumpção (2018) have proposed that lithospheric keels in the Amazonian craton, São Francisco craton and Paranapanema block are likely deviating mantle flow around them. From SKS splitting analysis, Bastow et al. (2015) reported low splitting times for most stations in the Borborema province and suggested several hypotheses to explain this seemingly lack of anisotropy, including little deformation of the mantle, poor backazimuthal distribution, and orthogonal fast axes describing the lithosphere and the asthenosphere, which counterbalance each other in the final observations.

Another class of information on anisotropic structure, known as radial anisotropy (or transversely isotropy with a vertical symmetry axis), is described by the difference in vertically (V_{sv}) and horizontally (V_{sh}) polarized shear waves, which are constrained by measurements of dispersion of Rayleigh and Love waves, respectively. In South America, radial anisotropy is still poorly constrained. Lynner et al. (2018) have mapped positive radial anisotropy in the Altiplano plateau at midcrustal depths and suggested that it

could be related to ductile deformation. Recently, [Poveda et al. \(2023\)](#) estimated both radial and azimuthal anisotropy beneath NW South America from analysis of ambient noise and earthquake dispersion curves. They found evidence for underplating beneath the Eastern cordillera from negative anisotropy at lower crustal depths, and also positive radial anisotropy characterizing sedimentary basins. Although these studies provide a view of the distribution of radial anisotropy beneath South America across a few smaller areas, a comprehensive, continental-scale study is still lacking.

Thus, motivated by the preceding discussion, I propose to derive new high-resolution models to constrain the three-dimensional shear-wave velocity structure of the South American lithosphere by inverting surface wave dispersion curves. Also, taking advantage of the Rayleigh-Love wave discrepancy, I propose to construct a new model for radial anisotropy beneath the continent. The combination of dispersion measurements obtained from ballistic waves (earthquakes) and seismic ambient noise is expected to provide better results than relying on one class of measurements or another, hence leading to models with improved resolution. Finally, as I will require many measurements of both Rayleigh and Love dispersion curves, I intend to create a new algorithm to extract group velocity from waveforms automatically, based on machine learning approaches.

1.2 Objectives

The main goal of this study is to generate high resolution models constraining the distribution of shear-wave velocities and radial anisotropy within the lithosphere of onshore South America by inverting surface wave dispersion curves. Secondary aims include:

- To create a baseline dataset of Rayleigh dispersion using only manual measurements;
- To cross-correlate diffuse ambient noise across several pairs of stations in South America;
- To create an algorithm capable of automatically extracting thousands of dispersion curves;

- To generate frequency-dependent 2D Rayleigh and Love wave velocity maps;
- To assess model quality by performing several synthetic resolution tests;
- To compare with other models whether smaller-scale structure could be retrieved;
- To identify the architecture of radial anisotropy in the crust and uppermost mantle beneath South America;
- To extract the maximum information from the results and to propose plausible geologic/tectonic explanations for them.

1.3 Structure of the thesis

The main contributions of this thesis are presented into three scientific papers. Chapter 2 (paper I), the first product derived during the present project, presents a baseline shear-wave velocity model derived solely from inversion of (manually measured) earthquake Rayleigh wave dispersion curves. The interpretations are focused on the cratonic features of South America, that is, the Amazonian, São Francisco, and Río de la Plata cratons, besides possible cratonic blocks concealed under the Parnaíba and Paraná basins. The content in Chapter 2 has been published in *Tectonophysics* ([Nascimento et al., 2024](#)). In Chapter 3 (paper II), I develop a new algorithm based on machine learning to automatically extract group velocity dispersion curves from waveforms, and I use it to image Rayleigh wave maps across the contiguous United States; these maps are based on nearly 200,000 dispersion curves. In Chapter 4 (paper III), using the algorithm presented in paper II, I build a comprehensive dataset of Rayleigh and Love wave group velocity dispersion curves from earthquakes and EFGs and use it to compute the first continental scale distribution of radial anisotropy beneath South America, up to 100 km depth. Finally, Chapter 5 presents a conclusion that wraps together all the main findings of papers I, II and III.

Chapter 2

Unraveling Precambrian cratonic roots beneath South America: A contribution from surface wave tomography

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Outline

In the present chapter, I present an article with a shear-wave velocity model for the lithosphere beneath South America derived solely from inversion of fundamental mode group velocity dispersion curves of ballistic Rayleigh waves. The interpretations discussed here are focused around the large-scale Precambrian cratonic roots of the South American Platform: the Amazonian, São Francisco, and Río de la Plata cratons. The material in this chapter is published as [Nascimento et al. \(2024\)](#).

Abstract

We examine some aspects of the tectonic evolution of Precambrian cratonic roots beneath South America based on lithospheric distribution of shear-wave velocities. We derive our model by inverting 26,984 fundamental mode Rayleigh wave group velocity dispersion curves, at periods of 9–180 s. We first regionalize our measurements and then invert the result for a 3D S-wave velocity model extending to 200 km depth. Fast velocities beneath the Amazonian and São Francisco cratons, and beneath buried cratonic units in the Parnaíba and Paraná basins, are long wavelength features consistent with previous tomography studies. For the Amazonian craton at 150 km depth, we find an increase of velocities with province age, except for the Maroni-Itacaiúnas province, where we hypothesize that K'Mudku intraplate tectono-thermal events at the middle-late Mesoproterozoic and emplacement of a large igneous province following the breakup of Pangea could have altered at least partially its lithosphere. Our results are consistent with a São Francisco paleocontinent whose borders extend beyond the surface limits of the present São Francisco craton into the neighboring Araçuaí and Brasília belts. Based on slow shear-wave velocities in the upper mantle beneath the Borborema province, consistent with lithospheric thinning, we argue that a possible cratonic root of the São Francisco Paleocontinent beneath this province has likely been eroded away. This analysis is further corroborated by tectonic events that led to the alteration of the Borborema mantle, including hydration in the Paleoproterozoic, rifting in the early-middle Tonian, reworking during Neoproterozoic Brasiliano events, and lithospheric stretching during the breakup of Pangea. Finally, we also image a fast shear-wave velocity structure in the region of the Río de la Plata craton, consistent with magnetotelluric studies.

Keywords: Precambrian cratonic roots; South America; Surface wave tomography; Amazonian craton; São Francisco paleocontinent; Río de la Plata craton.

2.1 Introduction

Cratons can be defined as the ancient nuclei of continents that have remained stable for hundreds of millions of years. The factors that keep large portions of the lithosphere from being recycled back into the convective mantle are still widely discussed: physical properties such as mantle neutral buoyancy caused by chemical depletion (Jordan, 1978; Lenardic et al., 2003), high viscosity (Lenardic et al., 2003), high integrated yield strength (Cooper et al., 2006), and thick lithosphere to a certain threshold (Bedle et al., 2021; Cooper & Conrad, 2009) are typically ascribed as conditions for craton stability. However, some phenomena may alter these properties and lead to decratonization, such as plume induced thermomechanical erosion (Foley, 2008), rehydration and refertilization caused by subduction at craton borders (e.g., Zhu & Xu, 2019) or magmatism (Lee et al., 2011; Bedle et al., 2021), and weakening by rifting (e.g., Ganade et al., 2021).

Moreover, reconciling all available rheological, seismic, geochemical, geophysical, geochronological, and heat flow data is a challenging task. Hypotheses that could explain, at least partially, the formation of cratonic keels during the Archean and early Proterozoic include plume models, in which keels are the residue of severe mantle depletion (Jordan, 1978; Boyd, 1989; Griffin et al., 2003; Arndt et al., 2009), and slab stacking models, in which keels are the result of progressive stacking of subducted oceanic lithosphere, followed by cooling (Helmstaedt & Schulze, 1989; Canil, 2004; Perchuk et al., 2020).

Seismic tomography is one of the main tools on which we rely to investigate present-day Earth's deep interior and has provided distributions of seismic velocities representative of active and stable tectonic scenarios. Archean cratons are generally imaged in global and regional tomography as regions with fast velocity lithospheric lids (e.g., Ekström et al., 1997; Ritsema & van Heijst, 2000; Feng et al., 2007; Schaeffer & Lebedev, 2013; Koelemeijer et al., 2016; Ciardelli et al., 2022). Regional seismic tomography can be performed using body and/or surface wave travel times. Surface wave travel times are sensitive to frequency-dependent kernels in such a manner that high frequencies sample shallower depths, and these kernels imply that, in theory, surface waves present better vertical resolution than teleseismic body waves, whose sensitivity is spread along nearly vertical incoming rays

([Simons et al., 1999](#)).

South America provides an interesting and intricate tectonic/geologic environment to be investigated, with distinct geologic entities such as Proterozoic cratons, Paleozoic synclises, complex mobile belts, large igneous provinces, and an active tectonic margin. In this study, we present a crustal and uppermost mantle shear velocity model for South America derived from surface wave tomography, in which we seek to image the expression of Precambrian roots underneath the continent with increased resolution due to the deployment of several new stations, mainly in Brazil ([Bianchi et al., 2018](#)).

2.2 Geologic setting of South America

South America can be separated into three main parts: the tectonically active Andean mountain chain along the western border, the Patagonian block in the southern portion, and the relatively stable South American Platform occupying the rest of the continent ([Almeida et al., 2000](#)). The main tectonic elements of South America are shown in Fig. 2.1.

Present-day Andes are the product of the interaction of the Nazca, Caribbean, Antarctica, and Scotia plates with the western border of the South American plate, but their origin is closely related to the onset of subduction along the Pacific Ocean margin after the breakup of Rodinia and can be traced back to the former Terra Australis Orogen ([Cawood, 2005](#)), a larger Neoproterozoic/Late Paleozoic accretionary orogen following the margin of Gondwana. When compared with the South American Platform, consolidated in Neoproterozoic times, the Patagonian block, consolidated in the Paleozoic, presents important differences that led workers to propose that it is a terrane with distinct origins from the rest of the continent. Whether it has an autochthonous or an allochthonous origin has long been a matter of debate (see [Ramos et al., 2020](#), for a review), but nowadays there is a consensus favoring the accreted terrane hypothesis, that is, favoring allochthony ([Ramos et al., 2020](#)).

[Brito Neves & Fuck \(2014\)](#) proposed to divide the basement of the South American Platform into two distinct domains, separated by the Transbrasiliano and the Araguaia lineaments: the Amazonian domain to the N-NW of these lineaments, and the Brasil-

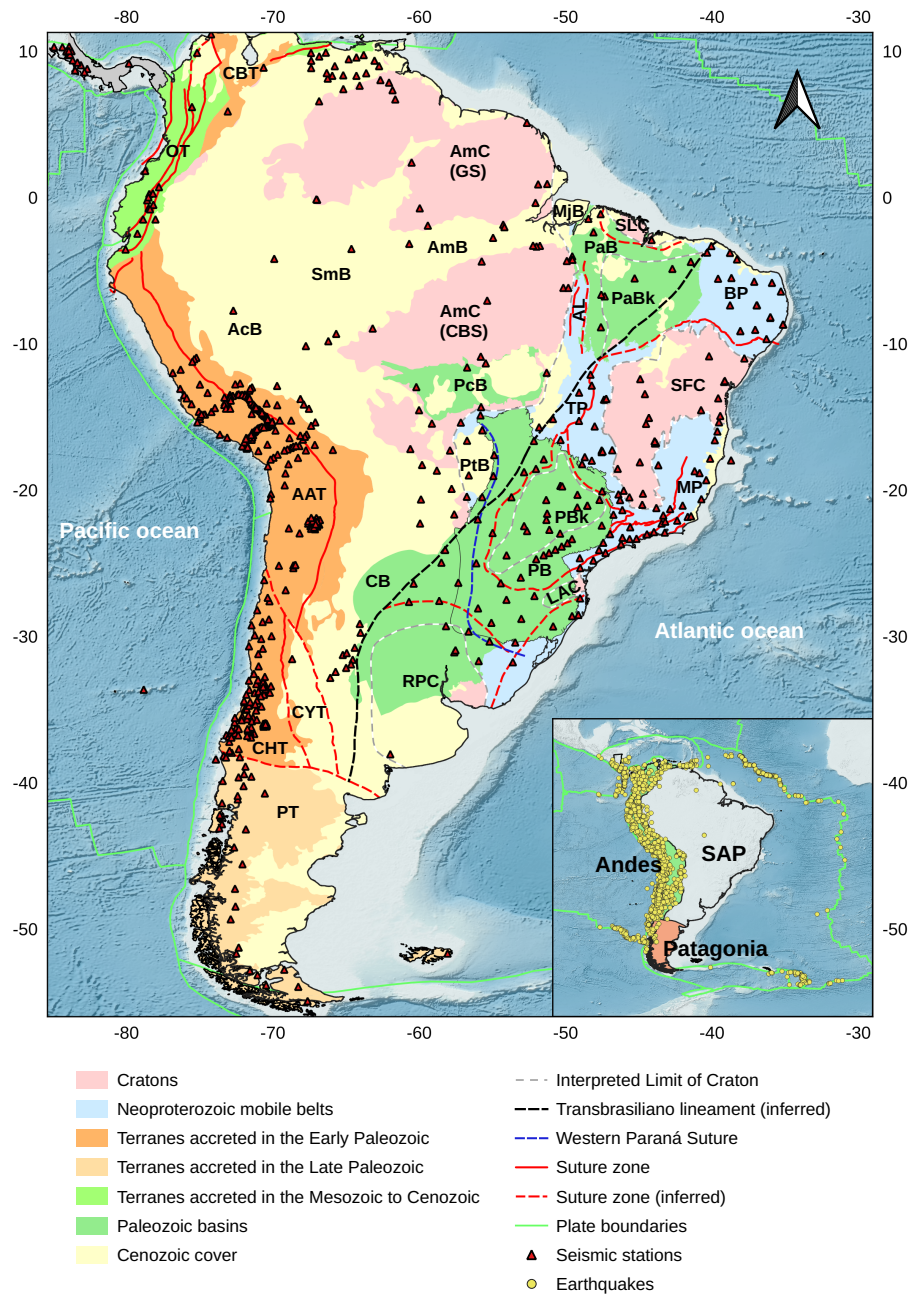


Figure 2.1: Main tectonic elements of South America (modified after [Cordani et al., 2016](#)). The labeled elements are the Amazonian (AmC), São Francisco (SFC), Rio de la Plata (RPC), São Luis (SLC), and Luis Alves (LAC) cratons; the Central Brazil (CBS), and Guyana (GS) shields; the Parnaíba (PaBk), and Paranapanema (PBk) blocks; the Borborema (BP), Tocantins (TP), and Mantiqueira (MP) provinces; the Amazonian (AmB), Solimões (SmB), Acre (AcB), Marajó (MjB), Parecis (PcB), Parnaíba (PaB), Pantanal (PtB), Paraná (PB), and Chaco-Paraná (CB) basins; the Patagonia (PT), Cuyania (CYT), Chilenia (CHT), Arequipa-Antofalla (AAT), Oceanic (OT), and Chibcha (CBT) terranes; the Araguaia Lineament (AL); the South American Platform (SAP).

iano (or Atlantic) domain to the E-SE. In the Amazonian domain, NNW-SSE Paleo- and Mesoproterozoic mobile belts circumscribe the central-eastern Archean nuclei ([Cordani & Teixeira, 2007](#); [Brito Neves & Fuck, 2014](#)). The Amazonian domain is represented by the Amazonian craton (AmC), which encompasses two shields separated by the Amazon, Solimões and Acre Phanerozoic basins along the E-W axis: Central Brazil (or Guaporé) shield to the south and Guyana to the north. A crucial difference between the Amazonian and Brasiliano domains is that while Neoproterozoic events of the Brasiliano orogeny were of only secondary importance to the Amazonian domain, the Brasiliano domain was strongly shaped by the Brasiliano orogeny ([Brito Neves & Fuck, 2014](#)). In the Brasiliano domain, the Neoproterozoic orogenic belts that make up the Tocantins province in central Brazil, the Borborema province in northeastern Brazil, and the Mantiqueira province along the Brazilian continental margin (toward the South Atlantic Ocean), separate the cratonic areas, more specifically, the São Francisco (SFC), Río de la Plata (RPC), and the smaller São Luís and Luís Alves cratons ([Brito Neves & Fuck, 2014](#)).

2.3 Data and group velocity measurements

Our S-wave velocity model is derived from a two-step inversion procedure of fundamental mode Rayleigh wave group velocity dispersion curves, with periods ranging between 9 and 180 s. We generated a new dataset constraining the South American continent by merging previous measurements by [Nascimento et al. \(2022\)](#) and [Feng et al. \(2004\)](#). In addition, we measured group velocities from new paths with epicenters near the South Sandwich Islands to improve azimuthal coverage (Fig. 2.2a), hence mitigating strong smearing effects in southern South America observed in the model of [Nascimento et al. \(2022\)](#). We also included dispersion curves from other stations not adopted in both studies, especially in the Andes, resulting in a total of 695 seismic stations and 2975 earthquakes. Fig. 2.1 shows the station distribution in South America over the tectonic elements of the continent, and Fig. 2.1 inset shows the distribution of earthquakes over the three main parts of South America. To minimize near-source effects and mitigate the interference from higher modes, we only used measurements with epicentral distances >1500 km and $<10,000$ km (Fig. 2.2b).

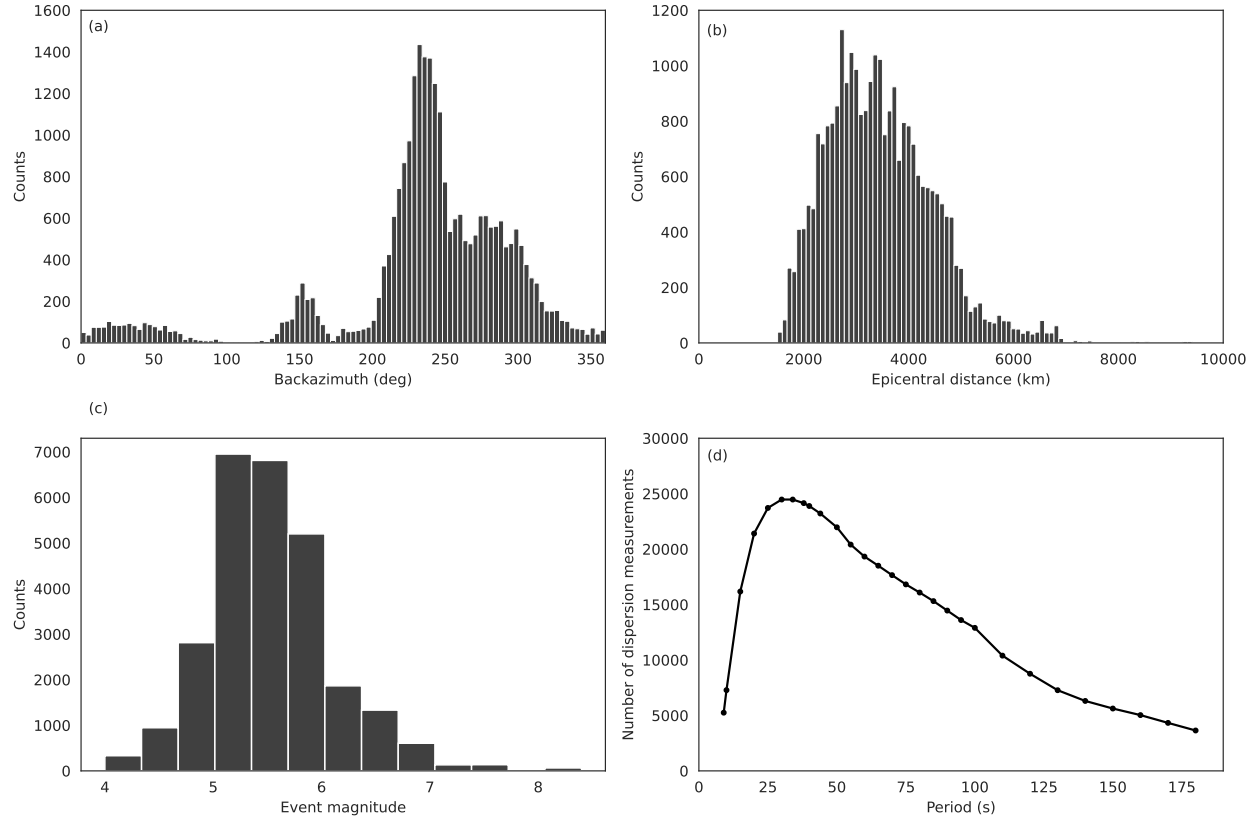


Figure 2.2: (a) Azimuthal distribution of the 2975 earthquakes recorded by 695 stations in South America. (b) Histogram showing the distribution of source-receiver distances within the dataset. (c) Magnitude range of the selected earthquakes within the dataset. (d) Number of rays as a function of period.

Most of the magnitudes range between 5 and 6 (Fig. 2.2c). The new dataset has a total of 26,984 unique paths, representing an increase of about 51% compared with the number of rays measured by [Nascimento et al. \(2022\)](#), with a peak of 24,473 rays (Fig. 2.2d) for the period of 30 s. The maximum number of rays decreases for periods both shorter and longer than 30 s (Fig. 2.2d). Fig. 2.3 shows the distribution of rays across South America, sorted by wave period. We applied pre-processing procedures, as in [Nascimento et al. \(2022\)](#), to each seismogram and then measured Rayleigh wave dispersion curves by manually picking a dispersion image generated using the Computer Programs in Seismology of [Herrmann \(2013\)](#).

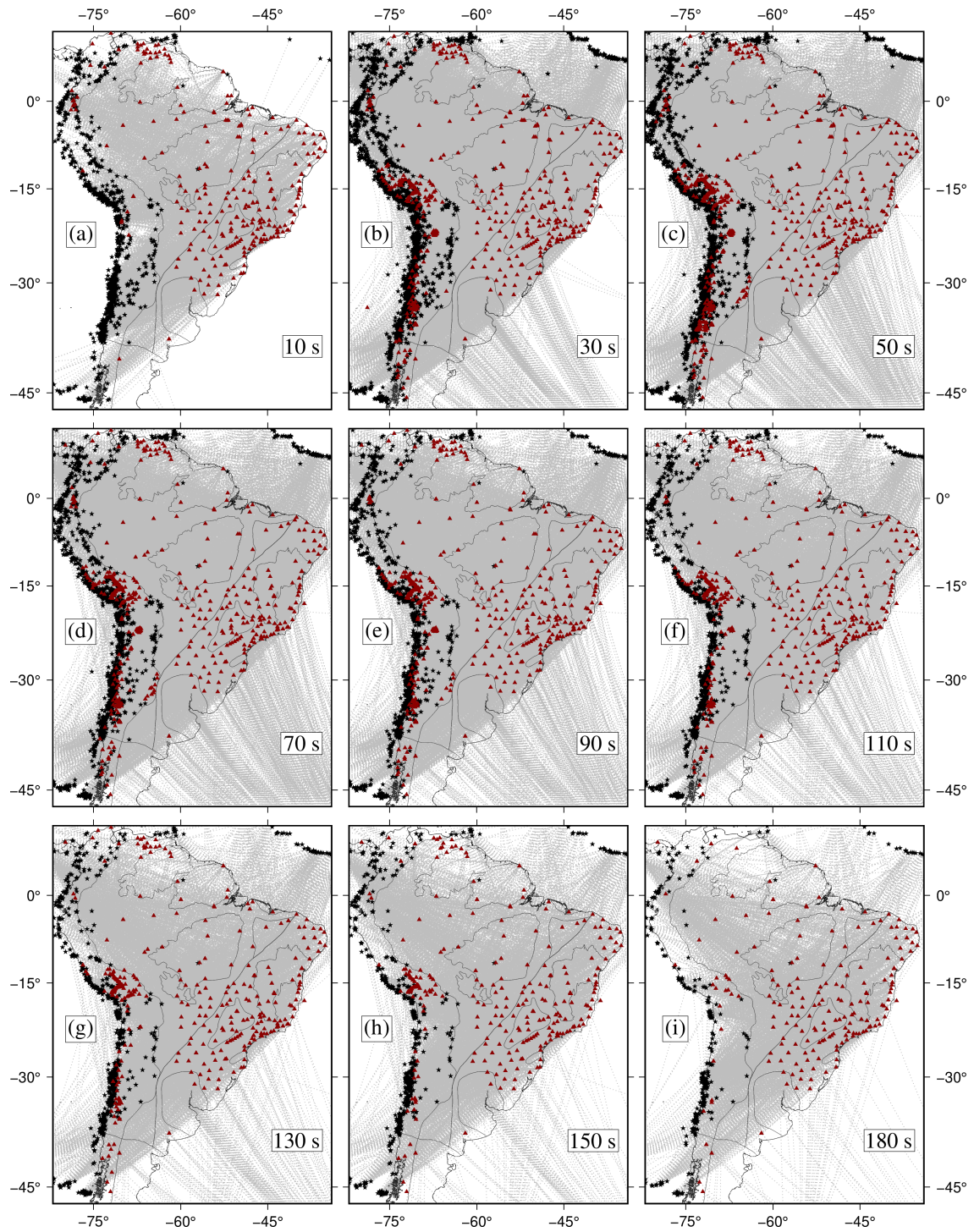


Figure 2.3: Distribution of seismic stations, earthquakes and rays used to constrain group velocities at periods of (a) 10 s, (b) 30 s, (c) 50 s, (d) 70 s, (e) 90 s, (f) 110 s, (g) 130 s, (h) 150 s, and (i) 180 s.

2.4 Rayleigh wave group velocity maps

In this section, we estimate the lateral variation of Rayleigh wave group velocities in the period range 9–180 s in South America based on our dispersion measurements. Section 2.4.1 describes our strategy, and Sections 2.4.2 and 2.4.3 show the results and their resolution, respectively.

2.4.1 Regionalization

The first step of our inversion strategy consists of constructing group velocity maps for each period, from 9 to 180 s, a process known as regionalization. To invert our group velocity measurements for lateral variations in Rayleigh wave velocity we adopted SeisLib ([Magrini et al., 2022b](#)), an open-source Python package that employs a linearized least-squares imaging algorithm ([Boschi & Dziewonski, 1999](#)), which relies on ray theory. Initially, at each period we discretized the velocity structure beneath South America into an equal area parameterization with a cell size of 1° by 1° . As SeisLib allows for adaptive regularizations (e.g., [Bijwaard et al., 1998](#)) dependent upon heterogeneous sampling, we refine our initial parameterization by splitting each block sampled by at least 150 rays into four $0.5^\circ \times 0.5^\circ$ sub-blocks, thus yielding a finer resolution over better-sampled blocks. Fig. S1 in the Supplementary File shows the final parameterization at each period, which is generally denser in SE Brazil.

Assuming that surface waves propagate along the great circle path between any two points on Earth surface and a parameterization grid with n blocks with constant slowness representing it, the forward equation (in discrete form) for the average slowness between these two points is given by ([Magrini et al., 2022b](#)):

$$s = \frac{1}{L} \sum_{k=1}^n s_k l_k \quad (2.1)$$

where s_k is the slowness of the k th block, l_k is the segment of the great circle path within block k and L is the length of the great circle path. If we have m observations, a convenient way to relate observables (path average slownesses) to model parameters (slowness of each parameterization block) is to construct a linear system by defining a matrix $A_{m \times n}$, which

contains the segments of each great circle path within each block of the parameterization. Therefore, in matrix notation:

$$\mathbf{A} \cdot \mathbf{x} = \mathbf{d} \quad (2.2)$$

where $\mathbf{x}$ is the n vector of model parameters and $\mathbf{d}$ is the m vector of observables. The problem of solving Eq. 2.2 to find $\mathbf{x}$ given $\mathbf{d}$ is generally ill-conditioned, so additional regularization constraints are introduced to stabilize the inversion. SeisLib implements a roughness operator $\mathbf{R}$ that minimizes the roughness of the solution (Magrini et al., 2022b), such that the regularized least-squares inversion solution becomes (Magrini et al., 2022b):

$$\mathbf{x} = \mathbf{x}_0 + (\mathbf{A}^T \cdot \mathbf{A} + \mu^2 \mathbf{R}^T \cdot \mathbf{R})^{-1} \cdot \mathbf{A}^T \cdot (\mathbf{d} - \mathbf{A} \cdot \mathbf{x}_0) \quad (2.3)$$

where $\mathbf{x}_0$ is an initial model close to the target model (we adopted the average Rayleigh group slowness at each period), and μ is a regularization coefficient that governs the roughness of the solution, which we chose using L-curves (Rawlinson & Sambridge, 2003, Fig. S2).

2.4.2 Group velocity maps

Fig. 2.4 presents the result of the application of the above procedure to our dataset of Rayleigh wave group velocity dispersion curves, at periods of 10, 30, 50, 70, 90, 110, 130, 150 and 180 s. In general, we find a good agreement between our regionalized maps and known surface geology features. For instance, the 10 s period map depicts a remarkable correlation between low group velocities and sedimentary basins, even in small-scale sedimentary basins, such as Pantanal (Assine et al., 2016) or Tucano-Jatobá (Ussami et al., 1986). Similarly, areas of shields and exposed crystalline basement are illuminated as fast group velocities, especially within the AmC and SFC.

A belt of slow group velocities marks the Andean range in the western boundary of South America at intermediate periods (30, 50 and 70 s). At longer periods (> 70 s) the seismic signature of the South American cratons becomes more evident, with the

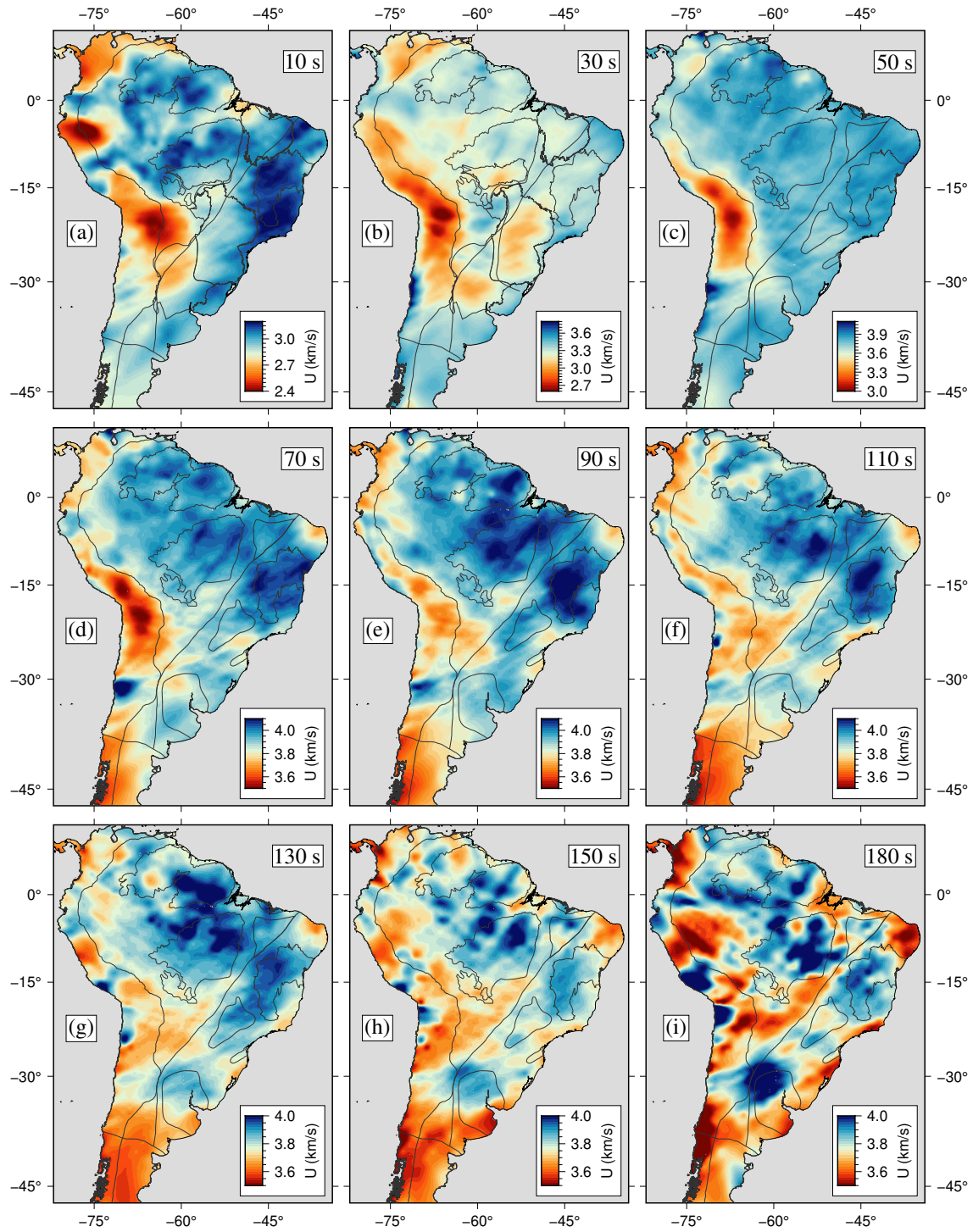


Figure 2.4: Rayleigh wave group velocity maps at periods of (a) 10 s, (b) 30 s, (c) 50 s, (d) 70 s, (e) 90 s, (f) 110 s, (g) 130 s, (h) 150 s, and (i) 180 s.

Amazonian, São Francisco and part of the Río de la Plata cratons showing prominent high velocities.

A direct interpretation of regionalized surface wave velocity maps is hampered by the fact that depths are not properly determined, so a second inversion of these maps for shear-wave velocity structure with depth is necessary. However, regionalized velocity maps are particularly useful for studies of joint inversion of receiver function and surface wave dispersion curves (Julia et al., 2000), which have become very popular worldwide (e.g., Li et al., 2008; Shen et al., 2013; Cedraz et al., 2020).

2.4.3 Resolution assessment

In this section, we qualitatively assess the spatial resolution of our model through synthetic tests, specifically checkerboard and spike tests at different periods. To generate our synthetic dataset for the checkerboard test, we calculate theoretical group slownesses of Rayleigh waves for the same source-receiver geometry as in observed data (Fig. 2.3), over a checkerboard pattern of velocities where a constant background velocity is perturbed by $\pm 10\%$. In order to simulate sources of error that are ubiquitous to observed data, the synthetic data are contaminated with 1% random noise prior to inversion. Following the procedure described in Section 2.4.1, we invert synthetic data using the same roughness coefficient μ as adopted in the inversion of actual observed data. Fig. 2.5 displays the result of such tests at periods from 10 to 180 s; the insets at the bottom right corner of each panel indicate the initial (target) model. As pointed out by [Lévêque et al. \(1993\)](#), a general idea in seismic tomography that can be misleading is that being able to retrieve small-scale structure implies long-scale structure being recovered as well, and so in the Supplementary Material we show additional tests (Figs. S3 and S4) where we constrain long wavelength structure with our source-receiver geometry.

Except in Patagonia, velocity anomalies in Fig. 2.5 are well recovered, attesting to the robustness of our model. A certain degree of smearing is observable at 10 s period, where azimuthal coverage is worst, and on all maps across southern South America, where there are fewer receivers. However, it should be stressed that the inclusion of new paths from

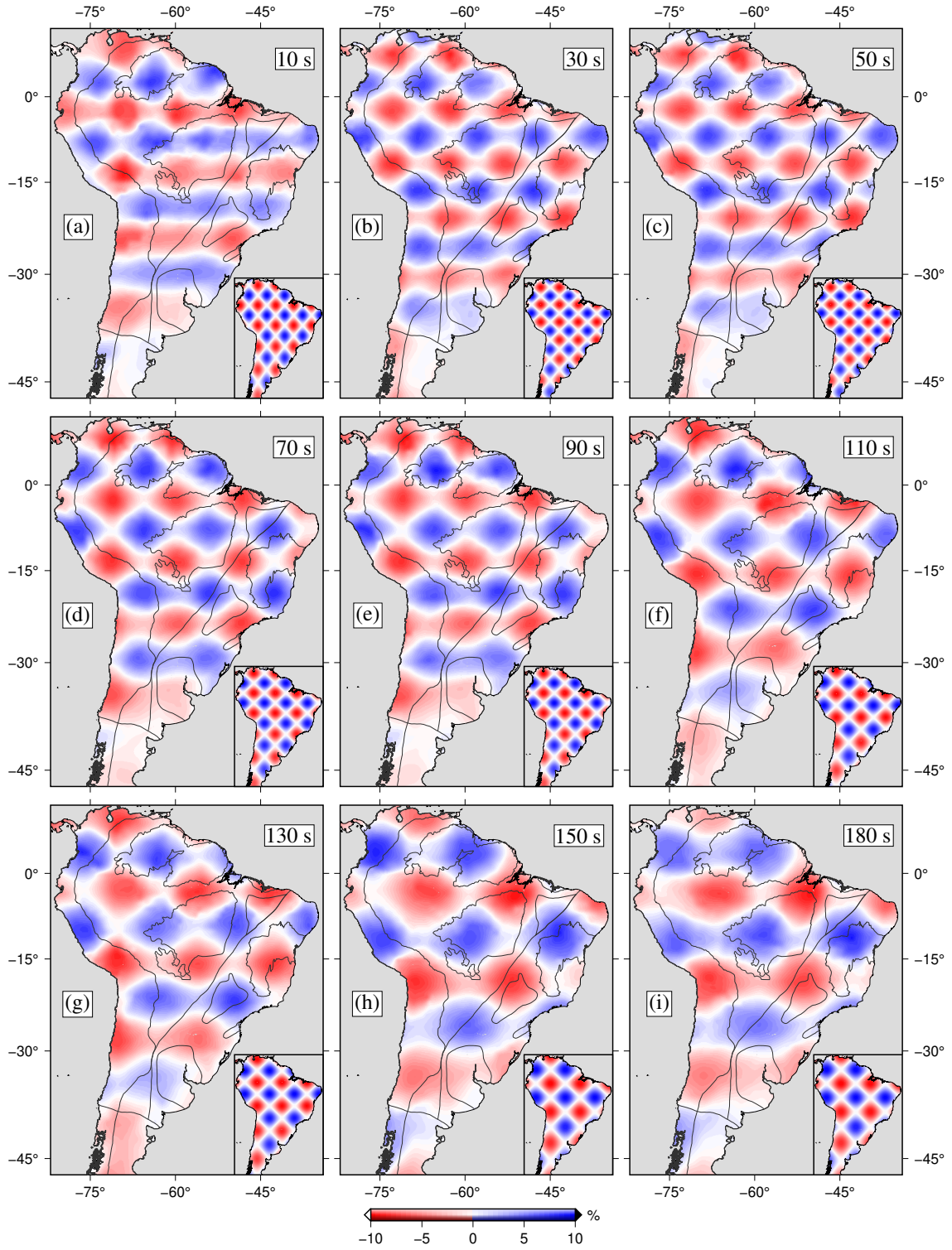


Figure 2.5: Checkerboard resolution tests of our group velocity maps, with perturbations of $\pm 10\%$, at periods of (a) 10 s, (b) 30 s, (c) 50 s, (d) 70 s, (e) 90 s, (f) 110 s, (g) 130 s, (h) 150 s, and (i) 180 s. The inset map in the bottom right corner of each panel represents the input velocity distribution that we aim to recover. Black lines indicate geologic elements shown in Fig. 2.5.

earthquakes with epicenters in the South Sandwich Islands, as previously mentioned, and the use of a parameterization adaptive to the data have mitigated smearing effects on our maps, in contrast with the group velocity maps of [Nascimento et al. \(2022\)](#). The maximum absolute amplitude of our retrieved maps is generally higher than 9%, and thus the overall amplitude loss is satisfactory, although it can be more significant in select regions. For the 10 s period map, however, we observe a stronger amplitude decrease in positive anomalies, where the maximum retrieved positive amplitude is about 8%.

To further investigate the ability of our dataset to constrain positive velocity anomalies beneath cratonic areas, we conduct a second suite of tests (spike tests) for long period waves (130, 150, and 180 s) that are sensitive to deep Earth structure and sample cratonic roots. We first generate a + 8% velocity perturbation over a constant velocity background at the expected positions of the AmC, SFC and RPC at the surface, and then we calculate synthetic data and invert them in the same way as for the checkerboard test. Fig. 2.6 shows that the spikes are robustly recovered for the AmC and SFC, and amplitude decrease is of the same order as for the checkerboard test. For the RPC, however, we note a significant decrease in amplitude, from 8% in the target to about 5–6% in the retrieved model. This implies that while our source-receiver geometry is able to detect a high velocity anomaly within the mantle in this area, it might be underestimated.

2.5 Shear-wave velocity model

We translate our Rayleigh wave group velocity maps to distribution of v_s as a function of depth using the surf96 routine implemented in the Computer Programs in Seismology ([Herrmann, 2013](#)). Section 2.5.1 is an overview of the method selected to invert surface wave velocity to shear- wave velocity and Section 2.5.2 presents the main features of our v_s model.

2.5.1 Inversion for S-wave velocity structure

Due to distinct ray coverage (Figs. 2.2d and 2.3), our parameterization varies for each period (Fig. S1), and thus we first interpolate our group-velocity maps into a regular grid

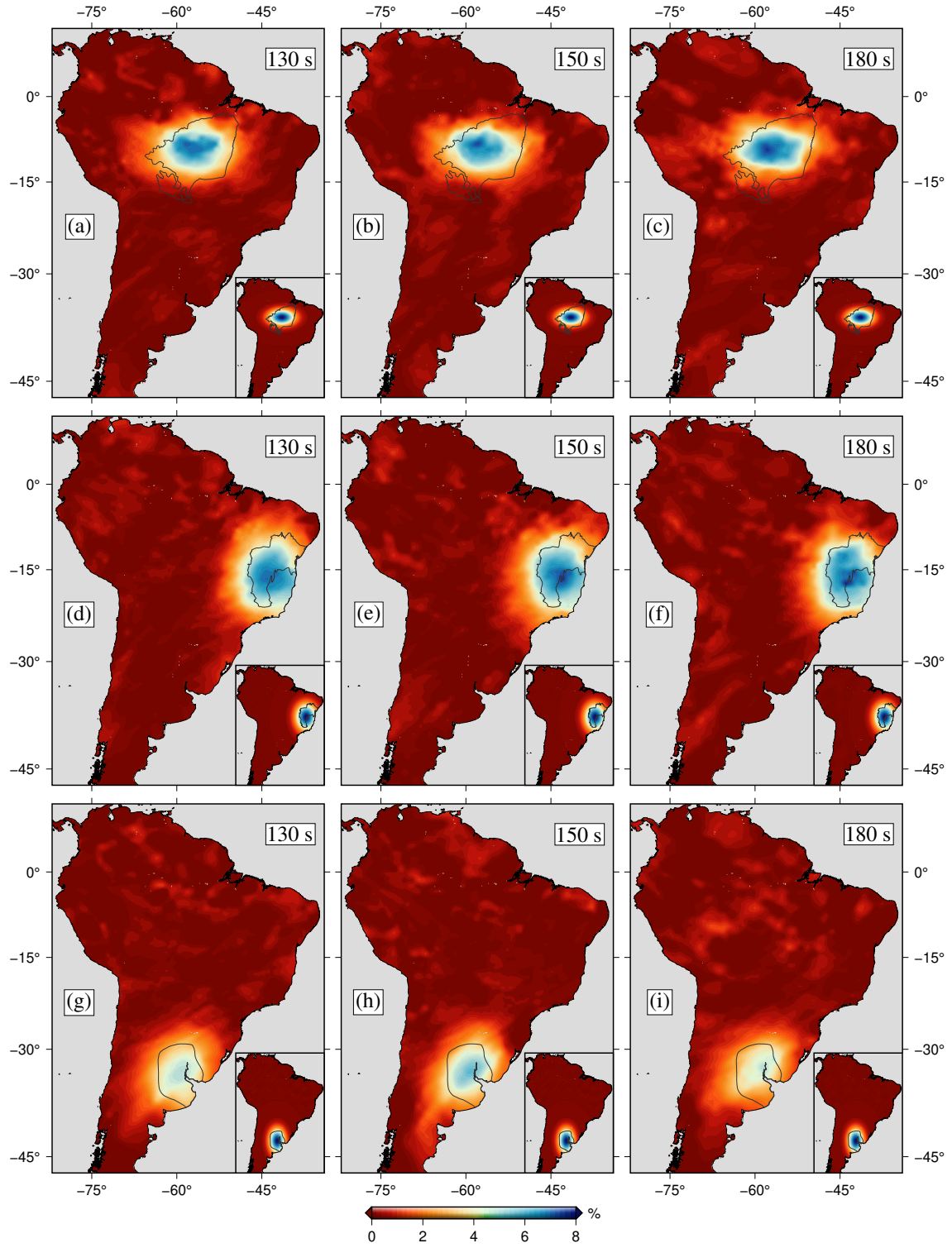


Figure 2.6: Spike tests at 130, 150, and 180 s showing how our source-receiver distribution would recover a + 8% velocity anomaly in the region of the Amazonian (a-c), São Francisco (d-f), and Río de la Plata (g-i) cratons. The inset map in the bottom right corner of each panel represents the input velocity distribution that we aim to recover.

of $0.5^\circ \times 0.5^\circ$, which is the same minimum grid spacing previously found in Section 2.4.1. Then, we extract regionalized dispersion curves at each grid node, which are used as input to the iterative linearized approach of [Herrmann & Ammon \(2002\)](#) to invert for 1D S-velocity depth profiles, that together compose our 3D model. The initial velocity model consists of a modified version of the AK135-F model ([Kennett et al., 1995](#); [Montagner & Kennett, 1996](#)), where structure at the upper 50 km is replaced by AK135-F values at 50 km depth, that is, velocities at crustal levels are made unrealistically high. This avoids inserting velocity bias from the initial model into the resulting model, namely, the sharp crust-mantle and upper-lower crust velocity contrasts at fixed depths, and therefore the data can change the model during each iteration. Although the sensitivity curve of fundamental mode surface waves becomes broader with increasing period, the period of 180 s is still sensitive to shear-wave structure at 200 km depth (Fig. S5), so this is the maximum depth that we choose to present our shear-velocity model. Finally, we conduct additional synthetic tests (Fig. S6) to evaluate the vertical resolution of our v_s model. These tests indicate that the inversion algorithm implemented in surf96 is able to satisfactorily retrieve input models in a variety of scenarios. For crustal structure, we observe that retrieved models can only recover a smoothed version of strong velocity discontinuities, and also that shallow layers (< 10 km) representing thick sedimentary basins might show overestimated velocity values because our minimum period is 9 s. Therefore, we only interpret structures deeper than 10 km. At mantle depths, the tests show that absolute velocity values might be slightly overestimated at depths > 130 km; this effect is stronger for mantle material with low-velocity anomalies. However, the method is able to distinguish fast from slow mantle.

2.5.2 Main features

Fig. 2.7 shows map views of our S-wave velocity model at depths from 10 to 200 km. Fig. 2.8 provides vertical cross-sections extending to 200 km depth, and to better distinguish lateral contrasts within the crust we additionally plot the same cross-sections using relative velocities, where anomalies are relative to the average continental S-wave velocity at each

depth. Due to poor coverage, oceanic areas have low resolution in our model. Therefore, to avoid the risk of misinterpretation, we mask the oceanic contribution in our figures, focusing our interpretation on the results obtained for the onshore area of South America.

Our results reveal that the main tectonic elements of South America, that is, the South American Platform, the Andean chain, and the Patagonian block, can be distinguished by their respective seismic velocity signatures, indicated by contrasts that are strongly marked, especially in the shallow crust.

Amazonian, São Francisco, and Río de la Plata cratons

At 10 km depth (Fig. 2.7a), our model depicts AmC and SFC as regions with fast S-wave speeds that correlate well with shields; in fact, the upper crust map has a strong correlation with surface geology, where the exposed crystalline basement has fast velocities in the upper crust, and areas with thick sedimentary covers (e.g., Paraná, Parnaíba, Amazon basins) have slow upper crust velocities. This could be an effect of profile smoothing during the 1D inversion (Fig. S6). Seismic refraction profiles in Brazil have shown that P-wave velocities in the upper crust range from 6.1 to 6.3 km/s with no systematic difference between shield regions and intracontinental basins (Berrocal et al., 2004; Lima et al., 2015; Soares et al., 2018; Bernardes et al., 2023). On the other hand, other shear-wave tomography studies using ambient noise (Shirzad et al., 2019) and Rayleigh wave phase-velocity (Quadros et al., 2024) have shown crustal S velocities in the Paraná and Parnaíba basins to be lower than the surrounding shield areas. For this reason, we believe our low v_s at 10, and especially at 30 km depth, reveal a real trend in the Paraná basin. Interestingly, the crustal low velocities in the Paraná and Chaco-Paraná basins are separated by relatively high velocities beneath the Western Paraná Suture (Dragone et al., 2021), a feature that was also observed by Shirzad et al. (2019) and Quadros et al. (2024).

Beneath the RPC, on the other hand, the fast velocity signal is masked by thick sediments of the Chaco-Paraná basin, but a faster velocity structure can still be seen along the continental margin, outside the surface boundary of the basin. The 10 km depth map is closely correlated with the 10 s period group velocity map in Fig. 2.4, which is also strongly influenced by surface geology.

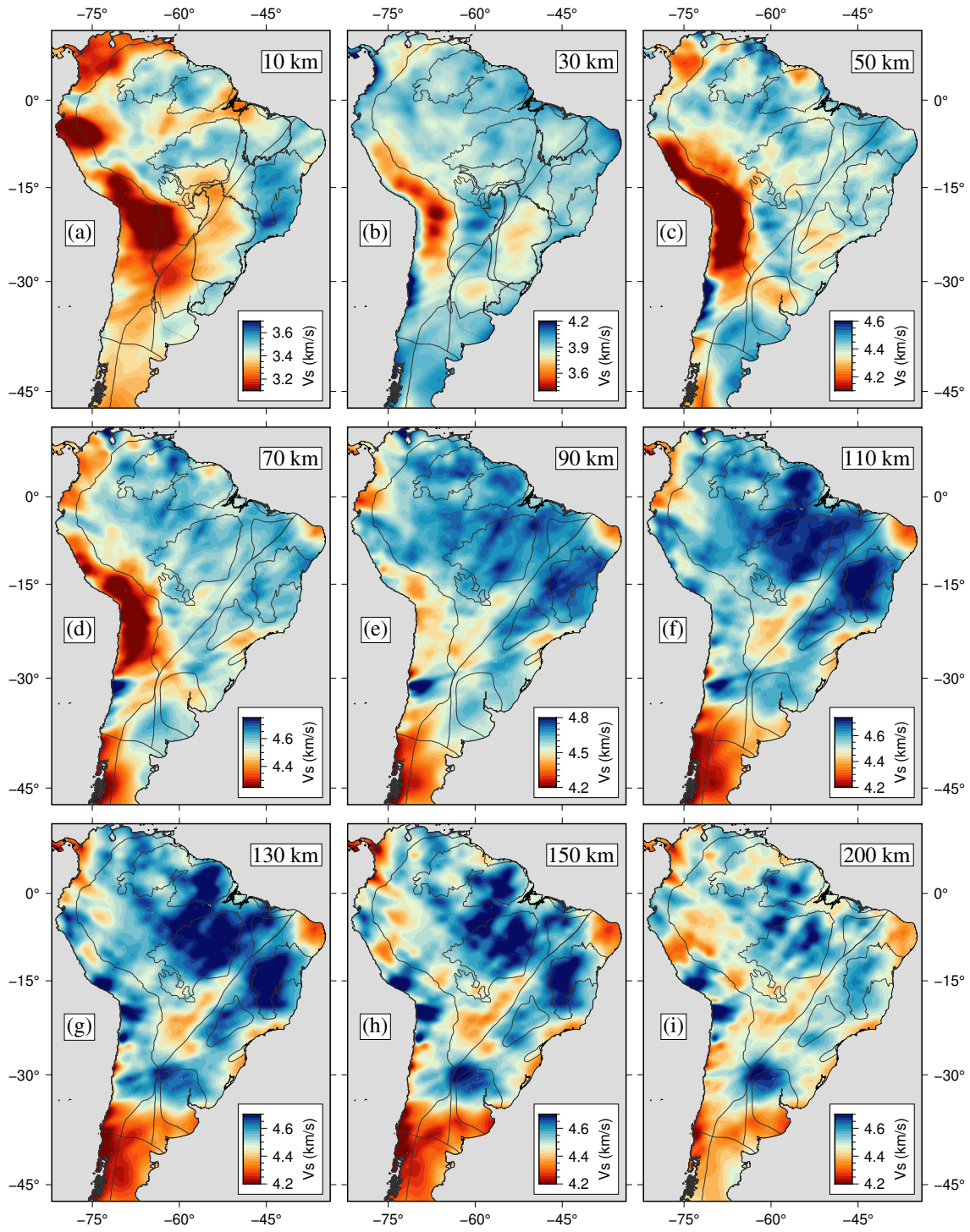


Figure 2.7: S-wave velocity slices at depths of (a) 10 km, (b) 30 km, (c) 50 km, (d) 70 km, (e) 90 km, (f) 110 km, (g) 130 km, (h) 150 km, and (i) 200 km. Black lines indicate geologic elements shown in Fig. 2.1.

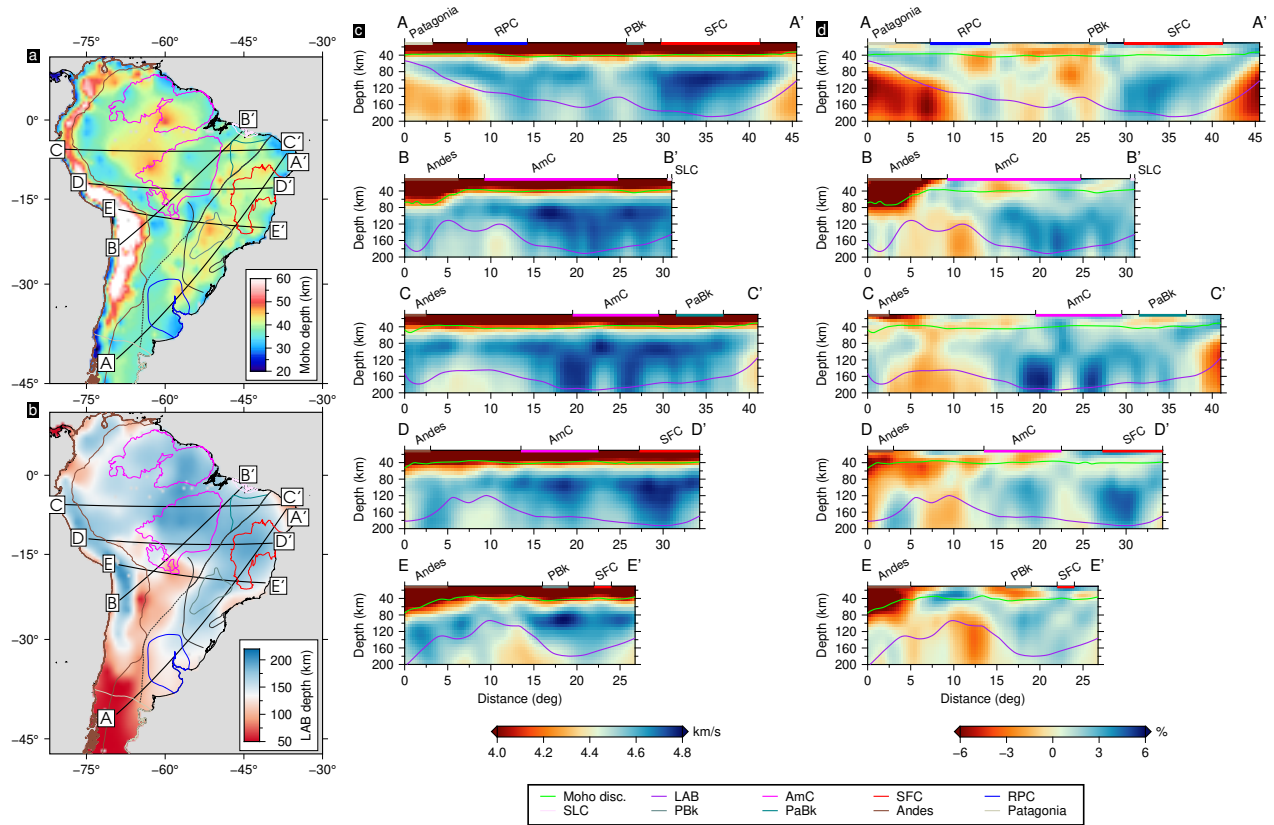


Figure 2.8: (a) Crustal thickness map of South America of [Rivadeneyra-Vera et al. \(2019\)](#). (b) Lithosphere-Asthenosphere boundary (LAB) depth from the global model CAM2016 ([Priestley et al., 2018](#)). Vertical cross-sections beneath five distinct profiles across South America are shown in (c) and (d) as absolute and relative velocities, respectively. Initial and final points of each profile are shown in (a) and (b). The green and purple curves in the profiles refer to the Moho and lithosphere-asthenosphere boundaries, respectively, extracted from (a) and (b).

At 30 and especially 50 km depth (Fig. 2.7b-c), the three cratons present heterogeneous velocities, which might characterize variable crustal thicknesses. Surface waves alone usually image sharp vertical velocity discontinuities as smooth curves (Supplementary Fig. S6). Hence, it is difficult to determine Moho depth accurately. However, absolute velocity profiles A-A' to E-E' (Fig. 2.8c) reveal a good correlation with the crustal thickness map of [Rivadeneyra-Vera et al. \(2019\)](#), which is shown in each profile as a green line. A brief look into the crustal section of the relative profiles (Fig. 2.8d) shows that there are strong lateral velocity heterogeneities within the crust across all profiles. A fast velocity between 30 and 50 km depth could indicate uppermost mantle velocities affecting the smoothed 1D inversion, i.e., regions with a thinner crust. Similarly, the low velocities at 30 and 50 km depth in the Paraná basin reflect a thicker crust (> 40 km, [Rivadeneyra-Vera et al., 2019](#)). Studies of receiver functions ([Albuquerque et al., 2017](#); [Rivadeneyra-Vera et al., 2019](#)) and gravity data ([Almeida et al., 2021b](#); [Lima et al., 2023](#)) indeed reveal a heterogeneous crustal structure beneath the AmC, which is probably related to the heterogeneous S-wave velocity distribution shown in Figs. 2.7b-c. Moho depth estimates by [Rivadeneyra-Vera et al. \(2019\)](#) (Fig. 2.8a) also point to a heterogeneous crustal structure beneath the SFC and RPC, but there is a gap in seismic stations in a significant portion of the area of these cratons.

At upper mantle depths (Figs. 2.7e-i), the three cratons exhibit, at least partially, roots with fast velocities, about 5–7% higher than upper mantle velocity from AK135-F. Yet being sampled by fewer rays crossing each other (Figs. 2.2d and 2.3), map views and vertical cross-sections sampling the depth range 150–200 km (Figs. 2.7h-i and 2.8c-d) reveal that fast S-wave velocities persist underneath the AmC, SFC and RPC, as expected for cratonic regions. For the AmC, fast velocities are more prominent along its eastern portion, correlating with its oldest geochronological provinces ([Tassinari & Macambira, 1999](#)). The SFC is underlain by a fast velocity structure up to 200 km depth, although a decrease in its amplitude is noticeable below 150 km depth. This structure includes a large fraction of the areas of the Archean Gavião, Jequié, and Serrinha blocks (e.g., [Barbosa & Sabaté, 2004](#)), located in northern and eastern SFC.

Only a few seismic stations are deployed within the inferred boundary for the RPC, which implies a remarkably low resolution in this area. Currently available tomography

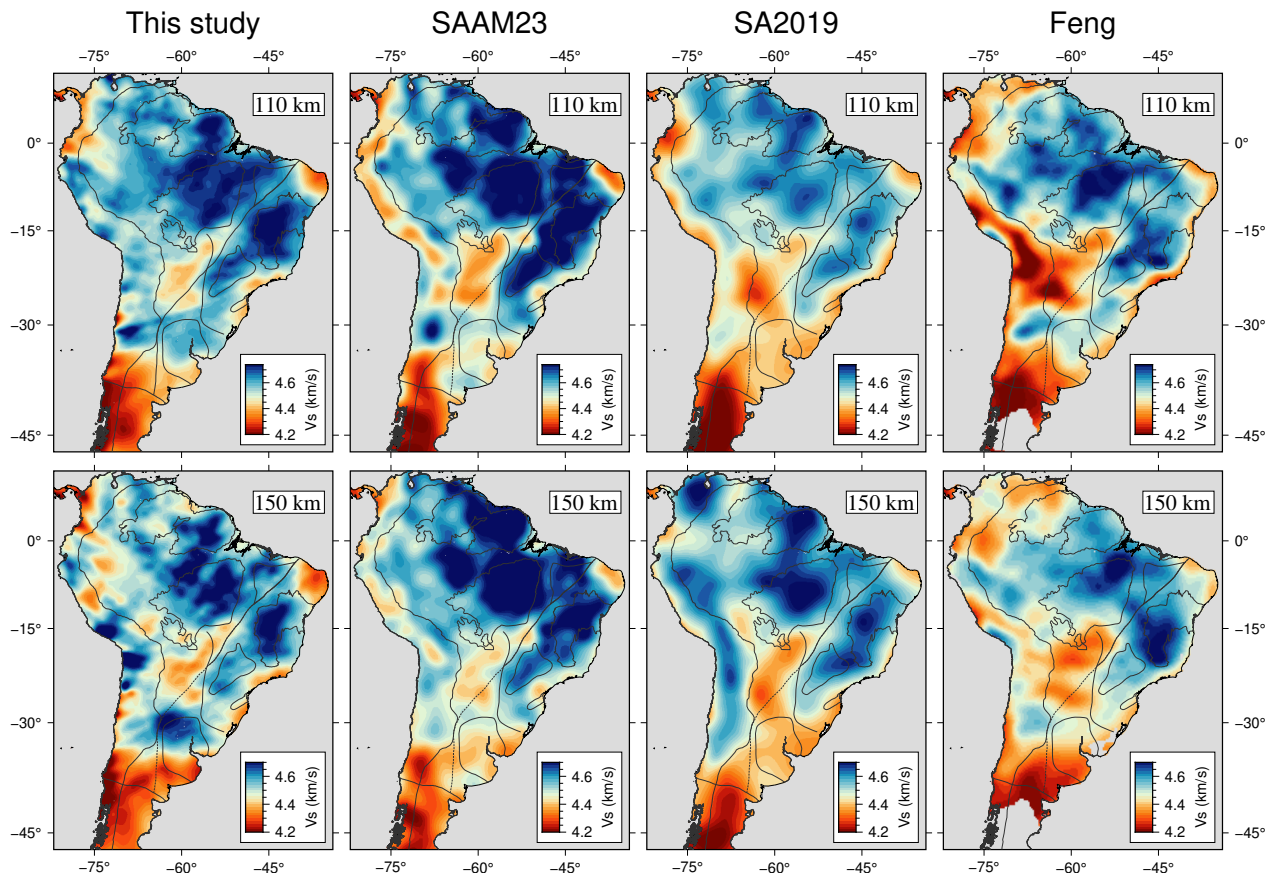


Figure 2.9: Comparison between our S-wave velocity model with tomographic models SAAM23 (Ciardelli et al., 2022), SA2019 (Celli et al., 2020), and the velocity model by Feng et al. (2007) at depths of 110 and 150 km.

models for South America (e.g., Feng et al., 2007; Celli et al., 2020; Ciardelli et al., 2022) image slow velocities within the RPC (see Fig. 2.9) that are usually not expected for a craton, and that are also inconsistent with a cratonic thickness of >200 km estimated from the magnetotelluric method by Bologna et al. (2019). Our model starts to reveal a fast velocity lithosphere beneath the RPC, at least in its northern half.

Inferred cratonic blocks

Blocks with cratonic properties have been proposed (e.g., Castro et al., 2014; Mantovani et al., 2005) to constitute the basement of the Parnaíba and Paraná basins, namely the Parnaíba and Paranapanema blocks, respectively. Thick sedimentary covers preclude direct observations, so indirect methods are better suited to investigate such geologic

features.

The Paranapanema and Parnaíba blocks are underlain by fast velocities that could be related to the presence of cratonic blocks. We observe at 150 km depth an approximately NE-SW fast velocity structure beneath the Paraná basin, partially persistent at 200 km depth, consistent with the P-wave tomography results of [Affonso et al. \(2021\)](#). Fast velocities for the lithosphere beneath the Parnaíba basin are also observed from 110 to 200 km depth (Fig. 2.7), although they do not conform to the triangular shaped basement proposed by [Castro et al. \(2014\)](#). These results are consistent with the models of [Celli et al. \(2020\)](#) and [Ciardelli et al. \(2022\)](#).

Neoproterozoic orogenic systems

The Neoproterozoic orogenic systems of the South American Platform, represented by the Borborema, Tocantins, and Mantiqueira provinces, have generally fast seismic velocities at 10 km depth (Fig. 2.7a). Within the lower crust (Fig. 2.7b), their seismic signature is relatively homogeneous, being difficult to distinguish them from the SFC. From ~70 km downwards (Figs. 2.7d-i, 2.8) all three provinces exhibit signs of lithospheric weakening/thinning in the form of slower velocities, especially the Borborema province in northeastern Brazil. Strong lithospheric thinning in the Borborema province was also observed by [Ciardelli et al. \(2022\)](#).

Andes

A notable crustal slow velocity belt marks the western active margin of South America, representing the Andes. This feature has an excellent agreement with the surface geology boundary down to ~70 km (Figs. 2.7b-d) but still can be observed at 90 km depth, probably due to vertical smoothing of dispersion inversions, as mentioned before. However, it is worth noting that crustal thickness in central Andes reaches values larger than 70 km ([Rivadeneira-Vera et al., 2019](#)). At 90 and 110 km, fast velocities are seen in Peru (~ 5° S) and Chile-Argentina (~ 33° S), corresponding to the two flat-slab segments of the Nazca plate (e.g., [Manea et al., 2017](#)). At 150 km depth, fast velocities are seen beneath the central Andes, a feature that is also present in the global model of [Schaeffer & Lebedev \(2013\)](#) but

was not retrieved by the Rayleigh wave group velocity maps of [Nascimento et al. \(2022\)](#) nor by the surface wave tomography model of [Feng et al. \(2007\)](#).

Patagonia

In our model, Patagonia has the lowest resolution (Fig. 2.5). In the central and southern portions of the Patagonian block, rays barely constrain our model (Fig. 2.3), and this precludes us from illuminating any smaller features in this region, such as the Somún Cura and Deseado massifs (e.g., [Ramos, 2008](#)). However, low velocities starting at ~50 km depth indicate a thin lithosphere beneath Patagonia and seem to be a reliable result, as profile A-A' (Fig. 2.8c) crosses a thin seismic lid beneath Patagonia that is very consistent with the lithosphere-asthenosphere boundary model of [Priestley et al. \(2018\)](#). Additionally, regional tomography models of South America agree on low velocities in Patagonia ([Feng et al., 2007](#); [Celli et al., 2020](#); [Ciardelli et al., 2022](#)).

2.6 Discussion

2.6.1 Comparison with previous velocity models

Tomography models for South America ([Ciardelli et al., 2022](#); [Celli et al., 2020](#); [Feng et al., 2007](#)) have been derived using different datasets and inversion schemes, but they all tend to agree with our model on long wavelength structure for the subcontinental lithosphere, as shown at depths of 110 and 150 km in Fig. 2.9. An aspect that attests the robustness of our model is that despite being derived using a more simple and less computationally demanding methodology, our model was able to image the same long wavelength features as the SAAM23 model of [Ciardelli et al. \(2022\)](#), calculated using adjoint tomography. Considering all models depicted in Fig. 2.9, commonly imaged features at 110 and 150 km depth include: (i) generally fast velocities under the South American Platform, namely the AmC, SFC, Paraná and Parnaíba blocks; (ii) slow velocities characterizing the Borborema province and to some degree the Brazilian coast, along which South America separated from Africa during the breakup of Pangea; (iii) an interesting

low velocity structure between the AmC, the RPC and the Paraná basin; (iv) slow velocities in Patagonia. All models present slight differences along the Andes. Quantitatively, to evaluate how similar our model is to the other ones presented in Fig. 2.9, we estimate the Pearson correlation coefficient between them. Averaged over the depths of 110 and 150 km, we find values of 0.77, 0.73, and 0.74 between our model and SAAM23 (Ciardelli et al., 2022), SA2019 (Celli et al., 2020), and the one by Feng et al. (2007), respectively. This high correlation, especially with the most recent model SAAM23, further corroborates our results.

Because we incorporated shorter periods, an advantage of our model over the ones previously mentioned is that it also provides the S-wave velocity distribution within the crust and uppermost mantle, allowing us to investigate the seismic structure of the continent more thoroughly, from the upper-middle crust to 200 km depth.

2.6.2 Seismic signature of the Amazonian craton

In the Amazonian craton, different boundaries and nomenclatures (e.g., Teixeira et al., 1989; Tassinari & Macambira, 1999; Santos et al., 2000; Teixeira et al., 2019) have been proposed for its geochronological provinces. Most of them build on the essential idea of a main eastern Archean cratonic nucleus bounded by Proterozoic mobile belts that were later cratonized (Cordani & Teixeira, 2007). Fig. 2.10 shows the geochronological provinces (Tassinari & Macambira, 1999) of the AmC overlaying our S-wave velocity model at depths of 30 (Fig. 2.10b), 90 (Fig. 2.10c), and 150 (Fig. 2.10d) km. Figs. 2.10e-f show velocity cross-sections across the Central Brazil and Guyana shields, respectively.

Compared with the Andes, shear velocities at 30 km depth for the AmC are faster, as found in Africa by Pasyanos & Nyblade (2007), where crustal shear velocities under cratons are generally faster than beneath orogens. Fig. 2.10b points to the existence of small-scale velocity heterogeneities within the AmC, especially when we consider the region overlaid by sedimentary basins (Parecis, Amazon, Solimões, and Acre basins). Correa et al. (2022) estimated the depth to the bottom of the magnetic layer underneath the Central Brazil shield between 10 and 80 km, supporting a variable temperature distribution either due to

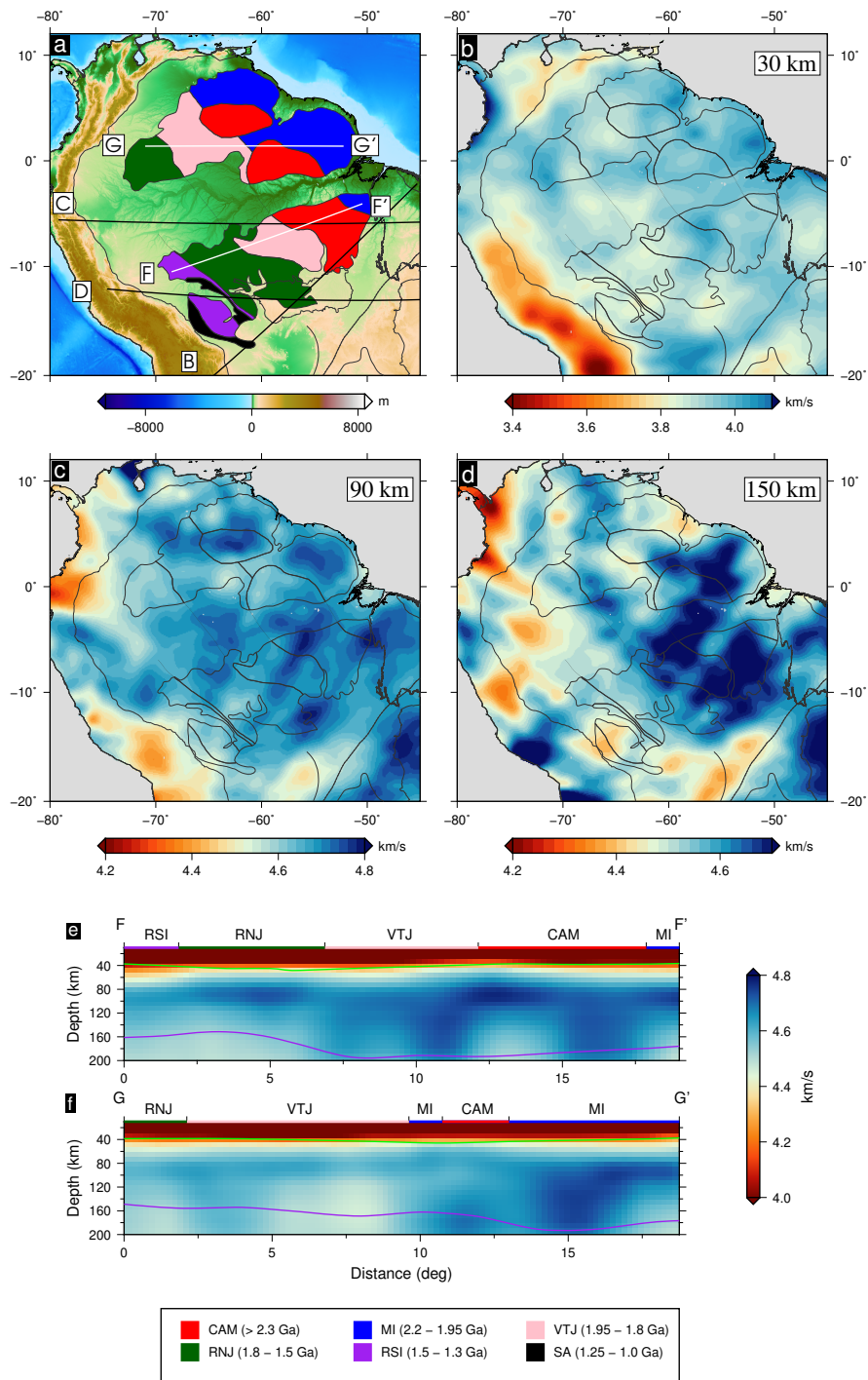


Figure 2.10: Geochronological provinces of the AmC, as proposed by [Tassinari & Macambira \(1999\)](#), overlaying the (a) ETOPO1 ([Amante & Eakins, 2009](#)) topography model and our S-wave velocity model at depths of (b) 30, (c) 90, and (d) 150 km. Panels (e) and (f) show velocity cross-sections across the Central Brazil and Guyana shields, respectively, at the positions shown by solid white lines in (a). Labeled acronyms stand for: CAM - Central Amazonian, MI - Maroni-Itacaiúnas, VTJ - Ventuari-Tapajós, RNJ - Rio Negro-Juruena, RSI - Rondonian San-Ignácio, and SA - Sunsas-Aguapéi provinces. Dotted lines indicate a possible extension of the provinces beneath the Phanerozoic basins. Solid black lines in (a) are the profiles shown in Fig. 2.8.

heat flow at the base of the lithosphere or due to the content of heat-producing elements in the crust. Therefore, it is challenging to discriminate compositional from temperature effects on crustal shear velocities, and a fast velocity at 30 km depth could be explained by, for example, low heat flow, underplating in the lower crust, or simply by a thin crust.

Relative shear velocity cross-sections that intersect the AmC (profiles B-B', C-C', and D-D' in Fig. 2.8d) reveal low-velocity anomalies at crustal levels below all intracratonic basins: profile C-C' shows that the Acre and Solimões basins are underlain by low-velocity anomaly crusts (to the west of the pink line segment indicating the AmC, that is, to the west of the exposed shield region), and profiles B-B' and D-D' show a comparable signature of the crust beneath the Parecis basin. In contrast, we observe high-velocity anomalies within the crust associated with regions where the crystalline basement of the AmC outcrops (profiles B-B' and C-C' in Fig. 2.8d). However, except for the southwestern tip of the AmC (see profile B-B'), regions beneath the sedimentary basins do not exhibit low mantle velocities suggestive of lithospheric thinning. This leads us to suggest that the tectonomagmatic processes responsible for the formation of these Paleozoic basins (e.g., [Almeida et al., 2000](#); [Milani & Zalán, 1999](#)) were of foremost importance in altering seismic properties of the crust under them but did not lead to a significant altering or weakening of the lithospheric mantle. In Fig. 2.9, none of the models show substantial differences at 150 km depth between Phanerozoic basins of the Amazonian domain and regions with exposed basement, except for the smaller Marajó basin (at the mouth of the Amazon River).

Following [Ciardelli et al. \(2022\)](#), we investigate whether there is a correlation between geochronological provinces (that is, ages) and the distribution of S-wave velocities in our model by plotting them in Fig. 2.11. We verify this behavior for the crust and the subcontinental lithospheric mantle, finding that the correlation between ages and shear velocities is somewhat disrupted in the Central Amazonian province at crustal levels and in the Maroni-Itacaiúnas province at 150 km depth.

In the Central Brazil and Guyana shields, Fig. 2.11a shows that the slowest velocities at 30 km depth are under the youngest geochronological provinces of the AmC, Sunsás-Aguapeí (1.25–1.0 Ga) and Rondonian San-Ignácio (1.5–1.3 Ga). During the formation of these provinces, the more dominant accretion and soft-collision processes across the

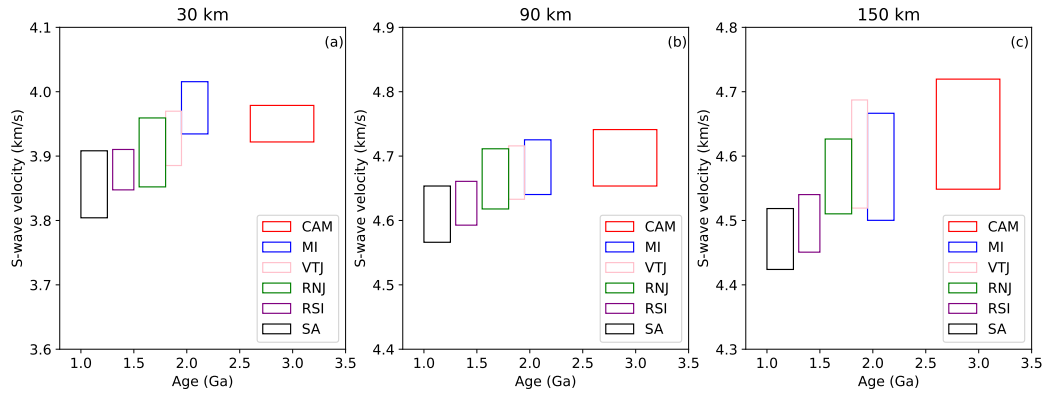


Figure 2.11: Distribution of S-wave velocities beneath the AmC sorted by geochronological provinces at depths of (a) 30, (b) 90, and (c) 150 km. The height of each box is equal to the corresponding average velocity $\pm$ one standard deviation. Velocities beneath the Marajó, Amazonas, Solimões, and Acre basins were not considered for computing the boxes. The width of each box is extracted from province ages reported by Tassinari & Macambira (1999). CAM - Central Amazonian, MI - Maroni-Itacaiúnas, VTJ - Ventuari-Tapajós, RNJ - Rio Negro-Juruena, RSI - Rondonian San-Ignácio, and SA - Sunsás-Aguapeí provinces.

southwestern border of the AmC that led to the formation of the Ventuari-Tapajós and Rio Negro-Juruena provinces were mostly interrupted in favor of a collisional-type orogeny (Cordani & Teixeira, 2007), which seems to be reflected in a slower crustal velocity signature beneath the Rondonian San-Ignácio and Sunsás-Aguapeí provinces, as attested in Fig. 2.11a. The cratonization time of the Rondonian San-Ignácio province is difficult to determine due to tectonic reactivations during the Sunsás orogeny (Cordani & Teixeira, 2007). In fact, both the Rondonian San-Ignácio and Sunsás-Aguapeí provinces are generally envisaged as correlated with Laurentia during the amalgamation of Rodinia (e.g., Sadowski & Bettencourt, 1996; Cordani et al., 2009; Brito Neves & Fuck, 2014).

For the subcontinental lithospheric mantle, Fig. 2.11 shows a general correlation between ages and velocities, as in Ciardelli et al. (2022), both decreasing from east to west. Explanations to this difference in upper mantle v_s across the eastern and western portions of the AmC include: (i) Ciardelli et al. (2022) argue that cooling and iron depletion alone are unlikely to explain a velocity decrease of this magnitude, and an alternative explanation would be recent asthenospheric flow that heats the lithosphere of the AmC from west to east; (ii) The younger portion of the AmC never developed a cratonic root or it has been

eroded (Celli et al., 2020). If the latter, we argue that later reworking during the Stenian Sunsás orogeny (Celli et al., 2020) is not a reasonable explanation, as the Sunsás-Aguapei province was formed during this period and would require some extra million years to stabilize and cratonize. Since the AmC was not much affected by more recent Neoproterozoic Brasiliano events (Brito Neves & Fuck, 2014), the second and more plausible hypothesis presented by Celli et al. (2020) for craton destruction across the western portion of the AmC is hydration of the mantle wedge induced by rollback of a past flat slab segment (Kusky et al., 2014), which would thin the cratonic layer above it. In fact, profile B-B' (Figs. 2.8c-d) shows a strong decrease in seismic velocities, coherent with CAM2016, that we interpret as a shallower asthenosphere at depths of ~120 km along the southwesternmost tip of the AmC. This lithospheric thinning is not as outstanding if we move to the north across the western boundary of the AmC, as shown by profiles C-C' and D-D'.

An interesting exception to the correlation between ages and mantle shear velocities in our model is the Maroni-Itacaiúnas province at 150 km depth. This province had a different crustal evolution compared with the other AmC Proterozoic belts. Starting at circa 2.0 Ga, accretion of material to the southwestern border of the AmC proto-cratonic nucleus (within the Central Amazonian province), followed by cratonization, formed the Ventuari-Tapajós and Rio Negro-Juruena provinces (Cordani & Teixeira, 2007), while the younger Mesoproterozoic Rondonian San-Ignácio and Sunsás-Aguapei provinces are usually regarded as related to the Grenvillian orogeny (Cordani & Teixeira, 2007; Cordani et al., 2010). The 2.2–1.95 Ga Maroni-Itacaiúnas province, on the other hand, was shaped by the Transamazonian/Eburnean orogeny and is likely the product of the amalgamation of large continental masses (Cordani & Teixeira, 2007) that shared a close evolution with the West Africa craton (Nomade et al., 2003).

Due to increased resolution of our model, we were able to detect a nuanced reduction in average lithospheric shear-velocity for the Maroni-Itacaiúnas province, as shown in Fig. 2.11c, which could be linked to intra-plate tectono-thermal events related to the K'Mudku episodes during the middle-late Mesoproterozoic (Cordani et al., 2010). These episodes led to heating of up to 350–400 °C in the Guyana shield (Cordani et al., 2010). Further inspection of Fig. 2.10d shows that the slowest velocity beneath the Maroni-Itacaiúnas

province, which strongly contributes to decrease its average velocity, is located close to the coast. This leads us to suggest that more recent events regarding the extension tectonics during the breakup of Pangea and the subsequent opening of the Central Atlantic might have played a role in modifying cratonic properties along the northeastern border of the AmC. The extrusion of a large flood basalt province following the breakup of Pangea, named Central Atlantic Magmatic Province, mainly at the end of the Triassic and beginning of the Jurassic ([Marzoli et al., 1999](#)), reinforces this possibility. Consequently, the Maroni-Itacaiúnas province, already weakened by K'Mudku events, could have acted as a buffer mobile belt to “shield” the Archean core of the AmC from deformation related to the breakup of Pangea; the idea that a weaker Proterozoic mobile belt could increase the longevity of Archean cratonic lithosphere has been investigated by [Lenardic et al. \(2000\)](#).

2.6.3 A greater São Francisco paleocontinent

[Almeida \(1981\)](#) envisaged a larger cratonic block encompassing the present SFC. Currently, there is a general agreement (e.g., [Heilbron et al., 2017](#); [Martins-Ferreira et al., 2018](#); [Neves, 2021](#)) that a greater São Francisco paleocontinent extended beyond the present-day surface limits of the SFC into large portions of the Araçuaí (in the Mantiqueira province, to the east of the SFC) and Brasília (in the Tocantins province, to the west of the SFC) belts; hence, these areas are seen as São Francisco crust that underwent reworking. Geophysical studies ([Assumpção et al., 2017](#); [Rocha et al., 2019b](#)) also claim that at depth the boundaries of a larger São Francisco paleocontinent are still preserved, further reinforcing this idea.

From about 90 to 200 km depth (Figs. 2.7e-i) we indeed observe that fast S-wave velocities spread out of the SFC into the neighboring Brasília and Araçuaí belts, in general agreement with the P-wave tomography model of [Rocha et al. \(2019b\)](#). Profiles D-D' and E-E' (Fig. 2.8) also suggest a continuation of the SFC to the west and to the east at lithospheric depths. A minor disagreement between our S-wave velocity model and the P-wave velocity model by [Rocha et al. \(2019b\)](#) is located close to the Brazilian coast. Velocities in our model tend to slightly decrease closer to the coast in the SFC and Araçuaí belt, and more noticeable in the Ribeira belt (to the south of the SFC), while the P-wave velocities

show no sign of decrease toward the coast in the Araçuaí belt. A possible explanation for this small difference is that the v_p/v_s ratio beneath the Araçuaí belt might be different from the one beneath the interior of the SFC.

Besides the basement beneath the Araçuaí and Brasília belts, some authors argue that the basement of the Borborema province is also the product of reworking of São Francisco crust (Neves, 2003, 2021), and therefore it should also be included in the São Francisco paleocontinent. Neves (2021) provides several geological/geochronological evidence for a shared evolution between the Borborema province and the SFC. The author conceptualizes an initial Archean core composed by the Gavião block (e.g., Barbosa & Sabaté, 2004) in the SFC and by the São José do Campestre massif (e.g., Dantas et al., 2013) in the Borborema province, around which several episodes of crustal accretion and collage of blocks (e.g., Jequié and Serrinha, northern SFC) led to the final amalgamation of the São Francisco-Borborema block by the end of the 2.2–2.0 Ga Transamazonian/Eburnean events (Neves, 2021).

Hydration via subduction is a common mechanism to weaken the craton lithosphere by changing its rheological properties, such as buoyancy and viscosity (Lee et al., 2011). As Neves (2021) states, several episodes of subduction during the Paleoproterozoic altered the cratonic lithosphere of the São Francisco paleocontinent, and it is likely that hydration was more critical in the Borborema province than in SFC, therefore considerably modifying the former in comparison with the latter. Although rifting alone might be incapable of destroying cratons (Bedle et al., 2021), rifting in the BP in the early-middle Tonian (Ganade et al., 2021) led to further decratonization of an already weakened mantle, providing ground for strong rework of its crust during Brasiliano events.

In our S-wave velocity model, we observe that slow velocities are present at ~70 km depth near the coast of the Borborema province, extending toward the continental interior with increasing depth and reaching the northern SFC and eastern Parnaíba basin by around 150 km depth (see map views in Figs. 2.7d-h and profiles A-A' and C-C' in Fig.2.8). As previously discussed in Nascimento et al. (2022), in accordance with several geophysical results, these slow velocities are coherent with a scenario of a thin lithosphere, in which the presence of hotter asthenosphere material at shallower depths would decrease shear-wave

velocities beneath the Borborema province. This is consistent with the aforementioned view of metasomatism and decratonization of the Borborema cratonic mantle over several million years. As shown by profile A-A' (Fig. 2.8), only the SFC-Borborema border is underlain by slow velocities that extend from the Borborema province at 150 km depth, reinforcing that decratonization processes in the São Francisco paleocontinent during the Paleoproterozoic were of uttermost importance in the Borborema province, while the SFC portion of the São Francisco paleocontinent remained relatively stable, as pointed out by [Neves \(2021\)](#).

We argue that the scenario of severe alteration of the Borborema cratonic mantle previously described, not only during the Proterozoic, but also in Meso-Cenozoic times (i.e., lithospheric stretching caused by the breakup of Pangea), most likely erased the cratonic signature of the São Francisco paleocontinent within the Borborema province at upper mantle depths, and thus slow mantle velocities within the Borborema province should not be used to delineate a northern border for the São Francisco paleocontinent within it. Note that this does not rule out the possible former connection between the SFC and the Borborema province ([Neves, 2003, 2021](#)), it merely states that the Borborema mantle was altered during the course of Earth history.

2.6.4 Río de la Plata craton: toward reconciling seismic and electric observations?

The RPC is a controversial piece in the puzzle of South American tectonic units. First of all, because most of it is concealed under sediments of the Chaco-Paraná basin, there is no consensus about its current architecture, and different boundaries have been proposed on the basis of borehole, isotopic, gravity and geologic data (e.g., [Rapela et al., 2007, 2011](#); [Oyhantçabal et al., 2011](#)), some even encompassing the Paranapanema block and the Luiz Alves craton ([Santos et al., 2019](#)).

The scarce number of publicly available seismic stations within the expected area of the RPC (Fig. 2.1) reflects itself in a notably lower resolution in tomography models for this area. Previous tomography models using different inversion strategies ([Feng et al.,](#)

2007; Schaeffer & Lebedev, 2013; Celli et al., 2020; Ciardelli et al., 2022) detect no particular fast velocity signature characteristic of cratons for the uppermost mantle beneath the RPC at depths >100 km (Fig. 2.9) and therefore suggest that the RPC might no longer retain cratonic properties. However, the electrical structure of the RPC as sounded by deep magnetotelluric studies, reveals a thick and resistive cratonic keel. According to Bologna et al. (2019), a highly resistive ($\sim 2000 \Omega\text{m}$) block with an expressive thickness of >200 km marks the northeastern boundary of the RPC. An approximately W-E magnetotelluric transect at 31.5°S by Favetto et al. (2008) reveals the western boundary of the RPC with the Pampean terrane, in which the RPC is presented as a highly resistive structure (up to $10,000 \Omega\text{m}$) with thickness around 150–200 km.

To the best of our knowledge, the high velocity at 150–200 km in the region of the RPC presented in this study is the first step toward reconciling seismic and electric observations. Although a considerable amplitude decrease is expected in this region (Figs. 2.5 and 2.6) at lithospheric depths, especially close to the Atlantic coast, our dataset and inversion strategy were able to image a fast velocity structure beneath the northern half of the RPC. Fig. 2.12 presents different boundaries for the RPC as proposed by Rapela et al. (2007), Rapela et al. (2011), Oyhançabal et al. (2011), and Cordani et al. (2016), over our map view at 150 km depth. We note that the limits proposed by Rapela et al. (2011) more closely match the lateral variation of v_s presented in Fig. 2.12. The black x indicates the approximate position of the boundary between the RPC and the Pampean terrane suggested by Favetto et al. (2008), which corroborates our results. Thus, we show evidence that rather than sampling a decratonized root, seismic velocities in the mantle are (at least partially) in agreement with magnetotelluric (Favetto et al., 2008; Bologna et al., 2019) and geologic (e.g., Rapela et al., 2011; Oyhançabal et al., 2011) findings. However, the deployment of more stations is still recommended to better constrain the seismic structure beneath the RPC and to determine its lithospheric architecture.

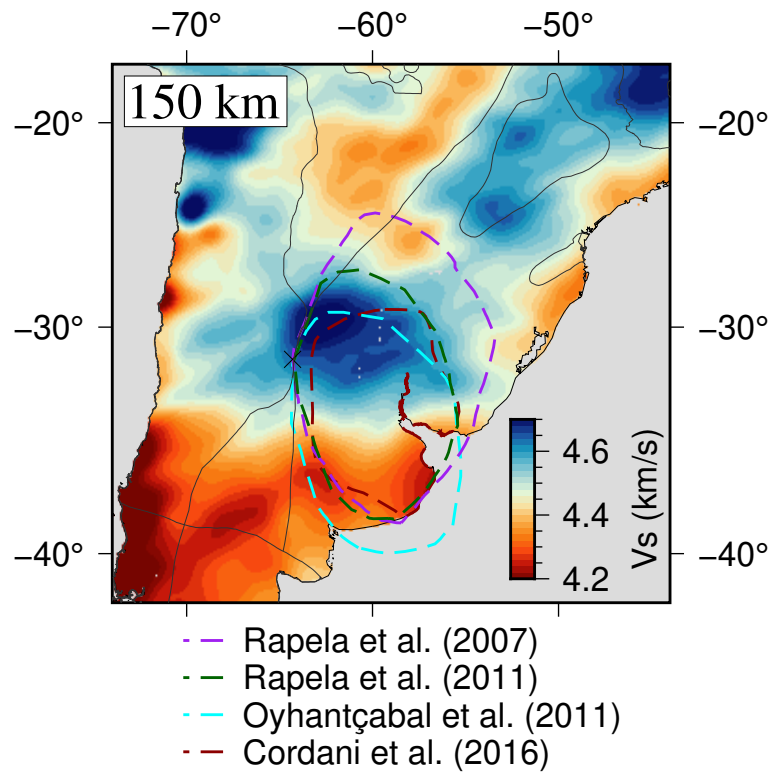


Figure 2.12: Different proposals for the boundaries of the Río de la Plata craton over our 150 km depth map view. The black x indicates the approximate position of the boundary between the RPC and the Pampean terrane suggested by Favetto et al. (2008).

2.6.5 Paranapanema and Parnaíba blocks

Blocks with cratonic characteristics have been proposed to be concealed under the Paraná and Parnaíba basins, more specifically, the Paranapanema and Parnaíba blocks, respectively. The basement beneath the Paraná basin raises controversies, and it is not clear whether it is made up of a single unit (e.g., [Mantovani et al., 2005](#); [Rocha et al., 2019a](#); [Affonso et al., 2021](#)), several smaller fragments separated by suture zones ([Milani et al., 1998](#); [Julià et al., 2008](#); [Dragone et al., 2021](#)), or even if it holds cratonic properties ([Padilha et al., 2015](#); [Chaves et al., 2016](#); [Bologna et al., 2019](#)).

Previous studies in the Paraná basin using seismic tomography ([Rocha et al., 2019a](#); [Affonso et al., 2021](#); [Ciardelli et al., 2022](#)) image the Paranapanema block as a single high-velocity unit in the upper mantle, coherent with a single block interpretation. Our results seem to suggest the presence of more than a single velocity unit at depths >90 km, but their small size and velocity contrast make it difficult to conclude so. A scenario that could reconcile variable crustal thicknesses ([Julià et al., 2008](#)) with seismic tomography of the upper mantle beneath the Paraná basin is a fragmented crust coupled to a single block lithospheric mantle. Another possibility is simply that all tomographic studies to this day still lack resolution (or have not incorporated high enough frequencies) to detect smaller cratonic units amalgamated along subtle sutures at mantle depths. In this case, only a smeared result representing all cratonic blocks would be retrieved.

The lithospheric v_s structure beneath the Parnaíba basin is more heterogeneous than beneath the Paraná basin, thus raising doubt about the idea of a single stable cratonic block basement concealed under the sediments. In fact, a recent study by [Porto et al. \(2022\)](#) advocates for several domains that contributed to the amalgamation of western Gondwana in a complex collisional setting. We image a fast velocity feature beneath the northern portion of the basin (depths >130 km) accompanied by a subtle decrease in velocity in the south, close to the Transbrasiliiano lineament, but this could still be a smeared representation of a more complex heterogeneous structure, especially considering that our receiver coverage in this area is scarce.

2.7 Conclusions

We have mapped the distribution of shear-wave velocity in the lithosphere beneath South America from inversion of group velocity dispersion curves of fundamental mode Rayleigh waves. Long wavelength tectonic features imaged by our model are in good agreement with previous tomography studies ([Ciardelli et al., 2022](#); [Celli et al., 2020](#); [Feng et al., 2007](#)), as also indicated by high Pearson correlation coefficients. Our dataset and inversion strategy have allowed the seismic structure beneath the Amazonian, São Francisco, and Río de la Plata cratons to be robustly determined.

A subtle interruption in the positive correlation between seismic velocities and province ages in the AmC at 150 km depth, across the Paleoproterozoic Maroni-Itacaiúnas province, is indicative that it underwent, at least to a small degree, some sort of modification. Good candidates for weakening the lithosphere beneath the Maroni-Itacaiúnas province are the middle-late Mesoproterozoic K'Mudku episodes, which led to heating of up to 350–400 °C in the Guyana shield ([Cordani et al., 2010](#)), and the extension tectonics during the opening of the Central Atlantic Ocean, which led to the emplacement of the Central Atlantic Magmatic Province ([Marzoli et al., 1999](#)).

Slow velocities in the Borborema province mantle starting at ~70 km depth, indicative of lithospheric thinning, are corroborated by several episodes that could have led to severe alteration of the lithospheric mantle, including hydration in the Paleoproterozoic ([Neves, 2021](#)), rifting in the early-middle Tonian ([Ganade et al., 2021](#)), strong reworking during Neoproterozoic Brasiliano events ([Brito Neves & Fuck, 2014](#)), and lithospheric stretching due to the breakup of Pangea. Thus, we suggest that the deep cratonic root of the São Francisco paleocontinent is not preserved in the upper mantle beneath the Borborema province, likely being eroded away.

Finally, a fast velocity feature in the northern half of the RPC most likely represents a first step toward reconciling seismic and electrical (e.g., [Favetto et al., 2008](#); [Bologna et al., 2019](#)) studies. The RPC is characterized by an expressive lack of publicly available seismic data, which is inevitably translated into lower resolution in tomographic models.

Chapter 3

DisperPy: a machine learning based tool to automatically pick group velocity dispersion curves from earthquakes

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Outline

In this chapter, I present a paper describing a new machine learning based tool developed by our team to automatically measure surface wave group velocity dispersion curves from earthquakes. It contains two main modules, one for assessing whether a good quality dispersion curve is associated with the surface waves in a waveform, and another to actually measure dispersion. To demonstrate the capability of the algorithm, I present an application to the contiguous United States based on thousands of Rayleigh wave dispersion measurements retrieved in an automated fashion. The material in this chapter

has been submitted to the journal Computers & Geosciences.

Abstract

Seismology has made significant progress in high-resolution Earth imaging, largely driven by the increasing volume of freely available data. As a result, automated tools and machine learning algorithms are becoming essential for processing this vast amount of information. In this study, we present DisperPy, an open-source Python library developed to automatically extract group velocity dispersion curves from earthquake data. The analysis framework of DisperPy is structured around two primary tasks: (1) assessing the quality of waveforms to determine if dispersion extraction is feasible, and (2) measuring the group velocity dispersion curve for suitable waveforms. To address the first task, DisperPy uses a convolutional neural network trained on dispersion spectrograms to classify waveform quality. The model, based on the ResNet-34 architecture, is initialized with ImageNet-pretrained weights and fine-tuned using the fastai deep learning library. The network achieves $\sim 94\%$ accuracy in distinguishing between high- and low-quality dispersion images. For the second task, DisperPy employs unsupervised learning techniques, starting with a Gaussian mixture model to separate dispersion energy from background noise, followed by k-means to separate the dispersion energy into clusters, making it easier to track amplitude maxima and then construct initial dispersion curves. Finally, a refinement of the initial dispersion is achieved using both the density-based spatial clustering of applications with noise algorithm and data quality criteria to remove possible outliers. To further test DisperPy, we conduct a surface wave tomography experiment across the contiguous United States using freely available vertical-component broadband waveforms. After processing the data with DisperPy and removing low-quality waveforms, the final dataset consisted of 194,325 unique dispersion curves. Consistent with previous studies, our maps reveal a prominent velocity dichotomy, with low velocities in the tectonically active western US and high velocities in the stable central and eastern US.

Keywords: Machine learning; Deep learning; Dispersion curves; Python; Surface waves; United States.

3.1 Introduction

Seismology is currently witnessing major advances in the ability to image high-resolution Earth structure due to the large volume of freely available data ([Arrowsmith et al., 2022](#)). Hence, automated tools and workflows are paramount to process such an overwhelming volume of data. In this context, machine learning approaches to process data and solve geophysical problems are becoming increasingly popular. Successful areas where machine/deep learning has been applied in seismology include, among many others, seismic data denoising (e.g., [Zhu et al., 2019](#); [Tibi et al., 2021](#); [Iqbal, 2023](#)), waveform quality control (e.g., [Chai et al., 2022](#)), phase picking (e.g., [Ross et al., 2018](#); [Zhu & Beroza, 2019](#); [Chen & Li, 2022](#)), seismic tomography (e.g., [Bianco & Gerstoft, 2018](#); [Araya-Polo et al., 2018](#)), and inversion of surface wave dispersion curves for shear-wave velocity structure (e.g., [Hu et al., 2020](#); [Luo et al., 2022](#)). Reviews of the usage, examples and challenges of machine learning applied to geophysics and solid Earth geosciences in general can be found in the papers by [Kong et al. \(2019\)](#); [Bergen et al. \(2019\)](#); [Yu & Ma \(2021\)](#); [Arrowsmith et al. \(2022\)](#); [Li et al. \(2023\)](#).

Since the pioneer works by [Aki & Lee \(1976\)](#), [Dziewonski et al. \(1977\)](#) and [Aki et al. \(1977\)](#), seismic tomography has provided astonishing images of the distribution of propagation speeds of seismic waves worldwide (e.g., [Ritsema et al., 2011](#); [Thrustarson et al., 2024](#)), at scales ranging from local to global. At present, there are several approaches, each with its own challenges, to translate seismic data to velocity models that can be used to infer the structure and dynamics of the Earth ([Fichtner et al., 2024](#)). An important class of such approaches, surface wave tomography, is based on the dispersive character of surface waves, that is, their frequency components travel with distinct (phase and group) velocities that are sensitive to Earth structure at different depths. Surface wave tomography uses as input dispersion curves (i.e., a set of velocity $\times$ period observations) generated from earthquakes (e.g., [Wagner et al., 2018](#); [Estève et al., 2021](#); [Nascimento et al., 2022](#)), estimates of the empirical Green's function between pairs of receivers (in which case the procedure is known as ambient noise tomography) (e.g., [Ward et al., 2013](#); [Sager et al., 2020](#); [Zhang et al., 2024](#)) or both (e.g., [Magrini et al., 2023](#); [Miao et al., 2024](#)). The usage of

high-frequency surface waves for retrieving near-surface shear-wave velocity structure is also widely popular in the exploration geophysics community (e.g., [Xia et al., 1999](#); [Guedes et al., 2023](#)).

Because surface waves provide a popular way to image subsurface structure at several scales, several strategies have been devised for measuring phase and group dispersion curves in an automated fashion, some of which are based on machine and deep learning algorithms. For example, [Zhang et al. \(2020\)](#) and [Yang et al. \(2022\)](#) trained convolutional neural networks based on the U-Net architecture ([Ronneberger et al., 2015](#)) to measure dispersion curves from ambient noise cross-correlations. [Dai et al. \(2021\)](#) treated the problem of dispersion extraction as a segmentation task and trained a neural network that can measure phase velocities. Based on unsupervised clustering learning, [Wang et al. \(2021\)](#) developed a method to extract multimode phase velocity dispersion curves, demonstrated with applications in near surface exploration geophysics. Other studies that used deep learning to measure phase velocities include [Dong et al. \(2021\)](#) and [Dai et al. \(2022\)](#).

Most of these machine learning measuring tools are intended to extract phase rather than group velocity, and although the models presented in [Zhang et al. \(2020\)](#) and [Yang et al. \(2022\)](#) can measure group velocities, they were designed to work with cross-correlations of ambient noise data, which generally has higher frequency contents compared with earthquakes. Group velocity dispersion curves derived from earthquakes can present some peculiarities that can make the problem of extraction considerably more challenging to tackle. First of all, in a real world continental-scale application of surface wave tomography, the dispersion curves associated with most waveforms will not have good enough quality, and hence should be discarded. Furthermore, compared to cross-correlations of ambient noise, earthquake surface wave data are generally noisier, and the presence of spectral holes is quite common ([Bensen et al., 2007](#)), making automated tools to extract group velocities more challenging to implement. The lower frequencies commonly present in surface waves of earthquakes are sensitive to deeper Earth structure, making them valuable tools to probe the velocity structure beneath the upper mantle, complementary to ambient noise.

This study presents DisperPy, an open-source Python library designed to automatically extract group velocity dispersion curves from earthquake data. By combining both supervised and unsupervised machine learning algorithms, DisperPy offers an efficient solution to this challenge. The library is freely available and easily accessible, as it can be installed and run on any Linux-based system. Built on the robust foundation of scientific Python libraries, including ObsPy ([Beyreuther et al., 2010](#)), NumPy ([Harris et al., 2020](#)), SciPy ([Virtanen et al., 2020](#)), Scikit-learn ([Pedregosa et al., 2011](#)), and fastai ([Howard & Gugger, 2020](#)), DisperPy integrates both supervised and unsupervised machine learning algorithms. Section 3.2 deals with the algorithmic implementation of DisperPy, which solves two primary tasks: (1) assessing waveform quality to determine if dispersion extraction is feasible, and (2) measuring the group dispersion curve for suitable waveforms. Additionally, we validate DisperPy by comparing its results with manual group velocity measurements obtained from the Computer Programs in Seismology suite ([Herrmann, 2013](#)). The automated and manual picks show strong agreement, with DisperPy providing a more systematic and conservative approach, especially at lower frequencies. Section 3.3 demonstrates the real-world applicability of DisperPy through a surface wave tomography experiment using data from seismic stations deployed across the contiguous United States. Finally, in Section 3.4 we discuss the broader implications of our findings.

3.2 Method

Fig. 3.1 presents the workflow implemented in DisperPy to analyze a seismic trace and try to automatically extract the group velocity dispersion curve from it. In essence, two main problems are tackled: given a waveform, the algorithm must decide whether the respective dispersion has good quality (i.e., whether it is possible to extract a dispersion curve from it); second, if the recording passes the first test, the algorithm will try to measure the group dispersion curve. The following sections present a description of the strategy we adopt to solve these problems.

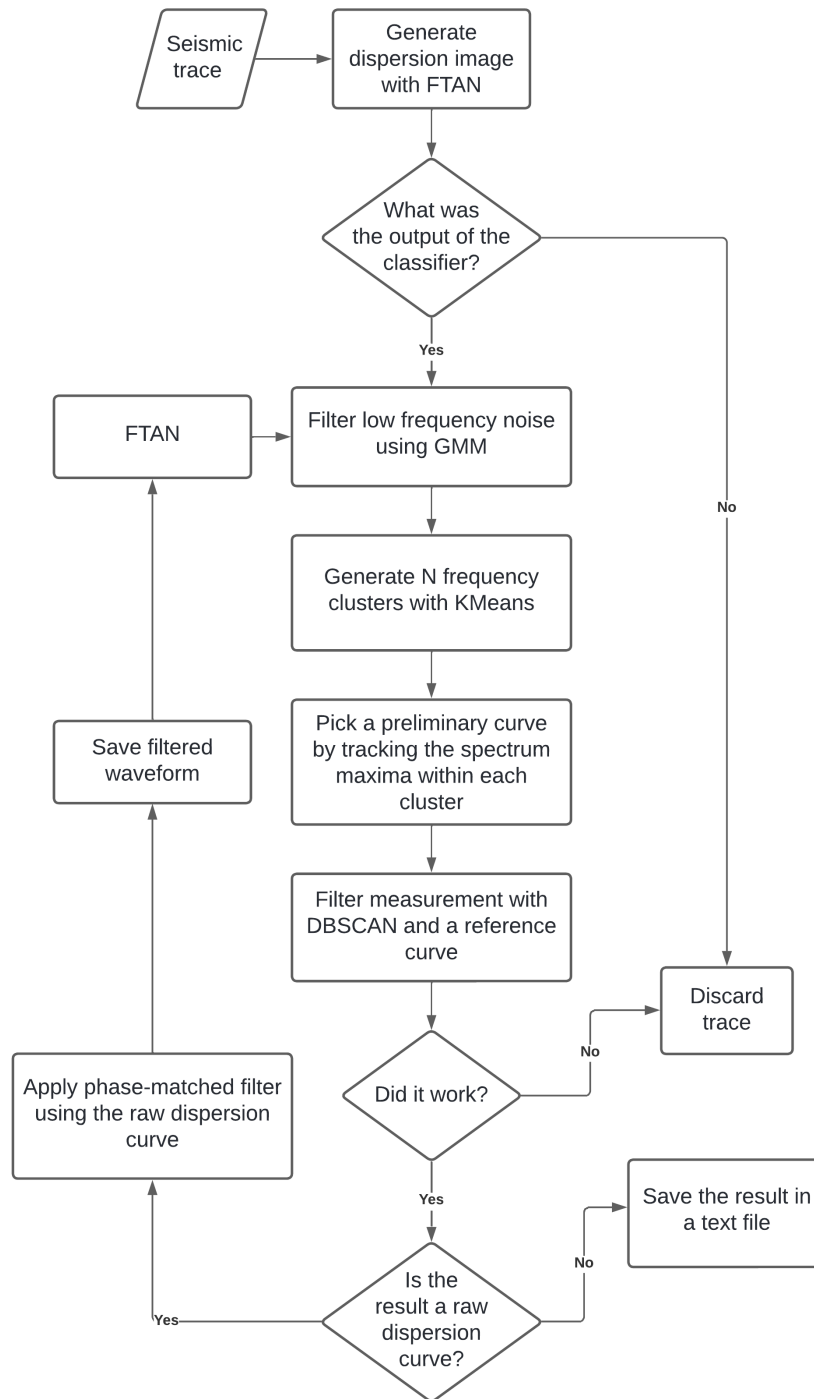


Figure 3.1: Flowchart representing the basic steps followed by DisperPy to estimate a group velocity dispersion curve from a waveform. FTAN: frequency-time analysis, GMM: Gaussian mixture model, DBSCAN: density-based spatial clustering of applications with noise.

3.2.1 Frequency-time analysis

The conventional way to measure group velocity from a seismic waveform, known as frequency-time analysis (FTAN) (Dziewonski et al., 1969; Levshin et al., 1972, 1992; Bensen et al., 2007), is to convert it to a dispersion spectrogram and then select velocity (or time) / period (or frequency) points riding through the amplitude maxima, which correspond to the dispersion curve. Assuming that a signal in the time domain has been already pre-processed (i.e., detrended, demeaned, deconvolved with instrument response, etc), the first step is to apply a set of narrow band Gaussian filters to the analytical signal representation of the input waveform in the frequency domain. These filters are defined as (Levshin et al., 1992):

$$H(\omega - \omega_0) = e^{\alpha \left(\frac{\omega - \omega_0}{\omega_0} \right)} \quad (3.1)$$

where ω_0 is the central frequency of the filter and α is a parameter related to its width, generally set to larger values with increasing source-receiver distance. For each frequency, applying an inverse transform will lead to a filtered signal from which a 2-D envelope ($|A(t, \omega_0)|$) and a phase function ($|\Phi(t, \omega_0)|$) can be extracted. From the maximum of the envelope of the analytical signal, surface wave travel times (and consequently, group velocities) can be computed at each instantaneous frequency (or instantaneous period) (Bensen et al., 2007). The dispersion spectrogram is therefore a graph whose x, y and z axes are period, group velocity, and amplitude, respectively.

Assuming that a raw dispersion curve has been measured, one can use it to design a phase matched filter to enhance the surface wave signal, hence maximizing the signal-to-noise ratio (Herrin & Goforth, 1977; Levshin et al., 1992; Levshin & Ritzwoller, 2001). To apply this filter, the waveform is first compressed (undispersed) via multiplication of the spectrum of the analytical signal with a correction factor $e^{i\phi(\omega)}$, with $\phi(\omega)$ given by (Levshin et al., 1992):

$$\phi(\omega) = \Delta \int_{\omega_0}^{\omega_1} \frac{d\omega}{U(\omega)} \quad (3.2)$$

where Δ is the source-receiver distance, ω_0 and ω_1 are the minimum and maximum

frequencies of the dispersion curve, respectively, and $U(\omega)$ are the group velocities. The compressed signal is then retrieved from an inverse Fourier transform of the filtered spectrum, which is in turn cosine-tapered to mitigate noise and unwanted signals (Levshin et al., 1992). Finally, the signal is redispersed again by the multiplication of its spectrum with $e^{-i\Phi(\omega)}$ (Levshin et al., 1992). Following this procedure, we can obtain a signal that emphasizes the surface wave content of the waveform, to which FTAN can be applied again to measure a clean, smoother dispersion curve.

3.2.2 Classifying dispersion curves

When working with a voluminous amount of seismograms retrieved from several data centers, such as the Incorporated Research Institutions for Seismology (IRIS) Data Management Center (Aster et al., 2005) and the European Integrated Data Archive (Strollo et al., 2021), it is unavoidable that a large fraction of the waveforms will be inappropriate for surface wave tomography. Thus, prior to picking the dispersion curve, it is important that such recordings are identified and eliminated from the data set.

Because computer vision is one of the areas in which deep learning excels (Voulodimos et al., 2018), one of the components of DisperPy is a convolutional neural network (CNN) (LeCun et al., 1998), trained to solve the supervised binary classification problem of separating high- and low-quality dispersion spectrograms. To train the CNN, we use the deep learning library fastai (Howard & Gugger, 2020), which is written in Python and has functionalities to deliver state-of-the-art performance in several application domains, including computer vision, natural language processing, and collaborative filtering. fastai relies heavily on PyTorch (Paszke et al., 2017), and adds several functionalities on top of it.

The input data fed to the CNN consists of dispersion spectrograms saved in the portable network graphics image format (henceforth named dispersion image), resized to 224×224 pixels, which is the size of the images in the ImageNet dataset (Deng et al., 2009). For each dispersion image (input), we manually generate a label (output) that can be one or zero, depending on whether a good curve is recognizable on the image or not. To prepare the images, we retrieve waveforms from random seismic stations across the world, pre-process

them (as in [Nascimento et al., 2024](#)), and calculate the respective dispersion spectrogram with FTAN, resulting in a total of 4895 images/labels pairs.

The CNN architecture, shown in Fig. 3.2, consists of the ResNet architecture ([He et al., 2015](#)) with 34 parameter layers. Each dispersion image has 3 channels (corresponding to the red, green and blue colors) and thus each input as a size of $3 \times 224 \times 224$; additionally, we use a mini-batch size of 64 (we omit the batch dimension in the following discussion for the sake of simplicity). The stem (that is, the first layer) is a plain convolutional layer with kernel of size 7×7 , with stride-2 and padding of 3 pixels, followed by batch normalization ([Ioffe & Szegedy, 2015](#)) and application of a rectified linear unit (ReLU) activation function. Then, a max pooling operation with stride of size 2 is applied, followed by 4 ResNet blocks (or simply layers in the PyTorch jargon) with a varying number of basic building blocks (convolution + batch normalization + ReLU). Note that apart from the max pooling aforementioned, downsampling occurs in ResNet blocks 2, 3 and 4 (Fig. 3.2) using a stride of size 2. The main difference between ResNet and a plain convolutional network is the addition of the output of shortcut connections obtained via identity mapping to the output of the stacked convolutional layers, which makes the network easier to train ([He et al., 2015](#)). Finally, adaptive average and max pooling are applied to the activations of the last block and a fully connected layer is at the end of the network, from which the final label is obtained by applying a sigmoid function.

Our CNN inherits an initial set of weights from a pretrained model on ImageNet ([Deng et al., 2009](#)) via transfer learning, with only the final layer being initially replaced by random weights compatible with our specific task. Weights are updated by minimizing the cross-entropy loss function using the Adam optimizer ([Kingma & Ba, 2015](#)). The model is then trained for a total of 13 epochs, of which in the first 3 the pretrained weights are frozen (that is, not updated by the learning process) ([Howard & Ruder, 2018](#)). The determination of the learning rate follows the "1cycle" policy of [Smith & Topin \(2018\)](#). The accuracy of the final model on the validation set reaches values of around 94%.

Fig. 3.3 presents examples of dispersion images generated from recordings at station BINY from the US network, located in the United States; DisperPy labeled them either as 1 (Fig. 3.3b) or 0 (Fig. 3.3d). Images labeled as 1 proceed to the measurement phase and

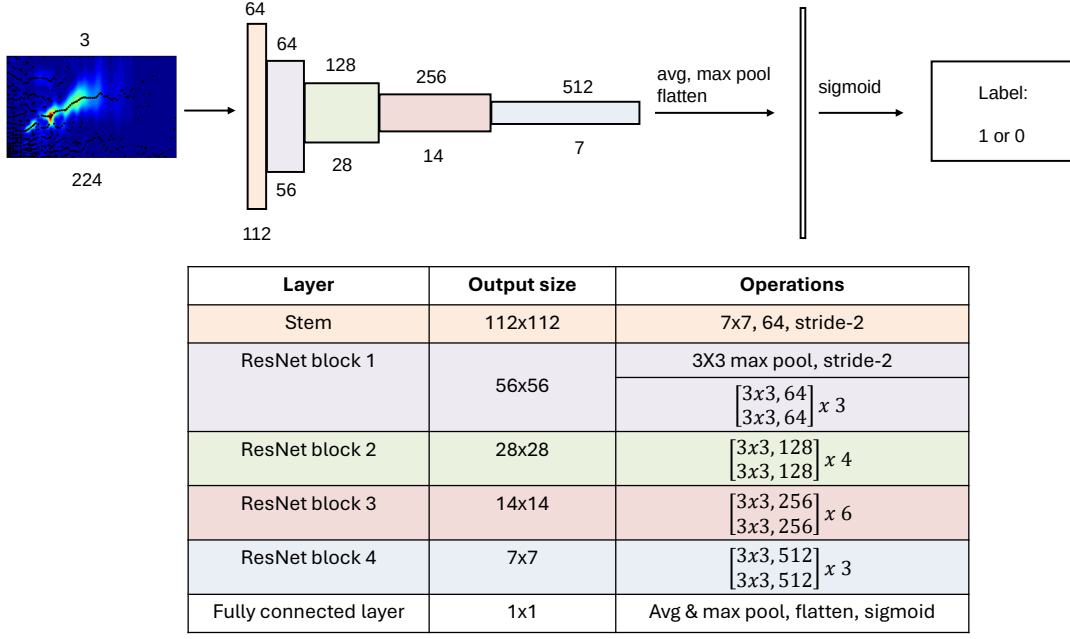


Figure 3.2: Architecture of the convolutional neural network used to classify dispersion spectrograms. In summary, the network is composed of a stem, four ResNet blocks and a fully connected layer at the end.

the ones labeled as 0 are discarded.

3.2.3 Extracting dispersion curves

We cast the problem of extraction of group velocity dispersion curves from the spectrograms as an unsupervised learning problem and solve it through a combination of algorithms and data quality criteria. In summary (Fig. 3.1), the first step is to separate the dispersion energy from the low frequency background noise using a Gaussian mixture model. A set of period clusters are then calculated using k-means (MacQueen, 1967), and for each cluster we track possible dispersion points riding the amplitude maxima, which are concatenated to construct an initial trial dispersion curve. Finally, possible noise points previously selected are filtered out with a combination of the density-based spatial clustering of applications with noise algorithm (Ester et al., 1996) and data quality criteria. In the next sections, we describe each of these steps in more detail. All unsupervised machine learning algorithms adopted in this stage are implemented in the Scikit-learn

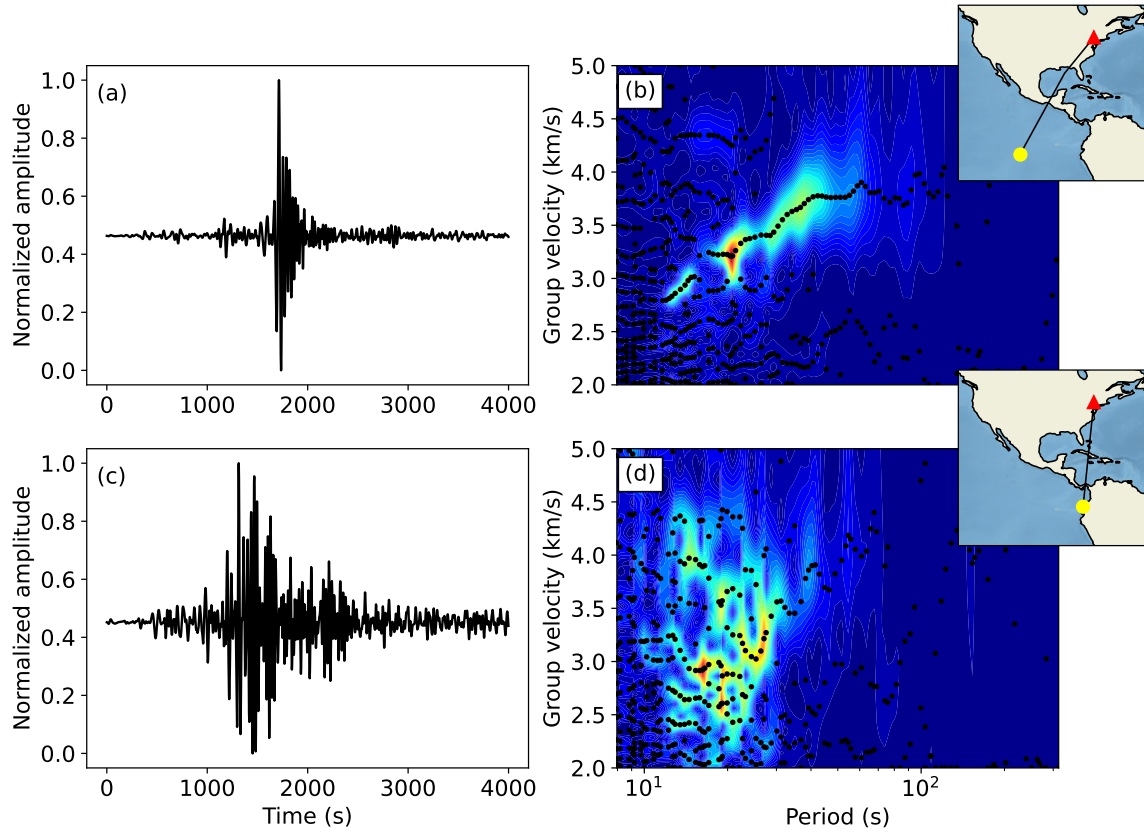


Figure 3.3: Examples of waveforms (left column) of earthquakes recorded by station BINY in the United States, with their respective dispersion spectrograms (right column). The upper panels show a good example of dispersion spectrogram (classified as 1) and the lower panels show a bad one (classified as 0). The inset shows the geographic locations of the earthquakes (yellow circles) and station BINY (red triangle).

Python library ([Pedregosa et al., 2011](#)).

Removing low frequency noise

The superposition of two or more Gaussian distributions with distinct parameters lead to probabilistic models known as Gaussian mixtures ([Bishop, 2006](#)), which can be used for clustering purposes. As in [Wang et al. \(2021\)](#), we start the measurement phase by fitting a Gaussian mixture model to the spectrum in order to isolate low amplitude/frequency background noise from the dispersion energy, the latter characterized by the largest amplitudes in the fundamental mode. The goal in this step is hence to label each period, velocity and amplitude triplet in the spectrogram as dispersion energy or background noise. Considering a data set $\{x_1, x_2, \dots, x_N\}$ of size N , the basic equation governing a Gaussian mixture model is:

$$p(x) = \sum_{k=1}^c \alpha_k N(x|\mu_k, C_k) \quad (3.3)$$

where c is the number of Gaussian distributions (2 in our case) and α_k , μ_k , and C_k are the weight, mean and covariance matrix of each Gaussian distribution, and are essentially the parameters to be learned from the data. We start with random parameters from data and iteratively update their values using the expectation-maximization algorithm ([Dempster et al., 1977](#)).

Fig. 3.4 provides an example of the application of Gaussian mixture to the dispersion spectrogram shown in Fig. 3.3b. Since for each waveform we do not know beforehand the maximum period excited by the respective earthquake, the usage of Gaussian mixtures allows us to apply FTAN utilizing a reasonably large period range (8-250 s in Fig. 3.4) corresponding to the period range where fundamental mode energy is usually found, and then consider for measurement only periods lower than the maximum period for this particular recording. In the case of Fig. 3.4, the maximum period classified as dispersion is around 120 s.

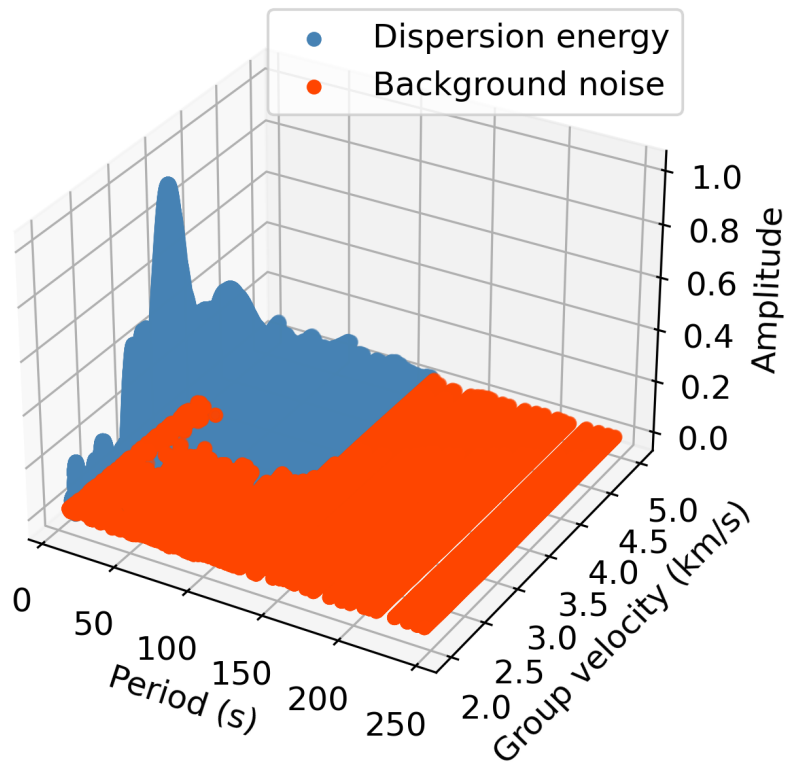


Figure 3.4: Application of a Gaussian Mixture model to the waveform shown in Fig. 3.3a, separating the dispersion energy from the background noise. The maximum period classified as dispersion is around 120 s.

Clustering and picking a trial dispersion curve

Next, we divide the dispersion energy into a number of clusters using k-means ([MacQueen, 1967](#)) and search for amplitude maxima within each cluster. K-means is one of the most popular unsupervised learning algorithms for partitioning a set of observations into a predetermined number of clusters, with the objective of grouping similar samples together in the same cluster and maximizing the distance between distinct clusters.

Fig. 3.5 shows the application of k-means to partition the dispersion energy of the waveform presented in Fig. 3.3a into 8 clusters, aiming to facilitate the search for amplitude maxima points. Fig. 3.6 illustrates the steps involved in measuring a dispersion curve with DisperPy, from a trial dispersion curve (picked at the present stage) shown in Fig. 3.6a, to the final curve in Fig. 3.6d. The result in Fig. 3.6a is obtained by concatenating the dispersion points measured in each cluster shown in Fig. 3.5. Spurious local maxima points that do not correspond to the dispersion energy might be picked at this stage, and so for several waveforms it is necessary to further enhance this initial measurement.

Refining the measurement

To remove possible group velocity points that are not related to the fundamental mode energy and to further enhance the overall quality of the picking, DisperPy adopts a few strategies. The first of them is to apply the density-based spatial clustering of applications with noise ([Ester et al., 1996](#)) (DBSCAN) algorithm to divide the trial dispersion curve (as the one in Fig. 3.6a) into an unknown number of clusters. DBSCAN has two advantages that make it a good choice for this step: it does not necessarily have to assign a class to an observation (i.e., it can classify observations as noise) and it does not require to specify the number of clusters beforehand. The two main parameters for DBSCAN in the Scikit-learn implementation are named `eps` and `min_samples`, corresponding to the radius around a point to consider neighbor points and a parameter related to the density of the resulting clusters, respectively. For our case, based on the Euclidean distance, we find that the values `eps = 0.10` and `min_samples = 5` tend to work well with most raw measurements from earthquake waveforms; for clean measurements, a larger value for `eps` (0.15-0.30) is

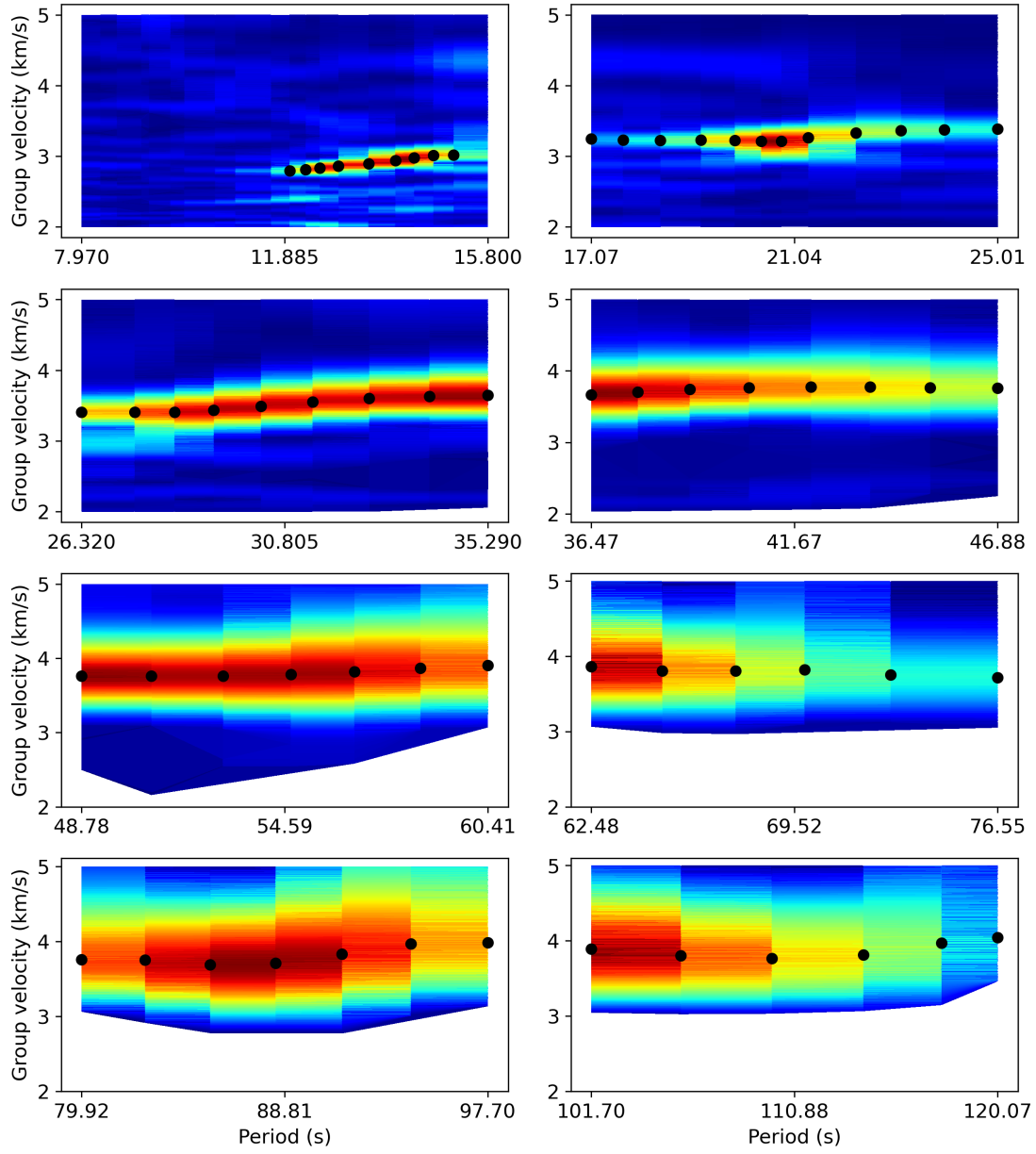


Figure 3.5: Example of separation of the dispersion energy into 8 different clusters using k-means.

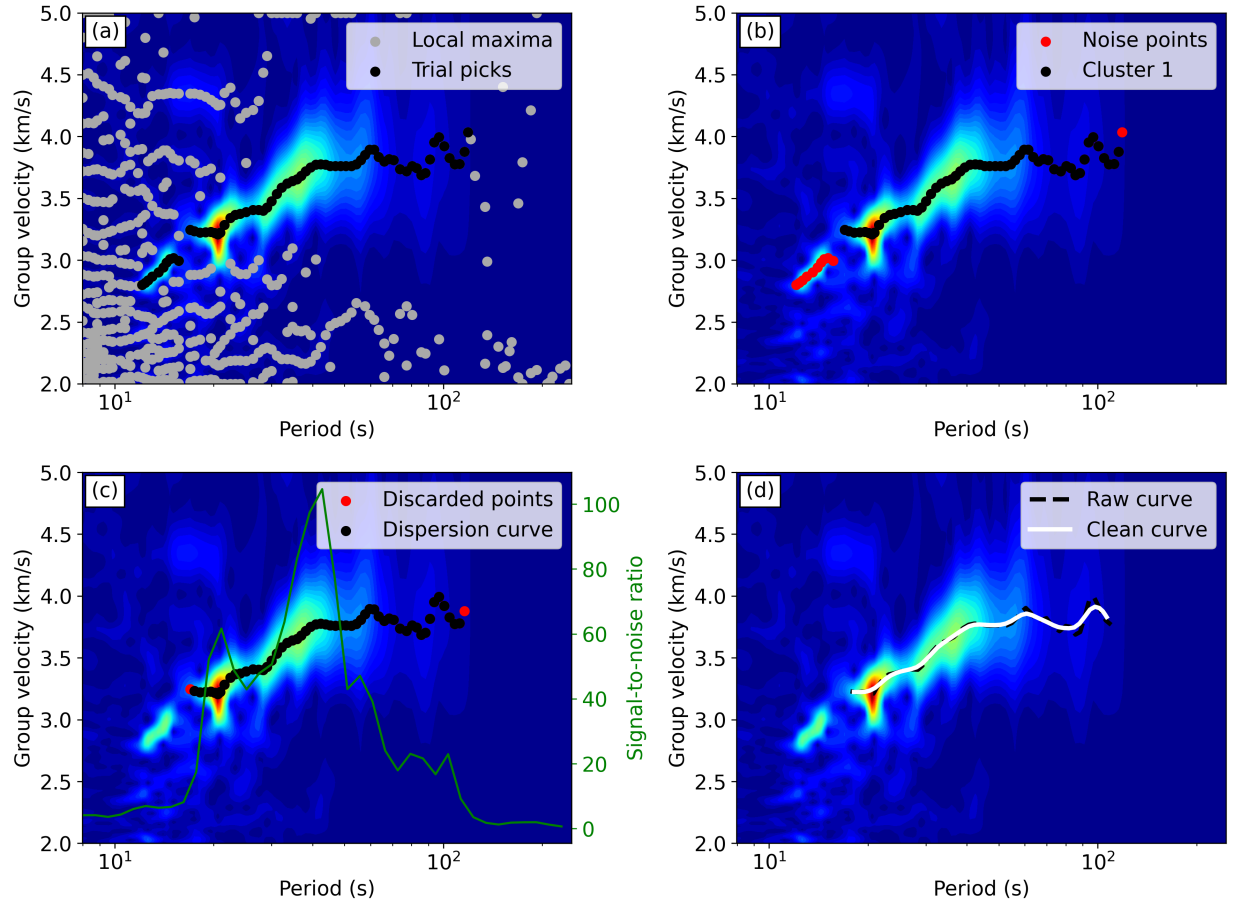


Figure 3.6: (a) Trial dispersion curve obtained by concatenating the individual dispersion segments within each k-means cluster shown in Fig. 3.5. (b) Dispersion curve filtered by DBSCAN. (c) Dispersion curve filtered following the signal-to-noise criteria. (d) Final dispersion curve retrieved by DisperPy, where ‘raw’ refers to the first measurement (used to create the phase-matched filter) and ‘clean’ refers to a second measurement on a phase-matched filtered trace where the fundamental mode is presumably isolated.

usually better.

Period/velocity pairs identified as noise are eliminated as soon as identified by DBSCAN. Next, each cluster is compared to a reference dispersion curve from the reference 1D model AK135F (Kennett et al., 1995) to discard possible bad clusters. In this comparison, we allow fluctuations around the reference values that decrease with increasing period from $\pm 30\%$ at periods < 30 s to $\pm 12\%$ at periods > 300 s, in order to reflect the decreasing extent of heterogeneity of the Earth from the crust to deeper in the mantle. Finally, clusters are analyzed with respect to each other, and in the case of spectral holes (curves with jumps) only the continuous smooth section of the dispersion curve with most points is stored. In the example of Fig. 3.6, DBSCAN identified one cluster, represented by black points, and was able to distinguish a few outlier noise points, shown as red points.

As a quality criterion, DisperPy allows the usage of a frequency-dependent ‘spectral’ signal-to-noise ratio, defined by Bensen et al. (2007) as the ratio between the peak signal in a signal window and the standard deviation of a trailing noise window. We compute a signal window defined by the travel times associated with minimum and maximum group velocities where the fundamental mode energy is typically observed in the period range excited by earthquakes (e.g., 2.0 ~ 5.0 km/s for Rayleigh waves) and a noise window trailing the signal window by a certain amount of seconds; both the size and trailing offset of the noise window might be set by the user, although values of 500 and 900 s, respectively, are default. As in Bensen et al. (2007), we define a set of frequencies around which to apply narrow bandpass filters to the waveform and then estimate the signal-to-noise ratio by taking the ratio between the signal window peak and the rms noise. Segments of dispersion (or entire curves) that fall below a certain threshold are discarded. By default, DisperPy uses a period-dependent signal-to-noise ratio threshold, set to 10 for periods < 80 s, 7 for periods between 80 and 120 s, and 5 for periods > 120 s. For a given epicentral distance Δ (in km), we also cut off measurements at periods larger than $\tau_{\max} = \Delta/12$ to ensure that the distance is at least 3 times larger than the maximum wavelength (Bensen et al., 2007). Fig. 3.6c presents an example of curve filtering based on the signal-to-noise ratio criteria, and Fig. 3.6d shows the final curve picked for the waveform presented in Fig. 3.3a. Note that the ‘raw’ curve in Fig. 3.6d refers to a first measurement performed

on the waveform, aiming to construct a phase-matched filter (Section 3.2.1), and that the ‘clean’, smoother, curve is retrieved from a pass of the algorithm on the filtered waveform where the fundamental mode energy was presumably isolated.

Besides the signal-to-noise ratio approach designed to work on a single seismogram, DisperPy also has the ability to identify bad dispersion curves with respect to a collection of measurements. Given a set of dispersion curves, DisperPy can compute the average group velocity values sorted by period, along with the respective standard deviation, and then identify and discard measurements that stray from the average curve by more than ± 3 times the standard deviation, hence allowing a stronger constraint on the quality of the measurements.

3.2.4 Comparing with manual picks

To illustrate how measurements obtained via DisperPy compare to consolidated options available in the literature to measure group velocity of surface waves, we use the Computer Programs in Seismology suite ([Herrmann, 2013](#)) to manually measure the group velocity dispersion curves related to four source-receiver pairs. Fig 3.7 shows that both the manual and automatic picks are very similar, which is expected since both DisperPy and the Computer Programs in Seismology rely on a transformation of the waveforms into a velocity/period spectrogram using FTAN. However, it should be stated that DisperPy might retrieve a different (and generally shorter) period range than an analyst manually picking a spectrogram would; this might be due to several reasons, the most important ones being a strong threshold on the signal to noise ratio, which is important for automatic procedures, and conservative values for the `eps` parameter previously mentioned, which might lead to segments of the dispersion curve being discarded. An example can be seen in Fig. 3.7b, where a segment of lower frequency was obtained manually whereas DisperPy yielded a more conservative pick.

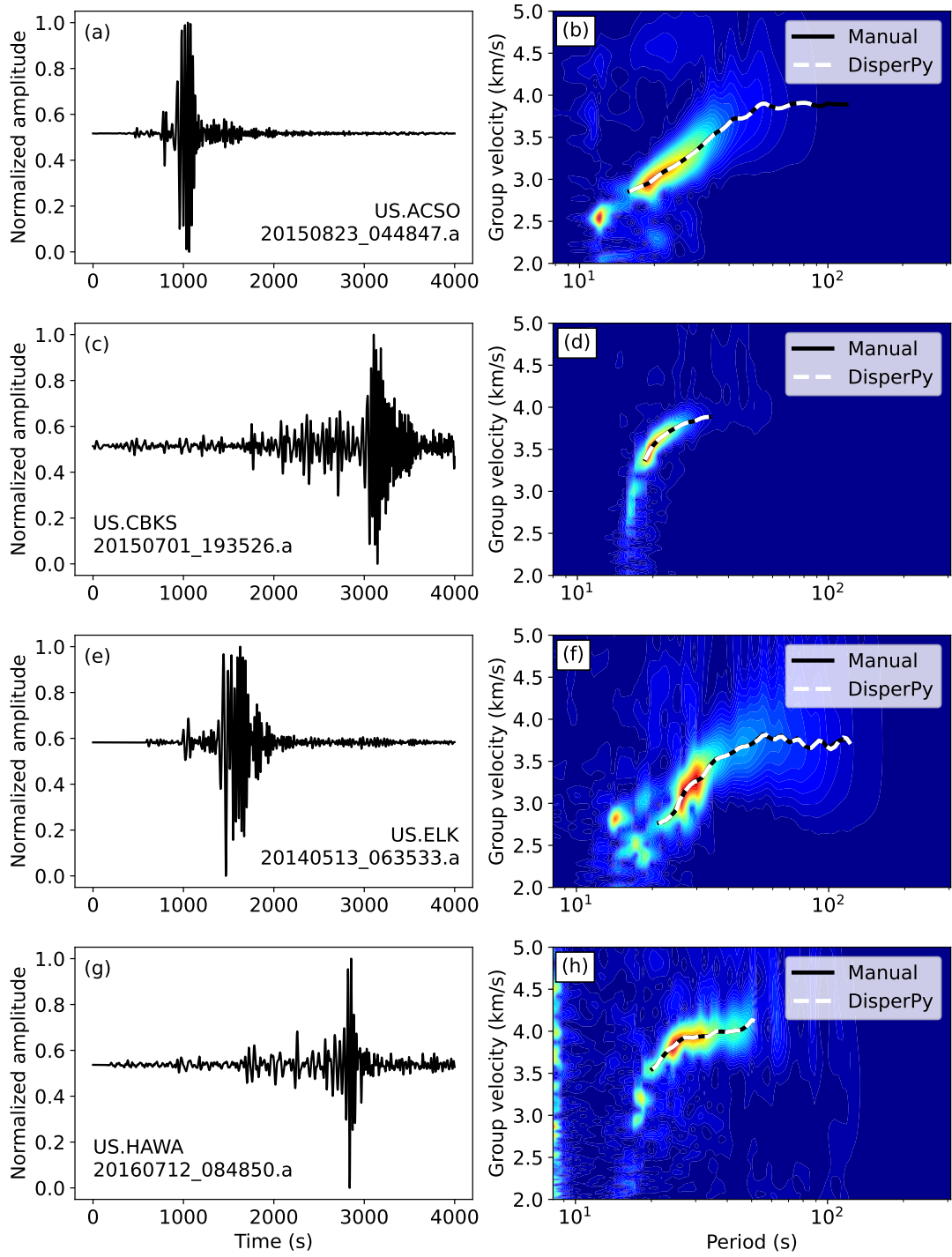


Figure 3.7: Waveforms (left column) and their respective dispersion spectrograms (right column), together with manual picks obtained using the Computer Programs in Seismology suite ([Herrmann, 2013](#)) and automatic picks from DisperPy.

3.3 Application to the contiguous United States

To demonstrate the applicability of DisperPy in a real world seismic imaging problem and to further evaluate the reliability of a collection of fundamental mode group velocity dispersion curves measured with DisperPy, we conduct a surface wave tomography experiment using data from seismic receivers deployed in the contiguous United States. With the aid of ObspyDMT ([Hosseini & Sigloch, 2017](#)) and based on the International Federation of Digital Seismograph Networks (FDSN) data exchange protocol, we fetch vertical-component broadband waveforms recorded by stations of the permanent backbone network of the United States, from 2011 to 2016. To improve the ray coverage of the maps, we also include data from all other publicly available stations in the IRIS Data Management Center from 2018 to 2019. Only waveforms that attend the following criteria were downloaded: (i) magnitude $M_w \geq 5.5$; (ii) maximum depth $z \leq 100$ km; and (iii) $12^\circ \leq \Delta \leq 160^\circ$, where Δ is the epicentral distance. Source parameters are from the Global Centroid-Moment-Tensor catalog ([Ekström et al., 2012](#)). After removing low-quality waveforms/measurements with DisperPy, our final data set comprises 194,325 dispersion curves, with a total of 2084 and 2403 unique stations and earthquakes, respectively. Fig. 3.8 shows the final spatial distribution of stations and earthquakes used in this experiment and Fig. 3.9 shows the number of ray hit counts per parameterization cell.

To translate the dispersion curves into maps of spatial variation of group velocity as a function of period, we adopt the least-squares ray theory algorithm implemented in SeisLib ([Magrini et al., 2022b](#)). Because SeisLib allows the usage of adaptive parameterizations, for each period we start by defining a global parameterization with a size of $4^\circ \times 4^\circ$, which is then refined twice around the United States area, leading thus to blocks of size $1^\circ \times 1^\circ$ around the US and $4^\circ \times 4^\circ$ elsewhere. Finally, the blocks sampled by more than 500 rays are refined once more, resulting in a variable parameterization with block sizes ranging from $0.5^\circ \times 0.5^\circ$ to $4^\circ \times 4^\circ$. The inverse problem for each velocity map is constrained by a regularization parameter that controls the roughness of the solution, determined via an L-curve analysis ([Rawlinson & Sambridge, 2003](#)). For details concerning adaptive parameterizations and inversion of dispersion curves for lateral surface wave velocity in

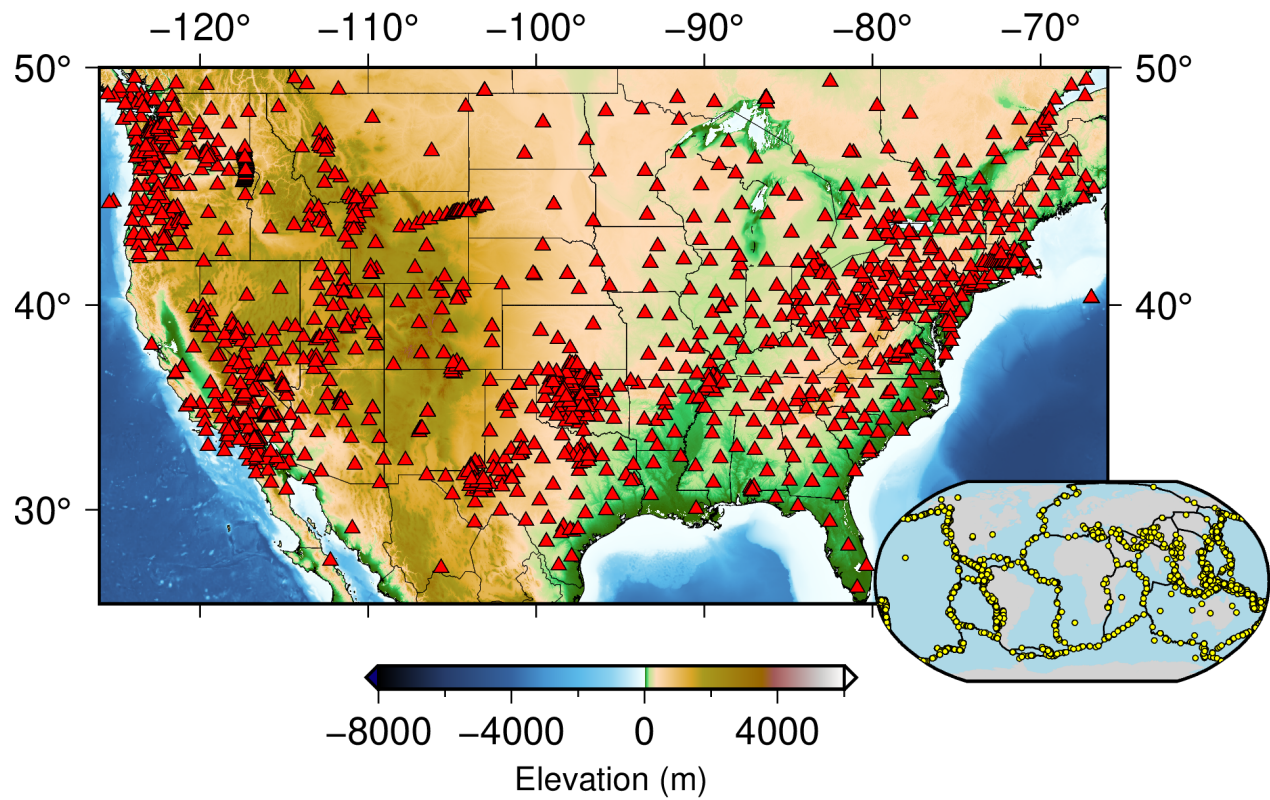


Figure 3.8: Geographic distribution of seismic stations (red triangles) and earthquakes (yellow circles) used in the surface wave tomography experiment across the United States.

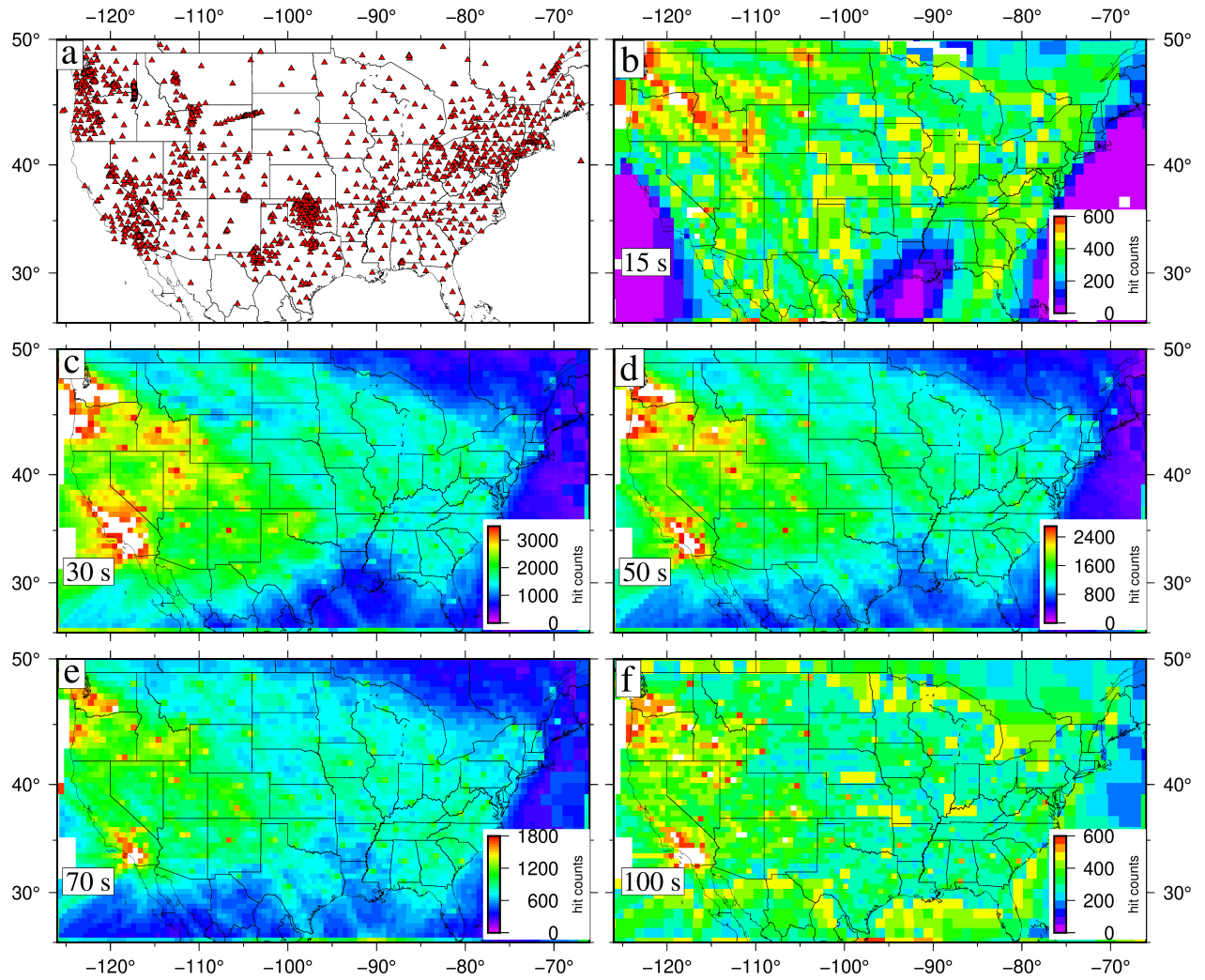


Figure 3.9: (a) Geographic distribution of seismic stations used in the surface wave tomography experiment. (b) - (f) Number of ray hit counts per parameterization cell in the period range 15 - 100 s.

SeisLib, the reader is referred to [Magrini et al. \(2022b\)](#). In Fig. 3.10, we present group velocity maps ranging from 15 to 100 s obtained following the above procedure. Note that because the intent of this experiment is only to showcase an application of measurements obtained with DisperPy to a real world problem, a second inversion for shear-wave velocity as a function of depth is beyond the scope of this study, and therefore we only qualitatively discuss the main features imaged in Fig. 3.10.

In accordance with several previous studies (e.g., [Bensen et al., 2008](#); [Shen & Ritzwoller, 2016](#); [Ekström, 2017](#); [Zhao et al., 2017](#)), the most important large-scale feature on our maps is the velocity dichotomy between the low velocity, tectonically active, western US and the high velocity, stable, central and eastern US (e.g., [Grand & Helmberger, 1984](#)). Smaller-scale features imaged in the tomography are discussed below.

Short-period group velocity Rayleigh waves (< 20 s) are mainly sensitive to shear-wave velocity structure in the upper and middle crust, and especially to the presence of sedimentary basins, which are generally characterized by slow velocities. In this sense, the most prominent (very) low velocity mapped at 15 s is related to the Gulf of Mexico and the Mississippi Embayment, where sediment thickness reaches values larger than 10 km according to the CRUST1.0 model ([Laske et al., 2013](#)). Other sedimentary basins imaged with slow velocities at 15 s period include the Anadarko, Denver, Green River, and Pasco basins. The Michigan Basin is imaged with slightly higher velocities, which can also be seen in the short period phase-velocity maps by [Zhao et al. \(2017\)](#), and the Williston Basin is not clearly detected, probably due to low resolution as a consequence of the small number of stations that we adopted in this area (Fig. 3.8). Low velocities can also be seen in the Basin and Range and have been suggested by [Bensen et al. \(2008\)](#) to be caused by a compositional or thermal anomaly within the crust.

The sensitivity peak of intermediate (30-50 s) period Rayleigh waves to shear-wave structure shifts to deeper portions, sampling mostly the lower crust and uppermost mantle. At these periods, crustal thickness plays an important role over the estimated velocities, and an inverse relation between seismic velocity and crustal thickness can be usually established. In this sense, the area located beneath the Rocky Mountain System, the Snake River Plain and the E-NE border of the Colorado Plateau is marked by a low velocity

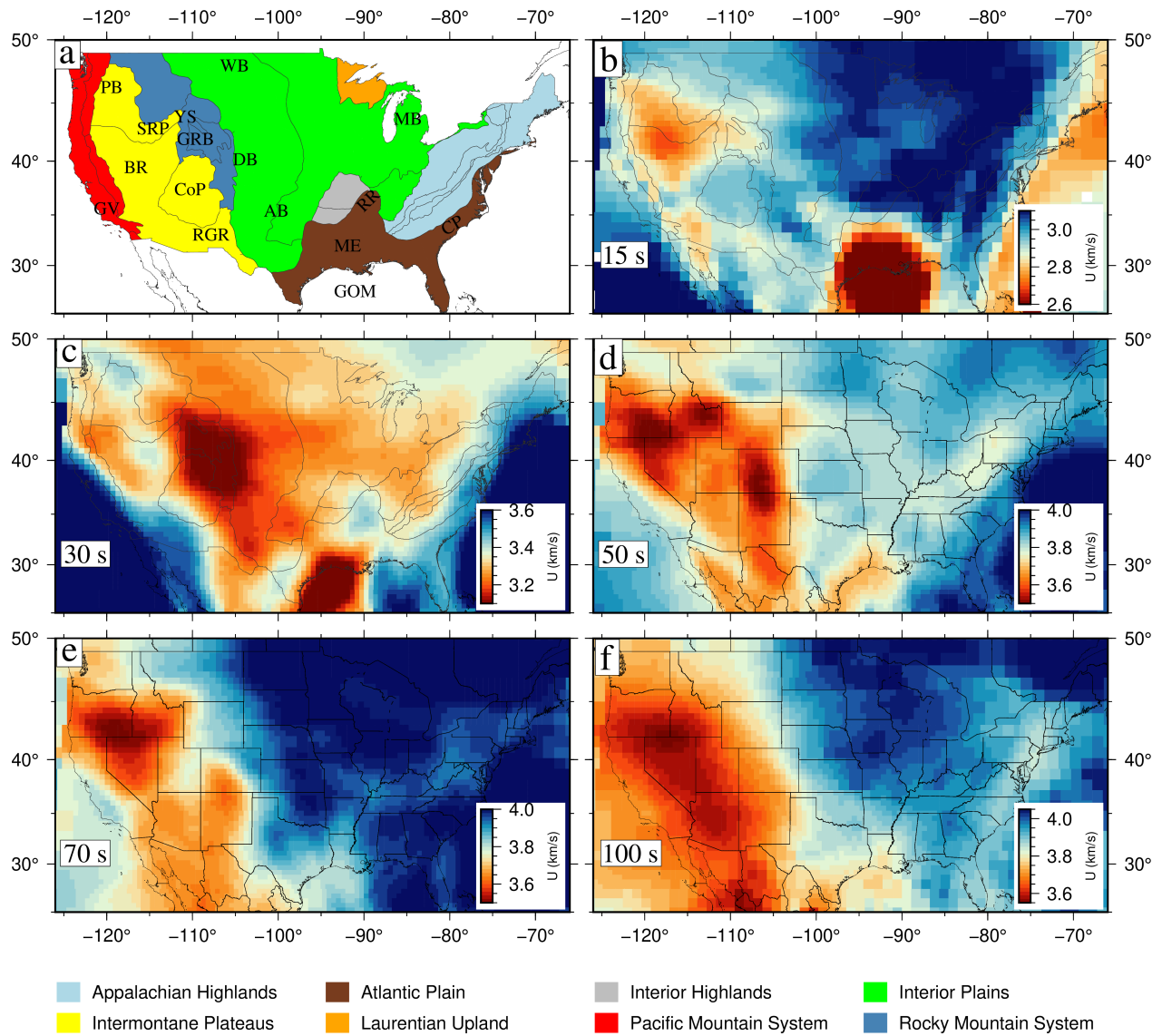


Figure 3.10: (a) Physiographic elements of the contiguous United States (modified after [Fenneman, 1917](#)). Rayleigh wave fundamental mode group at periods of (b) 15 s, (c) 30 s, (d) 50 s, (e) 70 s and (f) 100 s. Acronyms: Great Valley (GV), Basin and Range (BR), Pasco Basin (PB), Snake River Plain (SRP), Colorado Plateau (CoP), Green River Basin (GRB), Rio Grande Rift (RGR), Denver Basin (DB), Williston Basin (WB), Anadarko Basin (AB), Michigan Basin (MB), Mississippi Embayment (ME), Reelfoot Rift (RR), Gulf of Mexico (GOM), and Coastal Plains (CP).

anomaly, coherent with a thicker crust as shown in the model by [Shen & Ritzwoller \(2016\)](#). On the other hand, the high velocities along the western and eastern borders of the United States, at 30 s, agree with a thinner crust ([Shen & Ritzwoller, 2016](#)).

For periods longer than 50 s, Rayleigh waves are more sensitive to upper mantle structure and the effect of the velocity dichotomy becomes more evident, with the tectonically active west being imaged with slow velocities and the more stable, cratonic, central and eastern US depicting high velocities. In fact, [Priestley et al. \(2024\)](#) show a large difference in estimates of the lithosphere-asthenosphere boundary depth across the western and eastern US, with the west being much thinner.

3.4 Conclusions

DisperPy provides a robust, open-source solution for automating the extraction of group velocity dispersion curves from earthquake data, addressing key challenges such as noisy data and spectral gaps. The integration of a convolutional neural network to solve the task of classifying dispersion quality with conventional unsupervised machine learning algorithms to perform the actual picks allows for efficient processing of large datasets, offering a systematic and conservative approach to the problem dispersion curve measurement. Through validation against manual picks and a real-world application in surface wave tomography, DisperPy demonstrates its effectiveness in extracting reliable dispersion curves, even in challenging scenarios. Consistent with several previous studies (e.g., [Bensen et al., 2008](#); [Shen & Ritzwoller, 2016](#); [Ekström, 2017](#); [Zhao et al., 2017](#)), the group velocity maps for the contiguous United States reveal a significant velocity dichotomy between the low-velocity, tectonically active western US and the high-velocity, stable, central and eastern US (e.g., [Grand & Helmberger, 1984](#)). Overall, DisperPy represents a significant advancement in the use of automated tools for seismology, paving the way for more efficient and accurate Earth structure imaging.

Chapter 4

Crustal and uppermost mantle radial anisotropy beneath South America from joint inversion of ambient noise and earthquake dispersion curves

Outline

In this chapter, I present a paper (in preparation) containing a new radial anisotropy model for South America up to 100 km depth. This model is based on several thousands of Rayleigh and Love wave group velocity dispersion curves measured using DisperPy. The curves are derived from both earthquake and ambient noise data. The inversion schema roughly follows the one in Chapter 2, apart from differences in parameterization. The results show a heterogeneous upper crust with both negative and positive radial anisotropy and an upper mantle dominated by positive radial anisotropy in the continental area.

Abstract

Estimates of the anisotropic character of the materials that constitute the Earth are complementary to isotropic seismic velocities, and can provide additional insights into past and present deformation and flow. In this study, we constrain radial anisotropy beneath South America from the difference between vertically (V_{sv}) and horizontally (V_{sh}) polarized shear-wave velocity models. Using an automatic procedure, we measure 255,292 Rayleigh and 75,843 Love wave group velocity dispersion curves, from both earthquakes and cross-correlations of ambient noise between pairs of sensors. Our dispersion measurements span periods between 6 and 120 s for Rayleigh waves and 7 and 90 s for Love waves, thus being sensitive to crustal and uppermost mantle structure. Based on Rayleigh wave polarization, we identify and correct waveforms from stations that present large orientation errors of the horizontal components, which is important for Love wave analysis. The inversion strategy follows a two-step procedure, where in the first step we construct adaptively parameterized maps of spatial variation of surface wave velocity from the dispersion data, and in the second step we use a linearized approach to invert the surface wave velocity maps for V_{sv} and V_{sh} models, which together constrain the radial anisotropy model. Our model reveals a very anisotropic crust (and especially shallow upper crust) and a more homogeneous upper mantle, mostly characterized by positive radial anisotropy. We suggest that a large component of the shallow radial anisotropy might be related to shape preferred orientation caused by alignment of heterogeneous material related to the Paraná and Central Atlantic Magmatic Provinces.

Keywords: Radial anisotropy; Surface waves; South America; Ambient noise; Crust; Upper mantle.

4.1 Introduction

South America is home to a wealth of distinct tectonic features, including cratons, shields, large intracratonic synclises, mobile belts, a continental scale lineament that separates the major parts of the stable portion of the continent, large igneous provinces, and the

tectonically active Andean cordillera. A multitude of studies provided a better grasp on the geodynamic evolution and current architecture of the crustal and upper mantle structure beneath South America by employing a wide variety of geophysical techniques, including body (e.g., [Azevedo et al., 2015](#); [Simões Neto et al., 2019](#); [Portner et al., 2020](#); [Affonso et al., 2021](#)) and surface wave tomography (e.g., [Feng et al., 2004, 2007](#); [Nascimento et al., 2022, 2024](#); [Moura et al., 2024](#)), receiver function (e.g., [Julià et al., 2008](#); [Albuquerque et al., 2017](#); [Rivadeneira-Vera et al., 2019](#)), gravity (e.g., [Uieda & Barbosa, 2017](#); [Almeida et al., 2021a](#); [Santos et al., 2022](#)), seismic reflection (e.g., [Daly et al., 2014](#)) and refraction (e.g., [Soares et al., 2006, 2018](#); [Lima et al., 2015](#); [Bernardes et al., 2023](#)), and magnetotellurics (e.g., [Bologna et al., 2014, 2019](#); [Padilha et al., 2015, 2016](#); [Correa et al., 2024](#)). These studies attest the complex current architecture of the lithosphere beneath South America, which is the product of several Wilsonian cycles.

Since the 2010s, initiatives such as the Brazilian Seismographic Network ([Bianchi et al., 2018](#)) and the Seismic Network of Chile ([Barrientos, 2018](#)), besides several temporary arrangements (e.g., [Assumpção & Bianchi, 2016b](#)), provided a denser coverage of seismic stations in South America, allowing models of seismic wave speed with increased resolution to be computed. In this context, several recent continental scale models ([Celli et al., 2020](#); [Ciardelli et al., 2022](#); [Nascimento et al., 2024](#); [Melo et al., 2025](#)) have mapped the shear-wave velocity distribution of the upper mantle beneath the continent using different methodological approaches and datasets. Despite small-scale differences, these studies tend to agree on long-scale structure such as high velocities beneath Precambrian cratons and low velocities beneath Patagonia.

Isotropic seismic velocities provide information on the thermal and chemical structure of the Earth's interior (e.g. [Karato & Karki, 2001](#); [Kaban et al., 2003](#)). Anisotropy information, on the other hand, can provide additional insights into past and present deformation and flow inside the Earth ([Luo et al., 2013](#)), especially in the crust and upper mantle. A type of anisotropy known as radial anisotropy (RA) (or transversely isotropy with a vertical symmetry axis) is computed by the difference between the propagation speeds of vertically (V_{sv}) and horizontally (V_{sh}) polarized shear waves, which are constrained by dispersion measurements of Rayleigh and Love waves, respectively.

To date, most of the information on the anisotropic character of South America comes from shear wave splitting studies (e.g., [Assumpção et al., 2006, 2011](#); [Bastow et al., 2015](#); [Melo & Assumpção, 2018](#)), which approximately reflect azimuthal anisotropy ([Long & Becker, 2010](#)). Radial anisotropy, on the other hand, is far less investigated. A few exceptions come from the studies by [Lynner et al. \(2018\)](#) and [Poveda et al. \(2023\)](#), who investigated radial anisotropy in the Central Andes and NW South America, respectively. The continental-scale radial anisotropy under South America, however, is still poorly constrained.

The horizontal components of a waveform are usually noisier than the vertical component, which makes Love wave dispersion more difficult to measure than Rayleigh wave dispersion, and therefore previous surface wave tomography experiments ([Heintz et al., 2005](#); [Feng et al., 2007](#); [Nascimento et al., 2022, 2024](#)) preferred to invert Rayleigh waves for V_{sv} models only. A few continental scale Love wave group velocity maps are reported in the literature ([Vdovin et al., 1999](#); [Feng et al., 2004](#); [Rosa et al., 2016](#)), but the low resolution as a consequence of the low number of source-receiver paths precluded these maps to be inverted for V_{sh} , hence providing little to no constraints on continental radial anisotropy.

Anisotropy arises from several physical mechanisms. Under a finite strain regime, plastic deformation mainly by dislocation creep can align the crystallographic axes of anisotropic minerals in a specific direction, leading to what is called lattice-preferred orientation (LPO) ([Karato, 2008](#)). This is the most significant cause of anisotropy in the upper mantle, as its main constituent minerals, such as olivine, orthopyroxene and clinopyroxene, are very anisotropic, showing P-wave velocity differences between the fast and slow axes larger than 10% ([Montagner & Guillot, 2002](#)). The lattice-preferred orientation of micas ([Nishizawa & Yoshino, 2001](#)) and amphiboles ([Barberini et al., 2007](#); [Tatham et al., 2008](#)) is also thought to be the main factor for anisotropy in the mid and lower crust, respectively. Another class of anisotropy source, named shape preferred orientation (SPO), is associated with a preferential alignment of heterogeneous (isotropic or anisotropic) materials such as dykes, sills, fractures and sedimentary layers ([Crampin, 1981](#); [Luo et al., 2013](#)).

In this study, we wish to provide a comprehensive estimate of the distribution of radial anisotropy encompassing the South American continent, from the crust to the upper

mantle, based on a large number of surface wave measurements. To maximize ray coverage and improve azimuthal distribution, we measure Rayleigh and Love wave dispersion curves derived from both earthquake data and ambient noise cross-correlations between pairs of stations. In Section 4.2, we summarize the main tectonic elements that constitute South America. In Section 4.3, we describe our data set and how we extract Rayleigh and Love wave group velocity dispersion curves from waveform data, and in Section 4.4 we explain how we use these curves as the input data to construct models for V_{sv} , V_{sh} , and radial anisotropy up to 100 km depth beneath South America. Finally, in Section 4.5 we present our results, demonstrating that although variable across the continent, some degree of anisotropy is necessary to explain Rayleigh and Love observations.

4.2 Tectonic setting

The tectonic puzzle that constitutes South America can be conveniently summarized into three main pieces: the South American Platform, the Andean orogenic belt and Patagonia. The South American platform corresponds to the relatively stable portion of the continent not deformed by the younger Phanerozoic Andean and Caribbean orogenies located to the west of the platform (Almeida et al., 2000). The Patagonian block presents a distinct evolution compared with the South American platform, being amalgamated to the southern portion of Gondwana during the Permian (Ramos, 2008). Fig. 4.1 shows the main tectonic features of South America.

Brito Neves & Fuck (2013, 2014) identify two large domains within the South American platform separated by the Transbrasiliano and Araguaia lineaments: Amazonian to the N-NW, and Brasiliano to the E-SE of these lineaments. In fact, the Amazonian and Brasiliano domains present strong similarities with the Laurentia and Gondwana continents, respectively (Brito Neves & Fuck, 2014).

In terms of crustal provinces, the Amazonian domain encompasses two shields (Guyana to the north and Central Brazil to the south) separated by a central E-W axis containing the Amazon, Solimões and Acre Phanerozoic basins (Fig. 4.1). These shields together compose the Amazon craton (AmC). The Archean nuclei seed located in the eastern portion of the

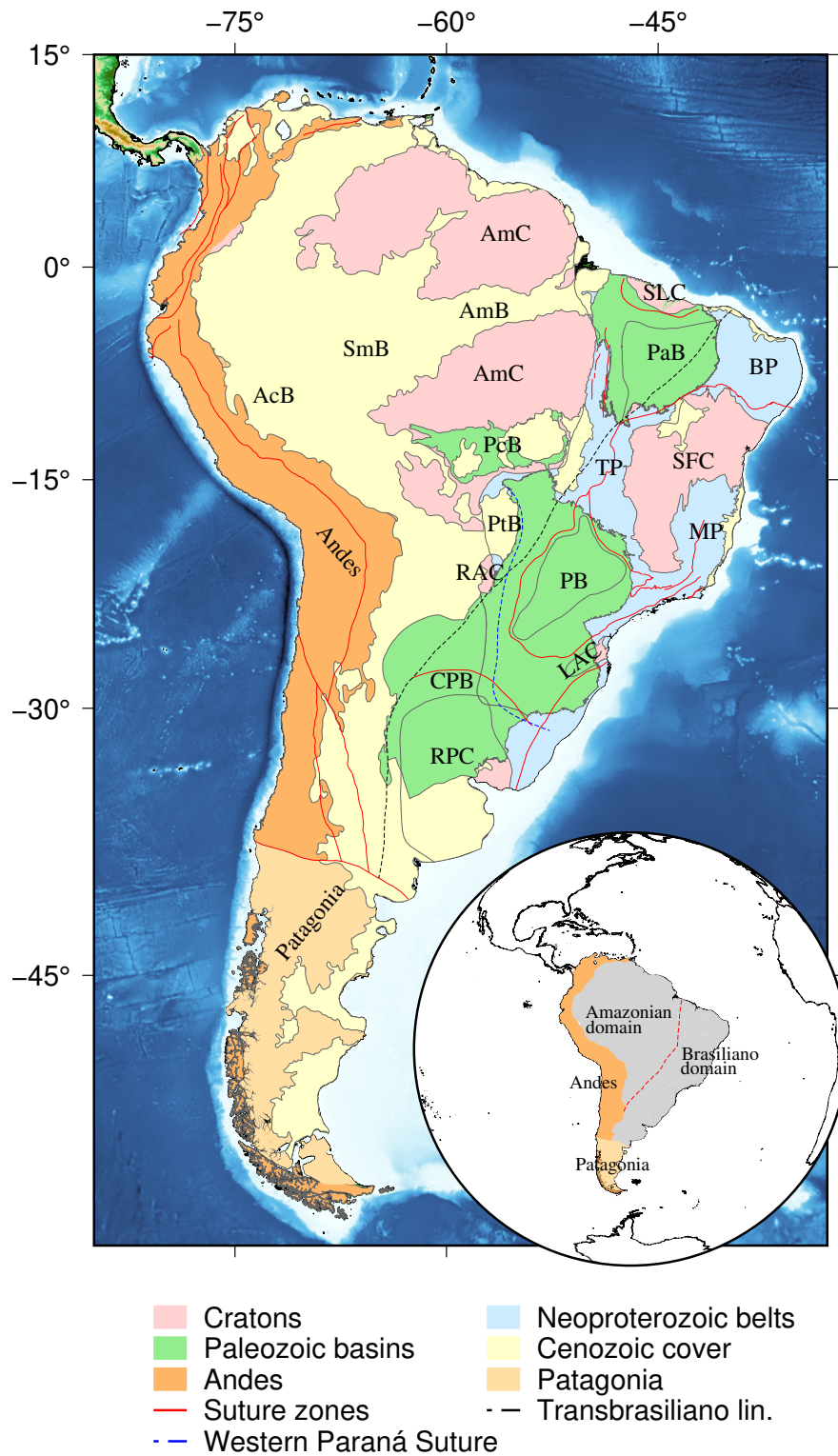


Figure 4.1: Tectonic map of South America (modified after [Cordani et al., 2016](#)). AmC: Amazon craton, SFC: São Francisco craton, SLC: São Luís craton, LAC: Luis Alves craton, RPC: Río de la Plata craton, RAC: Rio Apa craton, AmB: Amazon basin, SmB: Solimões basin, AcB: Acre basin, PcB: Parecis basin, PaB: Parnaíba basin, PtB: Pantanal basin, PB: Paraná basin, CPB: Chaco-Paraná basin, TP: Tocantins province, MP: Mantiqueira province, BP: Borborema province. Western Paraná Suture from [Dragone et al. \(2021\)](#).

AmC grew to the southwest following several episodes of accretion of orogenic belts during the Paleo- and Mesoproterozoic (Cordani & Teixeira, 2007), which were later cratonized. The youngest southwestern tip of the AmC, however, was involved in a collisional-type orogeny rather than accretion during the Stenian (Cordani & Teixeira, 2007). Recent tomographic images of the upper mantle (Celli et al., 2020; Ciardelli et al., 2022; Nascimento et al., 2024; Melo et al., 2025) show a reduced shear-wave velocity beneath the southwestern portion of the AmC in comparison with its eastern portion, which suggests absence of the cratonic root.

The current framework of the Brasiliano domain was strongly shaped by the Neoproterozoic Brasiliano/Pan-African orogeny (Brito Neves & Fuck, 2013) through several episodes of orogenic collage; on the other hand, only scarce Neoproterozoic records are found in the Amazonian domain. The Brasiliano domain is characterized by smaller Archean and Proterozoic cratonic blocks (São Francisco, Río de la Plata, São Luís and Luís Alves) separated by Neoproterozoic mobile belts that constitute the Borborema (NE Brazil), Tocantins (central Brazil) and Mantiqueira (along the Brazilian coast) structural provinces (Almeida et al., 1981; Cordani et al., 2016).

Located along the western margin of South America, the more than 8000 km long Andes are characterized by the highest mountains in a non-collisional setting in the world (Ramos, 1999), being affected by the complex interaction between several tectonic plates, including Nazca, South American, Caribbean, Antarctica and Scotia. Based on similar properties, a general subdivision of the Andes into northern, central and southern parts is usually proposed (Gansser, 1973; Ramos, 1999). The Andes are also characterized by the presence of three flat-slab segments: Bucaramanga (north of 5°N), Peruvian (2°S - 15°S), and Pampean segments (27°S - 33°S) (Barazangi & Isacks, 1976; Pennington, 1981; Ramos, 1999; Ramos et al., 2002).

Corresponding to the southern part of South America, Patagonia is likely an allochthonous block that was incorporated to Gondwana during the Permian (Ramos et al., 2020), presenting a strong contrast to the South American Platform (Ramos et al., 2020). In fact, recent tomography studies (Ciardelli et al., 2022; Nascimento et al., 2024; Melo et al., 2025) have shown that the upper mantle beneath Patagonia is dominated by low-velocity

shear-wave anomalies.

4.3 Data selection and processing

To investigate the complex lithospheric structure beneath South America, we use measurements of fundamental mode Rayleigh and Love wave dispersion curves, derived from both seismic ambient noise and earthquakes. The combination of ambient noise with traditional surface wave tomography using ballistic waves intends to improve resolution by maximizing path and azimuthal coverage. We extract group velocities from ambient noise and earthquakes using an automated approach. In the following sections, we describe the procedure to retrieve and process ambient noise and earthquake data and the strategy adopted to extract the respective dispersion curves.

4.3.1 Data

We adopt the Python open source library SeisLib ([Magrini et al., 2022b](#)) to perform routine tasks in an ambient noise tomography workflow ([Bensen et al., 2007](#)), including retrieval and pre-processing of data, calculation of cross-correlations between pairs of stations, and 2-D tomography. We download broad-band three-component continuous recordings spanning from January 2000 to December 2022, as well as data from a former temporary seismic array from 1992 to 1995 ([Snoke & James, 1997](#)). By doing so, we also include paths between pairs of stations deployed prior to the establishment of the Brazilian Seismographic Network in 2011 ([Bianchi et al., 2018](#)), thus resulting in a denser ray coverage. Data from a total of 590 seismic stations were employed for ambient noise analysis (Fig. 4.2). All traces have been pre-processed by removing their mean and linear trend, Hann tapering (5%), bandpass filtering, restoring displacement by deconvolution with the instrument response, and downsampling to 1 Hz. Note that dispersion curves of Rayleigh and Love waves are measured from the vertical and transverse components, respectively, after the horizontal channels are rotated to the radial-transverse (R-T) orientation system.

For each pair of stations with at least 3 months of simultaneous data available, we estimate the empirical Green's function between them by cross-correlating data in the

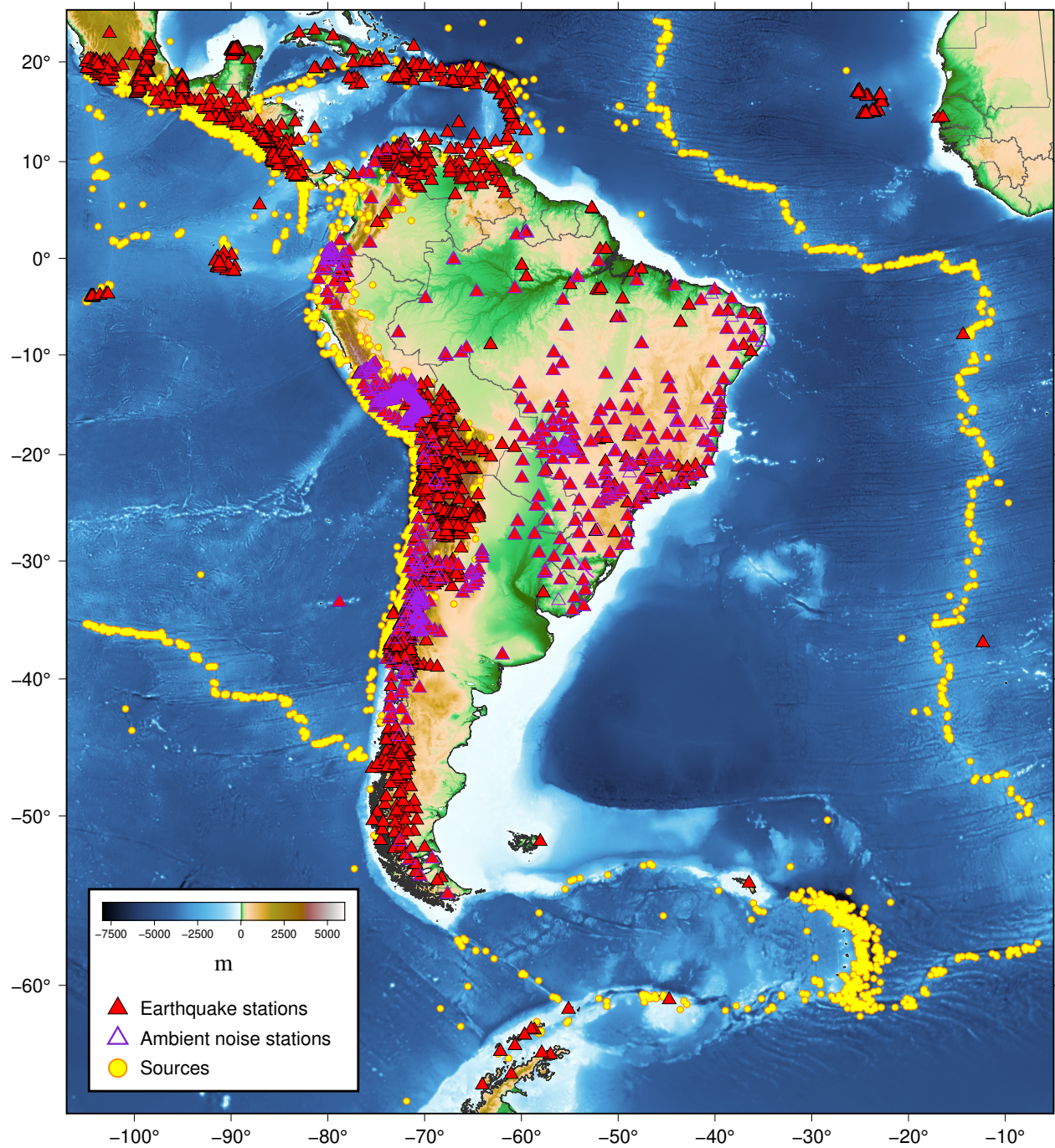


Figure 4.2: Distribution of the earthquakes (yellow circles) and stations (colored triangles) used in this study.

frequency domain along one hour time windows overlapping by 50% (Seatz et al., 2012). Spectral whitening is applied to normalize the amplitudes of each cross-spectrum (Bensen et al., 2007). The cross-spectra are then ensemble averaged to create a robust unique cross-spectrum (Magrini et al., 2022b), which is inverse Fourier transformed to obtain a signal in the time domain. The causal and acausal parts of this signal are then averaged to create a single ‘symmetric’ signal (Bensen et al., 2007), from which group velocities are measured.

We use the Python toolbox ObspyDMT (Hosseini & Sigloch, 2017) to download three-component seismic waveforms of earthquakes with source parameters reported in the Global Centroid-Moment-Tensor catalog (Ekström et al., 2012) from 1992 to 2022. We restrict the maximum depth allowed to 100 km and fetch earthquakes with magnitudes $M_w \geq 5.2$ for epicenters located in the vicinity of the South American, Nazca, Caribbean, Cocos and Scotia plates. Fig. 4.2 shows the final spatial distribution of the 4020 epicenters and 2617 stations used in this study. All the earthquake traces have been pre-processed in the same way as the ambient noise ones: removal of mean and linear trend, Hann tapering (5%) and filtering, removal of the instrument response, downsampling, and rotation of the horizontal components to the R-T system.

4.3.2 Dispersion measurements

We use DisperPy (Nascimento et al., 2025), a tool based on machine learning, to automatically pick Rayleigh and Love group velocity dispersion curves from a large number of waveforms. For the sake of completeness, below we summarize how DisperPy extracts dispersion curves from the seismograms, but the reader is referred to Nascimento et al. (2025) for more details. DisperPy has two main parts, one for classifying whether a dispersion spectrogram has a good quality for measurement and another for actually picking the group velocity/periods pairs. The classification phase is cast as a supervised problem and is solved with a convolutional neural network based on the ResNet architecture version with 34 layers (He et al., 2015). In this phase, a dispersion spectrogram is initially created by applying frequency-time analysis (e.g., Levshin et al., 1992) to the waveform, which is then stored in an image file. Each image file consists of three channels (red, green, and blue

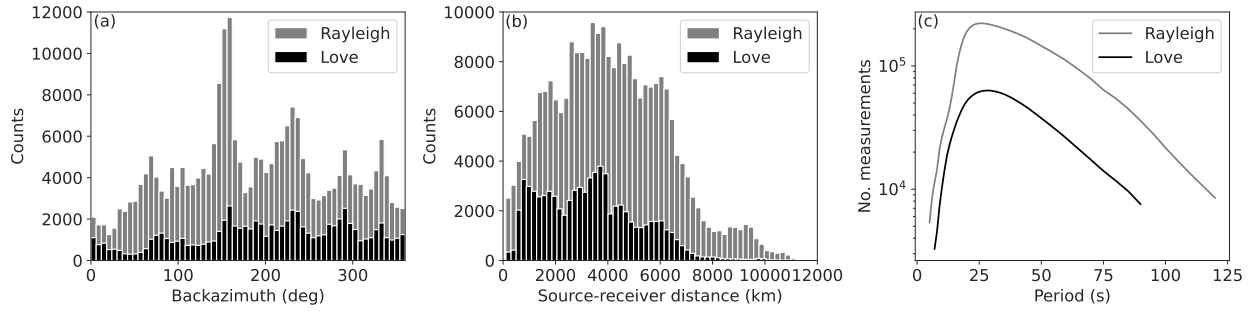


Figure 4.3: Basic properties of the Rayleigh and Love wave dispersion data sets: (a) Distribution of backazimuths and (b) Source-receiver distances. (c) Number of dispersion measurements as a function of period.

colors) and a size of 224×224 pixels and is then fed to the neural network; at the end of the parameter layers of the network, a sigmoid function generates the probability whether the curve belongs to class zero or one. In this study, we only consider for measurement those cases where the algorithm is at least 80% confident that the instance belongs to class one.

Upon approval for measurement, the second part of the automatic extraction method consists of the actual picks. This task is cast as an unsupervised machine learning problem, solved through a variety of algorithms. In essence, the measurement phase consists of the following steps: (i) removal of low frequency noise using a Gaussian mixture (Bishop, 2006); (ii) creation of clusters of dispersion energy with k-means (MacQueen, 1967), which facilitates the picking of a first trial dispersion curve; (iii) refining the trial dispersion curve by removing possible outliers and bad picks using both the DBSCAN algorithm (Ester et al., 1996) and a signal-to-noise ratio (as defined by Bensen et al., 2007) threshold; (iv) usage of the final ‘raw’ dispersion curve to create a phase-matched filter (Levshin et al., 1992; Levshin & Ritzwoller, 2001) and a second application of the algorithm on the filtered waveform to generate a ‘clean’ dispersion curve. By following the above procedure, we retrieve a total of 255,292 Rayleigh and 75,843 Love wave group velocity dispersion curves, respectively, in the period range 6 - 120 s (7 - 90 s for Love waves). Fig. 4.3a and b show histograms of the azimuthal and distance distribution of our data set, respectively, and Fig. 4.3c shows the number of Rayleigh and Love wave measurements sorted by period.

4.3.3 Analysis of misorientation of horizontal components

Love wave motion is recorded in the horizontal components of the waveforms, and thus a reliable extraction of Love wave dispersion theoretically depends on the correct alignment of the N-component of the seismometer with the north direction. [Luo et al. \(2013\)](#) mention that small orientation errors ($|\pm 10^\circ|$) might affect the seismograms, but not necessarily the respective dispersion curves. However, it is not uncommon for receivers to have orientation errors larger than $|\pm 10^\circ|$ (e.g., [Ekström & Busby, 2008](#); [Albuquerque et al., 2024](#)), hence leading to the introduction of errors in dispersion estimates (see Fig. 4.4).

A simple and yet powerful technique to measure seismometer orientation relies on the polarization of Rayleigh waves on the vertical (Z) and radial (R) components ([Chael, 1997](#); [Baker & Stevens, 2004](#); [Stachnik et al., 2012](#)). Put simply, the horizontal components are converted from the N-E (or 1-2) to the R-T system by rotating over backazimuths (θ) varying from 0° to 360° , and the estimated backazimuth is the one that presumably maximizes the similarity between Rayleigh waves recorded on the Z and Hilbert transformed R ($\bar{R}$) channels. The elliptical retrograde motion of Rayleigh waves causes a 90° shift on the waveform recorded on the Z and R components, and thus the application of the Hilbert transform intends to correct this shift so that they can be compared. An orientation residual is then given by the circular distance between the (theoretical) backazimuth along the great circle path and the estimated backazimuth. For each station, we prepare waveforms using the same parameters as [Stachnik et al. \(2012\)](#), which includes magnitude larger than 6.0, a window size of -20 s to 600 s around the time of arrival of a phase with velocity equal to 4 km/s, 10% taper, and bandpass filtering between 0.02 and 0.04 Hz. For each tested θ , the similarity between two channels is computed by the zero-lag cross-correlation ([Baker & Stevens, 2004](#)):

$$S_{jk} = \sum_{\tau=1}^N x_j(\tau)x_k(\tau) \quad (4.1)$$

where j and k refer to the vertical or Hilbert transformed radial components and x are the time series. Following [Stachnik et al. \(2012\)](#), we normalize the cross-correlations using two equations:

$$C_{z\bar{r}} = \frac{S_{z\bar{r}}}{\sqrt{S_{zz}S_{\bar{r}\bar{r}}}} \quad (4.2)$$

$$C_{z\bar{r}}^* = \frac{S_{z\bar{r}}}{S_{zz}} \quad (4.3)$$

Eq. 4.2 is used for assessment of data quality and Eq. 4.3 is used to find the direction of maximum relationship between both signals. The difference between the theoretical and the estimated backazimuth produces a residual value, and the final misorientation estimate is then computed by applying circular statistics ([Berens, 2009](#)) to all residuals measured for the station. We use the same data culling procedures as [Stachnik et al. \(2012\)](#). Overall, our estimates are in general agreement with the ones provided by [Albuquerque et al. \(2024\)](#) for the Brazilian Seismographic Network based on P-wave particle motion. We find that around 29% of the stations that we could calculate a misorientation estimate present absolute alignment errors larger than 10° . For earthquake traces of stations with errors greater than $|\pm 10^\circ|$, we apply a correction based on our error estimate, and for ambient noise traces we choose the more conservative approach of discarding such stations. Fig. 4.4 shows an interesting example recorded by station C1.MT16, where we found an orientation error of 64.5° . Prior to the correction, the Z and $\bar{R}$ channels present a strong mismatch; furthermore, the dispersion curve from the R component is largely contaminated by Love wave energy, showing faster velocities. After the correction, the dispersion curves from the Z and R components are alike, as expected.

4.4 Inversion strategy

We follow a two-step procedure to invert our dispersion measurements for vertically (V_{sv}) and horizontally (V_{sh}) polarized shear-wave velocity models, and then compute radial anisotropy for South America based on these models. In Section 4.4.1, we first describe the algorithm we adopt to translate our group velocity measurements of Rayleigh and Love waves into spatial variations of surface wave velocity beneath South America and neighboring oceans, and in Section 4.4.2 we discuss the inversion of the surface wave

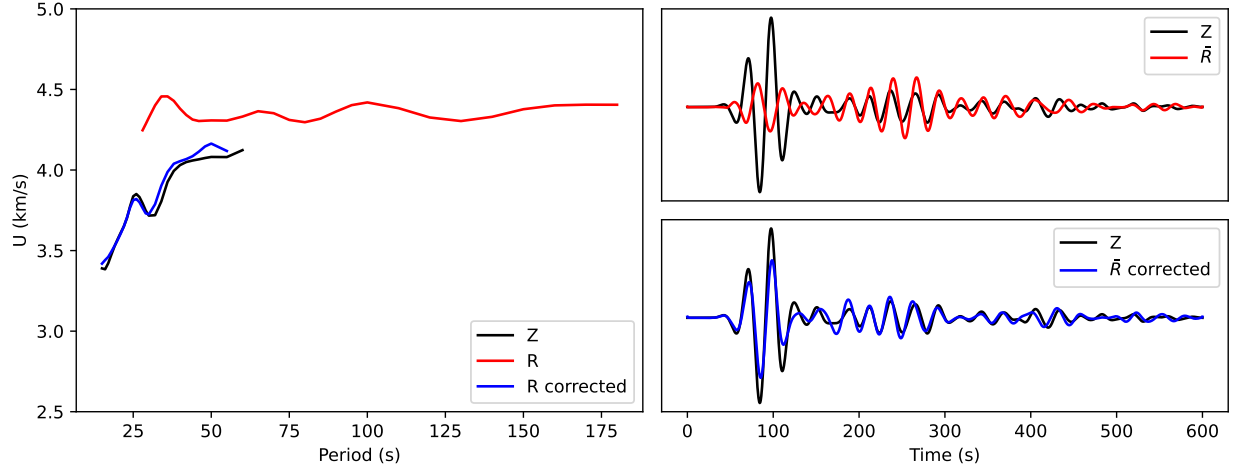


Figure 4.4: Record of earthquake 20180114_091852.a of the GCMT catalog at station C1.MT16. The left panel shows a comparison of the Z-component dispersion curve and the R-component dispersion curve before (red) and after (blue) orientation correction, with the respective waveforms shown in the right panels. Note that the R dispersion curve prior to correction is contaminated by Love wave energy.

velocity maps for shear-wave structure, and how we calculate radial anisotropy from the V_{sv} and V_{sh} models.

4.4.1 2-D Tomography

We follow a ray theoretical least-squares inversion framework, implemented in SeisLib (Magrini et al., 2022b), to map the lateral distribution of surface wave velocities based on dispersion measurements. Assuming that the propagation of surface waves between a source (or a virtual source) and a receiver does not deviate from the great circle path and considering a parameterization in n blocks, where each block has a constant slowness, the forward problem equation in discrete form is given by (Magrini et al., 2022b):

$$s = \frac{1}{L} \sum_{k=1}^n s_k l_k \quad (4.4)$$

where s is the average slowness along the path connecting source and receiver, L is the source-receiver distance, s_k and l_k are slowness and path segment length across block k , respectively. Given a velocity (slowness) model, Eq. 4.4 allows to compute the average slowness between any pair of points; however, in general we have a collection of obser-

variations related to several pairs of points, so it is convenient to rewrite Eq. 4.4 in matrix notation such that $\mathbf{A} \cdot \mathbf{x} = \mathbf{d}$, where $\mathbf{A}$ is a matrix of size m by n containing lengths of path segments within the parameterization blocks (normalized by the length of the respective ray segment), $\mathbf{d}$ is an m -sized vector of observables (measured group slowness between pairs of points) and $\mathbf{x}$ is the n -sized vector of model parameters (slowness of each parameterization block) that we wish to determine. The objective of the inversion procedure is hence to estimate $\mathbf{x}$ given $\mathbf{d}$.

As [Magrini et al. \(2022b\)](#) states, because generally matrix $\mathbf{A}$ is not invertible in real-world problems, it is not possible to directly solve the previous linear system for $\mathbf{x}$, so the common approach to solve it is via least-squares minimization ([Boschi & Dziewonski, 1999](#)). Regularization terms must be introduced as well to stabilize the inversion procedure, and SeisLib uses a roughness operator $\mathbf{R}$ that seeks to impose a smoothness constraint by minimizing roughness, leading thus to the following solution ([Magrini et al., 2022b](#)):

$$\mathbf{x} = \mathbf{x}_0 + (\mathbf{A}^T \cdot \mathbf{A} + \mu^2 \mathbf{R}^T \cdot \mathbf{R})^{-1} \cdot \mathbf{A}^T \cdot (\mathbf{d} - \mathbf{A} \cdot \mathbf{x}_0) \quad (4.5)$$

where μ is a scalar coefficient that governs the smoothness of the solution (determined via L-curve analysis, [Rawlinson & Sambridge, 2003](#)) and $\mathbf{x}_0$ is an initial model close to $\mathbf{x}$, which we adopt as the average slowness for each period. In practice, for each period the final distribution of surface wave velocities is calculated by taking the inverse of the solution of Eq. 4.5.

A very useful feature implemented in SeisLib is the possibility to adopt adaptive parameterizations ([Bijwaard et al., 1998](#); [Magrini et al., 2022b](#)). In large areas where the distribution of stations and rays is uneven, such as South America, adaptive parameterizations provide a way to increase resolution by having a denser distribution of parameterization blocks in regions where ray coverage is optimal. We start by defining an equal-area grid with blocks of size $2.4^\circ \times 2.4^\circ$. Then, we refine each block intersected by more than 300 (150 for Love waves) rays into four blocks of size $1.2^\circ \times 1.2^\circ$. Finally, we perform a second round of refinement where blocks with hit counts greater than 150 (75 for Love waves) are further subdivided into four blocks of size $0.6^\circ \times 0.6^\circ$. The Supplementary Material (Supplementary Figs. B.1 - B.4) presents the hit count and group velocity maps retrieved in

this step, and also several checkerboard tests to assess the lateral resolution of the surface wave velocity maps (Supplementary Figs. B.5 - B.10).

4.4.2 Depth inversion and computation of radial anisotropy

We perform the inversion of surface wave maps for shear-wave structure as a function of depth using the linearized least-squares approach implemented in the *surf96* routine of Computer Programs in Seismology (Herrmann, 2013). Rayleigh and Love wave maps are inverted separately, giving access to V_{sv} and V_{sh} models, respectively, and then radial anisotropy is computed from their differences.

Following Magrini et al. (2023) and Nascimento et al. (2024), because we use an adaptive parameterization that varies over the study area, we start by interpolating each surface wave velocity map into a regular grid with a spacing of $0.6^\circ \times 0.6^\circ$, which is the minimum parameterization block size. We generate group velocity Rayleigh and Love dispersion curves at each one of a total of 9801 nodes of the regular grid. We first invert the Rayleigh waves for V_{sv} structure, using a modified version of AK135-F (Kennett et al., 1995; Montagner & Kennett, 1996) as a starting model. The modification consists of replacing the crust by structure at uppermost mantle depths and intends to avoid vertical velocity jumps inherited from the starting model (e.g., Lynner & Porritt, 2017; Nascimento et al., 2024). As in Dreiling et al. (2018), we use the thus obtained V_{sv} model as the starting model for the inversion of Love waves for V_{sh} structure, expecting the result to change only when radial anisotropy is required to fit the Love data. The Supplementary Material presents the sensitivities of the considered data sets to shear-wave velocity structure with depth; Fig. B.11 shows that the peak sensitivity of Love wave group velocity is rather shallow compared with Rayleigh wave group velocity, and hence we limit the maximum depth with good resolution retrieved by our model to 100 km. The final V_{sv} and V_{sh} models are also shown in the Supplementary Figs. B.12 and B.13.

As previously mentioned, we compute the radial anisotropy from the V_{sv} and V_{sh} models that were determined separately. As in Dreiling et al. (2018), we compute RA from the following equations:

$$RA = (\xi - 1) \times 100\% \quad (4.6)$$

where

$$\xi = \left(\frac{V_{sh}}{V_{sv}} \right)^2 \quad (4.7)$$

4.5 Results and discussion

Prior to presenting our model, we start this section by testing the null hypothesis, that is, $V_{sv} = V_{sh}$, and hence that the lithosphere beneath South America is isotropic. To do so, we compute synthetic Love wave dispersion curves from the V_{sv} model at a few selected locations and compare them to the local dispersion curves at the same locations (Fig. 4.5), obtained from the Love wave velocity maps. Additionally, for illustration purposes we also show the local and the synthetic Rayleigh wave dispersion (computed from the V_{sv} model as well) for the same locations. The strong agreement between the synthetic and observed Rayleigh curves indicates that the V_{sv} model can satisfactorily explain the Rayleigh wave dispersion data. However, the same does not hold for Love dispersion; Fig. 4.5 shows a poor fit between synthetic and observed Love curves for all profiles, indicating that the V_{sv} model is unable to correctly predict Love wave data and hence that some degree of anisotropy is necessary to explain the Rayleigh/Love discrepancy.

Fig. 4.6 shows map views of the spatial distribution of radial anisotropy in South America at depths between 4 and 80 km, and Fig. 4.7 shows six cross-sections across the continent to better visualize the distribution of radial anisotropy as a function of depth. Notice that positive radial anisotropy refers to the case where $V_{sh} > V_{sv}$, whereas negative radial anisotropy means that $V_{sh} < V_{sv}$. Overall, the following conclusions can be drawn from Figs. 4.6 and 4.7: (i) radial anisotropy presents a stronger variation in the crust (and especially in the shallow upper crust at depths ≤ 10 km); (ii) negative radial anisotropy is common in the upper crust, with its presence diminishing as a function of depth; (iii) most of the mid and lower crust in South America is characterized by positive radial anisotropy, one exception being located in the Amazon craton; (iv) positive

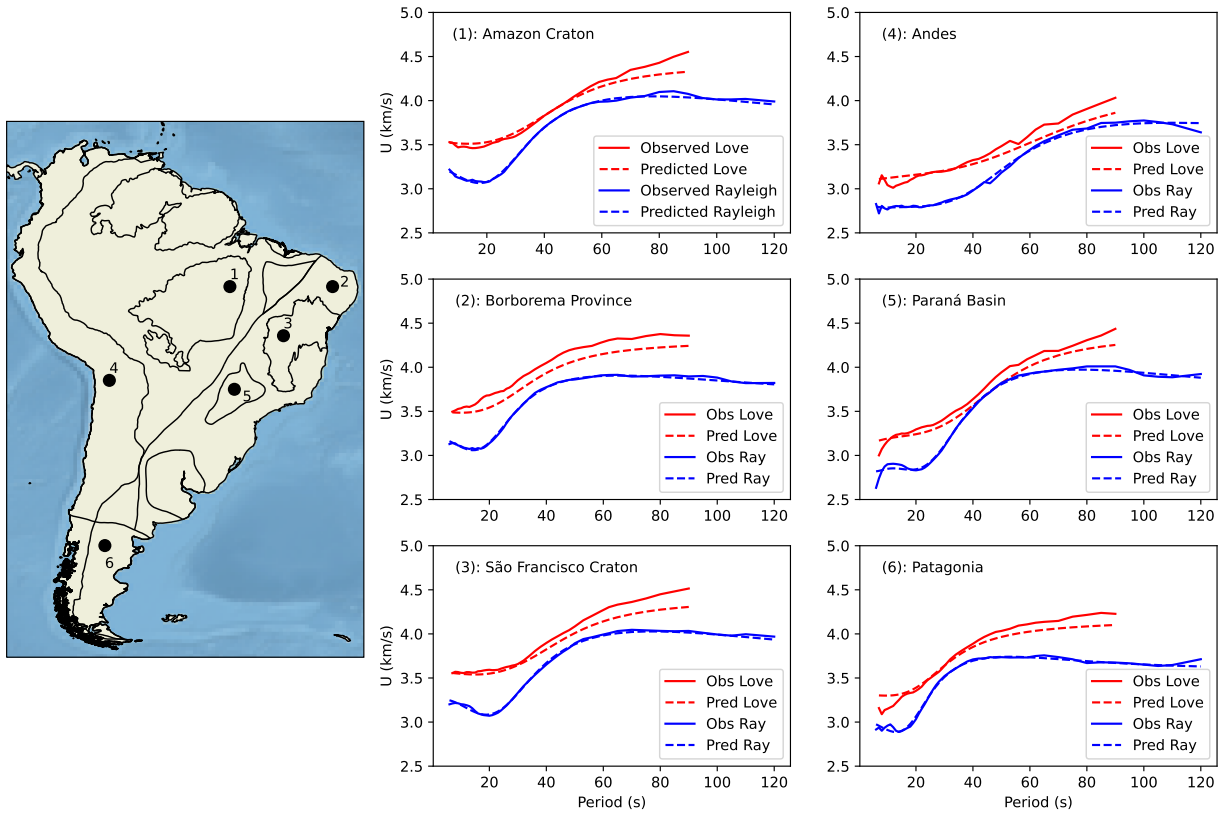


Figure 4.5: Results for the null hypothesis test for profiles at selected locations: Amazon craton, Borborema province, São Francisco craton, Andes, Paraná basin, and Patagonia.

radial anisotropy with varying strength is widespread across the upper mantle beneath the continent, one exception being the negative radial anisotropy at 80 km depth in the western portion of the Andes, possibly related to the dipping Nazca plate subducting beneath the South American plate and; (v) negative radial anisotropy is found at some locations of oceanic upper mantle.

The interpretation of LPO in the deep Earth assumes that present and past deformation events align the structure of anisotropic minerals into a specific direction, leading to an anisotropic signal that can be detected with seismological techniques. In the crust, the common aggregation of minerals such as micas into sheets has a quasi-hexagonal symmetry system (e.g., [Godfrey et al., 2000](#)), which is defined by a symmetry axis and a foliation plane perpendicular to it ([Xie et al., 2013](#)). According to [Xie et al. \(2013\)](#), the strength and sign of radial anisotropy is a function not only of the amount of anisotropic minerals interfering constructively, but also of the angle between the symmetry axis and the vertical: maximum positive values are related to a vertical symmetry axis, null values are related to intermediate ($\sim 50^\circ$) values, and negative values are found for larger angles. Therefore, positive crustal radial anisotropy is commonly associated to subhorizontal and shallowly dipping structures ($0-30^\circ$), while negative radial anisotropy suggests structures ranging from steeply dipping to subvertical ($60-90^\circ$) ([Xie et al., 2013](#)).

This notion is also common for interpretation of olivine derived anisotropy in the upper mantle (e.g., [Montagner & Guillot, 2002](#); [Park & Levin, 2002](#)), where positive and negative anisotropy are associated with horizontal and vertical flow, respectively ([Karato et al., 2008](#)). However, this analysis is further complicated at upper mantle depths by the recognition that olivine LPO is not as simple as previously thought in earlier experiments (e.g., [Nicolas et al., 1973](#); [Zhang & Karato, 1995](#)), and different olivine fabrics can arise as a consequence of varying water content, stress, temperature, pressure and partial melt ([Karato et al., 2008](#), and references therein). In this sense, it is possible for olivine to have a B-type fabric where the fast direction revealed by azimuthal anisotropy is perpendicular to the flow direction ([Karato et al., 2008](#); [Long & Becker, 2010](#)).

Although LPO resulting from the crystallographic alignment of shallow micas can influence the anisotropy seen in the upper crust ([Xie et al., 2013](#)), the much more significant

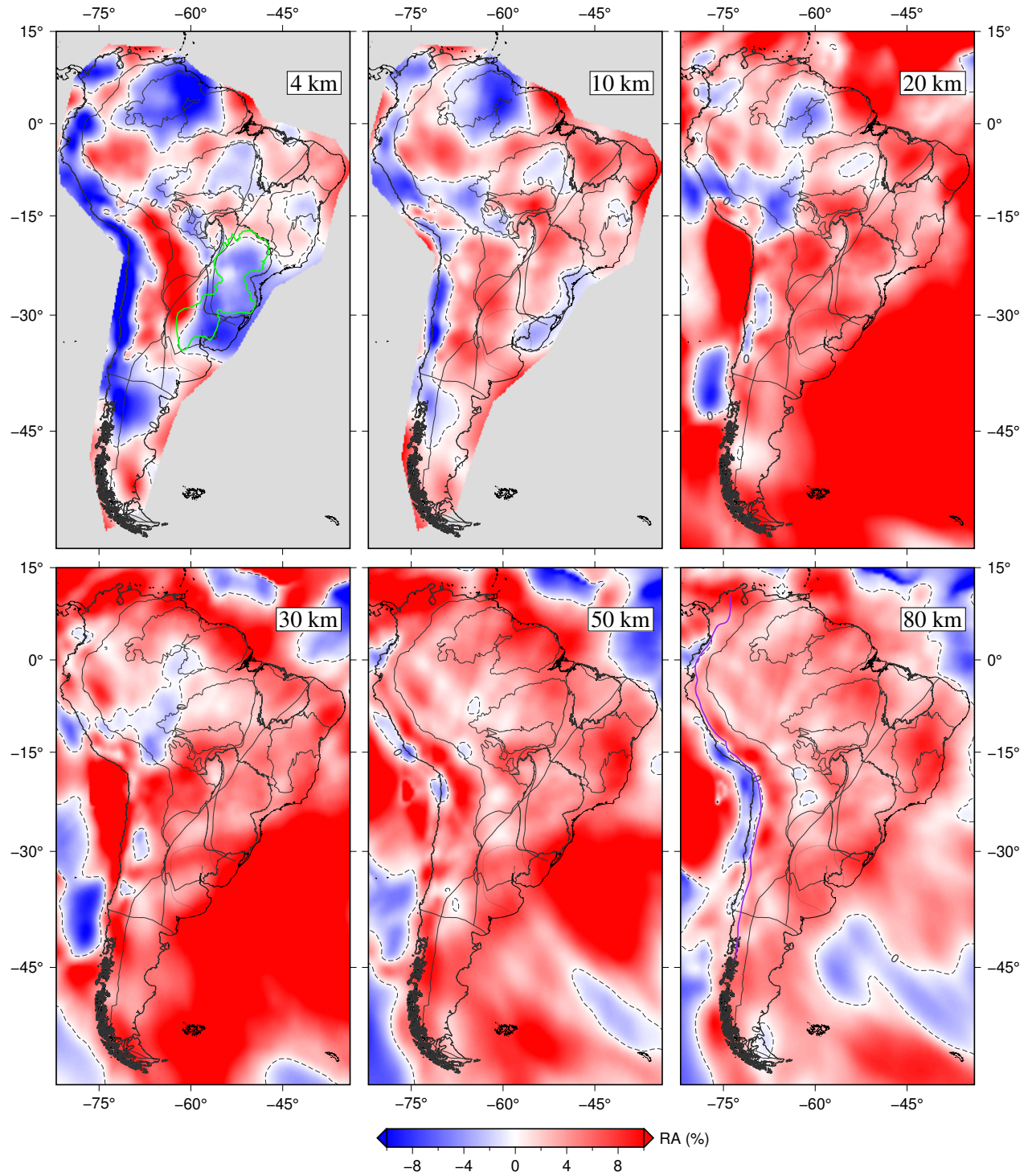


Figure 4.6: Map views of radial anisotropy beneath South America and neighboring oceans at depths between 4 and 80 km. The green contour at 4 km depth is the Paraná Magmatic Province (Peate et al., 1992; Pezzi & Mozetic, 1989) and the purple contour at 80 km depth is the Nazca plate from the Slab2 model (Hayes et al., 2018).

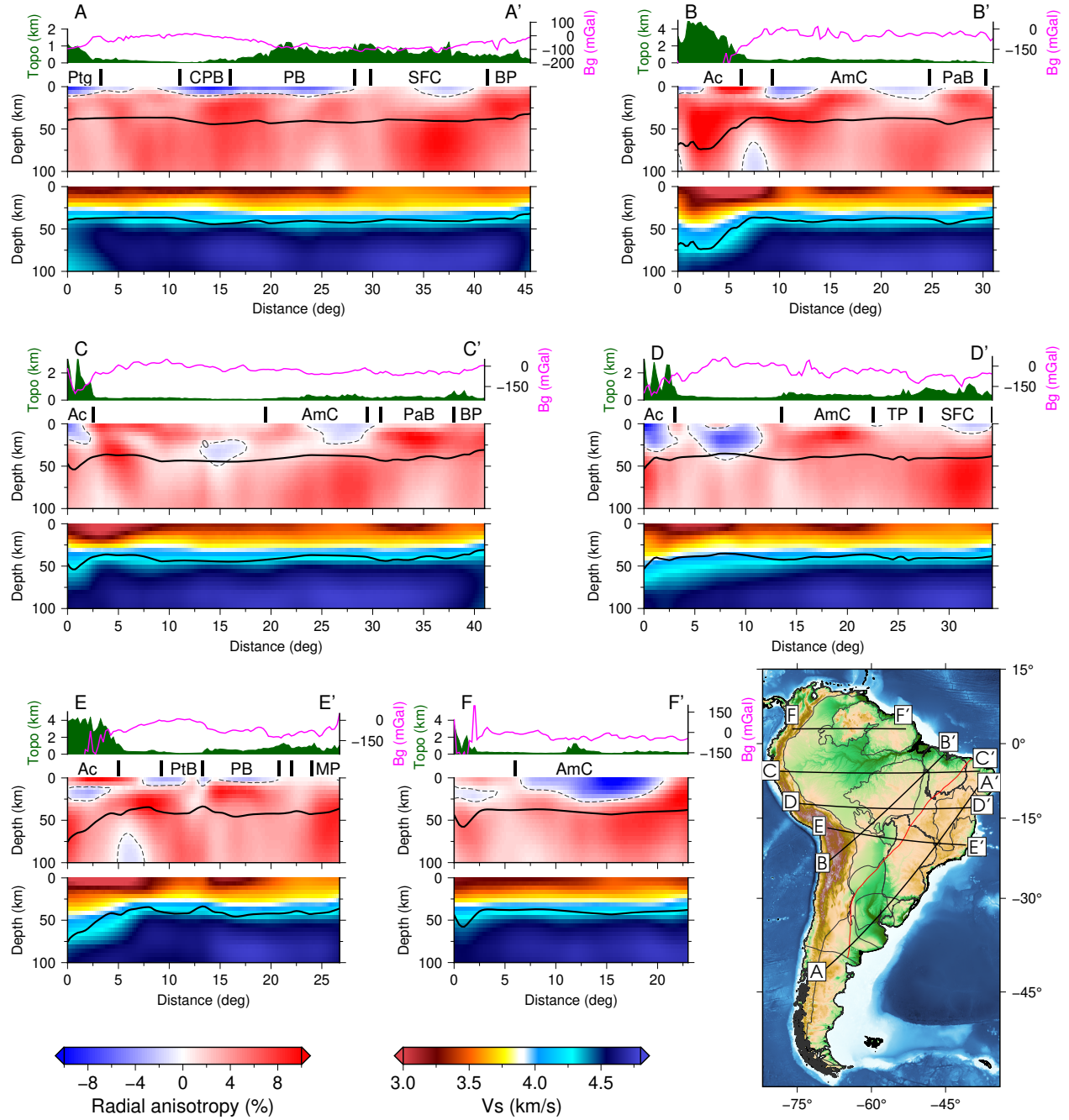


Figure 4.7: Vertical cross-sections of radial anisotropy and isotropic velocity ($\sqrt{(2V_{sv}^2 + V_{sh}^2)}/3$) beneath six profiles across South America. Topography and Bouguer anomaly extracted from the ETOPO1 (Amante & Eakins, 2009) and EGM08 (Pavlis et al., 2012) models, respectively, and Moho depth from (Rivadeneira-Vera et al., 2019). Ptg: Patagonia, CPB: Chaco-Paraná basin, PB: Paraná basin, SFC: São Francisco craton, BP: Borborema province, Ac: Andean chain, AmC: Amazon craton, PaB: Parnaíba basin, TP: Tocantins province, MP: Mantiqueira province.

change of anisotropy sign at shallow crustal depths compared with the mid and lower crust leads us to suggest that SPO play a key role at this depth range. SPO can arise as a consequence of the alignment of faults and cracks, fine layering and presence of dyke and sill swarms (Crampin, 1981; Crampin & Booth, 1985; Luo et al., 2013). Oriented open and filled cracks/microfractures can have a significant impact on SPO in the shallow crust (Luo et al., 2013; Dreiling et al., 2018; Movaghari et al., 2021).

Our model reveals extensive areas with negative radial anisotropy in the shallow upper crust beneath South America. An example of area with shallow negative radial anisotropy is beneath the Paraná and Chaco-Paraná basins in southeastern South America (Fig. 4.6 and profiles A-A' and E-E' in Fig. 4.7). Those basins are home to one of the world's largest continental igneous provinces, the Paraná Magmatic Province (Renne et al., 1992; Turner et al., 1994; Bologna et al., 2022) (shown in green in the 4 km depth slice in Fig. 4.6). Because large-scale magmatism has the potential to intrude the crust and lead to heterogeneities (Huppert & Sparks, 1988) that might be regarded as a transversely isotropic anomaly (Montagner & Guillot, 2002; Bodin et al., 2015), we argue that in such areas magmatism provide an explanation for shallow radial anisotropy, in addition to the presence of cracks. Hence, the shallow (up to 6-8 km depth) negative radial anisotropy observed below the Paraná and Chaco-Paraná basins might be linked to dyke intrusions related to the Early Cretaceous Paraná flood basalt magmatism. At 10 km depth, anisotropy below most of the basins becomes weakly positive, with only a faint negative ($\sim 2\text{-}3\%$) signal along the continental coast, corresponding to the Ponta Grossa (Gomes et al., 2011; Moura & Marangoni, 2023) and Rio Grande archs (Milani, 2004).

Another area characterized by emplacement of a voluminous magmatism is located in central-northern South America, from the continental margin into the Amazon craton (Min et al., 2003). This magmatism corresponds to the Central Atlantic Magmatic Province, a large igneous province with peak tholeiitic basalt activity at 200 Ma, present in Africa, Europe, South and North America (Marzoli et al., 1999). In this area, we observe a strong negative radial anisotropy anomaly in the upper crust that covers most of the Guyana shield, diminishing with increasing depth but extending to mid/lower crustal depths (Fig. 4.6 and profile F-F' in Fig. 4.7). As with the Paraná Magmatic Province case, some

shallow radial anisotropy features might be explained by magmatic SPO related to the Central Atlantic Magmatic Province and even some older intraplate magmatism (Cordani et al., 2010; Teixeira et al., 2019), but the extension of the negative anomalies deeper into the crust leads us to suggest that an LPO component related to the preferential orientation of micaceous rocks should be present as well. Positive radial anisotropy in the upper crust is also consistent with the extensive coverage of sills along the Amazon and Solimões basins area (Marzoli et al., 1999, 2018).

Our model shows that the upper mantle beneath South America is mostly dominated by positive radial anisotropy, which is coherent with the global scale model of Nettles & Dziewoński (2008), who mapped strong positive anisotropy anomalies at the shallow upper mantle (< 100 km depth) under continents, in contrast to oceanic mantle. For the North American craton, Nettles & Dziewoński (2008) found that the regions of strongest mantle anisotropy are in general accompanied by the fastest isotropic velocities; our results point to a similar scenario for the São Francisco craton and the eastern portion of the Amazon craton, which corresponds to its oldest, Archean and Paleoproterozoic proto-cratonic nuclei (Cordani & Teixeira, 2007; Brito Neves & Fuck, 2014). Close to the subduction zone of the Nazca plate beneath the South American plate, however, our model shows regions of negative anisotropy consistent with the depth of the Nazca plate estimated by the Slab2 model (Hayes et al., 2018). Interestingly, the negative anisotropy anomalies are interrupted by positive anomalies close to the flat-slab segments of the Nazca plate (Ramos, 1999).

4.6 Conclusions

In this study, we compute the radial anisotropy in the crust and upper mantle beneath South America from V_{sv} and V_{sh} models, constrained by a large number of automatically measured Rayleigh and Love dispersion curves, respectively. Our model shows that radial anisotropy is very heterogeneous in the crust, and especially in the shallow upper crust. On the other hand, an anisotropy more homogeneous is mapped in the upper mantle, being mostly characterized by positive values, except for a negative structure associated with subduction of the Nazca plate beneath the South American plate. We suggest that shallow

negative radial anisotropy imaged beneath the Paraná and Chaco-Paraná basins, and also beneath the Guyana shield in the Amazon craton could be associated with SPO features as a consequence of intrusions of basaltic material related to the Paraná and Central Atlantic Magmatic Provinces.

Chapter 5

Conclusions

In my thesis, I investigated the architecture of the lithosphere beneath South America as seen by inversion of surface wave data, more specifically group velocity dispersion curves. The variety of tectonic features and wealthy geological history of South America make it an intricate region to be studied with seismic imaging approaches. The contributions of this thesis are distributed into three papers presented in Chapters 2, 3, and 4, respectively.

Paper I (published as [Nascimento et al., 2024](#)) presents a baseline shear-wave velocity model, constructed from the inversion of 26,984 manually measured fundamental mode Rayleigh wave dispersion curves. Although the manual processing of dispersion curves is very time consuming, making it difficult to retrieve a very large data set, this model already included data from now established networks such as the Brazilian Seismographic Network ([Bianchi et al., 2018](#)) and the Seismic Network of Chile ([Barrientos, 2018](#)), besides data from temporary arrangements such as the Pantanal, Chaco and Paraná structural studies network ([Assumpção & Bianchi, 2016a](#)). A comparison of the model of Paper I with other modern models available at the time of publication ([Celli et al., 2020](#); [Ciardelli et al., 2022](#)) revealed high Pearson correlation coefficients, and thus that the models generally agree on long and intermediate scale features.

The interpretations provided in Paper I are focused on the cratons beneath South America: Amazonian, São Francisco, and Río de la Plata cratons, besides possible cratonic blocks concealed under the Paraná and Parnaíba basins. Beneath the Amazonian craton, the model at upper mantle depths reveals a velocity difference between the eastern

and western portions of the craton, with the younger western Amazonian craton being characterized by slower velocities. Possible explanations for this include asthenospheric heat flow from west to east ([Ciardelli et al., 2022](#)) or that the younger western region has never developed a cratonic root (or lost it through lithosphere erosional processes) ([Celli et al., 2020](#)). Furthermore, I found a general correlation between mantle seismic velocity and geochronological province age, which is however disrupted at the 2.2-1.95 Ga Maroni-Itacaiúnas province. I suggested that possible explanations for the decreased shear-velocity imaged beneath the Maroni-Itacaiúnas province are the intraplate tectono-thermal events of the Mesoproterozoic K'Mudku episodes ([Cordani et al., 2010](#)) and/or the voluminous magmatism of the Central Atlantic Magmatic Province following the breakup of Pangea during the Triassic/Jurassic ([Marzoli et al., 1999](#)).

A hypothesis concerning the São Francisco craton, which is in agreement with the model of Paper I, is that a larger São Francisco paleocontinent encompassing the craton and parts of the Mantiqueira and Tocantins provinces is still preserved at depth. A possible extension of the paleocontinent into the Borborema province is also envisaged (e.g., [Neves, 2003, 2021](#)), but I argued that the slow velocities imaged beneath it from 70 km depth downward are indicative of lithospheric thinning and preclude one from delineating the cratonic root of the São Francisco paleocontinent beneath the Borborema province. This analysis is further supported by geological evidence for hydration in the Paleoproterozoic ([Neves, 2021](#)), rifting in the early-middle Tonian ([Ganade et al., 2021](#)), reworking during Brasiliano events ([Brito Neves & Fuck, 2014](#)), and lithospheric stretching related to the breakup of Gondwana. Additionally, I imaged a high velocity anomaly beneath the northern area of the Río de la Plata craton, generally consistent with magnetotelluric studies ([Favetto et al., 2008](#); [Bologna et al., 2019](#)), but the deployment of more stations is required to further characterize the lithospheric architecture of this craton.

Note that a large number of high quality dispersion curves between source-receiver pairs were simply not measured in Paper I due to the very time consuming nature of manual analysis. Moreover, as in previous surface wave studies in South America ([Heintz et al., 2005](#); [Feng et al., 2007](#); [Nascimento et al., 2022](#)), I overlooked important Love wave data and only measured Rayleigh dispersion because it has a generally greater signal-to-

noise ratio. If I wanted to further increase the resolution of the seismic models and beat the baseline model in Paper I, I would require a large number of dispersion measurements, and hence an automatic tool to extract group velocity dispersion curves from earthquake data.

Motivated by this need, I developed DisperPy (Chapter 3, Paper II), a tool written in Python and based on machine learning algorithms to automatically extract group velocity dispersion from earthquakes (although it can be applied to ambient noise cross-correlations as well). DisperPy solves two primary tasks: (1) to assess waveform quality and determine if dispersion extraction is feasible, and (2) to measure group velocity dispersion from high quality waveforms. Therefore, it is a tool suitable for large-scale surface wave tomography problems, allowing waveforms with low-quality surface waves to be discarded. The first task is addressed using a convolutional neural network with the ResNet-34 architecture (He et al., 2015), trained on a data set of 4895 dispersion images/labels (0 or 1). The second task consists of the actual group velocity picks, which I solve by applying a set of unsupervised machine learning algorithms combined with some conventional metrics: (i) removal of low frequency noise using a Gaussian mixture (Bishop, 2006); (ii) creation of clusters of dispersion energy with k-means (MacQueen, 1967), which facilitates the picking of a first trial dispersion curve; (iii) refining the trial dispersion curve by removing possible outliers and bad picks using both the DBSCAN algorithm (Ester et al., 1996) and a signal-to-noise ratio (as defined by Bensen et al., 2007) threshold; (iv) usage of the final ‘raw’ dispersion curve to create a phase-matched filter (Levshin et al., 1992; Levshin & Ritzwoller, 2001) and a second application of the algorithm on the filtered waveform to generate a ‘clean’ dispersion curve.

To further test DisperPy’s capabilities, I used it to measure group velocity dispersion curves from vertical component broadband waveforms from stations across the contiguous United States, resulting in a total of 194,325 curves, which were inverted in a surface wave tomography experiment. The resulting group velocity maps reveal the most important seismic signature of the United States, the velocity dichotomy between the low-velocity, tectonically active western US and the high-velocity, stable, central and eastern US (Grand & Helmberger, 1984), in accordance with several previous studies (e.g., Bensen et al., 2008;

[Shen & Ritzwoller, 2016](#); [Ekström, 2017](#); [Zhao et al., 2017](#)). Additionally, short period maps illuminated small-scale structure including the Anadarko, Denver, Green River, and Pasco basins, besides a strong slow velocity anomaly beneath the Gulf of Mexico, where sediment thickness reaches values larger than 10 km according to the CRUST1.0 model ([Laske et al., 2013](#)).

Finally, in Chapter 4 (Paper III), I exploited another property that is largely overlooked in seismic tomography studies in South America: radial anisotropy. Isotropic seismic velocities provide information on the thermal and chemical structure of the Earth (e.g. [Karato & Karki, 2001](#); [Kaban et al., 2003](#)), but anisotropic information can provide additional insights into past and present deformation and flow inside the Earth ([Luo et al., 2013](#)). Radial anisotropy is constrained by the difference in propagation speed between vertically (V_{sv}) and horizontally (V_{sh}) polarized shear waves. V_{sv} and V_{sh} models are computed from the inversion of Rayleigh and Love dispersion data, respectively.

Using DisperPy, I collected 255,292 Rayleigh and 75,843 Love wave group velocity dispersion curves in an automated fashion. Note that the number of Rayleigh dispersion measurements is nearly ten fold the previous manual data set of [Nascimento et al. \(2024\)](#), hence providing stronger constraints on seismic structure. Additionally, the usage of dispersion curves derived from cross-correlation of ‘continuous’ noise data between pairs of receivers (i.e., ambient noise tomography) provides shorter period curves, which reduces the minimum inverted period to 6 s for Rayleigh waves (from 9 s in [Nascimento et al., 2024](#)) thus probing shallow structure (< 10 km) with a finer resolution.

Besides noisier waveforms, the analysis of Love wave dispersion is further complicated by the fact that it is common for the north component of stations to present large orientation errors. It is therefore important to correct misoriented data to ensure that the transverse component, from which Love waves are analyzed, are not contaminated by Rayleigh wave energy. To identify stations with misaligned horizontal components, I used a methodology based on the polarization of Rayleigh waves on the vertical and radial components ([Chael, 1997](#); [Baker & Stevens, 2004](#); [Stachnik et al., 2012](#)), and corrected earthquake waveforms where the absolute orientation error is larger than 10° (stations with orientation errors larger than 10° were simply discarded for ambient noise cross-correlation).

The model in Paper III shows that radial anisotropy is very heterogeneous in the crust, and especially in the shallow upper crust. On the other hand, an anisotropy more homogeneous is mapped in the upper mantle, being mostly characterized by positive values, except for a negative structure associated with subduction of the Nazca plate beneath the South American plate. I suggested that shallow negative radial anisotropy imaged beneath the Paraná and Chaco-Paraná basins, and also beneath the Guyana shield in the Amazon craton could be associated with shape-preferred oriented features as a consequence of intrusions of basaltic material related to the Paraná and Central Atlantic Magmatic Provinces.

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Appendices

Appendix A

Supplementary material for paper I

Supplementary material for: Unraveling Precambrian cratonic roots beneath South America: A contribution from surface wave tomography

Here, we present the following information complementary to the main manuscript:

- Spatial distribution of cells determined through adaptive parameterization for periods in the range 10-180 s. The parameterization depends upon the density of paths sampling the area (Section 2.4.1 of the main text) - Fig. A.1.
- L-curves used to choose the most appropriate μ regularization coefficient that governs the roughness of the solution. We choose $\mu = 5.5e - 3$ for all periods - Fig. A.2
- Additional checkerboard tests showing the recoverability of long wavelength structure at the same periods shown in the main text - Figs. A.3 and A.4.
- Sensitivity kernels of Rayleigh wave group velocity at periods between 10 and 180 s to shear-wave velocity structure as a function of depth - Fig. A.5. We compute these kernels by adopting v_s equal to the average value found at each depth, $v_p = 1.8v_s$, and $\rho = 0.32v_p + 0.77$ (Berteussen, 1977).
- Vertical resolution tests with different scenarios of lithospheric seismic structure - Fig. A.6.

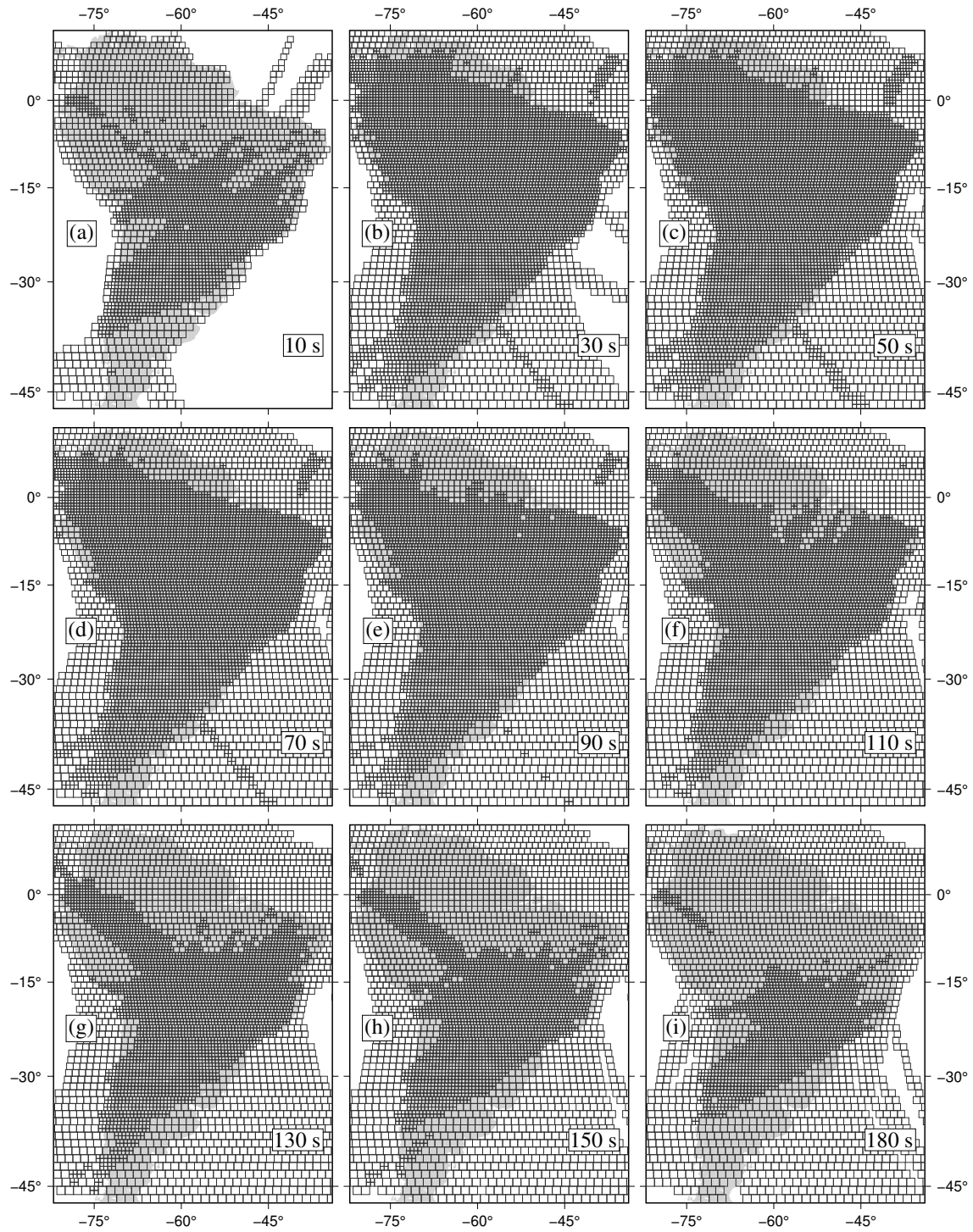


Figure A.1: Adaptive parameterization used at periods of (a) 10, (b) 30, (c) 50, (d) 70, (e) 90, (f) 110, (g) 130, (h) 150 and (i) 180 s. A denser distribution of cells characterizes central and southeastern South America.

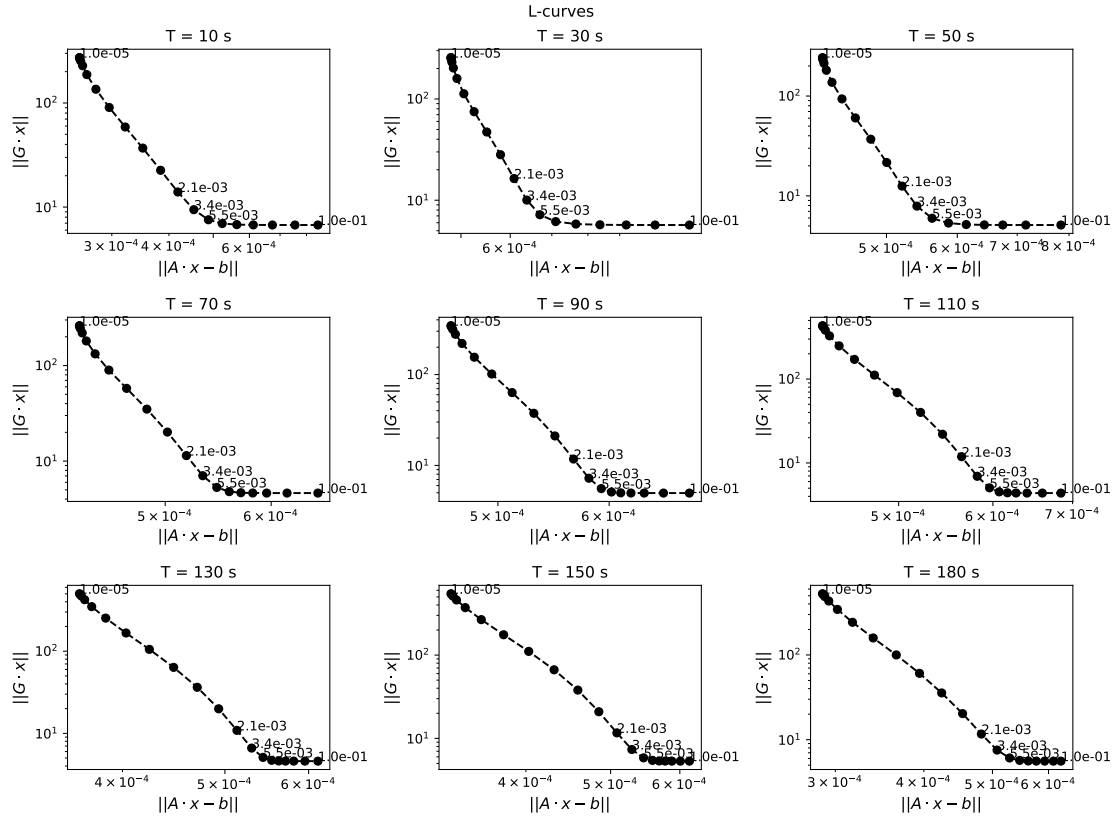


Figure A.2: L-curves used to select optimum values for the μ regularization term. The respective period is indicated in the title of each subplot. An optimum value $\mu = 5.5 \times 10^{-3}$ is chosen for all periods.

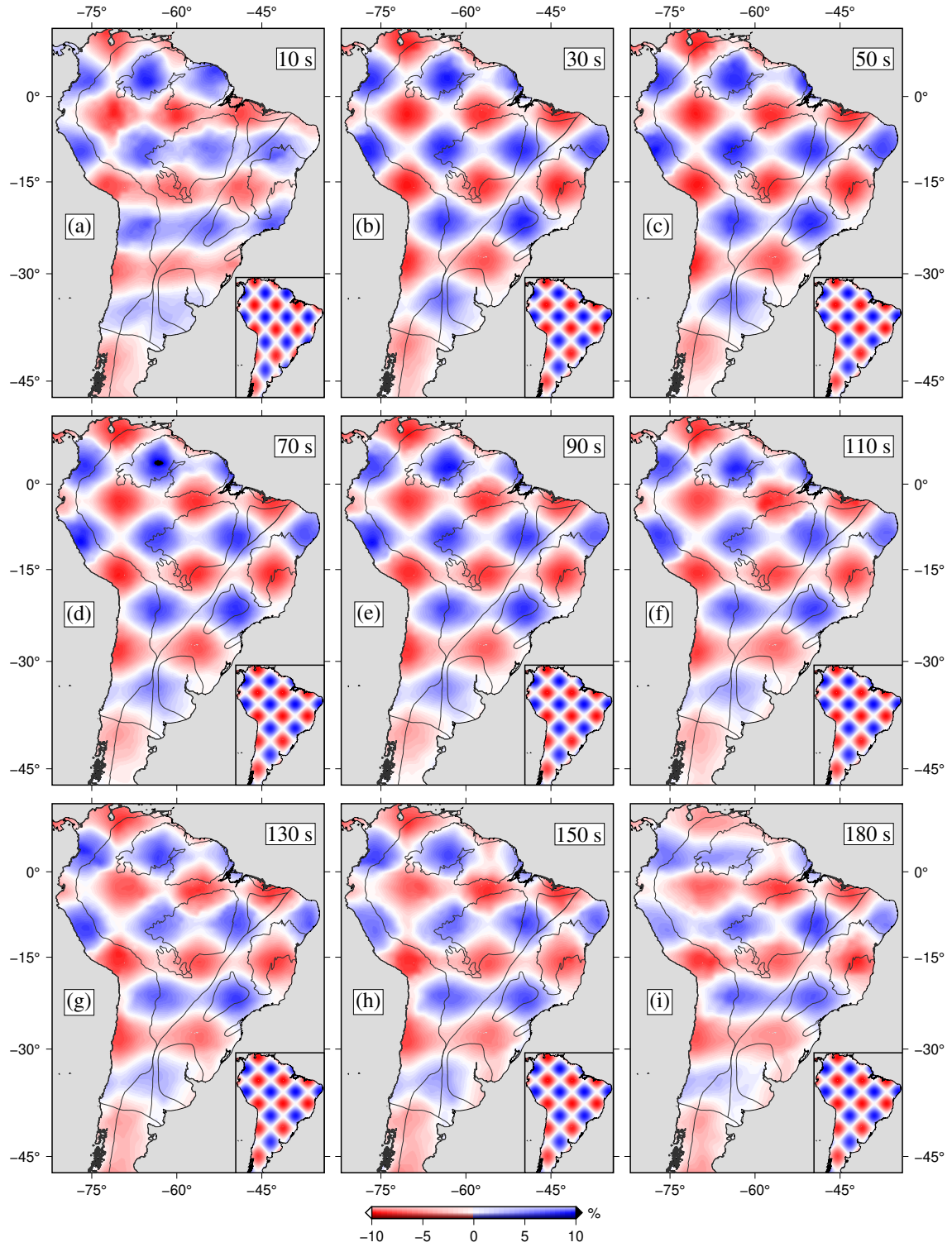


Figure A.3: Checkerboard resolution tests of our group velocity maps, with perturbations of $\pm 10\%$, at periods of (a) 10 s, (b) 30 s, (c) 50 s, (d) 70 s, (e) 90 s, (f) 110 s, (g) 130 s, (h) 150 s, and (i) 180 s. The objective of this test is to retrieve long-scale structure.

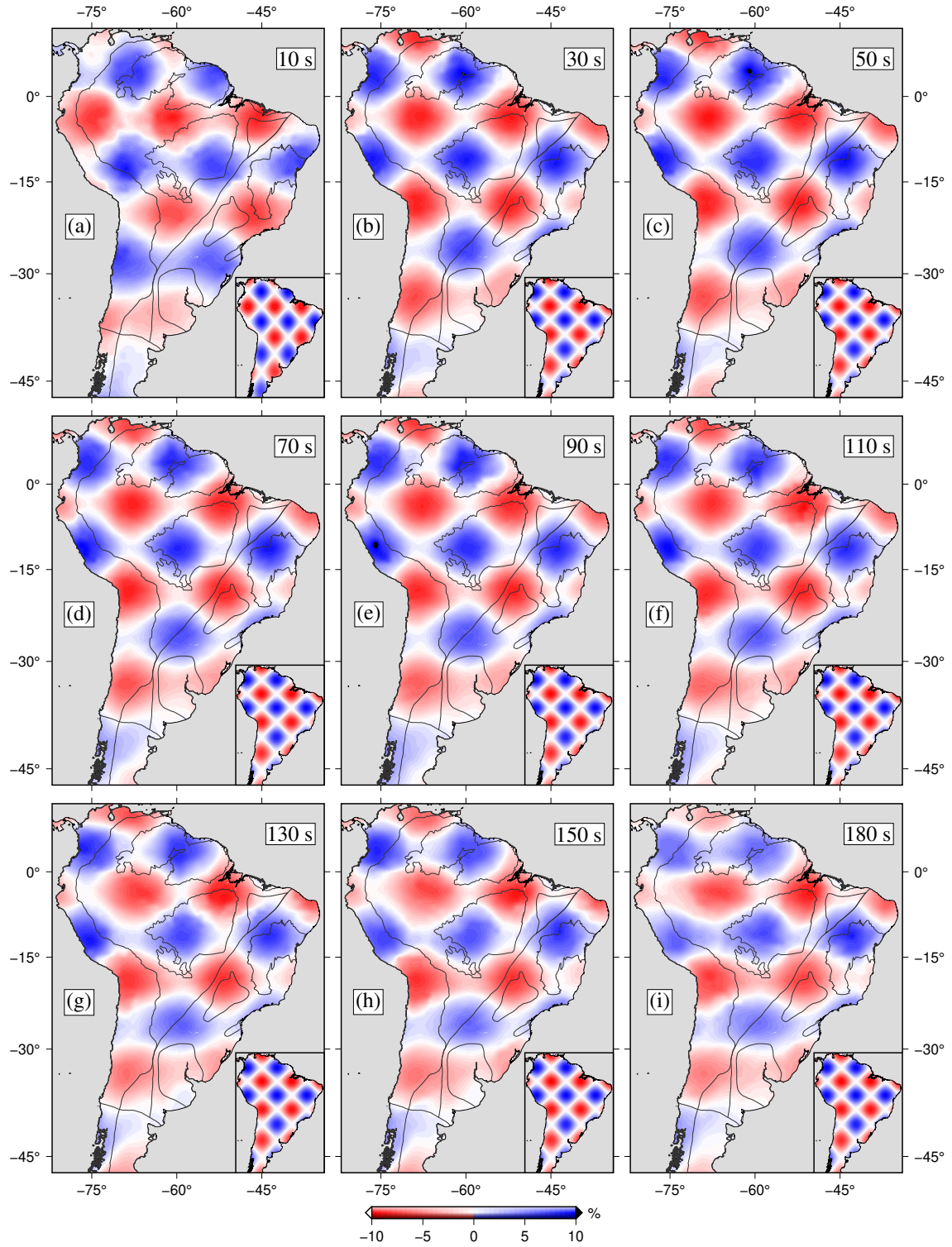


Figure A.4: Checkerboard resolution tests of our group velocity maps, with perturbations of $\pm 10\%$, at periods of (a) 10 s, (b) 30 s, (c) 50 s, (d) 70 s, (e) 90 s, (f) 110 s, (g) 130 s, (h) 150 s, and (i) 180 s. The objective of this test is to retrieve long-scale structure.

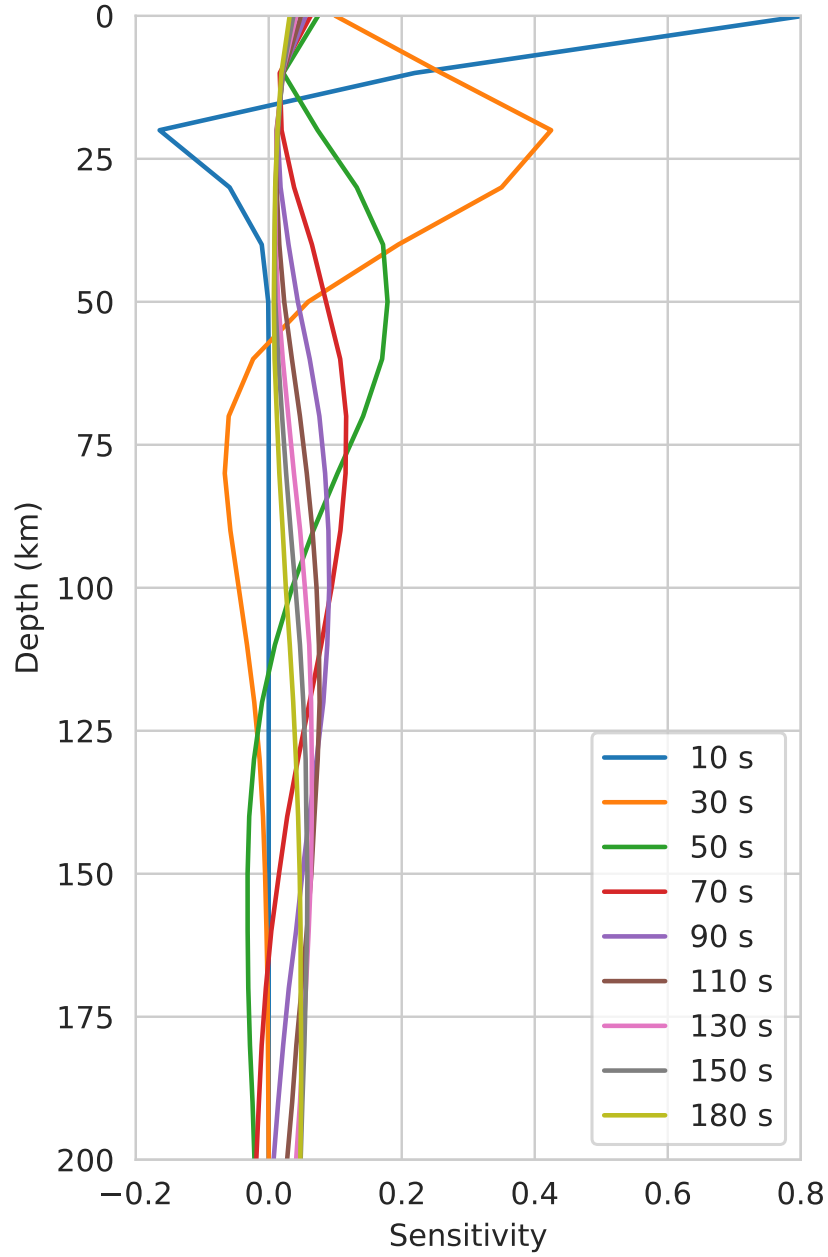


Figure A.5: Sensitivity kernels of Rayleigh wave fundamental mode group velocities to shear-wave velocity structure. The kernels are computed for periods between 10 and 180 s based on the average shear-wave velocity structure reported in this study. Additionally, we adopt $v_p = 1.8v_s$, and $\rho = 0.32v_p + 0.77$ (Berteussen, 1977).

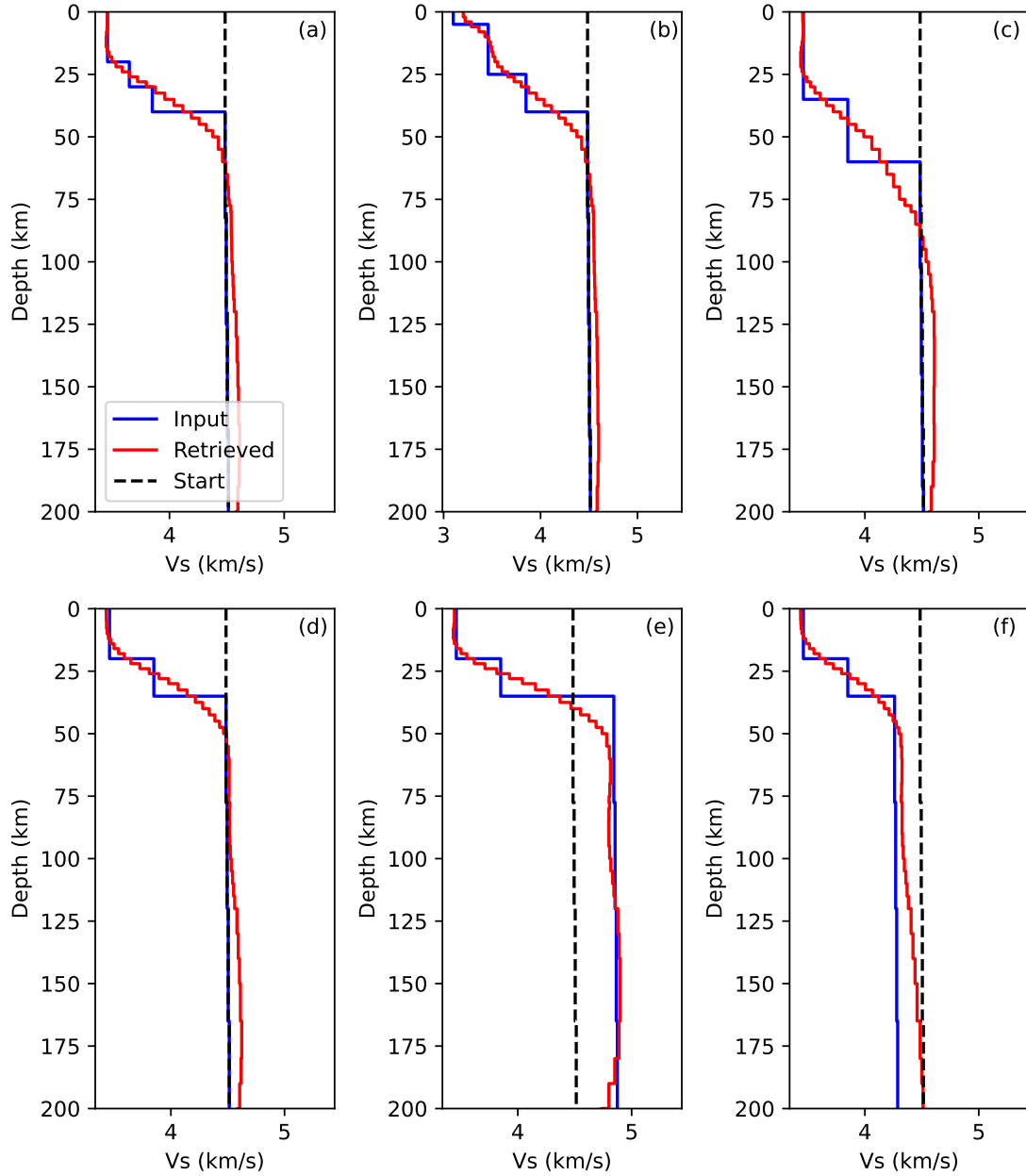


Figure A.6: Vertical resolution tests for the following lithosphere scenarios: (a) Crust with three layers over AK135-F mantle; (b) 5 km thick sedimentary layer over the AK135-F model; (c) Thick crust (60 km) over AK135-F mantle; (d) AK135-F model; (e) AK135-F model with mantle velocity perturbed by a +5% anomaly; (f) AK135-F model with mantle velocity perturbed by a -5% anomaly. The input, retrieved and start models are indicated by blue, red, and black lines, respectively. We perform these tests by generating a synthetic dispersion curve from each input model and then inverting it following the same procedure as described in Section 2.5.1, with the same start model (AK135-F modified in the crust).

Appendix B

Supplementary material for paper III

Supplementary material for: Crustal and uppermost mantle radial anisotropy beneath South America from joint inversion of ambient noise and earthquake dispersion curves

Here, we present the following information complementary to the main manuscript:

- Hit count maps for Rayleigh and Love wave group velocity maps. Each panel shows the number of rays that cross each parameterization block - Figs. B.1 and B.2.
- Rayleigh and Love wave group velocity maps - Figs. B.3 and B.4.
- Checkerboard tests for Rayleigh and Love waves with varying anomaly sizes - Figs. B.5 to B.10.
- Sensitivity kernels of Rayleigh and Love wave group velocities at periods between 6 and 120 s to shear-wave velocity structure as a function of depth - Fig. B.11. We compute these kernels by adopting V_s equal to the average value found at each depth in the study of [Nascimento et al. \(2024\)](#), $V_p = 1.8V_s$, and $\rho = 0.32V_p + 0.77$ ([Berteussen, 1977](#)).
- Vertically and horizontally polarized shear-wave velocity models - Figs. B.12 and B.13.

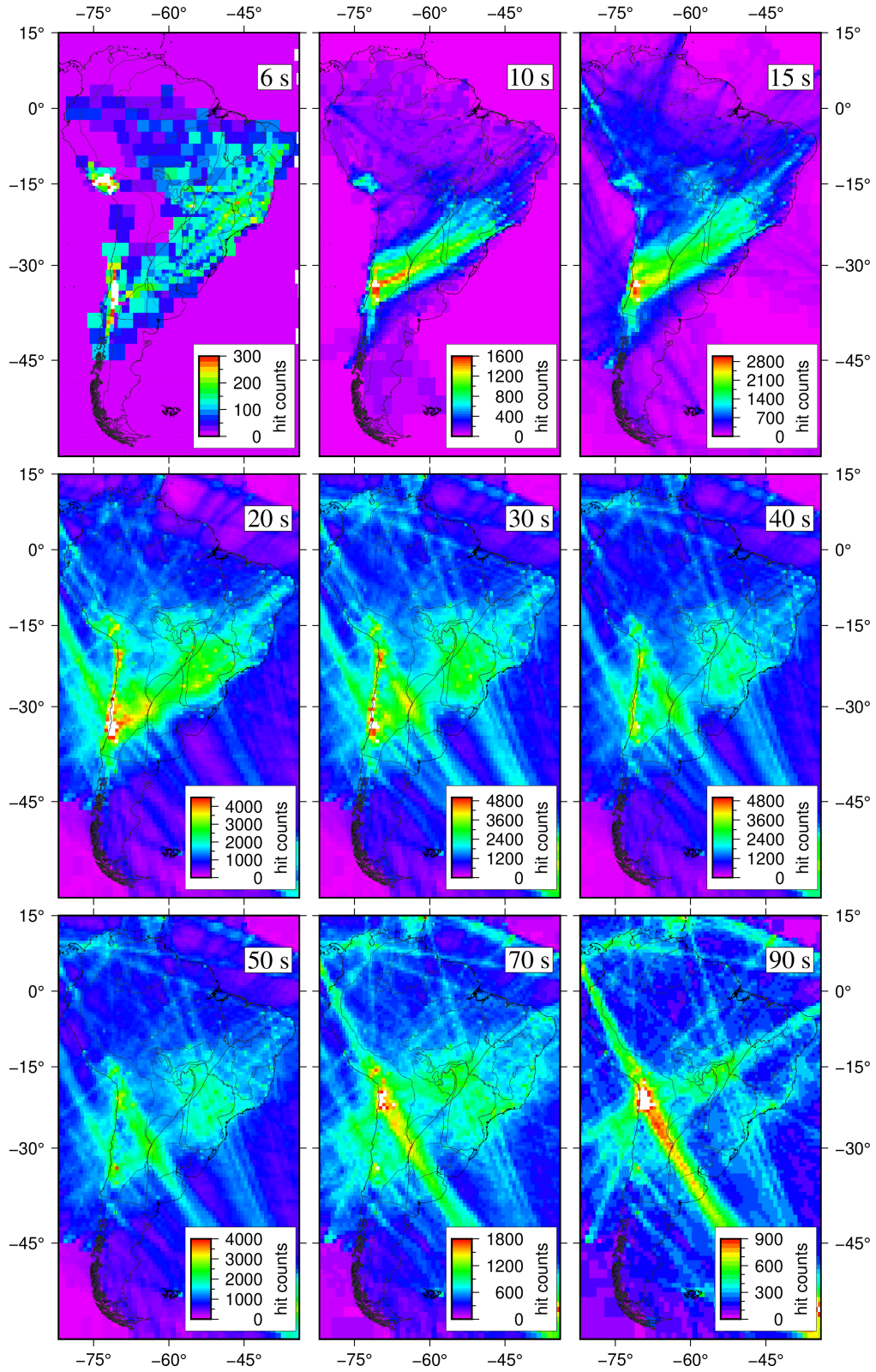


Figure B.1: Number of ray hit counts per parameterization cell for Rayleigh waves in the period range 6 - 90 s.

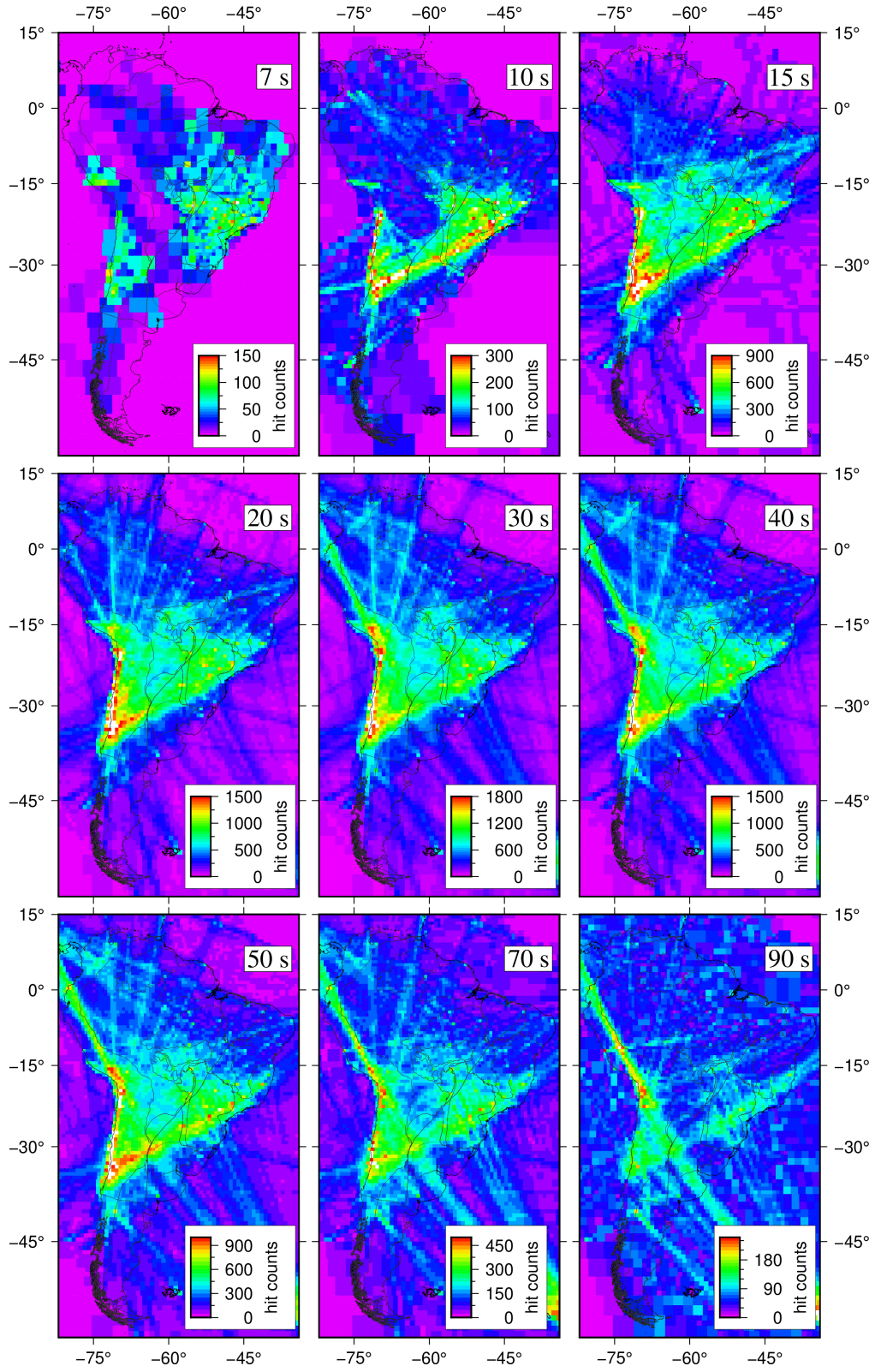


Figure B.2: Number of ray hit counts per parameterization cell for Love waves in the period range 7 - 90 s.

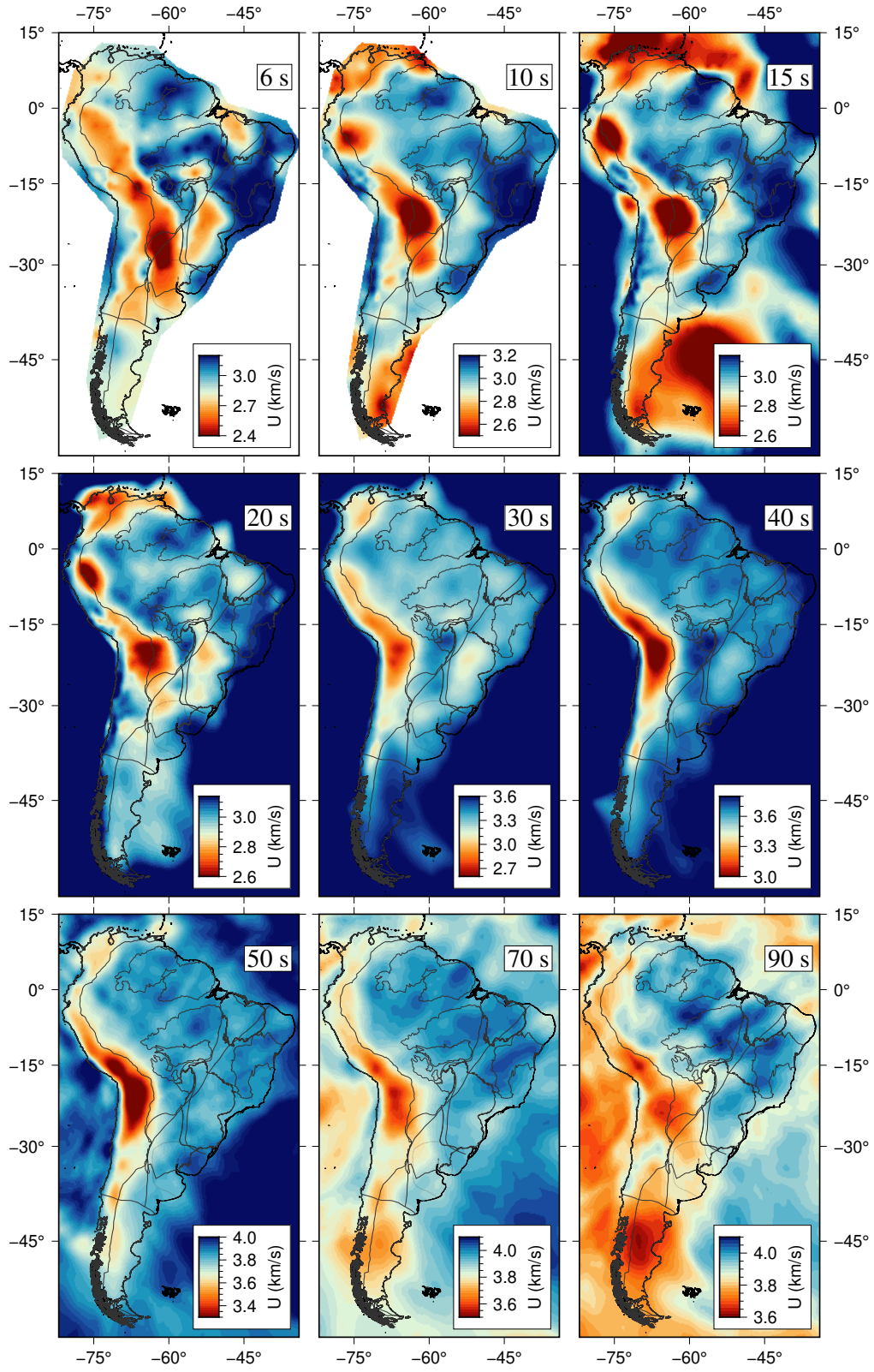


Figure B.3: Rayleigh wave group velocity maps at periods of 6, 10, 15, 20, 30, 40, 50, 70, and 90 s.

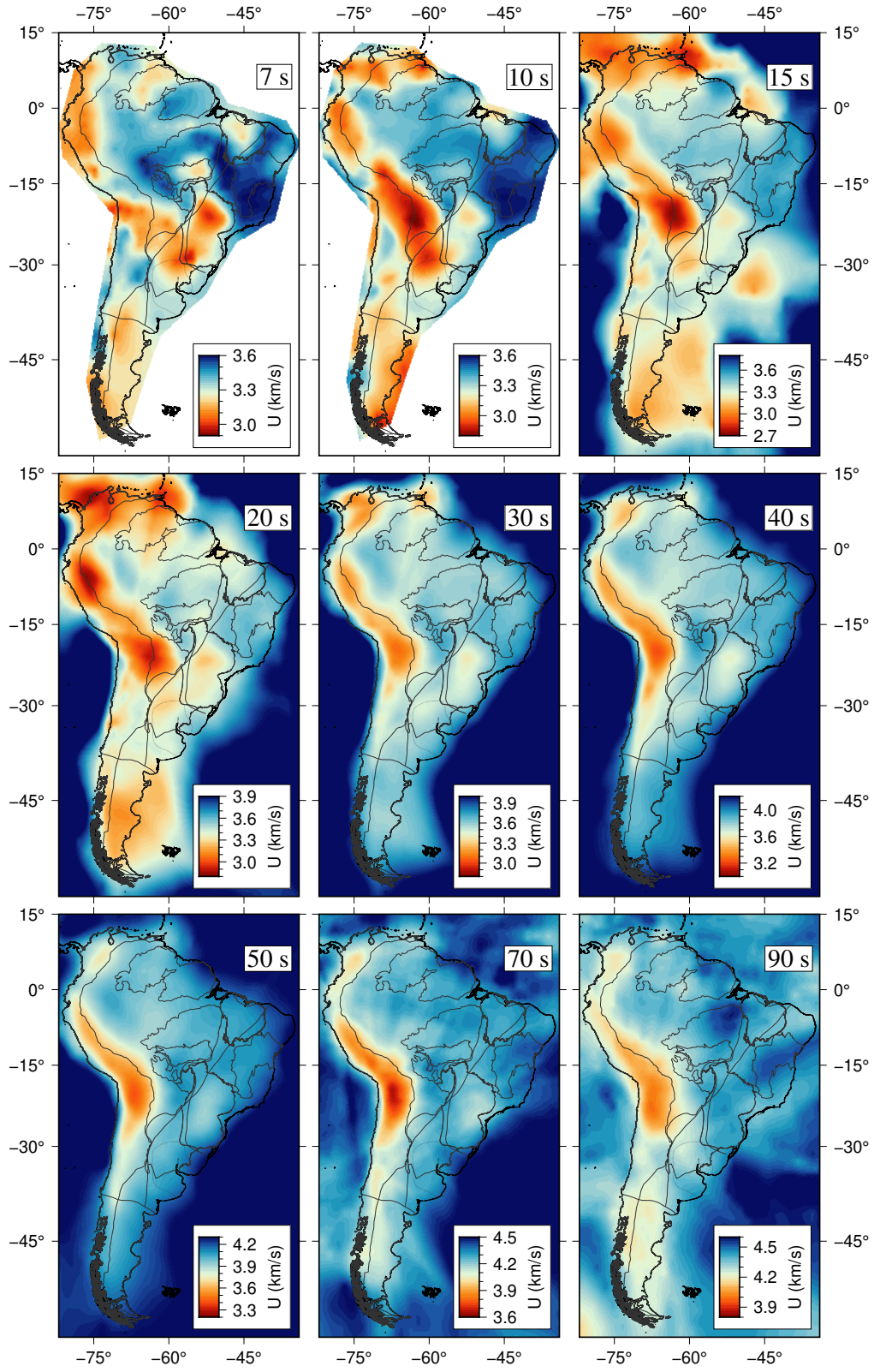


Figure B.4: Love wave group velocity maps at periods of 7, 10, 15, 20, 30, 40, 50, 70, and 90 s.

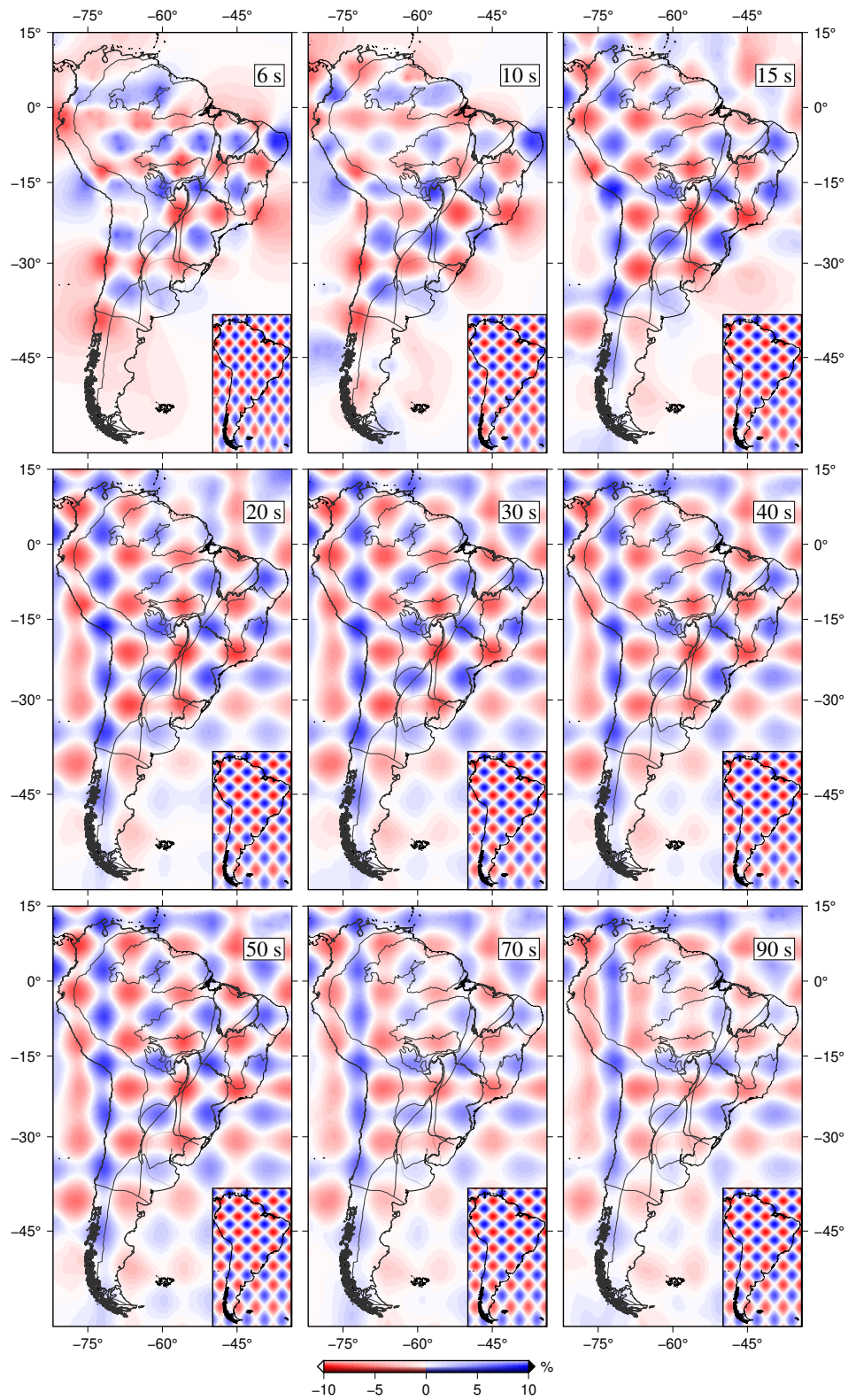


Figure B.5: Checkerboard resolution tests of Rayleigh wave group velocity maps, with perturbations of $\pm 10\%$, at periods of 6, 10, 15, 20, 30, 40, 50, 70, and 90 s. Maps obtained by setting $k_x = k_y = 10$ in SeisLib (Magrini et al., 2022b).

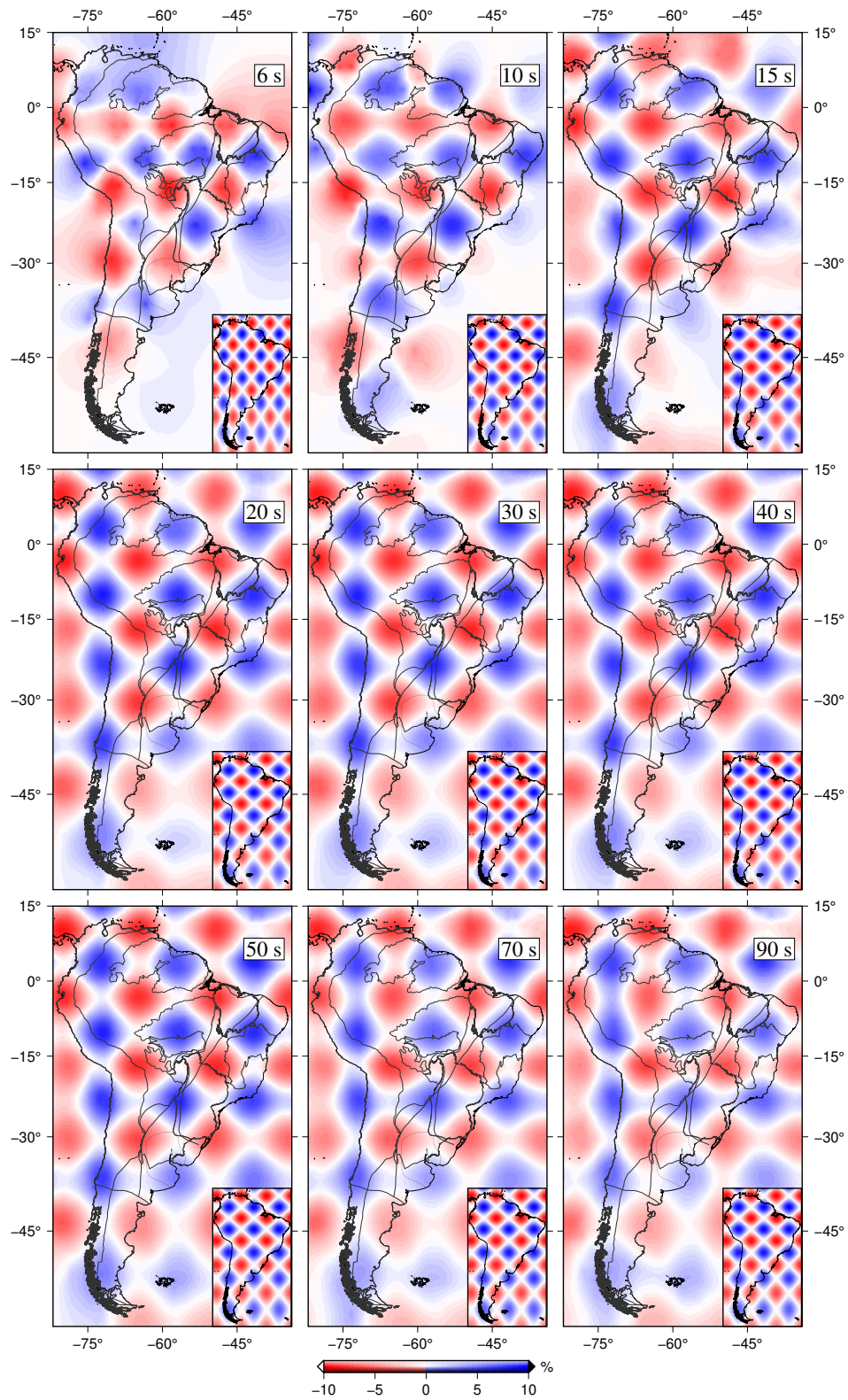


Figure B.6: Checkerboard resolution tests of Rayleigh wave group velocity maps, with perturbations of $\pm 10\%$, at periods of 6, 10, 15, 20, 30, 40, 50, 70, and 90 s. Maps obtained by setting $k_x = k_y = 7$ in SeisLib (Magrini et al., 2022b).

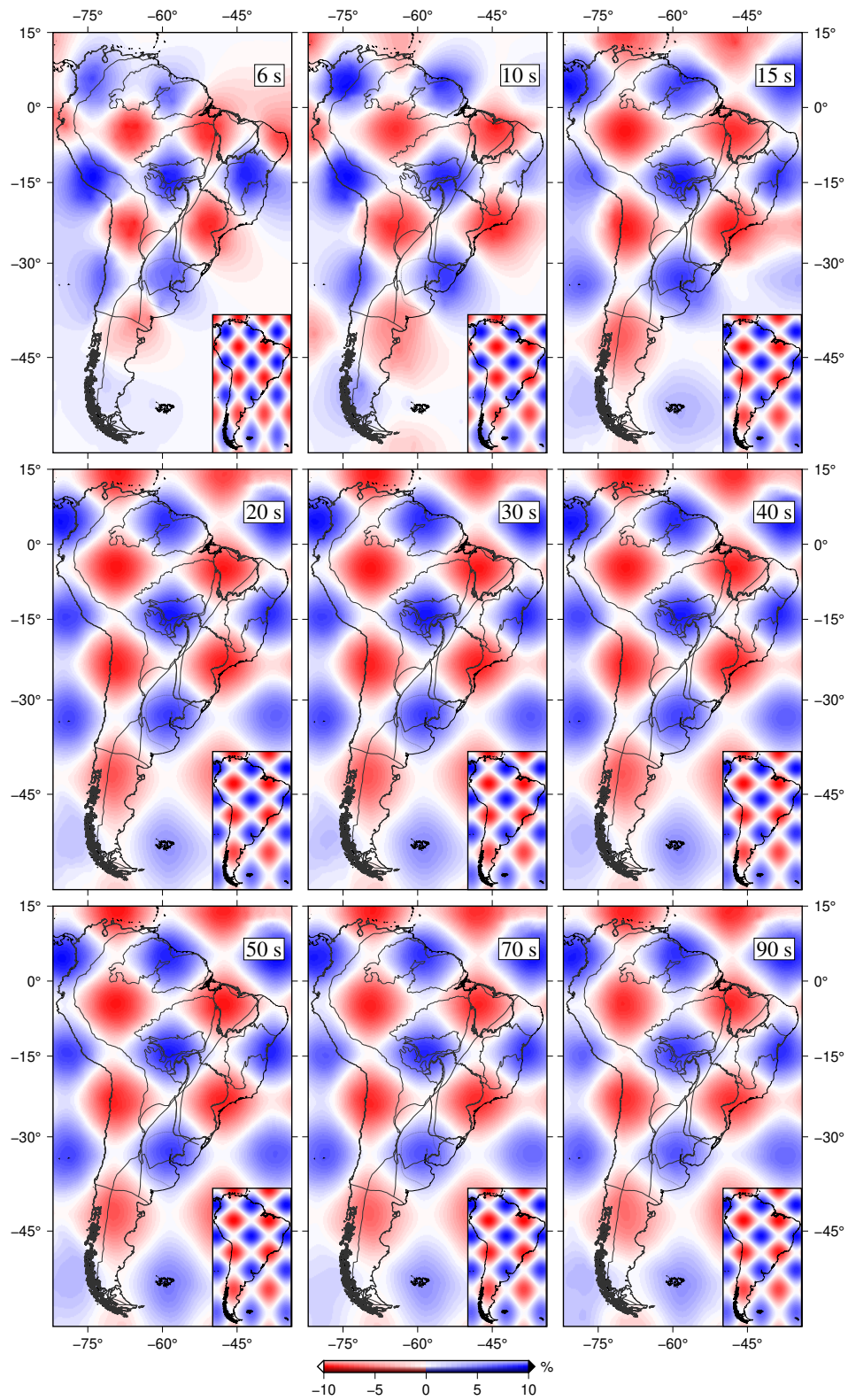


Figure B.7: Checkerboard resolution tests of Rayleigh wave group velocity maps, with perturbations of $\pm 10\%$, at periods of 6, 10, 15, 20, 30, 40, 50, 70, and 90 s. Maps obtained by setting $k_x = k_y = 5$ in SeisLib (Magrini et al., 2022b).

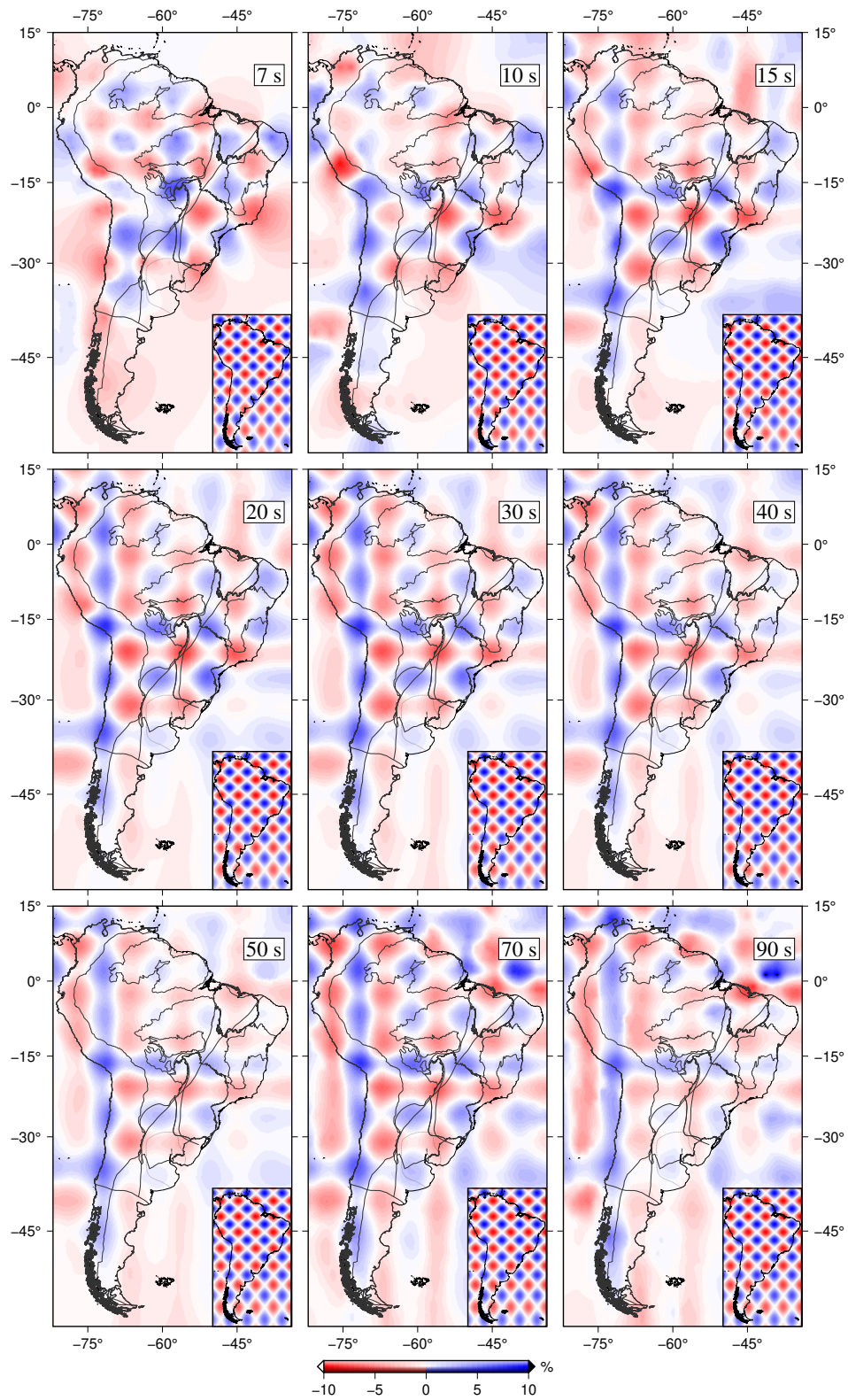


Figure B.8: Checkerboard resolution tests of Love wave group velocity maps, with perturbations of $\pm 10\%$, at periods of 7, 10, 15, 20, 30, 40, 50, 70, and 90 s. Maps obtained by setting $k_x = k_y = 10$ in SeisLib (Magrini et al., 2022b).

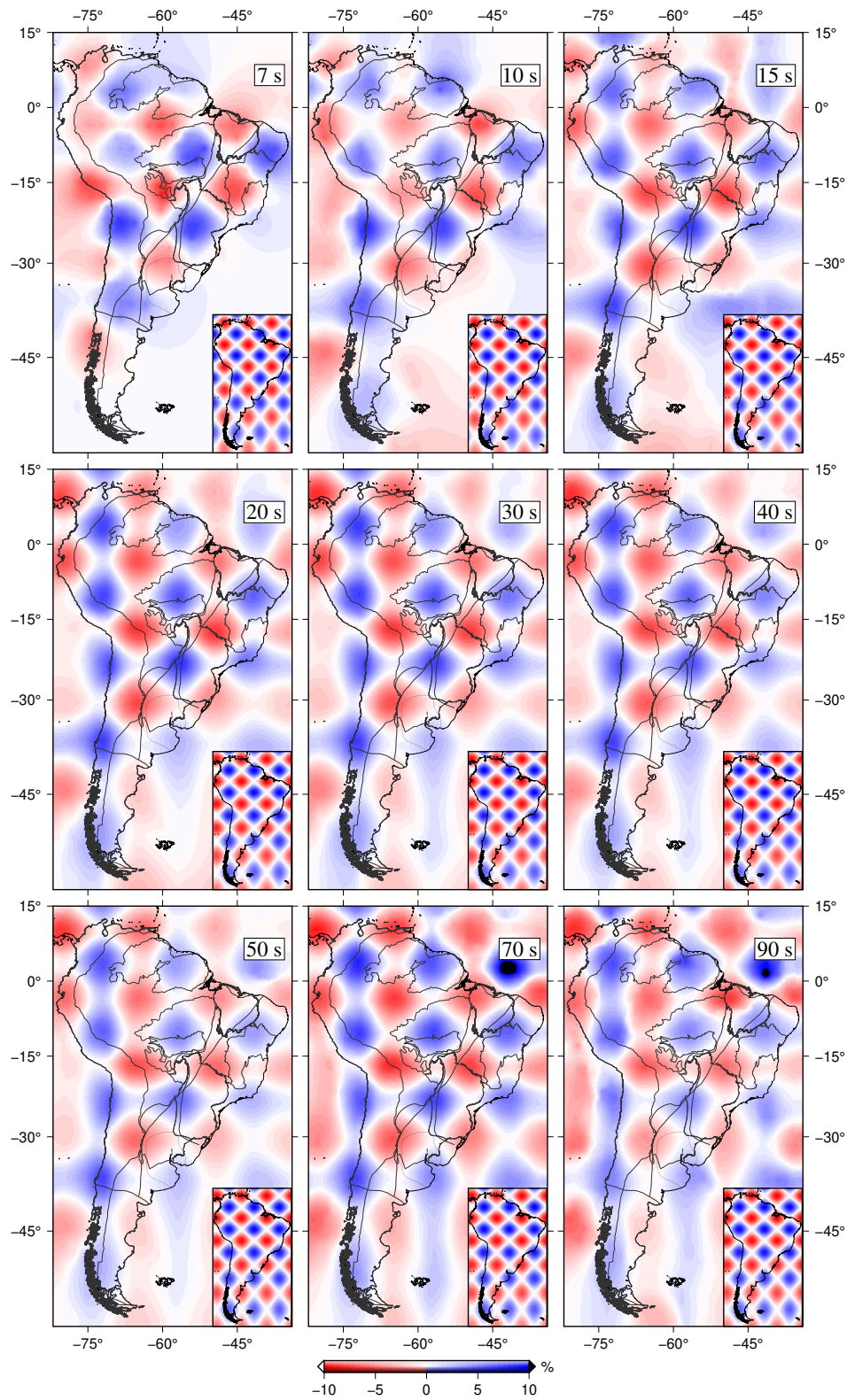


Figure B.9: Checkerboard resolution tests of Love wave group velocity maps, with perturbations of $\pm 10\%$, at periods of 7, 10, 15, 20, 30, 40, 50, 70, and 90 s. Maps obtained by setting $k_x = k_y = 7$ in SeisLib ([Magrini et al., 2022b](#)).

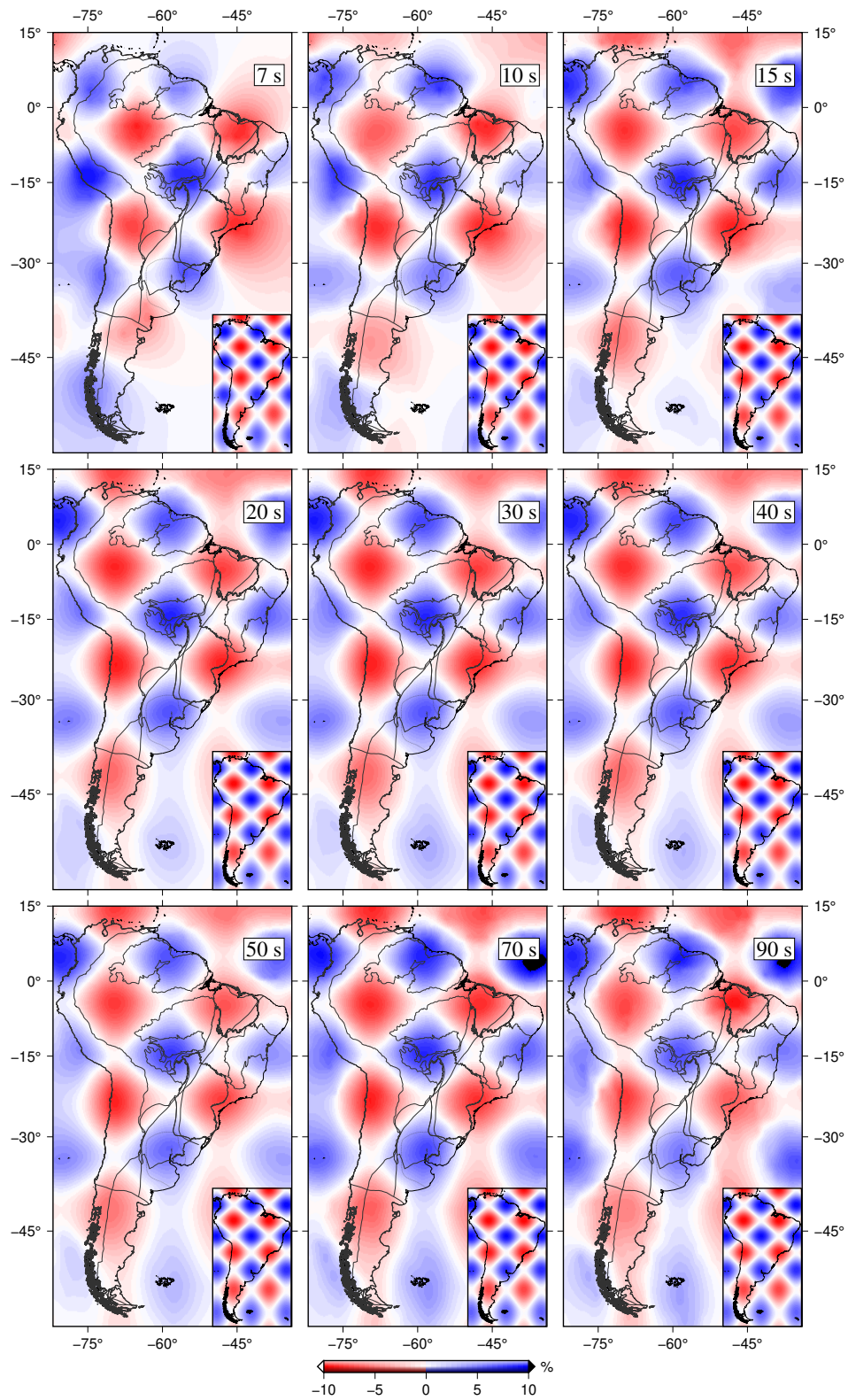


Figure B.10: Checkerboard resolution tests of Love wave group velocity maps, with perturbations of $\pm 10\%$, at periods of 7, 10, 15, 20, 30, 40, 50, 70, and 90 s. Maps obtained by setting $k_x = k_y = 5$ in SeisLib (Magrini et al., 2022b).

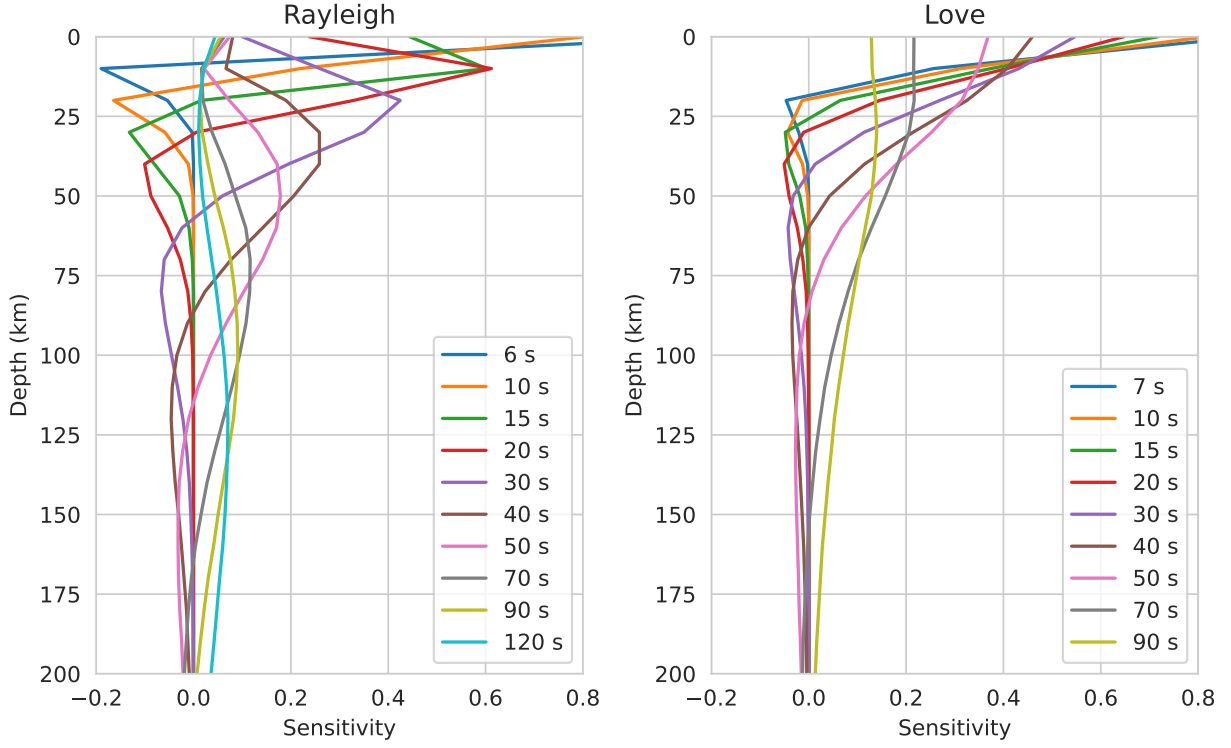


Figure B.11: Sensitivity kernels of Rayleigh and Love wave fundamental mode group velocities to shear-wave velocity structure. The kernels are computed for periods between 6 and 120 s based on the average shear-wave velocity structure reported in [Nascimento et al. \(2024\)](#). Additionally, we adopt $V_p = 1.8V_s$, and $\rho = 0.32V_p + 0.77$ ([Berteussen, 1977](#)).

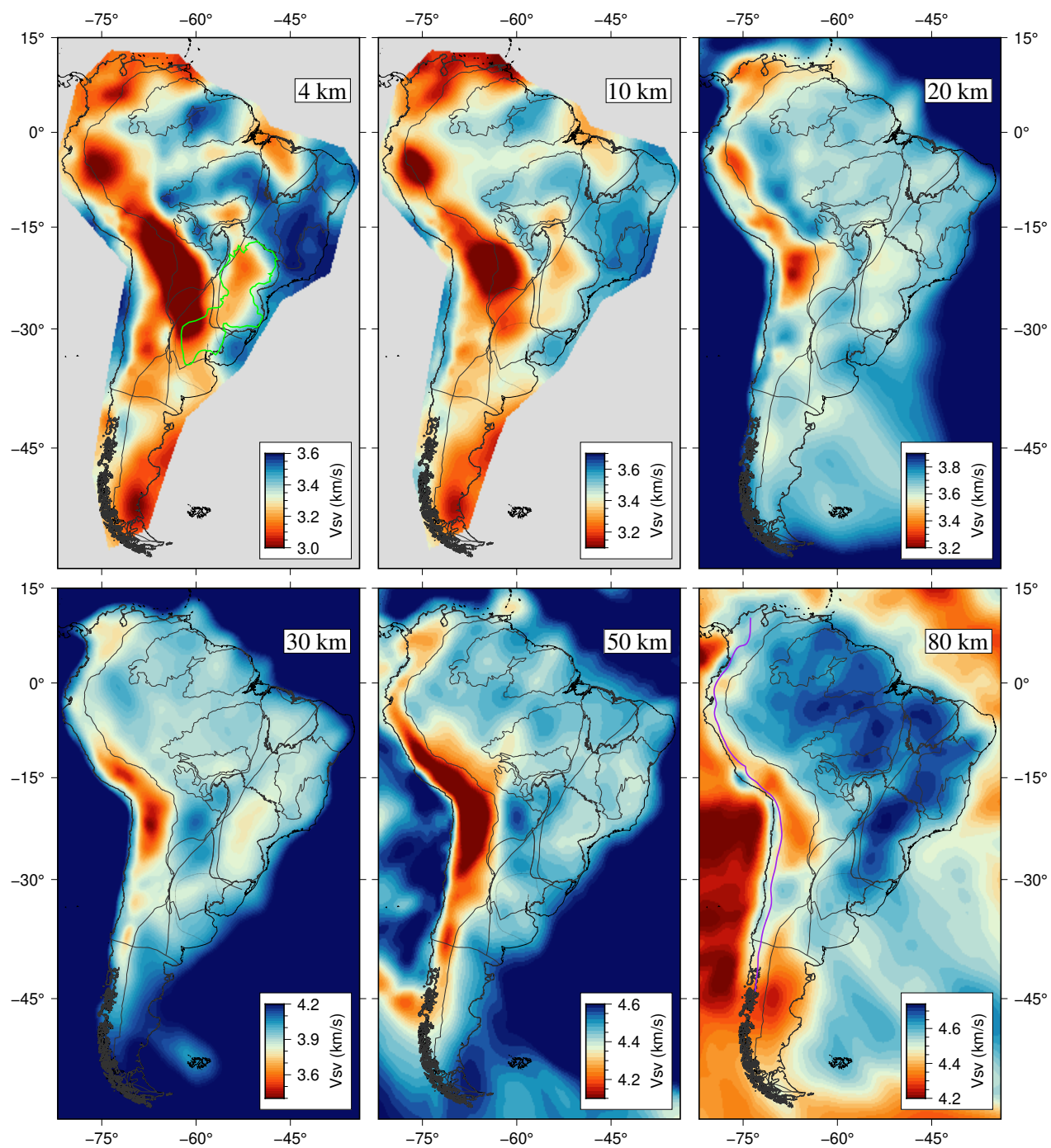


Figure B.12: Vertically polarized shear-wave velocity model at depths between 4 and 80 km.

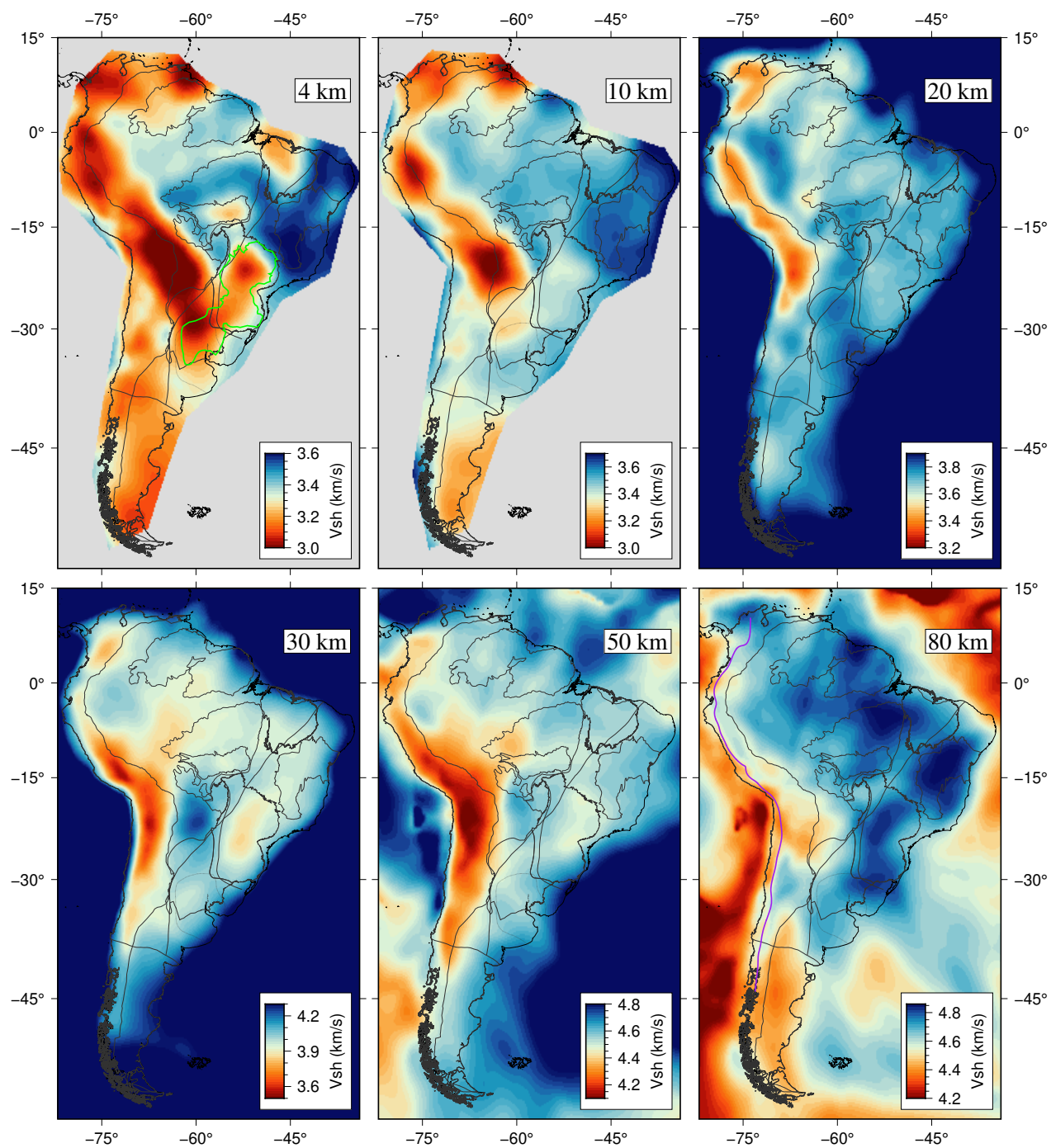


Figure B.13: Horizontally polarized shear-wave velocity model at depths between 4 and 80 km.