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Exploring the Capabilities of MyShake Citizen Science Seismology Data

by

Sarina C. Patel

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Earth and Planetary Science

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Richard Allen, Chair

Professor Roland Burgmann

Professor Khalid Mosalam

Summer 2023



# Exploring the Capabilities of MyShake Citizen Science Seismology Data

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by

Sarina C. Patel

## Abstract

## Exploring the Capabilities of MyShake Citizen Science Seismology Data

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Doctor of Philosophy in Earth and Planetary Science

University of California, Berkeley

Professor Richard Allen, Chair

MyShake is a free citizen science smartphone application that has been publicly available since 2016 and has been downloaded globally 2.6 million times. Since becoming an earthquake early warning delivery service for the US West Coast, MyShake has attracted its greatest concentration of users in the states of California, Oregon, and Washington. As a citizen science project, MyShake collects various types of data, which can be broadly categorized as long-form waveforms and real-time snippets. When a phone operating MyShake is still for 30 min, MyShake will begin monitoring the accelerometer, which is hardware built into all smartphones. A machine learning-trained pair of algorithms scan for earthquake-like motion and will record five minutes of waveform data when an earthquake is suspected to be occurring. Waveform recording can also be triggered by the delivery of an early warning message, in anticipation of imminent earthquake shaking. These data are uploaded to secure servers when phones are connected to wi-fi and power. Real-time data collected by MyShake includes state of health information sent in data snippets called heartbeats, alert receipts messages, short-term-average over long-term-average (STA/LTA) triggers whenever a monitoring phone suddenly moves, and aggregate peak acceleration values.

The data collected by MyShake represents an at-scale opportunity to explore the capabilities of a smartphone seismic network. In this work, I investigate four use-cases of smartphone data: 1) assessing how smartphones perform as early warning delivery tools; 2) using smartphone waveform data to measure ground shaking intensities; 3) incorporating real-time smartphone earthquake detections into a traditional earthquake early warning system; and 4) measuring the fundamental frequency of buildings using smartphone waveforms. The first and third objectives form a circle, generating and then delivering early warning to private citizens. We find that phones are both efficient delivery mechanisms, with warnings typically arriving on phones within 5 seconds of alert generation, and efficient earthquake detectors, with real-time triggers arriving at a backend server in the same amount of time as traditional data. Measuring acceleration and converting to shaking intensity helps evaluate the

accuracy of the shaking extent produced by early warning. Using waveform data to measure fundamental frequency ventures into the realm of structural health monitoring, a critical field for earthquake preparedness and rapid response. All together, MyShake represents a novel and high-potential opportunity to make seismology accessible and applicable within communities while also supporting the creation of seismic knowledge that can be used to make the same communities safer.

To Citizen Scientists Everywhere

Your contributions help us learn more and have greater community impact than we scientists ever could manage alone. Without you, this PhD would not exist.

To the MyShake Team

You are the cat's meow. Stay lit. Without you, this PhD would not exist.

# Contents

|                                                                                                          |           |
|----------------------------------------------------------------------------------------------------------|-----------|
| <b>Contents</b>                                                                                          | <b>ii</b> |
| <b>List of Figures</b>                                                                                   | <b>iv</b> |
| <b>List of Tables</b>                                                                                    | <b>vi</b> |
| <b>1 Introduction to the MyShake Project</b>                                                             | <b>1</b>  |
| 1.1 The MyShake App . . . . .                                                                            | 1         |
| 1.2 Characteristics of MyShake Sensor Data . . . . .                                                     | 3         |
| <b>2 Using MyShake Data to Evaluate User Experience of Early Warning Delivery and Earthquake Shaking</b> | <b>7</b>  |
| 2.1 Earthquake Early Warning Delivery . . . . .                                                          | 7         |
| 2.2 Early Warning Alerts . . . . .                                                                       | 9         |
| 2.3 Latency Data . . . . .                                                                               | 10        |
| 2.4 User Experience of Warning Time . . . . .                                                            | 12        |
| 2.5 User Experience of Intensity . . . . .                                                               | 15        |
| 2.6 Summary . . . . .                                                                                    | 19        |
| <b>3 Contributing Smartphone Data to a Traditional Earthquake Early Warning System</b>                   | <b>23</b> |
| 3.1 The US ShakeAlert Earthquake Early Warning System . . . . .                                          | 24        |
| 3.2 MyShake Triggering . . . . .                                                                         | 27        |
| 3.3 Retrospective Analysis . . . . .                                                                     | 27        |
| 3.4 Real-Time Test . . . . .                                                                             | 38        |
| 3.5 Discussion . . . . .                                                                                 | 41        |
| 3.6 Future Improvements . . . . .                                                                        | 43        |
| <b>4 Structural Health Monitoring Capacities of MyShake</b>                                              | <b>48</b> |
| 4.1 Introduction . . . . .                                                                               | 48        |
| 4.2 Fundamental Frequency . . . . .                                                                      | 49        |
| 4.3 Shake Table Test . . . . .                                                                           | 50        |
| 4.4 Citizen Science Measurements . . . . .                                                               | 57        |

|          |                       |           |
|----------|-----------------------|-----------|
| 4.5      | Discussion . . . . .  | 65        |
| 4.6      | Conclusions . . . . . | 70        |
| <b>5</b> | <b>Conclusions</b>    | <b>72</b> |
|          | <b>Bibliography</b>   | <b>76</b> |

# List of Figures

|      |                                                                                                       |    |
|------|-------------------------------------------------------------------------------------------------------|----|
| 1.1  | Global distribution of MyShake users . . . . .                                                        | 2  |
| 1.3  | Smartphone noise floor . . . . .                                                                      | 4  |
| 1.2  | Sampling rate comparison between a smartphone and a traditional MEMs sensor . . . . .                 | 5  |
| 1.4  | MyShake trigger and waveform timestamp accuracy . . . . .                                             | 6  |
| 1.5  | Smartphone location errors . . . . .                                                                  | 6  |
| 2.1  | Regions alerted in California . . . . .                                                               | 8  |
| 2.2  | Distribution of alert delivery times in the Carson earthquake . . . . .                               | 12 |
| 2.3  | Sample waveform containing alert vibration . . . . .                                                  | 13 |
| 2.5  | Peak ground shaking and alert delivery times for the El Monte earthquake . . . . .                    | 14 |
| 2.6  | Maps of alert delivery times for the El Monte and Lone Pine earthquakes . . . . .                     | 15 |
| 2.7  | Peak ground shaking and alert delivery times for the Lone Pine earthquake . . . . .                   | 16 |
| 2.4  | Warning time before S-wave arrival for the El Monte earthquake . . . . .                              | 17 |
| 2.8  | Peak Acceleration comparison between MyShake and traditional data . . . . .                           | 18 |
| 2.9  | Ratio of Peak Accelerations recorded on phones vs traditional seismometers . . . . .                  | 21 |
| 2.10 | Maps of the USGS ShakeMap contours overlaid by intensity measurements made by MyShake phones. . . . . | 22 |
| 3.1  | ShakeAlert System Workflow . . . . .                                                                  | 24 |
| 3.2  | Real-time triggering in the Granada Hills earthquake . . . . .                                        | 30 |
| 3.3  | Real-time triggering in the El Monte earthquake . . . . .                                             | 31 |
| 3.4  | Real-time triggering in the Compton earthquake . . . . .                                              | 32 |
| 3.5  | Real-time triggering in the Anza earthquake . . . . .                                                 | 33 |
| 3.6  | Effects of Integration of a MyShake waveform from the M 4.5 El Monte Earthquake . . . . .             | 34 |
| 3.7  | Detection rates with a lowered STA/LTA triggering threshold . . . . .                                 | 36 |
| 3.8  | Comparing Magnitude Estimates for the M 4.5 El Monte Earthquake . . . . .                             | 37 |
| 3.9  | Comparing Magnitude Estimates for the M 3.6 Granada Hills Earthquake . . . . .                        | 37 |
| 3.10 | Triggers contributing to the first Markleeville alert . . . . .                                       | 45 |
| 3.11 | Triggers contributing to the first Palomar Observatory alert . . . . .                                | 46 |
| 3.12 | Sample behavior of EPIC location estimates with time . . . . .                                        | 47 |
| 4.1  | Steel Test Structure on PEER Shake Table . . . . .                                                    | 52 |
| 4.2  | Apparent clipping of phone data during strong shaking . . . . .                                       | 53 |

|      |                                                                                |    |
|------|--------------------------------------------------------------------------------|----|
| 4.3  | Filtering 200 Hz data and its comparison to phone data . . . . .               | 54 |
| 4.4  | Measurements in three shake table replays of the 1999 Kocaeli earthquake . . . | 56 |
| 4.5  | Frequency spectrum effects when waveforms are rotated horizontally . . . . .   | 58 |
| 4.6  | Fundamental frequency measurements in an 8 story hotel . . . . .               | 60 |
| 4.7  | Fundamental frequency measurements in a 14 story condominium complex . . .     | 61 |
| 4.8  | Fundamental frequency measurements in an 18 story apartment building . . . .   | 62 |
| 4.9  | Fundamental Frequency Measurements in a 3 story apartment building . . . . .   | 63 |
| 4.10 | Fundamental frequency measurements in a 5 story apartment building . . . . .   | 64 |
| 4.11 | Fundamental frequency measurements in a 3 story hotel . . . . .                | 65 |
| 4.12 | Repeated fundamental frequency measurements in a 5 story apartment building    | 66 |
| 5.1  | Alert Delivery Latencies for Large Recipient Events . . . . .                  | 74 |



# List of Tables

|     |                                                                                                           |    |
|-----|-----------------------------------------------------------------------------------------------------------|----|
| 2.1 | Alert delivery latencies for five sample earthquakes . . . . .                                            | 11 |
| 3.1 | Comparison between initial alerts created by EPIC using traditional sensors vs a hybrid network . . . . . | 40 |
| 4.1 | Natural frequencies measured in a shake table test . . . . .                                              | 55 |
| 4.2 | Citizen science measurements of natural frequency . . . . .                                               | 59 |
| 4.3 | Variables for ASCE equation 12.8-8 . . . . .                                                              | 67 |
| 4.4 | Comparison of measured modal frequencies to standard estimates . . . . .                                  | 68 |

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# Chapter 1

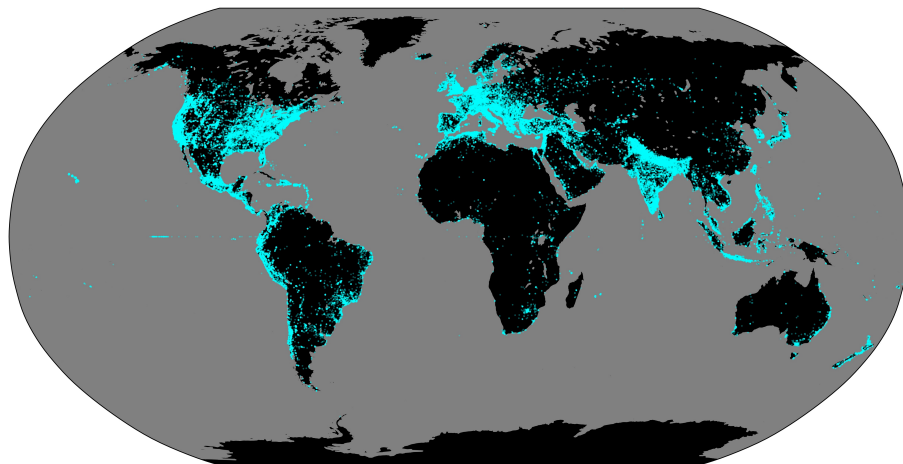
## Introduction to the MyShake Project

### 1.1 The MyShake App

MyShake is a free citizen science smartphone application developed and operated by the Berkeley Seismology lab. It has been available publicly and globally to Android phones since 2016, and to iPhones since 2019. As of July 2023, MyShake has been downloaded over 2.6 million times by mobile users (Figure 1.1). In 2019, MyShake became a delivery service for earthquake early warnings (EEW) generated by the United States ShakeAlert system in the state of California, sponsored by the Governor’s Office of Emergency Services (Patel and Allen 2022). In 2021, public alerts through MyShake became available in the state of Oregon, followed by Washington in 2022. As such, the greatest concentration of MyShake users is in the Western US. In addition to delivering warnings to smartphone users, MyShake offers additional user-centered features such as access to real-time earthquake information, community-sourced damage reports, and information about safety and preparedness (Rochford et al. 2018; Strauss et al. 2020). By offering an app which provides a variety of user features, we expect the app’s reach to continue to grow.

MyShake was originally developed as a citizen science project and this aspect of the app remains a strong component of the project mission even as more general user features have been added. The project grew out of the observation that all smartphones are equipped with a triaxial MEMs accelerometer (Kong, Allen, and Schreier 2016). With 6.4 billion smartphone subscriptions reported globally in 2022 (*Ericsson Mobility Report June 2023* 2023), smartphone ownership is becoming increasingly ubiquitous (Poushter 2016). This represents a tremendous potential seismic network implemented at a global scale at the cost of only app development and server maintenance. MyShake uses a machine-learning trained classifier to filter anthropogenic noise from acceleration observations and detect earthquake shaking (Kong, Allen, and Schreier 2016; Kong, Allen, Schreier, and Kwon 2016).

The MyShake app records vibrations only when the accelerometer is not already in motion. When a phone is left stationary for 30 minutes, the app begins monitoring the accelerometer, while retaining a moving one-minute buffer window of data. Phones can both



**Figure 1.1:** A global map of the distribution of MyShake downloads, marked in cyan points, since the app’s initial release in February of 2016, current as of June 2023.

be remotely and internally triggered to record a 5 minute waveform (4 minutes after the trigger in addition to the 1 minute buffer). To minimize power consumption and transmission stress, phones hold the waveform in memory until connected to power and WiFi, before uploading it to MyShake’s central server for analysis. Internally, the app runs an onboard machine learning-trained algorithm that can detect sudden earthquake-like motion and trigger recording (Kong, Allen, Schreier, and Kwon 2016). The MyShake backend server can also trigger ‘ready’ phones to record. All ShakeAlert earthquake early warning alerts sent to MyShake phones trigger recordings, in anticipation of the arrival of shaking. Recordings can also be initiated manually, in anticipation of an event of interest. We utilize this manual triggering function to collect the data described in the shake table test discussed in Chapter 4. Importantly, MyShake is not currently utilized to make extended ( $> 5$  min) continuous recordings out of concern for user battery and memory.

In addition to waveforms, the MyShake app also collects quick snippets of citizen science data and transmits it to a central server for use in real time. Real-time data includes small “heartbeat” messages, which contains items such as triggering information when an earthquake is detected using the onboard algorithm, and receipt timestamps when the phone receives an alert from the MyShake server. Being small, heartbeats are transmitted immediately upon creation to MyShake servers using whatever transmission method is available to the phone.

This dissertation began in August of 2017, a year and a half after MyShake’s initial release. At that time, thousands of waveforms had already been recorded and uploaded by user phones. What was not yet clear was the uses to which the data could robustly be put. Thus began an exploration of MyShake’s capabilities and limitations as a sensor network. In this work, I will explore MyShake’s performance as a delivery system for earthquake

early warning (Chapter 2), intensity mapping using smartphone-derived peak acceleration measurements (Chapter 2), the potential for smartphone-based early warning triggers to be incorporated into the ShakeAlert EEW system (Chapter 3), and a proof of concept study demonstrating MyShake’s capability to capture the fundamental frequency of buildings for the purpose of structural health monitoring (Chapter 4). In addition to these explorations, this work has supported efforts to investigate MyShake data in array-based seismology (Inbal et al. 2019), MyShake as a global earthquake detection system (Kong, Patel, et al. 2019), and MyShake’s potential to conduct phone-based earthquake early warning (Allen, Kong, and Martin-Short 2020; Kong, Martin-Short, and Allen 2020a; Kong, Martin-Short, and Allen 2020b).

## 1.2 Characteristics of MyShake Sensor Data

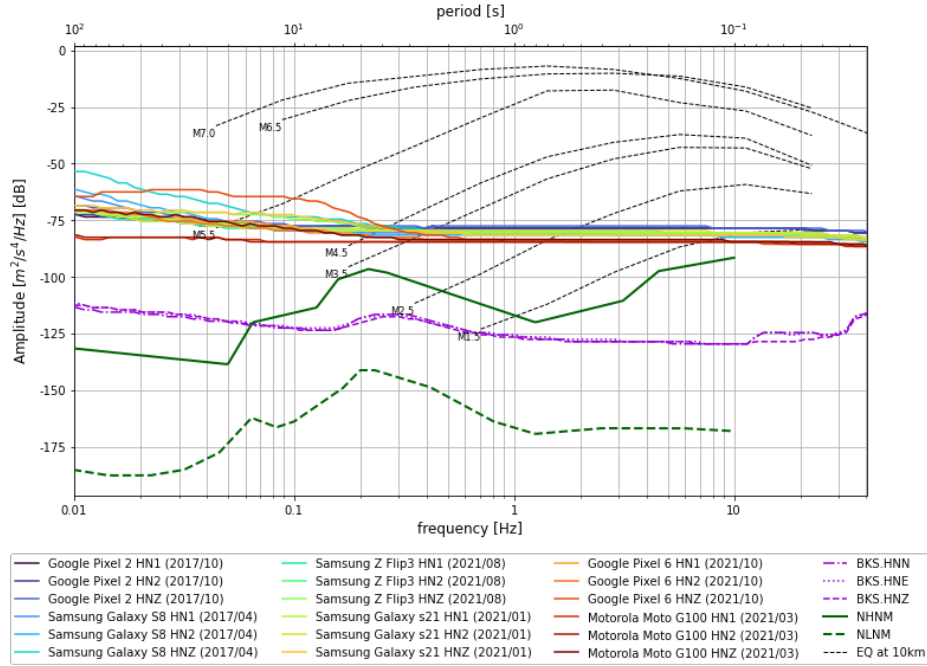
### Sampling Rate

Due to privacy-based restrictions in the iOS operating system prohibiting third party apps from monitoring the accelerometer as a background process, waveform collection using iPhones is not yet possible. Therefore, all waveform-based data assessed in this work were contributed by Android phones. Capabilities and limitations inherent to phone accelerometer hardware relative to a traditional higher quality seismic sensor were explored previously in (Kong, Allen, and Schreier 2016; Kong, Allen, Schreier, and Kwon 2016; Kong, Patel, et al. 2019). Specifications vary by manufacturer and phone model, but in general have improved in quality over time. For example, the average sampling rate in accelerometer recordings MyShake made between 2016-2018 was 25 Hz. More recent recordings average 50 samples a second.

The signal captured at this lower rate can also be compared to that recorded by an accelerometer representative of the typical instrument used in structural health monitoring - in this case a TE Connectivity 3022 accelerometer - which has a sampling rate of 200 Hz (Measurement Specialities Inc. 2017). The lower sampling rate of phones does cause small differences in the observed peak amplitude values, but overall we find very good agreement between the waveforms (Figure 1.2).

### Noise Floor

Smartphone accelerometers typically have a higher noise floor than dedicated seismometers, which reduces sensitivity (Feldbusch, Sadegh-Azar, and Agne 2017; Kong, Allen, Schreier, and Kwon 2016). This was first quantified in 2016 with typical smartphones at that time (Kong, Allen, Schreier, and Kwon 2016), and I update our expectations here using recent model phones. In the August 2023 test, 2 smartphones from 2017 and 4 from 2021 were set on an isolated concrete pier adjacent to the BRK seismic station on UC Berkeley’s campus, which is part of the regional Berkeley Digital Seismic Network (BDSN), and left to record in



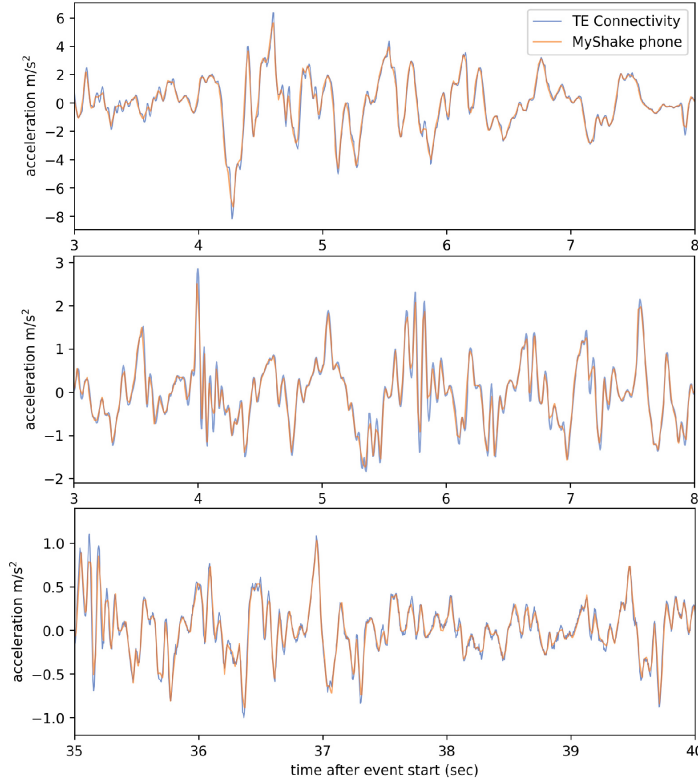
**Figure 1.3:** A power spectral density plot which averages over 1 hour recordings on three components for several smartphones and the BKS seismic station. The seismic station noise for all components is represented by the dashed and dotted purple lines. The green lines represent the high and low noise model (McNamara and Buland 2004).

quiet conditions for 1 hour (Figure 1.3). In this test, I find a  $\sim 35$  dB reduction in noise relative to the 2010-2013 model phones studied previously, with an average amplitude around -75 dB. Smartphone noise has greater variability in low frequencies (about -50 to -80 dB) and less (around -78 to -85 dB) in the high frequency range. As smartphone technology continues to evolve, it is possible their accelerometer noise floor will continue to improve.

## Timestamp

The waveforms collected by phones also depend on the internal clock of a phone to label their timestamps. The MyShake app prompts phones approximately hourly to compare their clocks to a Network Time Protocol (NTP) server and report both the round trip time required to ping the NTP server and the offset between phone and server clock times. MyShake is unable to change a phone's clock. Instead, we can interpolate between NTP reports to correct waveform timestamps before analysis. An initial analysis of 6 million NTP reports in 2018 found that phone clocks varied from NTP server times by up to 1.4 seconds 75% of the time (Kong, Patel, et al. 2019). The difference in reported clock error from one NTP report to the next was within 0.132 seconds for 75% of samples. We consider this 'offset change'

an upper boundary on how accurate MyShake timestamps become when NTP reports are used to correct them.

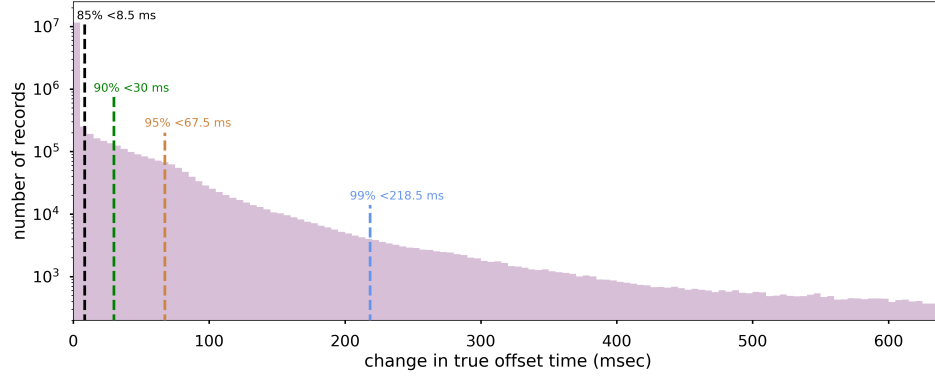


**Figure 1.2:** Horizontal component waveforms snippets recorded by phones at 50 Hz compared to those recorded by a co-located traditional MEMs sensor at 200 Hz during simulated earthquake motions on a shake table. Phone data has been demeaned and resampled.

We later updated our 2018 analysis using 14 million new NTP checks recorded on a random selection of 26 days between February 2022 and February 2023. We find that 50% of queries report an internal clock error better than 0.710 seconds, and 75% were better than 1.23 seconds. While these absolute offsets are fairly consistent with the 2018 values, the distribution of the errors is improved (Figure 1.4). In the new analysis, 50% of offsets changed by less than 32 milliseconds (very similar to the 27 ms median in 2018), but the tail is much shorter; 85% of offsets change less than 111 ms, compared to 330 ms in 2018. The typical MyShake waveform is 5 min long. With the target interval between NTP checks set at 1 hr, a median deviation of 32 ms spread over the course of 60 min is expected to exert negligible influence on the sampling accuracy within a given waveform. Therefore, we expect no error to be introduced by sampling accuracy to the frequency spectrums we discuss below.

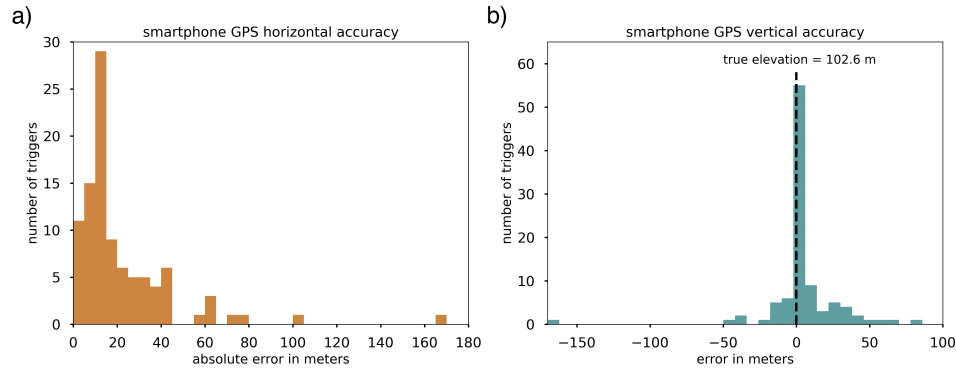
## Location

An experiment reported in the same 2018 study found 75% of phone GPS location accuracy varied within 28.8 m horizontally and 11.4 m vertically (3-4 stories in a typical building), based on a comparison of phone-reported locations and a ground truth location (Figure 1.5; Kong, Patel, et al. 2019). Phones also self-report estimated accuracy (defined by Android as the radius within which there is a 68% chance the phone is located; *getAccuracy* 2023) with their location data. This tends to be similar but not identical to our measured error; in the same test, the 75th percentile of phone-reported horizontal accuracy was 20.8 m. I restrict my analysis in Chapter 4 to phones with a self-reported error of 30 m or less, and use waveforms where a circle defined by the provided latitude and longitude and error ra-



**Figure 1.4:** Accuracy of MyShake trigger and waveform timestamps, as represented by the change in reported offsets from NTP server time. Data are extracted from 26 random days of NTP checks between February 2022 and February 2023, resulting in 14 million data points from 58,000 phones. The colored lines mark the 85th, 90th, 95th, and 99th percentiles. 99.8% of the range is shown. Note that the vertical axis is logarithmic and begins at 10.

dus substantially encapsulates the footprint of a building, or if the circle only meaningfully intersects with a single building (e.g. that building is surrounded by enough empty space that phone is not likely to be located anywhere else).



**Figure 1.5:** Accuracy of smartphone location using Global Positioning System (GPS) points reported with MyShake triggers and seismic waveforms, both **a)** horizontal and **b)** vertical. Ten phones were placed on a second-floor windowsill facing into a partially sheltered courtyard and periodically prompted to collect a spontaneous trigger and record a waveform. The resulting 98 GPS points cluster closely around the true location, both horizontally and vertically.

Our understanding of MyShake as a sensor network thus elucidated, I proceed to explore MyShake's data applications in seismology within the boundaries of what is appropriate to the data's capabilities.



## Chapter 2

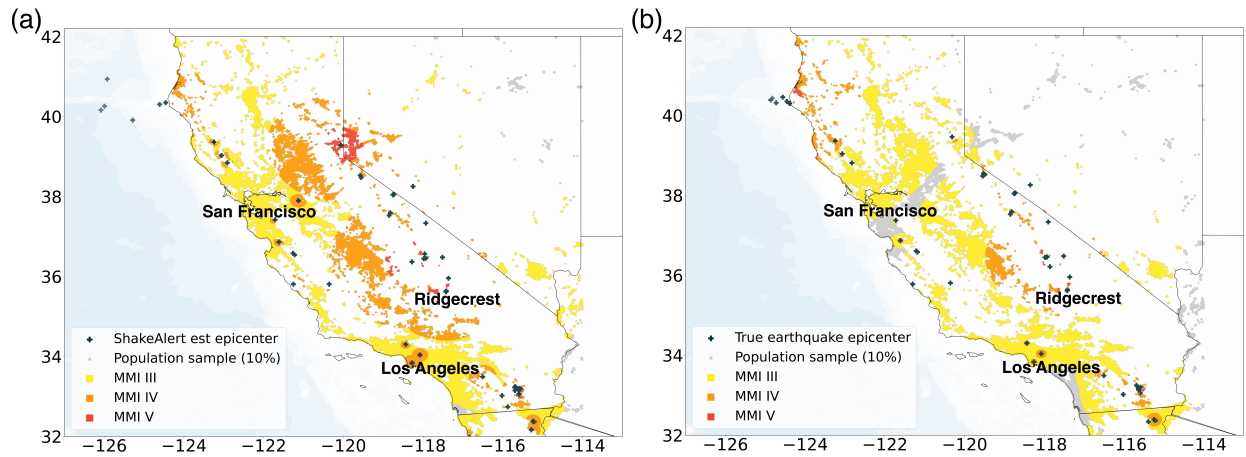
# Using MyShake Data to Evaluate User Experience of Early Warning Delivery and Earthquake Shaking

## 2.1 Earthquake Early Warning Delivery

Public earthquake early warning systems are expanding around the globe (Allen and Melgar 2019; Allen and Stogaitis 2022). To be effective, however, they require a reliable and efficient method of delivering alerts to private citizens in the seconds available before shaking is felt. Alarms on television and radio, personal devices, and a public siren system are all mass distribution systems used globally (Allen, Cochran, et al. 2018; Given et al. 2018; Hoshiba 2014). Alerts can also be sent to individuals via automated email subscriptions, SMS, and in the age of the smartphone, as an app notification. When the United States ShakeAlert system began public alerting across all of California in October of 2019, FEMA’s Wireless Emergency Alerts — commonly known for distributing Amber Alerts for missing children — were designated the default delivery method because it is a function native to phones sold in the United States, although there were concerns about alert delivery speed (Given et al. 2018; Kohler, Smith, et al. 2020). Since the 2019 launch, alerts have also been delivered via smartphone app notifications, which permit greater flexibility in how the alert is presented and how a user can interact with the information. Little data existed, however, to quantify the actual effectiveness and efficiency of delivering early warning as app notifications in the context of existing network technologies.

For the 2019 ShakeAlert launch in California, MyShake added the ability to deliver alerts to become the state of California’s official early warning app supported by the Governor’s Office of Emergency Services (CalOES). Since then, MyShake has delivered one or more ShakeAlerts to nearly every part of the state (Figure 2.1). Alert delivery was extended to the state of Oregon in March 2021, and to Washington in January 2022. As part of its function as an alert provider, MyShake has internally tracked the latency of its entire

system, from the receipt of a ShakeAlert message by a MyShake server through to alert delivery on individual smartphones, to quantify the system’s warning delivery efficiency and identify avenues for improvement. To our knowledge, MyShake is the only earthquake app to continuously monitor and report such data. Brooks et al. (2021) quantify delivery latency using test “alerts” sent to a cluster of 15 phones located close together in San Juan, Costa Rica, and found an average 4 s delivery latency. However, they acknowledge such a small sample size and distribution region may not be representative of more deliveries for a real earthquake over a wide region. Other research on smartphone earthquake early warning latency considers the time to detection and alert generation, but neglects the time required for delivery (Bossu et al. 2021; Kong, Martin-Short, and Allen 2020b). Google began delivery of early warning in the United States in 2020 and is piloting smartphone-detected early warning in New Zealand, Greece, Turkey, the Philippines, Kazakhstan, Kyrgyz Republic, Tajikistan, Turkmenistan, and Uzbekistan, however, delivery latency data has not been published nor publicized for privacy reasons.



**Figure 2.1:** Maps showing alert regions across California through the end of April 2022. **a)** Essentially all of California has been sent at least one alert. The points on the maps mark the distribution of a random 10% sampling of California’s population to show where people tend to be located. Population points in yellow have received a public alert and were in a region expected to experience Modified Mercalli Intensity (MMI) III shaking for at least one event. Orange represents MMI IV and red represents MMI V. The map on the left shows the epicenter and alert area for ShakeAlert’s largest magnitude estimate in each of the 48 events for which ShakeAlert issued an alert  $\geq M$  4.5 prior to 2022. **b)** The right side map represents the final ANSS catalog (“true”) locations of the earthquakes and what the alert area would have been if the magnitude estimate had been exactly correct.

In this chapter, we use the data retained by MyShake to analyze the speed and ground-motion accuracy at which ShakeAlert earthquake early warnings can be delivered to affected populations via app notification. We find that alerts reach the majority of individuals prior

to their experience of peak shaking. MyShake’s citizen science collection of acceleration data during earthquakes can also be used as a window into the user experience during earthquakes. In general, we find that smartphones record a higher acceleration than either the predicted ground motion or actual ground motions recorded at local traditional stations. We suggest this amplification might be accounted for by considering both the frequencies of building response and site-specific ground-motion amplification effects.

## 2.2 Early Warning Alerts

The United States early warning system is ShakeAlert, which is operated by the U.S. Geological Survey (USGS) in collaboration with the regional seismic networks, and with support in California from CalOES. In accordance with USGS thresholds, ShakeAlerts are distributed to private smartphones located in regions predicted to experience Modified Mercalli Intensity (MMI) III (weak shaking) or greater for earthquakes estimated by ShakeAlert to be magnitude 4.5 or greater (Kohler, Smith, et al. 2020). ShakeAlert approximates MMI distribution using a ground-motion prediction equation (GMPE) that ingests the estimated magnitude value and produces intensity radii around the estimated epicentral location—or around an estimated fault length if the event is large enough (Kohler, Smith, et al. 2020). The MMI III region is defined by the MMI 2.5 computed radius. Upon detecting an event, an alert message is sent from ShakeAlert to the MyShake backend system, which then determines which users’ locations fall within the MMI III radius and should receive the alert. The alert leaves the MyShake servers to be transmitted via cell tower and WiFi service to users.

When MyShake receives and begins processing a ShakeAlert, it retains a “processing-start” timestamp ( $t_0$ ). Timestamps for each targeted phone are also recorded at successive transition points in the backend processing system until the alert is forwarded to the distribution system, Firebase, for transmission to phones ( $t_3$ ). We refer to the interval it takes the MyShake servers to process the alert and push it to distribution ( $t_3 - t_0$ ) as the Server Processing Time. The messages travel via cell network and internet to reach target phones. When a phone receives the alert, it records the receipt time ( $t_7$ ) and reports it back to the MyShake servers for delivery confirmation. We refer to the interval from when MyShake received an alert until the phone received the alert as the Alert Acknowledgement Time ( $t_7 - t_0$ ).

During an earthquake, ShakeAlert often sends a sequence of alert updates. The MyShake backend fully processes one ShakeAlert update before seeking the most recent update (with the assumption that ShakeAlert’s accuracy generally improves with time and increasing quantities of data) and calculates whether any additional phones should be alerted. Once MyShake has alerted a given region, it will skip reprocessing that region during subsequent alert updates, so our total “Alerts Sent” count for each earthquake does not contain duplicates to the same device.

In addition to real events, MyShake’s alerting system is tested daily with “silent” alerts.

The system is fed a test alert message and performs the full delivery process to phones but does not show users a visible message. The majority of these silent tests check MyShake’s large-scale delivery capacity using a scenario magnitude 7.5 earthquake centered under an urban region of California.

## 2.3 Latency Data

We present the latency for five of the most significant earthquake alerts delivered to date in California as representative examples of MyShake’s alert delivery efficiency in Table 2.1. Three of these earthquakes occurred beneath urban areas, where the window to alert the nearest population center was small, and two are rural events. The urban events occurred in the Los Angeles and San Jose areas of California. All are relatively small events (M 4.5 El Monte, M 4.3 Carson, and M 3.6 Alum Rock) that ShakeAlert estimated to be at least an M 4.5, which triggered a public alert. The rural events were both aftershocks of the 2019 Ridgecrest earthquakes in southeastern California. They were somewhat larger in magnitude (M 5.5 Searles Valley and M 5.8 Lone Pine), and the MMI III alert region extended into the Los Angeles basin, some 200 km away. An example of the full distribution of the time to delivery ( $t_7-t_0$ ) is shown for the most recent event, (M 4.3 near Carson, California) in Figure 2.2.

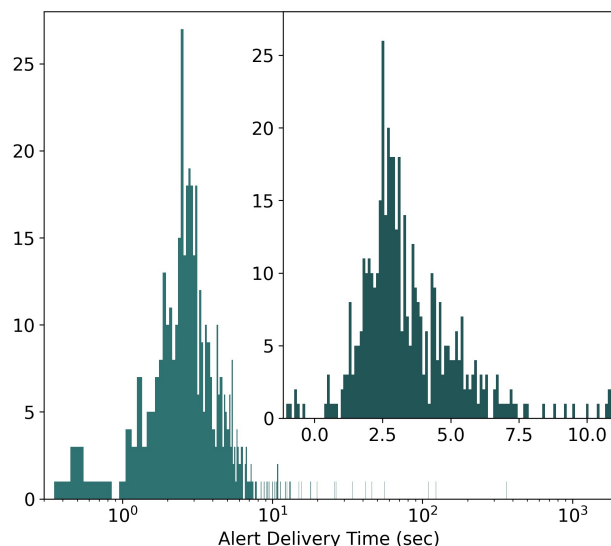
Outside factors that can influence latency include: whether users are located in an area with poor reception, whether a phone is connected to WiFi or cellular data, and how the Firebase messaging service employed by MyShake balances its bandwidth against message volume. Another issue is the accuracy of the timestamps recorded on the phones for alert acknowledgement. Previous research has shown that 75% of timestamps reported by phones differ from true server time by 0–1.6 sec (Kong, Patel, et al. 2019). Because phone clocks can be both ahead or behind true time, some Alert Acknowledgement times will be shorter than expected, making the 20th percentile times lower, and some timestamps will be later, making the 80th percentile value higher. The consistency of the median (50th percentile)  $t_7-t_0$  for each event being slightly larger than the median  $t_3-t_0$  time corroborates previous observations that phone time error is distributed around zero. Not all phones provide delivery receipts. This is due to messaging prioritization “features” of the operating systems, connectivity issues, and data security features on phones.

Monitoring system latency has lent insight toward opportunities for improvement. One important improvement made to the system was branching the data processing into three parallel “shards” that can process a batch of phones each, simultaneously. Implemented for the purposes of load balancing and efficient scalability as usership grows, this sharding went live on 25 June 2020. The improvement to server processing speed can be viewed in Table 2.1 when comparing the results for the 19 September 2020 El Monte event to the 4 June 2020 Searles Valley Ridgecrest aftershock, for which comparable numbers of phones were sent an alert. For the post-sharding El Monte event, the speed-up was about 5 sec. As usership grows, additional shards are added to maintain efficiency.

| Date     | Mag.  | Event             | Region                   | Depth<br>(km) | Time<br>between<br>1st and<br>Max Est |                    |                  | Alerts<br>Sent | t3-t0<br>(sec) | t7-t0<br>(sec) |
|----------|-------|-------------------|--------------------------|---------------|---------------------------------------|--------------------|------------------|----------------|----------------|----------------|
|          |       |                   |                          |               | Initial<br>Mag<br>Est.                | Max<br>Mag<br>Est. | Max Est<br>(sec) |                |                |                |
| 09/19/20 | M 4.5 | El Monte          | Los Angeles<br>area      | 17            | M 4.5                                 | M 4.8              | 7.73             | 20,169         | 20%            | 1.39           |
|          |       |                   |                          |               |                                       |                    |                  |                | 50%            | 1.84           |
|          |       |                   |                          |               |                                       |                    |                  |                | 80%            | 2.59           |
| 09/18/21 | M 4.3 | Carson            | Los Angeles<br>area      | 12            | M 4.7                                 | M 4.9              | 0.53             | 25,018         | 20%            | 1.07           |
|          |       |                   |                          |               |                                       |                    |                  |                | 50%            | 1.81           |
|          |       |                   |                          |               |                                       |                    |                  |                | 80%            | 3.17           |
| 06/03/21 | M 3.6 | Alum Rock         | Southern<br>Bay Area     | 7             | M 4.5                                 | M 4.5              | N/A              | 8,097          | 20%            | 0.97           |
|          |       |                   |                          |               |                                       |                    |                  |                | 50%            | 2.18           |
|          |       |                   |                          |               |                                       |                    |                  |                | 80%            | 3.87           |
| 06/04/20 | M 5.5 | Searles<br>Valley | Ridgecrest<br>aftershock | 8             | M 5.7                                 | M 5.8              | 150              | 20,825         | 20%            | 2.90           |
|          |       |                   |                          |               |                                       |                    |                  |                | 50%            | 4.53           |
|          |       |                   |                          |               |                                       |                    |                  |                | 80%            | 6.92           |
| 06/24/20 | M 5.8 | Lone Pine         | Ridgecrest<br>aftershock | 5             | M 5.0                                 | M 6.2              | 44.44            | 47,747         | 20%            | 5.42           |
|          |       |                   |                          |               |                                       |                    |                  |                | 50%            | 6.79           |
|          |       |                   |                          |               |                                       |                    |                  |                | 80%            | 8.54           |
|          |       |                   |                          |               |                                       |                    |                  |                |                | 9.50           |

**Table 2.1:** Alert delivery latencies associated with three urban and two rural earthquakes at the alert delivery level of MMI III. The “Alerts Sent” column indicates how many unique phones were identified as falling within the alerting region, processed by the server, and sent an alert. Each of the right-hand time columns is the equivalent of the Server Processing Time (t3-t0) and Alert Acknowledgement Time (t7-t0), respectively, in which t3 and t7 are measured on each phone and t0 is the time MyShake began processing the alert update that first included that phone. Latency values are provided for the 20th, 50th, and 80th percentiles for each earthquake.

## 2.4 User Experience of Warning Time



**Figure 2.2:** Histogram showing the distribution of the Alert Acknowledgement Time ( $t_7 - t_0$ , binned by 0.1 sec) for the M 4.3 Carson earthquake, from the 2nd to the 99th percentile on a log scale in the larger window, and the 1st to 85th percentile on a linear scale in the inset. Beyond these boundaries are a handful of anomalous records.

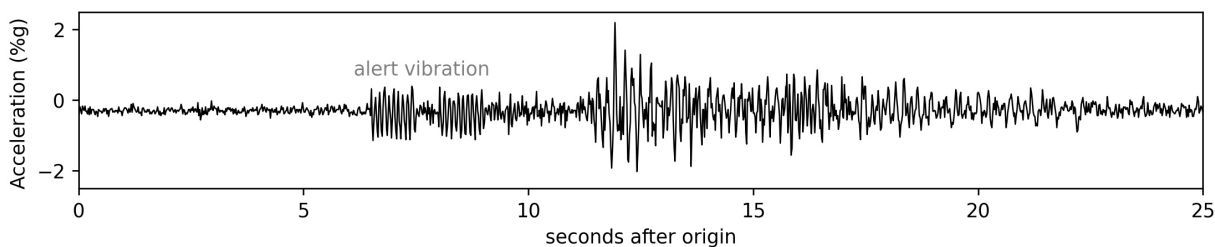
to warn, and a hypocenter directly beneath the population. For all three, about half of alerted users received an alert before the estimated arrival of the S-wave (Figure 2.4). Being 17 and 12 km deep, the Los Angeles earthquakes gave users a slightly longer lead time than the 7 km deep Alum Rock event, resulting in closer to 60% of users with a pre S-wave alert time versus 40%.

In the case of the M 4.5 El Monte earthquake, ShakeAlert produced an initial magnitude estimate of M 4.5, prompting the first set of alerts represented by the earlier linear trend in Figure 2.4 out to 37 km. Then, 7.7 sec later, ShakeAlert estimated the event to be a M 4.8, causing a new set of alerts for phones further away, represented by the second linear trend.

Peak acceleration was measured using waveforms collected by phones that also returned an alert delivery receipt (Figure 2.5.a). Figure 6b shows the shaking intensity measured by each phone (peak acceleration to intensity scaling is discussed in Section 2.5 on User Experience of Intensity) in the M 4.5 El Monte earthquake and also the time at which the peak shaking occurred relative to the origin time of the earthquake. Figure 2.5.c subtracts

To better understand the user experience, we consider the MyShake phones that both recorded waveform data and returned a receipt after receiving an early warning alert (or for which the vibration from the alert is visible in the waveform itself, such as in Figure 2.3). The waveform data are three orthogonal components of acceleration collected using the onboard accelerometer and encompasses 1 min prior and 4 min following an activation prompt to begin recording. All waveforms used for analysis are visually verified by a seismologist so that spurious non-earthquake signals are not included. To determine warning times, we subtract the alert delivery time from either the estimated S-wave arrival time, or the observed occurrence of peak shaking recorded by the same phone. We use both time measurements to quantify how much warning time users were given to respond.

The Los Angeles (El Monte and Carson) and southern Bay Area (Alum Rock) events represent the most challenging alerting cases. There is a small alerting area (due to the small magnitudes), a large population



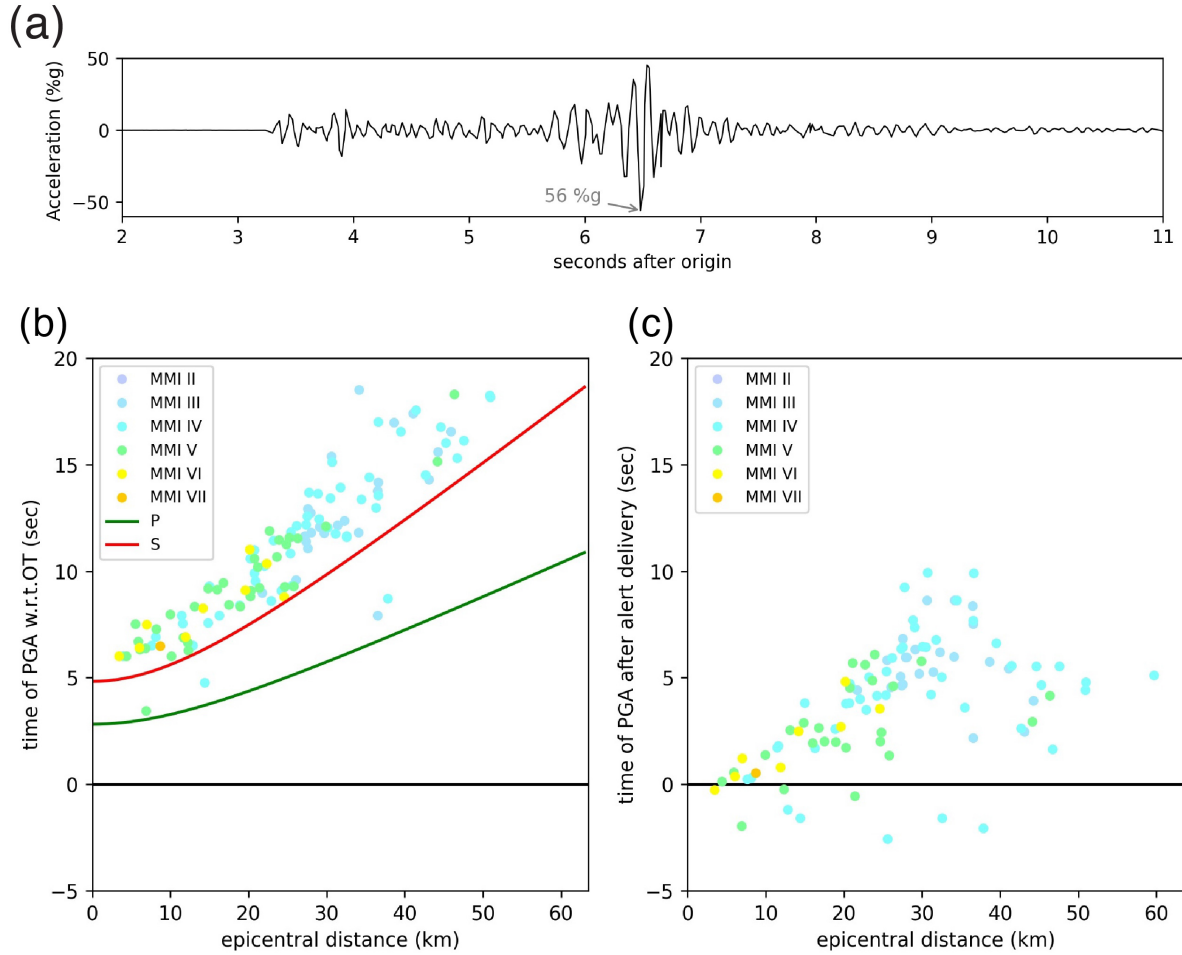
**Figure 2.3:** The vibration of the alert arriving overprints the horizontal component of a phone recording the P-wave arrival 29 km from the epicenter of the M 4.5 El Monte event in September 2020. The alert arrives 5 sec before peak shaking is recorded.

the alert delivery time from the peak shaking time so that the warning time until peak shaking is shown. In the case of the El Monte event, 90% of phones received 0–10 sec warning. The expansion of the alerting area at 7.7 sec is visible in the handful of phones in Figure 2.5c that are further away from the event but have shorter warning times between the alert delivery and observation of peak shaking. For the M 3.6 Alum Rock earthquake in the southern Bay Area, about half of alerted users received a warning of 0–10 sec before experiencing peak shaking. About three quarters of the phones had 0–15 sec warning before peak shaking in the M 4.3 Carson event. As intensity attenuates with distance, the longest warning times naturally tend to occur for the lower intensities.

We consider the geographic distribution of alert deliveries over time, relative to the ShakeAlert alerting extents for the M 4.5 El Monte and M 5.8 Lone Pine events (Figure 2.6). Each point represents a phone, which is colored by the time of alert delivery relative to the time that ShakeAlert produced its first alert. The concentric circles represent alerting regions computed using ShakeAlert’s successive magnitude estimates, beginning with the red circle at the center and going out to the largest alerting region encircled by yellow. For the El Monte event, the 7.7 sec delay between the first and largest estimates is evidenced by the color shift between the inner and outer circles. ShakeAlert can update its magnitudes several times over the course of a single event. For clarity, only a subset of these estimates is plotted in these figures.

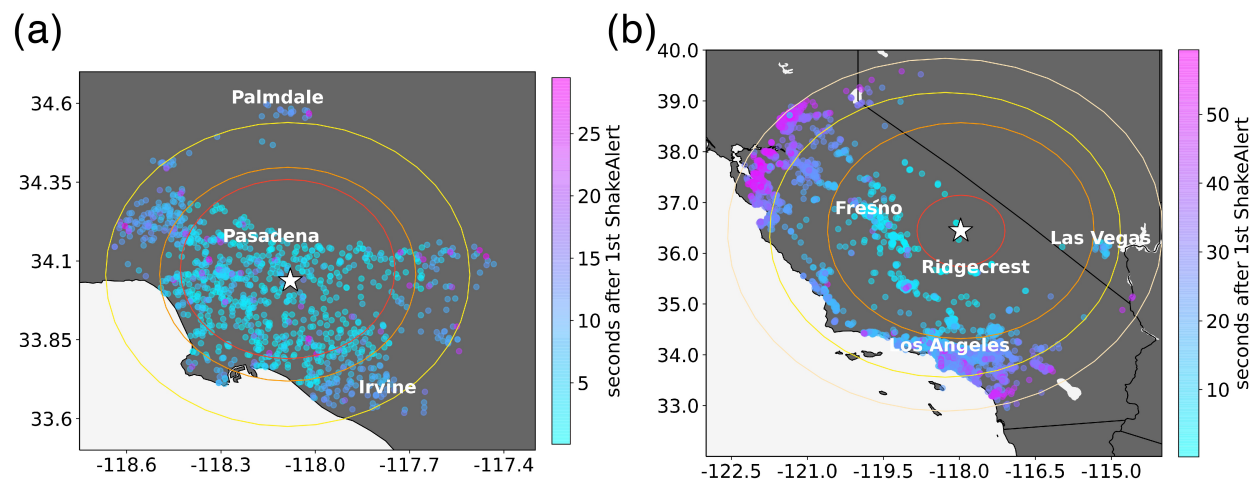
For the M 5.8 Lone Pine event (Figure 2.6.b), the estimated magnitude grew several times, causing multiple iterations of alert deliveries by MyShake. The initial estimate was M 5 (alerting area represented by the inner red circle). The estimate grew to M 5.6 four seconds later, and a M 5.8 six seconds after that. The largest estimate, M 6.2 was generated 44 sec after the initial alert, causing the distinct color difference in delivery times at the center of the map relative to the edges. Even with this much later alert, the phones alerted at the greatest distance received almost a minute of warning.

Two Ridgecrest aftershocks, one M 5.8 in Lone Pine on 4 June 2020 and the second M 5.5 in Searles Valley on 24 June 2020, demonstrate the longer warning times that are possible for larger magnitude earthquakes. In these events, users received up to a minute of warning



**Figure 2.5:** Peak ground shaking and alert delivery times for the M 4.5 September 2020 El Monte earthquake **a)** the largest amplitude acceleration waveform recorded at  $\sim 10$  km (represented by the orange MMI VII dot in panels b and c). **b)** The time and distance of phones when they recorded the maximum acceleration, with a ShakeMap color scheme to denote intensity. Peak acceleration is scaled to intensity using the MyShake scaling factor and the Worden et al. (2012) relationship (see the User Experience of Intensity section). P-wave speed is approximated as 6 km/s (Lin et al. 2010) and S-wave speed is computed as 60% of P. **c)** The time that phones at various epicentral distances recorded peak acceleration relative to the time of receiving an early warning.





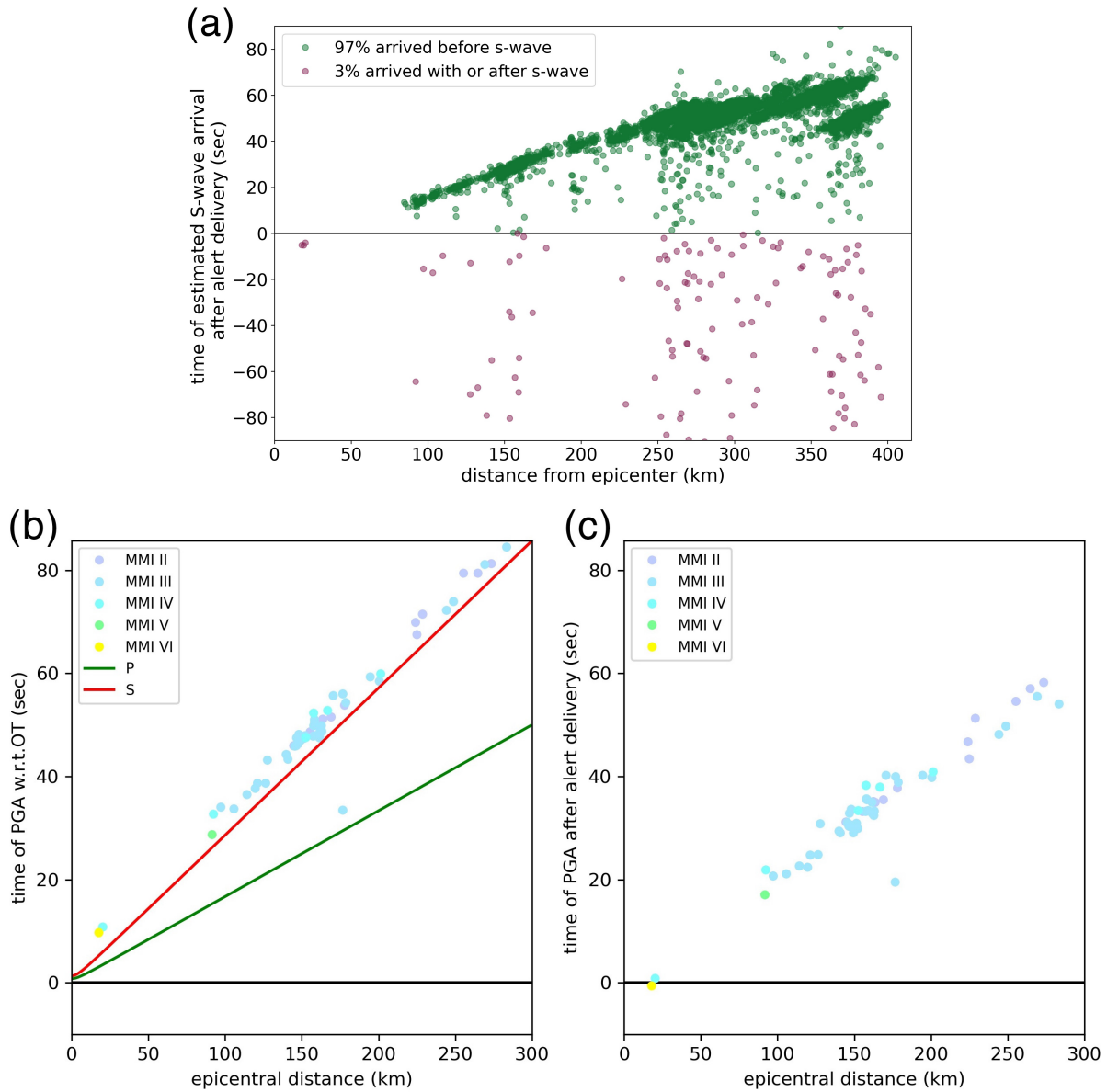
**Figure 2.6:** **a)** A map of alert delivery times for the September 2020 M 4.5 El Monte event, within 30 s of ShakeAlert producing its first alert (initial alerting radius marked by the red circle). The largest estimate (yellow circle) occurred 7.7 sec after the initial. **b)** A map of alert delivery times for the June 2020 M 5.8 Lone Pine earthquake within 55 sec of ShakeAlert producing its first alert. The colors of the circles representing key evolutions in the ShakeAlert magnitude estimate—and therefore alert radii—are ordered in rainbow sequence by time, beginning with red. The initial (red) estimate was M 5. A M 5.6 estimate followed 4 sec later, and an M 5.8 was produced 10 sec after the first estimate. The final M 6.2 estimate occurred 44 sec after the first.

time prior to shaking (Figure 2.7). Because of the rural location of the epicenter, nearly all users also experienced positive warning time prior to the occurrence of peak shaking at their location (Figure 2.7.b,c). Although warning times are expected to be greatest in further away, lower intensity shaking regions, at least one phone recording an estimated MMI V peak shaking intensity  $\sim 100$  km from the epicenter received  $\sim 16$  sec of warning.

## 2.5 User Experience of Intensity

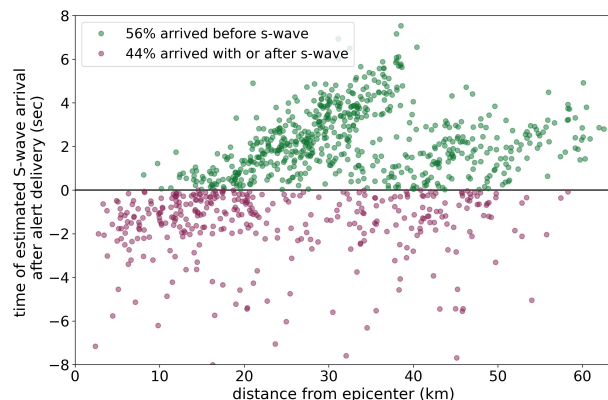
Because MyShake phones receiving alerts can also record the shaking during the earthquake, we can make in situ observations about user experiences of shaking and intensity. Companion research has found remarkable correlation between intensity maps generated using MyShake’s simple user experience survey versus the USGS Did You Feel It? survey (Kong, Allen, Allen, et al. 2023). Here, we use waveform data to compare to the USGS ShakeMap product.

The Modified Mercalli Intensity scale represents shaking severity, which can be estimated from peak ground acceleration (PGA) and peak ground velocity (PGV) recordings using the Worden et al. (2012) relationship, which is an empirical scaling relation determined by comparing PGA and PGV from seismometers coupled directly with the ground to proximal



**Figure 2.7:** Alert delivery times for the June 2020 M 5.8 Lone Pine earthquake. **a)** Warning time represented as the time that phones at various epicentral distances received an alert relative to the estimated arrival of the S-wave. The alert updates that promoted the expansion of the alerting region can be seen in the parallel diagonal linear trends at further distances. The green points above the central line have a positive warning time. **b)** The time and distance of phones when they recorded the peak acceleration, with a ShakeMap color scheme used to denote intensity. **c)** The time that phones at various epicentral distances recorded peak acceleration relative to the time of receiving an early warning.

human reports of ground shaking intensity collected through Did You Feel It? However, the Worden relationship was developed for traditional seismic data. Phones, meanwhile, typically exist within the built environment, such as within a building.



**Figure 2.4:** Alert delivery times for the September 2020 M 4.5 El Monte earthquake, represented as the time that phones at various epicentral distances received the alert relative to the estimated S-wave arrival time. The green points above the central line have a positive warning time. S-wave velocity is estimated to be 3.5 km/s (Lin et al. 2010).

the five sample events and all epicentral distance bins, we find the median of the ratio of MyShake to traditional station accelerations is 3.1. This amplification cannot be explained by variability in phone quality, as the standard deviation of the log of phone peak acceleration in each bin is typically lower than that of the traditional station PGAs (Figure 2.9.c). Therefore, there is a real amplification of shaking consistently being recorded by MyShake phones relative to traditional sensors.

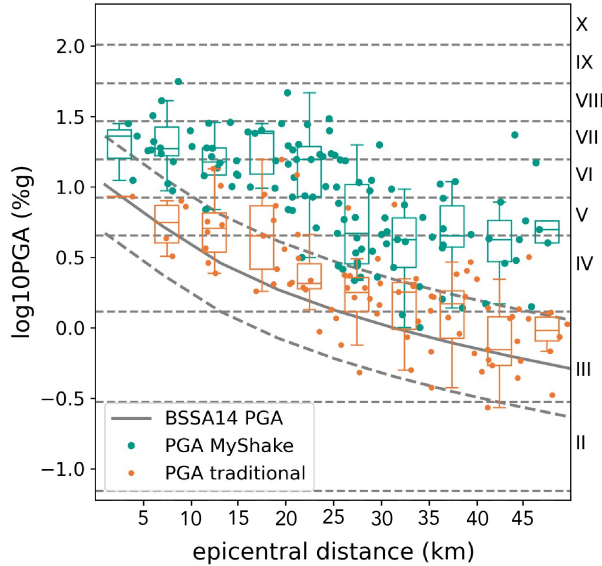
Buildings amplify shaking relative to the free surface at the natural resonance frequencies of the structure (Chopra 2012). Because phones are typically located inside buildings, some of the MyShake amplification is likely due to structural features. The fundamental period of a building can be roughly estimated as the number of stories times 0.1 sec (Dym and Williams 2007; Lee et al. 2003). Based on the geographic distribution of MyShake users, we assume the majority are located in single family homes or low-rise apartment buildings, for which the resonance period would be in the 0.1 to 0.3 sec range. Therefore, we compare MyShake peak acceleration to pseudospectral acceleration (PSA) at 0.3 sec, which is also provided for these events by the USGS ShakeMap product.

When we compare the ratio of MyShake PGA to traditional station PSA at 0.3 sec, we find a median ratio of 1.7 (Figure 2.9.b). This is lower than the factor of 3.1 when compar-

With their greater freedom of motion, buildings typically experience higher amplitude motion than the free ground surface. Therefore, we must revisit the PGA to MMI scaling relation before we can apply it to phone observations. To do this we first compare the accelerations recorded by phones and the traditional stations contributing to ShakeMap for each of the five sample events (Figure 2.8). We find that phones at a given epicentral distance record peak accelerations that are greater than both the PGA recorded by traditional stations at the same distance and the accelerations predicted by the Boore et al. (2014) (“BSSA14”) GMPE for shallow, crustal earthquakes in the western United States (Figure 2.8).

To quantify the amplification, we bin phones and traditional stations by epicentral distance in 5 km increments and compute the ratio of the peak accelerations recorded by each (Figure 2.9.a). In aggregate across

ing MyShake peak acceleration to traditional PGA, but also suggests that the acceleration amplification due to buildings alone cannot explain the full amplification effect. Possible additional causes of this amplification include hyper-local near-station site effects, the fact that most population centers (and thus phones and buildings) are in sedimentary basins that amplify shaking (Parker and Baltay 2022), and the resonance of the furniture on which the phones are located.



**Figure 2.8:** Peak acceleration recorded by traditional stations (orange) and MyShake phones (teal) for the M 4.5 El Monte event. Individual observations are shown as points, and the box plots show the distribution for waveforms collected within each 5 km epicentral distance bin. The gray curve represents the prediction based on the Boore et al. (2014) ground-motion model (BSSA14) with dashed lines  $\pm$  one standard deviation. The right side y-axis shows approximate equivalent MMI levels.

themselves smoothed representations of heterogeneous data too; some number of individual traditional station observations often deviate from the contours. Our conclusion, therefore, is that MyShake acceleration data can add granularity to our understanding of the heterogeneity of ground motion and user intensity experience. This is not only of intrinsic value but can also provide constraints on alert accuracy and event impact severity, especially in urban areas where densifying observations can improve the quality of situational awareness

Given the observed amplification effect, we first correct MyShake waveform accelerations by dividing by our preliminary 3.1 correction factor to better represent a traditional seismometer PGA, and then apply the relationship defined by Equation (3) and the coefficients from Table 1 in Worden et al. (2012) to determine MMI. This allows us to approximate the MMI for a given MyShake peak acceleration observation and compare it with other observations and estimates of MMI, for example, with an earthquake’s computed ShakeMap.

ShakeMap derives shaking intensity distribution from a combination of traditional seismic data translated to intensity using the Worden relationship and crowd-sourced Did You Feel It reports (Atkinson and Wald 2007). Intensity is a human-centric metric of impact. Because ShakeMaps are calibrated with reports of real experiences, they are a reliable depiction of shaking intensity for an event for which there are observations. We compare MyShake observations of intensity to ShakeMap intensity contours (Figure 2.10). The two sets of intensity estimates are as consistent as we would expect. Not all MyShake observations fall within their corresponding intensity contours, but ShakeMap contours are

products.

We find both instances of greater-than-expected-intensity, by as much as two MMI units for MyShake phones compared to ShakeMap contours, and instances of reduced, lower-than-expected intensity. For example, Figure 2.5.a shows the waveform for the phone that reached MMI VII peak acceleration (after application of the MyShake correction factor) in the M 4.5 El Monte event, yet there is no MMI VII contour depicted on the ShakeMap (Figure 2.10.a). Visual inspection of the waveform confirms that the peak shaking is earthquake-related and not spurious noise. The conclusion, therefore, is that although the event was relatively small, some users still experienced notably high intensities. In a larger, damaging event, extra high intensity measurements could be used to help emergency response target more heavily impacted structures. Visual inspection of other waveforms for surprisingly high and low accelerations confirm the data quality is good, and the observations are not spurious noise.

## 2.6 Summary

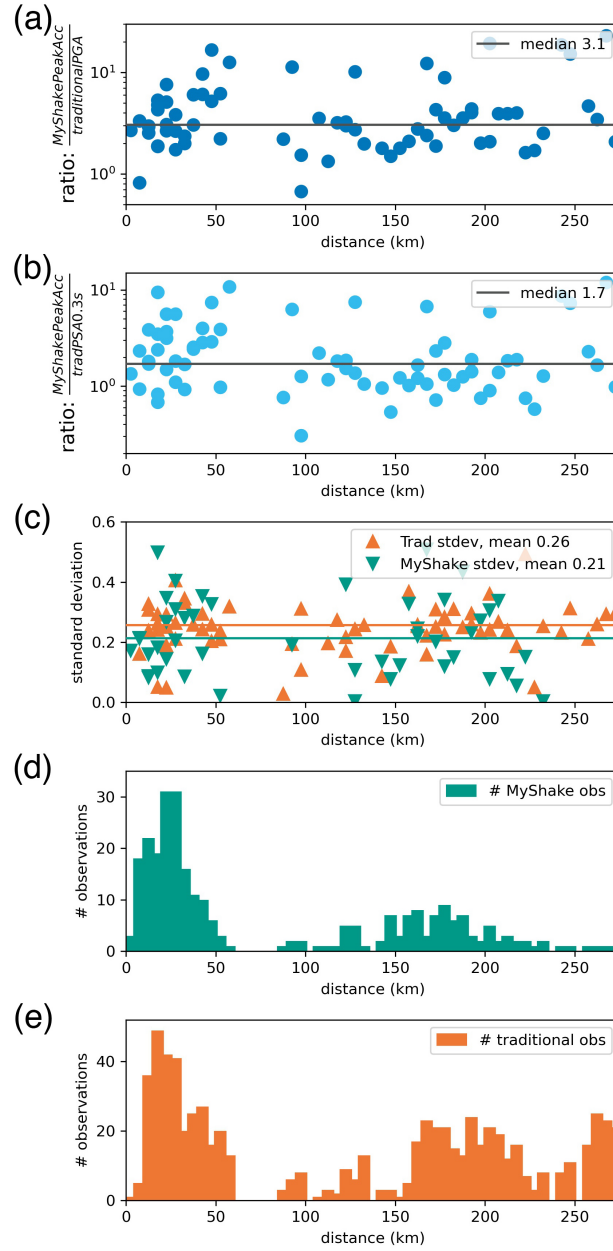
Although delivering early warning alerts to private individuals via smartphones has been a long-term goal within the ShakeAlert project (e.g., Given et al. 2018), there were few published empirical measurements to assess exactly how efficient and effective such an alerting method could be in the context of the United States ShakeAlert system. By tracking the latencies and alert deliveries by MyShake in its first two years of operation as a public warning service, we can confirm that MyShake is capable of delivering timely warning such that the majority of users receive an alert prior to experiencing peak shaking intensity, even for small magnitude earthquakes beneath urban centers when the available warning time is minimal.

As expected, warning time is greater when events occur outside population centers or when the magnitude is large. Also as expected, warning times for an individual event are greatest where epicentral distances are largest, and therefore tend to vary inversely with shaking intensity. It is worth noting, however, that in a large earthquake, higher intensity shaking will have a broader distribution. Thus, even with the latency induced short-to-late alert zone, many strong shaking regions have the potential to receive alerts in a useful timeframe.

MyShake waveforms also show accelerations greater than predicted using a standard GMPE, and greater than traditional stations nearby. This is likely due to local site effects and structural amplification of the built environment. Comparisons with local seismic stations recording peak ground acceleration leads to a median amplification factor of 3.1; comparison with response spectra at a period of 0.3 sec, which may be closer to a building's response, yields a median conversion factor of 1.7. Although derived using limited data, we find reasonably good correlation between MyShake data divided by this correction factor and the ShakeMaps for each of the five sample events. Therefore, with this preliminary correction factor, MyShake data can be incorporated into the larger discussion of the shak-

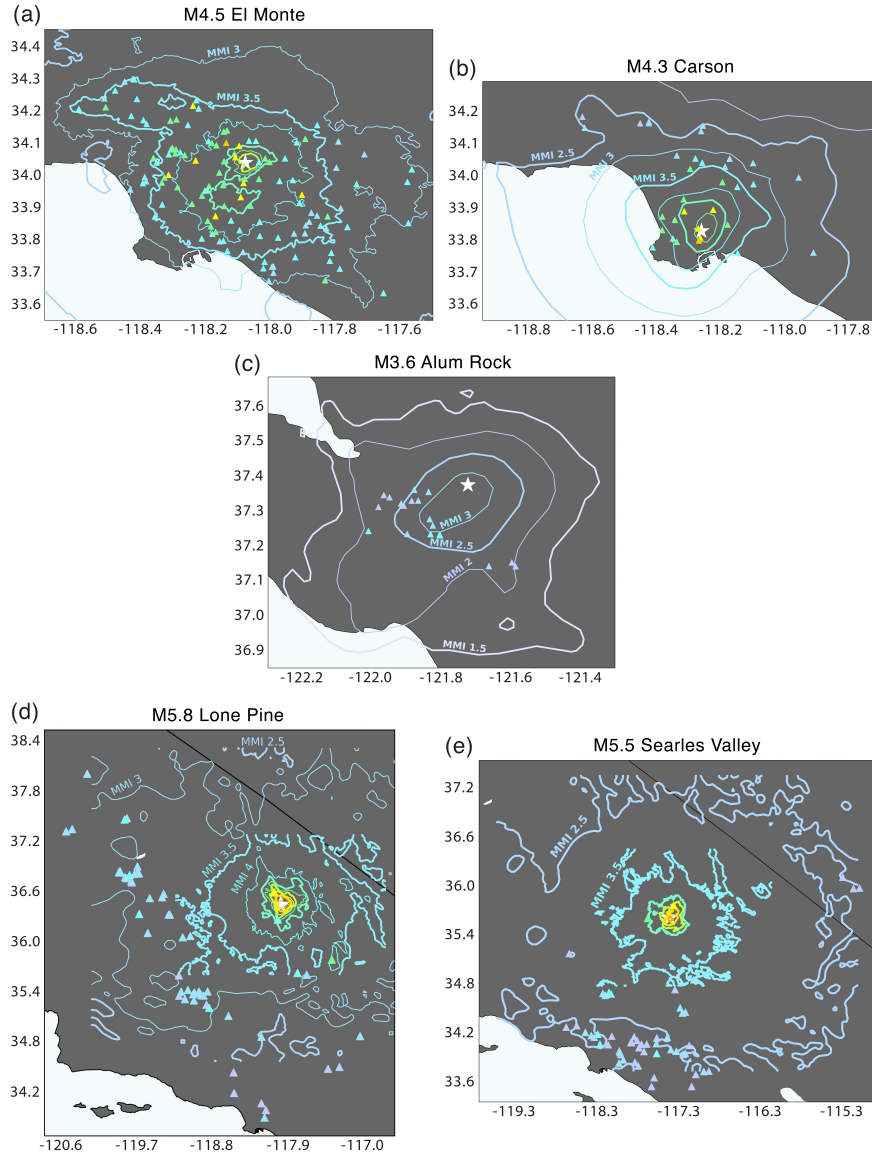
ing experienced by users relative to expected or estimated intensities. Because phones are located where users are, MyShake’s intensity observations inherently improve the shaking resolution where such granularity is most useful.

Over the course of operations as a public emergency notification service, the public has mostly responded favorably to receiving early warnings, with little concern expressed for over-alerting, such as when the magnitude is overestimated by ShakeAlert. One contribution to this may be that users seem to expect an alert anytime they feel shaking, as opposed to shaking of a specific threshold, as noted in Cochran and Husker (2019) and MyShake user feedback via email and Twitter. As ShakeAlert operation continues in the future, MyShake data can provide information on both the alerting timeline and the experience level of ground motion. This information can help us optimize the alerting strategy for ShakeAlert and other Earthquake Early Warning systems around the world.



**Figure 2.9:** **a)** The ratio of MyShake peak acceleration versus traditional station peak ground acceleration (PGA), as binned over 5 km increments for the five sample events. **b)** The ratio of MyShake peak acceleration versus 0.3 sec pseudospectral acceleration (PSA) from traditional stations. **c)** The standard deviation of the log10 of MyShake and traditional station peak acceleration measurements. **d)** The number of MyShake observations for all events binned by epicentral distance. **e)** The number of traditional station observations for all events binned by epicentral distance.





**Figure 2.10:** Maps of the U.S. Geological Survey (USGS) ShakeMap contours overlaid by intensity measurements made by MyShake phones, marked by triangles colored using the Worden et al. (2012) conversion and the MyShake Correction Factor. Only phones that returned a waveform we could use to make an intensity measurement are plotted. **a)** The September 2020 M 4.5 El Monte event; **b)** the June 2021 M 3.6 Alum Rock event; **c)** the September 2021 M 4.3 Carson event; **d)** the June 2020 M 5.8 Lone Pine Ridgecrest aftershock; and **e)** the June 2020 M 5.5 Searles Valley Ridgecrest aftershock. There are multiple ShakeMap versions available for each event; we present the maps produced by the most recent software iteration. For panels (d) and (e), however, the latest software version sets default area limits which exclude the lower intensity contours. We include MMI 2.5 and 3 contours from a less preferred ShakeMap version from the National Earthquake Information Center (NEIC), to provide an approximate sense of scale.



## Chapter 3

# Contributing Smartphone Data to a Traditional Earthquake Early Warning System

Earthquake early warning (EEW) comprises a system which takes advantage of an essential trait of tectonic earthquakes, wherein the fastest seismic wave, the P-wave, is the least destructive. By detecting and alerting on the early arriving P-wave, an earthquake early warning system can warn users of impending heavier shaking a few seconds before it arrives. The amount of warning a user will receive depends on their distance from an earthquake's epicenter; there is more warning for users further from the epicenter.

There are multiple modalities in global early warning systems. The first operational system was implemented in Mexico. The Mexican Seismic Alert System (SASMEX) had a specific target; to detect subduction zone earthquakes along Mexico's southwestern coast and provide about a minute's warning to Mexico City, which was built on a lake bed and can be subject to very strong seismic amplification effects (Suárez et al. 2018). The system was developed in response to the devastating Michoacán earthquake in 1985 and went live in 1993. Since then, the station network has expanded from 12 strong motion stations to 97, and now delivers alerts to a wide swath of the country (Suárez et al. 2018).

The SASMEX system waits for two strong motion stations to experience motions associated with at least a Mb 5.5 earthquake before issuing an alert. Alerts are delivered through a number of methods, in particular emergency radio and public sirens (Suárez et al. 2018).

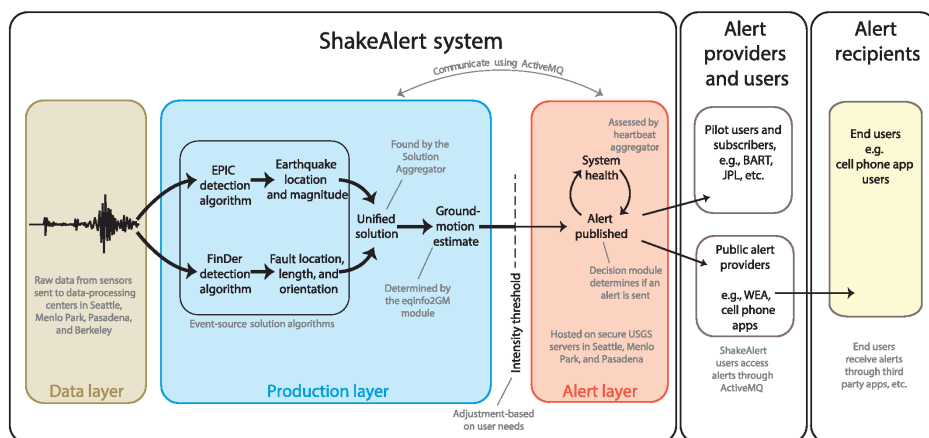
Since the initial launch of SASMEX, several other systems have joined the global stage. Japan, South Korea, and Taiwan now have nationwide systems, while India, Türkiye, Romania, and the US have joined Mexico in operating regional systems (Allen, Kong, and Martin-Short 2020). Beginning in 2021, Google also began using MyShake technology to use private Android phones globally to generate and receive earthquake early warnings (Allen and Stogaitis 2022).

A primary control on the speed of an early warning system is the density of its detection network. MyShake is an alert delivery service for the US EEW system, called ShakeAlert. As

such, MyShake’s densest usership is located within ShakeAlert’s service area of California, Oregon, and Washington. We therefore begin our exploration of MyShake’s capability to generate early warnings in conjunction with the ShakeAlert system. This work represents a preliminary evaluation of how MyShake real-time triggering data could be combined with traditional seismic data to produce an ad hoc high density detection network and potentially speed up or improve ShakeAlert’s initial estimates. To begin, an understanding of ShakeAlert’s technical implementation is required.

### 3.1 The US ShakeAlert Earthquake Early Warning System

The ShakeAlert earthquake early warning system is operated by the United States Geological Survey (USGS) in conjunction with regional networks and university partners at UC Berkeley, CalTech, the University of Washington, and the University of Oregon. It is supported by both federal and state funding. In California, support comes from the Governor’s Office of Emergency Services (CalOES). The system’s infrastructure is comprised of nearly 1700 low latency digital seismic stations, utilizing a combination of broadband seismometers and strong motion accelerometers across the states of California, Oregon, and Washington. Seismic data is streamed in real time to redundant servers in Seattle, Berkeley, Moffett Field, and Pasadena, and run through a waveform processing system to search for P-wave short term average over long term average (STA/LTA) triggers indicating the initiation of an earthquake.



**Figure 3.1:** The workflow of the ShakeAlert earthquake early warning system. Reproduced from Chung, Meier, et al. 2020

The alerting system is comprised of five main segments (Figure 3.1):

1. The seismic network contributing real-time data to waveform processing servers

2. Detection algorithms which estimate earthquake parameters, including origin time, epicentral location, and magnitude
3. Ground motion estimations which translate magnitude to intensity regions
4. A decision module which determines whether to publish an alert
5. An alerting apparatus comprised of technical partners who receive and distribute alerts to users. MyShake is an example of this.

Before triggers are passed to detection algorithms, ShakeAlert’s waveform processors adjust the incoming raw seismic data and put them through a series of quality checks (Chung, Henson, and Allen 2019; Kohler, Smith, et al. 2020). Processing includes a second-order Butterworth filter with coefficients based on sample rate, and a baseline correction via removing the average amplitude of the previous 60 seconds of data. The quality checks include:

1. a high-vs-low frequency content check to remove teleseismic triggers, since high frequency content attenuates faster with distance
2. a minimum amplitude threshold
3. a range post-trigger parameter aimed at identifying machine-noise boxcar functions
4. a vertical-vs-horizontal amplitude check to remove S-wave data since P-wave motion occurs primarily in the vertical direction and stronger horizontal motion begins with the S-wave

Approved data is passed to detection algorithms, of which there are two in current use; the Earthquake Point-source Integrated Code (EPIC) and the Finite Fault Rupture Detector (FinDer) (Chung, Meier, et al. 2020; Kohler, Smith, et al. 2020). EPIC is a point-source algorithm which uses partial seconds of seismic data to calculate the location, origin time, and magnitude of a source. Because EPIC neglects rupture length and treats earthquake energy as originating at a single point, it saturates in its magnitude estimations around M 7 (Kohler, Smith, et al. 2020). FinDer is the line-source algorithm designed to compute the orientation and length of the ruptured fault area in order to properly estimate the source parameters of larger earthquakes (Böse et al. 2018).

Multiple servers run each algorithm simultaneously, producing independent solutions. A solution aggregator uses weighted averages to combine multiple outputs into a unified solution (location, origin time, magnitude) (Chung, Meier, et al. 2020). As more data becomes available, both from the already triggered stations and from newly triggered stations, the algorithms will re-run repeatedly, generating updated solutions for the aggregator. Unified solutions are fed into the earthquake information to ground motion (eqInfo2GM) module, which uses ground motion prediction equations (GMPEs) and ground motion to intensity conversion equations (GMICE) to predict the geographic distribution of peak shaking intensities (Kohler, Cochran, et al. 2018; Thakoor et al. 2019). For the purpose of public

alerting, intensity regions are defined as nested octagons centered on the epicenter (or elongated around the fault length if FinDer produces a line source). It is these octagon vertices which alerting partners such as MyShake receive and use to determine who they will alert.

Currently, alerts are sent via smartphone notifications (through MyShake and Google) to users in regions expected to experience a Modified Mercalli Intensity (MMI) of 2.5 or greater, for earthquakes with a minimum magnitude estimate of M 4.5 (Kohler, Smith, et al. 2020). The Wireless Emergency Alert system, popularly known for distributing Amber Alerts, sends warnings to MMI 3.5+ areas for earthquakes with a minimum magnitude estimate of M 5.

With the increasing quantities of seismic stations in ShakeAlert’s network and the high quality of its algorithms, ShakeAlert is already capable of generating robust alerts when adequate data is available. The main opportunity for improvement is the speed with which a good initial solution is reached, thereby reducing the size of the region that receives an alert late (after the S-wave shaking has already started). Requiring the least amount of data and producing the simplest solutions, EPIC is responsible for the fastest, best quality *initial* alerts for ShakeAlert (Kohler, Smith, et al. 2020). I therefore focus this work on how real-time MyShake data could be used by EPIC to improve the speed of detection or the quality of the first earthquake estimates. In the following sections I will describe the EPIC algorithm in more detail, make use of archive data from MyShake and EPIC to recreate how the system might have behaved with the addition of phone triggers, discuss a live-running first version of an integrated algorithm, and close with additional improvements I expect will enhance our outcomes.

## EPIC

EPIC requires data from four proximal stations in order to associate triggers together to ‘create’ an event (detect an earthquake). Otherwise, the triggers are treated as spurious noise. Data typically arrives in one second packets, though the sensor-to-server latency can sometimes vary (Chung, Meier, et al. 2020). From the trigger times and station locations, EPIC performs a grid search for a minimum travel time residual to find a best fit location and origin time (Kohler, Smith, et al. 2020). Depth is fixed at 8 km depth (Chung, Meier, et al. 2020). Magnitude is estimated on a station-by-station basis using the peak displacement value observed so far in the P-wave, the estimated epicentral distance of the station, and the linear scaling relationship empirically derived in Kuyuk and Allen (2013):

$$M_{Pd} = 1.23\log_{10}(P_d) + 1.38\log_{10}(dist) + 5.39 \quad (3.1)$$

The station-by-station magnitude estimates are combined into a single estimate via arithmetic mean. Magnitude estimates for each station will stop updating after 4 seconds from the start of the P-wave, to avoid skewing the computation with S-wave data (Kohler, Smith, et al. 2020).

Over time, EPIC and its predecessor algorithm, ElarmS, have had components added or changed to improve the quality and speed of its estimates. This includes the data quality

checks described in the previous section. Other recent and ongoing improvements include using Bayesian analysis to improve the behavior of EPIC’s location function for earthquakes at the edge of the seismic network (Williamson, Lux, and Allen 2023), and exploring how a machine learning classifier could be used to improve trigger quality enough that the minimum triggers required to create an alert could be lowered to just two (Chung, Henson, and Meier 2021). Exploring how MyShake could contribute additional triggers to the network represents another example of a potential path to improvement.

## 3.2 MyShake Triggering

Because continuously streaming waveforms would be data and battery intensive, MyShake transmits only small periodic data snippets from phones to the backend server in real-time. These data snippets include GPS location updates and NTP clock checks. For the purpose of early warning, eleven data points per detection are sent: the initial STA/LTA trigger and ten peak acceleration (PA) updates sent in 1 Hz intervals. Each of these data points also includes a timestamp and the most recent GPS location.

Similar to the baseline correction used by ShakeAlert’s waveform processor, MyShake phones perform a grounding operation to demean all three components while the phones are in ‘ready’ mode (i.e. not moving and monitoring the accelerometer). In a moving window, a baseline is computed from data between one and three seconds before the current moment, and used to demean the most recent three seconds of data. The absolute maximum acceleration recorded on any of the three demeaned components is the PA. When a phone registers an STA/LTA trigger, it returns the maximum PA value from the second prior to the trigger. The following ten PA updates use two second windows of data.

## 3.3 Retrospective Analysis

### Data and Methods

EPIC logs the arrival of triggers and the solutions it produces with time, associating all activity for a given earthquake together using an event ID. For the events analyzed here, I seek MyShake STA/LTA trigger records from around an earthquake epicenter, based on their arrival time at the backend server (when they would have become available for use). Overlaying the EPIC and MyShake trigger arrivals chronologically permits me to simulate the data flow in a hybrid system, and compare its behavior to the traditional network-only solutions. Starting with a minimum of four triggers, EPIC’s grid search and magnitude calculation is run using increasing quantities of data. For this analysis, I assume EPIC’s computation time does not vary significantly between iterations and can therefore be neglected; update times shown here reflect the server arrival time of the latest trigger. Origin time residual computations use the time of trigger on the sensor (not trigger arrival time on a server).

Currently, MyShake records and reports only acceleration, which cannot be applied to EPIC’s magnitude estimation process. Instead, I recreate a possible magnitude estimation system using waveforms from phones near the epicenter. For these, I apply the grounding operation described in Section 3.2 and then simulate STA/LTA triggering on the demeaned waveforms. MyShake’s encoding for STA/LTA currently uses a ratio of 5 samples over 500 samples, and requires the ratio to exceed a threshold of 15 in order to trigger. In the analysis of simulating triggering using acceleration waveforms, I also test the feasibility of lowering the threshold to 10 to capture more subtle P-arrivals.

The grounded accelerations are integrated to velocity and displacement, with a highpass filter above 0.5 Hz applied between each. Anticipating that motions recorded by phones tend to be amplified relative to motion recorded by free-field seismometers, I try both integration of the raw data and integration of accelerations divided by the correction factor of 3.1 described in Chapter 2.

Starting with the second before the simulated trigger time, I measure the peak amplitude values for one second windows for 11 seconds, and use these values to compute magnitude. While EPIC uses only the peak displacement of the Z component, the MyShake analysis uses the maximum from all three components to account for the fact that phones are not always positioned horizontally. A sensor-to-server latency is added when setting the order in which waveform-derived peak values are added and processed. If there is a real-time trigger associated with a waveform, its latency is used. Otherwise a default 0.5 sec is applied.

Magnitude is computed from displacement using Equation 3.1. For velocity, I apply a similar empirical relation developed by Wurman, Allen, and Lombard (2007), their Equation 5, for broadband accelerometer data:

$$M_{Pv} = 1.63\log_{10}(P_v) + 1.65\log_{10}(dist) + 4.40 \quad (3.2)$$

Phones which streamed an STA/LTA trigger but uploaded no waveform are only permitted to contribute to the location and origin time portion of EPIC’s solution.

## Time and Location Results

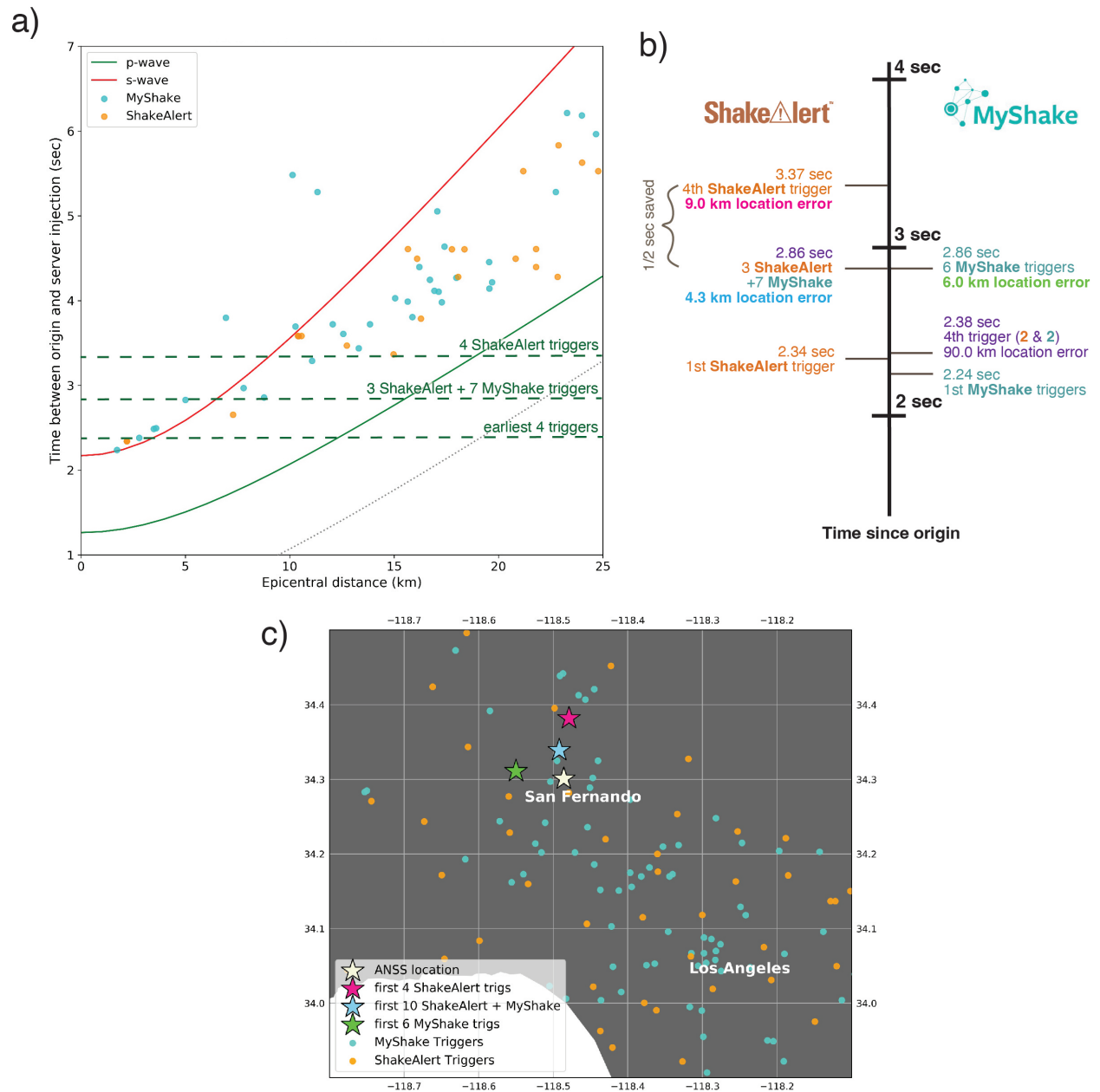
Four sample earthquakes serve to demonstrate how MyShake might have performed as part of a hybrid EEW system. The first earthquake is the M 3.6 Granada Hills earthquake which occurred in January of 2020 (Figure 3.2). Although this earthquake did not exceed ShakeAlert’s threshold to release a public alert, it represents a good example of detection system behavior. In this event, the first ShakeAlert trigger arrived at a server 2.34 sec after origin, and the fourth ShakeAlert trigger arrived a second later, at 3.37 sec. MyShake’s first trigger arrived at a server slightly earlier, at 2.24 sec post-origin, and a hybrid system would have registered four total triggers (2 traditional and 2 phone) 0.14 sec later, at 2.38 sec. The location error computed using the first four ShakeAlert triggers was 9.0 km. The location error using the first combination of 4 triggers (2 phone and 2 traditional) is 90 km. Incrementing forward with time finds that at 2.86 sec, with a combination of 3 ShakeAlert

and 7 MyShake triggers, the location error is reduced to 4.3 km, which is better than the ShakeAlert solo initial solution and half a second earlier. For thoroughness, we also test using only MyShake triggers and find a location error of 6 km using the first 6 MyShake triggers, a hair earlier. A map of the location errors can be found in Figure 3.2.c.

The second event is the M 4.5 El Monte event which occurred in September of 2020 (Figure 3.3). In this earthquake, 13 MyShake triggers had arrived at the backend server by the time EPIC received the first four ShakeAlert triggers, which arrived nearly simultaneously. The initial location estimate using four ShakeAlert triggers is 2.5 km away from the catalog ANSS location. Using the earliest four triggers (all MyShake), half a second earlier, the location estimate is 3.2 km away from the true location.

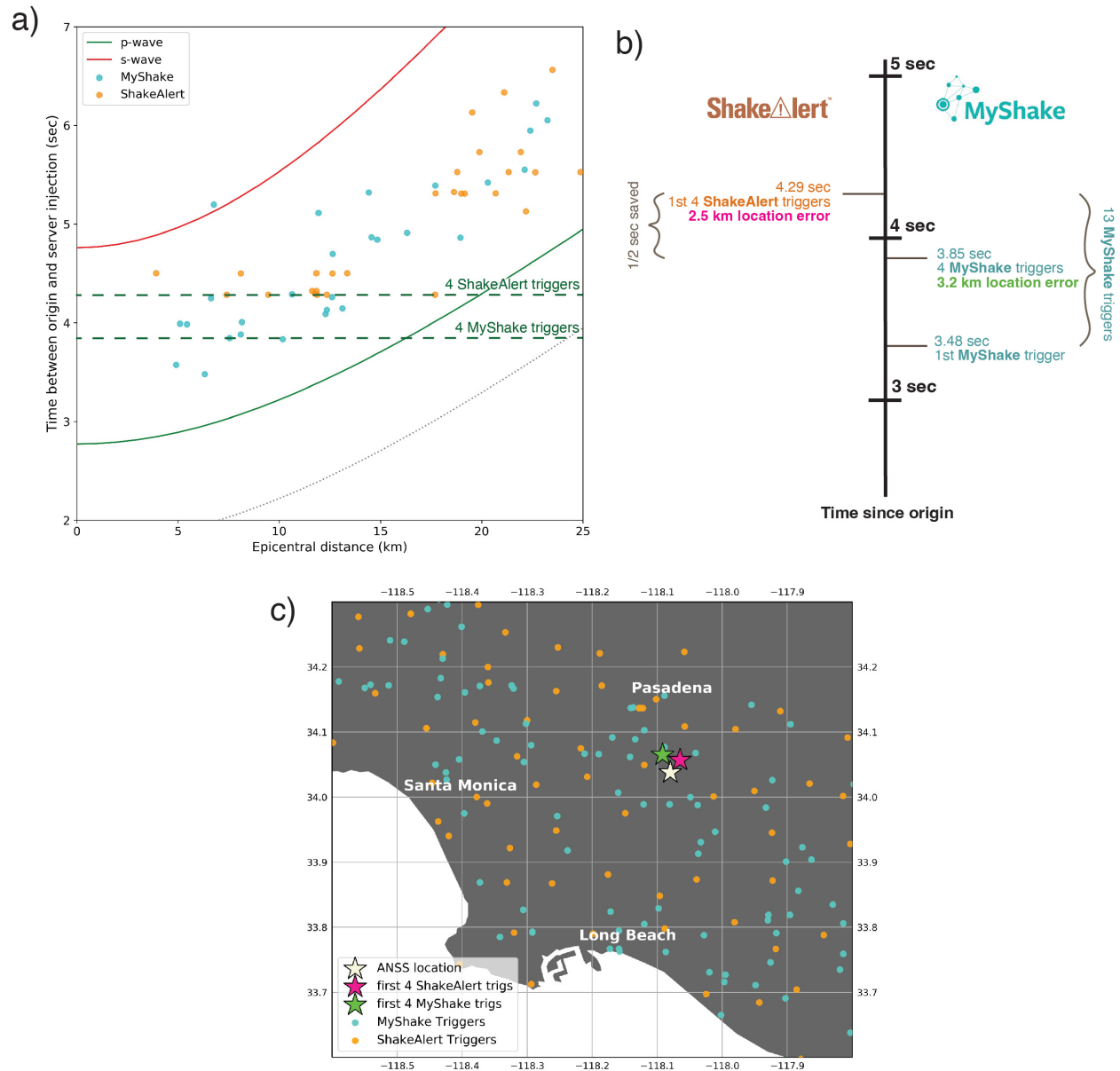
The M 3.5 Compton earthquake in October of 2019 resulted in the highest density of MyShake triggers we have observed for a single event (Figure 3.4). While in the initial 20 seconds of the earthquake, EPIC received input from 66 stations, MyShake's backend received 1224 STA/LTA triggers, nearly a factor of 20 more. 63 MyShake triggers had arrived at the server by the time 4 ShakeAlert stations had reported data. An initial estimate using the earliest 4 MyShake triggers detects the event a 1/2 second earlier than ShakeAlert's initial solution, with a location error of 26.9 km. The MyShake location error matches the initial ShakeAlert error of 3.0 km 0.2 sec later, when 16 triggers have contributed (a 1/4 sec before the first ShakeAlert estimate).

A M 3.5 earthquake in Anza, California, in April of 2020 provides an example of the MyShake network's population dependence (Figure 3.5). For this event, the nearest population center, Palm Springs, was 30 km away, while the nearest ShakeAlert sensors were less than 20 km from the epicenter. In this situation, MyShake is not able to meaningfully contribute to the initial alert's generation.

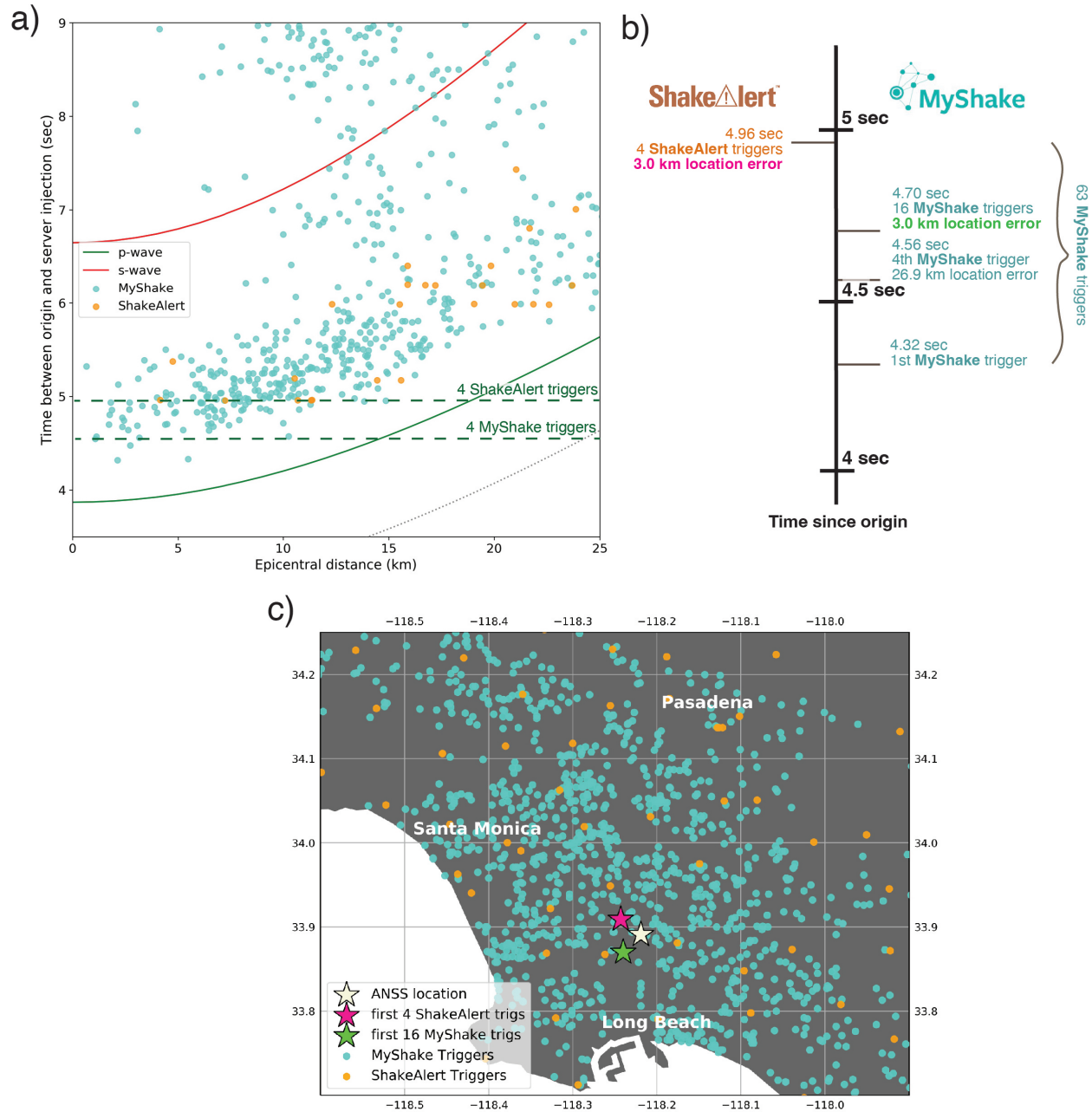


**Figure 3.2:** Real-time triggering in the M 3.6 Granada Hills earthquake. **a)** The arrival of MyShake (turquoise) and ShakeAlert (orange) triggers to their respective servers, plotted in terms of time and epicentral distance. The red and green lines represent the estimated P and S-wave arrival times. The dotted curve represents the P-wave arrival tolerance applied; triggers arriving above this threshold were accepted as part of the event. **b)** A timeline of trigger accrual and the associated location estimations. **c)** A map of sensors which triggered on this earthquake and the event locations using three initial trigger combinations as compared to the ANSS catalog location.

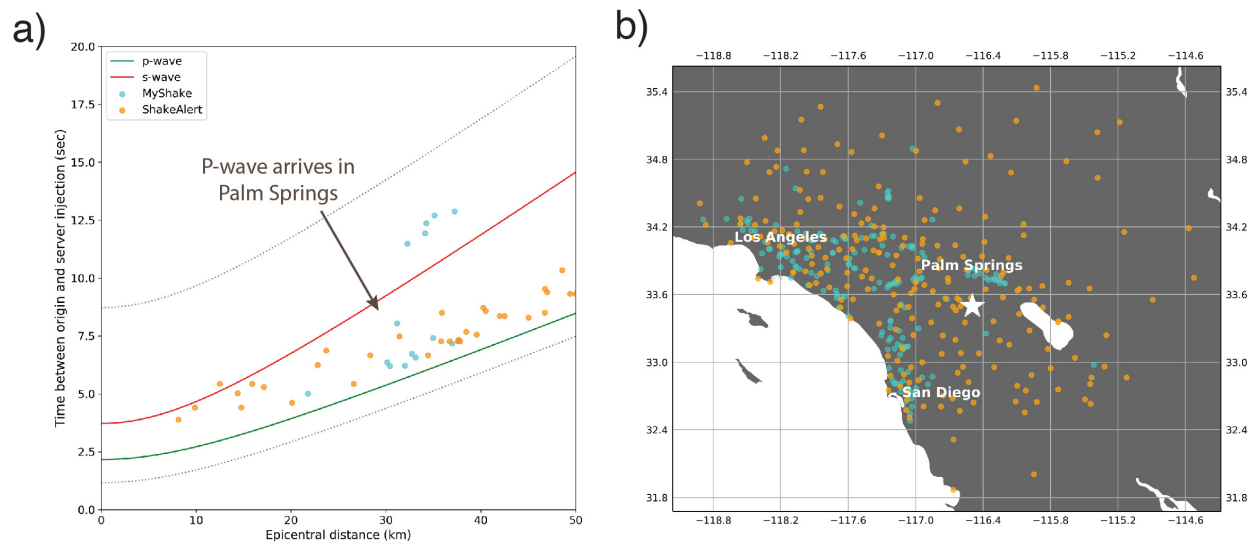




**Figure 3.3:** Real-time triggering in the M 4.5 El Monte earthquake. **a)** The arrival of MyShake (turquoise) and ShakeAlert (orange) triggers to their respective servers, plotted in terms of time and epicentral distance. The red and green lines represent the estimated P and S-wave arrival times. The dotted curve represents the P-wave arrival tolerance applied; triggers arriving above this threshold were accepted as part of the event. **b)** A timeline of trigger accrual and the associated location estimations. **c)** A map of sensors which triggered on this earthquake and the event locations using the earliest MyShake and ShakeAlert triggers as compared to the ANSS catalog location.



**Figure 3.4:** Real-time triggering in the M 3.5 Compton earthquake. **a)** The arrival of MyShake (turquoise) and ShakeAlert (orange) triggers to their respective servers, plotted in terms of time and epicentral distance. The red and green lines represent the estimated P and S-wave arrival times. The dotted curve represents the P-wave arrival tolerance applied; triggers arriving above this threshold were accepted as part of the event. **b)** A timeline of trigger accrual and the associated location estimations. **c)** A map of sensors which triggered on this earthquake and the event locations using the earliest MyShake and ShakeAlert triggers as compared to the ANSS catalog location.

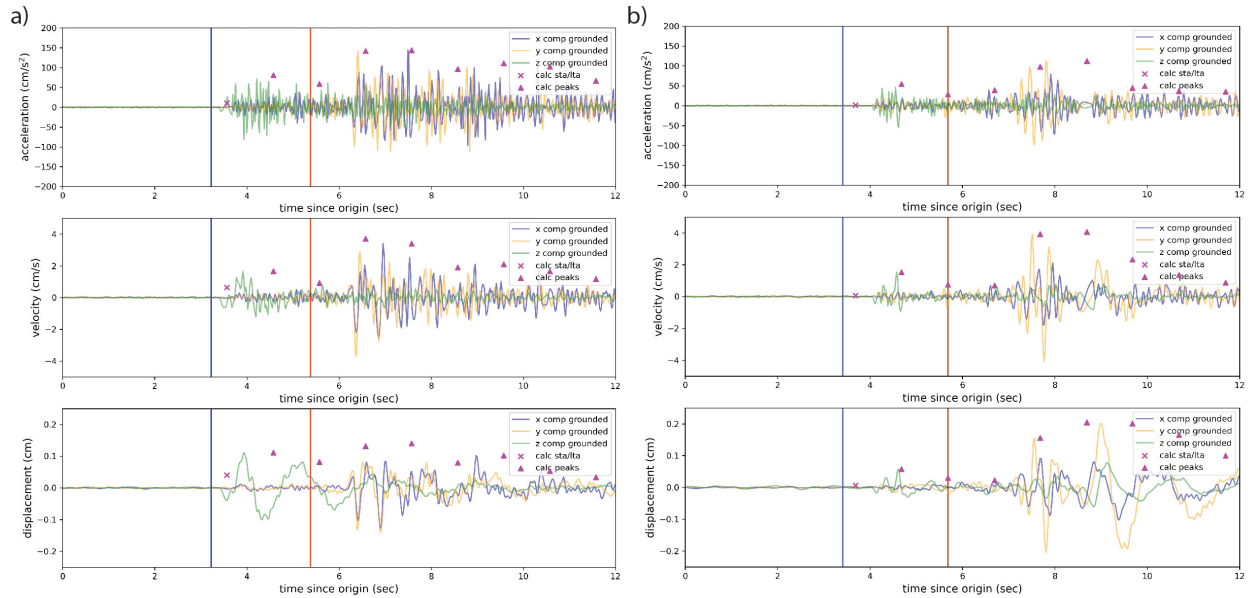


**Figure 3.5:** Real-time triggering in the M 3.5 Anza earthquake. **a)** The arrival of MyShake (turquoise) and ShakeAlert (orange) triggers to their respective servers, plotted in terms of time and epicentral distance. The red and green lines represent the estimated P and S-wave arrival times. The dotted curves represent the P and S-wave arrival tolerances applied; triggers arriving within these boundaries were accepted as part of the event. **b)** A map of sensors which triggered on this earthquake, with a star to mark the ANSS catalog location.

## Magnitude Results

Because not all phones which provided STA/LTA triggers also uploaded a waveform (and vice versa), an assessment of magnitude evolution using a hybrid system will not directly parallel our analysis of timeliness and location.

Two main observations stem from the process of simulating magnitude estimation using waveforms. The first is that it is challenging to develop an integration scheme which successfully and reliably filters out long period artifacts, especially in the second integration to displacement (Figure 3.6). While an effective filter can be found for each waveform via iterative manual assessment, it is harder to determine a standardized or self-scaling rule that could be hard-coded into the MyShake app and applied automatically to all waveforms. Additional development is required.

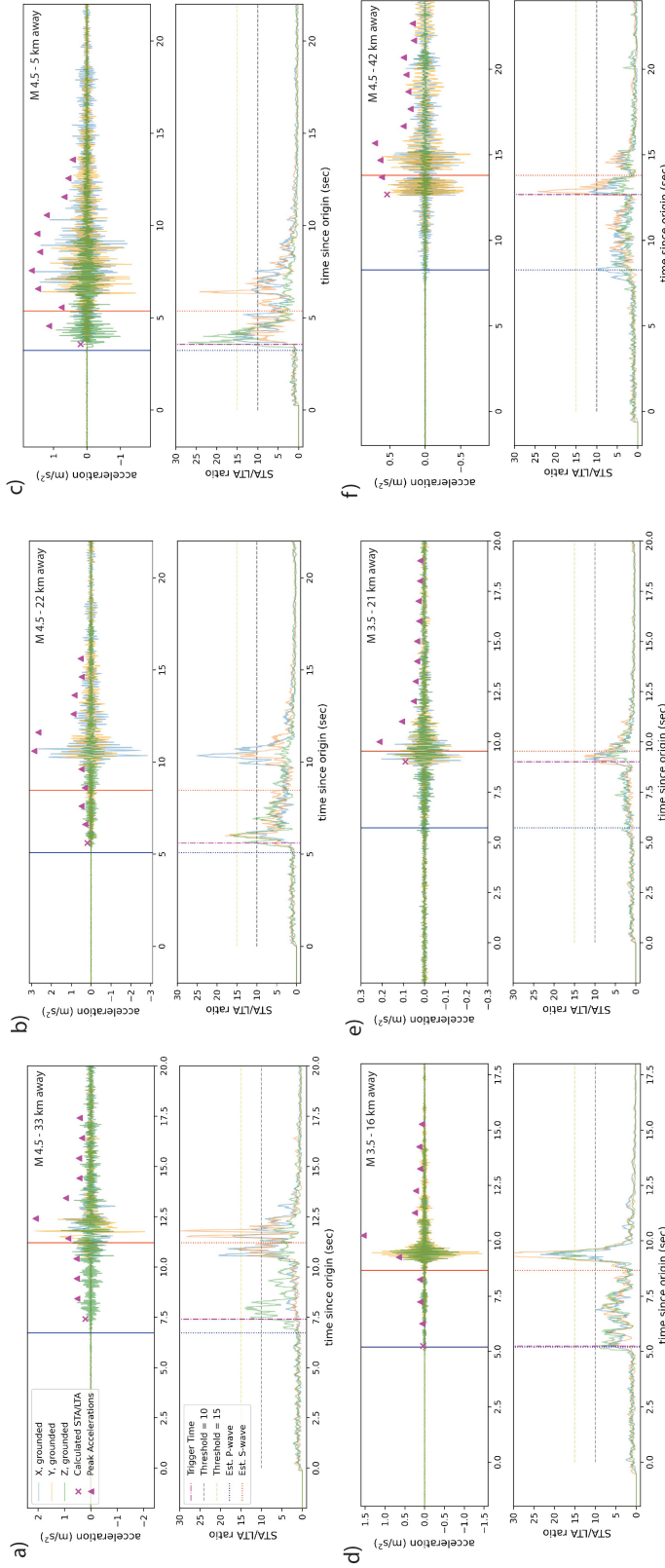


**Figure 3.6:** Effects of integration of a MyShake waveform from the M 4.5 El Monte earthquake. Visible long period artifacts can become amplified over the course of multiple integrations of acceleration data. The estimated P and S-wave arrivals are marked with vertical lines. Pink markings represent the absolute peak amplitude from the preceding one second for all three components **a)** an example of a persistent long period signal in the P-wave portion of a velocity and especially displacement waveform **b)** an example where filtering the waveform before integration appears to have removed most of the extraneous long period signal from the start of the shaking.

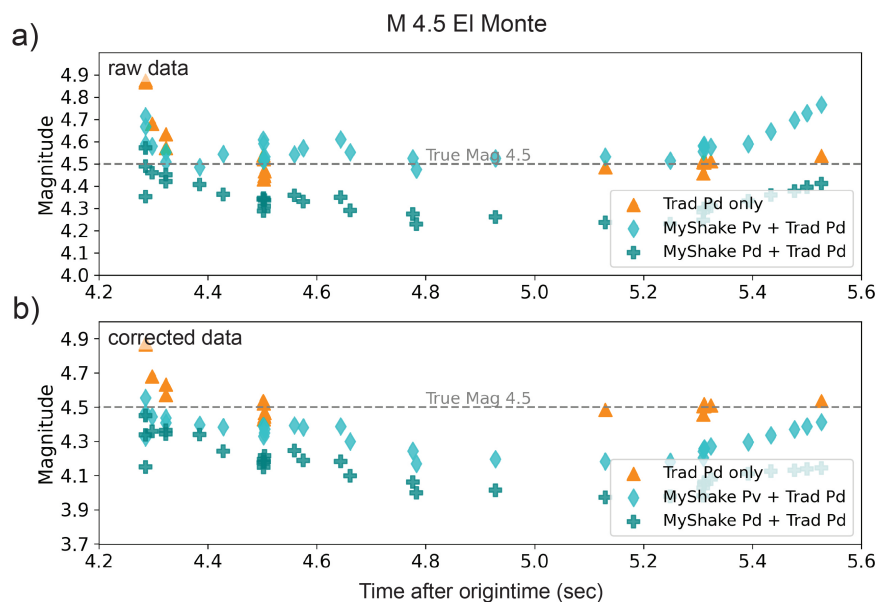
The second observation is that when the STA/LTA ratio is plotted as a time series for each waveform, the P-wave arrival is often visibly distinct from background noise (confirming it is a robust measure to use), but MyShake's current ratio threshold of 15 is not always low enough to pick it. This threshold was initially selected to account for phone noise. However, inspection of more recent data suggests that as phone sensor quality improves, it

is worth revisiting this threshold. In particular, I test whether a lower threshold could assist in detecting lower magnitude earthquakes, which produce lower amplitude P-waves, within about 50 km. As an example, Figure 3.7 demonstrates the improvements to triggering results from lowering the threshold to 10. While this new threshold is still too high to trigger on every P-wave arrival, it does not go so low as to introduce new spurious triggers. There is some nuance to it; in Figure 3.7.f, the threshold of 10 is just barely too high to trigger on the P-wave, at 42 km epicentral distance from a M4.5 earthquake (the minimum magnitude for which ShakeAlert alerts the public). However, Figure 3.7.e represents an example where a waveform would not have created a trigger at all at a threshold of 15, but lowering it to 10 caused a trigger on the S-wave while the P-wave remained too low.

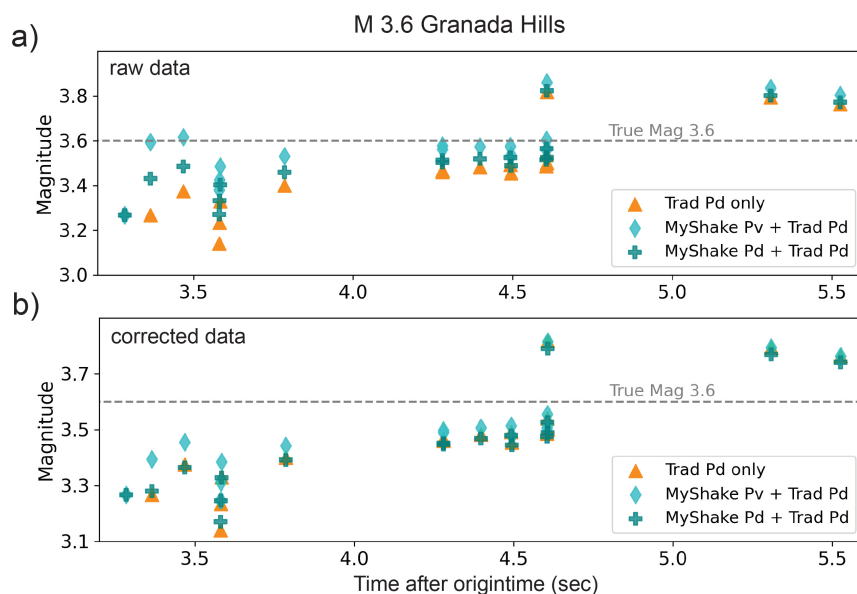
Using this preliminary lowered threshold of 10, trigger times were generated using waveforms, and fed into EPIC along with peak amplitudes sourced from waveform integration to velocity and displacement. When combined with EPIC values, the magnitude evolution for two events, a M 4.5 and M 3.6 can be observed in Figures 3.8 and 3.9. In these, the peak velocity (Pv) based estimates consistently produce larger magnitude estimates compared to solutions that use MyShake peak displacement (Pd) values. The data which was not divided by 3 before integration also predictably produces larger magnitude estimates compared to the corrected data. Interestingly, in both examples, the undivided data contributes to magnitude estimates that are closer overall to the ANSS true magnitude.



**Figure 3.7:** Example acceleration waveforms from within 50 km of small magnitude earthquakes, and their corresponding STA/LTA time series, to demonstrate detection results based on triggering thresholds. The triggering marked in pink is based on a threshold of 10. **a)** Lowering the threshold to 10 permitted detection to occur on the P-wave **b)** Lowering the threshold permitted detection to occur earlier in the P-wave. **c)** Lowering the threshold was not required to trigger on the P-wave at a very close epicentral distance. **d)** Lowering the threshold permitted detection of the P-wave for the smallest magnitude earthquake that ShakeAlert creates events for. **e)** The P-wave change in amplitude was too small 21 km from a small earthquake, and the trigger instead occurs for the S-wave. **f)** A threshold of 10 is almost, but not quite, low enough to detect a M 4.5 P-wave 42 km away



**Figure 3.8:** Magnitude estimates with time using traditional stations and a hybrid system for the M 4.5 El Monte Earthquake **a)** Magnitude results using MyShake data that has been integrated to velocity and displacement. **b)** Magnitude results using MyShake acceleration data that was divided by a correction factor of 3 before being integrated to velocity and displacement.



**Figure 3.9:** Magnitude estimates with time using traditional stations and a hybrid system for the M 3.6 Granada Hills Earthquake **a)** Magnitude results using MyShake data that has been integrated to velocity and displacement. **b)** Magnitude results using MyShake acceleration data that was divided by a correction factor of 3 before being integrated to velocity and displacement.

## 3.4 Real-Time Test

### Methods

In addition to the retrospective analysis combining data from both the traditional and phone networks to investigate a hybrid system performance, a real-time version was also implemented. For this, the location and time of MyShake STA/LTA triggers arriving at MyShake’s server were streamed into a development (test) machine running EPIC. To preserve user privacy but retain the ability to distinguish individual phones, phones are assigned numeric code names preceded by ‘#’ as their station IDs.

Initially, in February 2021, two versions of a hybrid system were implemented. One permitted EPIC to create events using only MyShake triggers. The second system required at least one traditional trigger before an event could be created. Both the traditional and the phone networks generate countless spurious triggers every day. ShakeAlert’s waveform processor, however, filters out a large quantity of bad triggers before they can be passed to EPIC. Because MyShake triggers are not accompanied by live streamed waveform data, MyShake data skip the waveform processor. This proved too much load for the test EPIC server, and the independent MyShake version was retired in July 2021. In the case of real earthquakes, however, this version never created an event using only MyShake triggers. Therefore, we expect that restricting to a traditional trigger-dependent version mainly had the effect of excising the creation of false alerts.

Without live-streaming waveform data, MyShake’s backend has no mechanism to compute the peak velocity or displacement that EPIC would require to estimate magnitude. Therefore, the real-time test version of EPIC uses MyShake triggers exclusively for detecting and locating earthquakes, and relies on traditional data for its magnitude estimates. In this assessment of how MyShake data affects a real-time system, we therefore neglect analysis of the magnitude estimates. On-phone processes which could be implemented within the MyShake app to enable magnitude estimation are discussed in Section 3.6 on Future Improvements.

It is important to note that even identical parallel versions of EPIC will produce slightly different results, because triggers do not leave the waveform processor and queue up in exactly the same order for each EPIC instance. As such, comparisons between the traditional data-only version and the two hybrid systems will not be perfect. It is also important to note that triggers often arrive so closely together that the initial EPIC estimate frequency includes more than the minimum required 4 stations.

### Results

The production version of EPIC that only uses triggers from the traditional seismic network created 301 events between February 22, 2021 and June 22, 2023. In the same time period, MyShake contributed at least one trigger to 24 initial event estimates for the hybrid test version(s) (Table 3.1). One of these was for a M 4.1 earthquake in northeastern



California, which the reference EPIC failed to detect. In 9 of the remaining 23, the speed results are comparable (alert times within 0.3 sec of the reference). The rest are split evenly between  $>0.3$  sec improvements to alert creation and  $>0.3$  sec delays.

For seven earthquakes, at least one hybrid version produced a better initial location estimate than the reference. For five events, the hybrid version's location error was larger but by less than 2 km. Five events had initial location errors that exceeded the reference by 2-5 km, and five more exceeded the reference by 5-15 km (the absolute errors are also  $<15$  km). Only one earthquake was seriously mislocated with an initial error of 57 km.

The M 4.1 earthquake which was created by the hybrid system and missed by the reference used three traditional and five phone triggers to create the event 10.5 seconds after origin time, with an initial location error of 9.2 km. The addition of another phone trigger dropped the error to  $\sim 7.5$  km in the second update, where it then remained. EPIC did not process a fourth traditional station trigger until the seventh alert update.

A closer look at two events, the M 4.6 Markleeville event in July 2021 (Figure 3.10), and the M 4.0 Palomar Observatory event in January 2022 (Figure 3.11), lends insight into the nuances of EPIC's function and the particulars of how phones contribute to initial solutions. The Markleeville earthquake occurred in a region with relatively low station density. Therefore, although the density of ready phones was also low, they had a higher likelihood of having a timely trigger.

The trigger logs for the Markleeville event (Figure 3.10.a) demonstrate the variation in trigger queue order that parallel versions of EPIC can receive. In the reference version, four stations contributed to the initial solution: 65654, MDPB, CMB, and 56678, with trigger times at 7.3, 10.5, 15.5, and 21.2 seconds after the origin time respectively. The initial solution was produced 22.6 seconds after origin time with a location error of 55 km. Both 65654 and CMB contributed to the initial solution in the hybrid test versions, but despite having an early trigger time, MDPB was present only in one. With the addition of phones #3021 and #3022, which triggered at 14.8 and 16.6 secs, one test version produced an initial alert 4.4 seconds faster than the reference version with a similar location error. The second version, using #3021 and the traditional station EBPB (trigger time = 5.1 sec) produced an initial alert 6.1 seconds faster than the reference and had a location error of nearly zero.

For the Palomar Observatory earthquake, the stations PLM, PALA, VCP, and 12092 contributed to the reference system's initial estimate, with trigger times of 3.6, 4.3, 4.5, and 4.6 seconds after the origin time. The hybrid solution used the same stations plus two phones, #9981 and #9982, which had trigger times of 5.3 and 5.5 seconds after origin time. Both versions produced their initial solution 4.9 seconds after origin time and had similarly low location errors; the reference solution had an error of 2 km and the hybrid solution had an error of 1 km. The phone trigger times are a few tenths of seconds later than the alert creation time because the logging system truncated the catalog origin time to whole seconds.

For the events for which the hybrid version produced larger location errors than the reference version, four categories of behavior occurred with time, represented by the four panels in Figure 3.12. The first and fourth panels show location estimates for earthquakes that occurred just outside the network boundary, in Nevada for the first and off the coast

| ANSS Catalog Info |           |            | Location Error (km) |                  |                | Alert Time (sec) |                  |                |
|-------------------|-----------|------------|---------------------|------------------|----------------|------------------|------------------|----------------|
| Catalog ID        | Magnitude | Depth (km) | Reference EPIC      | Hybrid Require 1 | Hybrid Indepen | Reference EPIC   | Hybrid Require 1 | Hybrid Indepen |
| nc73585291        | 4.6       | 3.7        | 54.98               | 50.09            | 0.49           | 22.6             | 18.2             | 16.1           |
| nc73585531        | 4.3       | 3.9        | 2.35                | 1.03             | 2.85           | 20.0             | 19.2             | 24.2           |
| nc73586416        | 3.8       | 2.5        | 0.68                | 8.91             | 4.77           | 19.3             | 18.5             | 322.4          |
| nn00832186        | 4.3       | 11.7       | 0.98                | 56.65            | -              | 15.0             | 12.4             | -              |
| ci39928087        | 4.0       | 13.3       | 2.26                | 1.39             | -              | 4.9              | 4.9              | -              |
| ci40095559        | 3.6       | 11.4       | 1.12                | 1.49             | -              | 4.7              | 5.5              | -              |
| uw61869652        | 3.7       | 23.3       | 3.76                | 6.63             | -              | 6.9              | 5.8              | -              |
| nc73798306        | 4.1       | 28.4       | 5.11                | 7.11             | -              | 7.7              | 7.4              | -              |
| nc73799091        | 5.1       | 8.4        | 0.89                | 1.17             | -              | 5.0              | 5.3              | -              |
| nc73799186        | 3.5       | 8.1        | 0.08                | 2.43             | -              | 5.7              | 6.3              | -              |
| nc73819746        | 3.6       | 5.5        | 2.14                | 1.13             | -              | 3.2              | 3.4              | -              |
| nc73821036        | 6.4       | 17.9       | 11.75               | 6.96             | -              | 7.8              | 7.7              | -              |
| ci40151807        | 4.1       | 3.9        | 1.28                | 1.36             | -              | 6.2              | 6.8              | -              |
| nc73827436        | 3.9       | 7.7        | 10.56               | 13.66            | -              | 3.7              | 10.0             | -              |
| nc73827571        | 5.3       | 30.6       | 2.04                | 10.89            | -              | 8.1              | 8.7              | -              |
| nc73831546        | 3.5       | 18.4       | 8.89                | 4.80             | -              | 7.0              | 10.8             | -              |
| nc73834441        | 4.3       | 25.3       | 2.27                | 7.76             | -              | 8.8              | 8.5              | -              |
| nc73838976        | 3.7       | 24.7       | 16.50               | 18.70            | -              | 7.8              | 8.0              | -              |
| nc73860415        | 4.5       | 18.1       | 8.74                | 6.94             | -              | 7.7              | 8.3              | -              |
| nc73875700        | 3.7       | 16.0       | 0.79                | 4.68             | -              | 6.0              | 6.0              | -              |
| ci40214151        | 4.1       | 10.4       | 1.65                | 12.92            | -              | 5.8              | 4.9              | -              |
| nc73887046        | 5.2       | 6.1        | 1.17                | 8.71             | -              | 12.4             | 12.2             | -              |
| nc73890906        | 5.6       | 10.0       | 50.56               | 50.00            | -              | 20.7             | 21.5             | -              |
| nc73890170        | 4.1       | 6.7        | -                   | 9.16             | -              | -                | 10.5             | -              |

**Table 3.1:** Earthquakes for which MyShake contributed at least one trigger to a test version of EPIC’s initial estimate between February 2021 and July 2023. Earthquakes are listed in chronological order. For the location error and alert times, results are listed from left to right for a live production version of EPIC, as reference, the hybrid system which requires at least 1 traditional trigger to create an event, and the shorter-lived system which permitted EPIC to create an event using MyShake triggers alone. Alert times are in terms of seconds after ANSS origintime.

of Mendocino for the fourth. Locating earthquakes when the azimuthal coverage of stations is one-sided is a known challenge for EPIC (Williamson, Lux, and Allen 2023), and the addition of phones, which are as land-bound as seismic stations, was not expected to solve the issue. In the first example, the hybrid version of EPIC wandered significantly for 20 seconds before stabilizing on a good solution. In the fourth example, the reference version of EPIC produced a  $\sim 50$  km error in the first estimate and then mislocated the earthquake by  $\sim 600$  km in all successive updates. In contrast, the hybrid version, which used three phone triggers in the first 20 updates, mislocated the earthquake by  $\sim 250$  km in one update but otherwise provided a stable solution at  $\sim 100$  km error. In each alert update, the hybrid version used a smaller total number of triggers than the reference version to create a solution.

Figure 3.12.b shows an earthquake for which the hybrid version produced a 10.8 km error in the initial estimate, but the addition of two new triggers in the next update brought the error down, where it then stayed. The initial estimate was based on triggers from three traditional stations and four phones. The next update included a new trigger from each network. Of the five stations used in the reference’s initial estimate, only one was also used by the hybrid.

Finally, four earthquakes saw the hybrid version of EPIC produce an initial location error 3-10 km larger than the reference value and did not deviate with successive updates. In the earthquake represented by Figure 3.12.c, 13 phones had contributed by the 7th update, in addition to 4 traditional stations.

## 3.5 Discussion

As is visible in the time-distance plots in Figures 3.2-3.5, the sensor-to-server latency for phones and traditional seismometers is approximately equal, with both sets of points elevated above the P-wave arrival line by similar amounts. This is critical; if MyShake data typically took longer to arrive, the enterprise of using phones to augment the initial alerting of a traditional early warning system might be moot until latency could be addressed.

With latency held roughly equal, the retrospective examples of triggering sequences suggest that the density of ‘ready’ MyShake phones relative to traditional stations around an earthquake epicenter is a driving factor in whether MyShake can contribute to the generation of a faster, but good quality, initial alert. As seen in the Compton event, however, increasing the quantity of sensors appears to have an upper limit beyond which alert speed and accuracy is not substantively improved. On the other hand, the quantity of phones required to have a positive impact is modest; in the Granada Hills and El Monte earthquakes, the number of phone triggers was of the same order of magnitude as traditional sensors, and half a second was saved in each. While a half second is not, in an absolute sense, a long interval, in a system operating as quickly as early warning, it is a significant percentage of the overall detection delay time (15% of the total Granada Hills detection time, including P-wave travel time from hypocenter to surface, and 10% for the deeper El Monte earthquake).

We also observe that a threshold of 4 stations is not always sufficient to produce a good location estimate when MyShake data is included. This is most likely due to errors in phone clock times, which would carry forward as an error in computed in P-wave travel time. Enough data rapidly arrives to correct the location estimate, but a deeper analysis of a much larger data set is needed to ascertain a robust average number of stations required by a hybrid system to produce a good estimate (by comparison to traditional EPIC's performance across events in the same time frame). It is possible that a hybrid system would need to require more than 4 stations, or the inclusion of a minimum number (perhaps 1 or 2) of traditional stations, to reliably produce initial estimates of equal or better quality as EPIC is currently able to produce using traditional data alone.

Because the live-running hybrid version of EPIC does not receive the same sequence of triggers as the active traditional data-only version used as a reference, it is somewhat challenging to isolate the specific impact to EPIC's performance when phone data is added. In particular, it appears that the latency to release triggers from the waveform processor to each iteration of EPIC is inconsistent, resulting in instances where the hybrid system is slower to alert. Logically, this should not happen; if MyShake data arrived too slowly, the same traditional data should still be available to each EPIC version to create the event. However, it is possible that the reference version of EPIC, which is in active use for early warning detections, is receiving triggers slightly faster or is operating on a more optimized machine.

Perhaps the most significant observation, however, is that despite originating from lower quality sensors, MyShake data does not typically degrade EPIC's estimates. In most situations, the quality of the estimates is roughly similar. In some cases, even the sparse addition of phones can have a positive impact, helping to detect earthquakes faster and locate them better. In the Markleeville earthquake, event creation by a hybrid version occurred 29% faster and reduced the location error by nearly 100%.

Dividing acceleration by the correction factor of 3.1 before integrating potentially appears to depress the resultant velocity and displacement amplitudes more than is needed for magnitude estimation. A broader statistical analysis across a wider variety of earthquakes is needed to elucidate this issue fully, but it is possible that a correction factor derived from whole-waveform peak accelerations might over-correct P-wave amplitudes. In particular, I anticipate this would be true if a substantial portion of the amplification experienced by phones stems from the response of the buildings in which the phones are located. The swaying of buildings is a horizontal motion. As such, we expect the greatest amplification effect in the horizontal components. Early warning, however, is largely concerned with P-wave behavior, which operates mainly in the vertical direction. In future, a more robust correction factor tailored to the EEW use-case could be derived using only P-wave or Z component data.

Our initial analysis into using MyShake data to augment traditional data streams in ShakeAlert's EPIC algorithm suggest that there are some situations when the addition of phone data could improve performance, either by speeding earthquake detection or by improving early estimates of location. Importantly, the addition of MyShake data does not,

on the whole, appear to degrade EPIC's performance (despite the inclusion of potentially "noisier" smartphone data); most hybrid solutions are comparable to those of the traditional system. Using MyShake data for magnitude estimation also appears possible, however, more development with a larger waveform data set will be required to determine the optimal methods. This includes determining the best filtering and tapering that can be applied to small moving windows of acceleration data to successfully integrate to the velocity or displacement values required to compute peak amplitudes for magnitude scaling. In a public safety system when even partial seconds matter, continuing to pursue and refine a phone-augmented early warning system is valuable.

## 3.6 Future Improvements

The following software updates appear warranted to improve EEW performance of the MyShake network. Some are simple changes which are already queued for implementation, and others require further development to iron out feasibility and optimal parameters for technical implementation:

- Apply NTP time adjustments to all early warning real-time data points to improve trigger time accuracy

- Adjust the PA calculation windows to be computed consistently between the STA/LTA triggers and the successive PA measurements. Either these values should be the maximum value from the previous one second, or it should be the cumulative maximum value since the initial trigger.

- If the primary goal of this real-time data is to improve the earliest early warning estimates, the PA sampling rate should be increased in the initial seconds. While still being mindful of constraints on data transmission, I suggest adding two more samples to the current set, at 1/2 second intervals between the STA/LTA trigger and the first two PA updates. If an early warning arrives at a phone, the initial detection of the earthquake has already occurred. Therefore, the STA/LTA trigger should be of a lesser priority in the heartbeat transmission queue than the alert receipts used to compile the latency reports discussed in Chapter 2.

- The STA/LTA threshold can be lowered to reflect reductions in modern phone noise. While the tests to demonstrate viability used a threshold of 10 as a starting point, a more robust threshold can be empirically derived by determining an average amplitude of recent phone noise (limiting to the previous year will best reflect the latest available hardware quality) and an average P-wave amplitude within a target detection distance for small magnitude earthquakes.

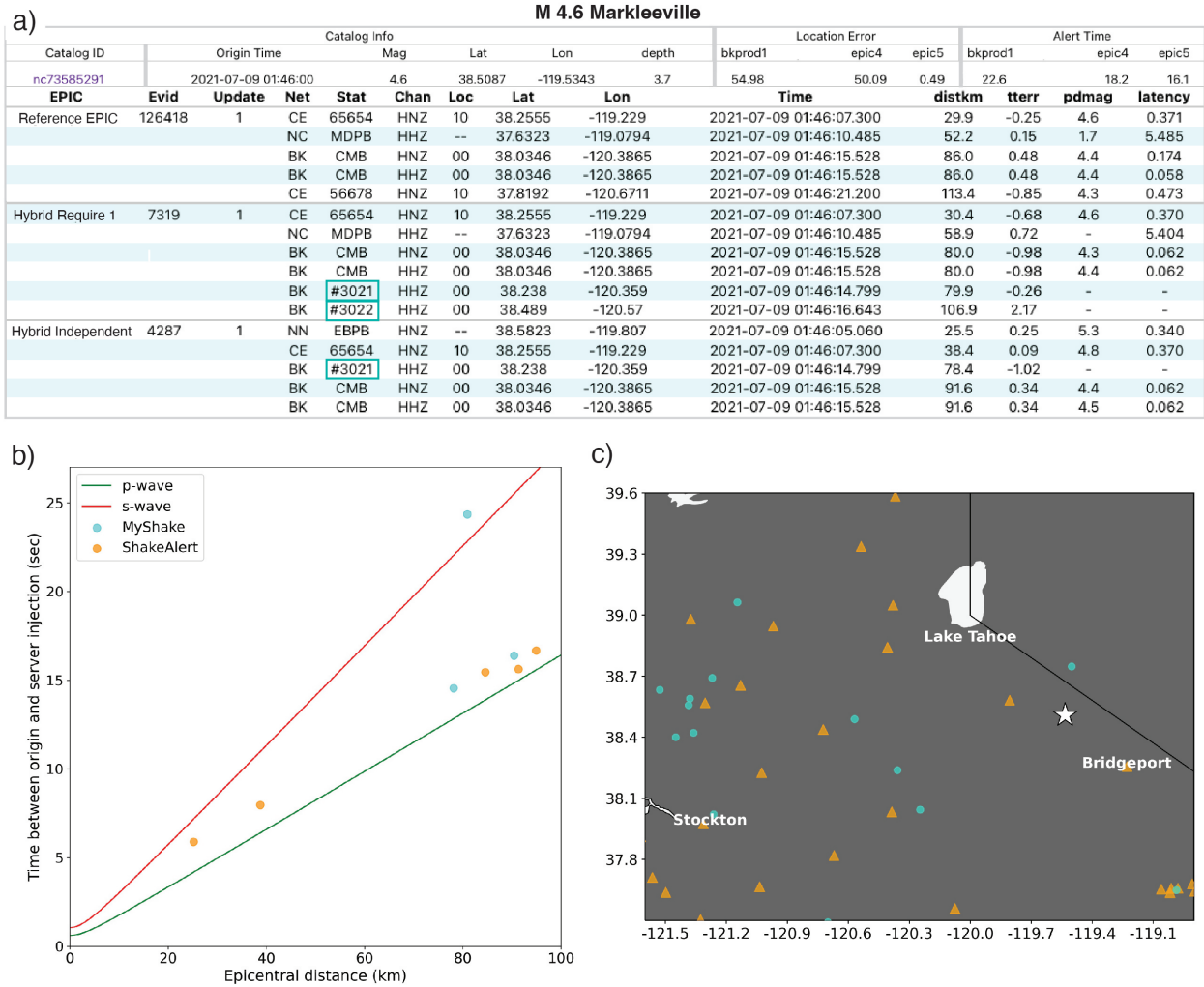
- Lowering the threshold will improve MyShake's ability to detect P-waves, but will also inevitably increase the number of spurious triggers recorded. Therefore a threshold reduction should be accompanied by the implementation of trigger quality filters. Some of these, like an amplitude minimum, can mimic quality checks used by ShakeAlert. Others, like a noise suppression filter, can be tuned to be smartphone specific or even specific to individual phones.

Implement quality rules for the PA updates, such as a rate-of-change or absolute amplitude upper limit, beyond which updates will cease because the phone has been jostled or picked up or received a vibrating alert, and the seismic data is compromised. As discussed in Chapter 4, shake table observations have found that phones begin to slide when shaken with 0.5 g acceleration; this can form a starting point for deriving an appropriate amplitude limit.

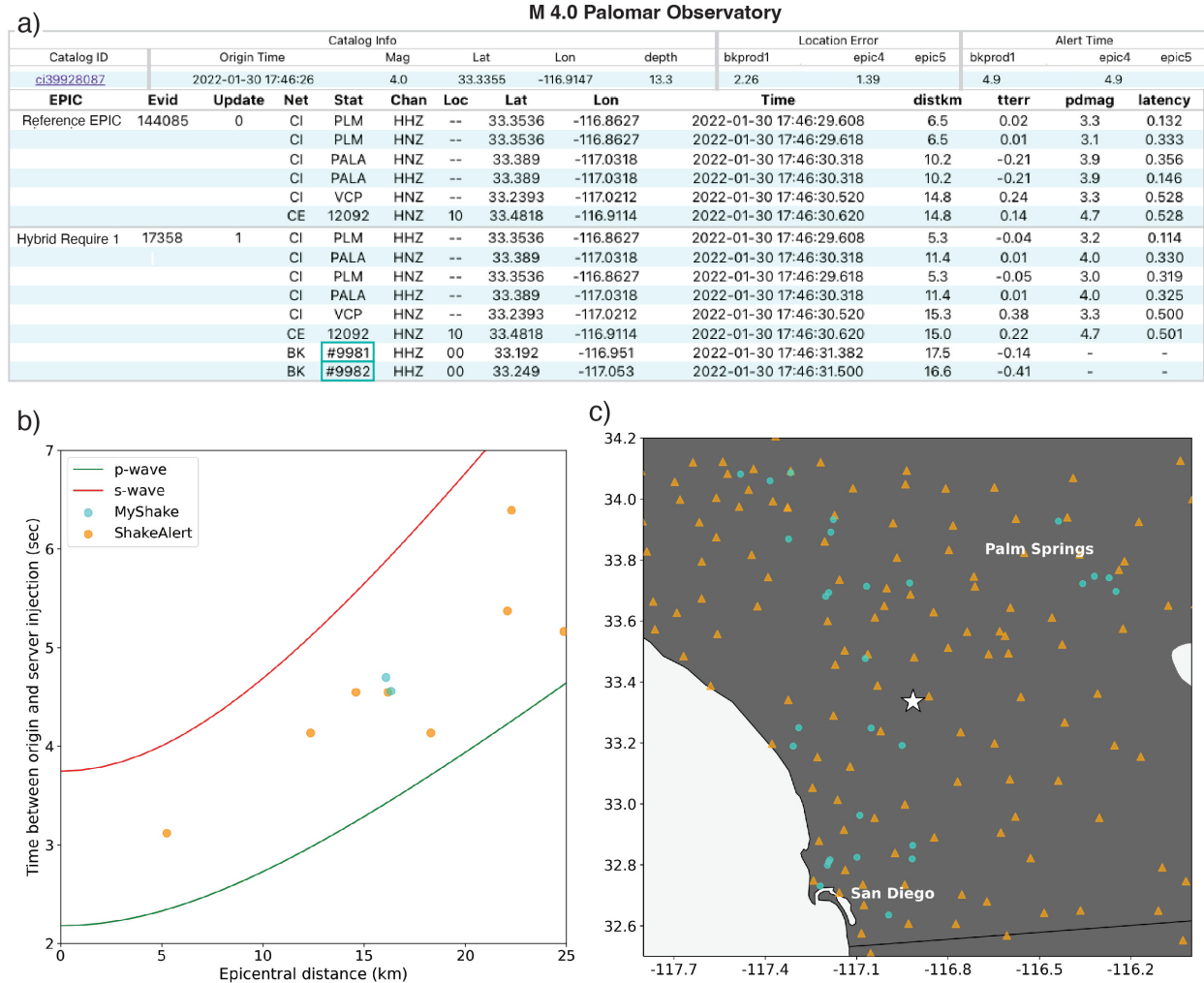
Use the MyShake waveform database to derive an amplification factor specific to P-waves, rather than the peak acceleration of the entire waveform. Alternatively, an amplification factor can be derived directly for velocity.

Implement real-time short-window integration of the acceleration signal to velocity or displacement, and report those peak values in real time as well. By using short, moving windows, this process can occur with limited additional resource load on the phone. A shorter window using grounded data may also help reduce long-term drift issues; this can be tested first using the waveform database.

If the above steps do not yield satisfactory magnitude estimations, consider using the MyShake waveform database to try deriving an acceleration-based magnitude scaling relationship to see if that performs better.

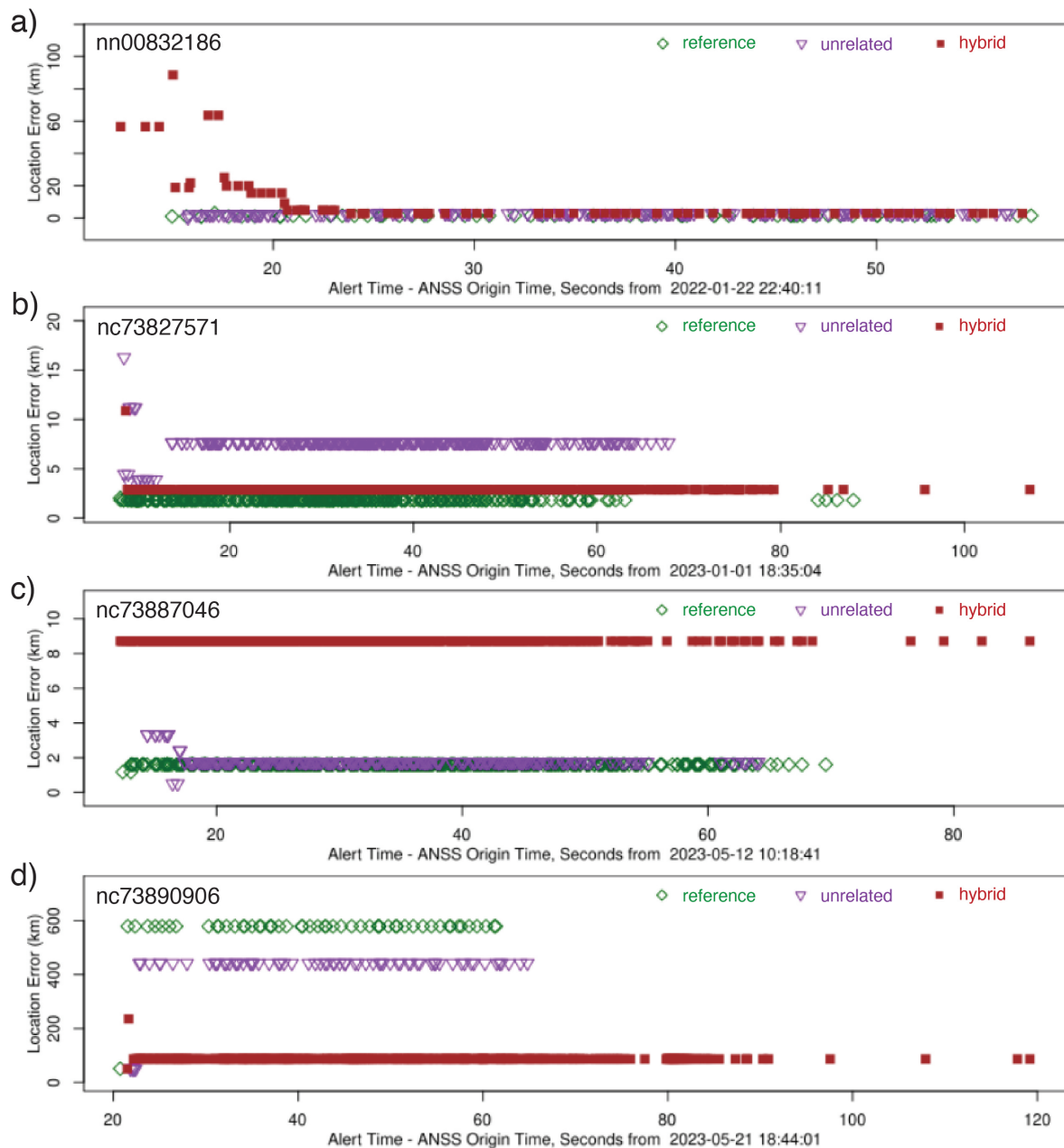


**Figure 3.10:** Data snippets from the test version of EPIC for the M 4.6 Markleeville earthquake. **a)** The station data tabulated. For this earthquake, both hybrid versions of the algorithm were operational, producing two independent initial alerts to compare to the reference version of EPIC. MyShake triggers are highlighted with boxes. The Time column indicates when the sensor triggered. Alert time is seconds after origin time. Location error is in km. **b)** A time distance plot of trigger arrivals in the first 27 sec of the earthquake. **c)** A map of sensors which triggered within 60 seconds of origin time. Because some internal latencies are not reflected in the trigger logs, the points in b and c do not match perfectly with the triggers listed in the table.



**Figure 3.11:** Data snippets from the test version of EPIC for the M 4.0 Palomar Observatory earthquake. **a)** The station data tabulated. MyShake triggers are highlighted with boxes. The Time column indicates when the sensor triggered. Alert time is seconds after origin time. Location error is in km. **b)** A time distance plot of trigger arrivals in the first 7 sec of the earthquake. **c)** A map of sensors which triggered within 60 seconds of origin time. Because some internal latencies are not reflected in the trigger logs, the points in b and c do not match perfectly with the triggers listed in the table.





**Figure 3.12:** The evolution of location estimate errors for the reference and hybrid versions of EPIC in four sample earthquakes, arranged chronologically. The purple triangles represent data from an unrelated EPIC test and should be disregarded. **a)** An event for which the hybrid version of EPIC wandered significantly for 20 seconds before stabilizing on a good solution **b)** An event for which a larger initial error rapidly dropped. **c)** An event for which the initial estimate did not deviate in successive updates. **d)** An event for which the hybrid system ultimately located the earthquake better than the reference.

## Chapter 4

# Structural Health Monitoring Capacities of MyShake

### 4.1 Introduction

Structural health monitoring (SHM) performed via vibration response of built structures is a well-developed field (Carden and Fanning 2004; Chopra 2012; *Minimum Design Loads and Associated Criteria for Buildings and Other Structures* 2022). A significant challenge to actually monitoring structures around the world, however, is the ‘barrier to entry’ inherent to instrumenting buildings and infrastructure. Traditional monitoring projects require permitting, installation, and maintenance of sensors, which is costly in time, human power, materials, and money (Hsu, Yin, and Wu 2018). As a result, the number of instrumented buildings in a region is only a tiny fraction of the total number of buildings. For example, there are only 340 instrumented buildings in California for which records are available in the Center for Engineering Strong Motion Data (CESMD) database (Hagos et al. 2023).

The use of personal smartphones as vibration sensors represents a novel solution (Alavi and Buttlar 2019; Feldbusch, Sadegh-Azar, and Agne 2017; Feng et al. 2015) as smartphone ownership is becoming increasingly globally ubiquitous (Poushter 2016). With approximately 6.6 billion smartphone subscriptions reported globally in 2022 (*Ericsson Mobility Report June 2023* 2023) smartphones are increasingly likely to be found in most buildings, especially in urban environments. Previous work evaluating smartphones for SHM have used dedicated phones fixed in specific locations (Feng et al. 2015; Naito et al. 2013), leveraged the phone camera for visual damage inspection (Xu et al. 2018, used the onboard GPS to detect large ground motions (Minson et al. 2015), enabled individual researchers to view vibrational frequency content (Feldbusch, Sadegh-Azar, and Agne 2017; Figueiredo et al. 2022, Yu et al. 2015), or experimentally estimated smartphone performance using a mechanical shaking apparatus (Feng et al. 2015; Kong, Allen, D. Kohler, et al. 2018; Xie, Li, and Zhao 2019; Zhao et al. 2016). The MyShake project seeks to leverage the ubiquity of personal smartphones by using their in-built accelerometers to crowd-source data from real building responses to

earthquakes. Data collection using citizen science holds major potential to exponentially increase the number of instrumented buildings.

While other SHM and earthquake smartphone apps have been launched or are under development (e.g. Alzughaibi et al. 2019; Feldbusch, Sadegh-Azar, and Agne 2017; Figueiredo et al. 2022; Xu et al. 2018; Yu et al. 2015), MyShake is distinct in two ways. First, the vibration recording function does not require user intervention, as described in MyShake’s auto-collection strategy described below. Second, MyShake offers additional user-centered features beyond its citizen science functions to encourage broad usership, beyond people specifically motivated to participate in seismology or SHM efforts. Users can access real-time earthquake information, submit and view community damage reports, and obtain safety and preparedness information (Rochford et al. 2018; Strauss et al. 2020). Usership is especially high in the US states of California, Oregon, and Washington, where MyShake also delivers ShakeAlert earthquake early warnings (Patel and Allen 2022). By offering an app which provides a variety of user features, we expect the app’s reach to continue to grow. This represents a potentially global scale SHM system implemented at the cost of only app development and server maintenance.

Initial observations of MyShake’s potential for SHM are detailed in Kong, Allen, D. Kohler, et al. (2018), in which phones were set to record vibration continuously in a fixed location on the top floor of a building equipped with a rooftop mechanical shaker. In the present paper, we further validate MyShake’s capabilities in a series of shake table tests, and demonstrate the app’s operation in field conditions. The field conditions mean that a private user’s phone is arbitrarily located in a building and is triggered to record. The uploaded waveform data is then used to extract the structure’s fundamental frequency. Our results, therefore, represent a proof of concept for MyShake’s capability to be leveraged for near-real-time SHM.

The sensor capabilities of MyShake smartphones were described in Chapter 1. In Section 4.2 of this chapter, we describe our methodology for collecting and analyzing the frequency content of MyShake’s seismic data. In Section 4.3 we present the results of a validation experiment performed at a shake table facility. In Section 4.4 we present real data collected on user smartphones. Discussion of our results and a summary of our conclusions occurs in Sections 4.5 and 4.6.

## 4.2 Fundamental Frequency

Some engineering parameters require the use of timeseries from sensors in multiple locations within the same structure. One example is interstory drift, which describes how much one story is displaced relative to those above and below (Alzughaibi et al. 2019). For such parameters, we must have high confidence in the accuracy of the timestamps and the vertical location of phones. Because of the uncertainty in the accuracy of absolute timestamps using phone clocks, especially for older records, and the absence of a real-life example of multiple waveforms recorded in the same building during the same event, we focus in this paper on a keystone SHM parameter which can be computed using a single sensor and does not depend

on multiphone clock synchronicity: fundamental frequency. In future, with the development and validation of a robust clock correction method, increased location accuracy, and with a growing stock of MyShake waveforms, new parameters can be explored.

Fundamental frequency (also called natural frequency) is an essential dynamic characteristic of a building that can be used to qualitatively and quantitatively characterize the response of a building to an earthquake ground motion or other dynamic loading, to update numerical structural analysis models, and to facilitate determination of the presence of damage due to material degradation, environmental conditions or extreme events, such as earthquakes. Damage to a structure (i.e. due to heavy earthquake shaking) generally results in a stiffness reduction of the building and corresponding reduction to the modal frequency (Chopra 2012; Salawu 1997).

For identifying the fundamental natural frequency using MyShake waveforms, we use multitaper spectral analysis as developed by Prieto (2022). This method is tailored for geophysical data to suppress noise by applying orthogonal tapers to overlapping windows of the timeseries before estimating the power spectral density.

In SHM, fundamental frequency is commonly measured by identifying the amplification in the structure’s response for each frequency in the input forcing signal through the use of a transfer function. Essentially a division of a spectrum recorded higher up in a structure by the spectrum of the motion input to the base, transfer functions require at least two measurements be made per structure. Because our ultimate goal is to measure structural behavior using smartphones whose locations we cannot control, we focus on methods which require only a single waveform measurement in any location in the building (output only methods).

In traditional SHM, baseline measurements of structural health can be made using ambient noise. Due to the high noise floor in phones, we rely on small input motions to excite the modal frequency to a level we can measure. In this study, we focus on earthquake motions as the input force. First is a controlled validation test, in which phones were co-located with higher quality MEMs sensors on a steel structure built atop a mechanical shake table. Second are ‘real world’ examples using small earthquakes recorded by user phones.

Since we expect the majority of buildings to have a fundamental frequency of about 10 Hz or less, smartphones are quite capable of capturing the information required for the structural analysis presented in this study (Lee et al. 2003).

### 4.3 Shake Table Test

A three story steel frame with replaceable SMA (Shape Memory Alloy) braces providing self-centering and energy dissipation capabilities was tested on the Pacific Earthquake Engineering Research Center (PEER) 6-DOF (degree of freedom) shake table (Figure 4.1.a). To record the structural response, each floor of the structure was instrumented with TE Connectivity 3022 MEMs accelerometers (Measurement Specialties Inc. 2017). We placed nine phones running the MyShake app alongside, in the arrangement depicted in Figure 4.1.b.

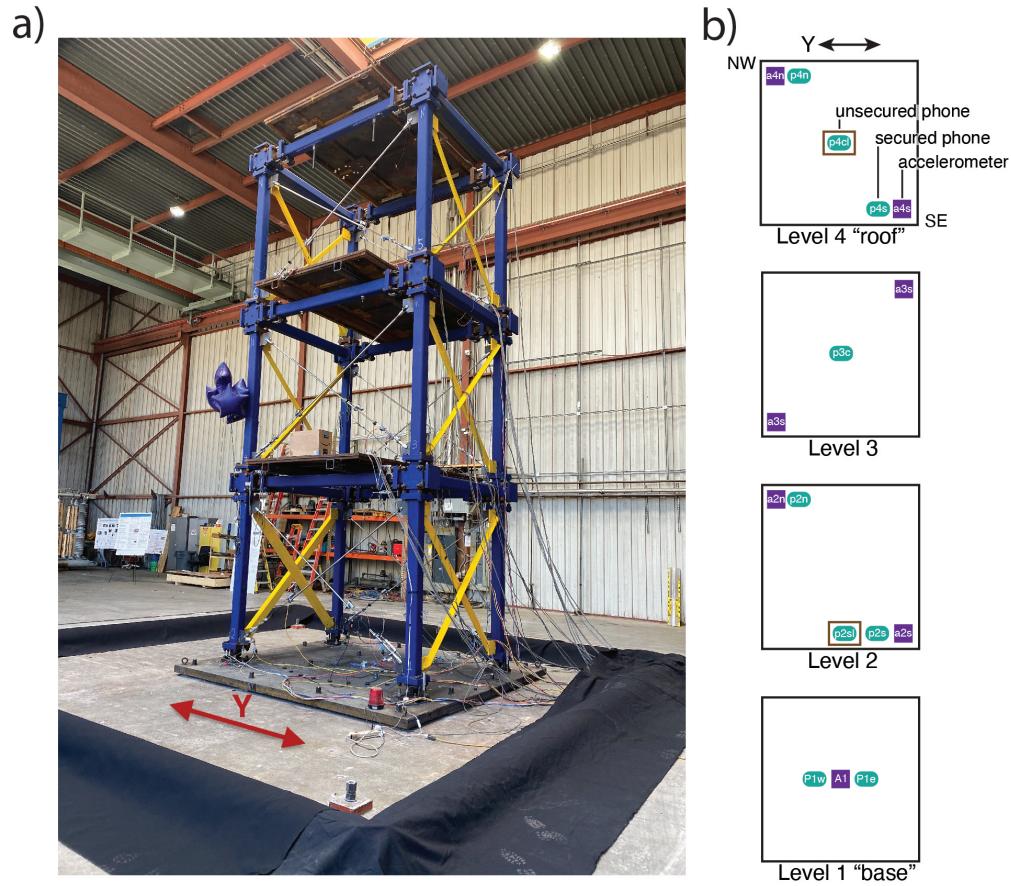
Most phones were firmly attached to the structure, in order to compare them directly with the conventional sensors. Two were placed on the structure but not adhered, to simulate more ‘natural’ circumstances. The unsecured phones were put in basic soft plastic cases and a box was taped over each, such that they could slide within the box confines but not be flung off the structure entirely. Previous shake table tests have demonstrated that phone sliding is recognizable in waveforms by its resemblance to clipping (Kong, Allen, Schreier, and Kwon 2016), and can be visually identified during processing. In the highest amplitude motions applied in this test, the unsecured phone on the structure’s top level appears to clip when subjected to greater than  $\sim 5 \text{ m/s}^2$  motion (Figure 4.2). This threshold for sliding is somewhat higher than was observed in the previous Kong, Allen, Schreier, and Kwon (2016) study, potentially due to the friction provided by the soft plastic cases. Notably, no observations of sliding appear to significantly affect the captured phase information; the phone slides during high acceleration, clipping the waveform, and begins capturing motion faithfully again as soon as accelerations drop again.

The shake table that was used in the tests can produce motions in three translation and three rotational degrees of freedom, however, because the main interest was to explore the performance of the SMA braces, ground motion inputs were only applied in the direction parallel to these braces (indicated by the double-headed arrows in Figure 4.1). As such, the time series and frequency plots we show in this section are all based on this single component of horizontal motion. It is noted that stiff braces (painted yellow) were placed in the orthogonal direction to completely separate the natural frequencies in the two orthogonal directions.

A series of motions was applied to the test structure, including ground motions from the 1999 Kocaeli/Izmit earthquake in Turkiye and the 2006 Kobe earthquake in Japan. In some cases the same motions were applied multiple times at increasing amplitude levels.

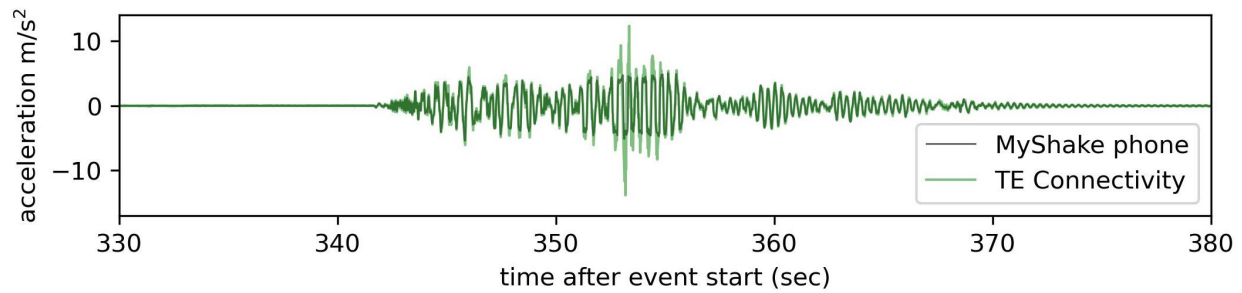
The conventional sensors had a 200 Hz sampling rate and the sensors located at the second level and above included high frequency noise that was not captured by phones with their average 50 Hz sample rate (Figure 4.3.a). To remove this noise and provide a more direct comparison between the behavior and record quality of the two sensor types, the TE records were filtered before analysis with a 50 Hz lowpass filter (Figure 4.3.b). This filtering also isolates the frequency band of interest ( $< 25 \text{ Hz}$ ) as there are no natural frequencies of the tested structure above 25 Hz that provide contributions to the dynamic response of the structure.

Using multitaper spectrum analysis (Prieto, Parker, and Vernon 2009; Prieto 2022), we transform three Kocaeli runs, applied consecutively and recorded by phones and the conventional sensors, into the Power Spectral Density (PSD) space. We use 20 second windows moving in 1 second increments, which provides good resolution in multiple test cases. To simulate an equivalent to the motion experienced by the phone at the center of the structure, we average the signals recorded by two conventional sensors installed on opposing corners of the same level. Sample frequency spectrum and associated PSD plots from the top of the structure, where the dynamic response is greatest, are shown in Figure 4.4. For each of the three Kocaeli motions, frequencies of the first three modes are identified before,



**Figure 4.1:** A three story test structure built upon the PEER shake table. **a)** A photograph of the structure and accompanying measurement equipment. The thin silver crossbraces that can be seen on the face of the structure closest to the viewer are the SMA braces; motion was mostly applied in their direction, as indicated by the red arrow. **b)** A layout, not to scale, of the structure to demonstrate where the sensors were located. Violet squares represent mounted TE Connectivity accelerometers. Turquoise ovals represent phones. ‘Secured’ means the phone was affixed directly to the structure and ‘unsecured’ means the phone was placed on the structure with no adhesive. To keep unsecured phones from flying off the structure, a cardboard box like the one seen in the photograph on Level 2 was secured over it.

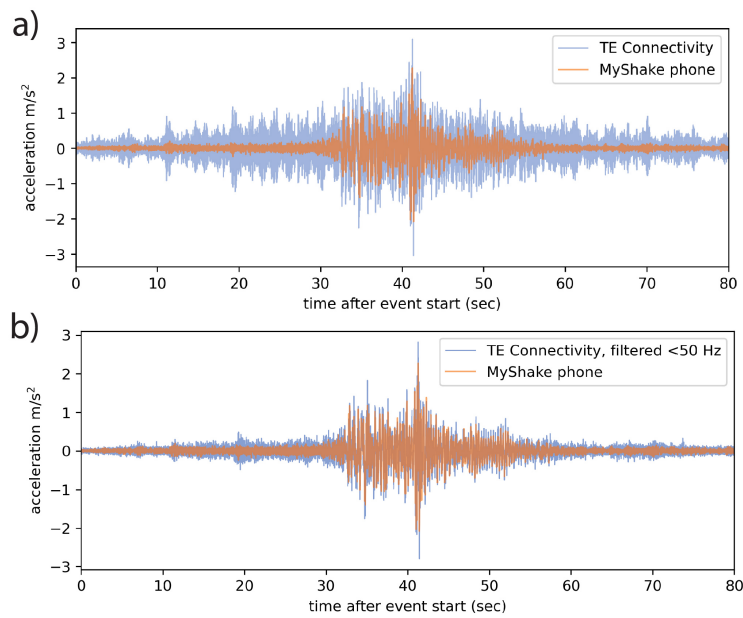
during and after the motion (denoted as pre-event, co-event, and post-event, respectively) using PSD plots of the MyShake and conventional accelerometer recordings. Note that there are still small vibrations of the shake table in the times between the application of the ground motions due to control dynamics of the table when the actuators are still pressurized to keep the table at a constant position. The first and second modes appear strongly for both the phone and TE sensors, and are consistent between them, especially pre- and post-seismic replays. Because the conventional data was not recorded continuously, we select the first



**Figure 4.2:** The waveform during which the unsecured phone at the test structure’s top level appears to have slid during high input accelerations (above a threshold of  $\sim 5 \text{ m/s}^2$ ), creating a clipping effect in the record. The black line represents the unsecured phone and the green is the same motion captured by fixed traditional accelerometers. This waveform is the third in a set of three replays of the 1999 Kocaeli earthquake in Turkiye; the timestamps are relative to the start of the first replay.

and final windows to represent the pre- and post-seismic PSDs. Across the three tests, the pre-earthquake baseline fundamental frequency varied between 3.50-3.52 Hz (0.284-0.286 sec period). The secondary baseline frequency varies between 10.7-10.87 Hz (0.092-0.093 sec period). The results were also consistent with the baseline frequencies observed in the later Kobe tests, varying between 3.42-3.50 Hz (0.286-0.292 sec period) for the first mode and 9.00-10.97 Hz (0.0912 - 0.1111 sec period) for the second. A summary of results can be viewed in Table 4.1.

The SMA braces utilized in this test provided restoring force capability only under tensile forces and did not provide any stiffness or strength under compression. Although some pre-stress is provided to maintain the tension forces, the braces were engaged at instances during the shaking in most of the tests, reducing the stiffness of the structure, resulting in a modal frequency reduction by as much as 22%. In a typical structure without similarly engineered components, the same signal would indicate that the structure has lost stiffness by other means, e.g., damage (Chopra 2012; Salawu 1997). When the earthquake motion ceased during the test, the braces disengaged, returning the structure to its original stiffness. In some cases, the bolts securing the rods loosened slightly, such that the stiffness did not fully recover. An example can be seen in Figure 4.4.d, where the pre-forcing modal frequency is slightly higher than the post-forcing value. The failure of a structure to recover to original stiffness indicates inelastic deformation occurred. Because the rods employed in the shake table test were experimental and their tensioning varied between tests, we cannot interpret the frequency changes we observed beyond simply ‘indicated damage’. However, the clear and repeated coseismic deviation and post seismic recovery (both partial and complete), visible in phone and traditional records alike, marks a first order validation that phones are capable of capturing subtle and important changes in modal frequencies and therefore in structural health information.

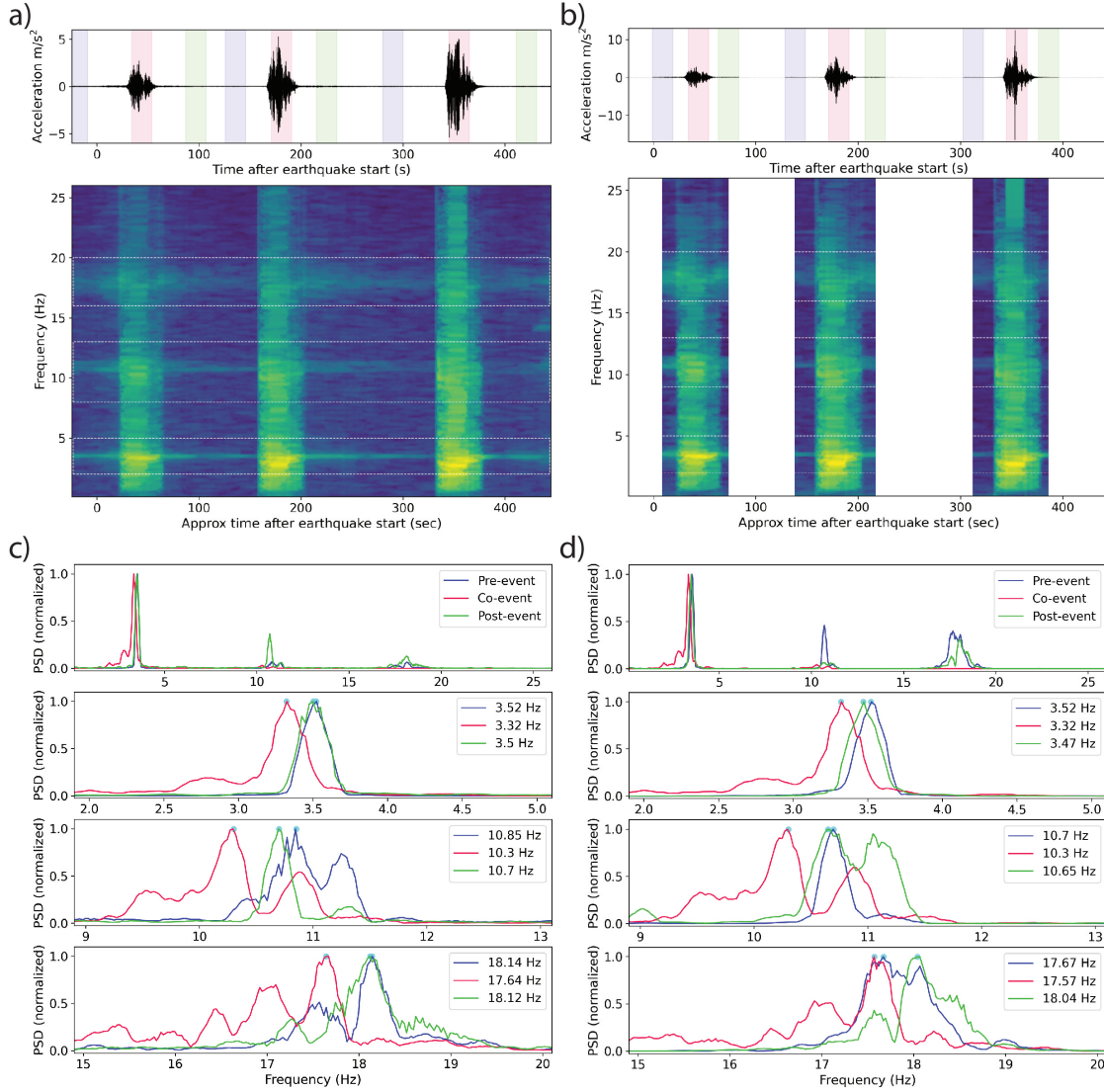


**Figure 4.3:** MyShake acceleration recordings in orange overprinting TE Connectivity acceleration recordings in blue, both from the roof of the test structure. **a)** Unfiltered 200 Hz TE data displays a high frequency noise signal. **b)** Once lowpass filtered below 50 Hz, the TE data resembles the MyShake record more closely.



| Event            | Mode # | Pre-event           |                     | Co-event            |                     | Post-event          |                     |
|------------------|--------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
|                  |        | MyShake<br>Hz (sec) | TE 3022<br>Hz (sec) | MyShake<br>Hz (sec) | TE 3022<br>Hz (sec) | MyShake<br>Hz (sec) | TE 3022<br>Hz (sec) |
| Kocaeli<br>Run 1 | 1      | 3.52<br>(0.284)     | 3.52<br>(0.284)     | 3.32<br>(0.301)     | 3.32<br>(0.301)     | 3.50<br>(0.286)     | 3.47<br>(0.288)     |
|                  | 2      | 10.85<br>(0.0933)   | 10.70<br>(0.0920)   | 10.30<br>(0.0969)   | 10.30<br>(0.0971)   | 10.70<br>(0.0930)   | 10.65<br>(0.0939)   |
|                  | 3      | 18.14<br>(0.0551)   | 17.67<br>(0.0566)   | 17.64<br>(0.0567)   | 17.57<br>(0.0569)   | 18.12<br>(0.0552)   | 18.04<br>(0.0454)   |
| Kocaeli<br>Run 2 | 1      | 3.52<br>(0.284)     | 3.52<br>(0.284)     | 2.77<br>(0.361)     | 3.45<br>(0.290)     | 3.50<br>(0.286)     | 3.32<br>(0.301)     |
|                  | 2      | 10.70<br>(0.0933)   | 10.87<br>(0.0920)   | 9.50<br>(0.1050)    | 10.52<br>(0.0951)   | 10.72<br>(0.0929)   | 10.67<br>(0.0937)   |
|                  | 3      | 18.09<br>(0.0553)   | 18.72<br>(0.05340)  | 17.62<br>(0.0567)   | 17.84<br>(0.0561)   | 17.94<br>(0.0557)   | 18.14<br>(0.0551)   |
| Kocaeli<br>Run 3 | 1      | 3.5<br>(0.286)      | 3.5<br>(0.286)      | 2.7<br>(0.370)      | 2.7<br>(0.370)      | 3.45<br>(0.290)     | 3.5<br>(0.286)      |
|                  | 2      | 10.75<br>(0.0930)   | 10.75<br>(0.0930)   | 9.7<br>(0.1031)     | 9.65<br>(0.1036)    | 10.52<br>(0.0951)   | 10.55<br>(0.0948)   |
|                  | 3      | 17.82<br>(0.0561)   | 17.59<br>(0.0569)   | 17.05<br>(0.0587)   | 15.02<br>(0.0666)   | 17.85<br>(0.0560)   | 18.39<br>(0.0544)   |
| Kobe<br>Run 1    | 1      | 3.47<br>(0.288)     | 3.45<br>(0.290)     | 3.20<br>(0.313)     | 3.20<br>(0.313)     | 3.45<br>(0.290)     | 3.47<br>(0.288)     |
|                  | 2      | 10.97<br>(0.0912)   | 9.07<br>(0.1103)    | 9.37<br>(0.1067)    | 10.10<br>(0.0990)   | 10.80<br>(0.0926)   | 9.02<br>(0.1109)    |
|                  | 3      | 17.72<br>(0.0564)   | 17.79<br>(0.0562)   | 15.94<br>(0.0627)   | 17.27<br>(0.0579)   | 18.19<br>(0.0550)   | 18.29<br>(0.0547)   |
| Kobe<br>Run 2    | 1      | 3.47<br>(0.288)     | 3.5<br>(0.286)      | 2.85<br>(0.351)     | 2.82<br>(0.355)     | 3.42<br>(0.292)     | 3.45<br>(0.290)     |
|                  | 2      | 10.77<br>(0.0929)   | 9.02<br>(0.1109)    | 9.17<br>(0.1091)    | 9.2<br>(0.1087)     | 10.82<br>(0.0924)   | 9<br>(0.1111)       |
|                  | 3      | 17.82<br>(0.0561)   | 18.67<br>(0.0536)   | 16.29<br>(0.0614)   | 16.29<br>(0.0614)   | 17.97<br>(0.0556)   | 17.97<br>(0.556)    |

**Table 4.1:** First three mode frequencies identified using MyShake and conventional accelerometer measurements at the top of a three story test structure tested on a shake table.



**Figure 4.4:** Measurements made over three replays of the 1999 Kocaeli earthquake on a shake table as recorded by both a MyShake phone and PEER sensors on the top of a 3 story steel structure. **a)** the MyShake waveform and corresponding frequency spectrum. Three modes are clear throughout the timeseries, brightening and dipping somewhat during the earthquake motions. The first three colored bands correspond to the windows in the time series represented in C. **b)** the PEER filtered and averaged waveform and corresponding frequency spectrum. The same modes present in the MyShake data are visible. **c)** Pseudospectral density (PSD) plots from discrete points in the frequency time series corresponding to the first earthquake replay visible in the waveform. Blue lines represent the PSD of the structure excited by table vibration before the earthquake. Red lines represent the strongest PSD observed during earthquake shaking, and green lines represent the PSD after the impulse is over. **d)** corresponding PSD plots for the PEER measurements, using the first and final windows for the pre- and post-seismic measurements respectively.

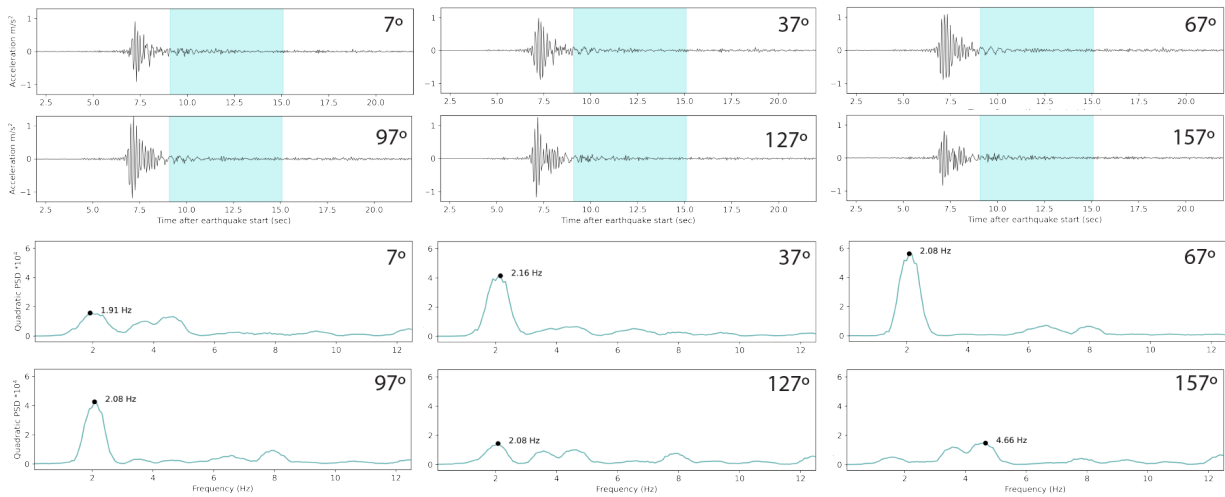
## 4.4 Citizen Science Measurements

Having demonstrated that we can use waveform data recorded by the MyShake app to measure the modal frequencies and changes in the modal frequencies of a building experimentally tested on a shake table, we now look to measure the modal frequencies using MyShake data from real buildings as provided by the crowdsourced MyShake data. This brings additional challenges. First, we have only the reported GPS location and barometric altitude to locate the phones. As previously discussed, this is accurate enough to place the phone inside a building, but not accurate enough to locate the phone in a specific location within that building. The exception is when the structure is very tall, in which case the altitude could be used to make generalized statements like ‘bottom’, ‘middle’, or ‘top’. Similarly, we do not know the orientation of the phone relative to the axes of the structure.

For a first order validation experiment, therefore, we begin with multistory buildings with a simple rectangular footprint. We expect the first mode to be most strongly expressed in the direction of one of the building’s axes and seek to rotate the waveforms into alignment. First, all three components are rotated to bring the mean of two components (which we name X and Y) to 0, such that the Z component is in the direction of gravity. Second, the newly identified horizontals are incrementally rotated and the coda is transformed to find the orientation in which the lowest frequency peak is at its strongest, which implies it is aligned with the one of the horizontal axes of the building. It is noted that it is not possible to identify for certain which horizontal axis it is, although general rules of thumb and engineering judgment can be used to make an educated guess. An example of how rotations affect the resultant frequency spectrums is in Figure 4.5.

While earthquake shaking results in motion of a building at its natural frequency, the frequency spectrum of a co-seismic waveform will also include the frequency content of the source. Lacking an input ground motion record which could be used to calculate a transfer function, we instead must measure the fundamental frequency of the building using the free vibration, which occurs after the strong motion is over, and which is dominated by the building’s dynamic characteristics. This transition is easily identifiable when the waveform and the power spectrum are viewed in parallel. We present six real-world examples of MyShake recordings from user phones in earthquakes from California and Japan (Table 4.2, Figures 4.6 - 4.11). Each is a rectangular structure varying between 3 and 18 stories tall. Images of each building are sourced from Google Street View and Google Earth 3D buildings. Additionally, we present the example of an irregularly shaped 5 story building whose response was captured in three different earthquakes (Figure 4.12). While a single response spectrum from this building can be interpreted with some ambiguity, repeat measurements across earthquake sources of varying magnitudes (M 3.6, 4.3, 5.1) and varying path effects (a 150 degree spread in back-azimuths) can be used to confirm that the approach of using the free vibration response is effective in capturing the building periods.

For each structure, a sample window of the body of the earthquake and a window dominated by free vibration are highlighted, demonstrating the time-based spectral variation and identifying the frequency peaks of each. Window size and number of tapers (and the



**Figure 4.5:** An example of waveform rotations in  $30^\circ$  increments in the horizontal plane, demonstrating the effects of changing orientations in both the time and frequency domain. The phone recording was located in an 8 story hotel in northern California, and located 16 km from a Mw 4.4 earthquake. The spectrums are computed from the free vibration portion of the waveform as highlighted in cyan. The maximum spectral peak corresponding to a frequency of 2.08 Hz is found at  $67^\circ$  from the phone's y-axis, and a smaller secondary frequency of  $\sim 4.7$  Hz is found in the perpendicular direction, potentially corresponding to the building's second axis.

corresponding selection of a time-bandwidth product) used in the multitaper analysis scale are based on earthquake duration (Prieto, Parker, and Vernon 2009). For each record, we identify the lowest strong peak as the likely natural resonance of the structure. These values are evaluated in the Discussion section.

## Taller Structures

Observations made in an 8 story hotel during the Mw 4.4 Berkeley earthquake and in a 14 story condominium complex during the Mw 4.3 Carson earthquake both provide good examples of buildings first experiencing forced vibrations from an earthquake, followed by a period of free vibration where the motion is dominated by the free oscillation of the building (Figures 4.6 and 4.7). This transition is visible in both the waveforms and the time-frequency plots. For the 8 story hotel, a frequency of 6.57 Hz (0.152 sec period) dominates during the main earthquake shaking. When the longer period oscillations start, the dominant frequency is 2.08 Hz (0.481 sec period), which is approximately consistent with the natural frequency expected for a structure this size. Being approximately three times the fundamental frequency, it is possible that the 6.57 Hz peak represents the building's secondary mode. We hypothesize that the higher frequency mode during the earthquake could be a result of the ground motion exciting the building's second mode, but ending with free vibration that more

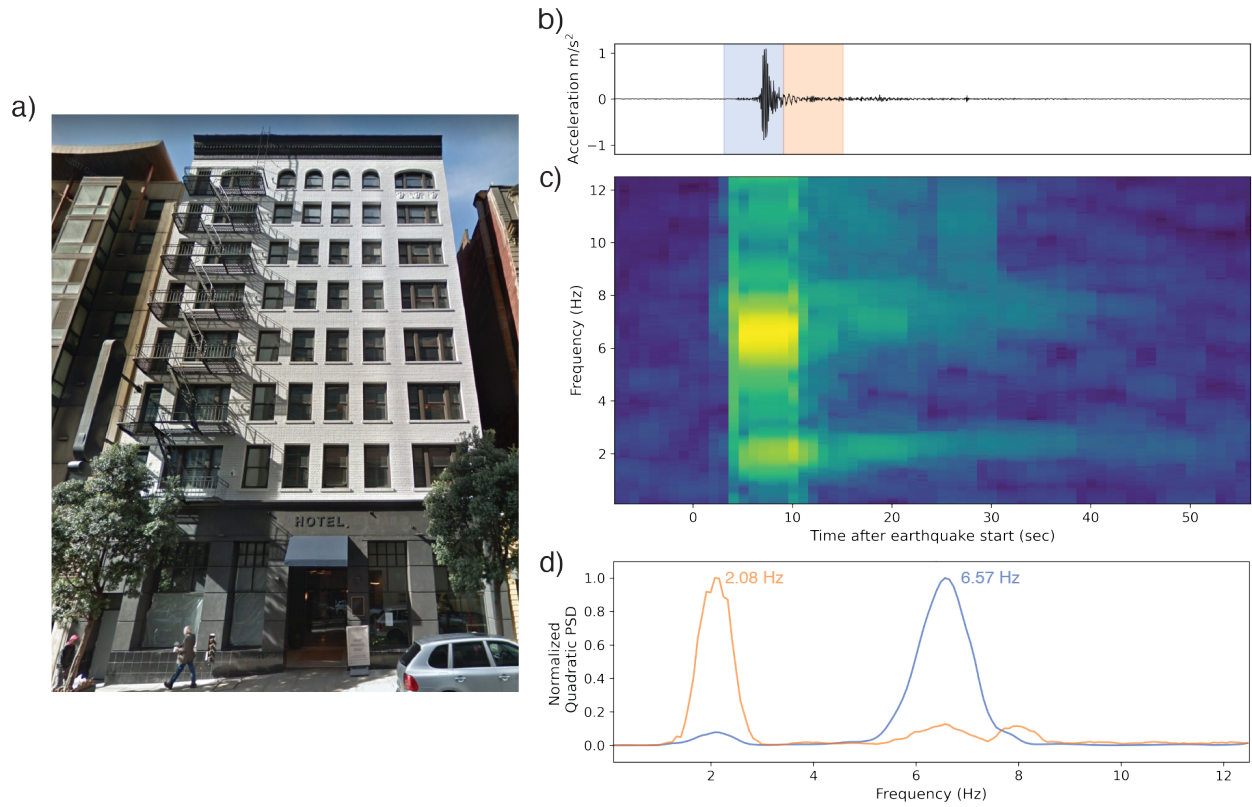
| Building<br># stories, use-type | Event Magnitude,<br>Location, and<br>UTC Datetime           | Epicentral<br>Distance | Identified<br>Natural<br>Frequency | Identified<br>Natural<br>Period | Potential<br>Second<br>Mode |
|---------------------------------|-------------------------------------------------------------|------------------------|------------------------------------|---------------------------------|-----------------------------|
| 8 story hotel                   | Mw 4.4<br>Berkeley, CA, USA<br>Jan 4, 2018 10:39:37         | 16 km                  | 2.08 Hz                            | 0.481 sec                       | 6.57 Hz<br>(0.152 sec)      |
| 14 story condo complex          | Mw 4.28<br>Carson, CA, USA<br>Sept 18, 2021 02:58:34        | 24 km                  | 1.42 Hz                            | 0.704 sec                       | 9.91 Hz<br>(0.101 sec)      |
| 18 story apartment building     | Mw 5.37<br>Searles Valley, CA, USA<br>July 5, 2019 11:07:53 | 212 km                 | 0.82 Hz                            | 1.22 sec                        | 2.9 Hz<br>(0.345 sec)       |
| 3 story apartment building      | Mw 4.28<br>Carson, CA, USA<br>Sept 18, 2021 02:58:34        | 25 km                  | 2.71 Hz                            | .339 sec                        | 8.95 Hz<br>(0.112 sec)      |
| 5 story apartment building      | Mwr 4.7<br>Tsukuba, Japan<br>Sept 7, 2016 04:28:49          | 73 km                  | 3.05 Hz                            | 0.328 sec                       | -                           |
| 3 story hotel                   | Mw 6.4<br>Ferndale, CA, USA<br>Dec 20, 2022 10:34:24        | 117 km                 | 4.26 Hz                            | 0.235 sec                       | -                           |
| 5 story apartment complex       | MI 4.29<br>Santa Rosa, CA, USA<br>Sept 14, 2022 01:40:20    | 80 km                  | 4.85 Hz                            | 0.206 sec                       | 11.54 Hz<br>(0.0867 sec)    |
|                                 | Mw 5.06<br>Alum Rock, CA, USA<br>Oct 25, 2022 18:42:02      | 85 km                  | 4.62 Hz                            | 0.216 sec                       | 13.33 Hz<br>(0.0750 sec)    |
|                                 | Mw 3.57<br>El Cerrito, CA, USA<br>Dec 17, 2022 11:39:42     | 17 km                  | 4.50 Hz                            | 0.222 sec                       | 11.04 Hz<br>(0.0910 sec)    |

**Table 4.2:** A summary of analyzed structures for which MyShake phones recorded a waveform during earthquake shaking, and the identified modal frequencies. Results are ordered in the sequence that their corresponding figures appear in the paper.

strongly excited the fundamental mode.

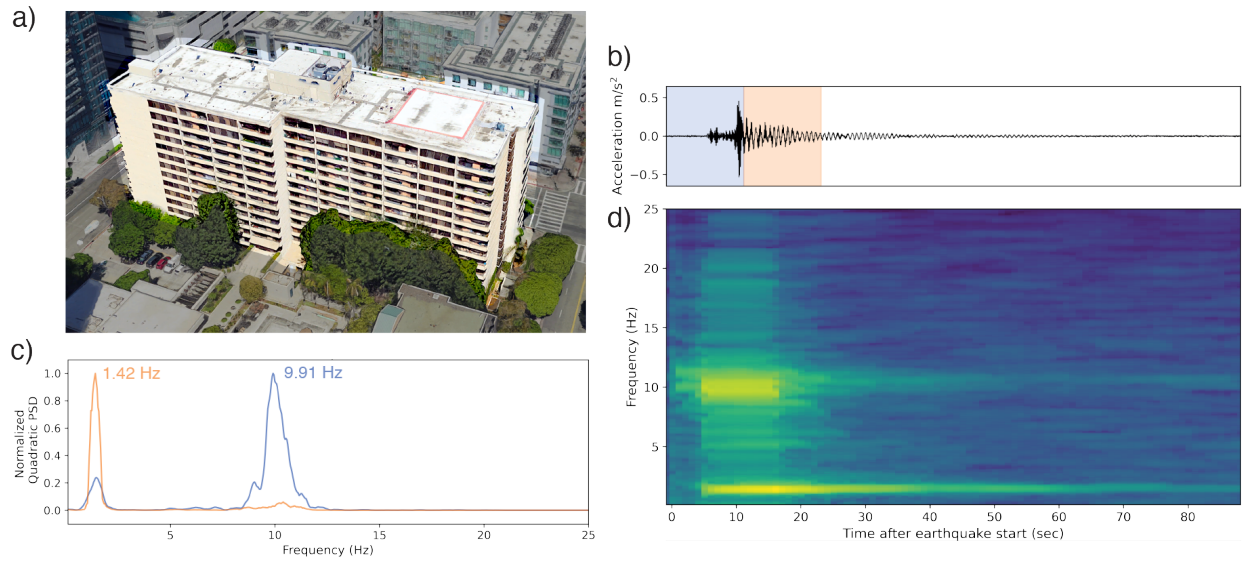
For the 14 story condominium complex, the strongest frequency excited by the earthquake's initial motion is 9.91 Hz (0.101 sec). Following the main pulse of earthquake energy, a longer period oscillation (1.42 Hz or 0.704 sec period) begins. As 9.91 Hz is so much higher than the lowest frequency peak of 1.42 Hz, it is possible it represents the third, not second mode of the structure.

The tallest structure for which we have a good observation is an 18 story apartment building in southern California, whose modal frequency was excited by a Mw 5.4 earthquake during the Ridgecrest earthquake sequence 212 km away (Figure 4.8). Although the waveform signal is much diminished by attenuation, a good quality spectra can still be obtained. In it, two dominant frequencies are visible, one at 2.9 Hz (0.345 sec in period) and another,



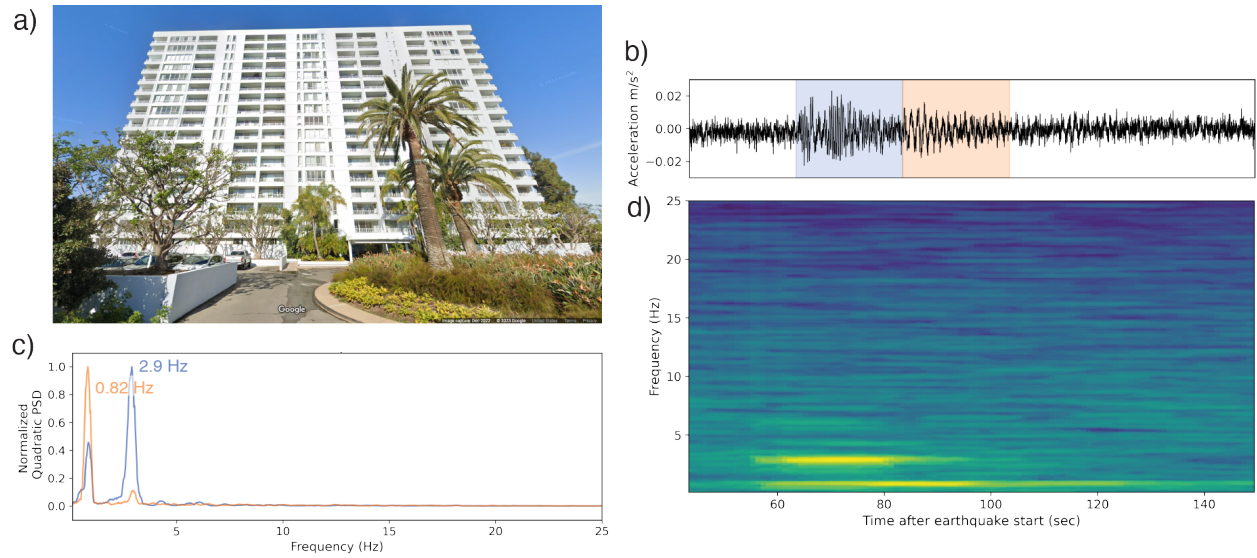
**Figure 4.6:** **a)** An eight-story hotel in the California Bay Area whose fundamental frequency was captured by MyShake during the Mw 4.4 Berkeley earthquake originating 16 km away. **b)** The waveform collected by the phone. The blue and orange overprints represent the windows over which the power spectral density (PSD) plots in part D were computed. **c)** The corresponding time-frequency spectrum computed using multitaper analysis. Spectrums are centered relative to their corresponding window in the accelerogram. The fundamental frequency of 2.08 Hz is visible in the spectra for the entire duration, including in the free vibration, though it is dwarfed in strength during the body of the earthquake by a peak at 6.57 Hz, approximately 3x the fundamental and potentially representing the building’s second mode. **d)** Normalized PSDs for two of the 6 sec windows identifying the dominant frequencies in each.

persisting longer, at 0.82 Hz (1.22 sec period). The lower frequency peak is roughly consistent with what would be expected of a building this size. The higher frequency, being three times the lower, potentially indicates a second mode that was excited during the earthquake excitation.



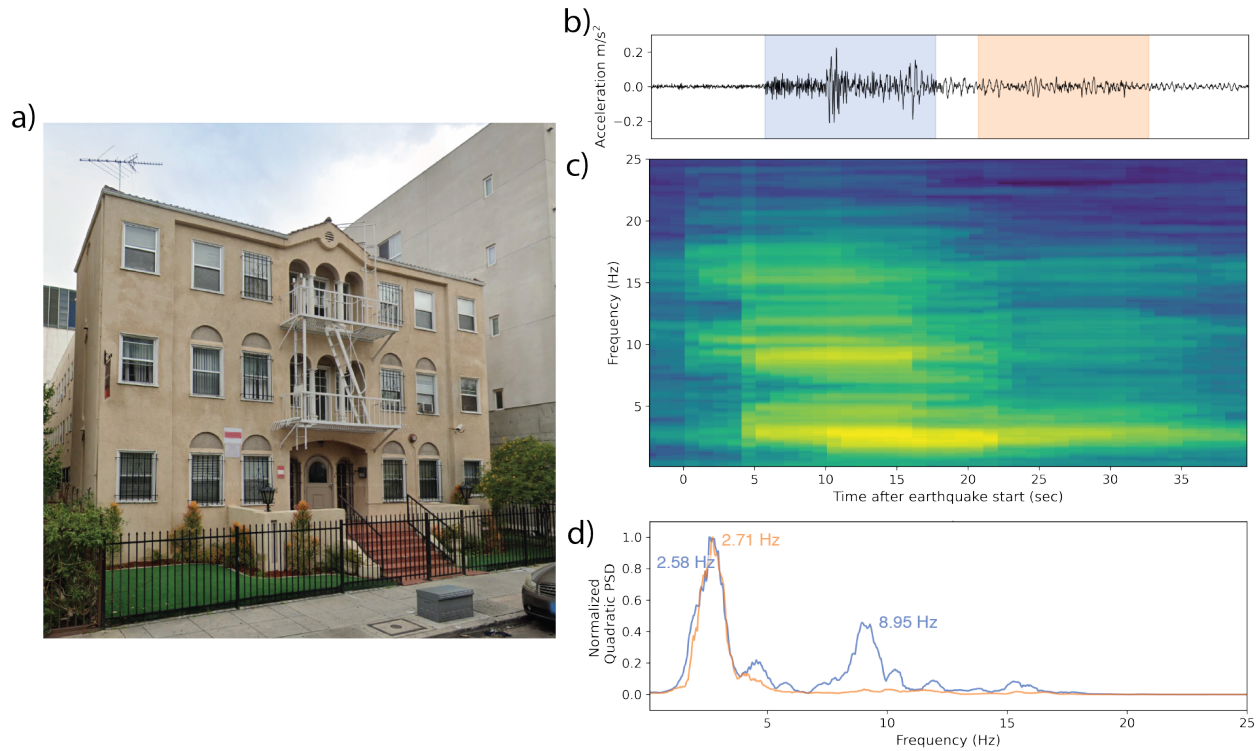
**Figure 4.7:** **a)** A 14 story condominium complex in southern California, which recorded a waveform of a Mw 4.3 earthquake 24 km away. The 3D rendering is sourced from GoogleEarth with a darkening mask applied to highlight the building of interest. **b)** the waveform collected by the phone, overprinted with the 12 sec windows whose PSDs are represented in part D. **c)** Normalized PSDs for two of the 12 sec windows identifying the dominant frequencies in each. **d)** The time-frequency spectrum computed using multitaper analysis. Spectrums are centered relative to their corresponding window in the accelerogram. A peak at 9.91 Hz is visible during the initial body of earthquake shaking, fading in strength later relative to a natural frequency peak at 1.42 Hz.





**Figure 4.8:** **a)** An 18 story apartment building in southern California, which recorded a waveform of a Mw 5.4 earthquake 212 km away. **b)** the waveform collected by the phone, overprinted with the 20 second windows whose PSDs are represented in part D. **c)** Normalized PSDs for two of the 20 sec windows identifying the dominant frequencies in each. **d)** The time-frequency spectrum computed using multitaper analysis. Spectrums are centered relative to their corresponding window in the accelerogram. A peak at 2.9 Hz is visible during the initial body of earthquake shaking, fading in strength later relative to a natural frequency peak at 0.82 Hz. Being  $\sim 3\times$  the latter, it is possible the 2.9 Hz peak is a secondary mode.



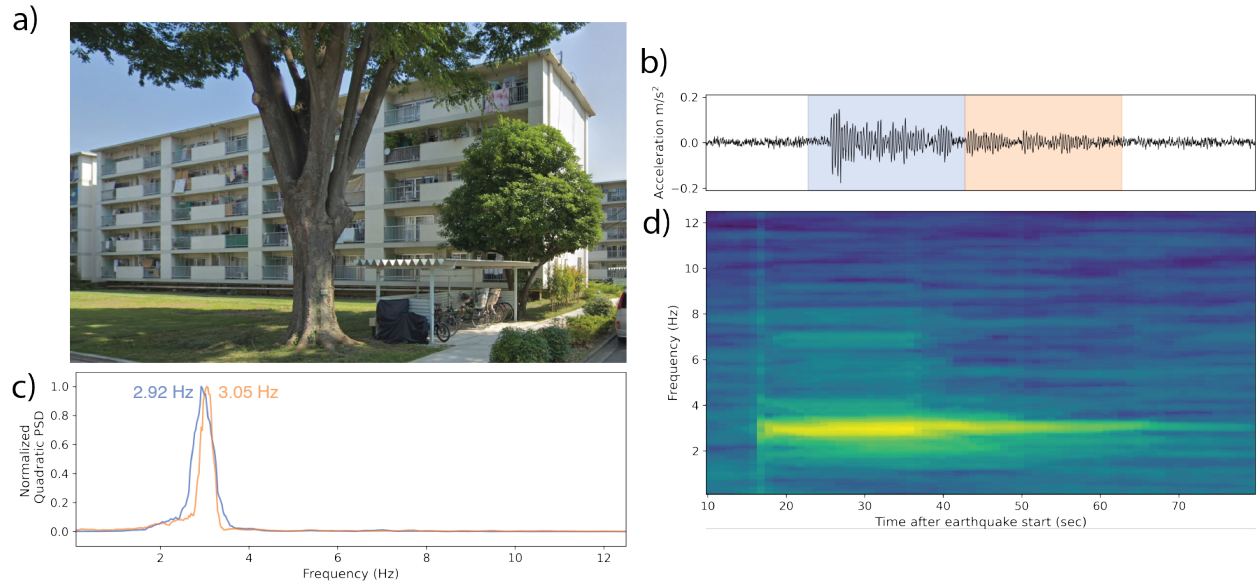


**Figure 4.9:** **a)** An 3 story apartment building in southern California, which recorded a waveform of a Mw 4.3 earthquake 25 km away. **b)** the waveform collected by the phone, overprinted with the 10 second windows whose PSDs are represented in part D. **c)** The corresponding time-frequency spectrum computed using multitaper analysis. Spectrums are centered relative to their corresponding window in the accelerogram. The strongest peak throughout occurs at 2.5-2.7 HZ (0.37-0.4 sec). During the body of the earthquake, there is a second peak at 8.95 Hz (0.112 sec), which later subsides. **d)** Normalized PSDs for two of the 10 sec windows identifying the dominant frequencies in each.

## Shorter Structures

The Mw 4.3 Carson earthquake was responsible for a second observation of a 3 story apartment building 25 km from the epicenter (Figure 4.9). This structure demonstrates two, possibly three strong frequency peaks during the main earthquake shaking, with the higher peaks (8.95 Hz, and 15.24 Hz) subsiding and giving way to a single lower dominant frequency (2.71 Hz, or 0.369 sec period) in the coda of the waveform.

In the case of observations made in a 5 story apartment building in Japan, which was shaken by a Mwr 4.7 earthquake 73 km away, and a 3 story hotel in Northern California, which was shaken by a Mw 6.4 earthquake 117 km away, a single dominant frequency is present throughout the timeseries (Figures 4.10 and 4.11). In the apartment building, the frequency is 3 Hz (0.33 sec period) and in the hotel it is 4.2-4.5 Hz (0.24-0.22 sec). Occurrence

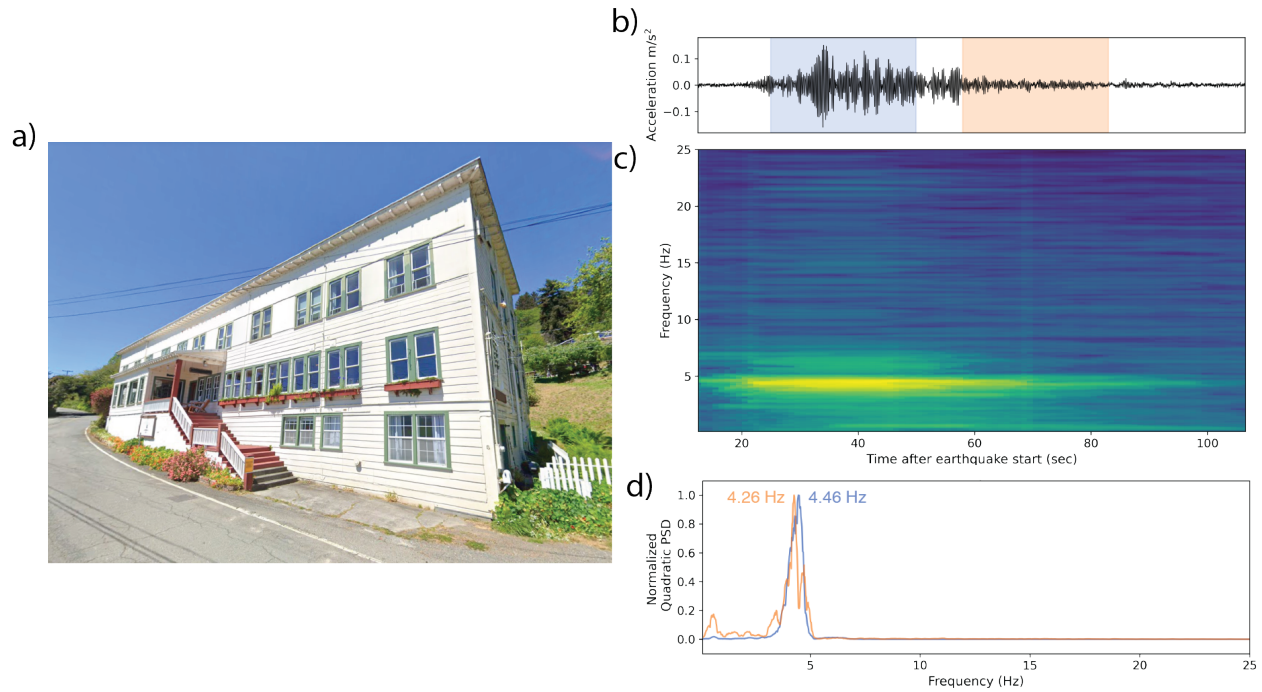


**Figure 4.10:** **a)** A 5 story apartment building in Japan, in which MyShake recorded the Mwr 4.7 Tsukuba earthquake originating 73 km away. **b)** The waveform collected by the phone. The p-wave arrives at  $\sim 12$  sec. A dominant frequency becomes visible after the start of the s-wave and persists for at least 50 seconds. The blue and orange overprints represent the windows over which the power spectral density (PSD) plots in part D were computed. **c)** Normalized PSDs for two of the 20 sec windows identifying the dominant frequencies in each. **d)** The time-frequency spectrum computed using multitaper analysis. Spectrums are centered relative to their corresponding window in the accelerogram. A single frequency peak at  $\sim 3$  Hz is visible across the majority of the spectra.

of the same frequency during earthquake shaking and the free vibration is a strong indication that these frequencies are the fundamental natural frequencies of the buildings and during the earthquake shaking, the building response is directly governed by the fundamental mode.

## Repeat Measurement

A MyShake waveform was collected in three earthquakes from the same L-shaped five story apartment building over the course of four months in 2022 (Figure 4.12.a). Being asymmetric in shape, it is more challenging to gauge the reasonableness of any given modal frequency measurement. Repetition, therefore, can serve as a form of verification. In the first earthquake, a Ml 4.3 event in Santa Rosa 80 km from the building, two frequencies peaked coseismically and a third arose as shaking subsided. The lowest of these was 4.85 Hz (Figure 4.12.b). In the Mw 5.1 Alum Rock earthquake 85 km away in the opposite azimuthal direction, a single primary frequency between 4.6–4.75 Hz was excited throughout the earthquake and coda (Figure 4.12c). The closer, smaller Mw 3.6 El Cerrito earthquake (17 km away) excited two main frequencies coseismically. The primary peak at 4.8 Hz

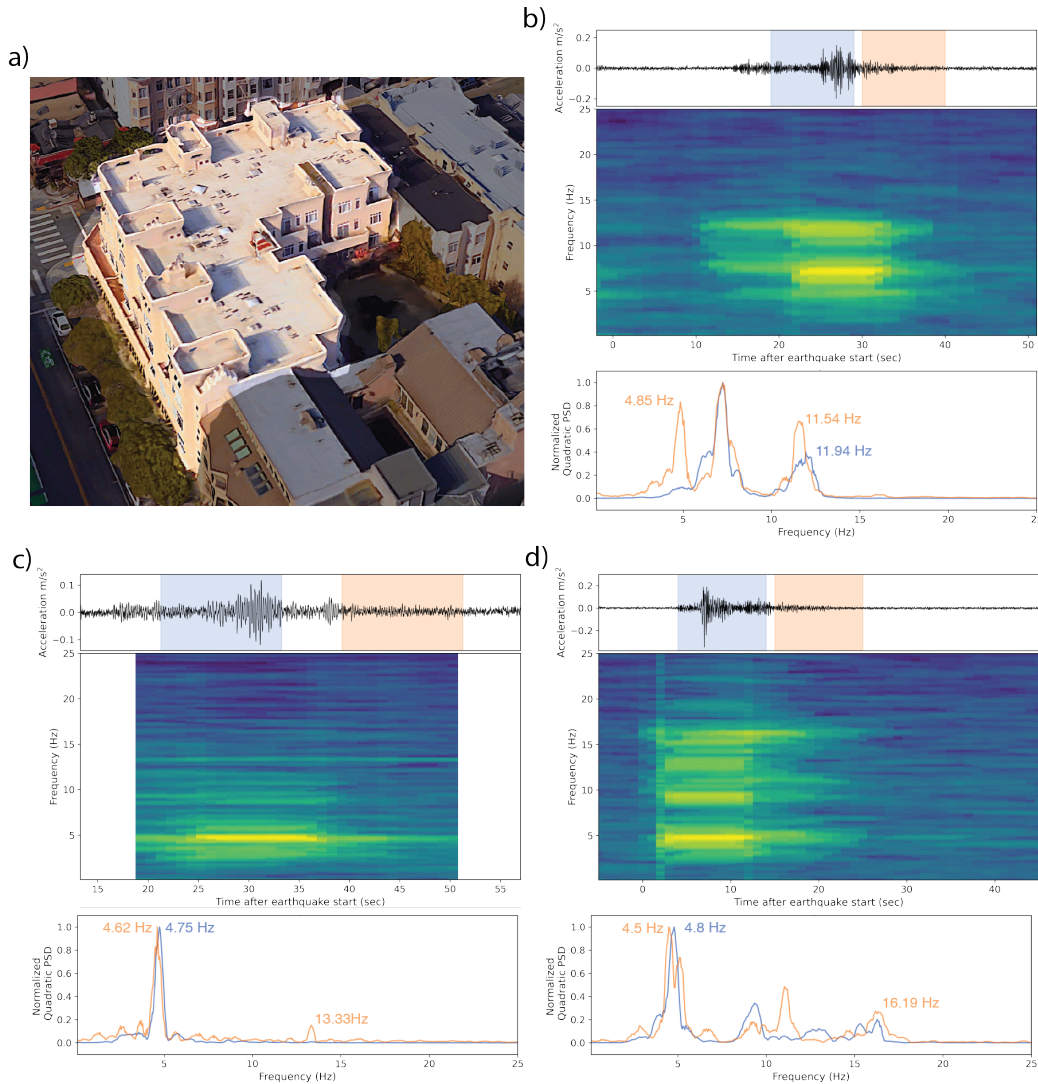


**Figure 4.11:** **a)** A 3 story hotel in northern California in which a MyShake phone recorded the Mw 6.4 Ferndale earthquake 117 km away. **b)** The waveform collected by the phone. The blue and orange overprints represent the 25 sec windows over which the power spectral density (PSD) plots in part D were computed. **c)** The corresponding time-frequency spectrum computed using multitaper analysis. Spectrums are centered relative to their corresponding window in the accelerogram. A dominant frequency peak at 4.25-4.45 Hz is visible across the majority of the spectra. **d)** Normalized PSDs for two of the 25 sec windows identifying the dominant frequencies in each.

decreased slightly into the coda, down to 4.5 Hz, while the second frequency became more apparent during the coda at 16.19 Hz (Figure 4.12.d). The variation in primary frequency over the three earthquake codas is therefore 4.85 - 4.5 Hz (0.206 - 0.222 sec period), decreasing slightly with each successive earthquake.

## 4.5 Discussion

We establish in a controlled shake table test that the modal frequencies identified by MyShake and traditional MEMs accelerometers are quite similar before, during and after the ground motion shaking. With a sufficient signal to noise ratio, a clear frequency spectrum can be derived even without a transfer function. With this in mind, we extract modal frequencies from several buildings in which MyShake phones recorded a small or distant earthquake. In some cases, we also observed frequency peaks at approximately 3 times the first. These we



**Figure 4.12:** a) A 5 story apartment building in the California Bay Area in which MyShake recorded a waveform in three earthquakes. The 3D aerial rendering is sourced from Google Earth, with a darkening mask applied to highlight the building of interest. b) The waveform and spectra collected in the Ml 4.3 Santa Rosa earthquake 80 km away. The blue and orange waveform overprints represent the 10 sec windows over which the normalized PSDs in the bottom panel were computed. The time-frequency spectrum in the center panel shows two dominant frequencies during the body of the earthquake and a third gaining relative prominence as shaking subsides. c) The waveform and spectra collected in the Mw 5.1 Alum Rock earthquake 85 km away. Normalized PSDs are computed using the highlighted 12 sec windows. The time-frequency spectrum shows a single dominant and persistent frequency peak excited for this event. d) The waveform and spectra collected in the Mw 3.6 El Cerrito event 17 km away. Both the highlighted windows and the time-frequency plot as a whole show a main, slightly time-variant frequency at  $\sim 4.65$ , and a few more mobile higher frequency peaks.

| Structural system type                            | $C_t$ | $x$  |
|---------------------------------------------------|-------|------|
| steel moment resisting frame                      | 0.028 | 0.8  |
| reinforced concrete moment resisting frame        | 0.016 | 0.9  |
| eccentrically or buckling-restrained braced frame | 0.030 | 0.75 |
| concrete shear wall                               | 0.020 | 0.75 |
| wood buildings                                    | 0.032 | 0.55 |
| other                                             | 0.020 | 0.75 |

**Table 4.3:** Variables for use in Equation 4.1

interpret as possible observations of secondary frequencies.

It is important to evaluate whether the modal frequencies we extracted from our observations are reasonable for the structures in which they were recorded. For this purpose, we make use of the standards set by the American Society for Civil Engineers (ASCE). In ASCE 7-22 standards, two simple, empirically-derived formulas are provided for estimating a structure's fundamental period when only a little information about the structure is known. ASCE 7-22's Eq 12.8-8, replicated here as Equation 4.1, is based on structure height and framing type. The commentary states that this estimate is deliberately conservative, and tends to underestimate the true period.

$$T_a = C_t h^x \quad (4.1)$$

Where  $T_a$  is the approximate fundamental period in sec and  $h$  is the height of the building in feet. The coefficient  $C_t$  and exponent  $x$  are provided in Table 4.3. We add to the ASCE values an additional option for wood frames from Camelo (2003), which was derived from a series of shake table experiments and performed fairly well for a wider range of building heights in Hafeez, Doudak, and McClure (2019). Goel and Chopra (1998) also found ASCE's variables for 'other' to apply well to structures with concrete shear walls. The fundamental frequency  $\omega_n$  (in Hz) is equal to  $1/T$ . Some structures can also exhibit higher order modes at odd-integer multiples of the first.

ASCE 7-22 Eq 12.8-9, replicated here as Equation 4.2, supplies a quick estimate for steel or concrete moment frames and is also empirically derived. In this,  $n$  is the number of floors and cannot be larger than 12.

$$T_a = 0.10n \text{ and } \omega_n = 10/n \text{ for } n \leq 12 \quad (4.2)$$

Using these estimates, we can then compare the frequency peaks derived from our observations to computed estimates of what we might expect from a simple model of each structure in Table 4.4. Our knowledge of the buildings is limited to what is logged in public databases like OSM buildings (<https://osmbuildings.org>) and what can be visually determined from Google Earth imagery. Therefore, in many cases, we do not know the framing material with certainty, and instead compare our observations with multiple possible estimates.

| Structure                      | Height<br>from OSM<br>Buildings | Observed<br>frequency<br>(period) | $10/n$<br>frequency<br>estimate<br>(period) | Framing<br>Types | $T_a = C_t h^x$<br>frequency<br>estimate<br>(period) | Observation<br>difference<br>from Eq 4.1<br>estimate |
|--------------------------------|---------------------------------|-----------------------------------|---------------------------------------------|------------------|------------------------------------------------------|------------------------------------------------------|
| 8 story hotel                  | 32 m                            | 2.08 Hz<br>(0.481 sec)            | 1.25 Hz<br>(0.8 sec)                        | Concrete         | 0.948 Hz<br>(1.055 sec)                              | +119%                                                |
|                                |                                 |                                   |                                             | Other            | 1.524 Hz<br>(0.656 sec)                              | +36%                                                 |
|                                |                                 |                                   |                                             | Wood             | 2.417 Hz<br>(0.414 sec)                              | -14%                                                 |
| 14 story<br>condo complex      | 45.2 m                          | 1.42 Hz<br>(0.704 sec)            | n/a                                         | Steel            | 0.655 Hz<br>(1.528 sec)                              | +117%                                                |
|                                |                                 |                                   |                                             | Concrete         | 0.695 Hz<br>(1.439 sec)                              | +104%                                                |
|                                |                                 |                                   |                                             | Other            | 1.177 Hz<br>(0.85 sec)                               | +21%                                                 |
| 18 story<br>apartment building | 51.3 m                          | 0.82 Hz<br>(1.22 sec)             | n/a                                         | Steel            | 0.591 Hz<br>(1.691 sec)                              | +39%                                                 |
|                                |                                 |                                   |                                             | Concrete         | 0.62 Hz<br>(1.613 sec)                               | +32%                                                 |
|                                |                                 |                                   |                                             | Other            | 1.07 Hz<br>(0.935 sec)                               | -23%                                                 |
| 3 story<br>apartment building  | 13.8 m                          | 2.71 Hz<br>(0.369 sec)            | 3.33 Hz<br>(0.3 sec)                        | Concrete         | 2.021 Hz<br>(0.495 sec)                              | +34%                                                 |
|                                |                                 |                                   |                                             | Other            | 2.865 Hz<br>(0.349 sec)                              | -5%                                                  |
|                                |                                 |                                   |                                             | Wood             | 3.838 Hz<br>(0.261 sec)                              | -29%                                                 |
| 5 story<br>apartment building  | 19 m                            | 3.05 Hz<br>(0.328 sec)            | 2.0 Hz<br>(0.5 sec)                         | Concrete         | 1.516 Hz<br>(0.66 sec)                               | +101%                                                |
|                                |                                 |                                   |                                             | Other            | 2.254 Hz<br>(0.444 sec)                              | +35%                                                 |
| 3 story hotel                  | 12 m                            | 4.26 Hz<br>(0.235 sec)            | n/a                                         | Wood             | 4.145<br>(0.241 sec)                                 | +3%                                                  |
| 5 story<br>apartment complex   | 16.9 m                          | 4.85 Hz<br>(0.206 sec)            | 2.0 Hz<br>(0.5 sec)                         | Concrete         | 1.684 Hz<br>(0.594 sec)                              | +167 to 188%                                         |
|                                |                                 | 4.62 Hz<br>(0.216 sec)            |                                             | Other            | 2.461 Hz<br>(0.406 sec)                              | +83 to 97%                                           |
|                                |                                 | 4.5 Hz<br>(0.222 sec)             |                                             | Wood             | 3.433 Hz<br>(0.291 sec)                              | +31 to 41%                                           |

**Table 4.4:** A comparison of the observed natural frequencies compared to a range of model-based options. Where appropriate, we use equations 1 and 2 to compute expected values. Since framing materials is not known for certain for most of the buildings we observe, we provide a range of likely values. The ‘steel’ category uses the coefficient for moment resisting frames. Other types of steel construction would be associated with a natural period in between that of moment resisting concrete and the ‘other’ category. Concrete shear wall construction uses the same values as ‘other’. Building heights were sourced from OSM Buildings and converted to feet for use in the ASCE standards.



All observation-based modal frequencies fall within 41% of at least one estimate. Most observation values are higher than the estimates computed using Equation 4.1 and the variables in Table 4.3. This is likely due, at least in part, to the presence of shear walls, which Goel and Chopra (1997) and Goel and Chopra (1998) found contributed to stiffness for accelerations  $< 0.15\ g$  ( $1.47\ m/s^2$ ). As visible in Figures 4.6 - 4.12, all accelerations used in the analysis of real structures fall well below this threshold. The 8 story hotel and 3 story apartment building records give modal frequency measurements that are somewhat lower than the Camelo (2003) based values for wood framed buildings. The closest match between observed and estimated (3% difference in frequency) occurs for the 3 story hotel, which is within the anticipated error range of the measurement.

While most of our real-structure analysis focused on simple, rectangular framed buildings, we showed an example of an L-shaped 5 story apartment building, for which we obtained 3 measurements in 3 different earthquakes over the course of 4 months. These observation-based modal frequencies match best with the wood-based estimate. Additionally, it matches well with similarly shaped and sized wooden structures observed in Hafeez, Doudak, and McClure (2019). This suggests that in addition to repeated measurements, future observation-based values in regular and irregular structures could also be validated against existing measurements in published compilations, like the instrumented buildings in the CESMD (Center for Engineering Strong Motion Data) database, and targeted campaigns, such as described by Hafeez, Doudak, and McClure (2019) in their study of 41 wood-framed structures in Canada.

Furthermore, the relative consistency of the three measurements, despite differences in source and path effects of the input motion, validates the accuracy of phone-based measurements. In addition to any residual contributions from the different input ground motions, the observed 7% decrease in the frequency over four months (from 4.85 to 4.5 Hz) at low levels of shaking can be due to several reasons, including material cracking, disengagement of nonstructural elements, such as partition walls that can provide minor contributions to stiffness, foundation rocking, etc. This level of change in the natural frequencies under low levels of shaking has also been observed in buildings instrumented with conventional sensors (e.g., the California Strong Motion Instrumentation Program, CSMIP).

Kohler, Davis, and Safak (2005) monitored a well-instrumented 17 story steel-frame building in Los Angeles and observed that forced vibration measurements resulted in lower fundamental frequency results than ambient noise vibrations, even when the forced vibrations were small. This is attributed to soil-structure softening interactions, which resolved elastically in the hours after the forcing (wind or earthquake) were over. This suggests that the measurements made with MyShake, which are labeled as the response of a structure at full stiffness, may be underestimating the modal frequency as compared to the frequency in ambient conditions. However, because the MyShake catalog will be forced-vibration based, the bias will be systematic unless the phone noise drops so low that we can begin incorporating ambient observations. Furthermore, as the small-motion deviations are elastic, MyShake's observations are still appropriate to use as a 'healthy' benchmark against which observations made after potentially damaging shaking can be compared. The deviations

between fully ambient and light-force motion observations are small, on the order of 0.01-0.1 Hz in the Kohler, Davis, and Safak (2005) study, in comparison to much larger changes in the natural frequency that would be indicative of structural damage.

## 4.6 Conclusions

The ultimate goal of the MyShake SHM project is to begin compiling structural health information from real buildings using citizen science data collected through the MyShake app. We begin here with a proof of concept study, starting with a baseline validation that smartphone seismic data could be used for this purpose. Taking the characteristics of our smartphone network into account, we determine fundamental frequency to be the appropriate entry point into SHM. Due to the higher noise floor inherent to phones, we established that a small impulse would be required to excite a structure’s fundamental frequency enough to be measured. We therefore make measurements while buildings are vibrated by a shake table and in the coda of low intensity earthquake shaking (when damage is not expected).

In a controlled shake table test, we compared the results recorded by phones running MyShake and traditional high quality MEMs accelerometers and found good agreement between them, suggesting that smartphones are suitable for making these observations. In a set of seven real-world buildings for which MyShake collected a waveform, the extracted modal frequency fell within 40% of the model-based estimate for the structure based on ASCE standards (Table 4.4). These modeled estimates were necessarily simple due to the limited structural information known about the buildings, and perfect matches were not expected. Instead, we use this comparison to determine if a measurement is reasonable. Over time, an accumulation of measurements for a given building can be used to establish a more robust baseline for its structural health. As an example of this, we present one five story structure for which three measurements were made in the coda of three earthquakes over the course of four months (Figure 4.12). The modal frequency measured in each varies within 7% of the first, decreasing from 4.85 to 4.5 Hz over time. All fit fairly well with a similarly shaped structure assessed using traditional methods by Hafeez, Doudak, and McClure (2019). This example begins to set expectations for the accuracy of our measurements, inclusive of the slight structural softening that can sometimes accompany even low intensity shaking.

Over time, an accumulation of ‘healthy baseline’ response information will assist in setting reasonable thresholds for how much a measurement must deviate from baseline before we should consider that a smartphone modal frequency observation indicates structural damage. Traditional structural health monitoring, based on fixed high quality sensors, looks for the natural period of a building to permanently change by a factor of at least 1.5 times to correspond with significant structural weakening (Arici and Mosalam 2005; Clinton et al. 2006; Gao et al. 2021; Muin and Mosalam 2017). Based on the preliminary observations presented here, MyShake smartphones should be able to observe a change of this magnitude if there is a baseline observation on the natural period of a building before a quake, and then a second observation after the quake or from the coda of the quake.



In the long term, we envision developing a database of structural information for buildings, based on ‘healthy’ behavior observed during smaller vibrations. When a severe event occurs, MyShake observations from the tail of the earthquake or successive aftershocks could be used to compute comparative values for the same structures. This rapidly available, remote diagnostic could then be distributed to local engineering first responders to assist in prioritizing inspections of buildings to those with suspected damage. Structural health monitoring and emergency response are life-critical, but resource-limited endeavors. We are hopeful that the MyShake SHM project can contribute to a solution by providing low-cost, low-maintenance remote sensing observations.

# Chapter 5

## Conclusions

When the MyShake project first launched in 2016 with an Android app, smartphone data was largely untried in seismology. Since then, smartphones have only grown in their ubiquity and their hardware quality. MyShake is now a global network with thousands of active phones a day contributing data. With a growing trove of data, this dissertation has explored the capabilities and limitations of smartphone seismology, both in directly measuring earthquake motion and in providing a tool to evaluate the efficacy and efficiency of earthquake early warning.

### Alert Latency

While it was always intended that smartphones would deliver early warnings to the public, it was not known exactly how fast smartphone notifications were for rapid alerting. In time-stamping backend processes and requesting message receipts from phones, MyShake provides the first real-world measurements of early warning delivery latencies. After implementing efficiency improvements to parallelize a back end processing step, MyShake's latency has reached an average 5 second latency between alert creation and arrival on phones (Figure 5.1). Alerting has remained stably efficient even when the size of the alert region and the number of recipients has grown.

Using MyShake data, we can also evaluate alert effectiveness using two metrics; time between alert delivery and the start of shaking, and between delivery and peak shaking. The first is defined as time until estimated S-wave arrival, and the latter is derived using data from phones which returned both a message receipt and a waveform from which a peak acceleration could be picked. Even in the most challenging case, when a large portion of the alerted population was very close to the epicenter of the M 5.1 Alum Rock earthquake, alerts still reached over half of recipients before S-wave shaking began. In the modestly sized M 4.5 El Monte earthquake, 90% of users received 0-10 sec of warning before experiencing peak shaking.

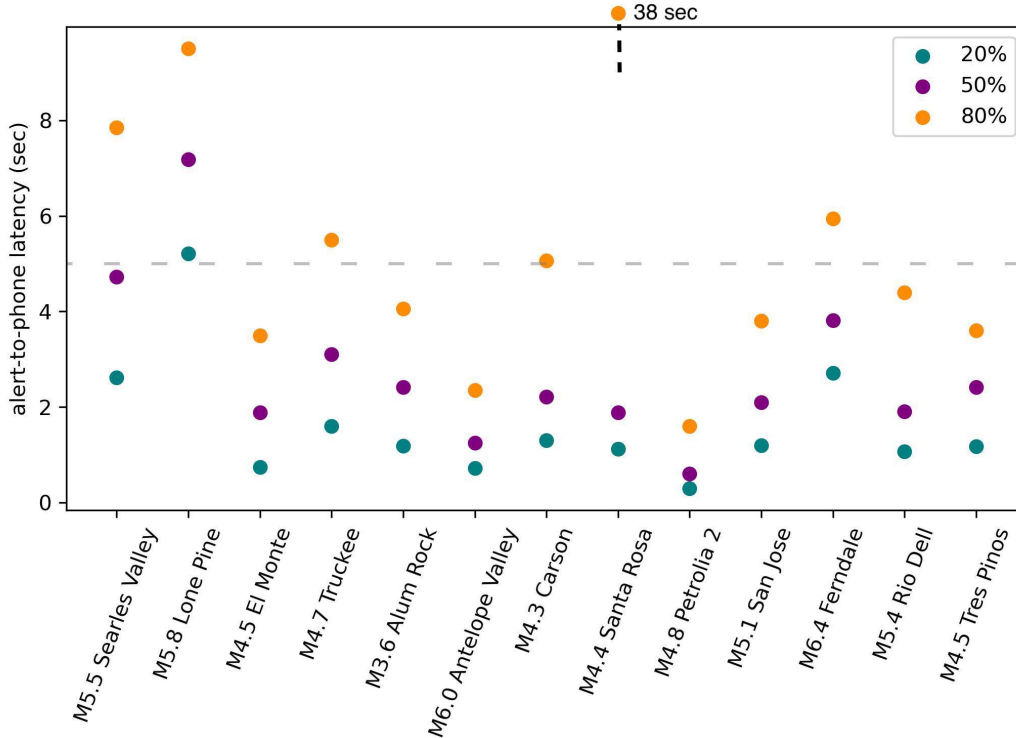
## Shaking Intensity

Waveform data can also be used to evaluate alerting area accuracy. ShakeAlert’s target is to send alerts to regions expected to experience MMI III shaking or stronger. The MyShake waveforms, however, show examples of stronger than expected shaking. A comparison of peak accelerations from five sample earthquakes finds MyShake waveforms tend to peak at accelerations 3.1 times the peaks of traditional stations at the same epicentral distance. This appears to be in part an effect of phones being located in buildings, which amplify shaking. Comparing MyShake peak values to a typical psuedospectral values, however, still leaves a 1.7x unexplained amplification factor. As phones are located where alert recipients are, they represent a realistic window into the user experience of early warning and can help guide future improvements to how alerting regions are designed. A more complete understanding of phone waveform amplification can be compiled by expanding the dataset to encompass earthquakes across a wider region and magnitude range.

## Contributing to Early Warning Generation

Closing the early warning loop, we also evaluate how MyShake’s real-time data collection could be used to augment the traditional station-based ShakeAlert earthquake early warning system. A retrospective analysis of past events which combines the triggering logs of MyShake phones and traditional stations provides examples of situations in which MyShake data could have contributed to faster alerts with comparable or better quality estimates of location. In general, it appears that the density of active phones required to provide helpful augmentation is of the same order of magnitude as traditional station density (essentially doubling the network); an ultra-dense phone network is not required. A live-running test version of ShakeAlert’s point-source algorithm, EPIC, ingesting MyShake triggers alongside traditional data, nets a few more examples of how phone data interacts. Critically, the addition of MyShake data does not degrade overall EPIC performance, despite coming from a lower quality source. Most solutions produced using a hybrid data feed were comparable in location estimate and speed to solutions produced with traditional data alone, and some solutions are notably better. The greatest gain in alerting speed observed was 6.5 seconds, representing a 29% reduction in the time between origin time and first alert when compared to the current ShakeAlert system using just traditional sensors.

Because MyShake presently transmits only discrete acceleration measurements in real-time, phone data could not contribute to magnitude estimation. Using waveform data, we explore different approaches that could be implemented. We integrate acceleration, both as-is and after dividing by the 3.1 amplification factor (to better simulate free field stations), to velocity and displacement and apply magnitude scaling relationships by Wurman, Allen, and Lombard (2007) and Kuyuk and Allen (2013), the latter of which is also used by EPIC. Initial results suggest that the process of integration reduces phone amplitudes such that dividing by the amplification factor first might be overcompensating; the magnitude estimates using pre-divided data tend to undershoot true magnitude, while the undivided data provides



**Figure 5.1:** 20th, 50th, and 80th percentiles for the alert delivery latencies for all events which delivered to at least 8,000 users since MyShake’s initial launch as an early warning delivery service. Latency is measured as the time between a ShakeAlert message arriving at MyShake’s backend for processing until phones logged an alert receipt. The dashed horizontal line represents the target 5 second latency. After a parallelizing process was implemented following the first two earthquakes, alert latency fell to 5 seconds or less for the majority of alerts, even as alert region size and number of recipients varied.

better estimates. Analysis of a larger data set representing a variety of magnitudes will be required to determine an optimal method for using phone data for magnitude, but a few improvements appear worth pursuing.

First, it is possible that the amplification factor, which is derived by comparing the peak amplitude of all three components of entire waveforms, is not representative of the amplification experience by phones during the P-wave detections largely in the vertical direction used for early warning. Re-deriving an amplification factor tuned to the P-wave may be better. Secondly, the process of integration introduces long-period artifacts even when low-pass filtering is applied beforehand. Therefore, it seems likely that using velocity, which requires integrating only once, will prove more reliable for magnitude estimation. Finally, it may be possible to both lower the STA/LTA threshold used for triggering and increase the first two seconds of peak amplitude sampling in order to increase the amount and speed of MyShake data that is contributed to real-time detection. Magnitude estimation will require

integrating phone accelerometer readings on the fly, which may be possible without too much additional load on phones if short ( $\sim 2$  sec) sampling windows are used.

## Structural Health Monitoring

In the final chapter, we found that earthquake vibrations can also be used to excite building resonance to a level detectable by phones, despite their high noise floor. Monitoring the fundamental frequency of buildings provides a valuable engineering window into structural health, but instrumenting real buildings is costly in time and manpower. User phones, being naturally located in buildings, provide a novel opportunity to collect observations of building response with very low overhead.

A shake table experiment comparing phone observations with those made by traditional sensors provides validation that despite their reduced quality, phones are capable of making high quality measurements of fundamental frequency. In real buildings, we use the coda of waveforms collected during earthquakes to capture the excited building response. A comparison to simple model-based estimates of natural frequency for these buildings validates that our measurements are reasonable. Repeat measurements, such as the example given in Figure 4.12, provide a route to measurement confirmation. When buildings are seriously damaged, their fundamental frequency reduces. With baseline knowledge of healthy behavior, measurements taken in the aftermath of a large earthquake could be used as a remote diagnostic of potential structural damage. In turn, this kind of information could be distributed to engineers on the ground to assist in prioritizing inspections when resources are limited.

## Into the Future

As the hardware quality on phones improves and the MyShake network grows, so too will the potential uses of MyShake data. Already, we are seeing how other forms of data collected by MyShake can supplement existing products based on traditional data. One example is the use of MyShake Experience Reports to map intensity similar to the USGS Did You Feel It product (Kong, Allen, Allen, et al. 2023). With a reduction in noise floor, MyShake data could potentially measure building responses using ambient noise or environmental forcing like wind. With improved real-time triggering functionality, MyShake could increase the quantity and quality of early warning triggers it contributes to a hybrid detection network. And with the proliferation of faster, higher data-volume cellular networks, alert delivery may become even faster.

While much of this work has focused on the use cases in the US, smartphone data also holds enormous potential to provide valuable seismic information in regions which cannot afford to build and maintain dense traditional networks. All told, MyShake illustrates the powerful synergy that is possible when providing a useful, educational public safety service to the public and using data contributions from the public to improve community safety and scientific knowledge.

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