NEAR-SURFACE SEISMIC CHARACTERIZATION AND MONITORING:
A DENSE SEISMIC ACQUISITION PERSPECTIVE

by
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A thesis submitted to the Faculty and the Board of Trustees of the Colorado School of Mines in partial fulfillment of the requirements for the degree of Doctor of Philosophy (Geophysics).

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ABSTRACT

Geophysical analyses made available by sensors such as geophones that are commonly used to measure signals from within the Earth are frequently constrained by intrinsic aliasing mainly due to sensor spacing. While in many cases it is possible and meaningful to deploy dense geophone arrays, the number of sensors installed has been constrained by the cost and effort required to install those devices. In contrast to conventional geophones, recently distributed acoustic sensing (DAS) using fiber offers both rapid deployment and dense spatial and temporal sampling. DAS has been widely used in many applications; however, horizontal (dark-)fiber DAS presents challenges including variable fiber-ground coupling, amplitude fluctuations in cross-correlation gathers, and (crooked) deployment directionality. To realize the potential of horizontal DAS, the work examines such deployments for near-surface characterization and monitoring.

I present research work in a case study that uses low-frequency ambient DAS data. I demonstrate that applying interferometric analysis can construct virtual shot gathers (VSGs) that are used in a multi-channel analysis of surface waves (MASW) to constrain the shear-wave velocity ($V_S$) up to 0.5 km depth. However, the amplitude variations by factors such as source types, gauge length, and orientation hinder the application of advanced inversion that require greater amplitude fidelity.

I investigate the usability of filtered deformation-rate DAS data under improved fiber-ground coupling. To achieve near-elastic coupling, I freeze a fiber in a trench and compare observations to those measured on fiber laid on the ground. The trenched-freezing method improves the data quality and shows enhanced signal quality and reduced time-varying effects from variable coupling. I also compare different filtering techniques and show that the 2D filtering approach leads to improved data quality.

I demonstrate the potential of DAS for long-term monitoring using a pre-existing fiber deployment. I acquire short-duration data every hour for ten months and use cross-coherence to convert observations into weekly sliding-window VSGs. I observe surface-wave travel-time variations of up to 6% for a range of fixed source-receiver offsets. I estimate time-lapse averaged S-wave velocity for the top 30 m ($V_{S30}$) using the computed VSGs and MASW. The surface-wave inversions reveal coherent 10% maximum fluctuations of $V_{S30}$, with the maximum slowdowns occurring after periods of heavy precipitation suggesting a negative empirical correlation between rainfall and $V_{S30}$.

The final study uses seismic data from a dense geophone array to assess refraction tomography and elastic full-waveform inversion (E-FWI) to comprehend the subsurface in Majes, Peru, near a suspected landslide. I use P-wave refraction travel-time tomography to generate a starting velocity model. I then estimate a $V_S$ model using low-frequency surface-wave data that exhibits a layered structure with a 450 m/s average velocity.
and a velocity reversal from 5 m to 15 m away from the cliff. However, the $V_S$ model closer to the cliff has $V_S$ values between 250 m/s and 400 m/s to 20 m depth. The significant surface-wave backscattering observed at 90 m along the line is likely to be caused by a strong sub-vertical discontinuity, while the corresponding S-wave velocity slowdown may delineate a former landslide complex. Further geotechnical research is needed to determine whether these geophysical insights are related to suspected landslide events.
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Figure A.1  A screenshot of granting permission after publication for inclusion within thesis (highlighted in red box) from Oxford University Press, publisher for *Geophysical Journal International*. 

Figure A.2  A screenshot of open access policy allowing material reuse (highlighted in red box) from MDPI, publisher for *Sensors*. 

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LIST OF ABBREVIATIONS

Central Business District .......................... CBD
Distributed Temperature Sensing ........................ DTS
Distributed Vibration and Temperature Sensing ........................ DVTS
Geological Survey of Western Australia ........................ GSWA
Helically Wound Cables .......................... HWC
Interrogator Unit .......................... IU
Optical Time-Domain Reflectometer ........................ OTDR
Perth Western Suburbs .......................... PWS
Western Australia .......................... WA
Zstandard .......................... ZSTD
Acoustic Wave Equation .......................... AWE
Center for Wave Phenomena ........................ CWP
Colorado School of Mines ........................ CSM
Distributed Acoustic Sensing ........................ DAS
Elastic Wave Equation .......................... EWE
European Association of Geoscientists & Engineers ........................ EAGE
Full Waveform Inversion .......................... FWI
Geophysics .......................... GP
Graphical Processing Unit ........................ GPU
Institute of Electrical and Electronics Engineers ........................ IEEE
International Meeting for Applied Geoscience & Energy ........................ IMAGE
Multi Channel Analysis of Surface Waves ........................ MASW
Multi-Channel Cross-Correlation ........................ MCCC
Partial Differential Equation ........................ PDE
Reservoir Characterization Project ........................ RCP
ACKNOWLEDGMENTS

Even if there may only be one author for the thesis, it is impossible to complete the voyage without the assistance of my folks. I am grateful for the opportunity to convey the sincerity of my appreciation.

First and foremost, I want to thank Dr. Jeffrey Shragge, my advisor. Jeff accepted me to join the Center for Wave Phenomena (CWP) for four and a half years. Before joining CWP, I rarely worked with real data, but thanks to Jeff, I’ve had the opportunity to work with anything from urban fiber optic datasets to near-surface data from Peru. Jeff also taught me a lot about academic writing, not just how to write a paper, but also how to develop and refine meaningful research questions. His advice made me feel better equipped as a self-sufficient and resilient researcher.

I’d like to thank my committee members Dr. Paul Sava, Ge Jin, Douglas Nychka, and Gabriel Walton for their assistance and insightful remarks on my research projects. I collaborated with Jin on the Fiber Optics course and research project. Thank you for your assistance and experience in Distributed Acoustic Sensing. I’d want to thank Paul again for being "Occam’s razor" and serving as department head.

The Geophysics department was supportive and helpful. Debra Marrufo and Michelle Szobody were excellent people for geophysics students like myself. It was a happy-sad time to see them retire, but ironically, it was only after they left that I realized how much we appreciated them. I also miss Debra’s homemade ranch and salsa. I’d want to thank Diane Witters for her compassion and devotion in writing for CWP students, as well as for the delicious orange rolls. But, owing to Lynn, my last semester was a breeze. I do not doubt that the GP department is fortunate to have a strong lineage of employees. Dawn Umpleby, Gina Schwieger, Emilia Clayton, and Noelle Vance were also very helpful in providing administrative support at CWP. I appreciate you, Dr. Ken Larner, for teaching me how to present better.

My CWP colleagues took up the majority of my time, and I owe a big thanks to both CWP professors and friends. I’d like to start by thanking my CTeam (Computational Team) brothers. Tugrul and Can deserve special mention. They are my bright, hardworking academic brothers who never forgot to pamper me and buy me Turkish food when I was in doubt, thanks kardes! Also, I am honored to have had great memories with Hani, Harpreet, Derrick, and Adesh. Patipan (Mickey) was my roommate and friend for four years, owing to a random Craiglist post. His calm demeanor and outstanding cooking skills drew me out of a mental fog, and I was delighted to share his graduation celebrations. Brother Ivan went too soon, but he was helpful. His random Korean phrases made me chuckle all the time. I’d like to thank Harpreet for his support and look forward to returning to the same company’s team.
It’s time to discuss the CWP ladies, Odette and Iga. Odette is a warm person who brings CWP together, a true skill that I cannot duplicate. Iga and I shared a summer internship at the end of our Ph.D. adventure, which included drinking good beer and trekking Rockie Mountain, and 14ers. Yanhua came later, and I appreciate her hard ethic and composure even more so given her age. It is a privilege for me to be able to recall great times with other friends, some of whom I share in common with Khalid, Werter, Hafiz, Asish, and Nick.

Terra15 contributed the majority of the dataset for this thesis. Nader and Michael generously supported our research and were always willing to discuss and accommodate our research requests. I also appreciate them convening a meeting for a meaningful discussion. Rosie and Youfang, RCP pals, will be sorely missed. They are my chit-chat partner on a variety of issues ranging from politics to the best Asian food in Denver. It was a delight to blow off steam with you, and I’m glad our timelines coincided so well. I’d like to thank Dr. Youzuo Lin and Renan Rojas-Gómez for being my co-authors throughout the summer at Los Alamos National Laboratory (LANL). I’d want to express my gratitude to British Petroleum (BP) for giving me two summer internship opportunities. During my internship, I was fortunate to meet CWP alumni; thank you Esteban Diaz and Simon Luo for your assistance.

Finally, I should dedicate this work to my family. They endure my up and downs and gave continuous support. My parents encouraged me to pursue the career of my choice, thanks for letting me roam randomly (I understand that can be more challenging for Asian parents). My older sister, I send you my love.
For my family
Seismic surveys provide useful data for subsurface investigation, but are often limited by acquisition parameters such as inter-sensor spacing. Seismic data acquired on dense geophone sensing arrays offer numerous advantages including improved resolution and enhanced signal-to-noise ratio (SNR) over data recorded on coarser grid counterparts. While in many cases it is possible and scientifically meaningful to deploy dense geophone arrays (including a case history presented herein), the number of sensors installed traditionally has been constrained by the cost and personnel effort required to install those devices.

Distributed acoustic sensing (DAS) is one of the dense seismic sensors at a relatively low cost. In contrast to conventional geophones, DAS is an emerging technology that uses optical fiber as a distributed sensor array to capture real-time vibration data with a high degree of sensitivity and offers both rapid deployment per sensor as well as dense spatial and temporal wavefield sampling (Hartog, 2018). Depending on the design of the deployed interrogator unit (IU), this ground-motion information may be presented in terms of strain, strain-rate (Farhadiroushan et al., 2009; Masoudi et al., 2013; Posey et al., 2000), or velocity (Issa et al., 2018) (also known as deformation rate) time-series data.

DAS has found widespread use in a wide variety of geophysical applications, including earthquake seismology, well bore, subsurface, and asset monitoring. Early examples investigate the use of dedicated downhole DAS installations for active-source vertical seismic profiling (VSP) employing body-wave arrivals (Li et al., 2015; Mateeva et al., 2012; Yu et al., 2018). Numerous studies show that active-source DAS data are well-matched with field geophone data and are suitable for subsurface geophysical characterization (Correa et al., 2017; Mateeva et al., 2012; Mestayer et al., 2011). Recently, Isaenko et al. (2022) present time-lapse (4D) DAS VSP monitoring of CO₂ volumes that detects plume evolution during injection and remobilization of previously injected CO₂ volumes.

While active-source DAS surveys are used effectively for borehole monitoring, passive seismic methods without controlled sources offer several advantages over active-source seismic technology, including lower-cost operations, reduced labor intensity, lower environmental impact, and the ability to acquire and process low-frequency ambient signals potentially over a broader frequency range. Recent research has demonstrated that DAS-based passive microseismic monitoring of subsurface fracturing activities in unconventional hydrocarbon settings successfully captures P- and S-wave arrivals, reflection, refractions, and mode conversions (Baird et al., 2020; Karrenbach et al., 2019).
Nevertheless, passive DAS seismic approaches have a number of drawbacks. The spatial resolution of passive seismic methods is typically inferior to that of controlled-source active-source methods (Song et al., 2019). Moreover, the directivity of incident ambient energy sources cannot be regulated directly. Therefore, an ambient seismic data set may not satisfy typical interferometry requirements (e.g., stationary phase assumptions, source distribution), thereby limiting or otherwise qualifying the research possible with passive seismic methods. In addition, unwanted coherent noise sources such as electro-mechanical equipment might impair passive seismic acquisition and are often challenging to eliminate with advanced signal processing techniques (Duncan, 2005).

1.1 Advantages and Opportunities of Horizontal DAS Deployments

While vertical borehole deployments are fast becoming industry standard, there has been a growing interest in the use of surface-based passive DAS acquisition for seismic investigations due to the lower cost of deploying optical fiber in trenched surface arrays (herein termed “horizontal DAS”) or even using pre-existing (so-called “dark fiber”) networks. Horizontal fiber networks can be deployed for surveys for several years using a single installation and can record along fiber distances of up to 20 km or longer using a single IU. Moreover, DAS systems enable dense channel spacing over long distances, which enhances the possibility of recording coherent surface waves and thereby offers an attractive option for using methods such as passive or ambient multi-channel analysis of surface waves (MASW). There are now numerous investigations in near-surface geophysics and geotechnical fields that show the successfully use of ambient-wavefield data in the MASW technique to estimate 1-D $V_S$ profiles of the top 30 m ($V_{S30}$) or 100 m ($V_{S100}$) (Dou et al., 2017; Kaufmann et al., 2005; Park et al., 1999).

Although the majority of reported imaging, inversion, and monitoring operations in the field of passive surface-based DAS research largely have been successful, the potential exists for constraining to deeper depths when considering the wide dynamic range of DAS at low frequencies. By conducting tests using low-frequency signals including ocean microseismic noise and teleseismic earthquakes as input signals, Lindsey et al. (2020b) verify that the DAS frequency range is broad as that found in broadband seismometers. Jin & Roy (2017) discuss the acquisition of the sub-0.05 Hz DAS data to constrain the length, density, and width of reservoir fractures. Because surface-wave penetration depths are inversely proportional to frequency (Soczkiewicz, 1997; Xia et al., 2003), DAS has a better chance of capturing low-frequency ambient signals resulting in deeper model constraints than conventional geophones, which are typically limited by strong instrument roll-off at, e.g., sub-4.5 Hz frequencies. For these smaller-scale investigations, the maximum depth of investigation is commonly controlled primarily by acquisition-geophone array lengths (e.g., 100 m) and the dearth of sub-2Hz frequency energy in acquired wavefield data arising from a
combination of source and geophone limitations. Furthermore, optical fiber can be easily deployed over much longer distances than nodal sensors, and a single DAS IU can capture the equivalent of an individual component of a broadband seismograph signal in a single data stream.

1.2 Challenges with Horizontal DAS Fiber Systems

Despite the advantages outlined above, horizontal DAS applications must confront a range of different challenges. Specifically, projects may encounter insufficient coupling between fiber and the surrounding medium, which degrades data quality and introduces data uncertainty. In addition, the DAS amplitude response can vary significantly across the array, depending on fiber azimuth and incident wave-mode type (Martin et al., 2021). Specifically for dark-fiber arrays that prohibit fiber orientation adjustment, typical variations in array geometry can increase the amplitude fluctuations across channels depending on the type of wave modes, the gauge length applied, the absolute fiber orientation, and the relative fiber orientation of cross-correlation pairs.

A second well-known drawback of strain-rate DAS acquisition is the limited broadside sensitivity (Mateeva et al., 2021), which limits the usable angles of incident waves. This limitation is mainly due to strain-rate DAS P-wave measurement sensitivity, which exhibits a $\cos^2 \theta$ pattern where $\theta$ is the P wave incidence angle to the fiber (Benioff, 1935). When compared with the conventional $\cos \theta$ relationship of geophones, strain-rate DAS has increased challenges when aiming to acquire the equivalent of near-vertical incidence reflected and refracted P waves used for conventional seismic imaging and inversion analyses. Accordingly, recording reflected or refracted body-wave arrivals commonly used in active-source seismic imaging and inversion experiments has been difficult for surficial horizontal array DAS deployments. One way to improve the broadside DAS response is to use helically wounded cable (HWC), which improves the response of vertical-incidence arrival but increases installation labor and costs. While HWCs can boost the broadside sensitivity to P-wave arrivals, they also hamper S-wave sensitivity due to the structure of the S-wave strain tensor (Baird, 2020).

It is important to note, though, that the default unit of measurement for DAS can vary based on the type of IUs and associated acquisition parameters on the specified optical interference pair. For example, Kuvshinov (2016) demonstrates that vertical seismic profile (VSP) direct-wave amplitudes from native deformation-rate DAS and geophones are nearly equivalent - even for broadside P-wave arrivals - under elastic fiber-ground coupling conditions. However, few studies have been conducted on horizontal DAS arrays with data acquired in the deformation format. This observation is presumably due to the challenges of establishing truly elastic ground-fiber coupling in a low-cost installation, which is usually achieved through more expensive and laborious cementing and grouting, such as fiber cemented in the wellbore.
1.3 Toward Robust Near-surface Characterization Using Horizontal DAS

In recent years, near-surface geophysical applications have expanded in numerous disciplines requiring long-term monitoring, including mining engineering, infrastructure, and groundwater research. Horizontal DAS provides a robust system for many active-seismic applications, such as non-intrusive pipeline and borehole monitoring (Daley et al., 2016; Stajanca et al., 2018), and for near-surface passive-seismic applications such as geological characterization (Shragge et al., 2021) and earthquake-induced subsurface structural heterogeneity analysis (Yang et al., 2022), as well as active landslide (Cole et al., 2022), permafrost and cryosphere thaw (Ajo-Franklin et al., 2017; Cheng et al., 2022), and urban subsurface (Fang et al., 2020) monitoring investigations. Moreover, DAS is useful for long-term monitoring projects due to its quick and potentially permanent deployment and repeatable time-lapse analysis capabilities.

Compared to other nodal-based sensing systems, though, DAS typically acquires high-density data with finer temporal and spatial sample rates. Thus, the corresponding data storage and processing strategies should be designed to handle data streams of terabytes per day. Consequently, calendar duration acquisition of DAS-based monitoring data imposes several challenges, such as increased IU rental expenses, data storage, and computation time (Lindsey & Martin, 2020). Recently, researchers have investigated ways to optimize and manage storage systems effectively. As examples, (Muir & Zhan, 2017) apply established compressive sensing methods to DAS data including the curvelet transform. Similarly, Dong et al. (2022) present a two-stage compression technique that could lower the storage requirements by 40% and show that their compression method is well-suited for real-time DAS acquisition because the algorithm finishes data compression activities before the IU needs to output the subsequent record. Nonetheless, ambient passive seismic approaches usually require storing months of files to generate stacked gather for time-lapse analysis, and few studies have examined the effects of data compression on the resulting analysis outcomes.

1.4 Thesis Aims

This thesis aims to present research that addresses several of the aforementioned challenges of horizontal DAS acquisitions and the ensuing construction of near-surface velocity models by creating and implementing novel DAS processing, imaging, and inversion techniques appropriate for the wave types for which horizontal DAS fiber deployments are most sensitive. To accomplish this, I first conduct seismic interferometric analysis and surface-wave inversion to assess the feasibility of using surficial DAS arrays to record low-frequency ambient signals and use the resulting observed waveforms to construct subsurface velocity models. I also investigate the influence of irregular array orientation on the amplitude variation of interferometric VSGs. Next, I examine the potential advantages of acquired DAS data in the deformation-rate format. In particular, I explore the potential for improved usable angular bandwidth made possible by improving ground-fiber
coupling by freezing fiber in the trench and designing and applying a 2D velocity-dip filtering method to remove low-wavenumber noise and use the result as “filtered deformation-rate” data. In addition, I present a computationally tractable, ten-month time-lapse study using an urban DAS array to circumvent the need for data storage and processing difficulties, while enabling long-term monitoring to track measurable seasonal subsurface variations interpreted to be caused by seasonal variations in precipitation. Finally, I examine the viability of applying seismic elastic full-waveform inversion using predominately surface-wave energy to estimate the S-wave velocity structure of a recent landslide complex as a precursor investigation to motivate the type of DAS-based surface-wave studies that could be conducted to better understand complex landslide environments.

1.5 Thesis Outline

The contents of this thesis consist of expanded abstracts presented at international conferences and articles that are either published or under review. The first two chapters have been published in peer-reviewed journals; the third is currently undergoing journal peer review; and the fourth will be submitted for publication after the thesis defense when the contributions of my collaborators have been finalized and integrated into the manuscript.

For the first paper, I contributed as a co-author to the data processing, dispersion analysis, surface-wave inversion, and DAS array sensitivity analysis sections and these sections have been extracted to form Chapter 2. However, the precursor interferometric work has been removed from the published paper due to its completion prior to my involvement with the project. As lead author of the work in Chapters 3 through 5, I substantially contributed to conceptualization, methodology, software, formal analysis, investigation, data curation, drafting of the original manuscript, and visualization. My PhD advisor Dr. Jeffrey Shragge contributed to methodology, resources, supervision, project administration, funding acquisition, and manuscript revisions. Project collaborator Dr. Ge Jin contributed to the supervision, data curation, validation, and manuscript revision for the published article presented in thesis Chapter 3. All authors contributed to the research discussion and manuscript development and refinement.

Chapter 2, titled “Low-frequency ambient distributed acoustic sensing (DAS): Case Study from Perth, Australia”, presents a case study evaluating the use of horizontal pre-existing fiber on recording low-frequency ambient signals and the utility of such signals for subsurface velocity model building. This work also investigates the effects of fiber orientation, gauge length, source type, and orientation on the interferometric analysis of a 16 km dark-fiber array. This experiment reveals that the majority of the ambient wavefield energy in the low-frequency (i.e., sub 2.0-Hz) band consists of surface waves. In addition, the DAS fiber network has sufficient sensitivity to incoming surface waves in a 4.0-km straight fiber segment.
but lower sensitivity in more curvilinear sections. By stacking several hours of low-frequency ambient data into a cross-coherence VSG and generating velocity-dispersion curves for use in MASW, I demonstrate the ability to constraint the S-wave velocity model to depths of 0.5 km or greater. Overall, this work demonstrates the utility of recording and analyzing low-frequency surface waves using DAS systems for near-surface geological characterization. This chapter was presented at an Annual Meeting of the Society of Exploration Geophysicists (SEG) and published in Geophysical Journal International:


The work found in Chapter 3, “Filtering Strategies for Deformation-rate Distributed Acoustic Sensing”, presents DAS data acquired in the Terra15 Treble IU native deformation-rate format as well as introduces higher-order filtering strategies for improving the signal-to-noise ratio for such acquisition modalities. Under elastic ground-fiber coupling conditions, the optical design of the Treble IU enables deformation-rate DAS and acquires seismic data that are theoretically equal to the along-fiber particle velocity motion recorded by (appropriately oriented) geophones. Although near-elastic coupling can be established in cemented installations, it is less obvious how to achieve such elastic coupling in low-cost horizontal deployments. This chapter presents an effort to establish near-elastic DAS fiber-ground coupling by reporting the results of an experiment involving freezing fiber in a shallow trench to achieve near-elastic DAS fiber-ground coupling. With the help of this acquisition strategy, processed deformation-rate DAS data can be viewed as a “filtered particle velocity” rather than the conventional strain-rate quantity. To eliminate low-wavenumber noise present in deformation-rate DAS data, I apply and compare a number of established higher-order denoising strategies: 1-D finite impulse response (FIR), 1-D infinite impulse response (IIR), and 2-D velocity-dip filtering. The results of applying our preferred strategy, 2-D velocity-dip filtering, suggest that the signal-to-noise ratio of refracted and surface-wave arrivals can be improved when applying this filtering approach. Thus, the procedure of trenching and freezing the cable increased ground-fiber coupling and potential angular bandwidth enhancement. These results were presented at First International Meeting for Applied Geoscience & Energy and published as a peer-reviewed technical manuscript in the journal Sensors:

In Chapter 4, titled “Long-term Ambient Seismic Interferometry for Constraining Seasonal Subsurface Velocity Variations in Urban Settings: A Distributed Acoustic Sensing (DAS) Case Study”, I present a case study to demonstrate that DAS is well-suited for long-term installations and time-lapse monitoring analyses. Because DAS systems commonly acquire data at a faster rate and greater density than other nodal-based sensing systems, long-term time-lapse investigations require novel data acquisition, storage, and processing strategies. This research uses a computationally tractable semi-continuous DAS data acquisition strategy whereby 150 s of data were recorded every hour for ten months on an urban subsurface array in the central business district of Perth, Australia. This unique data set enables us to perform seismic analyses that provide information about seasonal subsurface variations within the Perth area. To illustrate this, I apply an interferometric cross-coherence analysis to create weekly interferometric sliding-window VSGs from preprocessed ambient waveform data. Time-lapse VSGs show travel-time fluctuations across the 43-week recording period, with up to a 6% maximum calendar variation in surface-wave arrival times noted at some fixed source-receiver offsets. I use time-lapse velocity-dispersion panels to determine depth-averaged S-wave velocity for the top 30 m ($V_{S30}$) via MASW. Surface-wave inversions show coherent 10% maximum $V_{S30}$ variations between the drier summer and wetter winter seasons and suggest empirically that increasing rainfall decreases the S-wave velocity averaged over the top 30 m. This research was presented at Second International Meeting for Applied Geoscience & Energy, the 2nd EAGE Workshop on Fiber Optic Sensing for Energy Applications, and is currently in the R1 stage of peer review in *Geophysical Journal International*:


The work presented in Chapter 5, titled “Seismic Characterization of a Landslide Complex: A Case History from Majes, Peru”, represents an extension of the surface-wave analyses used in this thesis, and is...
aimed at applying more advanced surface-wave inversion techniques for seismic near-surface characterization of a recent landslide complex. This chapter examines the viability of seismic inversion for exploring the subsurface of a former landslide complex in Majes, Arequipa, southern Peru. At this arid location, irrigation and agricultural growth have altered the hydrology and groundwater table (Flamme et al., 2022). The suspected irrigation-induced landslides started evolved into a retrogressive failure along the ridge near key infrastructure. To better understand the subsurface in an area of a recent landslide, I employ seismic inversion techniques using vertical-component geophone data. The data set consists of prominent direct surface-wave arrivals with an observed strong slowdown in surface-wave velocities in the vicinity of the cliff face and significant backscattering energy from the location of the suspected sub-vertical landslide failure surface. I use P-wave refraction travel-time tomography to create an initial model estimate and then apply 2-D elastic full-waveform inversion (E-FWI) to the predominantly surface-wave data to produce final high-resolution velocity models that exhibit substantial lateral S-wave velocity variations. Waveform fitting, data misfit reduction, and previous Majes geology studies all help to confirm the inverted model. Subsequent interpretation suggests the presence of weathered soil in the top layer (depth of 20 m) and a significant sub-vertical anomaly that generates the observed surface-wave backscattering. The interpreted former landslide zone is distinguished by significantly lower S-wave velocities, indicating a geological fabric with weaker shear strength. Overall, these results encourages future DAS deployments to examine landslide features with the anticipated benefit of a dense sensing system.

I intend to soon submit the findings to *Environmental Earth Sciences*:


Finally, chapter 6 presents the general outcomes of the thesis are presented along with a discussion of prospective applications and suggestions for future research for the approaches introduced in this thesis.
CHAPTER 2
LOW-FREQUENCY AMBIENT DISTRIBUTED ACOUSTIC SENSING (DAS): CASE STUDY FROM
PERTH, AUSTRALIA

Work by Jihyun Yang extracted from a paper published in *Geophysical Journal International*¹ ²

Jihyun Yang ∗

2.1 Abstract

Ambient wavefield data acquired on existing (so-called “dark fiber”) optical fiber networks using
distributed acoustic sensing (DAS) interrogators allow users to conduct a wide range of subsurface imaging
and inversion experiments. In particular, recorded low-frequency (<2 Hz) surface-wave information holds the
promise of providing constraints on the shear-wave velocity ($V_S$) to depths exceeding 0.5 km. However,
surface-wave analysis can be made challenging by a number of acquisition factors that affect the amplitudes
of measured DAS waveforms. To illustrate these sensitivity challenges, we present a low-frequency ambient
wavefield investigation using a DAS dataset acquired on a crooked-line optical fiber array deployed in
suburban Perth, Western Australia. We record storm-induced microseism energy generated at the nearby
Indian Ocean shelf break and/or coastline in a low-frequency band (0.04 − 1.80 Hz) and generate high-quality
virtual shot gathers (VSGs) through cross-correlation and cross-coherence interferometric analyses. The
resulting VSG volumes clearly exhibit surface-wave energy, though with significant along-line amplitude
variations that are due to the combined effects of ambient source directivity, crooked-line acquisition
geometry, and the applied gauge length, among other factors. We transform the observed VSGs into
dispersion images using two different methods: phase shift and high-resolution linear Radon transform.
These dispersion images are then used to estimate 1-D near-surface $V_S$ models using multi-channel analysis of
surface-waves (MASW), which involves picking and inverting the estimated Rayleigh-wave dispersion curves
using the particle-swarm optimization global optimization algorithm. The MASW inversion results, combined
with nearby deep borehole information and 2-D elastic finite-difference modeling, show that low-frequency
ambient DAS data constrain the $V_S$ model, including a low-velocity channel, to at least 0.5 km depth. Thus,
this case study illustrates the potential of using DAS technology as a tool for undertaking large-scale
surface-wave analysis in urban geophysical and geotechnical investigations to depths exceeding 0.5 km.

¹Shragge *et al.* (2021): Shragge, J., Yang, J., Issa, N., Roeleens, M., Dentith, M., & Schediwy, S. Low-frequency ambient
²The copyright permissions from Geophysics Journal International is in Figure A.1.
∗Primary author and editor.
2.2 Introduction

Distributed acoustic sensing (DAS) is a rapidly developing technology that uses a standard optical fiber as a distributed sensor array to measure real-time vibration information at a high level of sensitivity. A DAS interrogator system sends a light pulse down an optical fiber and measures the Rayleigh backscatter, the measured amplitude and phase variations of which provide information about the ground motion detected along an array of densely sampled measurement points that are ideally elastically coupled with the subsurface. Depending on the design of the deployed interrogator, this ground-motion information may be presented in terms of strain, strain-rate or velocity (also known as deformation rate) time-series data. For an extensive overview of these methods, principles of operation, limitations, and applications, we refer the reader to the monograph by Hartog (2018).

DAS sensing systems offer numerous benefits for seismic investigations relative to conventional cabled or autonomous nodal acquisition. First, with a capability to measure signals from the mHz to the kHz frequency band, one can acquire data with a broader dynamic range than is possible with standard exploration geophone deployments. Second, seismic wavefields can be measured with much denser spatial samplings (i.e., < 1.0 m) than is practical with geophone arrays. Third, the deployment of low-cost optical fiber to lengths of 10.0 km or beyond is a fairly straightforward undertaking, which leads to a sufficient array aperture for undertaking subsurface geophysical and geotechnical investigations to depths up to or exceeding 0.5 km. However, there are known limitations of DAS acquisition that need to be taken into account when designing a survey, including limited cross-line sampling and the “broadside insensitivity” to wave modes with particle motions making oblique angles to the deployed fiber orientation.

An increasing number of papers investigate the utility of DAS-based seismic acquisition for seismic imaging, inversion, and monitoring applications. Early examples explore the use of dedicated downhole DAS installations for active-source vertical seismic profiling (VSP) using body-wave arrivals. There are now numerous examples showing that active-source DAS data are well-matched with field geophone data and are useful for subsurface geophysical characterization (Correa et al., 2017; Mateeva et al., 2012; Mestayer et al., 2011). In addition, Correa et al. (2017) show that DAS acquisition captures seismic reflection information at far offsets (i.e., > 1.8 km), but with lower SNR compared to co-located geophone recordings. More recently, passive DAS microseismic monitoring of subsurface fracturing activities in unconventional hydrocarbon settings captures not only P- and S-wave arrivals but also measures reflection, refractions, and mode conversions (Karrenbach et al., 2019). Baird et al. (2020) demonstrate the benefits of using DAS arrays for microseismic monitoring, such as source mechanism determination as shown in their synthetic examples.
There has been a parallel growing interest in the use of surface-based DAS acquisition for seismic investigations due to the significantly lower cost of deploying optical fiber in trenched surface arrays or even using pre-existing “dark fiber” networks. Researchers are exploring further cost reductions by eliminating the active-source survey component in favor of harnessing signals from passive events as well as ambient wavefield energy. (We differentiate between uncontrolled passive seismic energy events of estimable temporal and spatial location and ambient seismic energy measured from events of unknown spatial or temporal location). Martin et al. (2016) use passive vibrations from vehicle movements to extract the Green’s function from a parallel DAS array for permafrost monitoring. Lancelle (2016) presents a traffic monitoring study to calculate the quantity and velocity of passing vehicles. Martin & Biondi (2017) process 2-D DAS data using ambient noise interferometry and extract Love wave from cross-correlations on parallel lines. Dou et al. (2017) examine the use of ambient DAS recordings for time-lapse imaging. Ajo-Franklin et al. (2019) present a monitoring study using regional telecommunication fiber to demonstrate the potential of using signals (2-40 Hz) from a nearby railway line recorded on a 4 km fiber section for generating constraints on the subsurface shear-wave velocity \( V_S \) profile to 60 m depth. Lellouch et al. (2019) use downhole DAS arrays at the San Andreas Fault observatory for estimating P-wave velocity using earthquake records and ambient noise interferometry.

Our work examines whether one can use a DAS system to acquire lower-frequency ambient-wavefield information than reported in the above studies (i.e., < 2 Hz) to constrain \( V_S \) structure to depths exceeding 0.5 km. In near-surface geophysics and geotechnical fields, methods such as passive multi-channel analysis of surface waves (MASW) commonly use ambient-wavefield data to constrain 1-D \( V_S \) profiles of the top 30 m \( (V_{S30}) \) or 100 m \( (V_{S100}) \) (Dou et al., 2017; Kaufmann et al., 2005; Park et al., 1999). The investigation depths of these smaller-scale experiments are largely constrained by a combination of acquisition-limited (linear) geophone arrays (e.g., 100 m) and a lack of sub-2Hz frequency energy in the measured wavefield data. In contrast, optical fibers can be readily deployed for far greater lengths and a single DAS interrogator can record the equivalent of a broadband seismic response including low-frequency energy when and where available. As examples, Jin & Roy (2017) use sub-0.05 Hz DAS data to constrain the length, density, and width of reservoir fractures, while Becker et al. (2017) employ a DAS system to detect strain at mHz frequencies. Motivated by these lower-frequency DAS observations, we ask the following question: can we acquire low-frequency ambient-wavefield DAS data and apply standard MASW surface-wave analysis and full-wavefield modeling to constrain the \( V_S \) profile to 0.5 km depth or greater beneath dark-fiber arrays?

While there is significant community excitement about passive/ambient seismic investigations on dark-fiber arrays, there are also numerous associated practical challenges that naturally arise. First, given the pre-existing nature of this infrastructure, researchers have zero input on the deployment geometry of the
dark-fiber array. This commonly leads to practical challenges such as needing to geolocate the fiber, identifying any extra coiled sections present in fiber junction boxes, and addressing the consequences of a crooked-line deployment geometry. Second, passive/ambient acquisition means that the usable wavefield energy may arrive from directions where the fiber has limited-to-no sensitivity to the particular wave mode in question. This issue can be exacerbated for crooked-line scenarios where the variable fiber deployment azimuth causes significant along-fiber sensitivity variations and associated amplitude changes. Thus, before utilizing the full potential of DAS-based seismic acquisition in complex dark-fiber scenarios, one must better understand and ideally account for these issues during data preprocessing.

To illustrate the described benefits and challenges, we present a case study from Perth, Australia involving a low-frequency ambient DAS data set acquired on a 15 km section of an existing dark-fiber installation. Figure 2.1 illustrates the crooked-line deployment in the Perth western suburbs (PWS). The study area is situated between 2-6 km to the east of the Indian Ocean. We periodically acquired DAS data during a winter storm to investigate the associated fluctuations observed in ambient seismic wavefield measurements. Due to the proximity of the array to the Indian Ocean and the choice of a relative long interrogator gauge length (100 m), the array recorded significant low-frequency ambient microseism energy. To highlight these ambient signals, Shragge et al. (2021) applies a practical seismic interferometry analysis (i.e., cross-correlation or cross-coherence plus window stack) of 20 minutes of high S/N data to generate a virtual shot-gather (VSG) volume. The resulting interferometric data exhibit distinct sub-1.0 Hz arrivals with clear along-array amplitude variations that can be explained by the aforementioned fiber array sensitivity effects. We use different combinations of the VSG volumes to perform various MASW analyses of the fundamental Rayleigh wave mode. We partially validate the 1-D MASW inversion results through comparison with surface geology, local borehole data, 2-D elastic forward modeling, and the associated synthetic dispersion panels and MASW inversion results.

We begin with a discussion on the geologic setting of the survey area as well as the DAS data acquisition and preparation. Shragge et al. (2021) then highlights the cross-correlation and cross-coherence interferometry approaches used to generate the VSG volumes. Based on the observed energy patterns, we explore evidence for strong Rayleigh wave arrivals as well as the underlying causes of the observed amplitude signatures imparted by crooked-line DAS geometry and associated spatially varying sensitivity. We then discuss our particular MASW approach and the dispersion panels and 1-D $V_S$ profile estimated from a single 3.6 km straight fiber section. After accounting for crooked-line distance variations, we present MASW analysis results for partial and full array stacks. We then show the 2-D elastic modeling validation tests using the globally best-fitting 1-D $V_S$ model, and discuss a number of challenges associated with the surface-wave analysis of ambient DAS data acquired on dark-fiber arrays.
2.3 Geological Description of Survey Area

The PWS are situated on the Swan Coastal Plain (see Figure 2.1), which lies to the north and west of the Swan River and to the east of the adjacent Indian Ocean. The near-surface geology is of Tertiary age and younger sediments that unconformably overlie the mostly Mesozoic sedimentary rocks of the Perth Basin. Information about the geology of the uppermost 1.0 km in the study area is sparse, with the only outcrops occurring on the banks of the Swan River and near the coast.

One deep groundwater drill hole (AM79; 550 m termination depth) is located approximately 0.6 km to the east of the southeastern-most study area (purple star in Figure 2.1). AM79 well-log data (Figure 2.1b) show that the geologic succession in the immediate vicinity of the bore consists of three main formations (Davey, 2018). The deepest Gage Formation (GF) unit, encountered at 0.52 km, is well-lithified and mainly consists of sandstones with minor interbedded siltstones and shales (Davey, 2018). The 0.49 km-thick Kings Park Formation (KPF), unconformably overlying the GF, was regionally deposited in a deeply eroded river channel and consists of poorly lithified siltstones and shales with two more-sandy intervals of poorly understood lateral extent. The uppermost unit in the AM79 bore logs is Quaternary Alluvium (QA), which is found in the top 30 m.

Although not intersected in the AM79 well, a near-surface unit important in the context of this work and found throughout in the field area is the Quaternary-Late Tertiary Tamala Limestone (TL) (see Figure 23 in Davidson (1995)). The TL is an indurated calcareous eolinite with a maximum known onshore thickness of 0.11 km in the vicinity of the greater PWS area (Davidson, 1995). The TL is exposed in various outcrops on the banks of the Swan River and near the coast at elevations above mean sea level. In the vicinity of this AM79 bore, the TL likely has been eroded and replaced with fluvial alluvium (see Figure 2 in Bufarale et al. (2017)). Additional shallow groundwater drilling (< 50 m depth) throughout the study area region commonly encounters the TL formation from right at the surface to 40 m depth, and also reveals significant lateral stratigraphy heterogeneity with units often absent due to non-deposition or erosion; see Davidson (1995) or Davey (2018) for additional discussion.

The only other deep borehole in the area is the AM78 well (Figure 2.1c), located 5 km north of the study area (see arrow in Figure 2.1). The AM78 bore encounters a 15 m thick TL at 25 m depth, which directly overlies a 0.42 km thick KPF to 0.46 km depth. These observations again suggest strong lateral heterogeneity in the near-surface geology as well as significant variations in the thickness of the KPF unit.

The presented geological information allows us to generate a number of geophysical inferences. First, the regional presence of the TL unit suggests that a significant portion of the PWS optical fiber array will sit atop of a high-velocity near-surface layer with thicknesses potentially ranging between a few tens of meters to
0.1-km. Second, this fast near-surface layer (where present) is expected to overlie the poorly consolidated KPF unit, which likely represents a significant velocity inversion. Third, the KPF unit is expected to overlie the better consolidated and likely seismically faster GF formation. Thus, we expect near-surface velocity profiles ($V_P$ or $V_S$) can be modeled as a three-layer system with an embedded low-velocity channel.

2.4 Data Acquisition and Preparation

Our low-frequency DAS experiment used a 15 km section of the dark-fiber array, with mapped locations and approximate distances indicated in Figure 2.1. The overall 80-km fiber loop originates and terminates at the University of Western Australia (UWA) campus, traverses both residential and commercial areas, and has sections oriented at a wide variety of angles to the predominantly N-S Indian Ocean coastline. The commodity single-mode telecommunications fiber used in this study is buried at 0.45-0.60 m depth in standard conduit adjacent to other utilities under the street verge. Due to optical losses in the fiber network arising from connectors and splices, DAS measurements beyond 15 km increasingly suffered from diminishing signal-to-noise ratios (S/N) and were discarded from further investigation.

The DAS interrogator used for the seismic acquisition was a circa-2017 instrument provided by Terra15 Technologies Pty Ltd of Perth, Australia. This phase-based system has a proprietary design capable of acquiring seismic data with the gauge length adjustable in post-processing and is optically designed to eliminate amplitude and polarization fading (Issa et al., 2018). Seismic traces were provided in arbitrary units proportional to particle velocity, and subsequently converted in post-processing to the equivalent of strain rate (i.e., the temporal derivative of strain) along the optical fiber. For the purpose of this study, we applied a 100 m gauge length (i.e., a virtual strain gauge) prior to performing interferometric analysis. Our rationale for this choice was to improve the signal-to-noise ratio (S/N) at sub-2 Hz frequencies by applying broader spatial stacking over the longer seismic wavelengths of the expected surface-wave energy. This gauge length is significantly longer than the 5-20 m gauge lengths typically used for active-source seismic acquisition and compared to the other published investigations discussed above. This approach allowed us to optimize the seismic acquisition bandwidth from 0.017 Hz (i.e., a 60 s period) to 20.0 Hz.

The DAS interrogator provided synchronous seismic traces at all virtual receiver locations (10 m spatial sampling), as well as the distance between each virtual receiver and the DAS interrogation point. To geolocate the virtual receivers, we used a fiber deployment map to assign rough coordinates, the locations of which were refined by acquiring check shots to help validate locations and check for excess spooled fiber. This allowed us to assign GPS coordinates to the fiber receiver points at the check-shot locations. We then interpolated the fiber receiver coordinates between the check-shot locations along the mapped fiber path. Thus, there is a moderate degree of uncertainty in the assigned fiber geolocations between the known control
Figure 2.1 (a) Perth Western Suburbs field site with the optical fiber array colored in dark blue. The location of the DAS interrogation point on the UWA campus is indicated by the red square. The purple star denotes the neighboring well location (AM79), while the triangles and the light purple rectangle respectively show the locations of the virtual shot locations and the straight fiber section of $L = 3.6$ km length discussed below. The north-pointing arrow indicates the approximate location of a second deep borehole (AM78).

Inset: Location of Perth, Australia. The lithology of the (b) AM79 and (c) AM78 boreholes Davey (2018). QA: Quaternary Alluvium, TL: Tamala Limestone, KPF: Kings Park Formation, YF: Yarragadee Formation, and GF: Gage Formation.

2.4.1 Dataset Characteristics

Given the proximity of the dark-fiber array to the Indian Ocean, an obvious energy source to exploit is microseism waveforms that arise from the interaction of ocean gravity waves with the seafloor from the rising continental shelf to the coastline itself. While ocean waves are now frequently observed to generate ambient Rayleigh wavefield energy (Landès et al., 2010), this activity is known to intensify during and immediately after storms and generate significant measurable low-frequency wavefield energy in the sub-2 Hz frequency band.

Data acquisition for the present experiment occurred during such an evening winter storm, throughout which Terra15 personnel deployed the DAS interrogator to measure the associated ambient energy. They acquired data in 60 s windows every 10 minutes between 7.30 pm-1.00 am. The interaction between the storm approaching from an approximately westerly direction (i.e., $270^\circ$) with the roughly N-S oriented Perth continental shelf and shoreline arguably generated a quasi-planar line sources that may have included a
superposition of wave modes (i.e., Rayleigh, Love, P, SV and SH waves) that propagated roughly in an easterly direction \((\phi = 90^\circ)\).

### 2.4.2 Interferometric Analysis

Shragge et al. (2021) discusses our preferred approaches to denoising and interferometry (e.g., cross correlation and cross coherence) with representative examples presented therein. For illustration purposes, Figure 2.2(a) and Figure 2.2(b), respectively present the results of performing the cross-correlation and the cross-coherence interferometric analysis to the same 60-s ambient record. The interferometric analysis presented in Shragge et al. (2021) raises three observational questions: (1) what is the underlying cause of the observed amplitude variations in the coherent arrivals?; (2) what wave type(s) are being coherently stacked by the DAS interrogator and highlighted by interferometric analysis? (3) How have our observational parameter selections influenced these results? We examine these questions in the sections that follow.

![Image of cross-correlation and cross-coherence interferograms](image.png)

Figure 2.2 (a) Cross-correlation VSG at 2.4 km for a 60 s record that recovers a strong event with fairly linear though arguably dispersive moveout behaviour. (b) Cross-coherence VSG at the same location as (a). The imaged event appears somewhat more broadband and has fewer vertical streaks than in (a), though with a decreased S/N level.

### 2.5 Sensitivity Analysis

Our preferred approach to addressing these three questions is to perform a theoretical sensitivity analysis that combines information about the fiber acquisition geometry with other contributing experimental factors. In recent years, much research has examined the sensitivity of DAS interrogation of optical fiber to transient body- (P, SV, and SH) and surface-wave (Rayleigh, Love) disturbances (Hartog, 2018; Luo et al., 2020; Martin et al., 2018). Herein, we apply the theory developed in Martin et al. (2018), who present theoretical expressions for planar ambient body and surface waves incident upon a DAS fiber array. Readers interested in detailed derivations are referred to this work.
Martin et al. (2018) identify nine independent parameters that control the measured amplitude response in an ambient DAS experiment (excluding the true amplitude of the physical wavefield). Figure 2.3 illustrates these for a crooked-line fiber deployment assuming an incident plane wave characterized by the propagation azimuth $\phi_1$ and (for body waves) the vertical incidence angle in the propagation plane $\phi_2$.

Assuming a homogeneous velocity model $c$ (which could be for a P, S, or surface wave) and frequency $f$ effectively defines the wave-vector magnitude $k$. For the interferometric analysis, the incident plane-wave source is measured on deployed fiber sections of gauge length $g$ that are centered at points $x_A$ and $x_B$ and oriented at angles $\theta_A$ and $\theta_B$ (herein relative to north at 0°), respectively. Of these parameters, four are defined by the geometry of the deployed fiber array ($x_A$, $x_B$, $\theta_A$, $\theta_B$), one is fixed by the subsurface geology on which the fiber array is deployed (propagation velocity $c$), one is controlled by a DAS interrogator hardware or software parameter choice (gauge length $g$), and one is based on the selected frequency of observation $f$. However, in ambient DAS investigations observers are unable to explicitly control for the two plane-wave propagation angles ($\phi_1$ and $\phi_2$) or the wave-energy type(s) arriving at the array.

Given this experimental setup and assuming that we are measuring strain rate for a given gauge length, Martin et al. (2018) derive the following amplitude sensitivity patterns:

\[
S_R = \frac{4c^2k^2}{g^2}C_{(\phi_1-\theta_A)}C_{(\phi_1-\theta_B)} \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_A)} \right) \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_B)} \right),
\]

\[
S_L = \frac{4c^2k^2}{g^2}S_{(\phi_1-\theta_A)}S_{(\phi_1-\theta_B)} \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_A)} \right) \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_B)} \right),
\]

\[
S_P = \frac{4c^2k^2}{g^2}C_{(\phi_1-\theta_A)}C_{(\phi_1-\theta_B)}C_{\phi_2}^2 \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_A)}C_{\phi_2} \right) \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_B)}C_{\phi_2} \right),
\]

\[
S_V = \frac{4c^2k^2}{g^2}C_{(\phi_1-\theta_A)}C_{(\phi_1-\theta_B)}S_{\phi_2}^2 \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_A)}C_{\phi_2} \right) \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_B)}C_{\phi_2} \right),
\]

\[
S_H = \frac{4c^2k^2}{g^2}S_{(\phi_1-\theta_A)}S_{(\phi_1-\theta_B)} \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_A)}C_{\phi_2} \right) \sin \left( \frac{kg}{2}C_{(\phi_1-\theta_B)}C_{\phi_2} \right),
\]

where $S_i$, $i = R, L, P, H, V$, represent Rayleigh, Love, P, SV and SH waves, respectively, and $C_\gamma \equiv \cos(\gamma)$ and $S_\gamma \equiv \sin(\gamma)$. We use these theoretical expressions to explore how sensitivity variations caused by spatially varying parameters can explain some of the amplitude complexity observed in the VSG data presented above.
Figure 2.3 Schematic drawing showing (a) the horizontal azimuth of planar-source arrival $\phi_1$ in map view, (b) the (body-wave) arrival orientation in the vertical plane $\phi_2$, and (c) fiber orientations $\theta_A$, $\theta_B$ and $\theta_B'$ in terms of virtual source location at $x_A$ and virtual receivers locations at $x_B$ and $x_B'$.

2.5.1 PWS Fiber Array Sensitivity

To satisfy the underlying assumptions of Martin *et al.* (2018) and enable the calculation of sensitivity curves we assume that: (1) the microseism energy recorded on the PWS array predominantly originates at locations between the Western Australian continental shelf break and the coastline (see Figure 2.1); (2) the resulting ambient wavefield energy may be well approximated by an eastward-propagating ($\phi_1 = 270^\circ$) energy line source; and (3) fiber sections are approximately linear about the center point of calculation within a length scale corresponding to the chosen gauge length ($g = 100$ m). These assumptions allow us to calculate approximate fiber array sensitivity curves on the PWS fiber array.

Figure 2.4(a) presents the approximate sensitivity curves for three VSGs locations along the fiber array. To partially account for the influence of the gauge length, we convolve the theoretical results with a 100-m box-car filter. The red curve shows the sensitivity for a VSG located at $x_A = 2.4$ km where the fiber is deployed at approximately $\theta_A = 270^\circ$. Because this fiber orientation effectively parallels the (assumed) source propagation direction, we observe that a VSG measured at $x_A = 2.4$ km would have a high sensitivity
to Rayleigh-wave energy for much of the array including between $x_B = 2.4 - 6.1$ km and $x_B = 7.2 - 8.3$ km, but would experience reduced sensitivity beyond $x_B = 11.0$ km. This is broadly consistent with the amplitude variations observed in interferometric analysis, after accounting for minor lateral discrepancies likely caused by fiber geolocation errors. Due to the orientations of the deployed fiber at $x_A = 8.2$ km or $x_A = 12.0$ km, respectively at $\theta_B = 200^\circ$ and $\theta_B = 169^\circ$, we expect that the measured VSG would be significantly less sensitive to eastward-propagating Rayleigh-wave energy.

To further illustrate the spatially varying sensitivity, Figure 2.4(b) presents a measure of the root-mean-square (RMS) energy (i.e., stack over correlation lag) for the three corresponding sensitivity plots presented in Figure 2.4(a). For the VSG computed at $x_A = 2.4$ km (red curve), we observe the greatest amplitude at the autocorrelation location, which then falls off slowly to the right until about $x_B = 6.2$ km and much more rapidly to the left between $x_B = 0.0 - 2.0$ km. These amplitude observations are broadly consistent with the theoretical sensitivity curves (red curve) in the Figure 2.4(a). We also observe that the blue and green curves (for $X_B = 8.2$ km and $x_B = 12.0$ km, respectively) have reduced wavefield energy approximately in proportion to the decreased sensitivity levels noted in Figure 2.4(a).
Figure 2.4 (a) Approximate sensitivity of ambient planar Rayleigh wave as measured on the PWS DAS array at $x_A = 2.4$ km (red curve), $x_A = 8.2$ km (blue curve), and $x_A = 12.0$ km (green curve). The vertical colored dotted lines indicate the VSG locations. The globally normalized values were calculated assuming an incident planar Rayleigh-wave azimuth of $\phi_1 = 270^\circ$, a gauge length of $g = 0.1$ km, a frequency of $f = 0.5$ Hz, and a surface-wave velocity of $c = 1.5$ km/s. We convolved each curve with a 100 m box-car filter equal to the gauge length to partially account for the path-averaging effects. (b) Cumulative RMS energy of crosscorrelation results stacked over the correlation-lag axis along the fiber array for the three VSG locations presented in (a).

To further visualize the sensitivity variations from a geographical viewpoint, Figure 2.5a and Figure 2.5b presents the sensitivity curves computed for the scenario discussed above for VSG located at $x_A = 2.4$ km and $x_A = 8.0$ km. For both scenarios, we observe that the locations of strong sensitivity correspond with sections predominantly oriented in the E-W direction; however, the sensitivity is reduced for sections oriented N-S.
Figure 2.5 Map view of theoretical sensitivity of VSGs located at (a) 2.4 km and (b) 8.0 km (indicated by red circles) along the PWS fiber array. Values were calculated assuming an incident planar Rayleigh wave from azimuth $\phi_1 = 270^\circ$, a gauge length of $g = 0.1$ km, a frequency of $f = 0.5$ Hz, and a surface-wave velocity of $c = 1.5$ km/s.
2.5.2 Additional Factors Affecting Sensitivity

Equations 2.1-2.5 indicate that a number of key factors other than fiber orientation will also contribute to DAS array sensitivity: surface-wave type (Rayleigh or Love), gauge length \((g)\), frequency of observation \((f)\), and the surface-wave velocity \((c)\). Figure 2.6 presents examples of varying individual parameters while holding the remaining ones constant. Unless otherwise specified, these examples assume a frequency of \(f = 0.5\) Hz, a gauge length of \(g = 0.1\) km, and a surface-wave velocity of \(c = 1.5\) km/s.
Figure 2.6a-Figure 2.6c illustrates the effects of orientation for cross-correlation of ambient planar Rayleigh (R) and Love (L) waves for three different fiber segment orientations. Figure 2.6a shows the case
where the virtual source and receiver array segments are parallel (i.e., $\theta_1 = \theta_2 = 90^\circ$). We observe that the maximum ambient Rayleigh wave energy is expected to be four times larger than that of the Love wave. More important, though, is that plane waves arriving at an azimuths of $90^\circ$ or $270^\circ$ will be recorded at a maximum in the Rayleigh wave sensitivity pattern and a null in the corresponding Love-wave pattern. Figure 2.6b shows the scenario where the two fiber sections used in interferometric analysis are now oriented at $45^\circ$ to each other. Again, the Rayleigh-wave sensitivity dominates, though there may be a minor Love-wave contribution at this orientation. Finally, Figure 2.6c shows the scenario where the two fiber segments are orthogonal. In this case, the maximum Rayleigh wave sensitivity is still slightly higher than the Love wave; however, at the $\phi_1 = 270^\circ$ azimuth one expects equal contributions of the two wave modes. Thus, given these sensitivity curves, the majority of the recorded surface-wave energy is likely to be from the Rayleigh wave mode.

Figure 2.6d-Figure 2.6f present the effect of gauge length $g$ on the resulting theoretical sensitivity. Figure 2.6d and Figure 2.6e present the theoretical sensitivity for $g = 20$ m and $g = 500$ m gauge length choices. These figures show that this parameter has no real influence when the gauge length is 5x larger or smaller than the $g = 100$ m value employed during data acquisition. Figure 2.6f shows the sensitivity results for $g = 4000$ m, which now exhibits roughly half the theoretical sensitivity as the two corresponding plots. It is important to note, though, that these observations are frequency-dependent (see below), and that the choice of $g$ will also affect signal-to-noise (S/N) levels as well as lateral resolution. We stress that these effects are not considered by the theoretical sensitivity model and that an optimal experimental $g$ should be chosen with careful consideration of a number of different factors - ideally after conducting noise tests or through a post-processing analysis (if possible).

Figure 2.6g through Figure 2.6i respectively show the theoretical $f^2$ sensitivity (see equations 2.1-2.5) to observation frequency for $f = 0.5$ Hz, $f = 0.75$ Hz and $f = 1.1$ Hz. There is a clear strong dependence in the range of observation. The increasing sensitivity at higher frequencies (greater than 1.0 Hz) is not apparent in the (normalized) cross-correlation (magenta line) and cross-coherence spectra shown in Figure 2.7, likely due to the decreasing magnitude of available microseism energy predicted from the Peterson noise model. The decreasing sensitivity at lower frequencies (sub-0.5 Hz) is likely responsible for the lack of signal noted in Figure 2.7, even though again one should expect stronger signals at these frequencies from the Peterson noise model.
Finally, Figure 2.6j-Figure 2.6l present the sensitivity dependence on the surface-wave velocity for $c = 1.2$ km/s, $c = 1.8$ km/s and $c = 2.1$ km/s, respectively. This plots suggests that array segments over slower areas (i.e., without a fast TL layer) should observe higher sensitivity that those with faster velocity (i.e., where the TL layer is present). Overall, the sensitivity analysis of this section suggests that many factors are controlling measured amplitudes that need to be taken into account before attempting imaging or inversion approaches that require “true amplitudes” (e.g., full-waveform inversion).

2.6 MASW of Low-frequency DAS Data

The ambient DAS experiment has recorded low-frequency surface-wave energy (i.e., 0.05-0.80 Hz) that should be useful for estimating the 1-D averaged $V_S$ structure of the subsurface. However, given the aforementioned challenges of estimating “true-amplitude” ambient waveforms through DAS acquisition, herein we restrict our surface-wave analysis to the now-standard 1-D MASW inversion approach (Park et al., 1999), which aims to estimate the model $V_S$ values and interface depths of a 1-D layered earth model.
Undertaking a MASW analysis is a three-step process: (1) computing frequency-velocity dispersion images; (2) picking the (legitimate) maximum points on the dispersion curve; and (3) using a numerical optimization approach to estimate the 1-D layered Earth model that best fits the picked dispersion curves. The MASW examples presented below use the cross-correlation interferometric results, which led to slightly higher signal-to-noise dispersion images than those from the cross-coherence processing.

### 2.6.1 Dispersion Curve Analysis

We apply two different approaches to generate frequency-velocity dispersion images from the VSG volumes: the lower-resolution classical phase-shift approach (Park et al., 1998) and high-resolution linear Radon transform (HRLRT) method (Luo et al., 2008). The phase-shift method uses a temporal Fourier transform to extract the phase of wavefield

\[ P(x, \omega) = Ae^{i \frac{\omega}{v} x + \varphi_0}, \quad (2.6) \]

where \( x \) is the receiver location, \( v \) is the phase velocity, and \( \varphi_0 \) is the initial phase. The dispersion image is calculated via

\[ U(\varphi, \omega) = \int_0^L e^{i \varphi x} P(x, \omega) \, dx \approx \sum_{m=1}^M A e^{i(\varphi - \frac{\omega}{v})x_m + \varphi_0}, \quad (2.7) \]

where \( L \) is the length of the receiver spread, \( M \) is the number of receivers, and \( x_m \) is the distance from the virtual shot location to the mth receiver. Note that the approximate stationary-phase summation reaches the maximum value when phase \( \varphi \) is close to \( \frac{\omega}{v} \).

The discretized linear Radon transform (LRT) can be written as

\[ d(x, f) = \sum_{i=1}^M m(p_i, f) e^{i2\pi f p_i x}, \quad (2.8) \]

where \( d(x, f) \) is a frequency-domain shot gather, and \( m(p, f) \) is the Radon matrix. Equation 2.8 may be written in matrix form as

\[ d = Lm, \quad (2.9) \]

where \( L = \exp (i2\pi f p x) \). Low-resolution solutions are obtained using the adjoint operator \( L^T \) via

\[ m_{\text{adj}} = L^T d. \]

The HRLRT generates high-resolution dispersion images by solving the following least-squares inverse problem:

\[ m = (L^T L)^{-1} L^T d = (L^T L)^{-1} m_{\text{adj}}. \quad (2.10) \]

A standard approach would be to solve equation 2.10 using a weighted preconditioned conjugate gradient (CG) approach, where the resolution of the HRLRT image depends on the number of iterations. Mikesell et
al. Mikesell et al. (2017) present an alternative approach to HRLRT by interpreting matrix $A = L^T L$ as a blurring operator, and then introducing non-negative least-squares (NNLS) constraints (Hansen, 2010) to obtain a deblurred high-resolution HRLRT dispersion image.

We apply the two dispersion image methods to the straight fiber section located between along fiber distances of 2.4 km and 6.0 km (see Figure 2.4(a)). Our rationale for choosing this $L = 3.6$ km section is that its geometry explicitly satisfies the linear sampling requirements of the MASW approach. Figure 2.8(a) shows the dispersion image calculated by the phase-shift method. The surface-wave trend is illustrated by the dark-red color between 0.5-1.0 Hz; however, given the overall spread of the dispersion image, there is significant ambiguity in where to pick the dispersion curve. This observation is due to the relatively short array length ($L = 3.6$ km) given the low frequency range of investigation ($f = 0.5 - 1.0$ Hz) and relatively fast surface-wave propagation velocities ($c \approx 1.5$ km/s).

![Figure 2.8 Dispersion images estimated using the (a) phase shift and (b) HRLRT with a non-negative least-squares (NNLS) deblurring approach. White dots shown on (b) represent picks of the fundamental Rayleigh wave mode.](image)

Figure 2.8(b) presents the HRLRT results using the NNLS constraints. The fundamental Rayleigh wave mode displays the greatest energy; higher modes exist in both images $>1$ Hz, but mode separation is clearer in the HRLRT dispersion image. Overall, this approach has compressed the thickness of the LRLRT dispersion panel in Figure 2.8(a) thereby facilitating the picking of dispersion curves (shown as the white dots in Figure 2.8(b)).

### 2.6.2 Optimization Approach

The main goal of applying a MASW inversion analysis is to determine the layered 1-D Earth model whose synthetic dispersion curve optimally matches that constructed from the observed data. However, to
undertake such an analysis we first need to specify a method of forward modeling synthetic dispersion curves from the 1-D earth models. Herein, we choose the delta-matrix method (Dunkin, 1965; Thrower, 1965), which requires specifying the number of layers, the upper and lower bounds of the layer thicknesses, as well as the $V_P$, $V_S$, and density fields. We follow the layering ratio scheme of Cox & Teague (2016) to define our initial layer parameters, and use the L$_2$-norm misfit between experimental and theoretical dispersion curves as our quality-of-fit metric.

To solve our inverse problem, we turn to global optimization methods that are commonly used to address the non-linearity challenges of 1-D surface-wave inversion (Beaty et al., 2002; Dal Moro et al., 2007; Shirazi et al., 2009). We select the particle swarm optimization (PSO) approach (Eberhart & Kennedy, 1995), which is an evolutionary algorithm (EA) with good convergence rates and straightforward parameter tuning (Luu et al., 2018). Based on the geological considerations discussed above, we assumed the system is controlled to leading order by three layers. Inversion tests conducted with a greater number of layers (not shown) suggested that the additional level of model complexity is not necessary for explaining the data observations.

2.6.3 MASW Inversion Results

The inversion methodology obtained 18,000 three-layer multiparameter elastic models (layer thickness, $V_P$, and $V_S$) for the $L = 3.6$ km straight fiber section discussed above. Figure 2.9a shows the layered models

![Figure 2.9](image)

Figure 2.9 (a) MASW inversion results for the straight $L = 3.6$ km section between 2.4 km and 6.0 km along-fiber distance. The solid blue line is the model with the lowest misfit, while the solid green lines are the ten best-fitting models. The dashed red lines indicate the upper and lower bound constraints on the $V_S$ model. (b) Gamma-ray from the AM79 well log. Lithology from the (c) AM79 and AM78 wells Davey (2018). QA: Quaternary Alluvium, TL: Tamala Limestone, KPF: Kings Park Formation, YF: Yarragadee Formation, and GF: Gage Formation.
where the solid blue line is the model with the lowest misfit, the solid green lines represent the top ten models, and the dashed red lines denote the enforced parameter bounds. The recovered model ensemble indicates suggests the best-fitting models are all characterized by faster first and third layers bracketing a slower second layer. We note that the trade-off between velocity and thickness of the first layer in the top ten models suggests a moderate degree in uncertainty in these two parameters; however, this should be expected given the challenges of the MASW approach in constraining velocity inversions given the limited information available above 1.0 Hz. In addition, there is surprisingly little spread in the $V_S$ of the second layer, and only a moderate degree of variation in the depth to, and $V_S$ values of, the third (half-space) layer.

Figure 2.9b shows the gamma-ray log for nearby well AM79, which allows us to check for rough correlations between borehole data and the MASW inversion results. The log data show two zones of significant change. The lower zone at 0.52 km depth appears to be accurately estimated at the depth of the half space in the MASW result, while the shallower zone at 0.1 km depth likely corresponds with the velocity inversion. However, it is judicious to recall that the MASW approach represents a 1-D average over the entire $L = 3.6$ km spread, the center of which is 2 km away from the AM79 bore, and thus correlations between the borehole and spread-averaged MASW results should be taken with due caution. Finally, Figure 2.9c shows the lithology data extracted from the well logging and core description report. We observe that the low velocity values in the second layer (interpreted to be the Kings Park Formation) are consistent with the poorly lithified silty sandstones discussed in Section 2.2 above. Overall, the lithology data suggest that the observed velocity inversion is real; however, the fairly low resolution of the MASW approach indicating that the estimated thicknesses and contact depths are somewhat uncertain.

### 2.6.4 Ministack Processing

While the results shown above are encouraging, restricting MASW analysis to DAS data recorded on straight fiber segments represents a suboptimal strategy. This is because the fiber deployment geometry sets a hard upper limit on the maximum array length available for analysis, which can cause significant spreading of dispersion curves, especially when examining low-frequency data such as those used in this experiment. Furthermore, using only straight fiber sections also restricts the spatial locations where one can perform a 1-D MASW analysis.

To address these issues, we suggest moving away from a distance defined along the fiber in favor of regridding data according to the Euclidean distance between the virtual source and receiver points $x_A$ and $x_B$. We note that this approach does not formally account for any subsurface lateral heterogeneity and fiber sensitivity variations; however, this approximation is entirely consistent with MASW being a 1-D analysis method. We apply this regularization operation using sinc-based interpolation to compute interpolated VSGs.
to 7.5 km maximum offset every 30 m along the fiber array.

Because of the spatially varying sensitivity discussed above, the individual interpolated VSGs will have fairly low S/N levels. Thus, to enhance the signal we form “ministack” VSGs by combining ten consecutive VSGs (i.e., over approximately 300 m of virtual shot locations) and averaging over positive and negative cross-correlation panel lags and offsets. Figure 2.10(a) presents the ministack VSG centered at $x_A = 2.7$ km along the fiber array. We observe that signal is weakly captured to approximately 6 km offset though with spatially varying amplitudes due to averaging along-fiber sensitivity variations. Figure 2.10(b) shows another ministack gather centered at $x_A = 8.0$ km along the fiber. The surface-wave arrival is again fairly well recovered to 3.5 km offset, though the S/N is lower at offsets beyond this location. A further interesting observation is that the second ministack VSG exhibits somewhat faster moveouts between 0-1 km offset, which suggests the presence of lateral heterogeneity between the two ministack observation center points.

Figure 2.10 Ministack VSGs (with averaged positive and negative lag contributions) centered at (a) 2.7 km and (b) 8.0 km along the fiber array. (c) Superstack VSG for the entire array. (d) Synthetic full-wavefield elastic modeling for the average of the ten best-fitting MASW inversion model for the superstack VSG shown in Note that we are now showing only positive absolute correlation lags rather than two-sided correlation lags shown in figures above.
Figure 2.11(a) and Figure 2.11(b) present the dispersion panels that correspond to the ministack VSGs presented in Figure 2.10(a) and Figure 2.10(b). A comparison between these two panels indicates that the former has a somewhat higher S/N ratio as well as a more tightly focused high-energy zone than the latter dispersion panel. Figure 2.12(a) and Figure 2.12(b) show the inversion results for the two ministack dispersion volumes presented in Figure 2.11(a) and Figure 2.11(b). Applying MASW to the first minigather with a higher S/N has recovered a 1-D model that similarly exhibits the low-velocity structure observed in Figure 2.9; however, the depths of the two top-fitting layer estimates are shallower. The spatial variability of the second MASW result (Figure 2.11(b)) suggests that the data quality probably does not support undertaking 1-D MASW analysis on this ministack gather.

![Dispersion panels for two mini-stack VSG centered at (a) 2.7 km and (b) 8.0 km, for (c) the superstack VSG, and for (d) the synthetic VSG from the average of the ten best-fitting 1-D models shown in Figure 2.12(c).]
2.6.5 Superstack Processing

Taking the ministack VSG approach to the extremum, a global analysis strategy would be to use a “superstack VSG” that involves stacking all of the regularized VSGs over the selected fiber length. This superstack strategy effectively provides a global VSG response averaged over the full array. Figure 2.10(c) presents the superstack VSG result for the array using regularized data between 2.4 km and 12.0 km along the fiber array. Clearly, stacking over the entire array has lead to a higher S/N result with clear surface-wave arrivals to roughly 6.0 km offset.

Figure 2.11(c) presents the dispersion curve corresponding to the superstack section presented in Figure 2.10(c). The S/N of the dispersion panel is evidently higher than the first ministack dispersion curve shown in Figure 2.11(a). The superstack inversion result from the matching dispersion panel (Figure 2.11(c))
shows a similar trend of the MASW result of the straight fiber section (Figure 2.9) and first minigather (Figure 2.12(a)). The ten best-fitting models now exhibit a tighter spread, though with fairly consistent layer depths and $V_S$ velocity values.

### 2.6.6 Validation of 1-D Inversion Results from Elastic Forward Modeling

To evaluate the accuracy of the 1-D $V_S$ model, we conduct a full-wavefield elastic forward modeling exercise to see how well the results match the character of the observed signal in the superstack VSG. We created a three-layer model using the average of the top ten models from the superstack MASW inversion result (Figure 2.12(c)). To perform the modeling we first extract a source wavelet from the autocorrelation of the superstack gather, which effectively represents the wavelet squared. We then apply Kolmogoroff spectral factorization (Claerbout & Fomel, 2008) to extract a minimum-phase wavelet $s(t)$. The extracted wavelet has the property that the spectrum of its autocorrelation (i.e., $\mathcal{F}[s(t) \ast s(t)]$) will match the observed autocorrelation spectrum of the supergather (i.e., $U(x_A, x_B = x_A, \omega)$). We then inject this wavelet and propagate wavefield energy in a GPU-based 2-D elastic finite-difference code (Weiss & Shragge, 2013) that uses perfectly matched layer (PML) and free-surface boundary conditions. Finally, we extract synthetic waveforms up to 7.5 km offset at a 5 m spacing. Because the resulting synthetic data have the source spectrum as opposed to the source spectrum squared of the ambient VSGs, we correlate the elastic modeling output with the minimum-phase source wavelet used to forward model the data.

Figure 2.10(d) presents the processed forward-modeled waveforms. Overall, the character of the modeled waveforms represents a fair approximation of superstack gather (Figure 2.10(c)). The associated dispersion panel, shown in Figure 2.11(d), clearly shows greater energy in higher frequency (> 1 Hz) than noted in the ministack and superstack dispersion panels. However, to be consistent with field tests, we only produce picks of the synthetic dispersion curve between 0.5 Hz to 1.0 Hz.

Figure 2.12(d) presents the corresponding MASW inversion result for the synthetic experiment. We note that the results converges to similar $V_S$ values of the superstack inversion result. However, the thicknesses of the first and second layers are overestimated compared to the superstack models, which results in a downward shift of the two upper layers. Ideally, we would expect better resolved synthetic inversion results if we were to use a broader range of frequency picks. However, as Pan et al. (2013) show, perfectly recovering the model is still challenging in velocity inversions because the high-frequency components of the dispersion curve cannot be accurately fit using conventional algorithms (Pan et al., 2013). Moreover, Forbriger et al. (2020) shows Rayleigh waves can have multivalued dispersion curves for the single fundamental mode. Both of these theoretical studies suggests that slant-stack methods (including MASW) are to some degree sensitive to velocity inversions, one should treat the results with a certain degree of caution. Thus, it is quite likely that
the velocity inversion and low-velocity zone observed in the field data DAS MASW inversions are real, but the estimated depths, thickness and $V_S$ values of the second layer should be treated with a reasonable amount of uncertainty. This is particularly reflected in the synthetic results, which clearly demonstrate the challenges associated with recovering the target superstack average model using the 1-D MASW inversion approach.

2.7 Discussion

Based on our experience in the PWS DAS experiment, we think it is important to discuss potential issues with amplitude fidelity of ambient DAS data acquired on dark-fiber crooked-line arrays. As shown in Sections 2.5.1 and 2.5.2, the sensitivity of a DAS optical fiber array and associated measured amplitudes can vary significantly depending on the orientation of the fiber, the selected gauge length, the source wavelet frequency, and velocity of the medium. In addition, we have tacitly assumed perfect coupling between the soil, the conduit and the fiber, deviations from which can lead to further potential amplitude variations. Thus, considering that multiple factors could easily modify the resulting amplitudes of recorded DAS data, we emphasize that this can lead to drawbacks when researchers attempt to apply inversion methods that are moderately to strongly dependent on measuring “true” amplitudes.

One example of where there may be a drawback is in the ministack and superstack MASW analyses presented above. While spatial interpolation and averaging along absolute offset described above is a pragmatic way to account for along-fiber variations for crooked fiber deployments, when the resulting data are used in a 1D MASW analysis this approach potentially can lead to unwanted amplitude effects from effectively averaging lateral variations due to the underlying 2D or 3D velocity structure and/or along fiber sensitivity variations. Thus, we recommend that one should use this approach with caution, potentially even modeling the response of the crooked acquisition geometry to various wave types and azimuths for a 3D elastic model of the study area.

A second example of an amplitude-matching inversion scheme that would be challenging to apply is data-difference full-waveform inversion (FWI). Undertaking such an approach without first developing an comprehensive physics-based amplitude compensation for all of these identified factors (and likely others not identified herein) is not recommended. Because true-amplitude fidelity of ambient DAS data is hard to achieve, we suggest employing alternative tomographic approaches or analysis methods that are more heavily based on phase- rather than amplitude-matching criteria.

2.8 Conclusions

We present a case study to show that DAS acquisition on a dark fiber array is capable of acquiring useful low-frequency ($< 1.0$ Hz) ambient Rayleigh-wave signal. We process ambient events using cross-correlation
and cross-coherence interferometric methods to generate virtual shot gathers (VSGs) along the fiber. The VSGs exhibit spatially varying sensitivity due to a number of factors (i.e., incoming wave type and orientation, fiber orientation, observation frequency, gauge length, and near-surface velocity), which is broadly consistent with established theory. We transform the low-frequency DAS data to dispersion panels, pick the resulting 1-D curves, and input the data to a 1-D MASW inversion approach to obtain subsurface 1-D $V_S$ models. The real and synthetic results show that such signals are useful for constraining deeper subsurface $V_S$ structure to depth up to (and potentially exceeding) 0.5 km. While this might motivate some researchers to attempt applying full-waveform inversion to dark fiber DAS datasets, our experience suggests that the multiple factors affecting array sensitivity and measured DAS amplitudes will pose significant challenges to methods requiring high-amplitude fidelity of the observed data in any amplitude-matching inversion schemes. Thus, we recommend alternative full-wavefield inversion approaches that are based more on phase-matching criteria.

2.9 Acknowledgements

We thank the Geological Survey of Western Australia (GSWA) for their financial support of this project. We acknowledge the support of Center for Wave Phenomena consortium sponsors, as well as Australia’s Academic and Research Network (AAR-Net) for the provision of light-level access to their fiber network infrastructure. We thank Dylan Mikesell for providing the HRLRT code.
3.1 Abstract

Deformation-rate distributed acoustic sensing (DAS), made available by the unique designs of certain interrogator units, acquires seismic data that are theoretically equivalent to the along-fiber particle velocity motion recorded by geophones for scenarios involving elastic ground-fiber coupling. While near-elastic coupling can be achieved in cemented downhole installations, it is less obvious how to do so in lower-cost horizontal deployments. This investigation addresses this challenge by installing and freezing fiber in shallow backfilled trenches (to 0.1 m depth) to achieve improved coupling. This acquisition allows for a reinterpretation of processed deformation-rate DAS waveforms as a “filtered particle velocity” rather than the conventional strain-rate quantity. We present 1D and 2D filtering experiments that suggest 2D velocity-dip filtering can recover improved DAS data panels that exhibit clear surface and refracted arrivals. Data acquired on DAS fibers deployed in backfilled, frozen trenches were more repeatable over a day of acquisition compared to those acquired on a surface-deployed DAS fiber, which exhibited more significant amplitude variations and lower signal-to-noise ratios. These observations suggest that deploying fiber in backfilled, frozen trenches can help limit the impact of environmental factors that would adversely affect interpretations of time-lapse DAS observations.

3.2 Introduction

Distributed acoustic sensing (DAS) in permanent monitoring installations is increasingly being used for seismic investigations (Mateeva et al., 2017; Pevzner et al., 2020; Titov et al., 2021; Wang et al., 2020; Zhu et al., 2021). Permanent downhole fiber installations often achieve near-perfect elastic coupling with the surrounding earth (e.g., by cementing a fiber to the outside of casing), which enables some interrogator units (IUs) to acquire seismic data of a quality approaching the response of single-component geophones (Hubbard et al., 2022; Wang et al., 2018). However, for lower-cost surface fiber deployments (e.g., fiber directly laid on the ground, passed through buried conduits, or placed in shallow trenches), it is less obvious how to effectively achieve elastic ground-fiber coupling and thereby avoid the associated loss in data quality.
related important question is how significant the deleterious effects of imperfect coupling are on DAS recordings for scenarios involving spatial and/or temporal variations in the ground-fiber coupling.

Despite the complexities involved in near-surface horizontal fiber installations many successful DAS research examples using such deployments have emerged in the literature. For terrestrial deployments, Becker & Coleman (2019) present a laboratory experiment that demonstrates the possibility of DAS-based earth-tide observations. Fernández-Ruiz et al. (2020) show the promising performance of low-frequency (<1 Hz) DAS recording when compared to high-quality broadband seismometers. Spica et al. (2020) use the ambient recording from horizontal DAS array deployed on Stanford University campus to calculate the horizontal over vertical (H/V) spectral ratio and compute interpretable near-surface imaging results. Yuan et al. (2020) investigate Rayleigh waves excited by passing cars recorded on a roadside section of Stanford DAS-2 array and construct a pseudo-2D shear-wave velocity profile by integrating 1D inversions. Fang et al. (2020) demonstrate the feasibility of using an existing horizontal DAS array for near-surface velocity monitoring by measuring strong time-lapse variations. Lindsey et al. (2020b) analyze and calibrate the sub-1 Hz DAS instrument response using co-located broadband seismometer records as the reference of true ground motion. Shragge et al. (2021) present the results from a low-frequency DAS experiment that uses surface waves to constrain shear-wave velocity profile to 0.5 km depth.

There is also a growing number of examples that use optical fiber deployed in marine seafloor environments. For example, Williams et al. (2019) and Sladen et al. (2019) successfully record ocean microseism energy and detect regional earthquakes using ocean-bottom fiber arrays with onshore DAS IUs. Lindsey et al. (2019) present observations from four days of recording on an ocean-bottom “dark-fiber” array and detect various signals such as minor earthquakes, primary and secondary microseisms, and sediment transport due to storm action. Jousset et al. (2018) demonstrate the application of 15 km of dark telecommunication fiber deployed on the Reykjaness Peninsula, Southwest Iceland to record and process high-resolution seismic waveforms that show features such as normal faulting and volcanic dykes with unprecedented resolution. Cheng et al. (2021) construct a near-seafloor velocity model and develop improved constraints on shallow submarine faults by inverting multimodal dispersion curves obtained from ambient DAS records acquired on 20 km of ocean-bottom cable. Ide et al. (2021) observe many earthquakes using a submarine cable located near the Nankai subduction zone. Finally, Lindsey & Martin (2020) provide a review of the increasing number of long-term monitoring experiments conducted in US national labs and universities.

An interesting observation is that non-elastic coupling is not commonly discussed in the aforementioned DAS literature. We postulate this is because most IU designs either natively acquire DAS data in strain or strain-rate format that necessitates assuming a gauge length (GL) defined in hardware or applying a GL post-acquisition through digital processing to generate interpretable waveforms. Because applying a GL
generally involves introducing a 1D spatial filter, this can adversely affect the wavenumber spectra of DAS records by introducing spectral notches (i.e., zeros) as well as variable spectral weighting factors (Dean et al., 2017). While there are digital signal processing approaches that could be used to mitigate these effects, they are also susceptible to boosting unwanted signal or noise when aiming to recover "lost" or down-weighted spectral information.

This work presented here similarly examines DAS data acquired on a near-surface horizontal fiber array; however, we use a Terra15 Treble DAS IU with a novel optical measurement design that measures a “deformation-rate” quantity (Issa et al., 2018). Under ideal elastic fiber-ground coupling conditions, this deformation-rate measurement acquires data that are theoretically equivalent to the single component of the ground particle-velocity vector recorded on a fiber segment oriented in the fiber axis direction. This proprietary IU design leads to a particle-velocity-equivalent quantity $\tilde{v}(x,t)$ that effectively represents the integral of the strain rate $\dot{\varepsilon}$ from the interrogation point (at $u = 0$) to point $u = x$ on the fiber:

$$\tilde{v}(x,t) = \int_0^x \dot{\varepsilon}(u,t) \, du,$$  \hspace{1cm} (3.1)

where $t$ is time, $u$ is an auxiliary spatial integration variable, and the tilde symbol on $\tilde{v}$ emphasizes that the measured quantity is only equivalent to the true particle velocity of ground motion when the elastic fiber-ground coupling conditions are satisfied.

To demonstrate this near equivalence, Sidenko et al. (2020) acquire DAS data on a Treble IU in deformation-rate format on a completed downhole fiber installation to show the near identicalness to the ground motion recorded on a co-located borehole geophone array. Their observations indicate that when combined with a deployed fiber elastically coupled to the borehole casing, Treble IU acquisition can achieve a geophone-like $\cos \theta$ sensitivity pattern where $\theta$ is the incidence angle (Benioff, 1935) compared to the conventional $\cos^2 \theta$ relationship of strain-rate DAS measurements (Kuvshinov, 2016). Consequently, the strain-rate DAS measurement suppresses waves arriving at greater incident angles, resulting, e.g., in limited sensitivity to far-offset P-wave arrivals in vertical seismic profiling (VSP) experiments. This leads to a decreased usable angular bandwidth (i.e., $\cos^2 60^\circ = 0.25 \) (Mateeva et al., 2021). Comparatively, the deformation-rate format allows a broader usable angular bandwidth (i.e., $\cos 60^\circ = 0.5$). Importantly, Sidenko et al. (2020) demonstrated that this improved angular bandwidth can be achieved without post-processing spatial-derivative filtering for to recover high-quality particle-velocity-equivalent DAS signals in the deformation-rate format, which forestalled introducing the associated adverse filtering effects (e.g., spectral notches) commonly present in DAS strain-rate observations.

Motivated by these observations, this study investigates whether the advantages of the Treble IU in the native deformation-rate (i.e., particle-velocity equivalent) acquisition format highlighted by improved angular
bandwidth can be realized for surficial as opposed to downhole fiber installations, and whether different 1D and 2D filtering operations can be applied to data acquired in this format to improve the signal-to-noise ratio. Our initial deployment experiments involving imperfect elastic fiber-ground coupling scenarios (e.g., draped on the surface, deployment in conduits) acquired DAS data which exhibited low-wavenumber noise that accumulated along the length of the fiber. Unfortunately, this noise needed to be handled through post-acquisition spatial filtering operations (e.g., applying a first-derivative filter with an assumed GL) and thus offered no improvement over standard strain-rate acquisition. These initial experiments underscored the importance of elastic fiber-ground coupling when using the Treble IU for the purpose of deformation-rate DAS data acquisition.

Aiming to achieve a horizontal DAS deployment scenario that approaches near-elastic coupling, we report the findings from an experiment that used an alternate approach to establishing coupling - freezing the fiber to the ground. We describe a small-scale investigation where we deployed three parallel fiber segments of 120 m total length in a shallow trench in the frozen earth that was watered down and left to freeze in the ground overnight. Over the following day, we acquired repeat sledgehammer shots as the outside air temperature reached 6.5°C mid-afternoon and then fell to -6.5°C by mid-evening. In addition to a fiber-soil coupling improvement, we expect the trenched-in fiber to be better insulated from the air temperature fluctuations than the surface-deployed fiber section.

We begin by providing additional detail about the interrogator design and by describing the data acquisition, including the experimental setup to enhance the fiber-ground coupling and the presentation of raw data results. Due to unwanted residual signals in the data set, we then discuss the 1D and 2D filtering strategies used to improve the signal-to-noise levels of the filtered DAS data panels. We then show the processed DAS data that verifies the efficacy of the proposed filtering method and compare the shot gather with the data recorded from the conventional vertical-component geophones. A brief discussion section examines the amplitude fluctuations noted in the surface-deployed fiber and cautions for DAS data interpretation when acquiring data over calendar time. The last section summarizes the effects of enhanced coupling on the frozen trench and filter designs on particle-velocity DAS recording.

3.3 DAS Data Acquisition

To investigate the role that frozen ground can play in the ground-fiber coupling, we selected suitable test dates (15-16 February 2021) when the weather forecast for the investigated location (Arvada, CO, USA) predicted that the air temperature would remain well below freezing on the first day, rise above 0°C by mid-morning on the second day, reach 6°C by mid-afternoon, and then return below 0°C by the early evening. Our deployment involved in-ground trenching of 120 m of military-grade single-mode fiber, tactical
tight-buffered cable with aramid strength members, and a polyurethane jacket. We first trenched a 35 m section of fiber into the ground at approximately 10 cm depth (Section A), covered it with soil, compacted the soil by hand with a tamper tool, and then thoroughly watered it down. We then looped the fiber back along the same trench at approximately 5 cm depth (Section B), again covering the fiber, compacting the soil, and watering it down. Finally, we deployed the remaining fiber directly on the surface (Section C). The three sections allowed us to examine coupling effects at different depths with likely variable sensitivity to air-temperature fluctuations.

Figure 3.1a and Figure 3.1b respectively show the overall fiber deployment geometry in both plan and cross-sectional view with the following points: (1) the interrogator is housed in a garage at point ⁰ at 0 m distance; (2) the source point is located ¹ at 20 m; (3) Section A runs between 20-55 m up to the turnaround point at ²; (4) Section B runs between 55-90 m back to the turnaround point at ³; and (5) Section C runs between 90-120 m up to the end of the fiber at ⁴. Figure 3.2 depicts the installed fiber a few minutes after watering down the section. For comparison purposes, we installed vertical component geophones 0.3 m from the fiber for as a baseline for comparison. (Unfortunately, horizontal geophones that would have offered a better comparison were not available at the time of the experiment.)

Figure 3.1 Schematic drawing of DAS acquisition geometry in plan (a) and cross-sectional (b) view. Sections A and B correspond to the trenched fiber locations at approximately 10 cm and 5 cm depth, respectively (see lower panel). The fiber in Section C is laid on top of the ground. In this layout, sections A-C respectively are between 20-55 m, 55-90 m and 90-120 m in the along-fiber distance. The orange star indicates the source point at 20 m.
The DAS IU used for the seismic acquisition was a circa mid-2020 Treble IU developed by Terra15 Technologies Pty Ltd of Perth, Australia. The phase-based system has a proprietary optical design constructed to eliminate amplitude and polarization fading (Issa et al., 2018). The Treble IU can acquire DAS seismic data either in native deformation- or strain-rate format with the gauge length (GL) modifiable through post-processing. The IU measurement type and properties depend on the choice of interference pair of optical signals. The Treble IU generates two pulses at a fixed time interval, and then correlates the returned time-delayed first pulse and optically delayed second pulse to natively measure a deformation-rate rather than a more typical strain-rate quantity. For more details on the optical process, we refer readers to the patent document of Issa et al. (2018).

We acquired roughly 3.0 Tb of DAS data in continuous mode over the two-day experiment in the deformation-rate format at 0.038 ms and 0.8 m temporal and spatial sampling intervals, respectively. To test the temporal variability of ground-fiber coupling, we used a sledgehammer and metal plate as an energy source and generated shots at approximately 30-minute intervals for 12 hours from 9:00am to 9:00pm. Because of the fiber deployment pattern (see Figure 3.1a), the shot point was observed simultaneously at
three effective shot locations on Sections A-C: 20 m, 90 m (back up the fiber), and 90 m (again down the fiber) from the IU, respectively.

The first processing step involved window selection where we used the noted shot times to extract 60.0 s data streams of approximately 1.0 Gb size. Because the frequencies of interest from the sledgehammer shots were lower than 150 Hz, we low-passed filtered the extracted sections with a 150 Hz cutoff and subsampled the extracted shot windows to a more manageable data volume. We then corrected the polarity of the data acquired on Section B to compensate for the reversed fiber direction with respect to the shot location.

Figure 3.3a presents a shot gather recorded at 9:00pm in the deformation-rate data acquisition format of the Treble IU. Surface-wave arrivals are clearly identifiable in all three fiber sections. Although high-amplitude horizontal arrivals are observed in the raw data, the corresponding moveouts are too fast to be a passing seismic wave disturbance. However, these arrivals are repeatable and thus represent coherent “unwanted signals” that should be removed through signal processing. Figure 3.3b corresponds to a frequency-wavenumber \((f - k)\) spectra of the shot gather from Figure 3.3a. The identified coherent noise source maps to the strong low-wavenumber components observed as two lobes with between 20-60 Hz as well as the vertical “washboard” pattern corresponding to the quasi-horizontal signals in the time-space \((t - x)\) panel in Figure 3.3a.

We observe that the distortion-rate recording from section A enclosed in frozen soil captures traveling surface waves well throughout the day, which is consistent with our expectations of improved fiber-soil coupling. Despite the clear arrivals presented in the distortion-rate data panel, low-wavenumber noise persists that reduces the quality of the data and ensuing processing results. Herein, we suggest that one can apply low-cut filtering such as a 1D gradient operator to eliminate low-wavenumber noise persisting in the deformation-rate data. Thus, we next examine the efficacy of several 1D and 2D filter operators to find a judicious approach for processing low-wavenumber-contaminated deformation-rate waveforms.

3.4 DAS Data Filtering Procedure

The next conventional processing step (though not necessarily required for this data set) would be to calculate strain-rate data from the deformation-rate measurement by applying some variation of a spatial filtering operator (e.g., a GL or first-derivative filter). To illustrate the associated effects of undertaking such a filtering operation, we examine the effects of applying two classes of filtering operations: (1) spatial 1D finite impulse response (FIR) and infinite impulse response (IIR) filters of different orders of accuracy, and (2) 2D dip-velocity filtering.
3.4.1 Spatial 1D Filtering

The first approach in the 1D filter class is to apply a conventional GL filter of length $L_G$ through

$$\dot{\varepsilon}_E(x,t|L_G) \approx \frac{\tilde{v}(x + L_G/2,t) - \tilde{v}(x - L_G/2,t)}{L_G},$$

(3.2)

where $\dot{\varepsilon}_E$ is the estimated along-fiber strain rate.

The second approach in the 1D filter class is to use a 12th-order Taylor-series finite-difference (FD) approximation of the analytic first-derivative operator,

$$\dot{\varepsilon}_E(x,t|c_k) \approx \frac{1}{\Delta x} \sum_{k=1}^{6} c_k (v(x + k\Delta x,t) - v(x - k\Delta x,t)),$$

(3.3)

where $c_k = [23760, -7425, 2200, -495, -72, 5]/27720$ are the corresponding FD coefficients and $\Delta x$ is the spatial sampling interval along the fiber (a user-defined parameter).

To illustrate the behavior of the different filtering approaches, the left and right columns of the upper three rows of Figure 3.4 presents three different FIR filters along with their associated spectral responses. Overall, we observe that the different filtering approximations lead to very different strain-rate data results. In particular, a shorter GL introduces stronger near-zero wavenumber filtering (Figure 3.4a and Figure 3.4b), while a longer GL exhibits reduced near-zero filtering but introduces additional spectral notches (Figure 3.4c and Figure 3.4d). Conversely, the 12th-order spatial first-derivative filter (Figure 3.4e and Figure 3.4f) does not introduce the notches except at DC and the normalized Nyquist wavenumber (i.e., 0.5 m$^{-1}$). This filtering approach also imparts a more accurate representation of the expected $|k|$ spectral magnitude of the first-derivative operator that leads to a linear increase in the weighting factor with increasing wavenumbers until reaching the effective approximation limit at about 70% of the Nyquist wavenumber.
Figure 3.3 (a) Velocity data for a hammer shot recorded at 9:00pm after applying the polarity correction to Section B. Note that the record is contaminated with horizontal noise that has a moveout too fast to be a seismic event. (b) The associated frequency-wavenumber $f - k$ plot where the vertical “washboard” striping is due to the presence of the horizontal unwanted but repeated signals observed in (a). (c) 2D dip-filtered velocity data for the same shot in (a) that now shows refracted-wave arrivals. (d) The $f - k$ spectra for the filtered shot record shown in (c).

Figure 3.5 illustrates the denoising benefits of applying 1D filtering to obtain a strain-rate panel estimate for data windowed out for Section A. Figure 3.5a-1 and Figure 3.5a-2 present the raw deformation-rate data of the windowed subset as well as the corresponding $f - k$ spectra, respectively. We next apply the gauge-length filter with $L_G = \Delta x = 0.8$ m, equivalent to the spatial sampling interval. The low-order 1D spatial-derivative filter acts as a low-cut filter that through the strain-rate conversion removes the strong low-wavenumber noise in Figure 3.5b, but also significantly upweights signal and noise at higher wavenumbers. Figure 3.5c shows the results of applying a GL filter of length 6.4 m (i.e., $L_G = 8\Delta x$), which has done a poorer job of removing the unwanted horizontal signal and clearly introduces notches that adversely affect the observed $f - k$ spectrum (Figure 3.5c-2) and is consistent with the frequency response shown in Figure 3.4d. Figure 3.5d-1 presents the data panel filtered by the 12th-order FD approximation (Equation 3.3) while Figure 3.5d-2 presents the associated $f - k$ spectra. We observe that these higher-order
filtering operations do a better job than the lower-order GL counterparts, as indicated by the improved quality of the unwanted horizontal signal removal and the lack of notches in the $f-k$ spectra.

Figure 3.4 Impulse response filters with their associated magnitude spectra. (a) $L_G = 8$-unit FIR filter. (b) Magnitude spectrum of the filter in (a). (c) $L_G = 14$-unit FIR filter. (d) Magnitude spectrum of the filter in (c). (e) 12th-order FD first-derivative FIR approximation. (f) Magnitude spectrum of the filter in (e). (g) Filter coefficient of high-pass Butterworth IIR filter. (h) Corresponding magnitude spectrum of the filter in (g).
3.4.2 1D High-pass Wavenumber Filtering

Although applying a GL (or low-order first-derivative) filter to calculate a strain-rate quantity is by now a standard technique, we point out that the deformation rate (i.e., particle-velocity equivalent) \( \tilde{v} \) measured in the Treble IU allows for a different interpretation of the filtering process - namely, the purpose of applying a filtering operator is to denoise \( \tilde{v} \) rather than transform \( \tilde{v} \) into a derived strain-rate quantity \( \dot{\varepsilon} \). To illustrate this, we examine the application of an IIR filter to the same data as used in the 1D derivative filtering above. To implement the IIR filter, we used `scipy.signal.butter` package (Jones et al., 2016), which provides both digital and analog Nth-order Butterworth filters. Figure 3.4g and Figure 3.4h illustrate one example of a high-pass Butterworth IIR filter generated using numerator coefficients of

\[
a = [1.0, 4.4, 9.7, 14.1, 14.9, 12.1, 7.6, 3.7, 1.4, 0.4, 0.07, 0.06],
\]

and denominator coefficients of

\[
b = [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0].
\]

The resulting frequency response shows that one can effectively remove low-wavenumber noise while preserving the remaining signals. We apply the high-pass Butterworth filter to the same windowed subset (Figure 3.5a-1). Figure 3.5e-1 and Figure 3.5e-2 respectively show the resulting data panel and the corresponding \( f - k \) spectrum, which clearly displays the removal of low-wavenumber noise. However, the data panel also exhibits remnants of horizontal noise around 0.0 s to 0.05 s, which motivates the exploration of further filter designs.

3.4.3 2D Frequency-wavenumber (\( f - k \)) Filtering

The above 1D high-pass filtering approach conceptually can be extended into a 2D operation through the use of velocity-dip filtering (Yilmaz, 2001), which has been used for decades in seismic data processing to remove the types of unwanted coherent signal observed in Figure 3.3a and Figure 3.5a. Coherent linear events, such as guided waves and ground roll, are straightforward to identify by their associated dip and remove in the \( f - k \) domain (i.e., after applying a 2D Fourier transform). After locating an event in the \( f - k \) domain, one can apply a 2D multiplicative “fan-like” mute (with tapered edges) to reject the identified unwanted data components. One then recovers the filtered \( t - x \) domain section by applying an inverse 2D Fourier transform. The 2D velocity-dip filter is straightforward to implement, has few tunable parameters, and leads to high-quality filtered output when the desired signal and unwanted signal/noise dip spectra are clearly separated as they are in this data set. Following such an approach again allows for the resulting panel to be considered as a “filtered \( \tilde{v} \)” panel rather than an \( \dot{\varepsilon}_E \) panel estimate.
Figure 3.5 Data and $f-k$ spectra for a shot gather recorded on Section A. (a-1) Raw deformation-rate data and (a-2) the associated $f-k$ spectra. Strain-rate data with (b-1) $L_G=0.8$ m and (b-2) the associated $f-k$ spectra. Strain-rate data with (c-1) $L_G=6.4$ m and (c-2) the associated $f-k$ spectra. (d-1) Strain-rate data after applying a 12th-order accurate numerical first-derivative filter as shown in Figure 3.4e and (d-2) the associated $f-k$ spectra. (e-1) 1D low-cut Butterworth filter and (e-2) the associated $f-k$ spectra. (f-1) 2D velocity-dip filtering and (f-2) the associated $f-k$ spectra.

Figure 3.5f illustrates the benefits of applying the dip-filter approach to this data set. The fan-like pattern observed in the $f-k$ spectra, corresponding to a passband for waves traveling horizontally at apparent velocities ($V_{app} = df/dk$) between 0.1 km/s and 1.5 km/s, has removed the near-zero wavenumber energy without introducing notches or significant upweighting of high-wavenumber components. Applying the 2D filtering approach to the entire fiber section also highlights its benefit, as shown in Figure 3.3c. It presents a 2D dip-filtered version of the raw panel presented in Figure 3.3a. The resulting panel is largely free of the unwanted horizontal signals making the weak refracted waves more apparent. Figure 3.3d presents the $f-k$ spectra associated with Figure 3.3c. The dip-filter reject band about the DC wavenumber is quite apparent; however, the remaining components of the $f-k$ spectra are untouched. Thus, 2D velocity-dip filtering represents our preferred approach for this data set, though we point out that this approach is likely
3.5 Time-lapse Observations

Having applied our preferred approach for 2D filtering the observed shot-gather data, we now turn to the time-lapse nature of the experiment and investigate how the characteristics of the repeat shot gathers change with the varying surface environmental conditions as revealed by the filtering procedure. Figure 3.7a and Figure 3.7b present a series of three shot gathers acquired at 3:00 PM (air temperature of 2.5°C), 5:30 PM (-0.5°C), and 9:00 PM (-6.5°C) respectively recorded on Section A at 10cm depth and Section C lying on the surface. We applied a consistent 2D velocity-dip filter to each panel to remove any unwanted horizontal signals like those observed in Figure 3.5f. The shot gathers recorded on Section A (Figure 3.7a-Figure 3.7c) show consistent amplitudes during the six-hour recording period because they remain frozen at depth to the ground. Conversely, the shot gathers recorded on Section C (Figure 3.7d-Figure 3.7f) exhibit increasing surface-wave amplitudes over the same recording period. We expect the surface ground conditions to harden as the air temperature drops below freezing due to the formation of ice, which leads to improved ground-fiber coupling at the surface. Additional theoretical and experimental work, though, is required to more fully establish the physics behind the observed time-lapse amplitude variations.

3.6 Discussion

Having now specified our preferred form of 2D filtering and interpretation, we now turn to making two additional sets of comparisons: (1) how well do the filtered DAS panels match geophone data?; and (2) how repeatable were the shot gathers acquired on the DAS system over the acquisition period?

We first present a comparison between the recordings acquired on the horizontal DAS fiber with those made on the adjacent vertical-component geophones. Figure 3.6a and Figure 3.6b present shot gathers of geophone and DAS acquired, respectively. The surface wave recorded from both sensors displays comparable arrival phases and apparent moveout velocities. Figure 3.6(c) presents the stacked magnitude spectra for both records. We observe that the dominant frequency band of the DAS and geophone records largely overlap; however, the geophone data are shifted to lower frequency and appear to have a somewhat broader response.
Figure 3.6 Representative shot gathers recorded on (a) vertical-component geophones and (b) DAS fiber array (after 2D velocity-dip filtered). (c) Normalized magnitude spectrum of the two shot gathers presented in (a) and (b).

To examine the repeatability of the DAS shot gathers and the potential for diurnal variability, we evaluate three shots acquired at Sections A and C acquired at three different times of the day. Figure 3.7a-Figure 3.7c presents three different shot gathers recorded on fiber section A at 3:00pm, 5:30pm, and 9:00pm, respectively. These three shot gathers display consistent moveouts, waveforms, and amplitudes, which suggests that the shot records are largely repeatable throughout the time of the investigation. Figure 3.7d-Figure 3.7f presents
the same three shot gathers as presented in Figure 3.7a-Figure 3.7c; however, these were recorded Section C of the fiber deployed on the surface. Unlike in the top three panels, the bottom three panels exhibit significant amplitude and phase variations. These observations suggest that trenching and freezing in fiber improves not just ground-fiber coupling, but also measurement repeatability.

Finally, the significant variability of the shot gathers presented in Section C are unlikely to be due to significant time-lapse variations of the bulk properties of the near-surface earth model. Rather, a more likely explanation is that as the air temperature drops from above to below freezing, one should expect refreezing of moisture in the soil and likely improved adherence of the soil to the fiber. Accordingly, the shot gather acquired at 9:00pm (Figure 3.7f) exhibits stronger amplitudes and higher signal-to-noise ratio compared to those acquired at 3:00pm and 5:30pm (Figure 3.7d and Figure 3.7e). Thus, we stress that interpreting the amplitudes (and potentially phases) of DAS data prior to removing or controlling for external environmental factors require due caution. We encourage further examination using a hybrid system that measures strain and temperature simultaneously, such as a combined DAS and DTS (distributed temperature sensing) system or DVTS (distributed vibration and temperature sensing) Miah & Potter (2017). Such hybrid systems already provide solutions in various fields including oil and gas, mining, and civil engineering. For our work, future hybrid measurement will help to clarify the amplitude changes or help design a filter for the decoupling temperature effect.

3.7 Conclusions

We present an experiment that evaluates the Terra15 Treble IU DAS deformation-rate format recorded on a fiber array deployed at variable freezing conditions and trenching depths. We propose a suitable filtering methodology compared to the existing methods such as strain-rate transformation and low-cut filters. The recorded deformation-rate data showed coherent surface-wave arrivals; however, refracted arrivals only clearly appeared after applying our preferred 2D dip-velocity filtering approach. Therefore, we expect enhanced angular bandwidth from 2D dip-filtered deformation-rate data compared to that of the strain rate. The trenched and frozen-in fiber provided sufficient coupling to record usable deformation-rate data throughout the day; however, data recorded on the fiber section simply laid on the ground show decreased overall quality and exhibit time-dependent effects due to the variable ground-fiber coupling likely introduced by air-temperature fluctuations about 0°C. Our results suggest that trenching and freezing can provide improved ground-fiber coupling for recording in the Treble IU deformation-rate format. The benefit of enhanced coupled through freezing is likely similar for other IUs, which should encourage future DAS experiments such as installations on lakes, glaciers, and snowpack in sub-0°C environments.
Figure 3.7 Repeat deformation-rate DAS shot gathers recorded on the frozen, backfilled trench fiber Section A (upper panels) and the surface-deployed fiber Section C (lower panels). (a) and (d) 3:00pm. (b) and (e) 5:30pm. (c) and (f) 9:00pm.
3.8 Data and Resources

Processed data sets are available in DRYAD open repository:
(https://datadryad.org/stash/share/-Yq1WGlQmCGMM20yFELahjZtLHtHyeOctBuRyDnzH38 )

3.9 Acknowledgments

We acknowledge the sponsors of the Center for Wave Phenomena consortium, whose support made this research possible. We thank Aaron Girard and Iga Pawelec for help on this experiment, and Nader Issa and Michael Roelens (Terra15) for useful technical suggestions. Reproducible numerical examples were generated using the Madagascar software package.

3.10 Author Contributions

Jihyun Yang contributed to conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, and visualization, and also participated in writing the original draft and review and editing. Jeffrey Shragge contributed to conceptualization, funding acquisition, investigation, methodology, project administration, software, and supervision, and also participated in writing the original draft and reviewing and editing. Ge Jin contributed to data curation, supervision, and validation, and also participated in reviewing and editing.
CHAPTER 4
LONG-TERM AMBIENT SEISMIC INTERFEROMETRY FOR CONSTRAINING SEASONAL
SUBSURFACE VELOCITY VARIATIONS IN URBAN SETTINGS:
A DISTRIBUTED ACOUSTIC SENSING (DAS) CASE STUDY

A paper submitted to Geophysical Journal International (Under review)
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4.1 Abstract

Ambient seismic interferometry of distributed acoustic sensing (DAS) data acquired on optical fiber arrays is an increasingly common approach for subsurface investigation. The fixed infrastructure and low maintenance costs of commodity telecommunications fiber also supports cost-effective DAS-based seismic monitoring solutions over extended periods of time - especially when using repurposed telecommunication fiber infrastructure in urban settings. To investigate whether ambient waveform data acquired on such an urban DAS array are sensitive to seasonal subsurface variations, we present a case study using “semi-continuous” DAS time-series data with hourly 150 s sampling windows that were acquired over a ten-month interval in the central business district of Perth, Australia. We apply a cross-coherence analysis to transform preprocessed ambient waveform data into sliding-window weekly interferometric virtual shot gathers (VSGs). We then use these data volumes to compute time-lapse velocity-dispersion panels, which we input to a multichannel analysis of surface waves (MASW) to generate depth-averaged S-wave velocity estimates of the top 30 m ($V_{S30}$). Our time-lapse analyses show that weekly stacked interferometric VSGs exhibit up to 5.8% variations in observed surface-wave traveltimes while the MASW inversion results capture up to 9.4% variations in $V_{S30}$ estimates between the winter and spring months. We note that these observations are inversely correlated with time-averaged rainfall patterns in the Perth Metro region and are likely attributable to the associated seasonal variations in near-surface groundwater content. Overall, our analysis suggests that semi-continuous ambient seismic monitoring on urban DAS fiber arrays is a computational tractable acquisition strategy that records data volumes useful for monitoring the seasonal variability of groundwater resources beneath urban centers as well as potentially other time-lapse subsurface behavior occurring over calendar time.

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4.2 Introduction

Seismic interferometry is a now widely applied geophysical technique that uses ambient wavefield vibration data acquired on a monitoring array to, e.g., characterize the environmental conditions of the shallow subsurface. Using conventional geophone arrays for such a task over an extended period of “calendar” time, though, requires both a substantial personnel effort for array installation and maintenance as well as a sustained longer-term hardware commitment. However, the recent years have seen significant growth in the use of distributed acoustic sensing (DAS) approaches that deploy optical fiber - or even re-purpose existing telecommunications infrastructure (i.e., “dark fiber”) - to provide alternative monitoring solutions that can significantly reduce the deployment and maintenance costs associated with longer-term ambient-style seismic investigations (e.g., Ajo-Franklin et al., 2022, 2019; Biondi et al., 2021; Lindsey et al., 2020a).

The key principle behind this growing trend is that DAS effectively transforms deployed commodity optical fiber into a distributed sensing network (Hartog, 2018). When viewed as a “large-N” seismic array with dense spatial sampling, such fiber deployments have the significant potential for acquiring ground-vibration data appropriate for addressing a wide range of subsurface imaging and monitoring challenges. Ambient waveform analyses can take advantage of the high spatial and temporal sampling rates of DAS arrays, and such acquisition scenarios demonstrably can lead to improved tomographic results (Ranasinghe et al., 2018) and more accurate seismic event detection (Inbal et al., 2016; Li et al., 2018) when compared to analyses performed on conventional sparse geophone arrays. In addition, long-term DAS acquisition can be beneficial for numerous time-lapse investigations including near-surface characterization, environmental studies including groundwater level monitoring (Rodríguez Tribaldos & Ajo-Franklin, 2021), and infrastructure monitoring projects (Dou et al., 2017; Güemes et al., 2018; López-Higuera et al., 2011). Much research has explored near-surface imaging and monitoring applications of DAS technology. As examples, DAS demonstrably provides a robust system for active-seismic applications such as non-intrusive pipeline and borehole monitoring (Duley et al., 2016; Stajanca et al., 2018) as well as for near-surface passive-seismic applications including geological characterization (Shragge et al., 2021), earthquake-induced subsurface structural heterogeneity (Yang et al., 2022), permafrost and cryosphere thaw (Ajo-Franklin et al., 2017; Cheng et al., 2022), and urban subsurface monitoring (Fang et al., 2020). Other research demonstrates the capability of urban DAS arrays as multipurpose monitoring systems by detecting broadband signals ranging from earthquakes to larger anthropogenic events (Zhu et al., 2021).

While short-term event detection activities or short-window acquisition campaigns have led to the numerous DAS applications reported in the literature, this class of investigation is by design unable to capture longer-term or “seasonal” variations. Geophysical analysis of seasonal subsurface variations is useful
for a wide range of applications, from understanding groundwater hydrology (Terry et al., 2020) to near-surface environment of Mars (Compaire et al., 2022). DAS-based acquisition already offers robust solutions for long-term monitoring, as typified by pipeline monitoring projects in the oil and gas industry that largely focus on (unwanted) event detection. In contrast, our research focuses on the application of DAS for investigating the seasonality of urban near-surface environments and the potential for observing subsurface variations over calendar time. We stress that long-term DAS-based monitoring involves distinct challenges in terms of handling the associated large data volumes (i.e., potentially Tb per day). Therefore, this observation motivates the exploration of alternate long-term DAS data acquisition and analysis methodologies capable of addressing the corresponding DAS data volume challenges.

The work reported herein evaluates whether seasonal near-surface variations can be captured using ten months of ambient waveform data acquired on a DAS fiber array situated in the central business district (CBD) of Perth, Australia. The literature already shows the significant potential of DAS for near-surface urban monitoring (Fang et al., 2020; Lindsey et al., 2020a); however, these studies focus on data sets acquired over relatively narrow calendar windows of several weeks to a few months. In this work, we aim to observe the dynamics of seasonality in a time window covering the fall, winter, and spring seasons in Perth when the subsurface hydrological conditions are mostly likely to vary due to commonly significant rainfall events. An additional goal is to complete this time-lapse DAS analysis following a computational tractable approach that can be replicated by researchers elsewhere.

We begin by describing the ten-month ambient waveform DAS data set and preprocessing workflows. We then present interferometric cross-correlation results generated on different data subsets of variable stacking duration and complete a stacked image convergence analysis to determine a sufficient stacking time interval for generating comparable time-lapse virtual shot gathers (VSGs). Next, we present observations of seasonal velocity variations over the 43-week observation period in terms of the temporal variability of surface-wave arrivals as well as in the results of multichannel analysis of surface waves (MASW) applied to velocity-dispersion panels computed from the time-lapse VSG volumes. We conclude by discussing possible improvements in the ambient data processing flow, the computational efficiency of our approach, and further potential applications of urban DAS array for tracking calendar variations of the subsurface environment (e.g., variable saturation and/or groundwater levels).

4.3 Dataset and Methods

4.3.1 Urban DAS Dataset

The ambient DAS data set used in this case history was acquired on a 7.26 km-long fiber-optic array deployed throughout the Perth CBD. The fiber array and Terra15 Treble interrogator unit (IU) were
installed and are managed by Terra15 personnel for proprietary purposes (i.e., not purposefully intended for subsurface geophysical analysis). Figure 4.1 shows the relative coordinates of the array subsection relevant for the present investigation (3.8-5.2 km); absolute geographic locations are not presented for reasons of confidentiality. Note that the array geometry is color-coded by the Euclidean distance from each array measurement location to point A located at the start of the relevant fiber section.

Figure 4.1 Geometry of the urban Perth CBD DAS array subsection between 3.8-5.2 km pertinent to this investigation. The geometry is color-coded by the Euclidean distance from each array measurement location to point A located at the start of the relevant fiber section.

To support the investigation of calendar variations of measured ambient waveforms, Terra15 personnel recorded and archived a continuous 150 s-long segment every hour from March 2020 through January 2021. Due to maintenance and other circumstances, DAS acquisition occasionally was halted leading to some variance in the daily number of recorded snapshots. A total of 12.0 TB of HDF5-formatted DAS data were acquired with a monthly average of 660 recorded segment files or about 92% of an hourly data set without any acquisition disruptions. Each segment has temporal and spatial sampling rates of $\Delta t = 13.8$ ms and $\Delta x = 4.9$ m, respectively. We note that continuous as opposed to hourly DAS data acquisition “snap shots”
at these temporal and spatial sampling rates would have yielded an unwieldy 288 TB data volume. Thus, to reduce the data set to a more manageable size, we bandpass filtered the raw data between 0.1 Hz and 30.0 Hz and subsampled the resulting waveforms to a 72.0 Hz sampling rate. These data reduction steps resulted in the 436 Gb data volume that was used for the ensuing ambient seismic interferometry analysis.

Each Terra15 formatted file was recorded in “deformation rate” (an approximate particle-velocity format), which is enabled by the proprietary optical design of Treble IU (Issa et al., 2018). The deformation-rate recording consists of 1484 receivers at the user-specified ∆x=4.9 m spatial spacing interval. Data quality degrades after about 5.2 km due to optical reflections caused by a suboptimal fiber connection; thus, we only process the data for channels located up to this point. To make the ambient waveforms usable for interferometric analysis, we first transform the DAS deformation-rate data volume $v$ into a strain-rate estimate $\dot{\varepsilon}_E$ by applying a low-order spatial-derivative operator along the fiber axis,

$$\dot{\varepsilon}_E(x, t, L_G) \approx \frac{v(x + L_G/2, t) - v(x - L_G/2, t)}{L_G}, \quad (4.1)$$

where $x$ is spatial position along the array, $t$ is time, and $L_G$ is the applied gauge length. For this work, we use a gauge length of $L_G = 4.9$ m equivalent to the spatial sampling interval, $\Delta x$.

Figure 4.2a presents a 2.0 s snapshot of the raw strain-rate DAS recording from 14 July 2020 at 9:00 AM UTC. While coherent events with V-shaped quasi-linear moveouts likely related to moving vehicles are evident, we note that the section suffers from imbalanced amplitudes and undesirable vertical streaking. These observations motivated us to apply a preprocessing workflow consisting of temporal high-pass filtering (0.1 Hz corner) and linear detrending at each station prior to evaluating the strain-rate calculation. Applying these processing steps (Figure 4.2b) was effective for balancing section amplitudes, removing the unwanted DC component offset, and reducing the vertical streaking noted in Figure 4.2a.
Figure 4.2 Representative 2.0 s strain-rate panel recorded at 9AM UTC on 14 July 2020 (a) before and (b) after applying the data preprocessing sequence. The panel in (a) exhibits unbalanced amplitudes and vertical streaking that has been largely removed through high-pass filtering and linear detrending in the panel shown in (b).

Figure 4.3 presents a representative 18-day spectrogram for April 2020 computed using preprocessed ambient waveform data at a point located at 4.2 km distance along the fiber array. We observe energy peaks between 23-27 Hz and to a lesser extent between 12-16 Hz; energy is also stronger during the daytime, which is expected due to increased anthropogenic activities occurring during these time periods within the Perth CBD.
4.3.2 Interferometric Processing

To generate virtual shot gather (VSG) volumes, we follow the ambient interferometric data processing workflow presented in Bensen et al. (2007). The first step involves partitioning the preprocessed data volume into short window segments (here $\Delta T = 150$ s). We then transform the windowed ambient records into VSGs using a seismic interferometry approach (Snieder, 2004; Wapenaar et al., 2010). For reasons of computational efficiency, we perform the interferometric cross-coherence in the frequency domain. This workflow requires first computing a temporal Fourier transform of the nth DAS strain-rate event window, $u_n(x_i, t)$ to generate the frequency-domain response $u_n(x_i, \omega)$, where $x_i$ represents a spatial location, and $\omega$ is angular frequency. We then perform cross-coherence (i.e., through frequency-domain multiplication) of all permutations of virtual source and receiver traces and stack over the selected $N$ event windows. Finally, we compute the temporal inverse Fourier transform to create the output VSG volume $G_{XC}$. This process is equivalent to the following mathematical operation:

$$G(x_A, x_B, \tau) = \mathcal{F}^{-1} \left[ \sum_{n=1}^{N} \frac{u(x_A, \omega; n)\overline{u(x_B, \omega; n)}}{\sqrt{|u(x_A, \omega; n)|^2 |u(x_B, \omega; n)|^2 + \epsilon^2}} \right],$$  \hspace{1cm} (4.2)

where $\mathcal{F}^{-1}$ is the inverse Fourier transform operator, $n$ is the event window index, $\overline{u}$ indicates complex conjugate of wavefield $u$, $x_A$ and $x_B$ are the locations of a virtual source and virtual receiver, $\tau$ is two-sided temporal correlation lag, and $\epsilon$ is a small real value used to prevent zero division.

To investigate the stationarity of the ambient waveform energy distribution, we estimate the time-averaged ray parameter of weekly cross-coherence stacks between 27 March 2020 and 22 January 2021.
We calculate the ray-parameter distribution by first computing the $\tau - p$ transform of each weekly stack, calculating the envelope of the result, and then stacking over the $\tau$ coordinate. Figure 4.4 presents the results of this analysis for each week, which indicate that the ray parameter (i.e., slowness) is largely and consistently concentrated between +4.0 s/km to -2.0 s/km. We suspect the dominant positive slowness band is due to the off-end location of the Perth light rail station, which is the biggest station within the TransPerth network.

![Ray-parameter slowness analysis](image)

Figure 4.4 Ray-parameter slowness analysis of the weekly sliding-window cross-coherence stacks between 27 March 2020 and 22 January 2021.

### 4.4 Results

To investigate whether there were any observable changes in subsurface observations over calendar time, we first stack $N$ short-window (i.e., $\Delta T = 150$ s) gathers to improve the VSG signal-to-noise ratio (SNR), an important step for generating stable approximations of the desired empirical Green’s functions. We then compute the observed velocity-dispersion panels by slant-stacking the VSGs over the range of candidate phase velocities. Finally, we use the observed velocity-dispersion curves in a multichannel analysis of surface waves (MASW) inversion approach to generate (depth-weighted) shear-wave velocity estimates of the top 30 m (i.e., $V_{S_{30}}$). We select this quantity because it is a useful proxy for short-period ground-motion prediction (Code, 2005; Kanlı et al., 2006) and is widely used in geotechnical engineering field for soil characterization surveys.

#### 4.4.1 Interferometric Stacking Convergence

The main reason for applying any form of stacking process is to enhance the SNR of the observed quantity in the presence of experimental “noise”. In the case of the ambient waveform VSG estimation, stacking is required to reduce the effects of transient signals (i.e., singular events) while enhancing the contributions of
persistent ambient waveform phases. While stacking for an infinite time duration would be highly likely to achieve convergence, such a methodology is neither computationally possible nor desirable. Thus, an important question is what duration of stacking time (i.e., how many windows) is sufficient for ensuring converge of the seismic interferometry analysis (equation 4.2) and thereby forming a stable VSG estimate?

Here, we examine this question by comparing our interferometric VSG stacking results with a straightforward theoretical model (Issa et al., 2017) that predicts the convergence of the seismic interferometric stacking process in two-way correlation lag $\tau$ in terms of VSG “image variance” over a longer period of accumulation time $T$. The goal of stacking over $T$ is to recover a stationary (i.e., converged) estimate of VSG image volume $I_S(x_A,x_B,\tau)$. The ubiquitous presence of a noise field $N(x_A,x_B,\tau|T)$ (herein assumed to be a zero-mean random independent variable) means that the observed VSG image volume $I(x_A,x_B,\tau|T)$ will be non-stationary (i.e., dependent on $T$). Mathematically, the relationship between these three fields can be expressed as (Issa et al., 2017):

$$I(x_A,x_B,\tau|T) = I_S(x_A,x_B,\tau) + \frac{1}{T} \int_0^T N(x_A,x_B,\tau|T')dT',$$  \hspace{1cm} (4.3)

where $T'$ is a temporal dummy integration variable. The key question is what duration of accumulation time $T$ - or, equivalently, how many windows $N$ of duration $\Delta T$ (here $\Delta T=150$ s) - are needed such that the second term on the right-hand side of equation 4.3 no longer meaningfully contributes. This is the point when one can say that the VSG image volume has effectively “converged” to $I_S(x_A,x_B,\tau)$

The convergence model approach of Issa et al. (2017) addresses this question by evaluating the statistical variance of equation 4.3 (herein denoted by operator $\text{Var}_\tau(\cdot)$) and examining the asymptotic behavior of the resulting expression. By defining $I_{\text{var}}(x_A,x_B,\tau|T) \equiv \text{Var}_\tau(I(x_A,x_B,\tau|T))$ as an expression for the observed VSG image volume variance, one can derive the following relationship:

$$I_{\text{var}}(x_A,x_B,\tau|T) = \text{Var}_\tau(I_S(x_A,x_B,\tau)) + \frac{\Delta T}{T} \overline{N}_{\text{var}}(x_A,x_B,\tau|N\Delta T),$$  \hspace{1cm} (4.4)

where $\overline{N}_{\text{var}}$ is the mean random zero-mean noise field averaged over $N$ windows of duration $\Delta T$ (i.e., $T = N\Delta T$).

Several practical inferences related to the interferometric VSG stacking process can drawn from the relationship presented in equation 4.4: (1) the rate of image convergence is inversely proportional to the overall accumulation time $T$ and is dependent on the relative magnitude of the noise contribution $\overline{N}_{\text{var}}$ relative to the signal $\text{Var}_\tau(I_S)$; (2) the asymptotic behavior as $T \to \infty$ is independent of $T$ and the calculation will converge to the desired stationary VSG image volume; (3) panels exhibiting stronger “transient noise” sources will tend to increase $\overline{N}_{\text{var}}$ and thereby delay the convergence of the VSG image stacking process; and (4) $N$ and $\Delta T$ are the key parameters governing VSG image volume convergence and
should be determined through an analysis of the local SNR conditions.

We perform an image convergence test by stacked the VSGs from individual $\Delta T = 150$ s windows and examining image variance metric convergence as a function of the number $N$ of stacked windows (see Figure 4.5). We then fit the theoretical convergence model from equation 4.4 to the observed convergence curve. We note that image variance calculation achieved convergence after stacking between $N=48$ and $N=72$ windows, representing between two to three days of hourly $\Delta T = 150.0$ s recordings. Figure 4.5b presents the observed and theoretical image variance gradients computed by taking the numerical derivative of the time-series data and theoretical model curve presented in Figure 4.5a. As expected from equation 4.4, the two gradient curves exhibit a leading-order inverse-square relationship (i.e., $\propto \frac{1}{T^2}$). We note the observed gradient curves could be used as a calculation stopping criterion when reaching a user-established threshold; however, we did not use follow such a process during the present investigation. Finally, based on the image convergence analysis, we set the default stacking hours of one week (i.e., $N=168$) as our “base unit” of interferometric stacking to generate time-lapse VSG volumes. This value sufficiently exceeds the $N=48-72$ range and thereby represents a convenient yet conservative estimate for achieving stationary stacked VSG image volumes to a high degree of likelihood.
4.4.2 Time-lapse Observations

Having established an informed period of interferometric stacking, we next investigate the long-term time-lapse observations of the weekly stacked VSGs to examine their overall week-to-week consistency as well as to look for evidence for meaningful calendar subsurface velocity variations. We have used a seven-day moving window stack with a six-day overlap to increase the robustness and compute the time delay from the newly computed stack. The resulting data set consists of 289 seven-day stacked files representing a ten-month duration.

Figure 4.6 shows representative weekly stack VSGs using a master trace located at 4.61 km along on the fiber array for four different dates separated by a minimum of two months. The vertical black lines indicate the two points where the fiber array subset bends at 90° angles at 4.41 km and 4.68 km (see Figure 1). The
observed average apparent moveout velocity (0.22 km/s) of the (presumably) Rayleigh waves appears fairly stationary and is generally consistent with the values expected for the near-surface Quaternary Swan River deposits (Davey, 2018) that underlie much of the Perth CBD. The four representative panels exhibit moderate variations in wavefield attributes in terms of the observed coherent surface-wave amplitudes, phases, and frequency content.

Figure 4.6 Weekly VSG stacks on different dates: (a) 1 April 2020, (b) 12 June 2020, (c) 5 August 2020, and (d) 4 January 2021. The vertical black lines indicate where fiber array bend 90° (i.e., at 4.41 km and 4.68 km; see Figure 1.)
To investigate the potential for time-varying behavior in greater detail, we extract and concatenate traces at two fixed source-receiver offsets from the 43 weekly VSGs volumes to generate 2-D time-lapse trace panels. Figure 4.7a and Figure 4.7b show two such panels from fixed source-receiver offsets of 0.18 km and 0.21 km, respectively. Traveltime shifts are clearly evident in two panels showing the curvature of the same selected (presumably) Rayleigh-wave arrival phase. On Week 11 (the first week of June 2020), we observe a significant discontinuity at the two shown offsets (as well as others not shown), which may have been caused by extreme weather events, such as a winter heavy storm and associated rainfall commonly observed in Perth during the peak months of storm activity (June through August). We calculate the traveltime variation of different fixed offset panels from the earliest and latest observed arrivals of the single waveform (the red and blue dots, respectively, in Figure 4.7a and Figure 4.7b). The mean traveltime variation averaged over six selected source-receiver offsets is 3.2%. Figure 4.7c and Figure 4.7d shows a complementary 2-D time-lapse trace panels extracted at fixed relative time lags of -0.65 s and -0.85 s, respectively. We again observe waveform curvature as well as the Week 11 discontinuity previously noted in Figure 4.7a and Figure 4.7b.
Figure 4.7 Calendar time-lapse behavior over a 43-week period. Time-lapse 2-D trace panel extracted at (a) 0.18 km and (b) 0.21 km fixed source-receiver offsets. The blue and red dots are examples of picked arrival times for the latest and earliest arrivals of a consistent Rayleigh-wave arrival over the calendar time window. The mean traveltime variation calculated over six different offsets is 3.2%. 2-D offset-week panels extracted at (c) -0.65 s and (d) -0.85 s two-way correlation lag $\tau$. 
To analyze the relative variations in arrival times of the domain surface-wave waveforms shown in Figure 4.7a and Figure 4.7b, we apply the multi-channel cross-correlation (MCCC) technique of VanDecar & Crosson (1990). Originally developed for determining the relative phase arrival times and uncertainty estimates for teleseismic events, this approach can be used to calibrate an optimal set (i.e., in a least-squares sense) of alignment times for any batch of waveform data. The algorithm derives relative delay times based on the maximum correlation value between all possible pairs of traces. The computed delay times lead to an over-determined set of linear equations whose solutions are a set of optimal relative zero-mean traveltime corrections for trace alignment.

In our analysis we extract a trace from the 289 VSGs at two fixed source-receiver offsets (0.18 km and 0.21 km), which we use to form the set of linear equations for MCCC analysis. We solve the MCCC system of equations using a standard least-squares estimate to obtain an optimal set of waveform time-shift variations, which we apply to data panels presented in Figure 4.7a and Figure 4.7b. Figure 4.8 shows the MCCC-derived waveform time-shift variations for fixed 0.18 km and 0.21 km source-receiver offsets. Figure 4.9 shows a concatenation of the 0.21 km source-receiver offset panel before and after applying the MCCC-generated time-shift variations.

We next compare the MCCC time shifts with the daily rainfall of Perth Metro 2020 using data obtained from Bureau of Meteorology, Commonwealth of Australia. Because rainfall comes in largely isolated events, but groundwater infiltration occurs over longer periods of time, we apply a one-month moving window average to the estimated time shifts to highlight the overall rainfall trend. Figure 4.10 presents an overlay of the average MCCC-based time-shift lags and rainfall data. The solid yellow line shows the mean time shift averaged over three different source-receiver offsets (0.18, 0.195 and 0.21 km). The dashed red and solid blue lines show the one-month moving-window averages of the time shifts (in yellow) and daily rainfall of Perth Metro area, respectively.

Figure 4.8 Observed time-shift lags to align the surface-wave waveforms arrival shown in Figure 4.7a and Figure 4.7b estimated through the MCCC algorithm. The two fixed source-receiver offsets show the most significant calibration time lag between mid-June and mid-July 2020.
Figure 4.9 Concatenated windowed data of Figure 4.7b before (left half) and after (right half) applying the MCCC analysis. We extract a subset from 2-D panel between -0.62 s to 0.0 s and conduct MCCC calibration to estimate the time-shift variations. After applying the MCCC-derived time shifts, the curvature observed on the left half is flattened on the right half in a least-square sense.

Figure 4.10 Correlation between observed surface-wave waveform arrival lags and averaged precipitation recorded in the metro Perth area. The solid yellow line represents the mean time shifts averaged over three nearby source-receiver offsets (0.18 km, 0.195 km and 0.21 km) using MCCC analysis on the seven-day moving-window interferometric stack. The dashed red and solid blue lines show the one-month moving average of estimated time shifts and daily rainfall of Perth Metro area, respectively.
4.4.3 Surface-wave Dispersion Analysis

The next step is to apply MASW (Park et al., 1999, 2007) to the observed weekly VSG data. We first slant-stack the VSGs over a candidate range of phase velocities followed by computing a forward temporal Fourier transform. The resulting outputs from this process are velocity-dispersion panels, the picked dispersion curves from which are used in the MASW analysis. Figure 4.11 displays the computed velocity-dispersion panels for the weeks of 31 March, 4 May, and 8 June 2020. The significant energy observed in the 7-13 Hz frequency band appears to have a fairly consistent phase velocity of about 0.31 km/s. During Perth’s heavy rainfall season (i.e., mid-May through August) corresponding to the dispersion panel in Figure 4.11c, strong energy is observed around 7-9 Hz at about 0.55 km/s phase velocity (and is also visible in the two other panels), which we suggest is associated with a higher-order surface-wave mode. The 8 June velocity-dispersion panel also exhibits greater energy at lower frequencies between 2.5-5.0 Hz than the other two presented panels. Finally, the white dots on visible in Figure 4.11 represent examples of dispersion-curve picks based on the peak magnitudes of the observed velocity-dispersion panels that we use in MASW analysis.

We now generate $V_{S_{30}}$ estimates by inverting the picked dispersion curves (e.g., white dots in Figure 4.11a) following a MASW approach. We use particle swarm optimization (PSO) (Poli et al., 2007), one of a variety of global optimization schemes that evaluate large numbers of subsurface velocity models to find the earth model whose forward-modeled dispersion curve best matches that of the observed data. In practice, one can narrow the scope of parameter searches using prior or geologic information on the thicknesses and S-wave velocities of the three model layers. Accordingly, we respectively set the lower and upper S-wave velocity bounds at 0.001 km/s and 1.2 km/s. The minimum and maximum thickness are set to 1 m and 30 m, respectively. The PSO global optimization scheme sampled $6 \times 10^7$ velocity models within initial parameter bounds. Figure 4.12 shows the top 3000 models (as defined by having the lowest residuals), which correspond to the inversion result of weeks starting on 5 August and 4 September 2020. These 3000 models have varying velocities for the first shallow layers while showing consistent velocity reversal and similar shear velocity on the second and third layers.

To illustrate the fit of 1-D S-wave velocity models, we forward model the expected surface-wave dispersion panels from inverted model parameters using the delta-matrix extension approach of Dunkin (1965). We display observed and modeled dispersion of weeks starting on 5 August and 4 September. Figure 4.13 presents observed dispersion picks of fundamental and first higher modes as black and red $\times$ marks, while the forward modeled fundamental and first higher modes are displayed as solid blue and orange curves, respectively.
Figure 4.11 Velocity-dispersion panels of weekly stacked VSGs along with picked dispersion curves shown as white dots: (a) 31 March 2020, (b) 4 May 2020, and (c) 8 June 2020

We compute the depth-averaged $V_{S_{30}}$ of the estimated three-layered model according to (Commission et al., 2007)

$$V_{S_{30}} = \frac{\sum_{i=1}^{N} h_i}{\sum_{i=1}^{N} h_i / V_{S_i}}$$

(4.5)

where $h_i$ and $V_{S_i}$ are the thickness and shear wave velocity of each layer and $N$ corresponds to the number of model layers (here $N = 3$).

The resulting time-lapse model presented in Figure 4.14a shows the estimated $V_{S_{30}}$ value for eight selected weekly stacking periods roughly spanning the full ten-month range of the ambient DAS data set. The red line connects the mean $V_{S_{30}}$ estimate for each week, while the peach-shaded area displays the estimated standard deviation of each weekly calculation. In terms of a general trend, we observe a relative velocity decrease during the winter rainy period (mid-May through August) and a subsequent relative increase during the onset of spring (Figure 4.14a). The estimated maximum overall $V_{S_{30}}$ variation of 9.4% is
roughly comparable with the degree of traveltime variance noted in Figure 4.7a and Figure 4.7b.

Figure 4.12 1D MASW inversion results for the weeks of (a) 5 August and (b) 4 September. The green line shows the top 3000 models while the red line shows the mean of the top 3000 models as determined by the lowest residuals. The dashed blue lines denote the layer thickness and S-wave velocity parameter bounds.

Figure 4.13 Observed and modeled dispersion curves: (a) August 5th and (b) September 4th, 2020. Black and red "x" markers denote fundamental and secondary mode observed (picked) curves. Blue and yellow solid lines represent modeled fundamental and secondary mode curves from the top 3000 models.
As a possible explanation for the noted time-lapse variations, Figure 4.14b presents the mean monthly rainfall data for the Perth Metro area over the same calendar period which, interestingly, is generally inversely correlated with the $V_{S30}$ estimates. In addition, the Perth Metro area experienced anomalous monthly rainfall during November 2020 that is similarly inversely correlated with the slower $V_{S30}$ estimate noted during week of 30 November 2020. These observations suggest that a relationship may exist between available subsurface water content and near-surface S-wave velocity values. We display time-lapse slowness and rainfall data in the same plot to investigate the correlation. Figure 4.14(b) displays the similarity of the one-month moving average of the rainfall of 2020 in the Perth Metro area and reciprocal slowness result for mean $V_{S30}$ estimates of eight selected weeks from 2 May to 3 December, 2020. The slowness ($1/V_{S30}$) trend follows the general rainfall trend though with a temporal lag.

We note that we are not the first to make such an observation. Miao et al. (2018) apply ambient seismic interferometry to ambient, geophone-based observations from Northeast Honshu, Japan and demonstrate that near-surface S-wave velocities decrease by 1-3% for low-intensity rain events and up to 10% after significant rainfalls. This investigation also suggests that only events exceeding a threshold significantly affect near-surface S-wave velocities. In terms of the present study, some storms in the Perth Metro area June and July 2020 were classified as heavy rainfall events according to Perth meteorological records. Thus, the observed 5.8% surface-wave traveltime and estimated 9.4% $V_{S30}$ variations are generally consistent with the magnitude of similar observations reported in Miao et al. (2018). However, we stress that further work needs to be completed to more fully account for site-dependent geological effects and to establish a causal (as opposed to a correlated) relationship between rainfall, groundwater availability, and observed subsurface velocity change.
Figure 4.14 (a) MASW \( V_{S30} \) results from inverting the picked dispersion curves. The red line connects the mean \( V_{S30} \) estimates from the selected weeks, while the peach-shaded area displays the associated standard deviation of the calculation. (b) One-month moving average of the rainfall in 2020 in Perth Metro area (blue) and the reciprocal slowness result in for mean \( V_{S30} \) value (orange) shown in (a). Rainfall data are from the Bureau of Meteorology, Commonwealth of Australia.

4.5 Discussion

Interferometric stacking results converge around \( N=48-72 \) segments of \( \Delta T=150 \) s duration, which is equivalent to between two to three days of hourly 150 s window stacking. We suggest that our estimated image variance and gradient curves (Figure 4.5) achieve fairly rapid convergence due to the local noise
characteristics. However, further stacking and SNR improvements for the observed VSG volumes likely are possible with more sophisticated stacking approaches. For example, selective stacking based on the RMS ratio of signal and noise windows (Xie et al., 2020) or machine learning-based clustering (Viens & Iwata, 2020) could be useful techniques for identifying and removing noisy transient data windows known to adversely affect the quality of empirical time-lapse VSGs.

Finally, we point out that our “semi-continuous” DAS data acquisition strategy of archiving 150.0 s segments at a regular one-hour time intervals not only led to interpretable geophysical analysis results, but also allowed us to avoid an infeasible data volume of 288 Tb that would have been collected had we aimed for continuous acquisition over a full ten-month window. Moreover, we were able to process the acquired 12.0 Tb data volume down to 0.4 Tb through a bandpass filtering and data subsampling strategy. We stress that subsets of such a data volume easily can be routinely transferred across the internet from remote connections to data processing centers. Thus, we expect an automated data decimation workflow - potentially on DAS interrogators themselves - should facilitate the processing and archiving of longer-duration, semi-continuous DAS data sets that are still highly useful for making meaningful ambient waveform observations and undertaking assessments of seasonal variations in the subsurface environment.

4.6 Conclusions

We present a case study that investigates the seasonal subsurface changes observed in a ten-month ambient waveform data set recorded from an urban DAS fiber array located in the urban center of Perth, Australia. The seismic interferometry analysis resulted in time-lapse VSGs that exhibit travelt ime variations in observed wavefield arrivals over the 43-week recording period, with a 5.8% maximum calendar change in the observed surface-wave velocities and 9.4% maximum change of estimated average $V_{S30}$ values from the multichannel analysis of surface waves (MASW) of dispersion curves picked from the time-lapse velocity-dispersion panels. We note that these observations appear to be inversely correlated with increased monthly rainfall totals observed during winter storm periods in the Perth Metro area. Overall, our analysis suggests that ambient waveform data acquired on urban DAS fiber arrays are likely useful for monitoring the seasonal variability of groundwater resources beneath urban centers as well as potentially other time-lapse subsurface behavior occurring over calendar time.

4.7 Author Contribution Statement

The manuscript’s lead and communicating author, Jihyun Yang, contributed the following items to the preparation of the manuscript (with the degree of contribution): conceptualization (equal), data curation (lead), formal analysis (lead), investigation (equal), methodology (equal), software (lead), validation (equal),
visualization (lead), and writing – original draft (lead), writing – review & editing (equal).

The manuscript’s second author, Jeffrey Shragge, contributed to the following items (with the degree of contribution): Conceptualization (equal), formal analysis (equal), funding acquisition (lead), investigation (equal), methodology (equal), project administration (lead), resources (Lead), software (supporting), supervision (lead), validation (equal), visualization (supporting), writing – original draft (supporting), and writing – review & editing (equal).

4.8 Acknowledgments

We thank the Center for Wave Phenomena (CWP) sponsors, whose support made this research possible. The work would not be possible without the support of Colorado School of Mines Wendian HPC cluster resources. We also thank A. Noetzli, N. Issa, and M. Roelens (Terra15) for providing the data set and useful technical suggestions. The reproducible numerical examples and plots in this paper use the Madagascar (www.ahay.org) and Python Matplotlib (matplotlib.org) software packages.

4.9 Data Availability

Data were recorded at Perth by Terra15. Derived data supporting the findings of this study currently are not available due to proprietary considerations.
CHAPTER 5
SEISMIC CHARACTERIZATION OF A SUSPECTED LANDSLIDE COMPLEX: A CASE HISTORY FROM MAJES, PERU

A paper for submission to Environmental Earth Sciences
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5.1 Introduction

Landslides are a pervasive natural hazard involving large mass movements of soil and rocks that can occur even in the presence of minor topography. The social and economic costs of landslides are significant, killing and injuring thousands of people each year and destroying infrastructure such as railways, highways, and tunnels (Guzzetti, 2006; Schuster & Highland, 2001). Most landslides are triggered by rainfall or earthquakes (Lepore et al., 2012; Van Westen et al., 2008); however, an increasing number of cases are induced due to anthropogenic construction (Zhang et al., 2015), mining (Salmi et al., 2017), irrigation (Lacroix et al., 2020), and agricultural reclamation activities (Li et al., 2020). While characterizing sites prone to failure is an important geotechnical and engineering geology research area, site investigations on former landslides are not straightforward considering the structural and stratigraphic changes imparted by landslides on the associated geological materials.

Geophysical investigation methods provide an economical solution for characterizing the subsurface structure of former landslides. Various techniques including seismic, electrical resistivity, and borehole geophysical methods have been shown to be successful at site characterization before the major site diagnosis since the early work of Bogoslovsky & Ogilvy (1977). However, the cost of geophysical site characterization could be high due to the extensive volume of geomaterials involved in a landslide and the often challenging topography and structures induced by these events (Aleotti & Chowdhury, 1999).

The recent development of computation resources, portable sensors like nodal seismometers and distributed acoustic sensing (DAS) that facilitate deployment, and 2D and 3D geophysical imaging and inversion algorithms enable geophysical investigation as an attractive tool, as shown in the increasing number of successful geophysical landslide investigations. Jongmans et al. (1999) apply electrical and seismic tomography to check the rock quality and to detect instability of the slope along railway bedding. Pazzi et al.

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(2017) show that ambient seismic wavefield measurements can be sensitive to landslides and be used to construct landslide geometries. Stucchi et al. (2017) present an SH-wave depth-migrated image that profiles small slip surfaces that delineating minor landslides at shallow depths. Flamme et al. (2022) present an integrated hydrological and geophysical study using electromagnetic and seismic surveys to provide insights into irrigation and landslide management.

Perhaps surprisingly, seismic reflection methods are infrequently used to investigate landslides largely because the associated earth processes usually destroy established stratigraphy (Bichler et al., 2004; Ferrucci et al., 2000; Jongmans & Garambois, 2007), which makes it challenging to both record coherent reflection events in seismic data and therefore use such arrivals to estimate the often complex velocity models. Additionally, acquiring high-resolution seismic data requires high signal-to-noise ratio and sufficiently broadband content, which can be challenging to realize with seismically heterogeneous and attenuative near-surface earth models. Still, seismic methods have the advantage of producing properties such as P- and S-wave velocity that directly depending on mechanical properties, which are important for geotechnical slope stability calculations (Hack, 2000; Uhlemann et al., 2016).

This work investigates what other types of seismic investigations besides traditional reflection methods may offer the high-resolution constraints for which seismic techniques are known. We specifically address this question in the context of recently landslide activities in the Majes area of southern Peru, which are thought to have been caused by irrigation and evolved into a retrogressive failure near key infrastructure. In addition to more standard refracted P-wave first arrivals, we use lower-frequency (2-20 Hz) direct and scattered surface-wave arrivals recorded on vertical-component seismic data for our alternative seismic analysis. In particular, we observe that these surface waves are affected by slower velocities near the cliff face and generate significant backscattering from strong sub-vertical lateral discontinuities that we interpret to be part of the recent landslide complex. Given these surface-wave characteristics, we apply the following sequence of seismic inversion methods: (1) first-arrival seismic refraction tomography for P-wave velocity model building, and (2) low-frequency full-wavefield inversion (FWI) to estimate the near-surface S-wave velocity profiles.

The paper begins with an overview of the geological and hydrological conditions in the Majes area. We provide an overview of the near-surface geology as well as a brief history of irrigation and recent landslide activity. After presenting the 2D seismic data acquisition at the field site, we discuss our implementation of P-wave refraction travel-time tomography for developing starting models for the ensuing elastic full waveform inversion (E-FWI) analysis. We then present our E-FWI results, show comparisons between forward simulated and field data, and present our geological interpretations. We conclude with discussions on the prospective improvement in surface-wave elastic time-reverse imaging strategies, the implications for future landslide analyses, and the importance of follow-on geotechnical analysis.
5.2 Majes Geology and Hydrology

The Majes I region is situated 60 km west of the regional capital Arequipa in an arid, high-altitude desert environment (see Figure 5.1(a)) and is one of Peru’s largest agricultural developments. While meteoric water supply is limited by an average annual rainfall of 17 mm per year (Wei et al., 2021), snow melt from the Andes Mountains rising to the east supplies a significant water source for agricultural irrigation and development through both the adjoining Siguas River valley as well as a system of purpose-built irrigation aqueducts. Overall, the Majes I irrigation project has significantly contributed to the local food supply and created jobs; however, it has also affected the local hydrology and groundwater table and is suspected of contributing to a recent increase in landslide activities in the Siguas River valley (Graber et al., 2020, 2021; Lacroix et al., 2019). In particular, after the onset of the Majes-Siguas irrigation project in 1983, initial water seepage was discovered in 1996 at the slope of the El Zarzal area. Shortly after the appearance of another seepage zone in 2004, the first significant El Zarzal landslide followed in 2005 and failures have continued to occur causing the affected area to rapidly retreat toward the GLORIA dairy facility, agricultural fields, and Carretera Panamericana (Pan-American Highway) (Araujo Huamán et al., 2017; Flamme et al., 2022). Figure 5.1(b) presents a satellite image that shows the locations the El Zarzal landslide, the Pan-American Highway, the GLORIA dairy factory, as well as the particular Majes I 2D seismic survey line discussed below.

Figure 5.1 (a) Geologic model beneath the Pamap de Majes region. Modified from (Flamme et al., 2022). (b) Satellite map of Majes I survey line 1B-C survey line.
The near-surface geology at the Majes I site (see Figure 5.2(a)) consists of poorly consolidated sediments including conglomerates and ignimbritic tuff (Araujo Huamán et al., 2017). The uppermost Millo conglomerate layer has an estimated thickness of 20-30 m and overlies a laterally discontinuous tuff layer of variable thickness. The underlying upper and lower Moquegua formations respectively have estimated thicknesses of 120 m and 80 m, with the upper Moquegua unit comprised of sandstones and limestone gravels and the lower Moquegua containing sandstones and clays. Water from agricultural irrigation likely percolates through the Millo unit and consequently alters the groundwater table, thus potentially contributing to the recurring El Zarzal landslide and potentially other recent events in the vicinity (Graber et al., 2020).

At the area of the current investigation, shown in Figure 5.2(b), recent water seepage is visible in the steep Siguas valley walls located downslope of the 1B-C survey line (orange dots in Figure 5.2(b)). The elevation of the seepage show suggests that the water table resides within the Upper Moquegua formation, which consists is generally competent but may be prone to failure when fully saturated (Flamme et al., 2022).

![Geologic model beneath the Majes 1 region](image1.png)
![Satellite map of Majes I survey line 1B-C](image2.png)

Figure 5.2 a) Geologic model beneath the Majes 1 region; modified from Flamme et al. (2022). (b) Satellite map of Majes I survey line 1B-C. Geophones are denoted as orange dots. The blue tinted area depicts the seepage that occurred after the irrigation.
5.3 Seismic Data Acquisition

A line of 2D seismic data was acquired in June 2022 at the field location as a part of a multi-geophysics acquisition campaign. Figure 5.2(b) presents the acquisition geometry overlain on the satellite map. We used a 96-channel Geometrics Geode system to acquire seismic data with 14 Hz vertical-component geophones and a PEG-40 accelerated weight-drop source; geophone and source intervals were set at 5 m and 10 m, respectively. The end of the geophone line and shot points were located as close to the slope as possible while following reasonable safety considerations regarding slope stability (to the southeast of Figure 5.2(b)). The sampling rate for the recorded data was $\Delta t = 0.5$ ms with a total recording time of $T = 1.0$ s for each recorded shot gather. Figure 5.3 presents two examples of 2-20 Hz bandpassed shot gathers in which direct surface-wave energy is clearly dominant. We note significant backscattered energy originating around 90 m offset as well as significantly slower direct surface-wave moveouts between 0-90 m when compared to those between 90-320 m. Most other shot gathers show consistent direct-wave slowdowns and backscattered energy. Overall, these observations suggest the presence of a strongly laterally heterogeneous velocity structure.
Figure 5.3 Example of 2-20 Hz bandpassed shot gathers excited at (a) 195 m and (b) 235 m. Both panels exhibit a dominant direct surface wave that has backscattered energy originating at 90 m distance and significantly slower propagation between 0-90 m.

5.4 P-wave Refraction Travel-time Tomography

Body-wave refraction travel-time tomography is an efficient though low-order method for generating smooth subsurface velocity models based on a picked refraction travel-time data set. These algorithms estimate velocity models by iteratively minimizing the difference between the observed travel times and those forward modeled through a synthetic earth model using a ray-tracing algorithm. The inversion step commonly involves solving a linearized inverse problem, commonly using a numerical optimization approach (e.g., Gauss-Newton or nonlinear conjugate gradients).
The travel time $t_i(s,r)$ between a source $s$ and a receiver $r$ station (corresponding to travel-time index $i$) along the raypath can be computed by the summation of the travel times of the individual segments:

$$t_i(r,s) = \sum_{k=1}^{n} \frac{r_k}{v_k},$$

(5.1)

where $r_k$ and $v_k$ are the path length and velocity of the $k$th segment, and $n$ is the number of segments in any given raypath.

Following Ronczka et al. (2017), we formulate the linearized inverse problem to obtain model parameters from travel times according to

$$J\Delta m = \Delta d = d - f(m),$$

(5.2)

where $J$ is the Jacobian matrix of the travel times with respect to model parameters (i.e., $\partial t_i / \partial m_j$ where $i$ is a ray index and $j$ is grid node index); $m$ is the array of velocity model parameters $v_i$; $f(m)$ is the forward modeling operator; and $d$ is the array of observed travel times $t_i(r,s)$. Here, we use the shortest path method (Moser, 1991) with secondary nodes (Giroux & Larouche, 2013), which computes the fastest travel-time path from source to a receiver across a specified mesh.

The seismic refraction tomography inverse problem can be solved by minimizing a regularized (i.e., smoothness-constrained) objective function $E_{tt}$ (Ronczka et al., 2017):

$$E_{tt} = E_d + \lambda E_m = W\Delta d + \lambda \|Cm\|^2_2,$$

(5.3)

where $E_d$ is the weighted data misfit; $E_m$ is the model roughness; $W$ is a diagonal weight matrix based on the uncertainty of travel-time picks; $\lambda$ is the regularization trade-off parameters; and $C$ is a derivative matrix used to calculate the model roughness. Herein, the objective function in equation 5.3 is minimized using a generalized Gauss-Newton method.

We use the open-source pyGIMLi refraction travel-time tomography software (Rücker et al., 2017) with the Python-based Refrapy GUI wrapper (Guedes et al., 2022) for both picking P-wave first-arrival refraction travel times and solving the inverse problem. The pyGIMLi framework has been successfully applied in several recent geophysical investigations (e.g., Mollaret et al., 2020). We input our P-wave first arrival picks from 16 gathers separated by a 30 m shot interval into the pyGIMLi refraction tomography package. We use a starting model with initial values of $V_{min} = 500$ m/s at the surface and linearly increasing to $V_{max} = 1200$ m/s at the 70 m model base. We set allowable velocity bounds at 300 m/s and 2000 m/s, and use a $\lambda = 1000$ to bias the inversion toward a smoother model rather than over-fitting somewhat noisy P-wave refracted-arrival travel-time picks.

Figure 5.4 presents the estimated P-wave velocity model with a calculated relative RMS error of 5.6% after 20 iterations. The model exhibits significantly slower P-wave velocities in the top 15 m between
0-120 m horizontal distance. However, because of the limited resolution afforded by ray-based tomography, these results are largely used as a starting model for the ensuing E-FWI analysis rather than a final interpretation model.

Figure 5.4 Results of applying P-wave travel-time tomography, where the steep topography and Siguas River valley are located to the left of 0 m. Note the significantly slower $V_P$ between 0-120 m horizontal distance in the top 20 m.

5.5 Elastic Full Waveform Inversion

Full waveform inversion is a commonly applied method to recover a subsurface velocity model by setting up an optimization problem based on the “goodness of fit” between forward-modeled synthetic data and the observed field seismograms (Virieux & Operto, 2009). Because FWI has the potential for producing higher-resolution models than ray-based tomography (Robein, 2010; Schuster, 2017), we expect to build a more detailed and higher-resolution velocity model after applying FWI. However, because we use 2-20 Hz surface-wave data in our FWI analysis, it is necessary that undertake an (isotropic) elastic FWI (E-FWI) analysis so as to enable forward modeling of this wave type.

We forward model seismic data by solving the 2D Cartesian isotropic elastic wave equation in a displacement-stress formulation. This involves iteratively solving two first-order system of equations: conservation of linear momentum

$$\rho \frac{\partial^2 u_i}{\partial t^2} = \frac{\partial \sigma_{ij}}{\partial x_j} + f_i,$$  \hspace{1cm} (5.4)

and the isotropic Hooke’s Law of elasticity

$$\rho \frac{\partial \sigma_{xx}}{\partial t} = (\lambda + 2\mu) \frac{\partial u_x}{\partial x} + \lambda \frac{\partial u_z}{\partial z} + s_{xx},$$  \hspace{1cm} (5.5)

$$\rho \frac{\partial \sigma_{zz}}{\partial t} = \mu \left( \frac{\partial u_z}{\partial z} + \frac{\partial u_x}{\partial x} \right) + s_{zz},$$  \hspace{1cm} (5.6)

$$\rho \frac{\partial \sigma_{zz}}{\partial t} = (\lambda + 2\mu) \frac{\partial u_z}{\partial z} + \lambda \frac{\partial u_x}{\partial x} + s_{zz},$$  \hspace{1cm} (5.7)
where $\rho, \lambda,$ and $\mu$ are the density and two isotropic Lamé parameters; $u_i$ represents particle displacement components; $\sigma_{ij}$ is the stress tensor; and $f_i$ and $s_{ij}$ are the force density and stress source terms, respectively.

We set up the numerical simulation grid with the spatial and temporal sampling intervals of $\Delta x = \Delta z = 1.0$ m and $\Delta t = 5 \times 10^{-5}$ s, respectively. We enforce the free-surface boundary condition on the top face and apply a ten-point perfectly matched layer (PML) boundary condition (Komatitsch & Martin, 2007) on the left, right and bottom model faces. The overall dimensions of the model are $350 \times 72$ grid points.

We formulate the E-FWI problem to minimize commonly used $L_2$ norm data misfit (Gélis et al., 2007; Sears et al., 2008; Virieux & Operto, 2009):

$$E_{E-FWI} = \frac{1}{2} \sum_{N_S} \sum_{N_R} \int_0^T \| \Delta d(s, r, t) \|^2 dt,$$

where $\Delta d = d_{obs} - d_{mod}$ is the data residual vector representing the difference between the observed and forward modeled data; and $N_S$ and $N_R$ are the number of source and receiver points, respectively. Through the rest of this work we denote the $L_2$ norm data misfit $E_{E-FWI}$ as simply $E$. To estimate the velocity model that minimizes the objective function in equation 5.10, we apply the adjoint-state method to define the gradient with respect to the model parameters

$$\delta m'(X) = \frac{\partial E}{\partial m} = \sum_{N_S} \int_0^T \sum_{N_R} \left[ \frac{\partial u}{\partial m} \right]^* \partial u^i dt,$$

where $\left[ \frac{\partial u}{\partial m} \right]^*$ is the Frechét derivative; and $\partial u^i$ is the adjoint wavefield variable reconstructed by injecting and backpropagating information in the data residual vector $\Delta d$. It is possible to estimate the gradient with respect to the target S-wave velocity model parameter using the Frechét derivative, as has been shown in classical work in 2-D elastic scattered wavefield inversion (Mora, 1988; Tromp et al., 2005; Virieux & Operto, 2009).

We use velocity-density ($V_p, V_s, \rho$) E-FWI parameterization shown by Köhn et al. (2012) to provide more accurate inversion results with fewer artifacts than Lamé ($\lambda, \mu, \rho$) or seismic impedance ($I_p, I_s, \rho$) formulations. We then can use the estimated S-wave gradient at each iteration to update the S-wave velocity model $V_S$ using the steepest-descent formula

$$V_{S, k+1} = V_{S, k} - \alpha \frac{\partial E}{\partial V_S} = V_{S, k} - \alpha \Delta V_S,$$

where $\alpha$ is the calculated step length using parabolic fitting method (Métévier et al., 2014; Nocedal & Wright, 2006); the $k$ superscripts indicate iteration number; and $\Delta V_S$ is the estimated gradient vector.
5.5.1 2-D E-FWI on Majes I field data

We now apply the above E-FWI framework to reconstruct a high-resolution S-wave velocity model for the Majes I 1B-C data set. The Majes 1B-C seismic survey line is one of many acquired in the Majes I region. This line starts at 1B in an agricultural field and ends at 1C at the cliff. We initially updated the $V_S$ model parameter with a global optimization approach that used all frequencies simultaneously in the 2-20 Hz range; however, we observed that the data-difference misfit function suffered from local-minima issues (Hu et al., 2018; Virieux & Operto, 2009) and did not converge as expected. To mitigate this local minima problem, we adopted a multiscale approach (Bunks et al., 1995) by which we increased the maximum frequency of the data sequentially from 2 Hz to 20 Hz (i.e., covering the dominant surface-wave frequency band). After conducting a number of tests, we split the inversion process into four frequency sub-bands: 2-7 Hz, 2-12 Hz, 2-17 Hz, and 2-20 Hz.

We used a first-derivative Gaussian wavelet with a center frequency of 20 Hz bandpassed between 2-20 Hz as our source wavelet to better match the modeled frequency content to the dominant field-data frequency band. To improve the phase matching between observed and modeled waveforms, we applied a source-wavelet correction filter estimated through linearly damped least-squares optimization (Groos et al., 2014). This source-estimation approach approximated a wavelet appropriate for each frequency sub-band.

To build an isotropic E-FWI starting model, we use a smoothed version of the P-wave velocity model obtained from refraction travel-time tomography (Figure 5.5(a)) and then approximated the S-wave velocity model (Figure 5.5(b)) by assuming a Poisson solid (i.e., $V_S = V_P/\sqrt{3}$). We held the homogeneous density model constant during the inversion due to a lack of a priori information on this parameter.
To investigate the convergence of E-FWI, we present in Figure 5.6 the relative errors of models with iterations. According to Figure 5.6, E-FWI converges approximately at 45 iterations. Due to the multiscale approach, the error curve exhibits a staircase-like structure, as the loss decreases quickly at the beginning of each frequency sub-band.

![Figure 5.6 Normalized objective function for E-FWI iteration.](image)

We first show synthetic data generated through from the final estimated E-FWI model in gray scale in Figure 5.7 and overlay the observed data in wiggle-plot format. This representation facilitates comparison between the observed and forward modeled synthetic data, and is a visual representation of the differences that the E-FWI framework aims to minimize through model updating. Figure 5.7(a) and Figure 5.7(b)
respectively present overlay plots of shot gathers acquired at 215 m and 255 m. Both panels show coherent waveforms as direct and backscattered surface waves at locations throughout the panels.

Figure 5.7 Overlay of forward-model data (gray scale) and observed seismic waveforms (wiggle-trace plot) for shot gathers located at (a) 215 m and (b) 255 m horizontal distance.

Figure 5.8(a) presents the resulting estimated $V_S$ model from the E-FWI inversion, which has updated significantly from the initial tomographic model. Between 130 m and 350 m horizontal distance, we observe that the estimated $V_S$ model exhibits largely vertically dominant 1-D structure. Moving downward from the surface, we interpret a 6-8 m thick layer with average $V_S$ velocity of 550 m/s overlying a 6-8 m thick layer with average $V_S$ velocity of 350 m/s; these two layers likely are associated with the Millo formation. At approximately 16-18 m depth, we note a significant $V_S$ increase to about 700 m/s, which may be associated with a tuff layer and/or the upper Moquegua formations. Using these observation, we divide the estimated $V_S$ model into layers by black dashed lines, representing the potential interfaces between the layers (see Figure 5.8(b)).
Figure 5.8 (a) The E-FWI estimated $V_S$ model and (b) associated overlain interpretations. Between 130 m and 350 m horizontal distance, the estimated model is mostly 1D with a 6-8 m layer with an average velocity of $V_S$=550 m/s overlaying a 6-8 m layer with a 350 m/s velocity. The $V_S$ model shows significant differences at horizontal distances of 0-130 m. From the surface to 20 m depth, the estimated $V_S$ model is slower at 250-400 m/s, suggesting reduced shear modulus values with potentially less compacted and poorly sorted conglomerate materials. The inverted $V_S$ model between 70-120 m appears to have both stronger and shorter-wavelength heterogeneity.

Between 0 m and 130 m horizontal distance, though, the estimated $V_S$ model is significantly different than that from 130 m to the end of the survey line. We observe significantly slower $V_S$ values between 250 m/s and 400 m/s from the surface down to 20 m depth. We note that careful consideration should be given to the challenges of geological and geotechnical interpretations of geophysical imaging and interpretation results. Here, we interpret the lateral variability of the observed velocity changes (and associated reductions in shear moduli) are consistent with what would be expected in a former landslide complex zone characterized by less compacted and more poorly sorted conglomerate materials. The character of the inverted $V_S$ model between 75-100 m distance also appears to exhibit stronger and short-wavelength heterogeneity. At depths greater than 20 m, though, the $V_S$ values increase and approach those observed at these depths elsewhere in the 2-D S-wave velocity section, suggesting a possible base of suspected landslide activity. However, additional geotechnical investigation would be required to confirm these interpretations and determine the underlying causes and mechanisms that may have triggered the suspected landslide.
5.6 Discussion

This study illustrates that the combination of P-wave refraction travel-time tomography and elastic full-waveform inversion (E-FWI) can provide valuable subsurface constraints for seismic characterization of former landslide complexes. Combining different geophysical techniques for studying landslide environments is known to be useful for improved characterization (Grandjean et al., 2011); thus, we expect that integrating these results with, e.g., DC resistivity would more effectively constrain hydrogeophysical factors such as changes in water table depth (Flamme et al., 2022) and provide a more complete calibration and thorough investigation of this former landslide complex.

Given the high-quality backscattered surface-wave arrivals, it may be possible to develop an elastic time-reverse imaging (TRI) algorithm that could generate images of the discontinuities generating the scattered surface-wave energy. Ideally, these could be used to directly detect former failure surfaces and/or other sub-vertical velocity discontinuities associated with the landslide activities.

Successfully applying near-surface geophysical methods on former landslides remains challenging because these energetic events are affected by a wide variety of geologic, topographic, and hydrologic factors. While the deployment of additional sensors would require extra effort under strongly variable topography, we expect that multi-component geophones (2C or 3C) or an alternative sensing system such as distributed acoustic sensing (DAS) could improve the results present herein. Furthermore, DAS would enable cost-effective solutions for survey design. In addition, the dense temporal and spatial spacing afforded by DAS may provide higher-resolution characterization of sub-vertical velocity heterogeneity.

While seismic inversion provides velocity models for estimating shear moduli, identifying the underlying causes and failure mechanisms of suspected landslides remains challenging because mapping shear-modulus observations to actual soil strength is not a straightforward task. There is a large body of geotechnical research into mapping landslide vulnerability and investigating landslide mechanisms. For example, additional stability analysis of the failure stage can reveal the failure mechanisms and the mass movement, which can be used to classify landslide type (e.g., rotational or flow landslides). Thus, a supplemental follow-up study by geotechnical specialists is recommended for more a complete characterization of the suspected landslide complex.

5.7 Conclusions

We present a combination of seismic inversion methods to characterize a suspected recent landslide complex using vertical-component geophone seismic data acquired at a field site in Majes, Peru. The observed seismic waveforms in the sub-20-Hz frequency band are dominated by direct surface-wave arrivals, which exhibit significant lateral velocity variations and backscattered energy from points located along the
line. We use P-wave refraction first-arrival picks to build a starting P-wave velocity tomography model and employ this result in an elastic full-waveform inversion (E-FWI) analysis to construct final high-resolution models. We show that the final S-wave velocity model is significantly updated using surface-wave energy dominant in the 2-20 Hz frequency band. The resulting E-FWI $V_S$ model exhibits characteristics that match former geologic studies at this site and generate forward-modeled wavefields that have a sufficient waveform fitting with field data. At distances greater than 120 m from the cliff-face, our results reveal an earth model exhibiting vertically dominated 1-D velocity structure; however, at closer distances we observe 2-D velocity structure, significantly slower $V_S$ values in the top 20 m, and isolated velocity heterogeneity. While these observations are consistent with those expected in a recent landslide complex, we stress the need for follow-on geotechnical analysis to confirm these assertions. Overall, we expect this combined seismic inversion toolkit would be helpful for future (suspected) landslide characterization projects, though perhaps augmented with complementary geophysical analyses (e.g., DC resistivity) that would be more sensitive to hydro-geophysical properties associated with potentially groundwater-driven landslide activity.

5.8 Acknowledgements

We thank the sponsors of the Mines Center for Wave Phenomena (CWP), whose support made this research possible. We acknowledge the support of the CSM CIARC HPC group and the use of the CSM Wendian Cluster resources. The reproducible numerical examples and plots in this paper use the Madagascar (www.ahay.org) and Python-based Matplotlib software packages.
CHAPTER 6
CONCLUSIONS AND FUTURE WORK

This thesis investigates the potential for, and challenges of, horizontal deployments of dense seismic sensors for near-surface characterization. I mainly focus on distributed acoustic sensing (DAS), one of the emerging dense seismic sensors, by integrating ambient seismic interferometry, surface-wave inversion, and geophysical digital signal processing filtering techniques. These analyses are made possible due to the high spatial and temporal sampling capabilities of DAS interrogators as well as the improved sensitivity of the DAS acquisition system response to sub-3-Hz frequencies compared to that of standard (e.g., 4.5-Hz) geophones and seismographs. Accordingly, this thesis presents work that examines the opportunities and limitations of acquiring and using ambient signals using horizontal dark-fiber deployments, as well as the accompanying challenges of including crooked fiber geometry, handling amplitude variations in cross-correlations, and deployment directionality as DAS measures only fiber elongation along its length.

Chapter 2 presents a case study using low-frequency ambient wavefield DAS data acquired on a dark-fiber loop located in Perth, Western Australia. Our research collaborators opportunistically acquired DAS data during a significant winter storm during which storm-induced microseism energy produced at the nearby Indian Ocean shelf break and/or shoreline was clearly evident in the DAS recordings in a low-frequency range (0.04-1.80 Hz). After low-pass filtering (sub-2 Hz) and denoising raw data panels, the generated cross-coherence virtual shot-gather (VSG) volumes exhibit distinct surface-wave energy to frequencies as low as 0.1 Hz. I use VSG stacks of several hours to generate velocity-dispersion curves that are input to a multichannel analysis of surface waves (MASW) to develop depth constraints on the S-wave velocity model. Real and simulated data tests indicate that inversion of low-frequency ambient signals recorded on DAS systems can constrain shear-wave velocity profiles to depths of 0.5 km or greater.

While these results might encourage some researchers to apply full-waveform inversion to data acquired on dark fiber, our research shows that methods requiring high amplitude fidelity of the observed data in any amplitude-matching inversion schemes will encounter challenges due to the numerous factors affecting array sensitivity and measured DAS amplitudes (e.g., source type, gauge length, fiber orientation). Pre-installed dark fiber commonly exhibits crooked acquisition geometry that results in highly variable fiber orientation and associated amplitude sensitivity. Even for conventional linear fiber deployments, DAS represents a directional single-component sensor, which results in limited usable angles of strain-rate DAS. Consequently, horizontal DAS predominately records surface-wave energy with fewer reflected body waves that limit the scope of seismic applications on horizontal fibers. A further complication is that conventional DAS
interrogator units (IUs) are commonly designed to acquire data in a strain-rate format; however, the native measurement format depends on the specific IU optical design. The strain-rate data format suffers from reduced broadside sensitivity to compressional body waves (i.e., \( \cos^2 \theta \) sensitivity pattern where \( \theta \) is angle of incidence) compared to the standard geophone response (\( \cos \theta \)).

Chapter 3 presents DAS data recorded from the Terra15 deformation-rate native Treble IU as well as a different filtering philosophy and strategies that are enabled by a deformation-rate acquisition format. Under near-elastic ground-fiber coupling, the Treble IU acquires usable deformation-rate data that exhibits a geophone-like \( \cos \theta \) sensitivity pattern. To illustrate these potential benefits, this chapter reports the results of an investigation designed to achieve near-elastic DAS fiber-ground coupling by freezing a horizontally deployed fiber in the shallow back-filled trench. For comparison, three fiber sections are used: one directly laid on the ground and the other two placed at different trench depths. Converting deformation-rate data to an effective strain-rate quantity is straightforward to achieve by applying a low-order 1-D spatial derivative filter. Motivated by this observation, I examine other higher-order filtering strategies known to produce more accurate results. I compare 1-D finite and infinite impulse response (FIR and IIR) filters of different orders and 2-D velocity-dip filtering. I show that the latter approach leads to filtered data that exhibit improved data quality, as illustrated by more clearly visible refracted and surface-wave arrivals. Conversely, DAS data recorded on fiber simply laid on the bare ground exhibits degraded signal quality and time-varying effects from variable ground-fiber coupling, likely due to diurnal air-temperature fluctuations. This work suggests the potential usability of filtered deformation-rate DAS data under improved ground-fiber coupling enabled by the trenching and freezing operations, which would allow acquired deformation-rate DAS data to be considered as a “filtered deformation-rate” instead of an “effective strain-rate” format.

Chapter 4 presents a case study, using an existing telecommunication dark-fiber array located in the central business district of Perth, Australia, to demonstrate that DAS is an attractive option for long-term geophysical monitoring projects. Because DAS acquires high-density data with temporally and spatially finer sampling rates than conventional nodal sensors, the longer duration of time-lapse studies motivates investigation of novel data storage and processing solutions. These challenges, as well as a general lack of continuous availability of instruments over many months, have led to less work being completed on tracking seasonal variations using ambient DAS methodologies. This chapter presents a case study that analyzes the computationally tractable strategy of semi-continuous DAS data, whereby short duration (150 s) data are recorded every hour for ten months. This ambient data acquisition strategy allows for a time-lapse experiment to investigate the seasonality of the observed ambient waveforms as well as any subsurface velocity variations that may be revealed through data analysis.
I use a cross-coherence analysis to convert preprocessed ambient waveform data into weekly interferometric sliding-window VSGs. Examining the weekly stacked interferometric time-lapse VSGs in multiple fixed source-receiver offsets reveals that the surface-wave traveltime for a fixed source-receiver offsets varies by a maximum of 6% over the ten-month period. I then use the computed ambient VSG data volume to estimate time-lapse velocity-dispersion panels, which are used in a MASW to generate depth-averaged S-wave velocity estimates for the top 30 m \( (V_{S30}) \). The ensuing surface-wave inversions show coherent 10% maximum changes of \( V_{S30} \) over the ten-month period (though with greater uncertainty), where windows of most significant slowdown overlap with periods of heavy rainfall in the Perth metro area. Our empirical results suggest a positive correlation between increasing rainfall and an average \( V_{S30} \) slowdown, which is consistent with previous research from Honshu, Japan that reports similar observations of reduced surface-wave velocities in interferometric VSGs during and after periods of significant rainfall events.

Chapter 5 investigates the feasibility of using seismic data acquired on a dense geophone array to undertake seismic velocity model building and elastic full waveform inversion (E-FWI) analyses for the purpose of examining a previously failed landslide complex located in the Majes, Arequipa, Peru. This region is located in the high desert of southern Peru and has had extensive agricultural expansion and irrigation, which have demonstrably affected the local hydrology and groundwater table and are suspected of causing an increase in landslide activities that threaten local infrastructure.

To better geologically characterize this Majes site, I apply seismic inversion to better understand the geology of a suspected landslide complex. The acquired sub-20-Hz geophone data are dominated by surface-wave arrivals that exhibit significant lateral velocity variations and backscattered energy from a point located at 90 m along the line. I first use observed P-wave refraction picks to estimate a velocity model through seismic travel-time tomography. This model is then used for an elastic FWI analysis on the sub-20 Hz surface-wave data to build final high-resolution velocity models. The credibility of the inverted S-wave velocity model results is demonstrated through the quality of waveform fitting, the overall reduction of data misfit, and the overall consistency with previously reported Majes geology research. The final FWI inversion results exhibit significant updates in the \( V_S \) model when compared to the initial model. At distances more than 120 m from the cliff the \( V_S \) model shows a primarily 1-D layered structure, with a velocity reversal between 5 m and 15 m depth. However, the \( V_S \) model at distances closer to the cliff shows significant variability with the uppermost low-velocity anomaly having an approximately 20 m thickness and \( V_S \) values ranging between 260 m/s and 400 m/s. In addition, the observed significant surface-wave backscattering is likely to be caused by a strong, sub-vertical velocity discontinuity at 90 m distance along the line. Validating the underlying causes and processes that led to these observations (i.e., a suspected former landslide), though, requires additional geotechnical investigation that goes beyond the scope of this thesis.
6.1 Future Work

As demonstrated in this dissertation, dense seismic acquisition, a focus on DAS applications, and in particular surface waves recorded by horizontal deployments of DAS systems, provide a wide range of possibilities for near-surface characterization, ranging from constraining velocity models to tracking calendar variations in the subsurface S-wave velocity profiles. Here, I summarize several suggestions that arise for follow-up studies and possible directions for future research.

6.1.1 Chapter 2

Horizontal DAS datasets are difficult to employ with imaging and inversion methods that require high amplitude fidelity and may be affected by the fiber-orientation-induced sensitivity variations to incoming wave modes. Thus, the analyses discussed in this chapter have been limited to 1.5 D surface-wave inversion through MASW. To better handle the amplitude variation of interferometric analysis of horizontal DAS arrays and generate models of greater dimensionality, I recommended using imaging methods with reduced amplitude fidelity requirements compared to that of waveform-based inversion methods. For example, 2-D or 3-D image-domain (rather than data-domain) velocity inversions could use horizontal DAS VSGs depending on the acquisition geometry. Surface-wave travel-time tomography also could offer an imaging solution with reduced amplitude fidelity requirements and computational cost than full waveform inversion methods.

6.1.2 Chapter 3

My research on applying more advanced filtering algorithms to deformation-rate DAS data suggests that one can improve the angular sensitivity and allow horizontal fiber deployments to better capture body-wave arrivals at higher incident angles. This observation could lead to greater use of algorithms for body-wave imaging and inversion (e.g., seismic reflection waveform tomography). In addition, although near ground-fiber coupling can be achieved by freezing fiber in trenches, wavefields measured from fiber simply laid on the ground exhibit variations that are unlikely to be caused by actual subsurface changes. Because wavefields measured from fiber laid on the ground exhibit variations that are unlikely to be caused by actual subsurface changes, it is recommended to design an experiment that simultaneously measures strain and temperature by employing DAS and distributed temperature sensing (DTS) concurrently or using distributed vibration and temperature sensors (DVTS).

6.1.3 Chapter 4

While semi-continuous DAS acquisition has showed significant promise for ambient seismic investigation of calendar variations in subsurface properties, additional work is required for overcoming DAS data storage
constraints. In particular, I am advocating for the use of advanced data compression methods and state-of-art storage systems enable the longer duration of data to be preserved. For example, one could consider applying lossless file compression algorithms like Zstandard (ZSTD). For the specific case of DAS-based hydro-geophysical monitoring of subsurface velocity variations due to rainfall, I suggest a follow-on study that incorporates direct comparison with groundwater or aquifer level measurements for independent validation purposes.

6.1.4 Chapter 5

The research presented in this chapter points to several potentially interesting research directions that could extend this type of seismic imaging and inversion analysis to landslide or other geotechnical applications. First, to generate sharper images to identify discontinuities, one could develop and apply a surface-wave time-reverse imaging (TRI) method that could generate images capable of identifying former landslide failure surfaces and the locations of subsurface scattering points. By separating direct and backscattered waves, the TRI method can be utilized to pinpoint the scattering location as shown in related microseismic applications. Second, one could leveraging the advantages of DAS technology (e.g., ease of deployment, dense sampling) and surface-wave analysis at this and other sites to improve subsurface seismic characterization. Third, seismic landslide characterization would be more accurate and complete when combined other complementary geophysical techniques. In particular, electrical methods such as DC resistivity would be sensitive to variable hydrogeophysical parameters such as spatial changes in water table depth. The proposed combined multiphysics geophysical imaging toolbox could yield high-resolution near-surface images for infrastructure health monitoring in related geotechnical and civil engineering domains (e.g., dams and tunnels). Finally, established geotechnical data analysis techniques could be used to more fully determine the underlying cause(s), failure stage(s), and mass movement(s) associated with the suspected landslide activity. It is recommended to work jointly with geotechnical experts on a follow-up study to better understand the root causes and associated future risks posed by the landslide activity in the Majes area.
REFERENCES


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