An Exploration Of Passive Seismology: Applying Seismic Methods For Traditional And Exotic Source Characterization

David Lewis Guenaga

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AN EXPLORATION OF PASSIVE SEISMOLOGY: APPLYING SEISMIC METHODS FOR TRADITIONAL AND EXOTIC SOURCE CHARACTERIZATION

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Dedication

I dedicate this work to my current and future family. To my children, grandchildren, and the future generations that may come, the thought of you motivated me throughout my education.
AN EXPLORATION OF PASSIVE SEISMOLOGY: APPLYING SEISMIC METHODS FOR TRADITIONAL AND EXOTIC SOURCE CHARACTERIZATION

by

DAVID L. GUENAGA, M.S.

DISSENTATION

Presented to the Faculty of the Graduate School of
The University of Texas at El Paso
in Partial Fulfillment
of the Requirements
for the Degree of

DOCTOR OF PHILOSOPHY

Department of Earth, Environmental and Resource Sciences
THE UNIVERSITY OF TEXAS AT EL PASO
August 2021
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My academic triumph is not one of sole self-reliance, and I would like to give special thanks to those that played a crucial role in my success. Foremost, I cannot deny the support accompanied by my beliefs. I thank God Almighty for the answered prayers, blessings, and guidance provided in my academic pursuit. With that said, I would like to begin by recognizing those individuals who directly and significantly influenced my academic capacity, conviction, and progression.

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Abstract

As seismology continues to develop both theoretical and observational, so does its ability to be used in various applications. In this dissertation, I develop and apply new approaches to five distinct projects (chapters 2-6), leveraging large and small high-quality targeted datasets to decipher fundamental and applied processes utilizing the full seismic wavefield. The first chapter introduces this dissertation by providing broad context, continuity, and technical information about each of the five projects. Specifically, chapter 2 explores a seismic sensor’s ability to detect opera in Oak Ridge National Laboratory, TN, using a misfit power spectral density detector. Chapter 3 outlines work showing 42 of 46 seismic stations (located within 50 m from a U.S. campus) detecting a drop of anthropogenic seismic energy following the COVID-19 statewide school closures. Chapters 2 and 3 reiterate published work and can be found verbatim in their respective journals. Chapter 4 explores dynamic earthquake triggering in the Utah region occurring from 2000-2017, which proves to be limited besides the striking cases of extensive triggering caused by the 2004 Denali Fault, Alaska earthquake. Chapter 5 summarizes the potential dynamic earthquake triggering in Oklahoma from 2010-2016, revealing that dynamic triggering occurs along the regions with gas and oil well activity. Finally, chapter 6 outlines preliminary explorational work on Japanese seismic noise for 2011 using +100 TB worth of seismic data provided by 797 seismic stations from the High Sensitivity Seismograph Network in Japan. Initial results show a limited correlation between ecoregions and power spectral density noise makeup using a k-means analysis.
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Chapter 1: Dissertation Introduction

Dissertation Theme

This dissertation serves as a compilation of work that began in traditional earthquake seismological analysis and evolved into forensic seismology. As seismologists, we fundamentally study vibrations; regardless of the source, if it “shakes” we can record the vibrations as a waveform (capturing the disturbance along a direction of motion). For example, Figure 1.1 shows six seismic waveform records created by distinctly different sources. My doctoral work epitomizes this actuality in seismology. Although this work all relies on the same fundamental understanding of seismic waveforms, they are applied to various sources (i.e., earthquakes, industrial operations, environmental activity, etc.). The Chapters are distinct and serve as individual studies (some of which are published and/or are in review).

The dissertation itself contains five separate works (i.e., research projects). This first chapter provides some general context and background information for the following five chapters: (1) Chapter 2 examines vibrations created by operations linked to or conducted at a nuclear reactor. (2) In Chapter 3, we project frequency-domain data into the time-domain to detect ambient seismic energy drops, related to changes in anthropogenic activity, at schools in the U.S. following the COVID-19 lockdowns. (3) Chapter 4 outlines work and results of an earthquake analysis in the Utah, U.S. region. Specifically, examining the occurrence of dynamically triggered earthquakes (i.e., earthquakes cause by the arrival of seismic waves from another larger earthquake). (4) In Chapter 5 we examine the occurrence of dynamic triggering the Oklahoma, U.S. region. (5) Finally, in Chapter 6 provide the preliminary results for a study of Japan's regional ambient seismic noise.
The commonality between these works is not only the nature of the data used (i.e., seismic), but also the signal processing methods employed. As illustrated by Figure 1.1, seismic instruments can capture any relatively significant vibration—from large earthquake (Figure 1.1a) to people cheering at a football stadium (Figure 1.1e). The “squiggle” (or waveform) describes the ground motion along one direction. With this record, seismologist can interpret information about the seismic source and the medium from which the wave travels through. To discriminate between sources, we make an initial assumption that signal is relatively consistent for similar sources and unique from other sources (e.g., an explosion will produce a signal distinguishable from an earthquake). Sometimes to view these differences, we project data in the frequency domain. This is done to help reveal patterns from a different perspective and simplify certain calculations in signal processing (e.g., signal convolutions). Given that we do not lose information in Fourier transform (used to represent data between time and frequency domains) as defined by Parseval’s theorem (Parseval des Chenes 1806), we readily alternate between the domains to analyze the data more efficiently throughout these chapters.

For example, in the time domain, we can readily isolate signal duration and occurrence; in the frequency domain, we can more easily isolate the rate at which signals occur (i.e., the frequency makeup). Figure 1.2 provides an example showing the acoustic signal from two musical (piano) key sounds in the time and frequency domain to conceptualize this better. We can observe the musical note duration and instance by the abrupt amplitude change in the acoustic signal in the time-domain representation. However, the shape of the two sounds is nearly indistinguishable at the scale plotted. In contrast, the frequency domain is excellent for showing differences in how a musical note sounds (e.g., see the spectrograms at the bottom of Figure 1.2). Note the different patterns highlighted between the two signals. We use these
representations to seismically detect and characterize the phenomena of interest throughout the following chapters.

Furthermore, we utilize digital filtering to remove unwanted signals to reveal seismic trends and isolate frequency-dependent characteristics. We apply these signal processing methods throughout the studies described here; however, the intent and application vary. Perhaps the most evident example of this difference is between chapters 4 (or 5) and 6; in Chapter 4, we attempt to isolate earthquakes (removing the background noise) in the waveform data, while in Chapter 6, we isolate ambient noise signals (removing large events such as earthquakes).

Seismologists generally make an important expectation during this analysis—that the “squiggle” (or waveform) is unique, to the source type, to some significantly measurable degree. In dynamic triggering, we expect triggered events to be smaller (i.e., lower amplitude) and exist predominantly at higher frequencies than the inciting earthquake (Velasco et al. 2008). Earthquakes themselves usually manifest with predictable phases (i.e., wave packets); for an example of earthquake phases, see Figure 1.1a. These differences allow us to distinguish between the inciting earthquake, the triggered earthquakes, and other events (e.g., regional earthquakes). Thus, we can manipulate the waveform with signal processing to reveal or amplify specific signals (e.g., using frequency domain filters).

**Evolution of the Projects and Science Development**

The subsequent chapters of this dissertation outline all major projects that I contributed to or conducted during my tenure as a Ph.D. student; however, here I highlight how these projects evolved and how the chapters are linked as I continue developing into the scientist I am today. When I started at the University of Texas at El Paso (UTEP), I found myself proficient in applying the science learned in class into code. Thus, my graduate advisor, Dr. Aaron A.
Velasco, supplemented me with the intricacies of seismology and the methods used therein, especially digital signal processing (DSP). Whether it be to plot waveforms or utilize convolutions to accelerate sequential computations, there are elements of DSP in all my projects (e.g., convolving, correlating, and conducting Fourier transformations). Furthermore, I learned new specialty software, more programming languages (e.g., Python, Generic Mapping Tools, and Seismic Analysis Code) while developing code to serve my academic research. My advisor’s connection in government lead seismology allowed me to have the opportunity to adopt a less traditional approach to my education. As such, the doctoral research projects described in this dissertation differ in focus but utilize the same fundamental seismology and DSP methods.

Traditional seismology relies heavily on the physics involved in an earthquake’s occurrence and the seismic waves created. Thus, I carried over my M.S. thesis work related to the triggered earthquakes in Utah to my Ph.D. (Chapter 4). This work was expanded upon and amended to provide an improved analysis and manuscript. Chapter 5 also follows this same spirit; however, I only moderately contributed to this work and am noted as a coauthor. For the remaining chapters (i.e., 2, 3, and 6), my advisor and I worked with the seismo-acoustics team at Oak Ridge National Laboratory (ORNL) in Oak Ridge, TN. These projects utilize seismic data in novel ways to detect and identify sources often ignored in seismology. The methods include applications for characterizing industrial, anthropogenic, and ecological seismic noise. This work stemmed from a summer internship at this national laboratory. Post-internship, I adopted the project as part of my doctoral research (i.e., as Chapter 3 of this dissertation).

**Dissertation Structure and Chapter Publication Disclosures**

This dissertation contains a non-extensive synopsis of the work completed during the author’s doctoral education. I have ordered chapters by publication submission. We (the
respective coauthors and I) have published Chapters 2 & 3 in two reputable seismology-focused scientific journals (i.e., Seismological Research Letters and Bulletin of the Seismological Society of America). Hence, these works are presented here verbatim with minor edits made for format requirements, structure, and continuity (e.g., renumbering figures and consolidating references).

We have provided reference information for published chapters as footnotes on the title page of said chapters. Chapter 4 is currently under review for publication. We have provided the most up-to-date version at the time of writing. Note, the final published version may contain significant changes. This chapter also comprises expanded and updated work carried over from David L. Guenaga’s M.S. thesis. Similarly, Chapter 5 has been submitted by the primary author, Dr. Richard Alfaro-Diaz, for publication (again, David L. Guenaga is a coauthor for this work).

As such, there may be significant changes compared to the final published version. Chapter 6 outlines a preliminary manuscript for work that we plan to finalize and publish in the future. Lastly, we provide any supplemental material at the end of each chapter for completeness, when applicable.
Figures

Waveform Examples

(a) Station: WLF (BHZ), Network: GE

2010 Haiti M7 Earthquake

(b) Station: MDJ (BHZ), Network: IC

2017 North Korean Nuclear Explosion

(c) Station: AAM (BHZ), Network: US

2018 Meteorite (Near Walled Lake, MI)

(d) Station: BS080 (ELZ), Network: X9

Whale sounds (10 Sept. 2012)

(e) Station: KDK (ENZ), Network: UW

2011 (Beast Quake) Cheering

Figure 1.1
An assortment of seismic records for distinctly different sources. For the (a) earthquake waveform, the main seismic phases (i.e., P, S, and surface wave) are indicated by the red brackets.

![Acoustic Waveform and Spectral Plots](image)

Figure 1.2

A plot of waveform (top) and spectrogram (bottom) of acoustic signals for a (a) C major and (b) D major piano key. For spectrogram, lighter colors denote higher amplitudes than darker colors. Note that waveforms appear similar, however, the signal presents distinct frequency amplitudes (i.e., colors) in the frequency domain. We also included some random noise (at 0-2.5 Hz) to show how signal start and end times begin to become masked at certain frequencies in the frequency domain.
Chapter 2: Seismically Detecting Nuclear Reactor Operations Using a Power Spectral Density (PSD) Misfit Detector

Abstract

To explore the ability to indirectly detect and attribute various operations conducted at a nuclear reactor using waveform data, we investigated the seismic signals recorded near the High Flux Isotope Reactor (HFIR) located at Oak Ridge National Laboratory in Oak Ridge, Tennessee. Specifically, we processed seismic data collected from a single seismo-acoustic station, WACO, near the HFIR facility, and employed a power spectral density misfit detector to identify signals of interest and associate the detections with operational events. Initial results suggest that this method provides a promising means of regularly detecting at least 19 unique operations. With additional station deployment and more comprehensive data logs, we anticipate that future analysis will offer an additional means to seismically monitor nuclear reactors (such as HFIR) health and performance more accurately.

Introduction

Seismic waves recorded on seismic instruments have traditionally been analyzed to characterize and study earthquakes. However, anything that can generate mechanical energy to the ground can be studied using seismic methods. Furthermore, seismic measurements, alone as well as in combination with the air propagation counterpart or seismoacoustic measurements, have been shown to be a useful and sensitive method for detecting, locating, and characterizing

Note: This chapter comes from published work; David L. Guenaga, Chengping Chai, Monica Maceira, Omar E. Marcillo, Aaron A. Velasco; Seismically Detecting Nuclear Reactor Operations Using a Power Spectral Density (PSD) Misfit Detector. Bulletin of the Seismological Society of America 2021; 111 (3): 1378–1391. doi: https://doi.org/10.1785/0120200267
natural environmental phenomena (e.g., Bowman, Baker, and Bahavar 2005; Havens et al. 2014; Nishida and Ichihara 2016; Pichon et al. 2005; Zhu et al. 2016); animal communications (e.g., Freeman and Hare 2015; Langbauer 2000; Policht et al. 2008; Viljoen et al. 2015); and military activity (e.g., Aleqabi, Wysession, and Ghalib 2016; E. S. Cochran and Shearer 2006; Gitterman 2014; Naz et al. 2005; Rougier and Patton 2015). For example, seismic and infrasound (acoustic signals with frequencies below 20 Hz) are two of the four primary technologies of the International Monitoring System of the Comprehensive Test-Ban Treaty Organization used for the detection and discrimination of nuclear explosions from earthquakes (e.g., Evers et al. 2000; Gitterman and Hofstetter 2014; Maceira et al. 2017; Matoza et al. 2013; Pilger et al. 2015), illustrating the usefulness of seismic and acoustic analysis. Furthermore, advancements in seismology have also allowed for monitoring complex machinery indirectly (e.g., Der and Baumgardt 1997). It remains possible to even extrapolate information about seismically “silent” operations by observing and analyzing seismically detectable ancillary activity.

Here, and following the non-proliferation community interests, we test the feasibility of seismo-acoustics as a monitoring tool for ancillary equipment that spans a broad range of industrial operations of interest. Similar to the work by van der Ende et al. (2019) that used neutron count from a nuclear reactor for monitoring purposes, but using seismo-acoustic data we use a methodology based on detecting spectral changes in the background (Power Spectral Density (PSD) misfit detector) and test its performance as a monitoring tool in an industrial environment. Our present study focuses on the detection and attribution of seismo-acoustic signals resulting from operational events in the High Flux Isotope Reactor (HFIR), which is a research reactor located at Oak Ridge National Laboratory (ORNL) in Oak Ridge, Tennessee. Various supporting sub-systems in nuclear reactors, such as the reactor primary and secondary
cooling systems, produce prominent and detectable seismo-acoustic signals (Marcillo, Chai, and Maceira 2019). Snow (1997) noted that industrial environments such as power plants contain numerous machines that produce seismic and acoustic signals—even to the point of becoming a nuisance for nearby residents. Although there are efforts to mitigate these disturbances, these attempts aim to minimize audible acoustic signals rather than those at lower frequencies. Note that even though these observations focus on non-nuclear powerplants, nuclear facilities (such as HFIR) are supported by similar ancillary systems that produce the seismo-acoustic disturbances described. The presence of these signals has already allowed some (e.g., Hashemian, 2011) to indirectly monitor the health of and potential hazards to some nuclear reactors. We explore the detection of routine operations in HFIR and find that several operations related to the reactor’s ancillary structures, particularly those associated with the cooling tower and pumps, produce regularly detectable seismic signals.

**Seismic Signals from the Operations of HFIR**

ORNL built HFIR in the mid-1960s as a research reactor, and its operation varies compared to power-producing nuclear reactors. The reactor operates at 85 MW using highly enriched uranium-235. The facility is used for neutron scattering, irradiation materials testing, neutron activation, and isotope production. The reactor reaches a peak thermal flux of $2.6 \times 10^{15}$ neutrons per square centimeter per second. During normal operation, HFIR remains active for periods of between 21–23 days, followed by a period of inactivity during which reactor inspections, calibrations, and maintenance occur. The bottom of Figure 2.1 shows these intervals for the analysis period of activity (full-power operation) and inactivity (end-of-cycle outage) as blue and light-blue sequences, respectively. Note that even during periods of inactivity, detectable operations still occur at the facility, such as those related to system maintenance. During
operation, coolant flows through the reactor at about 1.01 m$^3$/s. A combination of pumps and fans distributes the coolant and offers one source of seismically detectable activity (Marcillo, Chai, and Maceira 2019). See Data and Resources section for further details on the HFIR facility.

HFIR’s primary functions involve the physical process of nuclear fission, a phenomenon that lacks any production of detectable waves (i.e., seismic-acoustic signals). However, the splitting of atoms during nuclear fission releases large amounts of energy in the form of heat that, in a nuclear reactor, is dissipated by the reactor cooling system; consequently, nuclear facilities rely on various seismo-acoustically noisy subsystems to maintain proper operation. Our preliminary observations have shown that some secondary system operations—specifically those related to the cooling systems—produce detectable seismic signals. This includes the activity resulting from the operation of a cooling tower and several fans, pumps, and other machinery supporting the reactor and its subsystems, which can all potentially be detected seismo-acoustically. For instance, cooling towers have shown to produce seismo-acoustic noise around 100 m from source with a broadband spectrum centered at 2 kHz with amplitudes of 60 dB(A) from the impact of water descending during its operation (Ellis 1971). The cooling fans’ operation can produce broadband and spectrally discrete signals that can be related to the structure (e.g., number of blades), forces present in the medium, and speed of operation (i.e., angular speed). Owing to the difference between these machinery, unique signals are produced and provide seismo-acoustic fingerprints.

By analyzing the spectral and temporal characteristics of these signals and relating them with documented operations from the reactor, we can associate the seismo-acoustic signals to the operations within HFIR and its supporting systems. Many of the activities at the facility produce signals at various frequencies, amplitudes, and durations. We are building a database with the
reactor operation based on plant operation logs to be used for associating the status and occurrence of key operations at the facility. As shown in volcano monitoring (e.g., Falsaperla et al., 2006), seismic data can provide insights into some internal processes that cannot be easily captured through other forms of observation. Here we identified signals of interest produced by HFIR and its supporting systems to build a catalog of seismo-acoustically detectable operations occurring at the facility. Figure 2.1 shows an illustration of the general setup and the potential types of sources commonly occurring in the facility.

Data Collection and Operational Logs

The seismic data used in this study consists of waveform recordings from a single station, WACO, which features seismo-acoustic sensors. WACO operations started in July 2017 using a three-component 4.5 Hz GeoSpace geophone, three Inter-Mountain Labs infrasound sensors, and a RefTek RT 130 Datalogger with Global Positioning System time synchronization and local storage. Sampling rate for all acoustic and seismic channels is 200 Hz. The station has experienced some periods of inactivity due to external disruptions. Owing to ORNL’s geographic setting, it is common to witness wildlife (e.g., turkeys, groundhogs, and raccoons) on the premises (Giffen 2007), all of which can potentially interrupt the instruments; an ant hill, in particular, has been reported to disconnect the sensor. Furthermore, there have been instances of accidental disconnections during the maintenance of the surrounding premises. The solid line, on the bottom chart of Figure 2.1, shows when the station was recording. Station WACO is located approximately 50–100 meters away from HFIR main building and its ancillary facilities. Between May and October 2019, an additional eight stations were added around HFIR and became active for future analysis. These new stations consist of three-component 2 Hz GeoSpace geophone and a 6-channel Nanometrics’ Centaur digitizer. The sampling rate of these stations is 1000 Hz. Like WACO, each
sensor has three 3-inch spikes that are buried in the topsoil with additional covering to protect them from external elements (e.g., wildlife). Figure 2.2 shows the location of all nine stations as red circles with a close-up of station WACO. For the analysis, we use WACO’s vertical seismic channel spanning from September 13, 2017, to July 10, 2018.

Our ground truth includes activity logs of the events occurring in or near the facility that we use to attribute detected seismic signals to specific operations. These logs span from June 23, 2017, to July 10, 2018. The log entries consist of procedure times and general descriptions of the operations conducted at HFIR. Entry times are recorded in local time, and we converted the local time to 24-hour Coordinated Universal Time (UTC) for analysis. The operation descriptions outline the activities observed or conducted at the facility with relevant system measurements if available (e.g., fan speeds, pump rates, and power percentages). However, the records only include information about internal procedures conducted at the facility with few additions (e.g., local lighting storm warnings).

**Power Spectral Density Misfit Detector and Database**

To detect signals of interest, we used the PSD misfit detector described by Marcillo et al. (2019). Here, we provide a quick overview of this detector and the parameters used for the analysis. In general, the detector relies on identifying changes in spectral characteristics of the waveform data (e.g., Shensa 1977; Y. Vaezi and van der Baan 2014). The detector operates by constructing sequences of PSDs using a 50 second Tukey (tapered cosine) window with a 50% overlap, studying the statistical behavior of the elements of each frequency component of the PSD in time, and identifying deviations or misfits to a baseline behavior. For our study, we consider four user defined parameters. (1) The Background Duration specifies the time window length for the construction of sequences of PSDs which are considered the baseline. This parameter can be
switched from a dynamic to a static window. The dynamic option uses data from a time window before the period of analysis to compute the baseline. As the analysis moves forward on the time axis, the background window is rolling forward as well. In contrast, the static option uses data from the entire analysis cycle to calculate the baseline—each cycle consists of 24 hours. (2) The Time Window Length controls the length of the candidate time window and the frequency interval used by the detector. The Time Window Length and Background Duration variables are analogous to the short-time average window and long-time average window in a short-time average/long-time average detector (Allen 1978; Yooes Vaezi and Van der Baan 2015), respectively. (3) The Minimum Group Length parameter defines the smallest duration that is accepted for a detection group (i.e., continuous signals). Defining a Minimum Group length can provide a mechanism to reduce random and spurious noise detections that exist by ignoring uncharacteristically brief signals (i.e., for operations of interest). (4) The Sigma variable specifies the minimum number of standard deviations between the spectrum of the background window versus that of the candidate window required (i.e., a significant enough change in frequencies) to be considered as a detection.

Because of the complexity of the recorded seismic wavefield (i.e., overlapping signals), we first established an overall hierarchy for operations of interest to help determine parameters for the detector. HFIR sequences through periods of transitional start-up and shut-down operation followed by steady periods of full-power operation and end-of-cycle outage that, in effect, create frequency changes (i.e., detections) that last until the detector moves to the next analysis cycle (e.g., the next 24 hours for the static option). Reactor start-up and shut-down sequences remain by far the most notable, well-documented, and relatively infrequent operation in the analysis, making their detection less substantial. Thus, we chose our detector parameters to favor the detection of more subtle procedures while still detecting the initial occurrence of the long-lasting events. We
applied a trial-and-error approach to determine the best parameter values. This involved evaluating a range of dates with known detectable operations and reviewing detector results. To account for operations with long duration changes in frequencies, as mentioned above, we use a dynamic 2-hour Background Duration for days with start-up and shut-down sequences. This allows the detector to register these sequences as 2-hour long detections and then return to a state from which further detections could be made (based on the new background spectrum changes). For the remaining dates, we used a static Background Duration of 24 hours. We used a Time Window Length of 30 seconds and Minimum Group Length of 200 seconds. We also required a candidate event to have PSDs at least two standard deviations away from the background to be considered a detection. Table 2.1 contains an overview of these parameters for the detector.

After running the detector, the analyst responsible for reviewing the PSD misfit detections updates the database by associating the resulting detections with the entries in the operational logs. To expedite and ensure consistent association, the analyst used a custom script to navigate and assign detections manually. In general, signals that occurred exclusively at lower frequencies (<10 Hz) were ignored; these detections appear to be random and created by factors not evidently related to the operations of interest. In some cases, where the analyst identified signals of potential interest, detections were cataloged regardless of frequency content. Furthermore, the analyst grouped discrete, but relatively neighboring detections, that appeared related to the same event. In the case of uncertainty, we opted to keep detections separate. For context, Figures 2.3–2.5 show examples of the detections, groups, and assignments made in this process. Additionally, the analyst assigned one of three confidence levels (low, average, and high) during the detection assignment in the database.
The logs have manual entries that can have up to 30-minute delays. Note that operators manually enter these entries, and in many cases, entries are entered during an operation’s initiation and not necessarily during its occurrence (i.e., during potential signal production); consequently, inconsistencies exist as a result of these expected delays. To account for these discrepancies, we allowed a 30-minute buffer between detections and log entries for the attribution process. Generally, we only attribute operations with greater than 15 minutes difference for high confidence detections that the analyst could readily identify. For context, the average association discrepancy in minutes was 3.90, with a maximum of 29.83, a minimum of 0, and a standard deviation of 5.20. A total of 13 attributions were made with +15min discrepancies; these attributions consisted of start-up sequences, shut-down sequences, and cooling pump activity. We attribute additional discrepancies to unaccounted interruptions during the manual entry process (i.e., where log entries detail an operation occurring after the related detection).

To analyze our results, we tallied the detected occurrence of each operation. To account for wording variations in the logs, we used an approximate string-matching algorithm that groups entries that describe the same or similar operation (Ratcliff and Metzener 1988). The algorithm itself relies on a version of the gestalt pattern matching algorithm described by Ratcliff and Metzener (1988). For our analysis, we combined entries with an 80% matching minimum threshold. The grouped entries that showed regular detection were then manually reviewed to ensure that the final analysis does not contain incorrectly grouped operations. Quite often, the reactor start-up and shut-down sequences appear as several operations that occurred almost simultaneously. In the assignment process, we attributed these detections to their closest operation (in time), which resulted in different start-up and shut-down related operations being attributed. We manually grouped and labeled these respective entries (i.e., detections) for our analysis. In the
final examination, we searched for repeatedly detected operations, and for operations detected during a single occurrence.

Detection Results and Discussion

In total, we attributed 156 distinct log operations to the PSD misfit detections with relatively short durations. Detection durations show a Poisson distribution in which 99% of detections have less than a 5-hour duration (see Figure 2.6). The longer duration signals appear to be associated to maintenance operations that only occurred once in our period of analysis. It remains unclear if the detection lengths accurately illustrate the operation’s duration as the logs do not provide end times for operations. Some operations have inferred end times (e.g., a system switches to another operation) that provided some insight into an operation’s duration. Specifically, operation Q7 (Started secondary coolant pump PU-6C. Secured PU-6A.) has recorded intervals of activation that show signals ending within the same minute as the inferred end times. This provides some confidence in these detections, but a more in-depth analysis needs to be done to quantify the regularity and accuracy at which detections match operation lengths.

Although durations may be analogous between an operation and its detection, we believe that the frequency content may be distinct for these operations and aid future identification efforts using matrix profiling, artificial intelligence, and machine learning algorithms. Ideally, the database would provide a foundation for higher-order associations capable of describing the status and occurrence of key operations at the facility. Thus, we only consider a first-order approximation of the frequency makeup for each detection (i.e., encapsulate detections by their maximum and minimum frequency with no breaks). For the attributed detections, we examined the frequency deltas (i.e., the relative difference between the maximum and minimum frequency) and observed a bimodal distribution with peaks near 1 and 92 Hz. The larger frequency deltas
mostly consist of the operation C9 (closing of the bypass tower) detections. Start-up and shut-down of the reactor (M1 and L9, respectively) also exclusively occur near these frequency deltas. Thunderstorm (J1) detections dominate the shorter delta frequencies (see Figure 2.3b for a detection example). When plotting the mean frequency and frequency deltas of these detections, we notice some subtle consistencies between detections.

A closer review shows that we repeatedly detect 19 unique operations. Figure 2.6 illustrates the number of times repeated for each operation we captured. The results also show that we captured all start-up and shut-down reactor occurrences during our period of study, provided WACO was recording. Operation C9 provides the most frequent and second most prominent set of logged detections. Since we detected operation C9 a total of 115 times, we could begin to examine the detected signal’s rudimentary characteristics. A two-dimensional histogram of these detections (Figure 2.7) revealed that operation C9 exhibited relatively consistent durations and mid frequencies (i.e., the median value between the minimum and maximum frequency). We believe that as the detections catalog grows, we may see a similar trend unique to each detectable operation. Inspection of multiple additional metrics (e.g., signal amplitude and locality) may also reveal stronger unique identifiers for each detectable system operation. However, given current observations, signal attribution remains limited. Inclusion of additional data and analysis will potentially reduce the limitation.

Note that around 40% of the logged occurrences of operation C9 remains absent in the PSD misfit detector results, and other operations show similar discrepancies. We know that the execution of many operations, including C9, varies and occasionally does not produce a discernible signal. An example of a missed operation is shown in Figure 2.8. Note that in the waveform and spectra, a discernable signal cannot be identified for the first occurrence of C9; in
contrast, we detect the second occurrence. This example shows the type of divergence we expect in the seismic data during this specific operation. This absence appears to be the case for all missed C9 operations. Therefore, rather than indicating that the detector failed to capture these events, the event itself failed to produce a notable signal. HFIR operates dynamically based on the facility’s needs, the external thermal environment, and the research conducted; thus, the duration, capacity, rates, and parameters of certain operations are routinely chosen to maintain safe and efficient operation. We speculate that the absence of the signals for these operations is likely due to certain specifications that constrain signal production or even produce a particular noise background state that reduces the sensitivity of the detector. However, we find that the seismograms captured a considerable number of operations that can be detected accurately with the PSD misfit detector. Table 2.2 provides a list of the repeatedly detected operations. Furthermore, 60 additional operations occurring only once during the period of analysis were detected.

When comparing attributed and unattributed detections, we found that the majority of detections could not be attributed to a logged operation. For unattributed detections, we opted to omit low confidence detections to minimize false positives (i.e., detections that do not relate to any logged operation). The database shows that about 20% of the detections correlate to logged operations when considering higher confidence detection only. We also noticed some repeating detections. Specifically, we noticed a recurring signal at 27-29 Hz, with a duration of 30 minutes spaced at 3-hour intervals that continued for months. Figures 2.4 and 2.5 contain occurrences of these unknown detections. The consistency of these signals seems uncharacteristic of random or natural noise. These detections may be related to HFIR operations that automatically occur in the facility or by activities from neighboring facilities and, as such, are not recorded by the HFIR.
operators. The bulk of the other unattributed detections require further investigations to identify and locate the signal’s source(s).

Our detections also capture activity not related to the HFIR facility. The operators at HFIR maintain a record of local lightning storms, and we detected many of these. Detected thunderstorms were marked as “operation” J1 and excluded from our result totals. However, the logs, in general, do not include an account of external sources unrelated to operating the HFIR reactor. A countless number of activities occur near station WACO and HFIR, such as lawn maintenance that can hypothetically create detectable seismic signals. Record of the mundane activities in the study area is unavailable, which has made it unfeasible to readily remove such detections from the results. Thus, it remains possible that some portion of the unattributed signals relates to these external disturbances.

Our ground truth includes monitoring data from the reactor’s monitoring and control system (we label this data as parametric data), a record created automatically by the systems at the facility, containing a comprehensive catalog of the processes occurring in the facility. The parametric data available would likely be suitable for a more in-depth analysis as it contains much more information from a wider variety of activities compared to the operational logs. We suspect that many unattributed detections may be associated with the operations contained in the parametric logs. Marcillo et al. (2020) explored the use of parametric measurements from the reactor monitoring system to validate the detector’s results. Their findings suggest that the measurements from the reactor monitoring system of HFIR, which includes 54 temperature probes in the different subsystems, have shown the potential correlation between seismic energy and automatic operations not recorded in the manually entered operational logs. For example, discrete changes in the temperature of the coolant (of the secondary coolant system) leaving the
cooling tower show a high correlation with changes in seismic energy. Studying this thermal signal and its fingerprint on seismic energy has allowed the identification of a bypass valve used for coolant temperature control before interaction with the heat exchangers. The monitoring system provides continuous measurements every few minutes, and we continue to explore the use of these signals to validate the results of the detector. However, because the operational logs provide an adequate report for this analysis, we opted to hold the parametric data for future inquiry.

With the addition of eight new stations and use of additional components, we expect to provide a more accurate and detailed analysis of the operations at HFIR using the approach described in this paper. Our preliminary results have already shown operation C9 detected on at least two additional stations (MIN05 and MIN06) on z-component recordings (see Figure 2.9). Note that WACO has since (starting on December 6, 2019) been configured to sample at 500 Hz.

We emphasize that each station provides distinct detection makeups for the same operation. Discrepancies likely exist due to source-to-sensor proximity, changes in seismic ray path (e.g., variances related to topography and medium composition), and differences in the makeup of background noise/signals. For this reason, we expect that different stations likely benefit from using specialized sets of parameters; for instance, MIN05 benefits from using the dynamic background parameters (refer to Table 2.1) when attempting to detect occurrences of C9. We speculate that the recorded waveform’s background makeup likely varies and contains more regular occurrences of “noise,” which can mask detections when using a static background, due to MIN05’s proximity to a parking lot with relatively high traffic. Using the static background parameters (which we use for days lacking start-up/shut-down sequences, such as the day in Figure 2.9), MIN05 effectively ignored some detectable occurrences of C9. The spectrogram of
MIN05 also shows a more apparent (but still subtle) signal during the C9 occurrences not captured in the current detection results, suggesting that we can obtain better detections with improved parameters. The detection of the same occurrence on at least three stations allows for the potential determination of source position; this would further allow for the identification or verification of a signal’s origin. Furthermore, the addition of detections will help increase the detection coverage (some operations may produce signals that favor certain azimuths or proximities) and isolate noise detections affecting single stations. We also limited our detections to the vertical component as visual inspections of different components showed that HFIR operations produced notable signals in the vertical component. However, inclusion of the acoustic and horizontal seismic components may lead to more detections. With more components and eight new stations we also expect improved detection accuracy, increased signal attribution, and better-vetted results for future studies.

**Conclusions**

We studied the occurrence and characteristics of the seismic signals recorded near the HFIR in Oak Ridge, Tennessee. This involved exploring the ability to distinguish and monitor the nuclear facility’s daily operations at ORNL using a PSD misfit detector. To accomplish this, we utilized vertical component seismic records from the seismo-acoustic station WACO located roughly 50 meters from HFIR related facilities. Our results show that we could repeatedly detect 19 distinct operations. Furthermore, we detected an additional 60 single-occurrence operations. Initial examination of these signals suggests that operations can be identified based on their frequency content. We anticipate that future studies on HFIR seismic detections may provide further insight that will provide the foundation for seismo-acoustically inferring the occurrence and status of operations at nuclear reactors.
Data and Resources

US Department of Energy (DOE) will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (http://energy.gov/downloads/doe-public-access-plan). Waveform and log data used in this study were collected using an official-use-only network of the DOE. An XCAMS account and formal request must be made to gain access to waveform data through ORNL’s XCAMS website (https://xcams.ornl.gov/xcams/). For assistance on obtaining an XCAMS account, please contact the ORNL Computer Helpline at 865-241-ORNL (6765) or send an email requesting assistance to helpline@ornl.gov. For further assistance accessing data, please contact Monica Maceira (maceiram@ornl.gov). Maps were made in part using Generic Mapping Tools version 5.4.4 (www.soest.hawaii.edu/gmt; Wessel et al., 2013). Satellite imagery was provided by Google via Google Earth (https://www.google.com/earth/). Codes for processing waveform data used the Obspy Python package (docs.obspy.org; Beyreuther et al. 2010; Megies et al. 2011; Krischer et al. 2015). Supplemental Material contains a Table S2.1 that provides a complete list of the detected operations. The High Flux Isotope Reactor (HFIR): Neutron Science at ORNL, 2010 (https://neutrons.ornl.gov/hfir) website (last accessed March 2, 2020) can provide further information on the HFIR facility.

Tables

Table 2.1: Detector Parameters

<table>
<thead>
<tr>
<th>Dates (09/09/2017—07/10/2018)</th>
<th>Background Type</th>
<th>Background Duration (hr)</th>
<th>Time Window Length (s)</th>
<th>Minimum Group Length (s)</th>
<th>Sigma</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-transition Occurrence Days</td>
<td>Static</td>
<td>24</td>
<td>30</td>
<td>200</td>
<td>2</td>
</tr>
</tbody>
</table>
Note: “Transition occurrences” refers to reactor start-up and shut-down operations.

<table>
<thead>
<tr>
<th>Transition Occurrence Days</th>
<th>Dynamic</th>
<th>2</th>
<th>30</th>
<th>200</th>
<th>2</th>
</tr>
</thead>
</table>

Table 2.2: Detectable HFIR Log Entries

<table>
<thead>
<tr>
<th>Key</th>
<th>Log Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>A2</td>
<td>Adjusted Pool-to-TPS crossover from 9 to 11 gph. Pool Surge Tank Level is 58.2%</td>
</tr>
<tr>
<td>A6</td>
<td>Adjusted Primary-to-Pool crossover from MAX to 0 gph. Head Tank Level is 83.4 %</td>
</tr>
<tr>
<td>C9</td>
<td>Closed the tower bypass valve.</td>
</tr>
<tr>
<td>D1</td>
<td>Commenced SOP-2967: Diesel Generator No. 1 Load Test</td>
</tr>
<tr>
<td>D2</td>
<td>Commenced SOP-2968: Diesel Generator No. 2 Load Test</td>
</tr>
<tr>
<td>F3</td>
<td>Daily start MWP-41924: Install New Isolation Valves in the Chilled Water System</td>
</tr>
<tr>
<td>G1</td>
<td>Daily start MWP-42090: Replace Valves 8-1011 and 8-1012 located on the north side of 7900 1AW DEV HFIR-2018-027</td>
</tr>
<tr>
<td>G5</td>
<td>Daily start MWP-604144: Calibration of UV-1 Instrumentation.</td>
</tr>
<tr>
<td>J1</td>
<td>Lightning Reports*</td>
</tr>
<tr>
<td>J5</td>
<td>Opened the tower bypass valve.</td>
</tr>
<tr>
<td>L9</td>
<td>Shut-down**</td>
</tr>
<tr>
<td>M1</td>
<td>Start-up**</td>
</tr>
<tr>
<td>M7</td>
<td>Secured PU-4B, exited Pressurized Submode.</td>
</tr>
<tr>
<td>M8</td>
<td>Secured PU-7B.</td>
</tr>
<tr>
<td>N5</td>
<td>Secured primary coolant pumps PU-1A, 1B, &amp; 1C</td>
</tr>
<tr>
<td>N7</td>
<td>Shipped Loop Transport Cask to 7920 per TXP-5126.</td>
</tr>
<tr>
<td>O3</td>
<td>Started Cooling Tower Fans 4A, 4B, 4C and 4D.</td>
</tr>
<tr>
<td>Q5</td>
<td>Started cooling tower fans FN-4A, 4B, 4C, &amp; 4D for weekly checks.</td>
</tr>
<tr>
<td>Q7</td>
<td>Started secondary coolant pump PU-6C. Secured PU-6A.</td>
</tr>
</tbody>
</table>

* Entries related to documented lightning alerts.
** Manually grouped entries.
Figure 2.1

(Above) Plot of power spectral density (PSD) for instance of tower bypass closure (blue), lightning (orange), and unknown detection at 27–29 Hz (green) with baseline (i.e., with no detected or logged activity) PSD in black. On the upper right, plot of vertical waveform (top) and spectrogram (bottom) with windows for PSD highlighted. (Mid) Illustration of the main seismic-acoustic sources near station WACO. (Below) A plot of the sequences of full-power operation (dark blue) and end-of-cycle outage (light blue) reactor operation and the periods that WACO remained active and recording (black lines).
Aerial image of the High Flux Isotope Reactor (HFIR) locality. Seismoacoustic station locations are marked by red triangles. Numbers relate to the new station’s naming scheme (i.e., 1 = MIN01, 2 = MIN02, and so on). (Top right inset) The WACO station setup. The top left inset shows the location of HFIR, as a black star, within the US.
Figure 2.3

Plots showing z-component seismic recording and detections from 20 February 2018. (a) Waveform and (b) spectrogram plots of seismic data. Red lines indicate a recorded occurrence of an operation, including those that produce no notable seismic signal, based on provided HFIR logs. (c) Frequency-domain plot showing PSD misfit detections in purple and recorded database
detections as blue boxes. Red texts indicate key for associated logged events. Note that
detections with no index were not linked to any logged operation and events with asterisks are
low-confidence associations. Operation labels correspond to those in Table 2.2.

Figure 2.4
Plots showing z-component seismic recording and detections from 25 March 2018. (a) Waveform and (b) spectrogram plots of seismic data. Red lines indicate a recorded occurrence of an operation, including those that produce no notable seismic signal, based on provided HFIR logs. (c) Frequency-domain plot showing PSD misfit detections in purple and recorded database detections as blue boxes. Red texts indicate key for associated logged events. Operation labels correspond to those in Table 2.2.
Figure 2.5

Plots showing z-component seismic recording and detections from 3 April 2018. (a) Waveform and (b) spectrogram plots of seismic data. Red lines indicate a recorded occurrence of an operation, including those that produce no notable seismic signal, based on provided HFIR logs. (c) Frequency-domain plot showing PSD misfit detections in purple and recorded database
detections as blue boxes. Red texts indicate key for associated logged events. Operation labels correspond to those in Table 2.2.

Figure 2.6

(a) A plot of attributed (blue) and unattributed (aquamarine) detections included in the database. (b) Histograms of duration and frequency deltas observed in the linked detections. (c) Histograms of duration and frequency deltas observed in the unlinked detections. (d) Bar graph of detection regularity for repeatedly detected HFIR operations. Operation labels correspond to those in Table 2.2. Purple and gray bars denote occurrences of detected and undetected events, respectively.
Figure 2.7

A 2D histogram plot of operation C9, characterized by detection duration and mid frequency (i.e., center frequency between maximum and minimum frequencies). The plot consists of 3 min and 3 Hz bins with darker cells indicating a higher count of detected C9 operations.
Figure 2.8

Plot of the (a) waveform and (b) spectrogram from station WACO’s vertical component. Red vertical lines indicate an instance during which operation C9 occurred according to log entries. The first logged occurrence [08:52:00 UTC] shows an example of a missed and seismically silent incidence of C9, whereas the second [14:52:30 UTC] shows an example of a seismically noisy and detected occurrence of C9.
Figure 2.9

Frequency-domain plots showing PSD misfit detections results and spectrograms based on z-component recordings for station (a, b) WACO, (c, d) MIN05, and (e, f) MIN06 from 6 December 2019. Plots show PSD misfit detections in purple, recorded occurrence of operation C9 as red lines (other operations occur but not marked), and potential C9 database detections as blue boxes. Note that we resampled MIN05 and MIN06 data to match the current WACO sampling rate (500 Hz) for comparison. In addition, detections were obtained using the dynamic background parameters (see Table 2.1).

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Table S2.1: Full List of Detectable Log Entries

<table>
<thead>
<tr>
<th>Key</th>
<th>Log Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>(LE 1735) Started Instrument air dryer AD-1B. Secured Instrument air dryer AD-1A.</td>
</tr>
<tr>
<td>A2</td>
<td>Adjusted Pool-to-TPS crossover from 9 to 11 gph. Pool Surge Tank Level is 58.2%</td>
</tr>
<tr>
<td>A3</td>
<td>Adjusted Primary-to-Pool crossover from 10 to 13 gph. Head Tank Level is 79.8%; Adjusted Pool-to-TPS crossover from 15 to 20 gph. Pool Surge Tank Level is 60.1%</td>
</tr>
<tr>
<td>A4</td>
<td>Adjusted Primary-to-Pool crossover from 8 to 10 gph. Head Tank Level is 78.5 %; Adjusted Pool-to-TPS crossover from 12 to 14 gph. Pool Surge Tank Level is 63.1 %</td>
</tr>
<tr>
<td>A5</td>
<td>Adjusted Primary-to-Pool crossover from 9 to 12 gph. Head Tank Level is 78.9 %; Adjusted Pool-to-TPS crossover from 13 to 15 gph. Pool Surge Tank Level is 55.7 %</td>
</tr>
<tr>
<td>A6</td>
<td>Adjusted Primary-to-Pool crossover from MAX to 0 gph. Head Tank Level is 83.4 %</td>
</tr>
<tr>
<td>A7</td>
<td>Adjusted V-438 to 25% open.</td>
</tr>
<tr>
<td>A8</td>
<td>All NE-1 loads secured, EDG #1 secured per SOP-2907: Operation of a Diesel Generator to Supply Normal/Emergency and Lighting Test Loads</td>
</tr>
<tr>
<td>A9</td>
<td>Annunciator H/I-12 (FIRE ALARM) in. Entered AOP-9004. Flow alarm for 7977 and 7903/7916 in. Fire dept. contacted and they said they were aware of the alarm and that it was due to utilities restoring a potable water header and it caused the fire valve in 7903 and the fire valve in 7901 to trip. Fire dept. is attempting to reset the valves and alarms at this time.</td>
</tr>
<tr>
<td>B1</td>
<td>Applied single source lockout on 7960 Panel ‘A’ Ckt. 3.</td>
</tr>
<tr>
<td>B2</td>
<td>Applied single source lockout on MCC-R for PU-18A.</td>
</tr>
<tr>
<td>B3</td>
<td>Applied single source lockout on Panel G Circuit 5.</td>
</tr>
<tr>
<td>B4</td>
<td>Applied single source lockout on Panel G ckt 2. For replacing Beam Room Lighting.</td>
</tr>
<tr>
<td>B5</td>
<td>CT FN-4B downshifted from fast speed to slow speed simultaneously with FN-4A downshift from slow speed to off. FN-4D was operating as trim fan at 30% (anticipated logic point for a fan downshift).</td>
</tr>
<tr>
<td>B6</td>
<td>Cleared TSR Tracking 18-58 Stack Flow Rate, FT/FI-984.</td>
</tr>
<tr>
<td>B7</td>
<td>Cleared C-1B bearing oil temperature alarm from loss of PU-6C placed C-1B in standby.</td>
</tr>
<tr>
<td>B8</td>
<td>Cleared TSR Tracking 18-76, PS-147 &amp; PS-148.</td>
</tr>
<tr>
<td>B9</td>
<td>Cleared single source lockout on V-5157.</td>
</tr>
<tr>
<td>C1</td>
<td>Cleared single source on V-20026.</td>
</tr>
<tr>
<td>C2</td>
<td>Closed MWP- 519387; Switchgear Batteries - QPM.</td>
</tr>
<tr>
<td>C3</td>
<td>Closed MWP- 604261: Functional Testing of Canberra Radiation Monitors (FFWW).</td>
</tr>
<tr>
<td>C4</td>
<td>Closed MWP-42046 TS/R SBHE Fan 3 failed to start.</td>
</tr>
<tr>
<td>C5</td>
<td>Closed MWP-519358 Plant Demin Water Pump PU-18B - 2 YPM</td>
</tr>
<tr>
<td>C6</td>
<td>Closed MWP-604079 Calibration of Pool Heating System Instruments.</td>
</tr>
<tr>
<td>C7</td>
<td>Closed MWP-604234 Calibration of Chiller Cooling Water D/P</td>
</tr>
<tr>
<td>C8</td>
<td>Closed MWP-604291 Calibration of HFIR Normal-Range Stack Monitor</td>
</tr>
<tr>
<td>C9</td>
<td>Closed the tower bypass valve.</td>
</tr>
<tr>
<td>D1</td>
<td>Commenced SOP-2967: Diesel Generator No. 1 Load Test</td>
</tr>
<tr>
<td>D2</td>
<td>Commenced SOP-2968: Diesel Generator No. 2 Load Test</td>
</tr>
<tr>
<td>D3</td>
<td>Commenced pumping Reactor Vessel Per NOP-2114: Drain and Fill of the Reactor Vessel to the Pool Water Storage Tanks. Inlet Strainer is open per PWP-1140: Reactor Inlet Strainer Assembly Manipulations, Step 1.</td>
</tr>
<tr>
<td></td>
<td>Description</td>
</tr>
<tr>
<td>---</td>
<td>-------------</td>
</tr>
<tr>
<td><strong>D4</strong></td>
<td>Completed Filling HX Cell 111 &amp; 110 Primary Heat Exchangers per NOP-2109: Draining and Filling the Primary Side of the Primary Heat Exchangers.</td>
</tr>
<tr>
<td><strong>D5</strong></td>
<td>Completed NOP-2210: Operation of the Pool Water Storage Tanks for pumping PWSTs to the Reactor Pool.</td>
</tr>
<tr>
<td><strong>D6</strong></td>
<td>Completed PWMWP Cycle 476-1 Target Bundle Work.</td>
</tr>
<tr>
<td><strong>D7</strong></td>
<td>Completed SOP-2950: End-of-Outage Equipment Checks.</td>
</tr>
<tr>
<td><strong>D9</strong></td>
<td>Completed STP-6110A: Standby/Start and Flow Testing of SBHE Fans- Pre-Startup Testing.</td>
</tr>
<tr>
<td><strong>E1</strong></td>
<td>Completed pumping PWST to Rx Pool.</td>
</tr>
<tr>
<td><strong>E2</strong></td>
<td>Cooling Tower Abatement Pump PU-30A placed in Hand to reduce Conductivity Cycles.</td>
</tr>
<tr>
<td><strong>E3</strong></td>
<td>Daily start MWP- 41537: Inspect and Refurbish Cooling Tower Fan Blades. Remove equipment from top of Cooling Tower.</td>
</tr>
<tr>
<td><strong>E4</strong></td>
<td>Daily start MWP- 41613: Install Shield Wall in Experiment Room for PROSPECT, remove &quot;c&quot; channel and perform pull test.</td>
</tr>
<tr>
<td><strong>E5</strong></td>
<td>Daily start MWP- 41699: Supply Chilled Water to Experiment Equipment in 7970/7972, insulating pipes in cold guide hall.</td>
</tr>
<tr>
<td><strong>E6</strong></td>
<td>Daily start MWP- 41836, Routine Millwright Work, attachment 8, Install handles to waste bin lid located in the truck airlock.</td>
</tr>
<tr>
<td><strong>E7</strong></td>
<td>Daily start MWP- 41846: Perform Back Flush of Beam Tube HB-1 Cooling Channels</td>
</tr>
<tr>
<td><strong>E8</strong></td>
<td>Daily start MWP- 42084: Install 480V 3Ph Power at HB-3A per MM HFIR-2017-085, work start is for original work scope, NO bus duct work.</td>
</tr>
<tr>
<td><strong>E9</strong></td>
<td>Daily start MWP- 42153: Perform MINOS Monitoring for Cycle 479</td>
</tr>
<tr>
<td><strong>F1</strong></td>
<td>Daily start MWP- 42170: Troubleshoot and Repair DAV-03 Data Acquisition Viewer.</td>
</tr>
<tr>
<td><strong>F2</strong></td>
<td>Daily start MWP-41863: 41863: TS/R Intercom Staff Boxes. Today's work will be on staff 19.</td>
</tr>
<tr>
<td><strong>F3</strong></td>
<td>Daily start MWP-41924: Install New Isolation Valves in the Chilled Water System</td>
</tr>
<tr>
<td><strong>F4</strong></td>
<td>Daily start MWP-41924: Install New Isolation Valves in the Chilled Water System. Continuing with experiment room AC units.</td>
</tr>
<tr>
<td><strong>F5</strong></td>
<td>Daily start MWP-41955: Monitor WRCC During Cycle 476 Startup.</td>
</tr>
<tr>
<td><strong>F7</strong></td>
<td>Daily start MWP-42064: Perform Routine Electrical Work (Including Work in Radiological Areas), task #18. Adjusting UC-8 current rating from 2.96A to 3.26A.</td>
</tr>
<tr>
<td><strong>F8</strong></td>
<td>Daily start MWP-42067: Perform Routine Painting in 7900 Area; today's plan is to paint yellow lines in front of AC-1.</td>
</tr>
<tr>
<td><strong>F9</strong></td>
<td>Daily start MWP-42068 Perform Routine Hoisting and Rigging and Ironworker Activities ATT. #2 to repair safety latch on 3 Ton Crane Hook and ATT. #3 Cell 111 grating next to handrail at pump is loose.</td>
</tr>
<tr>
<td><strong>G1</strong></td>
<td>Daily start MWP-42090: Replace Valves 8-1011 and 8-1012 located on the north side of 7900 IAW DEV HFIR-2018-027</td>
</tr>
<tr>
<td>G2</td>
<td>Daily start MWP-42189: Install Locking Mechanisms on the GFWW Equipment Hatch</td>
</tr>
<tr>
<td>G3</td>
<td>Daily start MWP-519484: RE-1 Chiller - APM.</td>
</tr>
<tr>
<td>G4</td>
<td>Daily start MWP-519550: Servo and Rod Drive Gearboxes and Air Motor Lubricants - APM.</td>
</tr>
<tr>
<td>G5</td>
<td>Daily start MWP-604144: Calibration of UV-1 Instrumentation.</td>
</tr>
<tr>
<td>G7</td>
<td>East plant demin column row 1 isolated.</td>
</tr>
<tr>
<td>G8</td>
<td>Ejected Rabbit Configuration 475-B.</td>
</tr>
<tr>
<td>G9</td>
<td>Entered ES-0.1</td>
</tr>
<tr>
<td>H1</td>
<td>Entered Pool Work Sub Mode (PWSM).</td>
</tr>
<tr>
<td>H2</td>
<td>Established Refueling Submode to Defuel the Reactor.</td>
</tr>
<tr>
<td>H3</td>
<td>Filled and reconnected the HB-2 fast neutron filter external Dewars per NOP-2801.</td>
</tr>
<tr>
<td>H4</td>
<td>HOG FN-4 placed in STBY</td>
</tr>
<tr>
<td>H5</td>
<td>Initial Start MWP- 41914: Install Fuel Shipping Trailer Storage Shed (Building 7980G).</td>
</tr>
<tr>
<td>H6</td>
<td>Initial Start MWP- 42057: Repair Latch on Stairwell Door Third Floor East in 7900 (01-70.3-DR-316).</td>
</tr>
<tr>
<td>H7</td>
<td>Initial Start MWP- 42208: Repair 7900 Sewer Line from South Wall of Beam Room to Manhole SA-6</td>
</tr>
<tr>
<td>H8</td>
<td>Initial Start MWP- 519423: AC-2 - 2YPM</td>
</tr>
<tr>
<td>H9</td>
<td>Initial Start MWP- 519618: Emergency Shower Functional Test - QPM.</td>
</tr>
<tr>
<td>I1</td>
<td>Initial Start MWP- 604184: Calibration of Channel #2 Safety Power Rate of Rise System STP-3117.</td>
</tr>
<tr>
<td>I2</td>
<td>Initial Start MWP-42125: Delivery and Preparation of ISO Tank to HFIR.</td>
</tr>
<tr>
<td>I3</td>
<td>Initial Start MWP-518733: Test Secondary Relief Valves 5YPM.</td>
</tr>
<tr>
<td>I4</td>
<td>Initial Start MWP-519500: Inner Truck Airlock Door - 2YPM</td>
</tr>
<tr>
<td>I5</td>
<td>Initial Start MWP-519553: Primary Recycle Pump PU-6 PM</td>
</tr>
<tr>
<td>I6</td>
<td>Initial Start MWP-519728: Operate AEPG #1A with No Load - MPM</td>
</tr>
<tr>
<td>I7</td>
<td>Initial Start MWP-604292: Monthly Preventive Maintenance Activities May 2018</td>
</tr>
<tr>
<td>I8</td>
<td>Instrument Battery Chargers C-1 &amp; C-2 returned to float.</td>
</tr>
<tr>
<td>I9</td>
<td>Instrument air pressure low alarm in. Loss of secondary coolant pump PU-6C, no indications on the motor starter as to why. Loss of secondary cooling to the instrument air compressors caused C-1B to trip, C-1A and C-1C started in standby. Secondary coolant pump PU-6B started, C-1B taken to off to allow bearing oil cooldown. CSSM and Waste Ops informed. C-1A is running and C-1C is in standby.</td>
</tr>
<tr>
<td>J1</td>
<td>Lightning Reports*</td>
</tr>
<tr>
<td>J2</td>
<td>Lowered Primary Deaerator Level from 66.1% to 29.9%.</td>
</tr>
<tr>
<td>J4</td>
<td>Opened V-23031 to supply cold guide hall with instrument air</td>
</tr>
<tr>
<td>--------</td>
<td>-----------------------------------------------------------------------</td>
</tr>
<tr>
<td>J5</td>
<td>Opened the tower bypass valve.</td>
</tr>
<tr>
<td>J6</td>
<td><strong>PU-30A running in hand to lower conductivity cycles.</strong></td>
</tr>
<tr>
<td>J7</td>
<td><strong>Performed DRAFT NOP-2415: Operation of the Auxiliary Emergency Portable Generators (AEPGs) for AEPG #1A per MWP-41669.</strong></td>
</tr>
<tr>
<td>J8</td>
<td><strong>Performed NOP-2150: Operation of the Primary Cleanup System and pressurized to 50 psig via PU-11 and PU-2A.</strong></td>
</tr>
<tr>
<td>J9</td>
<td><strong>Performed NOP-2251: Operation of the Pool Coolant Filter (FL-2). Backwashed FL-2.</strong></td>
</tr>
<tr>
<td>K1</td>
<td><strong>Performed NOP-2300: Operation of the Secondary Coolant System Att. A to remove blowdown HX from service. Maintenance has been informed to pick up and store.</strong></td>
</tr>
<tr>
<td>K2</td>
<td><strong>Performed NOP-2500: Operation of the Steam System. Secured steam systems due to Melton Valley steam plant outage. Steam is isolated at V-3004.</strong></td>
</tr>
<tr>
<td>K3</td>
<td><strong>Performed NOP-2610: Switching of the SBHE Filter Trains, Section 2 &quot;Switch from the west filter train to the center filter train&quot;.</strong></td>
</tr>
<tr>
<td>K4</td>
<td><strong>Performed PWP-1200: Handling/Storage of Non-Fuel Components; PWMWP 'Cycle 480-3'.</strong></td>
</tr>
<tr>
<td>K5</td>
<td><strong>Performed STP-3121c: Mode 3 Reactor Protection System Testing/Reactor Startup</strong></td>
</tr>
<tr>
<td>K6</td>
<td><strong>Performed a rapid drain of the surge tan to 48.3.</strong></td>
</tr>
<tr>
<td>K7</td>
<td><strong>Placed Tower Abatement Pump PU-30A in Service.</strong></td>
</tr>
<tr>
<td>K8</td>
<td><strong>Placed abatement pump PU-30A in HAND to lower secondary conductivity cycles.</strong></td>
</tr>
<tr>
<td>K9</td>
<td><strong>Placed main coolant pumps PU-1A, 1C and 1D in service.</strong></td>
</tr>
<tr>
<td>L1</td>
<td><strong>Pony Motor Battery Charger for PU-1H is in EQUALIZE.</strong></td>
</tr>
<tr>
<td>L2</td>
<td><strong>Pumped down Primary Deaerator from 67% to 31%.</strong></td>
</tr>
<tr>
<td>L3</td>
<td><strong>Pumped down the primary deaerator from 65% to 20%</strong></td>
</tr>
<tr>
<td>L4</td>
<td><strong>Pumped reactor pool to clean pools using PU-7A.</strong></td>
</tr>
<tr>
<td>L5</td>
<td><strong>Reactor Scram for testing, entered E-0.</strong></td>
</tr>
<tr>
<td>L6</td>
<td><strong>Received 4 carts of C-Zone laundry, shipped 3 carts. Shipment number ORNL-2017-197-506.</strong></td>
</tr>
<tr>
<td>L7</td>
<td><strong>Replaced single source lockout on V-3872 for PT-726 (Transfer Tank Pump Discharge Pressure) with a LOTO.</strong></td>
</tr>
<tr>
<td>L8</td>
<td><strong>SHBE fans and HOG fans switched per SE instruction to evaluate noise at the fan shed. The HOG fans were returned to their previous lineup.</strong></td>
</tr>
<tr>
<td>L9</td>
<td><strong>Shut-down</strong></td>
</tr>
<tr>
<td>M1</td>
<td><strong>Start-up</strong></td>
</tr>
<tr>
<td>M2</td>
<td><strong>Scrammed the Reactor via Time of Flight. Entered E-0.</strong></td>
</tr>
<tr>
<td>M3</td>
<td><strong>Seal flow verified and oil mist mitigation placed in service, started Pony Motor PU-1E, PU-1G, PU-1H.</strong></td>
</tr>
<tr>
<td>M4</td>
<td><strong>Seal flow verified and oil mist mitigation placed in service, started Pony Motor PU-1H.</strong></td>
</tr>
<tr>
<td>M5</td>
<td><strong>Secured Cooling Tower Fan FN-4C.</strong></td>
</tr>
<tr>
<td>M6</td>
<td><strong>Secured PU-1A.</strong></td>
</tr>
<tr>
<td>M7</td>
<td><strong>Secured PU-4B, exited Pressurized Submode.</strong></td>
</tr>
<tr>
<td>M8</td>
<td>Secured PU-7B.</td>
</tr>
<tr>
<td>M9</td>
<td>Secured Pool Cleanup Pump PU-7A to ensure Pool Deaerator Barometric Leg is full. Noticed that Pool Deaerator pressure on PI-400 was fluctuating from approximately 0.8 to 1.2 psia.</td>
</tr>
<tr>
<td>N1</td>
<td>Secured Primary coolant pumps, PU-1A, 1C &amp; 1D.</td>
</tr>
<tr>
<td>N2</td>
<td>Secured abatement pump PU-30B.</td>
</tr>
<tr>
<td>N3</td>
<td>Secured cooling tower Fan 4C.</td>
</tr>
<tr>
<td>N4</td>
<td>Secured cooling tower fan FN-4B.</td>
</tr>
<tr>
<td>N5</td>
<td>Secured primary coolant pumps PU-1A, 1B, &amp; 1C</td>
</tr>
<tr>
<td>N6</td>
<td>Secured secondary blowdown and blowdown treatment for jetting the sulfuric acid dike.</td>
</tr>
<tr>
<td>N7</td>
<td>Shipped Loop Transport Cask to 7920 per TXP-5126.</td>
</tr>
<tr>
<td>N9</td>
<td>Started AC-14, secured AC-10.</td>
</tr>
<tr>
<td>O1</td>
<td>Started Auxiliary Pressurizer Pump PU-11.</td>
</tr>
<tr>
<td>O2</td>
<td>Started CHOG FN-3, placed FN-4 in off.</td>
</tr>
<tr>
<td>O3</td>
<td>Started Cooling Tower Fans 4A, 4B, 4C and 4D.</td>
</tr>
<tr>
<td>O4</td>
<td>Started EDG #2 per SOP-2906: Operation of a Diesel Generator with the Lighting Test Load and Load Bank. Lighting Loads transferred to EDG #2.</td>
</tr>
<tr>
<td>O5</td>
<td>Started Main Secondary Pump PU-6C. Secured Main Secondary Pump PU-6A.</td>
</tr>
<tr>
<td>O6</td>
<td>Started PU-14 in High speed, secured PU-6A. Shut V-438.</td>
</tr>
<tr>
<td>O7</td>
<td>Started PU-18A, secured PU-18B.</td>
</tr>
<tr>
<td>O8</td>
<td>Started PU-18B, secured PU-18A.</td>
</tr>
<tr>
<td>O9</td>
<td>Started PU-4A, established Pressurized Submode.</td>
</tr>
<tr>
<td>P1</td>
<td>Started PU-4B, established Pressurized Submode.</td>
</tr>
<tr>
<td>P2</td>
<td>Started PU-6C. Secured PU-14. HV-438 FULL OPEN.</td>
</tr>
<tr>
<td>P3</td>
<td>Started PU-7B, PU-9B, PU-6A. Secured PU-7A, PU-9A, PU-6C.</td>
</tr>
<tr>
<td>P4</td>
<td>Started Pool Coolant Pump PU-9B, secured PU-9A for maintenance activity request.</td>
</tr>
<tr>
<td>P5</td>
<td>Started Pool Coolant Pump PU-9B, secured PU-9A.</td>
</tr>
<tr>
<td>P6</td>
<td>Started Primary Coolant Pump PU-1D.</td>
</tr>
<tr>
<td>P7</td>
<td>Started Primary Coolant Pumps PU-1A, PU-1C, PU-1D.</td>
</tr>
<tr>
<td>P9</td>
<td>Started Secondary Coolant Pump PU-14 in High Speed, Secured PU-6C for maintenance.</td>
</tr>
<tr>
<td>Q1</td>
<td>Started Secondary Coolant Pump PU-6C, secured PU-6A.</td>
</tr>
<tr>
<td>Q2</td>
<td>Started Secondary Cooling Pump PU-14 High Speed. Secured Secondary Cooling Pump PU-6A</td>
</tr>
<tr>
<td>Q3</td>
<td>Started Secondary coolant pump PU-6A, secured PU-6B.</td>
</tr>
<tr>
<td>Q4</td>
<td>Started cooling tower fan FN-4B in slow speed to lower secondary coolant temperature.</td>
</tr>
<tr>
<td>Q5</td>
<td>Started cooling tower fans FN-4A, 4B, 4C, &amp; 4D for weekly checks.</td>
</tr>
<tr>
<td>----</td>
<td>---------------------------------------------------------------</td>
</tr>
<tr>
<td>Q6</td>
<td><strong>Started secondary coolant pump PU-6A. Secured PU-14.</strong></td>
</tr>
<tr>
<td>Q7</td>
<td>Started secondary coolant pump PU-6C. Secured PU-6A.</td>
</tr>
<tr>
<td>Q8</td>
<td>Supplied Guide Hall Instrument Air System with HFIR Instrument Air System per guidance in MWP-23031 &quot;AD-1C PM for Ingersoll Rand Air Dryer.&quot;</td>
</tr>
<tr>
<td>Q9</td>
<td>Swapped Process Water Backflow Preventers. Removed SP-01-5 from service and placed SP-01-6 into service.</td>
</tr>
<tr>
<td>R1</td>
<td>The PT-1 Rabbit is in the NAA Lab.</td>
</tr>
<tr>
<td>R2</td>
<td>The PWST Fill/Drain Piping has NOT been drained following lowering of the reactor pool to the PWST.</td>
</tr>
<tr>
<td>R3</td>
<td>The reactor is in Operating Mode 1.</td>
</tr>
</tbody>
</table>

*Note: Entries in bold occurred and detected once during our period of analysis.*

* Entries related to documented lightning alerts.

** Manually grouped entries.

Abstract

In response to the COVID-19 global pandemic, many populated and active regions have become deserted and show significant reductions in their background seismicity, especially campuses across the United States (US). Seismic sensors located in the vicinity of or within US campuses show that anthropogenic seismic noise remains elevated during the ordinary, non-pandemic, academic year—only subduing during periods of recess (e.g., winter break). Here we use power spectral density data (PSD) computed by the Incorporated Research Institutions for Seismology Data Management Center (IRIS DMC) for quality assessment to calculate root mean square (RMS) amplitude and analyze the effects of the COVID-19 school closures. We processed and analyzed PSD data for 46 seismic stations located within 50 m of a US university or college. Results show that 42 campus stations show an overall RMS drop following a statewide school closure (SSC).

Introduction

With the significant increase in the number of broadband seismic instruments distributed throughout the world, the ability to detect all types of ground motion over a wide frequency and large dynamic range has never been better. Global, regional, and local networks of seismic

Note: This chapter comes from published work; David L. Guenaga, Omar E. Marcillo, Aaron A. Velasco, Chengping Chai, Monica Maceira; The Silencing of U.S. Campuses Following the COVID-19 Response: Evaluating Root Mean Square Seismic Amplitudes Using Power Spectral Density Data. Seismological Research Letters 2021; 92 (2A): 941–950. doi: https://doi.org/10.1785/0220200391
instruments allow for an increased ability to study ground motions from natural and induced phenomena (e.g., earthquakes, volcanic eruptions, and landslides), plus they allow for better resolution of Earth models derived from traditional modeling approaches, such as travel time tomography. Broadband seismic sensors also reveal that anthropogenic seismic noise remains a ubiquitous by-product of inhabited regions around the globe, and seismic sensors have allowed seismologists to detect and monitor human activity (and lack thereof) (Lecocq et al. 2020). The fingerprint of industrial operations can also be detected in seismic data at both local and regional scales. For example, seismic data were used to detect and monitor mechanical operations at a small nuclear reactor (Marcillo et al. 2020) and a large seismic network was used to explore industrial seismic noise throughout the US (Marcillo and MacCarthy, 2020). Other studies have used seismic and acoustic (infrasound) sensor measurements to identify, locate, and characterize natural environmental phenomena (e.g., Bowman, Baker, and Bahavar 2005; Havens et al. 2014; Nishida and Ichihara 2016; Pichon et al. 2005; Zhu et al. 2016), animal communications (e.g., Freeman and Hare 2015; Langbauer 2000; Policht et al. 2008; Viljoen et al. 2015), and military operations (e.g., Aleqabi, Wysession, and Ghalib 2016; E. S. Cochran and Shearer 2006; Gitterman 2014; Naz et al. 2005; Rougier and Patton 2015). Concurrent with the increased capability for measuring ground motion, new approaches in seismology, such as ambient noise tomography (e.g., Shapiro et al. 2005; Young et al. 2011), have been developed that utilize noise generated by natural noise sources (such as oceans) and anthropogenic sources to determine Earth structure.

With the extraordinary response to combat the COVID-19 pandemic, most, if not all, academic institutions effectively closed in-person learning by the early summer of 2020, making campuses ideal for studying the impact of COVID-19 on seismic noise. Reduction in seismic
noise due to the COVID-19 responses have already been observed globally (Lecocq et al. 2020) and locally (Dias et al. 2020; Lindsey et al. 2020; Xiao et al. 2020); however, none have focused on academic institutions. Utilizing metadata archived at the Incorporated Research Institutions for Seismology Data Management Center (IRIS DMC), we determined that 80 IRIS-reporting stations reside within 50 m of a university or college in the US. Of these stations, we focus on 46 seismic stations with high-sample rate (between 80 and 250 samples per second), high-gain broadband vertical motion channels: HHZ and BHZ (Ahern et al. 2007). To assess the quality of data archived at the IRIS DMC statistical and noise measurements (metrics) are produced and stored routinely, e.g.: sample minimum and maximum, number of spikes and root mean square on 24 intervals. Power spectral density (PSD) estimates are also computed using the approach described by McNamara and Boaz (2006). This paper focuses on identifying the impact of COVID-19 closures on the seismic sensors at academic institutions, recognizing that many campuses shut down almost all in-person learning, sporting events, and extracurricular activities. Explicitly, we compute the root mean square (RMS) amplitude for each station using the hour-long IRIS DMC PSD data for frequencies between 4 and 14 Hz, a frequency band previously shown to be sensitive to anthropogenic quieting (Lecocq et al. 2020). Our results show a significant drop in seismic energy around, and in most cases after, the announcement of a statewide school closure (SSC) corresponding to the campus’ state. Furthermore, many of the campuses that show a significant drop are commuter campuses, suggesting that the dominant reduction in noise in the 4-14 Hz frequency range originates from a decrease in automobile traffic.
Identifying Campus Stations and School Closures

To identify stations near institutions of higher education (campus stations), we used a catalog of IRIS-reporting stations and a map of US universities and colleges. We considered only permanent stations located in the continental US and Hawaii that were active from January 2019 – July 2020. We obtained geospatial vector data for universities and colleges from the Homeland Infrastructure Foundation-Level Data and determined which stations with data in the IRIS repository are located within 50 m of a university or college (Figure 3.1). We used a proximity buffer given that some universities and colleges only have a seismic station a short distance outside the mapped campus area. Given that Pakhomov et al. (2003) have shown that footsteps—which we presume provides an important cumulative source of campus noise—can be detected 50-70 m away from a seismic sensor, we opted to limit the buffer zone to 50 m. That is not to say that the sensors nor our analysis predominantly focus on detecting “footstep” seismicity in this region. Rather, we use this metric to offer a suitable limit to where we may still detect the anthropogenic noise of interest while increasing our coverage of campuses (i.e., number of stations).

To gather school closure data, we used a combination of school, government, and media provided data. Specifically, we gathered academic recesses (i.e., winter and spring closure) dates from their respective school websites, academic calendars, or academic catalogs. We used the provided final date of required class attendance, i.e., with the inclusion of dates when final examinations occurred (provided these dates were available). SSC and lockdown or stay-at-home order dates came from Ballotpedia, a nonprofit and nonpartisan digital encyclopedia of American politics and elections. We collected the dates of interest from Ballotpedia’s published list of enactment dates for the COVID-19 related policies and orders.
**IRIS PSD Seismic Data**

We used IRIS’ Modular Utility for STAtistical kNowledge Gatherng (MUSTANG) system (Casey et al. 2018) to request PSD estimates. Originally designed to provide an avenue for quality analysis to IRIS DMC data, MUSTANG offers more than 40 metrics that can conveniently and quickly be employed in other analyses without the need to obtain and process raw waveform data. MUSTANG calculates stacked PSD estimates at a half-hour interval, as described by (McNamara and Boaz, 2006). In this study, we considered PSD data from January 2019 to July 2020. We retrieved tabulated PSD data for instrument response-corrected miniSEED waveforms from MUSTANG’s database of data quality metrics. We opted to use HHZ over BHZ data when available because of the increased sample rate (typically 100 and 40 sps, respectively). The MUSTANG PSD metric consists of one-hour PSD measurements estimated every 30 minutes binned at periods in 1/8 octave and 1 dB power intervals (McNamara and Boaz, 2006).

**Estimating RMS from MUSTANG PSD**

From Parseval’s relation and the understanding of physical waves, the energy, $E_x$, of the waveform $x(t)$ remains constant between time-domain and frequency-domain representations for a given signal. Mathematically, this relationship established that:

$$E_x = \int_{-\infty}^{\infty} |x(t)|^2 \, dt = \int_{-\infty}^{\infty} |X(f)|^2 \, df$$  \hspace{1cm} (3.1)
which means that the area (i.e., the total energy) under the energy spectral density curve equals the area under the square of the magnitude of the signal in the time domain (Petre Stoica and Randolph Moses, 2005). To convert PSD to RMS, we use equation 3.1 as:

$$RMS_{f_1-f_2}(t) = \sqrt{\int_{f_1}^{f_2} |PSD(f)| \, df}$$  \hspace{1cm} (3.2)

were $f_1$ and $f_2$ are the lower- and upper-frequency limits, respectively. Note, equation (3.2) converts between RMS in units of $m/s^2$ and PSD in units of $(m/s^2)^2/Hz$—MUSTANG provides PSD in decibels ($10 \log_{10}((m^2/s^2)/Hz)$). Thus, we revert PSD into units of acceleration $(m/s^2)/Hz$ using the decibel conversion equation,

$$P_{dB} = 10 \times \log_{10}(P)$$  \hspace{1cm} (3.3)

where $P_{dB}$ is power in decibels (dB), and $P$ is in non-logarithmic magnitude. For RMS plotting, we convert the values back into dB with equation (3.3); thus, note that our calculated analysis and results are made with non-dB values of RMS. To compute the integral in equation (3.2), we used Simpson’s rule to approximate the integration (i.e., calculate the area under the PSD curve),

$$A = \int_{f_1}^{f_2} PSD(f) \, df \approx \frac{f_2 - f_1}{3n} \left( A_0 + 4A_1 + 2A_2 + 4A_3 + 2A_4 + \cdots + 4A_{n-1} + 2A_n \right)$$  \hspace{1cm} (3.4)

where $A$ is the area under the PSD curve between $f_1$ and $f_2$. $A_1, A_2, \ldots, A_n$, are the equally spaced segmented areas under the curve, and $n$ is the total (even) number of segments. For this study, we
consider each frequency interval provided by MUSTANG as a segment. For an odd number of
intervals, we use the trapezoidal rule on the first and last segment, calculating the remaining area
with Simpson’s rule, and use the average between the two values as the area.

**Processing Data**

MUSTANG estimates PSD values using 24-hour waveforms with one-hour estimations
every 30 minutes. This processing does not include the last one-hour window that starts at 23:30
as it does not have the data for the next 24 hours. To avoid these missing segments, we chose to
use only PSD data at 1-hour intervals such that the daily gap does not affect our analysis. We
then only consider frequencies between 4 and 14 Hz, a frequency window shown to be sensitive
to the anthropogenic quieting following the COVID-19 response (Lecocq et al. 2020). Since
MUSTANG bins periods in 1/8 octave intervals, our analysis used the closest interval equivalent
ranges from 4.15 to 13.96 Hz (D. E. McNamara and Boaz 2006). We excluded any PSDs that
provided less than 25% coverage from February 1st to April 30th, 2020 (due to data gaps) or
have no available data for 2019. Using the method described above to convert PSD to RMS, we
calculated RMS values for this data set.

We obtained day and night measurements by sorting RMS measurements based on local
times. RMS measurements occurring from the hours 0-4 were designated as nighttime
measurements, and we considered daytime measurements occurring from the hours 13-17. These
local times tend to provide reasonable estimates for night and day seismic energies; i.e., based on
similar studies on analyzing urban seismicity (Boese et al. 2015; Díaz et al. 2017; Green et al.
2017; Groos and Ritter 2009; D. E. McNamara and Buland 2004).

To analyze long-period changes in RMS, we apply a 4th-order low-pass Butterworth filter
with a 30-day period. To avoid a phase shift in the RMS signal, we applied the filter forward and
backward using cascaded second-order sections. To apply the filter, we subtracted the mean from the RMS values, applied the filter, and then added the mean back into the filtered RMS values. We applied this filter to the full, daytime, and nighttime RMS. Filtered (full) RMS values were used to calculate relative seismic energy drops 30 days before and after the SSC announcement. We supplemented missing data in RMS measurements to allow for RMS signals to be filtered and stackable. For RMS gaps, we filled in missing values by linearly interpolating nearby values. To reveal common changes in the RMS between locations, we stacked unfiltered RMS signals. To make RMS values stackable, we padded in missing front and end RMS values with the first and last low-pass RMS values, respectively, to match the total analysis window. We also normalized values relative to their range (i.e., difference between maximum and minimum value) to prevent bias towards stations with larger RMS measurements. We summed the values across time to conduct the stack and normalized the final value once more to maintain a relative measurement between 0-1. However, some stations suffer from apparent instrument glitches that may skew our stack and results. In anticipation of this, we reviewed the RMS signals visually and constructed a second stack with data from stations deemed to provide stable recordings. We identified 21 stations as potentially suffering from significant instrument glitches. Table S3.1 in the electronic supplement provides an account of the stations considered to be unaffected by instrument or communication issues. We interpreted problematic stations as those with large transient jumps in RMS, random semipersistent changes in the apparent RMS baseline, and gaps in the data.

Results

Of the 46 stations investigated, 42 stations show a drop in RMS following the 30-days after an official SSC. On average, these stations display a 14% drop in absolute energy. Of these
42 stations, 36 also had a reduction in daytime RMS on average of 17%. For a complete summary of the RMS drops measured at each station and station specific information, see Table S3.1 in the electronic supplement to this article. Figures 3.2-3.3 show the results for a few selected stations. Each of the plots shows the daily RMS values, the nighttime RMS, the daytime RMS, and the respective low-pass filter of 30 days to see the long-term impact. We also plot the lower threshold for campuses for winter break, in which a consistent minimum occurs over all schools for the nearly 2-yr period. This threshold is reached for most campuses after the closures, with many falling below this threshold. We also plot when SSC, stay-at-home orders, and initial reopening dates occur. Almost all 36 stations show the announcement of an SSC as the proverbial catalyst for an RMS drop—only nine stations did not reach or drop below the winter break minimum threshold. In some cases, the RMS recovers when the state begins to reopen (e.g., stations KIDD, USC, and MPH; see Figure 3.2-3.3). Furthermore, we observe that 33 of these stations also displayed an RMS drop for nighttime measurements.

The stacked RMS values show common changes in RMS at all campuses, removing signals from isolated seismic disturbances. Figure 3.4(a) shows the resulting stacked RMS signal with the mean SCC and academic recess dates for reference. Expectedly, we observe a drop of 7.3% in normalized RMS dB energy relative to the average SSC dates. For daytime and nighttime RMS, we measured a 9.0% and 5.1% drop, respectively. The second stack calculated that omits the problematic stations, shown in Figure 3.4(b), shows an RMS drop of 6.0%, with a day drop of 7.0% and a night drop of 4.7% in normalized RMS dB. Also, 19 of the remaining 25 stations reached the winter break minimum after the SSC date. Overall, we see that the removal of the potentially problematic measurements causes little difference in the signal. We emphasize that the (average) winter break window provides a baseline minimum for our period, and the
(average) SSC provides a good indication as to what the presumed COVID-19 RMS drop will reach in both stacks.

**Discussion**

Our analysis shows that 91% of the campus stations we studied experienced a drop in RMS following the 30 days after an official closure. A local minimum in the pre-SSC RMS is present in 22 stations around the winter season (we ignore decreases that occur from station dropouts); 9 additional stations show only limited drops (with 1-2 instances) below this minimum. Expectedly, these RMS decreases almost perfectly match a school’s winter break period. The slowdowns offer us a minimum threshold of activity during a typical academic year that we can compare to the COVID-19 signal. We speculate that for many of these campuses, a significant portion of students commute to campus. For instance, The University of Texas at El Paso reports to only house up to around 3.5% of its students (i.e., when considering its 2017 dormitory capacity), see Data and Resources section for source. We believe that a significant portion of the campus seismic noise comes from vehicle travel; thus, the presumed lack of travel during the SSC in and out of these campuses likely contributes to the observed COVID-19 RMS drop. Curiously, we also see a decline during the night after a school’s closure. This, in contrast, may indicate the dislodging and closure of dormitories following the school closures, as residing students would otherwise remain active near campus and contribute to continuous noise. Furthermore, the night change might occur due to staff, faculty, and graduate students no longer remaining on campus to conduct late-night work. Beyond the analysis described above, we also considered the dates for statewide state-of-emergency and end-of-academic-year announcements. We found that these dates offered no better correlations with the presumed COVID-19 RMS
drop. However, it remains uncertain how any of the subtleties seen in the RMS signal and COVID-19 drop directly relate to the activities implemented on or near these campuses.

It remains likely that some of the features shown in the RMS relate to various instances of ambient campus activity (academic and non-academic). For example, with our local understating of the activities occurring at The University of Texas at El Paso, we suggest that station KIDD detects activities related to the annual Monster Jam event, which is a monster truck show that occurs at the university’s Sun Bowl stadium in early March. We argue that the features seen in the RMS relate to noise from semi-trucks bringing in dirt for the event (starting a week before) and the event itself, which occurs during the weekend. Figure 3.2(b) highlights the week of elevated noise related to the occurrence of the Monster Jam events as regions MJ. Other stations appear to show an increase in RMS during the college football season (e.g., BAK, PSBV, and USC). However, the seismic increases occur 1-2 weeks before the regular season (August 24, 2019 – December 14, 2019) begins. Note that a more comprehensive study can use local information such as school event calendars and even newspapers to build an event catalog for associating the features observed in seismic noise.

We also identified annual, weekly, and diurnal changes in the RMS amplitudes. The night and day periodic measurements show distinct RMS amplitudes related to daily activities. Seismic energy at night times remains at its lowest, whereas daytime activities evidently produce higher amounts of seismic energy (see Figures 3.2-3.3). A few exceptions exist where the nighttime RMS values overshadow daytime measurements, and we find that these occurrences appear to match instances of large events—presumably, those occurring in the evening time (e.g., the monster truck rallies and, potential, football seasons mentioned above). The weekends also appear regularly in all stations as relative minimums. As other studies have suggested, this seems
to show the end of the workweek (Monday-Friday) when people are less active (Díaz et al. 2017; Green et al. 2017; Groos and Ritter 2009). The stacks (as do some of the individual stations) provide RMS values that show dips during many US national holidays. We attribute these drops to the lack of activity during these dates as, historically, academic institutions tend to cancel classes, and attendees may leave campus early during these holidays. However, to understand all the unique RMS changes, including those related to the COVID-19, a more in-depth analysis—with knowledge of campus events, academic culture, and instrument placement—needs to be conducted. This would likely involve estimating an effective radius for recording certain operations.

Our results suggest that seismic noise from stations located in academic campuses, or their vicinities may be able to assess a school in terms of campus activity and even provide a proxy for the activity during a major event (i.e., with similar impact to the COVID-19 response). At a limited scale, we detect periods of relatively low school activity and attendance (i.e., holidays and academic breaks). We expect that a long-term (e.g., decades) RMS record can provide a pseudo-metric for campus enrollment, level of campus liveliness (i.e., frequency and scale of campus activities), and periods of renovation, expansion, or downsizing. Also, RMS records can reveal other trends of activity. For example, an RMS increase in multiple campus stations in a single region may indicate countrywide or statewide activities—these campuses may serve as proxies for the communities that they reside in. To explore this, we examined a non-campus HHZ station part of the Cooperative New Madrid Seismic Network operated by St. Louis University and archived by IRIS, HDAR2 (location code 10) from the NM network located near the city limits of Memphis, TN—the city where campus station MPH resides. Station HDAR2 appears to be near a weigh station just west of the Hernando de Soto Bridge connecting
Tennessee and Arkansas. The passing traffic likely dominates the seismic energy seen. Figure 3.5 displays the RMS for this station and reveals a similar holiday and COVID-19 drops to those seen from the local campus station, MPH. Admittedly, this anecdotal observation far from establishes a strong connection between campus and citywide activity. However, the conformity between the RMS signals observed near this interstate shows the potential that the two institutions produce comparable seismic features related to community events or impacts.

We would also like to emphasize the advantages of using the metric computed by the IRIS DMC system MUSTANG. MUSTANG contains data quality metrics for seismic data from more than 35,000 stations with data that spans almost five decades. This resource offers over 40 separate metrics, including for data arriving in near-real-time (Casey et al. 2018). Thus, we did not need to download, process, and locally store any raw waveform data for this study. Although the MUSTANG system’s primary purpose is providing a method for assessing data quality assurance, the metrics available (e.g., PSD estimations) can be used for scientific analysis and data exploration. For instance, we successfully downloaded one year’s worth of vertical component PSD data from 46 stations in less than 10 hours, amounting to roughly 3 GB. Collecting the equivalent data as raw waveforms then calculating the RMS would likely take significantly longer and certainly require more storage space. Mustang PSD estimates are well suited to explore smooth spectral features. However, as described by Anthony et al. (2020), the processed data, particularly the frequency smoothing, may not be appropriate for studies requiring finer resolution of spectral resolution.

Conclusion

By collecting and analyzing the PSD measurements between ~4-14 Hz frequencies for 46 stations located at college and university campuses, we successfully observed a drop in seismic
energy likely related to the COVID-19 response. We accomplished this by utilizing Parseval’s relation, specifically as it relates to the conservation of waveform energy between time and frequency domains, to convert PSD to RMS. When considering the overall filtered RMS values, 91% of stations showed a drop following an SSC. Additionally, results suggest that the winter break offers a good baseline for seismic silence on the campuses. Of the stations with the COVID-19 drop, 83% reached the RMS minimum threshold set during the academic winter break period. We also make other observations suggesting that this method may be able to detect additional anthropogenic activities at or near these campuses. This includes the regular detection of weekends with weekly RMS drop, higher RMS during daytime due to diurnal activity, and jumps in RMS for significant events held at the schools (i.e., monster truck shows). Stacking the RMS signal also reveals ostensible drops in RMS during many of the US national holidays.

Data and Resources

We obtained our catalog of stations from IRIS’ GMap web application (http://ds.iris.edu/gmap/). PSD data used in this study was collected using IRIS’ MUSTANG system (Casey et al. 2018). Statewide school closure and lockdown (stay-at-home) order dates were gathered from Ballotpedia (https://ballotpedia.org). The University of Texas of El Paso housing information was obtained from (http://news.utep.edu/a-history-of-housing/). Shapefiles containing geospatial vector data for post-secondary education facilities were obtained from HIFLD (https://gii.dhs.gov/HIFLD). Maps and spatial analysis were conducted with QGIS (QGIS.org 2020). QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.org). Python code was used for processing waveform data, in particular we used the Obspy Python package (docs.obspy.org; Beyreuther et al. 2010; Krischer et al. 2015; Megies et al. 2011). Plots were made in part using the Plotly Python package (Plotly

Figures

Figure 3.1

Map showing the location of campus stations (triangles) scaled to the campus population, as provided by the Homeland Infrastructure Foundation-Level Data (HIFLD), through the continental U.S. and Hawaii used in this study. Dark-colored region indicates a larger density (i.e., count per area) of colleges and universities. Inset: Map of Hawaiian Islands showing the density of schools and location of station HILB. The color version of this figure is available only in the electronic edition.
Root mean square (rms) plots showing the unfiltered rms (rms), low-pass filtered rms (LPF-rms), low-pass filtered daytime rms (LPF-day), and low-pass filtered nighttime rms (LPF-night) signals for three campus stations. (a) CI BAK at California State University, Bakersfield (Bakersfield, California); (b) EP KIDD at The University of Texas At El Paso (El Paso, Texas)—regions MJ indicate the occurrence of Monster Jam; and (c) CI USC at the University of Southern California (Los Angeles, California). Periods of winter break highlighted by region WB and spring break by region SB. Solid vertical line, vertical dashed line, and vertical dotted line denote statewide school closure (SSC) date, stay-at-home lockdown order date, and initial reopening date, respectively. The horizontal dotted line indicates the winter break minimum. The color version of this figure is available only in the electronic edition.
Figure 3.3

Plots show three more rms plots with unfiltered rms (rms), LPF-rms, LPF-day, and LPF-night signal for three campus stations. (a) PT HILB at the University of Hawaii at Hilo (Hilo, Hawaii); (b) PE PSBV at Pennsylvania State University, Penn State Beaver (Monaca, Pennsylvania); and (c) NM MPH at the University of Memphis (Memphis, Tennessee). Periods of winter break highlighted by region WB and spring break by region SB. Solid vertical line, vertical dashed line, and vertical dotted line denote SSC date, stay-at-home lockdown order date, and initial reopening date, respectively. The horizontal dotted line indicates the winter break minimum. The color version of this figure is available only in the electronic edition.
Figure 3.4

Normalized stacked rms plots with averaged periods of winter break highlighted by regions WB and spring break by region SB. Arrows mark select U.S. national holidays. Solid vertical line, vertical dashed line, and vertical dotted line denote averaged SSC date, stay-at-home lockdown order date, and initial reopening date, respectively. The horizontal dotted line indicates the winter break minimum. Panel (a) stacks all 46 stations, but panel (b) only uses the 25 stations.
determined to be free from instrumental errors. The color version of this figure is available only in the electronic edition.

Figure 3.5

Rms plots showing the unfiltered rms (rms), LPF-rms, LPF-day, and LPF-night signal for station HDAR2. The normalized low-pass filtered rms for campus station MPH has been included for reference. University of Memphis’ winter break period is highlighted by region WB and its spring break by region SB. Arrows mark select U.S. national holidays. Solid vertical line, vertical dashed line, and vertical dotted line denote averaged SSC date, stay-at-home lockdown order date, and initial reopening date, respectively. The horizontal dotted line indicates the winter break minimum for station HDAR2. The color version of this figure is available only in the electronic edition.

Electronic Supplement (Copy)

Table S3.1: Table of station information and station specific results.

<table>
<thead>
<tr>
<th>NW¹</th>
<th>STA²</th>
<th>CHA³</th>
<th>SCHOOL NAME</th>
<th>LOCATION</th>
<th>RMS DROP (%)</th>
<th>Q⁵</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>All</td>
<td>Day</td>
</tr>
<tr>
<td>BK</td>
<td>CMB</td>
<td>HHZ</td>
<td>COLUMBIA COLLEGE</td>
<td>SONORA, CA</td>
<td>-2.22</td>
<td>-6.33</td>
</tr>
</tbody>
</table>

62
<p>| CI | BAK | HHZ | Institution                                           | City, State         | CI   | BAK   | HHZ | CI   | BAK   | HHZ | CI   | BAK   | HHZ | CI   | BAK   | HHZ | CI   | BAK   | HHZ | CI   | BAK   | HHZ | CI   | BAK   | HHZ |
|----|-----|-----|------------------------------------------------------|---------------------|------|-------|-----|------|-------|-----|------|-------|-----|------|-------|-----|------|-------|-----|------|-------|-----|------|-------|-----|------|-------|-----|
| CI | SDD | HHZ | SADDLEBACK COLLEGE                                    | MISSION VIEJO, CA   | 18.71| 17.80 | 24.69|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| CI | USC | HHZ | UNIVERSITY OF SOUTHERN CALIFORNIA                     | LOS ANGELES, CA    | 17.70| 21.93 | 19.83|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| EP | KIDD| HHZ | THE UNIVERSITY OF TEXAS AT EL PASO                    | EL PASO, TX        | 13.58| 13.15 | 14.29|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| LD | ALLY| HHZ | ALLEGHENY COLLEGE                                     | MEADVILLE, PA      | 29.02| 34.98 | 25.76|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| LD | CCNY| HHZ | MEDAILLE COLLEGE                                      | BUFFALO, NY        | 12.66| 14.73 | 5.04 |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| LD | FOR | HHZ | FORDHAM UNIVERSITY                                    | BRONX, NY          | 13.74| 12.16 | 16.56|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| LD | GCMD| HHZ | GARRETT COLLEGE                                       | MCHENRY, MD        | 9.06 | 1.77  | 6.79 |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| LD | MVL | HHZ | MILLERSVILLE UNIVERSITY OF PENNSYLVANIA               | MILLERSVILLE, PA   | -11.83| 3.90  | -34.25|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| MB | BUT | HHZ | MONTANA TECH OF THE UNIVERSITY OF MONTANA              | BUTTE, MT          | 2.31 | 13.74 | -6.70|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NE | BCX | HHZ | BOSTON COLLEGE                                        | CHESTNUT HILL, MA  | 21.14| 19.41 | 32.73|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NE | EMMW| HHZ | UNIVERSITY OF MAINE AT MACHIAS                        | MACHIAS, ME        | 3.94 | 1.19  | 4.69 |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NE | HNH | HHZ | DARTMOUTH COLLEGE                                     | HANOVER, NH        | 20.54| 17.67 | 18.89|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NE | TRY | HHZ | RENSSELAER POLYTECHNIC INSTITUTE                      | TROY, NY           | 13.14| 11.90 | 10.45|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NE | WES | HHZ | BOSTON COLLEGE - WESTON OBSERVATORY                   | WESTON, MA         | 9.65 | 7.86  | 5.31 |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NE | WVL | HHZ | COLBY COLLEGE                                         | WATERVILLE, ME     | 7.42 | 7.13  | 5.48 |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NM | BLO | HHZ | INDIANA UNIVERSITY - BLOOMINGTON                      | BLOOMINGTON, IN    | 10.02| -10.02| 15.46|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NM | FFIL| HHZ | FRONTIER COMMUNITY COLLEGE                            | FAIRFIELD, IL      | 5.14 | -1.90 | 11.13|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NM | MPH | HHZ | UNIVERSITY OF MEMPHIS                                 | MEMPHIS, TN        | 19.64| 19.03 | 0.47 |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NM | OLIL| HHZ | OLNEY CENTRAL COLLEGE                                 | OLNEY, IL          | 10.50| 17.49 | 6.79 |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NM | PBMO| HHZ | THREE RIVERS COLLEGE                                  | POPLAR BLUFF, MO   | 0.84 | -1.98 | 5.60 |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NM | SIUC| HHZ | SOUTHERN ILLINOIS UNIVERSITY - CARBONDALE              | CARBONDALE, IL     | 5.57 | 3.08  | 5.92 |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NM | SLM | HHZ | SAINT LOUIS UNIVERSITY                                | SAINT LOUIS, MO    | 4.47 | 1.76  | -0.98|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NM | USIN| HHZ | UNIVERSITY OF SOUTHERN INDIANA                        | EVANSVILLE, IN     | 3.99 | -31.33| 16.72|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |
| NM | UTMT| HHZ | THE UNIVERSITY OF TENNESSEE-MARTIN                    | MARTIN, TN         | 8.76 | -11.40| 11.17|      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |      |       |      |</p>
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64
(Filtered) RMS percent changes are calculated such that positive values indicate an average decline in seismic energy 30 days before and after a statewide school closure. 

The quality (Q) factor indicates if the observed RMS was considered to be unaffected by instrument issues.
Chapter 4: Limited Dynamic Triggering in the Utah Region, USA

Abstract

The state of Utah, USA experiences around 3,800 cataloged earthquakes per year, highlighting that the region is seismically active and susceptible to earthquakes. Following the 2002 Denali Fault ($M_{7.9}$) earthquake in Alaska, the region showed an elevated seismicity rate for three weeks following the passage of high amplitude surface waves, suggesting that the region may be particularly susceptible to dynamic triggering. With over 23,396 faults and each fault presenting a potential fault for triggering, we systematically search for dynamic triggering throughout the state of Utah caused by large, global earthquakes with $M_{\geq 7}$. Specifically, we analyze earthquake catalogs and all available waveform data to determine statistical increases of seismicity rate following the passage of seismic arrivals. While we do find instances of dynamic triggering, our results show that these events occur sparsely in the region. In total, less than 20% of the 273 mainshocks that occur from 2000 to the end of 2017 show a statistical indication of dynamic triggering throughout the Utah region, highlighting that dynamic triggering is limited for stresses created by transient signals from global $M_{\geq 7}$ earthquakes, with the exception being the Denali Fault ($M_{7.9}$), Alaska earthquake (i.e., an instance of significant triggering).

Introduction

Understanding the nature of faulting and earthquakes requires an understanding of the state of stress of faults and determining mechanisms for fault failure. Earthquakes release stored stresses in the lithosphere created by long-term scale stress accumulation from tectonic and

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Note: This Chapter comes from a work currently under review for publication and expands/revise on M.S. thesis work done by Guenaga, David L.; Guenaga, David Lewis, "Dynamic Triggering Of Earthquakes Within The State Of Utah, Usa" (2019). Open Access Theses & Dissertations. 79. https://scholarworks.utep.edu/open_etd/79
regional forces. However, the amount of energy release, the timing and the mechanism of when an earthquake occurs remains elusive. The study of triggered earthquakes, here defined as earthquakes that have had their natural earthquake cycle advanced, may reveal unique aspects of the nature of fault stress and specific conditions needed for failure. Triggered earthquakes result from a variety of mechanisms, including static stress increases caused by nearby fault motion (e.g., King, Stein, and Lin 1994; Stein, King, and Lin 1994; 1992; Toda et al. 1998), dynamic stress from transient stresses (seismic waves) caused by distant, large earthquakes (e.g., Alfaro-Diaz et al. 2020; Brodsky, Karakostas, and Kanamori 2000; J. Gomberg et al. 2001; David P. Hill et al. 1993; Deborah Kilb, Gomberg, and Bodin 2000; Kristine L. Pankow et al. 2004; Parsons, Kaven, Velasco, and Gonzalez-Huizar 2012; Prejean and Hill 2018; Velasco et al. 2008), and induced stress caused by the injection of fluid into the crust, enhanced oil recovery practices, and/or hydraulic fracturing (e.g., Ellsworth 2013; Savvaidis, Lomax, and Breton 2020; Skoumal, Kaven, et al. 2020).

We focus on observing the conditions of fault failure caused from dynamic triggering in Utah, a region with documented dynamic triggering, to investigate the frequency of occurrence in specific tectonic subregions that may be susceptible to transient stresses and identify any common attributes of failure caused by these stresses. Dynamically triggered seismic events can occur either instantaneously during the passage of seismic waves (termed instantaneous triggering) or after the passage of the seismic wave (termed delayed triggering). Delayed dynamic triggering has been proposed in regions of induced seismicity related to deep wastewater injection (van der Elst et al. 2013). Deciphering the stress needed to trigger earthquakes can reveal the current state of stress of faults in natural and anthropogenic (induced)
tectonic settings, the potential for triggering large events, and a basic understanding of fault dynamics and interactions.

The region encompassing the state of Utah, USA has experienced notable, but limited instances of dynamic triggering as exhibited with widespread dynamic increase following the 2002 M7.9 Denali earthquake (Linville et al. 2014b; Kristine L. Pankow et al. 2004; Kristine L. Pankow and Kilb 2020). The Utah region is seismically active with over 23,396 active faults intersecting the state (U.S. Geological Survey and Utah Geological Survey n.d.) (Figure 4.1). From 2000 to 2017, over 33,000 local earthquakes were recorded in Utah by the University of Utah Seismic Station (UUSS), which has maintained a stable, regional seismic network with ~175 stations throughout the Utah and Yellowstone regions since 1981. Utah is a prime candidate for analyzing dynamic triggering given the observations of previous studies (Kristine L. Pankow et al. 2004; Kristine L. Pankow and Kilb 2020; V. Tang, Chao, and van der Lee 2021), the number of active faults in the region, the temporary (2 year) station coverage (70 km grid) provided by the USArray from the EarthScope project, and the coverage provided by UUSS seismic network. Here, we examine 273 mainshocks M ≥ 7 from 2000 to 2017 occurring throughout the globe as their seismic waves arrive in the state of Utah, defined by the area between 36° and 42.5° of latitude and -115° and -108.5° of longitude. Although significant triggering was observed following the M7.9 Denali Fault (2001) earthquake within the state, we find limited triggering to occur within the state of Utah.

**Dynamic Triggering**

Dynamic triggering has been a widely observed phenomenon. In the past decades, previous studies have identified the occurrence of dynamic triggering throughout the world and in specific regions (Aiken, Meng, and Hardebeck 2018; Brodsky, Karakostas, and Kanamori 2000; J.
Gomberg et al. 2004; 2001; David P. Hill et al. 1993; Deborah Kilb, Gomberg, and Bodin 2000;
Kristine L. Pankow et al. 2004; Kristine L. Pankow and Kilb 2020; Parsons, Kaven, Velasco, and
Gonzalez-Huizar 2012; Prejean and Hill 2018; Velasco et al. 2008; B. Wang et al. 2015; 2018;
V. Tang, Chao, and van der Lee 2021). On November 3, 2002 the $M_{7.9}$ Denali fault earthquake
in Alaska triggered an abrupt increase in seismicity throughout Utah. Specifically, an observed
increase in seismicity lasted ~24 days after the passage of the large amplitude surface wave from
the Denali earthquake (J. Gomberg et al. 2004; Kristine L. Pankow et al. 2004; Velasco et al.
2004). Most triggered events occurred along normal faults in the region including along the
Wasatch fault ranging in magnitude from 0 to 3.2 (Kristine L. Pankow et al. 2004).

Dynamically triggered earthquakes can provide insight into the complex physical thresholds
that lead to fault rupture and nucleation (Alfaro-Diaz et al. 2020). Generally, natural earthquakes
occur at depths beyond our ability to measure in situ stress conditions at seismogenic depths,
such as friction coefficients, slip geometries, and absolute stress of an earthquake fault.
Currently, these measurements can only be inferred indirectly during an event, or from direct
drilling into a fault (e.g., the San Andreas Observatory at Depth; Zoback et al., 2010). However,
the seismic waves of a triggering mainshock earthquake cause discernible and measurable
changes in a region’s state of stress, providing a direct measurable property that can trigger a
fault to rupture. Previous studies have proposed various mechanisms for these triggered events,
including changes in Coulomb failure, rate-state friction, viscous fault creep, and subcritical
crack growth, amongst others (Brodsky and Prejean 2005; Brodsky and van der Elst 2014;
Gonzalez-Huizar and Velasco 2011; David P. Hill 2008; Debi Kilb, Gomberg, and Bodin 2002;
Peng and Chao 2008). By investigating the stress caused by transient signals that triggered an
earthquake, we can better understand the nature of faulting and the conditions needed to promote earthquake failure.

Previous studies have shown that dynamic triggering often transpires during the passage of surface waves, and on occasion S-waves, suggesting that triggering occurs by either an adequate transient increase in Coulomb stress or lowering of the rupture threshold through a decrease in normal stress (e.g., Alfaro-Diaz et al. 2020; Gonzalez-Huizar and Velasco 2011). Unlike static changes in stress, a transient disturbance that does not cause the fault to fail allows the fault to return to its initial stress state, indicating that any impending earthquake would occur during its normal cycle, assuming no static changes occur (J. Gomberg et al. 1998). Figure 4.2 illustrates the general relationship we describe between a transient stress change, permanent stress change, and unaltered stress change leading to a local event. Both transient and permanent stress changes can lead to earlier fault rupture relative to an undisturbed fault. Although this type of simplified model can explain the relationship between stress and the triggering of faults, there has been little consensus on what is the exact failure mechanism for dynamic triggering, especially for delayed dynamic triggering. Here, we evaluate how susceptible the Utah region is to triggering and explore how triggering manifests with possible failure mechanisms for dynamic triggering.

Data and Quality Control

Earthquake Catalog Data

For a catalog of global mainshocks, we relied on United States Geologic Survey (USGS) catalog. The USGS earthquake catalog (commonly referred to as ComCat) is an accumulative collection of recorded events relying on various seismic networks and provides a reliable list of $M \geq 6$ magnitude earthquakes that have occurred in the past two decades. Since the USGS
reports less confidence and varying levels of completeness for lower magnitude events (such as those for triggered earthquakes), we do not rely on this catalog for our triggering record ("ComCat Documentation - Data Availability" 2019). We also limit our mainshock list to earthquakes with $M \geq 7$ occurring from 2000—2017, which equals a total of 273 mainshocks that met our specifications. We obtained the catalog using the USGS Search Earthquake Catalog web service.

We obtained the local event catalog from UUSS to analyze and compile an initial list of dynamically triggered events in the Utah region. The UUSS digital catalog contains earthquakes from 1981 – 2020. UUSS reports the catalog complete for magnitudes ranging from 1.5 to 3 depending on the region ("Quality and Completeness of UUSS Catalog Data: 1981-Present | U of U Seismograph Stations” n.d.). Furthermore, UUSS also reviews their detections to verify that their catalog remains free from confirmed non-earthquake detections (Arabasz, Pechmann, and Burlacu 2016). Here, we extracted catalog data for all events occurring in the Utah region from 2000—2017 (Figure 4.1). As a result, our initial local catalog comprised of 33,634 events. In additional, we analyze waveform data for each mainshock earthquake to identify triggered events that may have been masked by the teleseismic wavetrain (described below).

**Waveform Data**

We collected seismic waveform data from the Incorporated Research Institutions for Seismology (IRIS) Data Management Center for 101 stations in the Utah region (Figure 4.3). Stations included 63 from EarthScope’s Transportable Array (TA) network (USArray), 3 from United States National (US) network, and 35 from University of Utah Regional (UU) network (Figure 4.3). The waveform data collected encompasses (±5 hours) each mainshock’s origin time.
and consists of 3-component (North, East, and Vertical) seismic records that include either broadband or high-broadband channels of each station.

**Removing Noisy Stations**

To minimize bias due to excessively noisy or problematic waveforms recordings, we evaluated the frequency response of each station’s daily Probability Density Functions (PDF) mode station for over the past three years. We obtained daily PDF mode plots from the Incorporated Research Institutions for Seismology’s (IRIS) Modular Utility for STAtistical kNowledge Gathering (MUSTANG) data quality metrics web service (Casey et al. 2018). Past research suggests that cultural noise primarily propagates as high-frequency (greater than 1-10 Hz) surface waves while large, teleseismic earthquakes mainly express at lower frequencies (0.1-1 Hz) (D. E. McNamara and Buland 2004). Local earthquakes, such as those identified as dynamically triggered, generally have dominant frequencies greater than 5 Hz (Velasco et al. 2016). Given these frequency ranges, we gauged the potential presence of noise recorded at each station relative to the seismic signals of interest i.e., local earthquakes. Stations that demonstrated consistently higher power at 10 (9.870) Hz frequencies versus 0.1 Hz frequencies were, thus, determined to contain high amounts of noise (Casey et al. 2018; D. E. McNamara and Buland 2004). Figure 4.4 displays two station’s daily PDF mode plot, one (station CCUT - UU network) with negligible and another (station O16A - TA network) with large amounts of apparent high-frequency noise. We omitted waveform data collected from stations with apparent high-frequency noise (e.g., station O16A) to limit noise related skews in our results. Figure 4.3 marks these omitted stations with white circles.
Local Mining

In this study, we used the available quarry blast record from Linville et al. (2019) to help isolate earthquake detections. The catalog includes occurrences of quarry blast from October 1, 2012—April 26, 2016, and indicates which UU, TA, and US station(s) recorded the event. The Utah Geologic Survey reported in 2008 that Utah contains roughly 105 large and 184 small active mines (Bon and Wakefield 2008). In these regions, quarry blasts can appear seismically as earthquakes if not analyzed properly. Past efforts have been made to discriminate between these signals with some success (Hedlin, Minster, and Orcutt 1990; Joswig 1993; Musil and Plešinger 1996; Wiemer and Baer 2000). However, these types of discrimination methods require complex algorithms, or a comprehensive understanding of the quarry blast signals. Due to our limited scope, we do not implement these methods. Instead, we use available quarry blast records to remove detections likely related to mining activity. Since many quarry events lack location or explicit arrival time for a given station, we lacked the ability to precisely remove any mining detections (data only provides the mining event origin time and the station(s) where the event was detected). Thus, we opted to remove the first detection that occurs following a two-minute window after any given quarry blast occurrence. We only applied this detection removal for stations that the quarry blast catalog indicates detected the quarry blast event.

Analysis of Utah Seismicity

Due to Utah’s tectonic setting and anthropogenic activity, the region experiences regular occurrences of detectable seismicity. The region divides into three geologic provinces with more than 23,000 active faults—again, the Wasatch fault being the largest and most seismically active (Figure 4.1). Based on the UUSS catalog, the Utah region averages over 3800 local earthquakes per year for the years 2000—2017. During this period, local events occur throughout the region,
not appearing to favor a geologic province, but most notably appearing along the boundary between east and west geologic provinces (Figure 4.5). These events have magnitudes that range from -1.02 to 5.91, and the reported magnitude of completion ranges from 1.5—1.7. The USGS catalog also offers a list of non-earthquake events in the region. Anthropogenic activity consists of 17 mining related events such as quarry blasts, rock bursts, and mine collapses. These events have magnitudes that range from 1.10 to 3.93 with a mean of 2.07. Note that Figure 4.5 does not necessarily show all the quarry blast events identified in our analysis given the lack of location for many quarry blasts. Rather we provide them to show the expected localities for such events based on available data.

**STA/LTA Detector**

To enhance the UUSS catalog, we utilized a short-term-average to long-term-average (STA/LTA) detector. We applied a 5 Hz high-pass filter to the waveform before employing the detector. As shown by Velasco et al. (2016) and Alfaro-Diaz et al. (2020), a 5 Hz high-pass filter effectively removes the mainshock’s coda while preserving local triggered event due to its higher frequency content – this helps ensure that the detector ignores teleseismic (≥ 30°) and, to a lesser extent, far regional events (13°- 30°). Furthermore, we adopted a method described by Velasco et al. (2016) that involves removing detections that fail to appear on at least two of the three components of waveform data to reduce random noise related detections.

**Manually Identifying Local Events**

After we obtained the STA/LTA detector results, we manually reviewed a portion of the detections and waveforms. Specifically, we reviewed waveforms with a two-to-one or greater increase in local seismicity following the mainshock arrival based on the UUSS catalog data.
This helps ensure that we ostensibly, based on catalog data, review all potential triggered sequences. We treated all mainshocks as having at least one pre-event (an event occurring before the mainshock arrival) to account for zero pre-event mainshocks; thus, at minimum, all potential triggered sequences contain at least 2 post-events (i.e., events occurring after the mainshock arrival). A total of 65 mainshocks met the two-to-one or greater threshold.

We then manually examined each detection result and waveforms for the 65 mainshocks. This process involved identifying missed events, confirming existing detections, and removing false positives (e.g., detections related to far regional, anthropogenic, and noise signals). During review, we utilized a 5 Hz high-pass and 1-5 Hz bandpass filter to aid in signal identification—the bandpass filter was used to help identify signals related to far regional events. Figure 4.6 illustrates the types of signals that the analyst interpreted as regional/local events (with examples of pre- and post-events). Figure 4.7 shows an example of an STA/LTA detected potentially triggered event absent from the UUSS catalog, presumably due to a low magnitude.

Results

We use a statistical threshold to evaluate if a mainshock dynamically triggered local earthquakes. For this evaluation, we rely on the following Poisson distribution formula:

$$P(v_i) = (e^{-\mu}) \frac{\mu^{v_i}}{v_i!}, \text{ given } \mu = \begin{cases} N_i & N_i > \bar{N} \\ \bar{N} & \text{otherwise.} \end{cases} \tag{4.1}$$

where $N_i$ and $v_i$ are equal to the number of events occurring before and after mainshock $i$’s P arrival, respectively. We assume the $P$-wave does not trigger any events due to its relatively small amplitude given the remote distance from the mainshock, for this reason it serves as our
cut-off between post- and pre-events. Nonetheless before we assess dynamic triggering, we
determine the average number of events occurring within the five hours before the mainshock
arrival and round up to nearest integer (\( \bar{N} \)); we use this value to replace \( N_i \) for, presumably,
uncharacteristically seismically silent pre-event periods to combat overrelaxed triggering
thresholds. Given an increase in seismicity following the mainshock arrival, we classify
mainshocks as potentially triggering if we observe a 95% certainty of triggering (i.e., about a 5%
probability of the random occurrence of \( v_i \) post-events happening by chance) using equation
(4.1).

Besides the statistical approach, we also considered “special case” dynamic triggering
(e.g., Alfaro-Diaz et al. 2020). We classified special cases as mainshocks promoting an
insignificant increase in seismicity following its arrival but having a local event occur during the
passage of the S- or surface waves. For this process, we calculated expected arrivals for each
phase based on the \( iasp91 \) velocity model (Kennett and Engdahl 1991), and we confirmed that all
events contained at least one observable local earthquake during the passage of the S- or surface
waves. Alfaro-Diaz et al. (2020) employed this approach to identify additional potential dynamic
triggering. However, we found that only 14 mainshocks satisfy the special case criteria
(potentially triggering 61 Utah events). These events do not significantly influence the overall
results; thus, they are not marked in our triggering analysis plots (Figures 4.8-4.10). Table S4.1
shows all triggering mainshocks including special case events.

Thirty-six (36) mainshocks appear to trigger 623 local events in the Utah Region. Figure
4.8 shows the occurrence of these potentially triggered events and their associated mainshock.
Relative to triggering phases, 17, 5, and 220 potentially triggered events occur during the
passage of the S, Love, and Rayleigh wavetrains, respectively. A total of 381 events occurred as
delayed triggered events (i.e., triggered earthquakes between the mainshock coda and the 5-hour cut-off after the mainshock arrival). We calculated an average number of events before the mainshock arrival as 4, the value $\bar{N}$ in equation (4.1), with a standard deviation of 5. Peak dynamic stress reveals no tendencies relative to the azimuth of the incoming wavetrain to a station (back-azimuth) (Figure 4.9a)—unlike what was identified in Coso Geothermal Field, California (Alfaro-Diaz et al. 2020). Figure 4.9 presents how triggering mainshocks, colored circles (based on occurrence), compared to the other, gray colored, mainshocks. Triggering mainshocks appear at various depths with two-thirds occurring at depths <40 km (Figure 4.9b).

Non-triggering mainshocks share this distribution. For most mainshocks, great arc distances (i.e., to the Utah region) are greater than 10,000 km (Figure 4.9c). Again, triggering and non-triggering mainshocks show no obvious distinguishing qualities in great arc distance distribution. Triggering also does not appear to distinctly correlate to mainshock magnitude. Mainshock magnitudes for non-triggering sequences range from $M 7$ (the cutoff magnitude) to 9.1 and from $M 7$ to 8.2 for triggering mainshocks (Figures 4.9d).

**Discussion**

Our results show very limited instances of potential dynamic triggering in Utah with less than 20% of the mainshocks being considered as triggering events. When exclusively considering potentially triggered instances, we also observe characteristics reminiscent of dynamic triggering; Figure 4.8b shows that seismicity increases during the arrival of the $S$ and surface waves, as expected for dynamically triggered areas. We observe some strong instances of triggering (e.g., the events following the Denali Fault earthquake), but the region does not statistically appear to experience frequent increases in local seismicity following large earthquakes. Furthermore, there appears to be no distinct trend of characteristics in the triggered
events, which suggests that triggering in Utah is not controlled by depth, great arc distance, or peak dynamic stress experienced from the mainshock.

The type of inferential statistics that we rely on, a p-value (5% probability value in our case) approach, has some limitations (e.g., Wasserstein and Lazar, 2016). For example, p-value approaches are susceptible to producing false positives (i.e., the existence of a phenomena where not present); however, here we show a lack of triggering, at least for the magnitudes considered in our analysis. Recent papers have offered methods to supplement statistical analyses to improve the validity of claimed dynamic triggering. Pankow and Kilb (2020), who applied a new statistical method that considers spatial and temporal factors, also found limited triggering in Utah. While our analysis finds more instances of potential triggering, we consider missing local events in the catalogs and use a more generous triggering threshold of 95% certainty. Thus, our results are consistent with those findings using a different approach, illustrating that the Poisson method offers some insight as it relates to assessing seismic triggering in the past (Linville et al. 2014b; Velasco et al. 2008; Kristine L. Pankow et al. 2004; Brodsky, Karakostas, and Kanamori 2000). Fundamentally, statistical approaches remain an effective and practical approach to systematically identify earthquake triggering—given that there currently does not exist a physical or definitive characteristic to determine triggering. However, in many cases with dynamic triggering, we must account for limited sampling due to the magnitude of completeness of catalogs, the location of the mainshocks relative to the study region, and to the location of seismic sensors in relation to small, dynamically triggered events when using waveforms alone.

Our results are limited to the UUSS catalog and our ability to manually detect smaller events than those recorded in the catalog. The UUSS catalog provides an excellent record of the larger or more prominent local earthquakes in the region and supplementing with manual review for
smaller magnitude events allows us to extend our results to lower magnitude (Figure 4.7). Generally, when generating a conventional seismic catalog, events need reporting of arrivals at four or more stations; thus, a lower threshold in any seismic catalog is determined by the geometry of the network being used. To supplement this, we rely on manual review in some cases to search for small events that are near the seismic station but not large enough to be recorded on several stations (thus not making it into the UUS catalog).

We also observe two instances of increase seismicity not related to the passage of large magnitude events. Around March 2004 and January 2010, we see a >100 event increase in roughly a few weeks’ time. During these sequences, no large magnitude mainshocks occur within the 5 hours before the increase, and thus might be isolated clusters over events. If a mainshock occurred before these series events, we would likely interpret this as significant instances of triggering (likely larger than any other series of potential triggering in the area). We suspect that these may be natural clusters of events; however, it remains unclear as to what is the cause of this increase in seismicity.

Unexpectedly, our results lack any common traits for triggering that have been recorded in past studies. Compared to the Alfaro-Diaz et al. (2020) finding in the Coso Geothermal Field, California, dynamic triggering in our region lacks preferential back-azimuth angles and peak dynamic stresses. However, the large spatial region of our study is much greater that the study of Alfaro-Diaz et al. (2020), and specific regions with common local stress regime may respond differently to dynamic stresses. Regardless, in this study, peak dynamic stress measurements show no tendencies relative to the direction of the incoming wave relative to the local stress field (Figure 4.9a). Rather, events seem to mirror the overall trend seen when including non-triggering mainshocks—i.e., triggering pattern is not an identifier using these measurements. Triggering
mainshocks occur at various depths with two-thirds occurring at crustal depths of <40 km (Figure 4.9b); mostly occur at distances greater than 10,000 km away from the region (Figure 4.9c); varying from $M_w$ 8.2 to 7 (Figures 4.9d). Again, we observe no distinct pattern in these measurements when we include non-triggering mainshocks. In Figure 4.10, we plot triggered events and show that most events occur near the mapped faults. Triggering seems to favor the faults marking the eastern boundary of the Basin and Range province (the Wasatch fault encompassing a significant portion). Note that we do not map triggered events not found in the catalog as we have not located these earthquakes.

Dynamic triggering has been attributed to large transient stresses (generally surface waves) created from distant, large earthquakes, yet correlating the seismic phase responsible for triggering has not been thoroughly documented. Mechanisms for instantaneous dynamic triggering include changes in Coulomb failure, rate-state friction, viscous fault creep, and subcritical crack growth (Brodsky and Prejean 2005; Brodsky and van der Elst 2014; Gonzalez-Huizar and Velasco 2011; David P. Hill et al. 1993; Debi Kilb, Gomberg, and Bodin 2002; Peng and Chao 2008). We find that $S$, Love and Rayleigh wavetrains trigger 17, 5, and 220 events, respectively. We also document 381 delayed triggered events. $S$ and Love waves are transversely polarized waves, which generate shear stress. Thus, dynamic triggering created by shear stress suggests that the addition of shear stress in a local region will advance the earthquake cycle for small faults near failure. Our results, however, show that Rayleigh waves are the dominant seismic phase responsible for triggering, which are elliptically (vertical and radial) polarized waves and can generate both shear and compression/tension stress. Thus, for triggered faults, Rayleigh waves could reduce normal stress, increase shear stress, and/or move fluids in the crust (and thus reduce normal stress). Fluid movement has also been invoked to explain delayed
dynamic triggering (e.g., van der Elst et al. 2013), which suggests that Rayleigh waves may be the responsible seismic arrival. It is difficult to determine, with certainty, which mechanisms are at play in the Utah region. However, we propose that much of the triggering occurs on small faults that are near failure in the Utah region, and the failure mechanism can be created from small changes in shear stress (in the case of $S$ and Love wave triggering) and normal stresses (from Rayleigh), with fluids likely the cause of delayed triggering.

As more cases of dynamic triggering are documented, some trends in dynamic triggering illustrate the complexities of this phenomena. For example, Velasco et al. (2008) identified dynamic triggering of 15 events that can occur throughout the world in different tectonic regions, but do not consider any specific region. Alfaro-Diaz et al. (2020) show that a specific region can be susceptible to triggering when transient stresses align complimentarily to the local stress field (ShMax). Recently, Tang et al. (2021) documented instances of triggering in the U.S. and suggest that triggering occurs when surface waves approach from a favorable direction in Utah, Wyoming, and Colorado. However, we use different stations (they primarily use one station in Utah), catalogs, and a statistical approach which likely results in different results from their study. Pankow and Kilb (2020) investigated Anza, California, Utah, Yellowstone, and Montana and showed that, in these regions, triggering is limited. However, Utah itself was dramatically triggered by the M 7.9 ($M_S$ 8.5) Denali Fault earthquake, throughout the region’s main seismogenic belt (Kristine L. Pankow et al. 2004), resulting from the large amplitude surface waves that were amplified over 100 times from directivity and source effects (Velasco et al. 2004). Essentially, the Denali fault created surface waves approaching a $M_S$ 9.0 that propagated through the continental U.S., which explains the large reported $M_S$ from the USGS (Velasco et al. 2004). We also observe dynamic triggering throughout Utah’s main seismogenic belt (Figure
and in regions throughout the state, but the amount of triggering is not widespread for events $M \geq 7.0$. In fact, the amount of triggering is limited, illustrating the complexity of dynamic triggering susceptibility in Utah.

**Conclusion**

We find that from 2000 to 2017, the Utah region experienced very limited instances of dynamic triggering. Only 50 (including the 14 special case) of the 276 mainshocks considered in this study potentially triggered 507 events given a Poisson distribution for event occurrence in the region. This is not to say dynamic earthquake triggering did not occur. Our findings overall support results and interpretation by Pankow et al. (2004) and Pankow and Kilb (2020) that limited triggering occurs in Utah. Many of the potentially triggered events occurred during the passage of the surface waves as seen in other studies (e.g., Alfaro-Diaz et al. 2020; Gonzalez-Huizar et al. 2012; Kristine L. Pankow et al. 2004)—further substantiating the existence of these events in the region. Rayleigh waves are the dominant seismic phase responsible for instantaneous triggering and may also be responsible for delayed triggering through fluid movement. Finally, dynamic triggering appears to be a limited occurrence in the Utah region from 2000 to 2017 from global $M \geq 7$ earthquakes, except for the Denali Fault ($M7.9$), Alaska earthquake.

**Data Availability**

All seismic waveform data can be obtained from the Incorporated Research Institutions for Seismology’s (IRIS) Data Management Center ([www.iris.edu](http://www.iris.edu), last accessed on March 2018) including the following seismic networks: the UU (University Of Utah. (1962). University of Utah Regional Seismic Network. International Federation of Digital Seismograph Networks.

https://doi.org/10.7914/SN/US), the US (Albuquerque Seismological Laboratory (ASL)/USGS. (1990). United States National Seismic Network. International Federation of Digital Seismograph Networks. https://doi.org/10.7914/SN/TA). Daily Probability Density Functions (PDF) Mode plots and data were obtained from IRIS’ Modular Utility for STAtistical kNowledge Gathering (MUSTANG) system (http://service.iris.edu/mustang/, (Casey et al. 2018), last accessed April 2019). The University of Utah Seismic Station (UUSS) catalog for Utah earthquakes was downloaded from the University of Utah Seismograph Stations (https://quake.utah.edu/earthquake-information-products/earthquake-catalogs, last accessed on March 2018). The ANSS Comprehensive Earthquake Catalog (ComCat) (which was produced by various contributing seismic catalogs and seismic networks, see https://earthquake.usgs.gov/data/comcat/#avail for more information) and mining event locations were downloaded from U.S. Geological Survey’s (USGS) Search Earthquake Catalog web service (https://earthquake.usgs.gov/earthquakes/search/, last accessed on March 2018). Mining event data provided by Linville et al. (2019) and used to remove quarry blast detections was obtained from git (https://github.com/quapity/Utah, last accessed on May 2019).
Map of the Utah region showing provinces, faults, and study area. The major Quaternary faults and topography are based on the USGS classification for faults (U.S. Geological Survey and Utah Geological Survey n.d.). Additional faults were provided by the UUSS. The dashed rectangle area encompasses the region analyzed.
Figure 4.2

Illustration of the idealized stress change leading to an earthquake following a transient stress change (dark blue), permanent stress change (blue), and unaltered stress change (light blue) leading to a local event (star). Note that both (significant) transient and permanent stress changes lead to earlier fault rupture at tD and tS relative to an unaffected sequence at tO, respectively; tM denotes the arrival of the disruptive mainshock phase. After rupture of the system due to transient changes in stress, the system may relieve some stress (solid dark blue) or potentially return to the baseline stress (dashed dark blue) if only a small portion of the fault ruptures – leading to a normal rupture in addition to the triggered event.
Figure 4.3

Map of mines and seismic stations considered in dynamic triggering analysis. Mine locations (black dots) provided and considered active in 2003 by USGS (U.S. Geological Survey 2005). Triangles mark seismic stations with circled stations considered noisy. Stations colors relate to their network; US stations (red), UU stations (light blue), and TA stations (beige). Note, UU adopted TA stations P17A, P18A, and Q16A as BRPU, PNSU, and CVRU, respectively.
Figure 4.4

Daily Probability Density Functions (PDF) Mode plots from vertical channels for stations (a) CCUT and (b) O16A obtained from IRIS’s Mustang web service. Plot (a) shows an example where high frequency signals (0.10 sec period – related to earthquakes) consistently maintains a lower power than the lower frequency signals (10 sec period – related to ambient noise) recorded at the station. In contrast, plot (b) shows the inverse relationship and suggests significant susceptibility to noise detections (i.e., false positives).
Figure 4.5

Map of regional seismicity occurring from 2000 to the end of 2017. Seismic events (circles) are scaled to magnitude – scale caps for magnitudes smaller than 0.5. Earthquake events are marked as red circles with black outlines. Non-earthquake or anthropogenic related events (consisting of mining activity) are marked as dark blue circles with white outlines.
Figure 4.6

Recording of three-component unfiltered (black) and 5 Hz High-pass filtered (red) waveforms provided by station NLU from the UU network encompassing the M 7.2 Northern Sumatra 2012 earthquake. Top plot (a) shows the entire 10 hours of analyzed waveform. The segment highlighted in light blue (b) shows the occurrence of an earthquake before the Northern Sumatra mainshock arrival. The segment highlighted in blue (c) shows the occurrence of three (presumably dynamically triggered) events during the passage of the mainshock’s Rayleigh wave.
Figure 4.7

Recording of three-component unfiltered (black) and 5 Hz High-pass filtered (red) waveforms provided by station NLU from the UU network encompassing the M 7.1 Maule, Chile 2012 earthquake. Top plot (a) shows the entire 10 hours of waveform analyzed. The segment highlighted in light green (b) shows the occurrence of a (presumably dynamically triggered) event that is not found in the UUSS catalog.
Figure 4.8

(a) Plot of local event (circles) across magnitude and time of occurrence. Events are colored based on triggering mainshock occurrence—black events are not considered triggered. (b) Relative cumulative seismicity plot (black line). In both plots, mainshocks are shown as vertical-colored lines (see Table S4.1 in Supplemental Material for additional details on earthquakes) with trigger inducing mainshocks are numbered in order of occurrence—gray mainshocks non-triggering events. Special case events are not colored.
Figure 4.9

(a) Plot of peak dynamic stress experienced in the Utah region for each mainshock relative to the back-azimuth wrapped to 180°. (b) Plot of mainshock depths. (c) Plot of mainshock distance

(a) Plot of peak dynamic stress experienced in the Utah region for each mainshock relative to the back-azimuth wrapped to 180°. (b) Plot of mainshock depths. (c) Plot of mainshock distance
from Utah, USA. (d) Plot of mainshock magnitudes. Triggered (non-special case) mainshocks are marked by colored solid circles (based on occurrence and consistent with Figure 4.8) with gray transparent circles being non-triggering events.

Figure 4.10

Map of the Utah region showing provinces, faults, and triggered earthquakes (marked by colored solid circles, based on occurrence). Events are colored based on (non-special case) triggering
mainshock occurrence consistent with Figure 4.8. Faults and topography are those described and shown in Figure 4.1.
Electronic Supplement (Copy)

Table S4.1: Large Magnitude Earthquake Data and Key

<table>
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<tr>
<th>Date (mm/dd/yyyy)</th>
<th>Earthquake Locality</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Depth (km)</th>
<th>Magnitude</th>
<th>MagType</th>
<th>Special Case</th>
<th>EQ_ID</th>
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<td>7.1</td>
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<td>Kermadec Islands region</td>
<td>-28.993</td>
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<td>33</td>
<td>7.4</td>
<td>mww</td>
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</tr>
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<td>01/10/2012</td>
<td>Northern Sumatra, Indonesia</td>
<td>2.433</td>
<td>93.21</td>
<td>19</td>
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<td>Oaxaca, Mexico</td>
<td>16.493</td>
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<td>20</td>
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<td>mww</td>
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<tr>
<td>03/25/2012</td>
<td>Maule, Chile</td>
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<td>7</td>
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<td>173.1167</td>
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<td>mww</td>
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<td>Latitude</td>
<td>Longitude</td>
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<td>Magnitude</td>
<td>Magnitude Type</td>
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<tr>
<td>------------</td>
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<td>12/08/2016</td>
<td>Kirakira, Solomon Islands</td>
<td>10.6812</td>
<td>161.3273</td>
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<td>168.857</td>
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<td>7.7</td>
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<tr>
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<td>Tres Picos, Mexico</td>
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<td>-93.8993</td>
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<td>8.2</td>
<td>mww</td>
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Table uses USGS “magnitude type” notation (e.g., mww = moment W-phase magnitude, mwc = centroid magnitude (using long-period surface waves), mwb = body wave magnitude). For more information, refer to [https://www.usgs.gov/natural-hazards/earthquake-hazards/science/magnitude-types?qt-science_center_objects=0#qt-science_center_objects](https://www.usgs.gov/natural-hazards/earthquake-hazards/science/magnitude-types?qt-science_center_objects=0#qt-science_center_objects).

†EQ_ID corresponds to mainshock numbering in Figure 8. "Special Case" events are not numbered.

Note: Earthquake data provided by USGS’s ComCat.
Chapter 5: Unraveling earthquake stresses: Insights from dynamically triggered and induced earthquakes in Oklahoma\(^4\)

**Abstract**

Induced seismicity, earthquakes caused by anthropogenic activity, has more than doubled in the last decade resulting from oil and gas production practices. Furthermore, large earthquakes have been shown to promote the triggering of other events within two fault lengths (static triggering) due to static stresses caused by physical movement along the fault and remotely from transient stress changes following the passage of seismic waves (dynamic triggering). To understand the mechanisms for earthquake failure, we investigate regions where natural, induced, and dynamically triggered events occur. Specifically, we target the state of Oklahoma (OK), where documented induced earthquakes have occurred. Utilizing seven years of data (2010-2016) from EarthScope’s USArray Transportable Array and OK’s regional network, we search catalog and waveform data for dynamically triggered seismicity in OK. We first apply a short-term to long-term average ratio detector to high-pass (5 Hz) filtered waveforms spanning ±5 hours encompassing 126 \( M \geq 7 \) global earthquakes, then visually inspect these waveforms to identify uncatalogued local earthquakes. We compile an augmented local earthquake catalog to investigate remote earthquake triggering in OK and flag mainshocks with a statistically significant increase in seismicity following the \( P \)-wave arrival. We find that of the 126 remote mainshocks, 25 (20\%) statistically triggered seismicity in OK and that transient stresses can contribute to natural and induced stress states that advance the earthquake cycle, providing insight into the constantly changing stress state of induced systems. Utilizing the distribution of

\(^4\)Note: This Chapter comes from a manuscript where David L. Guenaga contributed and is a coauthor—the primary author being Richard Alfaro-Diaz. Additionally, this work is currently under review for publication.
triggered earthquake populations in the OK region, we identify regions particularly susceptible to earthquake hazards associated with sustained fluid injection. We also find that the regional stress field does not dominate remote triggering, unlike other regions. This suggests a local fault may be weakened from a reduction in normal stress created by fluid injection, and, thus, fail with a small stress disturbance (independent of the local and transient stress orientation).

**Introduction**

A growing body of evidence has demonstrated a strong link between earthquakes, from the near- to far-field. For example, large earthquakes have promoted the triggering of other events within two fault lengths due to static stresses caused by physical movement along the fault (e.g., King, Stein, and Lin 1994; Stein, King, and Lin 1992; 1994), called static triggering. Seismic waves originating from large magnitude earthquakes ($M \geq 7$) also create transient stresses from propagating waves that can trigger small earthquakes and tremor at remote distances, called dynamic or remote triggering (Alfaro-Diaz et al. 2020; Brodsky, Karakostas, and Kanamori 2000; Chao et al. 2012; J. Gomberg et al. 2001; 2004; Guilhem, Peng, and Nadeau 2010; Han et al. 2017; David P. Hill et al. 1993; Deborah Kilb, Gomberg, and Bodin 2000; Parsons, Kaven, Velasco, and Gonzalez-Huizar 2012; V. Tang, Chao, and van der Lee 2021; West, Sánchez, and McNutt 2005). Alfaro-Diaz et al. (2020) showed the potential for triggering increases when a transient signal aligns with the regional stress field for the area around the Coso Geothermal Field, and they suggest some regions may be more susceptible to triggering if an earthquake aligns with the regional stress field. Some studies have suggested that delayed dynamic triggering can even promote large earthquakes (Gomberg et al., 1997; Pollitz et al., 2012), yet the physical mechanism has many possible explanations with little consensus (Brodsky and Prejean...
Beyond the link between earthquakes, recent studies have demonstrated that seismic activity can be tied to anthropogenic activities such as hydraulic fracturing, water injection, and enhanced oil recovery (e.g., Atkinson et al. 2016; Cheng and Chen 2018; Elizabeth S. Cochran et al. 2018; Ellsworth et al. 2015; Ellsworth 2013; Goebel and Brodsky 2018; Huang et al. 2018; Johann, Shapiro, and Dinske 2018; Kim and Lu 2018; Langenbruch, Weingarten, and Zoback 2018; Maghsoudi et al. 2018; McGarr and Barbour 2018; D. McNamara et al. 2015; Norbeck and Rubinstein 2018; Peterie et al. 2018; Schultz et al. 2018; Skoumal, Brudzinski, et al. 2020; Snee and Zoback 2018; L. Tang et al. 2018; Zhai et al. 2019). Injection-related earthquakes can be narrowly defined as induced earthquakes created due to fault disturbance from fluids reducing the normal stress of ancient faults. Despite the small seismic hazard of instantaneous dynamic triggering, regions that have been subjected to sustained fluid injection and induced seismicity may host larger, hazardous triggered earthquakes, and beyond areas of injection, some researchers suggesting moderate to large size earthquakes can result from delayed dynamic triggering a week or more after a mainshock (Joan Gomberg 2013; Gonzalez-Huizar et al. 2012; Pollitz et al. 2012; 2014).

Induced earthquakes can impact local populations, which prompted the United States Geological Survey (USGS) to develop an induced seismicity hazard map beyond the traditional natural seismicity hazard map (Petersen et al. 2017). Much of the increase in induced seismicity results from practices to extract and/or stimulate oil and gas production, which results in an abundance in wastewater that is later injected into the ground (e.g., Ellsworth et al. 2015). Although the mechanism for these injection-induced earthquakes results from weakening a
preexisting fault through elevated fluid pressure, only a small fraction of the events appears to be dangerous. Thus, the challenge remains to understand the exact mechanisms of failure such that stress changes can remain below a threshold to reduce activity and perhaps prevent larger earthquakes from occurring.

In this study, we address the fundamental physical mechanisms driving remote triggering in a region of documented induced seismicity by investigating a tectonic region where natural, induced, and dynamically triggered events occur, focusing on the state of Oklahoma. Oklahoma (Figure 5.1) presents an ideal study site to observe the interaction of dynamic stresses produced by $M \geq 7$ earthquakes and the local induced stress fields. We select data 5 hours before and 5 hours after the origin times for 126 $M \geq 7$ earthquakes at stations from the EarthScope Transportable Array (TA) and the local Oklahoma seismic network over seven years (2010-2016). We use an optimized detection algorithm to detect high-frequency signals (Alfaro-Diaz et al. 2020; Velasco et al. 2016) and visually inspect these signals to verify earthquakes. All newly identified earthquakes are added to an existing template match catalog (Skoumal, Brudzinski, et al. 2020). This augmented catalog is then used to identify statistically significant changes in detection rates assuming a Poisson distribution (Alfaro-Diaz et al. 2020; Linville et al. 2014b; Velasco et al. 2008). Of the 126 mainshocks, we find 25 (20%) have statistically significant rate increases coincident with the passing surface waves consistent with dynamic triggering. Specific regions in Oklahoma appear to be more susceptible to remote triggering and are associated with sustained fluid injection. Unlike other regions, we find that the regional stress field does not dominate remote triggering, supporting the idea that a local fault may be weakened from a reduction in normal stress created by fluid injection, and fault failure results from a small transient stress disturbance.
Dynamic Triggering in Regions of Induced Seismicity

A large body of work has focused on various aspects of dynamic triggering (e.g., Alfaro-Diaz et al. 2020; Brodsky, Karakostas, and Kanamori 2000; Chao et al. 2012; J. Gomberg et al. 2001; 2004; Gonzalez-Huizar et al. 2012; Guilhem, Peng, and Nadeau 2010; Han et al. 2017; David P. Hill et al. 1993; Deborah Kilb, Gomberg, and Bodin 2000; Parsons, Kaven, Velasco, and Gonzalez-Huizar 2012; Velasco et al. 2008; West, Sánchez, and McNutt 2005), yet relatively little work has explored dynamic triggering in regions related to active oil and gas exploitation and induced seismicity. Recent increases in seismicity in the midwestern United States have been related to deep wastewater injection sites. Fluid injection sites are susceptible to triggering via small changes in stress, induced by the passage of seismic waves of distant large earthquakes (Peña-Castro et al. 2019; van der Elst et al. 2013; B. Wang et al. 2018). Most triggered injection sites have a delay between the beginning of fluid injection and the start of seismicity, suggesting fluid injection can push a fault system into a critical state (van der Elst et al. 2013). By investigating dynamically triggered seismicity in natural and induced settings, we can address fundamental questions about the state of stress of faults in the crust and the possible role of fluids in promoting failure. Alfaro-Diaz et al. (2020) studied dynamic triggering around the Coso Geothermal Field, an area with fluid and heat in the crust, and they showed a relationship between dynamic triggering and the regional stress field. Here, we explore the stress type, orientation of the incoming seismic waves, and stress magnitude needed to trigger earthquakes in OK.
Data and Methods

Waveform data

Oklahoma presents an ideal region to observe the interactions between dynamic stresses produced by $M \geq 7$ earthquakes, the local stress field (maximum compressive stress SH-max), and the role of fluids in fault failure since regional networks have been operational since the arrival of the USArray Transportable Array (TA) stations in ~2009 (Busby et al. 2019; Walter et al. 2020) and Oklahoma’s local network. We obtain seismograms from ~70 (permanent and temporary) stations within the state of Oklahoma, which are from the EarthScope Transportable Array (TA), Oklahoma’s local network (OK), and the USGS’s network (GS) focusing on 126 $M \geq 7$ earthquakes over a seven-year period (2010-2016). We then apply a tuned short-term average over long-term average (STA/LTA) detection algorithm to detect high-frequency signals (Velasco et al. 2016). For each of our 126 $M \geq 7$ mainshocks, we collect 10 hours of waveform data (5 hours before and after the mainshock)—Bracketing the origin time of each earthquake. We chose a ±5 hour window as it has been a proven effective time window to observe dynamic triggering (e.g., Aiken and Peng 2014; Alfaro-Diaz et al. 2020; Linville et al. 2014a; Velasco et al. 2008; 2016). An analyst visually inspected each of the detections within our 1260 hours of waveform data (10-hours for each of our 126 mainshocks) to identify uncatalogued local earthquakes in Oklahoma (Figure 5.2).

Catalog Data

For the same period and geographic region, we analyze cataloged earthquake data from a template match catalog produced by Skoumal et al. (2020). There are 3843 events in the template match catalog for this period, and from our visual inspection, we identified an additional 33
earthquakes, bringing the total augmented catalog to 3876 events. All newly identified earthquakes are added to the existing catalog. The augmented catalog is then used to identify statistically significant changes in detection rates assuming a Poisson distribution (Alfaro-Diaz et al. 2020; Linville et al. 2014b; Velasco et al. 2008).

**Statistical Analysis**

We calculate the probability of increased seismicity rates by comparing the number of local earthquakes immediately before and after the teleseismic mainshock. We recognize an elevated seismicity rate in OK since around 2010; thus, our statistical approach must account for increased seismicity baselines. Regardless of the increased baseline, we should be able to identify rate changes in specific time windows. In order to identify statistically significant increases in numbers of local earthquakes, we process a time window of ±5 hours for each mainshock ($M \geq 7$) earthquake and assume that earthquakes occur independently (randomly) at a constant rate, following a Poisson distribution (Shearer and Stark 2012). We consider a mainshock event to successfully trigger remote aftershocks in OK if the number of events in the 5-hour window following the arrival of the mainshock $P$-wave significantly exceeds the number of events within the prior 5-hours. We categorize the seismic triggering as (1) *instantaneous* if the significant increase in events begins in the mainshock’s wavetrain—we then associate these triggered events with the $S$-, Love, and Rayleigh phases—or (2) *delayed* if there is a significant increase in events after the wavetrain but within 5 hours of the initial mainshock.

To determine statistical significance, we follow what is expected for a Poisson distribution. To do this, we compare the frequency of events in the 5-hour windows before ($N_{\text{pre}}$) and after ($N_{\text{post}}$) the $P$-wave arrival. We assume that the $N_{\text{pre}}$ for each of the 126 mainshocks is a reasonable approximation to the background rate for a 5-hour window. To determine significant
changes in rates, we calculate the Poisson probability of getting $N_{\text{post}}$ events ($n$), again given the expected number of events ($\mu = N_{\text{pre}}$).

$$P_\mu(n) = e^{-\mu} \frac{\mu^n}{n!}$$  \hspace{1cm} (5.1)

Based on these probabilities, we determine mainshocks that may have triggered remote aftershock(s) in OK if the probability of $N_{\text{post}}$ events given $\mu < 5\%$. Using this criterion, we identified 25 mainshocks dynamically triggered aftershocks in OK (Table 5.1). We further analyze these events in the subsequent sections. In addition to looking at statistically significant changes in earthquake rates, we also identify mainshocks that have local earthquakes embedded within the surface waves. Considering the elevated background rate in OK, we do not classify them as that dynamically triggered as they may have occurred by chance. We report these observations in Table 5.1.

**Instantaneous and Delayed Triggering**

We define instantaneous triggering as the process where local earthquakes occur coincident with the arrival of the $S$-, Love, or Rayleigh waves from a mainshock. We define delayed triggering as the process where triggered seismicity occurs within 5 hours of the $P$-wave but after the passage of the mainshock energy (Figure 5.3), where the duration of the mainshock energy pulse relates directly to the distance away from a source as a result of surface wave dispersion. With instantaneous triggering, we can identify the stress orientation that caused the event to trigger. However, with delayed triggering, the direct relationship between stress created by the passage of the seismic waves and triggering is ambiguous.
Results

To assess the occurrence, frequency, and causal factors related to dynamic triggering in Oklahoma, we analyze our earthquake catalog, obtain stress field orientation, and measure peak dynamic stress.

Statistical Identification

We begin with our statistical approach to identifying dynamic triggering, categorize triggering in terms of instantaneous and delayed triggering, and then investigate possible causal factors for dynamic triggering. Of our 25 triggering mainshocks, 24 instantaneously triggered local seismicity, of which the majority of the triggering occurred within the wavetrain of the passing surface waves (Figure 5.2 and 5.3, Table 5.1). Of these 24 instantaneous triggering events, 7 (29%) display no seismic activity in OK in the 5 hours prior to the mainshock seismic waves. The one remaining mainshock is classified as a delayed triggering event, where the triggered seismicity occurred within 5-hours of the P-wave but after the passage of the mainshock energy (Table 5.1). We identify 483 local events ranging in magnitude ($M_L$) 0.2-3.3 with depths of 0-15 km (Figure 5.4) that were triggered within the 5 hours following the 25 mainshock earthquakes ($M \geq 7.0$).

Identifying Possible Contributing Factors

In order to investigate the physical mechanisms in remote dynamic triggering, we explore a suite of factors—including focal mechanism, mainshock depth, peak dynamic stress, and orientation of the incoming mainshock seismic waves (Figures 5.5 and 5.6). We compute an average peak dynamic stress (PDS) for each mainshock (across available network stations for each event). In order to compute PDS, we estimate peak vector velocities using three-component
broadband data and multiply by shear modulus/Love wave group velocity (\(\mu = 33000 \text{ MPa, } U = 3.5 \text{ km/s}\)) (Alfaro-Diaz et al. 2020; K. L. Pankow 2004; Velasco et al. 2004). In this way, we can examine the average PDS values as a function of mainshock magnitude, depth, and back-azimuth for each triggering and non-triggering mainshock (Table 5.1 and Figure 5.5). The average mainshock PDS values, for both non-triggering mainshocks and triggering mainshocks, range between 0.0001–0.06 MPa (Figure 5.5). As expected, the general trend shows that larger magnitude mainshocks produce larger PDS values. The highest PDS value we computed was 0.025 MPa for the non-triggering mainshocks and ~0.06 MPa for the triggering mainshocks.

The 126 mainshocks display a suite of focal mechanisms: normal, strike-slip, thrust, transpression, and transtension mechanisms (Figure 5.6). Analysis of the 25 events identified as triggering mainshocks reveals no obvious preference for one type of mainshock mechanism to promote instantaneous or delayed triggering (Figure 5.6). As various mainshock focal mechanisms appear to trigger seismicity, we do not assign any mainshock focal mechanism type to be of preference to trigger sites in Oklahoma. Mainshock depth was typically shallow to intermediate ranging from 10-206 km, with one mainshock occurring in the depth range of 440-600 km (Figure 5.5).

Finally, we investigate the relationship between the local stress field (maximum compressive horizontal stress, SHmax) and the orientation of incoming surface waves (Figure 5c and 7). Figures 5.7c and 5.7d indicate the current regional stress state defined by Lund Snee and Zoback (2020). Back-azimuth orientations are calculated from each mainshock source location to Oklahoma City (35.4676° N, 97.5164° W) (Table 5.1). We separate azimuthal orientation into S-, Love, and Rayleigh waves, plus delayed triggering categories (Figure 5.7). We calculate and compare the mean and standard deviation of the delayed and instantaneous back-azimuths. We
find the back azimuths of each triggering phase ranging widely per phase with S-wave (≈98° ± 48°), Love (≈112° ± 52°), Rayleigh (≈124° ± 48°), and delayed (121° ± 52°) (Figure 5.7). We analyze these trends further in the subsequent section.

Discussion

Unraveling the mechanisms behind dynamic triggering remains a significant challenge, requiring the identification and characterization of triggered earthquakes along with their variations from site to site and the uniqueness of mainshock earthquakes. However, our ability to better understand the physical mechanisms and initiation of remote dynamic triggering has improved with the increasing availability of data and observations. We examine Oklahoma and systematically explore characteristics related to remote triggering. Generally, we observe dynamic triggering primarily initiates small magnitude events, making it difficult to rely solely on standard earthquake catalogs. Therefore, we investigate a template match catalog (Skoumal et al. 2020), augmented with additional events identified via high-frequency detection and analyst inspection. This augmented catalog allows for a detailed examination of factors controlling remote dynamic triggering; we highlight observations and characteristics of triggered seismicity in Oklahoma.

Preferential Triggering

Examining the back-azimuth angles of our triggering mainshocks, we find a range of azimuths in which both instantaneous triggering from S-wave (≈98° ± 48°), Love (≈112° ± 52°), Rayleigh (124° ± 48°), and delayed triggering (121° ± 52°) occur. However, upon further inspection of these triggered earthquakes to the mapped stress regimes in Oklahoma as defined by Snee and Zoback (2020) (Figures 5.6), we observe several triggered earthquakes that
ostensibly align favorably (i.e., roughly perpendicular) to local stress (SHmax) and/or faulting orientations in the Oklahoma region, analogous to past observations from Gonzalez-Huizar and Velasco (2011), Alfaro-Diaz et al. (2020), and Tang, Chao and van der Lee (2021). The regional stress (SHmax) of Oklahoma predominantly trends (~80°) (Figure 5.7). Orientations of the incoming dynamic stresses appear to play a role in the instantaneous triggering (Figure 5.7). However, active oil and gas exploitation in the region (Figure 5.8) may allow localized perturbations in stresses not previously documented. If these areas exhibit complex behavior, instantaneous dynamically triggered events may provide a proxy to understanding the local stress field (Alfaro-Diaz et al. 2020).

The relationship between the local stress orientations and transient stresses propagating through Oklahoma appears similar to observations of triggered seismicity in the Coso Geothermal Field region (Alfaro-Diaz et al. 2020). We do note that in contrast to Alfaro-Diaz et al. (2020), we observe a wide variation in azimuths that trigger seismic events; although some triggered earthquakes align favorably (approximately perpendicular to the local stress (SHmax) and faulting), other events diverge from this trend. Triggered events that diverge from this trend may indicate localized changes in the stress field related to anthropogenic activities such as injection and extraction, which can alter the stress state and fluid flow in localized areas in Oklahoma (Figure 5.8).

As previously observed in cases where we observe an alignment of stresses (e.g., Alfaro-Diaz et al. 2020), the retrograde-elliptical particle motion of a Rayleigh wave propagating perpendicular to a local fault may promote unclamping of the fault and reduce the fault’s normal stress, since the particle motion has both compressive and shearing components. The compressive stresses may interact with fluids and promote a reduction in normal stress (e.g.,
David P. Hill 2008; Miyazawa, Brodsky, and Mori 2008; Peng et al. 2009; 2010; Peng and Chao 2008; Rubinstein et al. 2007; 2009). Any sudden reduction in normal stress may overcome the frictional influence on the fault (especially if it is already near failure), resulting in shear stress driving fault rupture. In the case of Love wave triggering, particle motion is purely shear (except for specific orientations of the failing fault and the incoming wave). Therefore, a Love wave propagating in a direction perpendicular to the strike of a fault may increase the shear stress across the fault (Tape et al. 2013), thus promoting failure. In both cases, the imposed transient stresses can cause an effective increase in shear stress within the system, in turn promoting fault slip, consistent with Coulomb failure criteria (Gonzalez-Huizar and Velasco 2011; David P. Hill 2008; Debi Kilb, Gomberg, and Bodin 2002; Peng et al. 2009; Peng and Chao 2008).

**Delayed Triggering**

Our observations of delayed earthquake triggering compromise the majority (54%, 262 events) of all locally triggered seismic events in the Oklahoma region, such that the local earthquakes occur after the passage of the remote mainshock seismic waves (Bodin and Gomberg 1994; J. Gomberg et al. 2001; Gonzalez-Huizar et al. 2012; D. P. Hill and Prejean 2015; Jagla 2011; Morton and Bilek 2014; Peng et al. 2010; Pollitz et al. 2012; Tzanis and Makropoulos 2002; van der Elst et al. 2013). There have been several triggering mechanisms proposed to explain these delays, such as the excitation of crustal fluids (e.g., Hill and Prejean 2015 and references therein), a change in frictional contact along a fault (Parsons 2005), arrival of multiple surfaces waves circling the Earth (Peng, Wu, and Aiken 2011), pore fluid diffusion, and transient pore-pressure changes (Bodin and Gomberg 1994; Brodsky 2006; Brodsky et al. 2003; Brodsky and Prejean 2005; Syracuse et al. 2010). In Oklahoma, a combination of these mechanisms may incite a delay in the local triggered response.
Parsons et al. (2017) found that delay times appear to correlate with the magnitude of triggered earthquakes, as fluid needs to diffuse across a locked fault asperity before failure. Delay times related to this process, specifically in seismically active areas such as Oklahoma, can be short (seconds-minutes-hours) as the distance between pockets of elevated pore-pressure and adjacent faults is short (Prejean and Hill 2018). Our observations of delayed triggering results are likely most consistent with the excitation of crustal fluids, pore fluid diffusion, transient pore-pressure, and changes in frictional contact. Anthropogenic fluid injection and extraction activity have continually altered the stress state of faults and fluid flow within production basins of Oklahoma (Figure 5.8). Fluids associated with injection sites in Oklahoma may migrate after the passage of the mainshock-generated transient wavetrain, eventually triggering local seismicity. The normal stress and strength of a fault may by these processes and promote failure by shear stresses. Thus, unlike other regions, a local fault may be weakened from a reduction in normal stress created by fluid injection and fail due to a small stress disturbance that is not aligned with the regional stress field.

Given the active oil and gas exploitation in Oklahoma, many events may be related to fluids and anthropogenic influences, especially where anthropogenic activities have weakened subsurface fracture networks which can increase the likelihood of dynamic triggering in a region surrounding the anthropogenic footprint of the production wells (Ellsworth et al. 2015; Ellsworth 2013; D. McNamara et al. 2015). We identify a local triggering mechanism that favors shear-induced failure, which is fundamentally different from the fluid migration mechanism. Several events were instantaneously triggered by either the $S$-wave (18 events) or Love-wave (9 events) arrivals. We note the cases of local earthquakes triggered by the onset of Love-wave and Rayleigh-wave arrivals may also be consistent with failure by the Coulomb failure criteria.
Dynamic triggering in the context of Oklahoma offers insight into the region’s state of stress. By identifying dynamically triggered events here (specifically instantaneously triggered events), we posit that we can infer faults in these areas are critically stressed. These critically stressed regions are particularly susceptible to earthquake hazards associated with sustained fluid injection by identifying dynamically triggered earthquakes (Figures 5.6, 5.7, and 5.8).

**Conclusions**

Here we investigate 126 global mainshocks $M \geq 7$ capable of triggering remote seismicity in Oklahoma. We find 25 remote earthquakes trigger local seismicity in Oklahoma within 5 hours of the mainshock passage. These 25 mainshocks produced 483 local triggered earthquakes, of which 211 are considered instantaneously triggered (within the wavetrain of the mainshock), 18 are coincident with the arrival of the S-phase, 9 with the Love wave, and 184 with the passage of the Rayleigh wave. The remaining 262 triggered events are delayed triggered events, occurring after the passage of the mainshock seismic waves but within 5 hours of the mainshock passage. From these results, we find dynamically triggered earthquakes in Oklahoma help delineate critically stressed regions, particularly those susceptible to earthquake hazards due to sustained fluid injection, by identifying dynamically trigger earthquakes. Furthermore, dynamic triggering Oklahoma is dominated by delayed triggered events. We attribute this dominance to anthropogenic exploitation of the region. Altering the natural stress of these areas may have pushed localized regions of Oklahoma into a critical state, easily triggered by remote transient stresses. Regions susceptible to delayed dynamic triggering may indicate fluid diffusion as the primary mechanism, which may be associated with fluid injection and CO2 sequestration.

(Gonzalez-Huizar and Velasco 2011; David P. Hill 2008; Debi Kilb, Gomberg, and Bodin 2002; Peng et al. 2009; 2010; Peng and Chao 2008).
regions of induced seismicity, delayed-triggered seismicity may indicate areas in which CO2 sequestration and fluid injection should be avoided.
## Table 5.1: Mainshock parameters of our set of 25 M ≥ 7 “Triggering Mainshocks.”

<table>
<thead>
<tr>
<th>DateTime</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Magnitude (Mw)</th>
<th>Depth (km)</th>
<th>Region</th>
<th>Npre</th>
<th>Npost</th>
<th>SV-Wave</th>
<th>Love Wave</th>
<th>Rayleigh Wave</th>
<th>Delayed</th>
<th>Back-Azimuth</th>
<th>Peak Dynamic Stress (GPa)</th>
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<td>29</td>
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<td>6</td>
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<td>1</td>
<td>4</td>
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<td>Magnitude</td>
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<td>Month</td>
<td>Day</td>
<td>Hour</td>
<td>Min</td>
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<td>10.811</td>
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<td>7.6</td>
<td>28</td>
<td>Philippine Islands region</td>
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<td>6 4 0 1 1</td>
<td>2012</td>
<td>08</td>
<td>31</td>
<td>12</td>
<td>47</td>
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<td>05</td>
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<td>00</td>
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<td>2012</td>
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<td>10</td>
<td>05</td>
<td>30</td>
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<td>7.1</td>
<td>21</td>
<td>31km SE of Lata, Solomon Islands</td>
<td>3 8 0 0 3 5</td>
<td>2013</td>
<td>02</td>
<td>08</td>
<td>26</td>
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<td>173.7</td>
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<td>2</td>
<td>6 0 0 1 5</td>
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<td>17</td>
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<td>7</td>
<td>16.54</td>
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<td>41</td>
<td>55 2 1 14 38</td>
<td>2014</td>
<td>10</td>
<td>09</td>
<td>14</td>
<td>31</td>
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<tr>
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<td>27:33:82</td>
<td>10.401</td>
<td>165.1409</td>
<td>7</td>
<td>11</td>
<td>83km WNW of Lata, Solomon Islands</td>
<td>36 49 2 1 18</td>
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<td>07</td>
<td>18</td>
<td>27</td>
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<td>82</td>
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<td>22.44</td>
<td>48km W of Illapel, Chile</td>
<td>34</td>
<td>55 2 1 11 41</td>
<td>2015</td>
<td>09</td>
<td>16</td>
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<td>32</td>
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<tr>
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<td>25km WNW of Illapel, Chile</td>
<td>39</td>
<td>54 0 1 14 39</td>
<td>2015</td>
<td>09</td>
<td>16</td>
<td>23</td>
<td>18</td>
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<tr>
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<td>38.210</td>
<td>72.7797</td>
<td>7.2</td>
<td>22</td>
<td>104km W of Murghob, Tajikistan</td>
<td>0 9 0 1 8</td>
<td>2015</td>
<td>12</td>
<td>07</td>
<td>50</td>
<td>05</td>
<td>95</td>
</tr>
</tbody>
</table>

115
Note: We compute distance and back-azimuth relative to Oklahoma City (35.4676° N, 97.5164° W). We calculate the average mainshock generated peak dynamic stress (PDS) at available stations (configuration changes over time). PDS values are averaged dependent on available stations. The table also includes information about locally triggered seismicity classified as instantaneous or delayed. We indicate which phases of the mainshocks wavetrain trigger seismicity.
Seismicity in Oklahoma (2010-2016) (Skoumal, Kaven, et al. 2020) (a) Smaller magnitude earthquakes plotted as blue circles, moderate-sized earthquakes M≥5 are red stars, faults are red lines. (b) Histogram of earthquakes (2010-2016), moderate-sized earthquakes M≥5 are marked as red lines. Black triangles indicate stations used in the study; networks include TA, GS, and OK.
Figure 5.2

Example of identified dynamic triggering in Oklahoma. Waveform recording of the 10-25-2010 M=7.8 Kepuluan, Indonesia earthquake at TA station X34A. The raw waveform is displayed in black. Filtered traces high-passed at 5Hz (yellow) display local earthquakes triggered by Love and Rayleigh waves in Oklahoma.
Figure 5.3

Remote triggering evidence of temporal step-like increases in (top) seismicity and the spatial distribution of triggered earthquakes (bottom). (a, c) Instantaneous triggering incited by seismic wave arrivals from the M7.7 2013-11-17 Scotia Sea Earthquake. (b, d) Delayed triggering incited by seismic wave arrivals from the M7.0 2010-02-26 Ryukyu Japan. Red lines display mapped faults in Oklahoma (Marsh and Holland 2016).
Figure 5.4

Analysis of local earthquakes triggered in Oklahoma (ML) 0.2-3.3 (2010-2016). Triggered earthquakes are color-coded by triggering phase and depicted as dots. (a) Magnitude versus date of local earthquakes. (b) Depth versus date of local earthquakes. (c) Histogram of locally triggered earthquakes based on their magnitude.
Figure 5.5

Analysis of 126 $M \geq 7$ mainshocks (2010-2016). (a) Mainshock depth versus measured peak dynamic stress (PDS) in MPa. (b) Earthquake magnitude versus measured PDS in MPa. (c) Back-azimuth orientations versus measured PDS. Colored dots indicate a triggering mainshock earthquake, see figure 5.6 for mainshock occurrence by color and location.
Figure 5.6

(a) Oklahoma map and seismicity. White dots indicate background seismicity in Oklahoma (2010-2016, Skoumal et al., 2020). Colored dots are locations of triggered earthquakes (color) associated with a triggering mainshock. Red lines display mapped faults in Oklahoma (Marsh and Holland 2016). (b) Global map and earthquakes M\geq7 (2010-2016, USGS-ComCat) and moment tensor solutions (GCMT). Colored moment tensors indicate mainshocks that triggered
local seismicity in Oklahoma. (c) Peak dynamic stress versus teleseismic mainshock occurrences. Colored dots indicate a triggering mainshock earthquake. Gray dots indicate teleseismic mainshocks that did not trigger activity in Oklahoma.

Figure 5.7
(a) Map of Oklahoma and locations of locally triggered earthquakes are color-coded by triggering phase and depicted as lines, indicating the back azimuth orientation of the associated triggering mainshock. (b) Histogram of locally triggered earthquakes and calculated back-azimuths associated with triggering mainshocks M ≥ 7 (2010–2016). Color-coded by associated triggering phase. The back azimuth angles are wrapped between 0–180°. (c) Map of Oklahoma. Lines indicate regional orientations of SHMax from Lund Snee and Zoback (2020). (d) Histogram of SHMax azimuths from Lund Snee and Zoback (2020). Red lines in (a,c) display mapped faults in Oklahoma (Marsh and Holland 2016).
Figure 5.8

The background color displays the cumulative volume (m$^3$) of saltwater injected into the Arbuckle formation between 2010 and December 2016 in different regions of Oklahoma. The cumulative saltwater injection volume has been calculated in 0.5° bins at the center of each box. Remotely triggered earthquakes identified in this study (2010–2016) are shown as white circles. Cumulative volume results calculated from Oklahoma Corporation Commission (https://oklahoma.gov/occ/divisions/oil-gas/oil-gas-data.html).
Chapter 6: Unravelling Seismic Ambient Noise in Japan

Abstract

Japan experiences an immense amount of seismic activity and has an extensive network of seismic stations throughout the country that allows for all types of regional seismic analyses. Ambient seismic noise (or background microseism) has been explored recently to analyze anthropogenic activity and even Earth structure. Here we examine vertical seismic data collected throughout the country in 2017 to characterize regional ambient seismic noise in Japan. To analyze ambient seismic noise, we temporally normalize data (removing any transient signals, e.g., earthquakes) and calculate the power spectral density (PSD) for each waveform. Afterwards, we stack standardized PSD data that occurs during the same temperate season and hour-of-day for each station, and cluster the results into four groups using a k-means algorithm. We merge cluster groups for each hour-of-day result, producing four merged PSD cluster results (one for each season) and find that stations group geographically. Additionally, we find some correlation between Japan's ecoregions and the merged PSD cluster groups plus identify diurnal changes reminiscent of anthropogenic trends (i.e., more, presumably quiet, stability during the less anthropogenically active evening hours).

Introduction

Japan lies in a significantly seismically active region since it is located on or near the boundary of four tectonic plates: the Pacific, North American (or Okhotsk), Eurasian, and Philippine Sea plates. Unfortunately, this activity has led to instances of deadly and economically catastrophic earthquakes, as seen with the March 11, 2011, Tohoku, Japan (M9.1) earthquake, which generated a large tsunami that caused approximately 15,800 casualties, and created $211B
in economic losses (Government of Japan 2012; Kajitani, Chang, and Tatano 2013). Because of these losses from earthquakes and tsunamis, many scientific and government organizations have funded and deployed seismic instruments to monitor the continental island seismically. This investment and resources make Japan a frontrunner in its capability to monitor seismic vibrations at a regional scale. Specifically, the National Research Institute for Earth Science and Disaster Resilience (NIED) High Sensitivity Seismograph Network (Hi-net) offers a centralized and geographically dense seismic station network, as the network contains up to approximately 1000 total stations with station spacing of 15-20 km throughout Japan. By Comparison, EarthScope’s USArray had 400 stations recording simultaneously with a 70 km station spacing, as it marched through the U.S. Thus, the dense and high-quality data being recorded by Hi-Net has made Japan ideal to explore many elements of seismology.

Past studies, using Hi-Net data, have explored Japan’s polarization of ambient seismic noise (Takagi et al. 2018) and seasonal crustal seismic velocity changes (Q.-Y. Wang et al. 2017). Here we take advantage of Hi-net’s seismic station density and availability to analyze ambient seismic noise (or background microseism) for broadscale ambient source detection. Specifically, we consider regional ecological effects on ambient seismic noise and include an analysis of ambient noise related to topographic (a proxy for areas with coastal and high-elevation wind turbulence) and anthropogenic activity. Preliminary results show some correlation between seismic noise characterization and ecoregions. Using a k-means clustering process on temporally normalized seismic data, we find grouped stations experience similar ambient seismicity. Furthermore, we observe variability across preliminary station cluster results, suggesting a strong anthropogenic component present in the data.
Seismic Waveform Data

For this project, we used seismic waveform data from the NIED Hi-net. Hi-net was established in October 2000 and continues to provide continuous seismic data. The network contains up to 1000 total stations located densely (station spacing of 15-20 km) throughout Japan (Figure 6.1). Each station consists of a three-component velocity seismometer placed in boreholes (> 100 m) and a three-component strong motion accelerometer at the surface. Seismometer near large cities (i.e., Tokyo, Osaka, and Nagoya) are placed at depths > 1000 m, the deepest at 3510 m. Hi-net also reports seismometers to have a natural frequency of 1 Hz, sensitivity of 200 V/m/s, and record at a sample rate of 1000 Hz. Continuous data is decimated to a sample rate of 100 Hz before being sent to the NIED data management center (DMC) (Obara et al. 2005).

We collected a year’s worth from 2007 of vertical component seismic waveform data from 797 Hi-net stations, amounting to over 100 TB of data. NIED DMC provided waveform data in the WIN32 data file format. We converted waveform data from WIN32 format to Seismic Analysis Code (SAC) format to prepare the data for processing. We used the HinetPy Python package to retrieve, convert waveform data, and extract instrument responses. Waveform data was requested and stored in one-hour increments.

Temporally Normalizing Seismic Data and Calculating PSD

To remove transient signals (e.g., those created by earthquakes, explosion, and thunderstorms) in the waveform data, we apply a temporal normalization (TN)—a method shown by Marcillo and MacCarthy (2020) to be effective at a continental level of analysis for isolating and analyzing ambient seismicity. We implemented this method of waveform
processing based on Bensen et al. (2007) work for obtaining surface wave dispersion measurements. Specifically, we used the following formula to temporally normalize the data,

\[ \tilde{d}_i = \frac{d_i}{\omega_i} \]  

(6.1)

where \[ \omega_i = \frac{1}{2N+1} \sqrt{\sum_{j=i-N}^{i+N} d_j^2} \]  

(6.2)

and \( \tilde{d}_i \) is the temporally normalized sample; note, this method normalizes each sample \( (d_i) \) discretely in the waveform by its local root mean square (RMS; \( \omega_i \)). We calculate the window for the RMS such that we use \( 2N+1 \) values: the value \( v_i \) itself, \( N \) values before \( v_i \) and \( N \) values after \( v_i \). To preserve waveform length at edges, we padded with zero values (i.e., \( d_j = 0 \) for \( d_j \) outside our dataset). Finally, we save the normalized output as a SAC file, maintaining the original data structure (i.e., files consisted of one-hour waveform segments with matching metadata).

To consolidate PSDs, we partition and stack data into periods where we anticipate comparable seismic source phenomena to dominate the PSDs for each station. Past studies (e.g., Guenaga et al. 2021; D. E. McNamara and Buland 2004) have shown that variability in anthropogenic activity, especially related to work hours, can manifest as significant changes in the seismic energy at specific frequencies; thus, we opt to analyze each GMT hour separately. Given that hour-of-day PSDs tend to remain similar, primarily provided that temporal normalization removes transient signals, we opt to average PSD for each given hour-of-day by stacking. However, studies have also found that tonal seismic noise varies between seasons, likely due to changes in weather patterns (Marcillo and MacCarthy 2020; D. E. McNamara and Buland 2004; Stutzmann, Roult, and Astiz 2000). Distinctively, Wang et al. (2017) have already
shown that Japan experiences seismic velocity changes based on the season at a regional scale. Thus, we divide PSD into annual quarters characterizing seasons (i.e., Spring, March-May; Summer, June-August; Fall, September-November; Winter, December-January-February), only stacking hour-of-day PSDs provided they occur during the same season. With these time and season windows, we stack corresponding PSD data for each station—producing four (season) sets of 24 (hour-of-day) PSDs. To account for anomalous abrupt changes in amplitude, we standardize PSDs using the following equations,

$$z = \frac{x - \bar{x}}{\sigma}$$  \hspace{1cm} (6.3)

where $x$ is the PSD values, $\bar{x}$ is the PSD mean, $\sigma$ is the PSD standard deviation, and $z$ is the standardized (z-score) PSD.

**Clustering Stations with PSDs (using K-Means Method)**

To reveal affiliations between stations, we cluster z-score PSD using the $k$-means method. We also construct elbow plots using the distortion results (i.e., an average of the squared Euclidean distances from their respective cluster centers) from $k$-means using 1-10 clusters. These elbow plots and clustering results were then used to inform us of the number of appropriate clusters to use in our results. Only PSDs with matching season and hour-of-day were clustered together using all available stations. Each PSDs are inputted as points in $n$-space, where $n$ is the number of samples (along the frequency axis) in a PSD. For the clustering process, we rely on the Python module, Scikit-learn. Note, the module uses Elkan’s (2003) algorithm to solve the $k$-means problem, by default—which we use. Based on the elbow plots, the mean
recommended number of clusters was between 3.54 and 4.375 (see Figure 6.2). Thus, we opted to use 4 (the closest integer) for the number clusters during our analysis.

**Geospatial Data**

We collected data with ecological and geospatial information to provide context and contrast clustering results (Fig. 6.3., See Data and Resources for details on data availability. The collection includes data containing Earth's ecoregions, categorized into 14 biomes with 867 ecoregions, created by Olson et al. (2001). Based on this dataset, Japan contains seven unique ecoregions: **Hokkaido Deciduous Forests, Hokkaido Montane Conifer Forests, Honshu Alpine Conifer Forests, Nihonkia Evergreen Forests, Nihonkia Montane Deciduous Forests, Taiheiyo Evergreen Forests, and Taiheiyo Montane Deciduous Forests.** These make up the two biomes present in Japan (i.e., the **Temperate Conifer Forests** and the **Temperate Broadleaf and Mixed Forests**).

**Station Group Consolidation and Correlation Method**

For each of the four seasons, we perform the following processing of our data.

For each of the 24 hours, we use the PSDs corresponding to each of the 797 seismic stations to cluster the stations into four groups. This way, we get 24 clusterings, i.e., 24 ways to divide the seismic stations into groups. For different hours, we get, in general, different division of stations into groups. Let us analyze how correlated are clusterings corresponding to different hours.

Let $p$ and $k$ be groups corresponding to two different clusterings. Each of these groups can be described by describing which stations are contained in this group and which are not. This can be described by binary variables $b_{pn}$ which are:
equal to 1 if the station $n$ belongs to the group $p$ and

equal to 0 if the station $n$ does not belong to group $p$.

When the two groups are identical, i.e., when each station $n$ belonging to the group $p$ also belongs to the group $k$ and vice versa, then we have $b_{pn} = 1$ if and only if $b_{kn} = 1$. If there are stations that belong to one of the groups but not to another one, this is an indication that the groups $p$ and $k$ are different. In other words:

- every time we have a station $n$ that belongs to both groups, this increases our belief that these groups are similar; while
- every time we have a station $n$ that belongs to only one of the two groups, this decreases our belief that these groups are similar.

So, if we start with the initial value 0 and go over all the stations:

- adding 1 when the station belongs to both groups and
- subtracting 1 when the station belongs to only one group,

then we get a reasonable measure of similarity/dissimilarity between the groups. This measure—we will denote it by $r_{pk}$—can be formally described as follows:

$$ r_{pk} = \sum_{n=1}^{797} x_{pkn} $$

(6.4)

where, for each station $n$, the variable $x_{pkn}$ is defined as follows:

- when the station $n$ belongs to both groups, i.e., when $b_{pn} = b_{kn} = 1$ (and thus, $b_{pn} + b_{kn} = 2$), then we take $x_{pkn} = 1$;
• when the station $n$ belongs to only one of the two group, i.e., equivalently, when $b_{pn} + b_{kn} = 1$, then we take $x_{pkn} = -1$;

• finally, when the station $n$ does not belong to any of the two groups, i.e., equivalently, when $b_{pn} + b_{kn} = 0$, then we take $x_{pkn} = 0$.

By computing similarity $r_{pk}$ between a group $p$ corresponding to hour $t$ and groups $k$ corresponding to the next hour $t + 1$, we can match the groups corresponding to different hours: namely, we match each group $p$ with the group $k$ which is the most similar to $p$, i.e., for which the similarity value $r_{pk}$ is the largest.

• We start with groups corresponding to hour 1—which we arbitrarily mark as Group 1, Group 2, etc.

• Then we match these groups with groups corresponding to hour 2. This way, one of the hour-2 groups—namely the one that best matches with hour-1 Group 1—is marked Group 1, etc.

• After that, we use the matching between groups corresponding to hours 2 and 3 to mark groups corresponding to hour 3, etc.

For each station and for each hour $t$, the group containing this station in hour-$t$ clustering, is, in general, marked differently:

• in some hours, the station may belong to a group marked as Group 1,

• in some other hours, this station belongs to the group marked as Group 2, etc.

To merge this information:

• we count, for each station $n$, how many times it was marked by different marks (1 through 4), and

• we assign, to the station $n$, the mark that occurs most frequently.
(We did not have ties, but in general, in the case of a tie—when several marks occur the same number of times, we can randomly select one of these marks.)

This way, we divide all the stations into four “merged” groups:

- the group of all stations marked by 1,
- the group of all stations marked by 2, etc.

During this process, we also track, for each season, what is the groups variability, i.e., how much the groups change from each hour to the next one. For this purpose, for each hour \( i \), we computed the *hourly variability* \( v_i \) as the proportion of stations whose group changed when we go:

- from groups corresponding to the current hour \( i \)
- to groups corresponding to the next hour \( i + 1 \);

namely:

- we counted the number \( c_i \) of stations that change their group from hour \( i \) to the next hour \( i + 1 \), and
- we divided the resulting count by the overall number of stations (797):

\[
v_i = \frac{c_i}{797}
\]  

This way, we get 23 hourly variabilities \( v_1, v_2, ..., v_{23} \). To measure overall variability \( v \), we computed the arithmetic average of hourly variabilities:

\[
v = \frac{v_1 + v_2 + \cdots + v_{23}}{23}
\]  

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For this variability measure \( v \):

- variability \( v = 0 \) means that all the stations remain in the same group hour after hour,
- variability \( v = 1 \) means that each station changes its group every hour, and
- intermediate \( 0 < v < 1 \) values of variability \( v \) indicate the average proportion of stations that change their group from one hour to the next one.

Next, we study the relation between our clustering results and biogeographic information. We expect it to be correlated with the known division of Japan into seven ecoregions. To check this relation, for each ecoregion \( e \) and for each merged group \( g \), we find the number of common elements, and select the group with which this ecoregion has the most elements in common. Let \( n(e) \) denote this largest number of common elements. We then consider the sum \( N = \sum_e n(e) \) as a natural measure of correlation between seismic-based merged groups and ecoregions.

- If there was no correlation, then each element of each ecoregion would have an equal probability to be in each of the four merged groups. Thus, on average, the ecoregion \( e \) with \( |e| \) elements would have \( |e|/4 \) elements in common with each merged group. In this case, we would have \( n(e) = |e|/4 \), and so, the sum \( N \) of all these values will be simply equal to the number \( N_e \) of stations which are in one of the ecoregions—which is more than 700—divided by 4, i.e., to approximately 175.
- On the other hand, in the ideal case, when each ecoregion belongs fully to one of the merged groups and has no common elements with other merge groups, then for each \( e \), we have \( g(e) = |e| \), so the sum of these values will be equal to the total number of stations in ecoregions \( N \approx 700 \).

So:
• if the value $N$ is larger than 175, there is a correlation between seismic clustering and ecoregions, and

• the larger $N$, the larger the correlation.

Results

Upon visual inspection of the cluster groups, we observe strikingly coherent geospatial groupings. This uniformity is true for both the hourly and merged cluster results. Figure 6.4 shows the station grouping (in colors) geographically. Analytically, we evaluate the union between the four merged cluster groups and seven ecoregion groups with a similarity matrix, as shown in Figure 6.6. The largest of these unions (i.e., $n(e)$) are highlighted by dashed cell borders. We find that Taiheiyo Evergreen Forests have the largest match with the merged PSD cluster group dominating southwestern Japan for all four seasons. We also see that Nihonkia Montane Deciduous Forests group shows some limited match with the merged PSD cluster group in central-northeast Japan. These unions are also the best along the ecoregion axis for both Taiheiyo Evergreen Forests and Nihonkia Montane Deciduous Forests. In contrast, ideal unions for Hokkaido Montane Conifer Forests and Honshu Alpine Conifer Forests do exist for some merged PSD cluster results but are less substantial; the union are less consistent across merged PSD cluster results and not offering the absolute best union for the given ecoregion. Using $N$ as a natural measurement of correlation, we find that each merged cluster result shows notable but limited overall correlation (i.e., $N > 175$ but $N << 797$).

In addition, we measured variability across stations and time in the clustering results. Examining station variability provides some context into the reliability of station group assignments. Figure 6.5 maps the station variability, $v_i$ (triangle color and scale), with insets plotting time variability, $v$ (red line), as described in the Station Group Consolidation and
Correlation Method section above. Most stations appear to be relatively consistent across time, with no station displaying a $v_i$ greater than 0.625. For $v$ we consistently observe a general minimum around 11:00 until 20:00 UTC. Overall, $v$ also remains relatively low, never going above 0.3. The relatively low $v_i$ and $v$ suggest clustering groups remained relatively consistent.

Discussion

Ecoregions are distinct regions containing a collection and amount of biodiversity before any changes from anthropogenic related land use (Olson et al. 2001). We concede that this definition of regions is firmly ecological and does not directly consider the variability of seismically participating phenomena in a region. However, we anticipate that these regions potentially contain a unique combination and number of seismic factors, leading to distinct seismic noise (e.g., turbulent weather interacts with the environment to produce potentially unique seismic signatures (Bromirski 2001; Hsu, Finnegan, and Brodsky 2011; Zhu et al. 2016)). Colombi et al. (2016) and Muhammad et al. (2020) have also shown that vegetation, in particular forests, can attenuate Rayleigh waves at frequencies $\leq$110 Hz. Some animals (including terrestrial) appear capable of regularly producing unique seismic signals (e.g., Baratchi et al., 2013; Gordon et al., 2001; Podolskiy et al., 2021; Wood et al., 2005). With all these factors pseudo-continuously contributing or disrupting vibrations in an area, we hypothesize that ambient seismicity may be distinct between certain ecoregions. Our results show that there is some agreement between the cluster results and ecoregions. This is particularly striking when visually examining the merged cluster results. Given we provided that only seismic data (i.e., no geographical information), the groups created recover some geospatial consistency that vaguely mimics the shape of some ecoregions. Taiheiyo Evergreen Forests and Nihonkia Montane Deciduous Forests demonstrate this consistency and general agreement. Thus, we tentatively
propose that *Taiheiyo Evergreen Forests* and *Nihonkia Montane Deciduous Forests* create
distinct seismic ambient noise signatures, creating these observed cluster patterns.

However, the results in the context of considering mismatched stations reveal that unions
are imperfect. For example, *Taiheiyo Evergreen Forests* provide the largest link to one of the
four groups in the seasonally merged cluster results, yet over 50% of stations are mismatched for
any given similarity matrix assessment. The correlation metric $N$ also reveals this discrepancy.
When considering all the largest matches (i.e., $n(e)$ values), we find an overall weak correlation.
We speculate that such significant discrepancies are caused by seismically noisy phenomena not
accounted for when exclusively considering the ecoregions. For instance, coastal proximity
undoubtedly affects tidal seismicity, a seismic phenomenon regularly observed near coasts
(Bromirski and Duennebier 2002; Okeke and Asor 2000). Additionally, the urbanization of a
region would also influence the observed ambient seismicity of an ecoregion—human traffic
would begin to dominate ambient noise instead of ecological seismic noise contributing
phenomena.

Many studies have shown seismometers sensitive to urban anthropogenic activity or lack
thereof (e.g., Boese et al. 2015; Díaz et al. 2017; Green et al. 2017; Groos and Ritter 2009;
Guenaga et al. 2021; Lecocq et al. 2020; Lindsey et al. 2020; Ojeda and Ruiz 2021; Wu et al.
2021; Xiao et al. 2020). These studies tend to agree that metropolitan (including tram) traffic
likely contributes, to a significant degree, to the urban seismic noise observed in urban areas.
Thus, relatively modern metropolitan areas will likely exhibit increase noise. Also, as an *a priori*,
a higher human population will likely lead to higher seismic noise levels in an area during
anthropogenically active periods (e.g., humans tend to produce more seismic noise during
ordinary work hours than in evening hours—a phenomenon regularly observed in previous
works (Díaz et al. 2017; Groos and Ritter 2009; Guenaga et al. 2021; Xiao et al. 2020)). In particular, the low $v_{hr}$ from 11:00 UTC (20:00 JST) to 20:00 UTC (5:00 JST) may be a consequence of less anthropogenic activity.

**Future Work**

Given that urbanization often overtakes its natural environment, transforming biomes into “anthromes”, we presume that such alterations progressively change the seismic noise signature to one dominated by anthropogenic activity. In the future, we plan to determine the significance of human density on seismic noise. We assume that urban noise regularly remains present and dominant at 1-10 Hz. That is not to say we dispute alternately proposed anthropogenically sensitive frequency bands, rather we compromise on the 1-10 Hz band as it consistently exists in many of the anthropogenic sensitive bands proposed (Asten 1978; Asten and Henstridge 1984; Boese et al. 2015; Bowman, Baker, and Bahavar 2005; Díaz et al. 2017; Green et al. 2017; Groos and Ritter 2009; Gutenberg 1958). We would calculate RMS in 1-10 Hz frequency band to evaluate the presumably urban sensitive seismic energy present in each station’s record; this filter should, in theory, magnify changes contributed from anthropogenic RMS. We would then compute the mean workday ($\Delta \bar{\omega}_{work}$) and weekend ($\Delta \bar{\omega}_{end}$) RMS change (between day- and nighttime RMS). Given the $v_{hr}$ trend seen in Figure 6.5, we would presuppose that hours 6–18 is daytime (i.e., the most active anthropogenic period) and 19–5 to be (less active) nighttime, based on 24-hr local time as similarly done by Guenaga et al. (2021). We hypothesize that urban stations will express significantly larger $\Delta \bar{\omega}_{work}$ compared to $\Delta \bar{\omega}_{end}$ for any given week. To determine this difference, here defined as apparent urban RMS ($\omega_{urban}$), we would rely on the following equation,
\[ \omega_{urban} = \Delta \omega_{work} - \Delta \omega_{end} \text{ where } \Delta \omega = \bar{\omega}_{day} - \bar{\omega}_{night} \] (6.6)

where \( \bar{\omega}_{day} \) is the mean daytime RMS, \( \bar{\omega}_{night} \) is the mean nighttime RMS, \( \Delta \omega_{work} \) is the average change in RMS for a workday, and \( \Delta \omega_{end} \) is the average change in RMS for a weekend day. We then relate \( \omega_{urban} \) to its stations sampled human density measurement. Note, we would conduct this analysis using the unnormalized waveform data as we are interested in changes in RMS magnitudes—temporal normalization smooths these essential amplitude differences.

Additionally, we plan to omit \( \Delta \omega \) if the corresponding \( \omega_{day} \) or \( \omega_{night} \) is a certain number of standard deviations away from the mean, indicating a large transient event (e.g., an earthquake). The cutoff for the omission process would be determined based on observations made of \( \omega_{day} \) and \( \omega_{night} \) measurements containing known earthquake instances. Given the abundance and intensity that Japan experiences large events, including such measurements would likely adversely skew our results. The newly determined urban stations would serve as a new distinct “ecoregion” (i.e., the anthro-region). Thus, we would override the original ecoregion for these stations, increasing the total ecoregion count to eight in Japan, and then repeat our correlation process.

Furthermore, we would be able to plot population density versus \( \Delta \omega \) for each given station—ideally revealing a relationship between increase RMS and human population density. For this, we rely on population densities data for 2011 in Japan provided by the Global High Resolution Population Denominators Project (see Data and Resources section for more information). The data provide a 30 arc seconds resolution that estimated population density
using a per grid-cell (People/km²), see Figure 6.7. Station locations would serve as the sample points for the population density analysis.

We also began considering the use of pseudo-topographic variations (i.e., as a proxy for coastal and high-elevation noise). With this objective, we conducted a preliminary cluster analysis of elevation, see Figure 6.8. The employed topographic measurements come from the waveform data's metadata, containing information about the recording station and instruments. Note that this clustering result utilizes the same number of groups as the merged PSD cluster results. There seem to be some analogous groupings on initial examination with those observed in the merged PSD clustering results. However, we have yet to conduct any proper analytical assessment. We anticipate observing some complexity matching merged PSD clustering results that we do not observe in ecoregion groups—perhaps explaining some of the significant disparity seen in the similarity matrix. To potentially improve results, we may also need to conduct an elbow curve analysis for elevation. Using more inherent or ideal breaks in the elevation grouping could provide a more precise correlation.

**Conclusion**

Although further consideration is required to reinforce observations from preliminary results, we find that Japan’s ambient seismic noise (as viewed through PSD measurements) correlates to a degree with the ecoregions and, potentially, anthropogenic activity. In particular, the *Taiheiyo Evergreen Forests* and *Nihonkia Montane Deciduous Forests* ecoregions seem to correlate well with merged PSD clustering results. The hourly variability factor also shows a period stability during nighttime hours (i.e., 8–5 JST). Given anthropogenic noise can vary hourly (e.g., rush-hour traffic is liable to look seismically different than mid-day traffic), we suspect anthropogenic activity is likely contributing to this trend in variability. We expect with
continued examination of this dataset to reveal quantifiable correlations between population density and seismic noise and improved ecoregion correlations—demonstrating that ambient seismic noise is not random but rich in interpretable environmental signals.

**Data and Resources**

Waveform data was provided by the National Research Institute for Earth Science and Disaster Resilience (2019), NIED Hi-net, https://doi.org/10.17598/NIED.0003. Copies of the waveform data used in this study can be retrieved from Hi-net website (https://www.hinet.bosai.go.jp/). Biome and ecoregion geospatial data were collected from the World Wildlife Fund (https://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world). Human population geospatial data provided by WorldPop (www.worldpop.org - School of Geography and Environmental Science, University of Southampton; Department of Geography and Geosciences, University of Louisville; Departement de Geographie, Universite de Namur) and Center for International Earth Science Information Network (CIESIN), Columbia University (2018). Global High Resolution Population Denominators Project - Funded by The Bill and Melinda Gates Foundation (OPP1134076), https://dx.doi.org/10.5258/SOTON/WP00674. Maps and spatial analysis were conducted with QGIS (QGIS.org (2020). QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.org). Python code was used for processing waveform data, in particular we used the Obspy Python package (docs.obspy.org; Beyreuther et al. 2010; Krischer et al. 2015; Megies et al. 2011). Note, all websites were last accessed on July 2, 2020.
Figure 6.1

Map showing the location of Hi-Net seismic stations (red triangles) from which waveform data were retrieved from for our analysis.
Figure 6.2

K-Means elbow plots for (a) spring, (b) summer, (c) fall, and (d) winter PSD clustering results. For each day within the season, the elbow curves are plotted as gray line translucent lines. The dashed black vertical lines mark the average recommended group number—the solid black vertical line the closest integer to said average. The red region shows the integer range of recommended groupings based on the all the corresponding elbow plots.
Figure 6.3

Map of biome and ecoregions throughout Japan based on classifications by Olson et al. (2001).
Figure 6.4

Merged seasonally segregated PSD clustering results. Triangles represent stations with colors corresponding to cluster group. Note: Color grouping between (a) spring, (b) summer, (c) fall, and (d) winter results do not necessarily correspond to one another.
Figure 6.5

Four merged segregated PSD clustering variability results corresponding to seasons; (a) spring, (b) summer, (c) fall, and (d) winter. Triangles represent stations with colors and size corresponding a station’s $\nu_i$ (i.e., darker larger stations expressed more variability between cluster results. Inset plots show overall variability for each hour ($\nu$) of the merged 24 hours in PSD cluster results.
Figure 6.6

Four similarity matrices displaying the union of ecoregion and merged PSD cluster group stations. Note: Cluster group numbering is not consistent between (a) spring, (b) summer, (c) fall, and (d) winter results. Center cell values display number of stations present for a given union. Perimeter values indicate total stations for a given ecoregion or merged PSD cluster group. Cells emphasized by dashed border are those marked as best match \( n(e) \) for a merged PSD cluster group (for ties, both instances are marked). Bottom right inset plots \( N \) for each result with \( N=175 \) being of no significance and \( N=797 \) (a full correlation) having a max significance of 100\%. 
Figure 6.7

Heatmap of Japan’s 2011 discretized human population density using a per grid-cell (People/km²) at a 30 arc seconds resolution.
Figure 6.8

Map of elevation station clustering results (using 4 groups). Colors correspond to grouping. Groups progressively consist of higher elevation from station groups “a” (lowest elevation, with a minimum elevation of 0 m) to “d” (highest elevation, with a maximum elevation of 1,376 m).
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Vita

David L. Guenaga was born in San Bernardino, California. He graduated from Summit Leadership Academy High Desert High school and was given an Award of Excellence during his senior year. He also earned his B.S. degree in Geophysics from the University of California, Riverside in 2015 during which he received an Academic Excellence Award. He joined UTEP’s doctoral program in Geological Sciences in 2017 and subsequently received his M.S. in Geophysics in 2019 at UTEP. In the summer of 2019, he also interned at Oak Ridge National Laboratory with the Department of Energy. David L. Guenaga is a recipient of the DGS/Karen Kellogg Shaw Memorial Scholarship and Earl D. and Reba C. Griffin Memorial Scholarships. He has also been selected to receive the Science, Mathematics, and Research for Transformation (SMART) scholarship provided by the National Defense Education Program. As part of the SMART scholarship, he will work for two and a half years at the Naval Oceanographic Office (NAVOCEANO) in Stennis Space Center, MS for the Department of Defense upon graduation with an opportunity remain with a permanent position at the Department of Defense as a scientist.

During his doctoral program, David L. Guenaga also regularly participated in geosciences outreach events and as a Teaching Assistant for undergraduate and graduate level courses in at UTEP’s Geosciences Department. He has to date, two published scientific works (which are included in this dissertation).

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This thesis/dissertation was typed by David L. Guenaga.