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UNIVERSITY OF CALIFORNIA
RIVERSIDE

Combining Seismology and Geodesy to Better Constrain
Earthquake Source Parameters and Shallow Fault Behavior

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Geological Sciences

by

Nader Shakibay Senobari

March 2019

Dissertation Committee:

Dr. Gareth Funning, Chairperson
Dr. David D. Oglesby
Dr. Keith Richard-Dinger

The Dissertation of Nader Shakibay Senobari is approved:

Committee Chairperson

University of California, Riverside

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This thesis is dedicated to my love Ani. You are the reason that I breathe.

And to my son Adrian

And to my parents, Mostafa and Roghaieh, and my brother Ahmad

ABSTRACT OF THE DISSERTATION

Combining Seismology and Geodesy to Better Constrain Earthquake Source Parameters and Shallow Fault Behavior

by

Nader Shakibay Senobari

Doctor of Philosophy, Graduate Program in Geological Sciences
University of California, Riverside, March 2019
Dr. Gareth Funning, Chairperson

Our current understanding of the Earth's interior structure and processes is limited to observations made at the surface that are mapped to the subsurface using inverse methods. The complexity of geophysical inverse problems mainly arises from the existence of many free parameters that sometimes have traded off with each other. This can cause inaccuracies, low resolution and non-uniqueness problems in geophysical models. The main focus of my dissertation is on how we can use two independent geophysical data types – geodesy and seismology – to increase knowledge, resolution and accuracy of Earth's structure, and of interseismic and coseismic processes in the earthquake cycle.

For example, in my first project (Chapter 2) I search for repeating earthquakes (REs) using similarity search on recorded seismic waveforms from the northern San Francisco Bay Area. Evidence from the San Andreas fault and elsewhere indicates that REs are correlated with, and likely driven by, aseismic slip (creep) at depth. This is complementary knowledge to the geodetic observation of creep at the surface. The source information of REs can also be used to constrain the interseismic slip models inverted from geodetic data such as GPS and InSAR.

By using a new fast similarity search algorithm, that I developed specifically for probing big seismic data sets (described in Chapter 3), we found 198 RE groups, including periodic and nonperiodic repeating earthquake 'families', and repeating event pairs. Our results can not only help us to map the depth and extent of creep on several major faults but also reveal previously unknown structural complexity – e.g. that subparallel strands of the Maacama fault are active and creep simultaneously. Source parameters and locations of these REs can be used to update seismic hazard models, by better constraining the creeping areas of faults in the region, and to improve community models of fault geometry.

In a second major project (Chapter 4), I aim to reconcile earthquake source parameters and locations determined by long-period teleseismic source inversions with those obtained from InSAR data. The latter observes earthquakes in situ and thus, we presume, accurately locates them. Previous studies suggest that the discrepancies between these two catalogs arise from the existing inaccuracy in Earth models and are caused by the historic (and circular) problem that earthquake locations estimated using inaccurate velocity models are themselves inaccurate, and vice-versa.

In several case studies of various locations (e.g. California, Iceland, central Italy) we observe and quantify the biases of the S40RTS Earth velocity model that cause a delay or early arrival of the predicted seismic waves to the seismic stations at certain azimuths. We gather these mis-estimations of predicted seismic wave arrivals as corrections that can be applied to teleseismic source inversions in order to improve location accuracy. The similarity of corrections that we observe for events in the same region suggests they could be used as regional corrections. We also show that these corrections not only can be used to accurately locate global events but also can help us to accurately obtain the source mechanisms of these events. In future, by gathering these corrections for all the events with existing InSAR source models (i.e. more than 120 global events so far) we might be able to increase accuracy of velocity models of the upper mantle, e.g. by using finite-frequency tomography.

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Chapter 1

Introduction

1.1 Seismology and geodesy: complementary methods for studying the solid Earth

Geophysics is a broad field of Earth science that focuses on exploring Earth from all different aspects including its gravity, interior structure, magnetic field, and plate tectonics. Our current knowledge about Earth's physical processes and behavior mainly comes from two main sub-branches of geophysics – geodesy and seismology. While seismology deals mainly with elastic waves, their sources and propagation, geodesy is the study of the shape of the Earth (including changes in shape), its rotation and its gravity. Usually, these two fields are complementary to each other and each one usually covers a different aspect of Earth physics. For example, seismic data are a primary source of information about Earth's interior structure and processes while geodetic data are a primary source of information about near-surface behavior such as plate tectonic motions. As they deal with two independent sources of data, scientific discoveries that provide evidence from both of these datasets are usually more robust. For example, non-volcanic tremor (NVT) was first discovered by Obara (2002) but mainly became the center of attention after Rogers and Dragert (2003) discovered geodetic observations that were well correlated with the period of NVT activities in the Cascadia subduction zone. Combining geodesy

and seismology becomes more important when each lacks sufficient resolution or precision to capture all aspects of a process.

Tectonic geodesy and seismology overlap in different domains of geophysics but mainly they overlap around topics relating to the solid Earth, such as plate tectonics, fault behavior, and earthquake cycle (i.e. coseismic, postseismic and interseismic processes). The main focus of my dissertation is to combine data and methods from these two independent fields to study the coseismic and interseismic behavior of the earthquakes.

1.2 Seismic investigation of earthquakes

In geophysics, seismic data are a primary source of information about Earth's interior structure and processes. We define seismic data as any recorded motion (i.e. displacement, velocity, acceleration) measured using seismic instruments at the Earth's surface. This motion can be caused by earthquakes, volcanic activity, thunderstorms, wind, ocean waves, nuclear tests, landslides, the movements of glaciers, and more. Seismic data are versatile, but one of the most important applications is to detect and locate seismic events (earthquakes). Detected and located seismic events can be used for studying earthquake source processes and source physics, fault behavior and interactions, for determining Earth's velocity structure, and in general to constrain seismic hazard (e.g. UCERF3, Field et al., 2014). Other main application of seismic data is to study Earth structure from local scale (e.g. Zelt et al 1998) to global scale (e.g. Montagner and Tanimoto, 1991; Ritsema et al., 2011).

Along with the improvement of seismic instrumentation, reductions in cost, improvements in networking, data management and repositories, have resulted in a power law increase in seismic data volume (e.g. IRIS DMC, Hutko, et al., 2017) in recent decades. In this time a wealth of different techniques, methods and codes have been developed to detect earthquakes and invert for source location and source mechanism, each with its own strengths and weaknesses. These methods range from those applied to local data (e.g., Olson and Apsel, 1982; Hartzell and Heaton, 1983) to those that use global, or teleseismic data (e.g., Aki, 1966; Langston and

Helmberger 1975). Some methods are based on the time domain (e.g. Dziewonski et al., 1981) and others use the frequency domain (e.g., Kanamori and Given 1981; Romanowicz and Guillemant 1984).

In this dissertation, I use different types of seismic data for different purposes. In Chapters 2 and 3, where my focus is on repeating seismic signals in microseismicity, I mainly use archived local seismic data (i.e. distances closer than 100 km to the earthquake source location) with short periods (i.e. frequency bands of 1-15 Hz). This frequency band is appropriate to study events at low magnitudes ($M_w < 3$) which radiate most of their energy in that range. In contrast, in Chapter 4, where the focus is on moderate-to-large magnitude earthquakes ($M_w \geq 6$) located across the globe, I use archived global teleseismic data (i.e. from distances larger than 30 degrees from the earthquake source location) at long-periods (longer than 25 seconds) to study them. Data at such long periods effectively reduces earthquakes at the magnitude range of interest to point sources, simplifying the source modeling process. The earthquake source informations obtained can be used to improve earthquake hazard assessment at local and global scales, respectively.

1.3 Interferometric synthetic aperture radar and the earthquake cycle

Within months after the first European remote sensing satellite (ERS-1) successfully launched, geodesists could apply a technique called ‘Interferometric Synthetic Aperture Radar’ (InSAR) in order to process the remote sensing radar data it produced. This method allows researchers to measure ground displacement (with sub-centimeter precision) at fine spatial resolution ($< 100\text{m}$) covering areas 100 km-wide, or more (See Massonnet and Feigl, 1998, and Bürgmann et al., 2000, for comprehensive reviews). Fine spatial resolution and a high level of precision in this method provide a means of measuring Earth surface deformation resulting from individual earthquakes (i.e. coseismic surface deformation, Chapter 4) or, if more sophisticated time series

methods are used, the ongoing tectonic loading that occurs between large earthquakes (i.e. interseismic surface deformations, Chapter 2).

InSAR measures surface deformations directly and ‘in situ’, and therefore many of the source parameters that we obtain from InSAR data, notably the location of the earthquake source, are largely independent of assumptions (in contrast to seismology, where we typically assume Earth’s seismic velocity model in order to obtain locations). Through elastic dislocation modeling (e.g. Okada, 1985) the displacement fields measured by this method can be inverted in order to infer both interseismic (e.g. Schmidt et al., 2005) and coseismic slip at depth (Massonnet et al., 1993 ; Wright et al., 1999; Funning et al, 2005), and/or the geometry of the fault that slip occurred upon. Since the response of the displacement field to perturbations in many of these geometric parameters is non-linear, such inversions must be solved by optimization methods involving repeatedly calculating and adjusting forward models, and assessing their fit to the InSAR data.

1.4 Topics covered by this dissertation

In my first major project (Chapter 2), I compare and combine geodesy and seismology data to better constrain the depth and extent of aseismic fault slip (usually referred to ‘creep’; Wesson, 1988) in the northern San Francisco Bay area (hereafter “North Bay”), California. Creep plays a major role in seismic forecast programs as it can potentially reduce hazard (e.g., Wisely et al., 2008; Field et al., 2014). Creeping faults accumulate less elastic strain than faults that are locked; according to some models of rate-strengthening friction, they may also act as barriers to seismic rupture (e.g. Dieterich, 1978; Ruina, 1983). In addition to the role that they play in seismic hazard models, accurate mapping of creep at the surface and at depth is also important for investigating possible geological causes of creep, and in general the physics behind the spectrum of faults’ interseismic behaviors from full locking to full creep.

Geodetic models and observations of creep are well constrained near the surface, but as we move to deeper parts of the fault, we lose resolution (e.g. Chaussard et al., 2015). Therefore, the

accuracy of creep estimation can become limited if we rely only on geodetic data (e.g. Schmidt et al., 2005). For resolution at depth, seismic data may play an important role. It has been observed that some creeping faults produce a seismic signature – repeating earthquakes (REs; e.g. Ellsworth and Dietz, 1990; Nadeau and Johnson, 1998;). We define repeating earthquakes as sequences of events which are quasi-periodic in occurrence and almost identical in terms of their waveform and source characteristics. They are identified by examining the similarity of waveforms recorded at the same stations; a high degree of similarity (a high cross-correlation coefficient) implies that all the events in a RE sequence have the same source characteristics and the same location, and the seismic waves follow the same path. In almost all proposed mechanisms and physical models of REs, creep is the main controlling factor that allows the continual reloading to failure of RE sources (e.g. Nadeau and McEvilly 1999; Sammis and Rice, 2001; Anooshehpour and Brune, 2001; Beeler et al., 2001). The implication is that any detection of REs along a fault is a signature of the creep at depth on that fault. In addition, REs can be used for locating faults and determining their geometries at depth, studying time-dependent fault slip, investigating temporal change in velocity structure of the crust and in general for understanding the physics of earthquakes (e.g. Vidale et al., 1994, Anooshehpour and Brune, 2001, Chen and Lapusta, 2009).

Searching for REs is a time consuming and computationally expensive effort that requires a careful comparison of seismic waveforms from several stations on time spans several times longer than the REs' recurrence intervals. As our study area covers many faults and large areas with high seismicity rates, we developed and employed a new fast method, SEC-C (Super Efficient Cross-Correlation; described and demonstrated in Chapter 3) that accelerates the calculation by over one order of magnitude compared with other methods for pairwise similarity search, using a rapid calculation of the normalized cross-correlation coefficient in the frequency domain. The development of the SEC-C code became a significant research project in its own right, and the code is now published and available for use by the scientific community (Shakibay Senobari et al., 2018).

In this project, we show how using the complementary information from geodesy and seis-

mology can help us to find and constrain fault creep behavior. We find evidence for pervasive creep along several of the faults of the northern San Francisco Bay Area, and use the locations of REs to infer structural complexity of these faults, such as areas where subparallel strands of the Maacama fault are creeping simultaneously. In addition, we show how the recurrence and magnitude information from some RE sequences can be used to estimate creep rates at depth. This information can be used as inputs into future seismic hazard assessment models.

In my other major dissertation project (Chapter 4), I attempt to combine and reconcile results from seismology and geodesy to better constrain the source parameters of intermediate to large global earthquakes (e.g. $5.5 < M_w < 7.5$). Accurate knowledge of earthquake source parameters such as the locations of the hypocenter and centroid, the magnitude and mechanism play an important role in the response to potentially damaging earthquakes. Rapid natural disaster response programs such as the US Geological Survey (USGS) Prompt Assessment of Global Earthquakes for Response (PAGER) system estimate the potential damage using earthquake source parameters, as well as ground motion prediction equations and estimates of population density (Jaiswal et al., 2011). Such damage evaluations based on earthquake source parameters become even more important for remote areas with poor communications links, or where those links are disrupted by earthquake damage. For example, after the 2017 Mw 7.3 Iran–Iraq earthquake (e.g. Farahani, 2018) the roads and communications of several villages near the epicenter of the earthquake were destroyed, and there were no reports of the level of damage originating from within these villages, in some cases, for several days. In such cases, having the most accurate assessment possible of the likely ground shaking intensity, from the most accurate earthquake source models available, is important for managing and allocating resources in response to the event.

Accurate and timely knowledge of earthquake source parameters can also be used to estimate the likely severity of tsunami, the likely distribution of aftershocks, to calculate stress transfer to nearby faults, and hence provide short-term forecasts of the likelihood of triggered large earthquakes. Although rapid estimation of earthquake source parameters is important, there are major problems with rapid earthquake models. The most commonly used rapid earth-

quake models, such as those produced by the Global Centroid Moment Tensor (GCMT) project, are often inaccurate in location and depth, often by tens of kilometers, and this can reduce their usefulness for short-term hazard forecasting (Weston et al., 2011 and 2012).

On the other hand, earthquake source models determined by geodetic data such as Interferometric synthetic aperture radar (InSAR) are typically more accurate as they use direct, in situ measurements of surface displacement (e.g. Talebian et al., 2004). Unfortunately, the number of earthquakes for which we have InSAR data is low, compared with the number of earthquakes recorded seismically. Also, the process of earthquake centroid moment tensor inversion (i.e. solving for the location and mechanism of the event) using InSAR data is time-consuming, due to both the time taken in acquiring the data, data processing and also the inversion process itself. Combined, these can take from several days to several weeks, depending on the satellite coverage available and the complexity of the event.

As we mentioned above, geodesy and seismology typically provide complementary information for geophysical problems. In the specific case considered here, earthquake models derived from seismology are fast and versatile (i.e. applicable to any large event globally) but suffer from inaccuracies, particularly in location. Conversely, geodetic models are more accurate but data may not be available in a timely manner for use in earthquake response. Here we evaluate the possibilities of the use of geodesy data as a means of accurately locating earthquakes, and then using these accurate locations to estimate biases in the velocity models used to locate earthquakes seismically. In so doing, we hope to use new and upcoming satellite missions, such as Sentinel-1 and ALOS-2 (and in future, NISAR), to improve our ability to respond to devastating earthquakes.

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Chapter 2

Repeating earthquakes detected by a new fast method reveal complex creep behaviour in the northern San Francisco Bay Area

Abstract

We develop a method to detect repeating earthquake (REs) for regions where seismic networks are sparse, such as the northern San Francisco Bay area (hereafter 'North Bay'). Our method is carefully and purposely developed to eliminate false negatives and false positives as much as possible. By using this method, we found 198 RE groups, including periodic and nonperiodic repeating 'families' and repeating event pairs. If we assume that REs are indicators for fault creep, our results can not only help us to map the depth and extent of creep on several major faults, but also reveal previously unknown structural complexity – e.g., subparallel strands of the Maacama fault creep simultaneously. Source parameters and locations of these REs can be used to update seismic hazard models, by better constraining the areas and rates of creep on faults in the region, and to improve community models of fault geometry.

2.1 Introduction

2.1.1 Repeating earthquake definition and importance

Repeating earthquakes (REs) are defined as sequences of events that are identical with regard to waveforms recorded at common stations (e.g., Poupinet et al., 1984; Ellsworth and Dietz, 1990; Vidale et al., 1994; Nadeau et al., 1995). As the waveform of an earthquake is a function of source characteristics and the receiver location, the extreme similarity of waveforms is a signature that events of a RE family have the same source characteristics and the same location. It is been observed that these REs recur either irregularly (aperiodic REs) or nearly regularly (quasi-periodic REs) with recurrence interval from months to years (e.g., Nadeau and Johnson, 1998 ; Igarashi et al., 2003). Earthquakes, in general, are comprised of a very complicated system of behaviors that involve numerous parameters that can affect the time, location, size, and mechanism. The regular behavior of REs requires an initial condition that will repeat over time. This situation is only possible if the source of these earthquakes is isolated from the complexity and variability of this system. One plausible and mostly accepted model among seismologists is that the sources of these REs are small locked patches that are surrounded by a stable system (creep) that can load these patches regularly over time (Ellsworth and Dietz, 1990; Nadeau and Johnson, 1998; Schaff et al., 1998; Nadeau and McEvilly, 1999; Igarashi et al., 2003; Schaff and Beroza, 2004; Chen et al., 2007). Most repeating earthquakes that have been found were detected in areas of creep that support this hypothesis (e.g. Nadeau et al., 1995; Matsuzawa et al., 2002; Chen et al., 2008). Additionally, simulations support that small locked patches surrounded by creep is a viable physical setup for regenerating REs (Chen and Lapusta, 2009, 2010; Richards-Dinger and Dieterich, 2012).

The implication is that any detection of characteristic REs at a given depth on a fault implies there is creep nearby at similar depths on that fault. Therefore they can be treated as virtual creep meters at depth for studying time-dependent deep fault slip (Schaff et al., 1998; Nadeau and McEvily, 2004; Templeton et al., 2008; Chen et al., 2009). They are also have been used

to constrain interseismic slip models of transform faults (e.g., Schmidt et al., 2005) and also subduction zones (Igarashi et al., 2003). Beside mapping creep and measuring slip rates at depth, they have also been used in seismology as a tool for monitoring changes in the velocity structure of the crust either after a large earthquake (e.g., Chen et al., 2011) or without (e.g., Poupinet 1984) and exploring seismic station clock errors (e.g. Rubin, 2002).

One main importance of REs with respect to regular seismic events is that they bring a new important parameter to the earthquake complex physics and faults behavior – i.e., the recurrence interval. This extra knowledge has made them a focus of several studies related to earthquake physics and simulations (Vidale et al., 1994, Anooshepoor and Brune, 2001, Chen and Lapusta, 2009). Chen et al. (2007) discussed a possible universal rule between the empirical relationship between the magnitudes of REs and their recurrence intervals, an idea introduced by Nadeau et al. (1998).

2.1.2 Creep and seismic hazard

As mentioned above, one foremost importance of REs that they have been used to study fault creep at depth. Creep is continuous or episodic aseismic slip on a fault. In contrast to locked areas where strain accumulates for long periods of time and most slip occurs instantaneously (stick-slip behavior), creeping areas accumulate strain at a reduced rate (if at all), and fault-separated blocks slip past each other slowly. Whether a fault is locked or creeps is governed by frictional and material properties of the rocks involved, the stress field and the parameters of fault rheology (Hetland et al., 2010). Potential earthquake seismic moment is a function of accumulated slip deficit and the potential fault rupture area, a product of its length and width. Aseismic creep reduces both of these parameters and therefore reduces the potential size of an earthquake.

2.1.2.1 The effect of creep on strain accumulation

Fault slip can be considered as a spectrum between two end-member states. On one side there is stick-slip behavior, where faults are locked for the whole interseismic phase and accumulate

a slip (moment) deficit and elastic strain at a fault's long-term slip rate. On the other is fully creeping behavior where a fault creeps at its long term slip rate, and no elastic strain is accumulated. Most creeping faults lie somewhere in between, creeping at a rate that is slower than the long-term slip rate (e.g. Wisely et al., 2008). Thus while a slip deficit and elastic strain still accumulate in such a scenario, the amount is less than there would be if the fault were fully locked, and therefore we would expect that the fault would sustain smaller earthquakes. The current Uniform California Earthquake Hazard Forecast (UCERF3; Field et al., 2013) deals with this effect by applying a 'coupling coefficient', that represents the amount of slip accommodated aseismically, and therefore reduces moment accumulation on the fault by the same proportion. This formulation requires accurate information on the depth dependence of creep, for which RE locations are a primary source (e.g. Weldon et al., 2013).

2.1.2.2 The effect of creep on earthquake propagation and nucleation

Fault creep can be successfully modeled using rate-strengthening friction (Dieterich, 1979, 1994; Ruina, 1983; Rice and Ruina, 1983; Beeler, 1996). Areas of faults with rate-strengthening friction can act as a barrier for earthquake rupture propagation as frictional strength will increase at seismic slip speeds (e.g. Lozos et al., 2015); this effect is implemented in UCERF3 by the inclusion of an 'aseismicity factor' related to the area of the fault undergoing aseismic creep, and that therefore will not sustain seismic rupture (Field et al., 2013). In addition to the reduced likelihood of rupture propagation, earthquake nucleation is also suppressed by rate-strengthening friction, placing constraints on the distribution of future earthquake hypocenters, and thus on the potential directivity of future earthquakes. Therefore, developing a more accurate knowledge of the extent of creep on major faults should significantly improve future seismic-hazard forecasting and scenario rupture modeling.

2.1.3 Methods for measuring creep

Aseismic fault creep is mainly measured at the surface by a number of independent methods, e.g. field observations, alignment arrays, creepmeters, strain meters, and can be estimated

at depth by using elastic dislocation models or boundary element models (e.g. Savage and Lisowski, 1993, Simpson et al., 2001). More recently, geodetic data, such as InSAR and GPS have been used to constrain these models (e.g. Bürgmann et al., 2000; Funning et al., 2007; Tong et al., 2013). Although geodetic measurements are very sensitive to shallow creep, the slip inferred from elastic dislocation modeling of geodetic data is not resolved well at depth (e.g. Page et al., 2009) and also the results are sensitive to several uncertain fault and crust parameters, in particular, the fault geometry. In addition to this issue, these models require good spatiotemporal coverage from geodetic data, which is not always available or possible.

2.1.4 Motivation and overview

In this study, we use archived seismic data as to search for REs and therefore determining possible creeping sections of the faults of the northern San Francisco Bay Area (hereafter, ‘North Bay’) including the Rodgers Creek, Maacama, Bartlett Springs, Concord-Green Valley, West Napa and Greenville faults, each of which has shown some surface creeping behavior along some part of their traces (e.g. Galehouse and Lienkaemper, 2003; Funning et al., 2007; McFarland et al., 2015; Floyd et al., 2016; Jin and Funning, 2017). We then use the REs’ source parameters (e.g. location, moment and stress drop) to provide new constraints on the locations and rates of creep at depth for these faults. The major fault systems in the area are thought to be capable of destructive earthquakes that could threaten local and regional populations (e.g. Field et al., 2014), and our knowledge of the details of fault movement and strain accumulation for each is far less certain than for analogous structures further south in California. Most recently, the West Napa fault, the source of the M6.0 2014 South Napa earthquake, showed rapid and laterally extensive shallow creep in the month that followed in amounts, in some areas that equaled the maximum coseismic surface slip (e.g. Hudnut et al., 2014; Floyd et al., 2016). The South Napa event served as a reminder that partially-creeping faults present an ongoing seismic hazard, and that the creep – which caused repeat damage to some lifelines repaired in the immediate aftermath of the earthquake – can pose a hazard in its own right.

In addition, because REs originate on the fault plane (unlike ordinary earthquakes that may or may not occur on the fault plane), they can be used for locating faults and determining their geometries at depth. Before, as RE searches typically required comprehensive effort and were limited to areas with good station coverage, they were targeted at the known creeping faults.

Here beside all other applications of REs, we use REs as a tool for exploratory mapping of active fault strands in this region.

As mentioned above, searching for REs usually is a vigorous effort that requires a careful comparison of seismic waveforms from several stations on time spans several times longer than the REs' recurrence intervals. This can be challenging work and depends on many instrumental, technical and logistical variables that can be easily affected by false dismissals (i.e. true REs that were not initially detected and whose waveforms were thus not retained) or false positives (e.g. nearby, but not identical, events with similar focal mechanisms that may have very similar waveforms at far-field stations). These variables range from seismic network-based problems such as station coverage, noise and operational time span, or can be technical problems such as the Cross-Correlation Coefficient (CCC) threshold used for detection or the specific frequency ranges used as bandpass filters.

These challenging detection problems, along with being a computationally expensive procedure, have, in the past, limited RE search efforts to small study areas or limited numbers of target faults or fault segments (e.g. Nadeau et al., 1995; Matsuzawa et al., 2002; Uchida et al., 2003; Igarashi et al., 2003; Chen et al., 2008). Here by using a range of different techniques such as: automated retrieval and pre-processing of seismic data, using a fast pairwise CCC calculator, clustering events for each individual station, re-clustering events using hierarchical techniques by combining multi-station clusters, calculating S-P time based on the cross-spectral method and using these S-P times to precisely relocated the RE candidates, we could systematically search for REs in a larger study area as mentioned above.

2.2 Data

2.2.1 Data selection and retrieval

We divide the North Bay study area into 16 subregions, on average 30×50 km in dimension, each centered on a fault of interest (Figure 2.1). We base our subregion selection on the number of events within an area; for reasons of computational efficiency we aim for 6000 events or fewer per subregion. We allow for overlap of up to 10 km between subregions to ensure no repeating event families were missed at the edges. We then retrieve event and station information from the Northern California Earthquake Data Center (NCEDC) for the events within each subregion at the stations located inside these subregions and at distances up to 60 km outside their edges.

We include a station in our event search if two criteria are met: i) it has a duration of operation longer than 10 years; ii) it has detected over 100 events or more in the target subregion. For subregions with good station coverage (e.g. >150 stations with 100 detected events or more) we raise these thresholds to 15 years and 500 events, respectively. Our final station selections for each subregion range from a minimum of 10 stations to a maximum of 104, with the southernmost subregions typically covered by the greatest numbers of stations.

Considering each subregion in turn and using phase arrival information from the Northern California Seismic Network (NCSN) catalog, we retrieve 20 seconds of waveform data from the NCEDC archive for each detected event at each station, starting 5 seconds before the P arrival and 15 seconds after. We use `IrisFetch.m`¹ for this data retrieval. This window size is based on the small sizes (i.e. $< M_p$ 4; M_p is the preferred NCSN catalog magnitude), and therefore short durations of the events, and the short event-station distances (i.e. < 100 km), such that we expect both the P- and S-arrivals to occur within it. Note that earthquakes with M_p larger than 4 are rare in our search area.

¹ <https://ds.iris.edu/ds/nodes/dmc/software/downloads/irisFetch.m/>

2.2.2 Data quality control and preprocessing

After data retrieval, we band-pass filter each waveform between 1 and 15 Hz, a frequency range that spans most of the energy release of the regional microseismicity (e.g. Waldhauser and Schaff, 2008). Next, we check all the data for each individual station for changes in sample rate, resampling all the waveforms to the minimum sample rate during the operation time or 100 Hz, whichever is larger. We also check for gaps in the data – gaps less than 5 seconds in duration are filled with zeros; we discard waveforms with gaps greater than 5 seconds. Finally, we cut a window of 10 seconds duration starting at the catalog P-wave pick time to be used for waveform cross-correlation purposes.

2.3 Method

2.3.1 Traditional methods of detection of repeating earthquakes

The most common and traditional method for detecting REs is by computing pairwise cross-correlation coefficients (CCCs) of individual event waveforms for a targeted region (e.g. Nadeau et al., 1995; Matsuzawa et al., 2002; Uchida et al., 2003; Igarashi et al., 2003; Chen et al., 2008). The CCC is a measure of similarity between pairs of waveforms, with values ranging from -1 to 1. The values of 1, 0 and -1 indicate identical waveforms, completely dissimilar waveforms and identical waveforms except for reversed polarity, respectively. In practice, waveform noise can perturb RE waveforms, mean that pairs of RE have CCC values somewhat lower than 1. By defining an appropriate CCC threshold, events that are highly similar at several stations (e.g. Nadeau et al., 1995; Matsuzawa et al., 2002; Uchida et al., 2003; Igarashi et al., 2003; Chen et al., 2008), and thus are candidates to be REs, can be identified.

In general, there are two main challenges for detecting REs using CCC thresholding: i) False positives, i.e. incorrectly classifying groups of events as REs. This can result from a loss of diagnostic features in event waveforms due to attenuation or filtering – e.g. closely spaced, but not identical, events detected at distant stations can have high CCCs (e.g. Schaff and Walhouser,

2005), and be incorrectly associated as REs. In such cases, defining a high CCC threshold, using higher frequency bandpass filters or excluding stations based upon distance might be a way to decrease false positives. ii) False negatives, i.e. incorrectly classifying REs as not repeating events. This can result from perturbations to waveforms, for example from station noise, temporal changes in the crust (e.g. Poupinet et al., 1984, Schaff et al., 2004), and/or differences in rupture propagation from event to event. These issues can be mitigated through defining a lower CCC threshold or using a lower frequency bandpass filter. Given that the solutions to the two challenges are, in effect, opposites, care must be taken in the selection of CCC thresholds, and, ideally, additional information should be used in the RE selection process rather than the operator's opinion.

Another issue with this traditional method is that we need a minimum of several stations (e.g. at least two; Uchida et al., 2003) with long periods of operation, each of which includes all the events of an RE family. This might be a possible approach for areas with good station coverage, a long instrument operation time and good quality of data such as Parkfield (Nadeau et al., 1995; N. This becomes a problem for a region with a sparse seismic network and a changing station configuration over time (i.e. station operation time does not cover several events of an RE sequence, see Figure 2.2).

Another approach for detecting REs is by using precise earthquake locations and considering that RE sequences are generated at the same fault patch. In this case, we would classify events as REs if the rupture areas of a pair of events overlap by some percentage (e.g., 50 percent; Waldhauser and Ellsworth, 2000). One possible source of error in this procedure is that nearby events will influence the location of REs. These errors come from this fact that the CCC values of intermediate distances (i.e. distances that produces $0.5 < \text{CCC} < 0.8$ between pairs; Schaff et al., 2004) events are respectively low and therefore the relative timing cannot be precisely measured (Schaff and Waldhauser 2005). Another source of error in relocation catalogs are the event origin time errors and timing inconsistencies among station clocks (e.g. Rubin 2002; Chen et al., 2008). On the other hand, searching for REs based on relocated seismicity requires the precise relocating of all events – potentially a large and unnecessary effort if the only goal is the

detection of REs.

To address both the challenges of false positives and negatives in RE detection, as well as the computational demand required to relocate events, we adopt a multi-stage approach in this study explained below.

2.3.2 Identifying repeating earthquake families through a multi-stage procedure

We use a multi-stage approach to detect potential RE families. First, we systematically cross-correlate waveforms from different earthquakes at common stations using a pairwise approach and assemble groups of events with high cross-correlation coefficients (CCCs) into single station clusters. Next, we compare the results for groups of similar events at multiple stations, in order to obtain more robust, multi-station clusters. After these initial filtering steps, we then apply three additional detection steps to discriminate between events that have similar locations, and events that are truly repeating: i) hierarchical clustering on the basis of CCCs at multiple stations; ii) measuring differential S–P arrival times at multiple stations in order to estimate hypocentral separation; and iii) estimating relative hypocentral locations using the HypoDD code.

2.3.2.1 Identifying high cross-correlation event clusters at each station

For each station, in turn, we start by calculating the CCC for each pair of events within each applicable subregion, and grouping similar events together. We employ a new fast method, SEC-C (Super Efficient Cross-Correlation; Shakibay Senobari et al., 2018; chapter 3) that accelerates the calculation by over one order of magnitude compared with other methods for pairwise similarity search, using a rapid calculation of the normalized CCC in the frequency domain. We group together events with high CCCs into clusters, setting a minimum CCC threshold of 0.9. We cluster events for each station based on this rule that for each event waveform there would be at least one another event that has CCC value of more than 0.9 in that cluster. Note that at this stage this threshold is designed to exclude dissimilar events, rather than definitively select repeating events.

2.3.2.2 Producing multi-station clusters

We next merge all the clusters for different stations if they share a single event to make multi-station clusters (MSCs) for each subregion. Each event pair in an MSC has a CCC of 0.9 or greater on at least one station. We then make a three-dimensional matrix of CCC values for each MSC. This $n \times n \times m$ matrix, where n is the number of events in the cluster and m is the number of stations, is populated with the CCCs for each event pair for all detecting stations for a single MSC. Note that not every event in a MSC was detected by every station; in those cases, the corresponding elements of the matrix are assigned a null value.

In the next step, we make a $n \times n$ matrix of averaged CCC values for each event pair from the $n \times n \times m$ matrix for each MSC by taking the average for the six highest CCCs along the station dimension (m). If fewer than six stations detected an individual event pair, we take the average for all available detecting stations, so long as there are at least three. We call the resulting matrix the ‘average CCC matrix’ for a given MSC. Example of waveforms from such a cluster are shown in Figure 2.2.

2.3.2.3 Identifying repeating earthquake candidates through hierarchical clustering

As explained above, relying on a high CCC threshold alone to detect REs can be problematic. Therefore, we employ an RE selection method that makes use of hierarchical clustering of average CCCs for each event pair (Figure 2.3). Another main importance of using a hierarchical clustering approach is that we can clearly observe the similarity of an RE family with itself and with nearby seismicity.

We use the hierarchical clustering algorithm linkage and the plotting routine dendrogram in MATLAB to produce dendrograms – tree diagrams showing the hierarchy of similarity between events in a cluster based on average CCC values – and plot them for each average CCC matrix, using a graphical user interface (GUI) that also provides magnitude and event time information for each event cluster (Figure 2.3). Using this GUI at the same time we check for CCC values between sequences, magnitude, origin time and also the CCC values with nearby stations. Note

that however, we chose 0.9 for CCC threshold for single station clustering but for the average matrix sometimes the minimum average CCC values can be as low as 0.7. This is because two events are in the same cluster if they have CCC above 0.9 in at least one station that sometime can be a relatively far distance station, while the average CCC averages the CCCs from several stations. This becomes problematic as there might be too many events in each cluster to check visually. As mentioned above, keeping these low CCC connections is used for observing the similarity of RE sequences with each other and also nearby events. In those cases where each cluster based on average CCCs contains many events (and therefore maybe contains many sub-clusters as well) making visual inspection impractical, we break the major cluster into smaller, minor clusters simply by disconnecting the linkage between them. We do this by applying a high CC threshold (e.g. 0.85, 0.9 or 0.95, based on the size of the main cluster). The lowest CCC threshold for the visualization inspecting is 0.8. In most cases using the 0.8 of CCC threshold, RE family candidates become disconnected from nearby events (Figure 2.3). Based on these plots, we classify event clusters (or subsets of events in those clusters) into four groups:

1. Robust repeating earthquake candidates. These consist of three or more events with high average CCC (typically >0.95), quasi-periodic recurrence intervals, and similar magnitudes.
2. Anemic repeating earthquake candidates. These consist of three or more events that either do not have obvious periodic recurrences, but have a high CCC (>0.9) or have a lower CCC but do have a clear periodic recurrence. We also consider the similarity between magnitudes as a deciding factor to categorize the candidate families. For example if the magnitude differences between a pair of sequences in a family were more than 0.5 we categorize them as anemic RE candidates.
3. Repeating earthquake pair candidates. These are pairs of earthquakes with an interevent time of more than 3 yrs, and with high CC (>0.95). We do not know if these events are part of an RE sequence in which some events were either not detected or have yet to occur, or if they are simply an earthquake source that repeated only once.
4. Nonrepeating earthquakes. These are groups of events that are similar, on the basis of high CCC, but not similar enough (e.g. 0.85-0.92) to be considered repeating earthquake

sequences. Typically, we expect that these are earthquakes whose hypocentral locations are close in space, but not close enough that they have overlapping source radii. If they did not form isolated clusters with respect to near similar events or had very short temporal recurrence intervals (i.e. many events within a day or week that did not recur again), we assign them to this category.

Using these procedures, we reduce false negative detections as we consider RE recurrence intervals, magnitude, cluster isolation, and CCC at the same time without defining a rigid CCC threshold.

Note that at this level we used a qualitative method for detection rather than solid quantitative detections based on conservative CCC thresholding and human visualization. As we mentioned above our main focus in this level was to have minimum number of false negatives. Next, we remove the false positives quantitatively using the procedures described below.

2.3.3 Confirming RE candidates, removing false positives

2.3.3.1 Relocating REs based on differential S-P times and HypoDD

In order to confirm that REs are coming from the same source region on a fault or not (i.e. to check if we get false positives) we apply a check on event similarity, based on similarity of location. Our approach is based on that of Waldhauser and Ellsworth (2000), that considers that REs can be identified if they share at least 50% of their source regions, estimated by their double-difference relocations. As all of the RE candidate magnitudes are relatively small (i.e. $< M_p 3$ and mostly between $M_p 1-2$), and as most of our study region has sparse station coverage, we came to the conclusion that regular relocating based on the approach of Waldhauser and co-authors might not be precise enough for our case as the error in station clocks might play an important role on detecting REs. In order to avoid station timing errors (e.g., Rubin, 2000), clock inconsistencies and to account for any errors in event original times, we adopted the approach of Chen et al. (2008), where S-P time is used for relocating seismic events instead of

direct P and S phase arrival picks. In this method, the relative time for P and S are derived from S-P time and an assumed S to P ratio as below:

$$tt_p = \frac{S_m P}{((V_p/V_s) - 1)} \quad (2.1)$$

$$tt_s = \frac{-S_m P}{(1 - (V_s/V_p))} \quad (2.2)$$

Here $S_m P$ is S-P time. For more information about this method see Chen et al., 2008.

In order to use EQ1 and EQ2 for relative relocations of our RE candidates using the HYPODD code (Waldhauser and Ellsworth, 2000) we need to have a precise estimate of differential S-P times with high enough precision for relocating small events (e.g. of the order of milliseconds for M_p of 1). Data from NCSN stations (Figure 2.1), mostly have sample rates of 100 samples/sec. This sample rate allows for a 0.01 second precision time lag calculation using the time domain cross-correlation function. This degree of precision is inadequate for resolving the source separation that we require, which is of the order of 10 meters. Here we test three different methods for upsampling seismic waveforms.

We tested two time-domain methods – spline interpolation of the waveforms with a sample spacing of 0.001 s (e.g. Chen et al., 2008), and fitting a polynomial function to the cross-correlation function in the vicinity of its peak, and finding its maximum (e.g. Schaff et al., 2004). For a third method, we measured P-wave, S-wave and S–P travel time differences using the cross-spectral method of Poupinet et al. (1984). The delay times were estimated from the phases of cross spectra in a frequency band of 1–20 Hz with squared coherency of greater than 0.88, at a precision of 0.001 s (See Figure 2.4). All of the methods tried can determine S–P times at the desired level of precision; we prefer the cross-spectral technique since based on our tests it seems time domain methods underestimate the lag times respect to the cross-spectral method (fig 3) and also cross spectral technique avoids errors from interpolation and curve fitting.

In order to calculate precise differential S–P times for a pair of events using the cross-spectral method, we first select 1 s time windows around the P and S arrival phases in each waveform.

If the S-wave onset is unclear, we use a 1 s time window centered on the peak of S-wave energy (Schaff et al., 2004). The process of picking P- and S-wave arrivals is based on visual inspection, however, we use two different methods to help the user pick the arrivals or the centroids of the P- and S-waves – one that uses the event location with respect to the station and an assumed average velocity model to predict arrival times, and the other that applies a moving cross-correlation of a 1-second window. For the latter, the CCC of windows containing the P or S arrivals is typically higher than the values obtained for their codas. These two tools are very useful for choosing appropriate windows for cross-spectral analysis, especially for the S-wave arrivals that, in some cases, are not visually pickable.

We next use the HYPODD code (Waldhauser and Ellsworth, 2000) and the methodology of Chen et al. (2008) to estimate precise relative locations for our candidate RE families. In this procedure, we use the precise S-P times, as estimated above, as well as the 1D velocity model provided for this area at the HYPO2000 ftp website ². We then perform the double-difference relocation procedure for both robust and anemic candidate families (Figure 2.5). We relocated each family separately to ignore inaccuracies arising from low CCC values. Note that in our relocation procedure there are no human picked phase arrivals, and it is just based on precise relative S-P times, estimated independently of station clocks (Figure 2.6).

Based on the double-difference relative locations and errors and also considering the circular crack model of Eshelby (1957) as a means of estimating rupture area, we classify our RE candidate families into three categories:

i) Good: HypoDD converged, produced no errors, the relocation results have uncertainties less than the estimated source radii for the events, and each RE sequence source overlapped with at least one other's rupture area by more than 50% (e.g. Waldhauser and Ellsworth, 2000). Hereafter we refer to these REs as CCpH REs(confirmed by both CC plus HypoDD filters)

ii) Bad: Same as above but sources were separated, such that their rupture areas did not overlap by more than 50

iii) Ugly: We could not produce stable HYPODD results either because there were insufficient

² <ftp://ehzftp.wr.usgs.gov/klein/hypfiles/multmod4.hyp>, last accessed July 2018

links for the events such that the inversion became unstable, or because the location uncertainties were large due to limited or unfavorable station coverage. For the cases with large location uncertainties, in most cases the greatest uncertainties were in depth, due to having relatively distant stations or bad azimuthal coverage. Note that to obtain the best constraints on depth, nearby stations (e.g. <10 km) are the most important. However, if the number of links is large the effect of not having direct stations above the events might become less critical. Hereafter we refer to these REs as CCO REs (confirmed only by their high CC between their pairs)

In general, it is possible that CCO RE candidates could be ‘true’ RE families but based on the limited numbers of recorded waveforms for most of these events, there is no robust way of confirming this.

2.3.3.2 Confirming RE pair candidates using location filtering

As we cannot use HYPODD to relocate only two events, we use another location-based filter in this case. Instead, we measure differences in S–P times (Poupinet et al., 1984, Schaff et al., 2004, Chen et al., 2008, Uchida et al., 2007). S–P time is a function of source location and if we find identical S–P times for two events at stations with a variety of azimuths, we can say that the events originated at the same location. We can relax this constraint a little to include a maximum difference in S–P time that is related to the estimated rupture size of an event, such that events with differential S–P times less than that maximum had significant overlap in their rupture areas.

To use these differential time estimates in detection, we next must determine an appropriate threshold, based on the source dimension. We estimate this for each event pair assuming a back azimuth of 45° from the line connecting their epicenters, a V_p/V_s ratio of 1.72, the regional seismic velocity model, the circular crack model of Eshelby (1957) and an assumed stress drop of 3.0 MPa. For a M2.0 event, the threshold time is 0.008 s. Two examples, for RE families sequences and RE pairs, are shown in Figure 2.7 and Figure 2.5A. We find that for more than 73 percent of our single-pair RE candidates the S–P difference times are lower than the threshold

for all the stations, consistent with their being repeating events. We confirmed these candidates as true RE pairs if the threshold is satisfied by all of the stations.

2.3.4 Result statistics

In total we selected 120 RE candidate families and 118 RE candidate pairs, based on CCC thresholding and clustering. Of these, 36 were robust candidate families, from which we confirmed 25 CCpH families, 11 CCO families. We did not find bad families for our robust candidates, indicating that our initial detection criteria based on hierarchical clustering for this category were effective. For the anemic candidates, out of 84 families, 34, 37 and 13 were respectively CCpH, CCO, bad and repeated. Using our S-P time location filter for our RE candidate pairs, we confirmed 91 RE single pair repeaters out of 118 candidates; 27 pairs did not pass the location filter.

Overall, then we find 59 RE families and 118 RE pairs. These are distributed along three major creeping faults in the region, the Maacama, Rodgers Creek and Bartlett Springs faults that have been observed to be creeping at the surface least in some segments, as we shall discuss in section 4 below (See Figures 2.8 and 2.9).

2.3.5 Creep rates estimated from RE recurrence intervals and magnitudes

The magnitudes and recurrence intervals of RE sequences have been used to estimate deep slip rate in many tectonic settings (e.g. Nadeau and McEvilly, 1999; Bürgmann et al., 2000; Matsuzawa et al., 2002; Uchida et al., 2003; Turner et al., 2013). Almost all of these studies make use of an empirical relation between the seismic moment (M_0) of REs and the surrounding aseismic fault slip (d_i) developed by Nadeau and Johnson (1998):

$$d_i = 10^\alpha M_0^\beta \quad (2.3)$$

The main motivation behind this equation was the observation of both time and slip predictable behavior (i.e. characteristic earthquake behavior) for 53 RE families on the creeping

segment of the San Andreas fault near Parkfield. Nadeau and Johnson observed a good linear fit to the cumulative moment and time of recurring events and calibrated this empirical relationship against the creep rate model of Harris and Segal (1987). They also discussed that this could be calibrated by long-term loading rate, however, this would be an upper bound as the cumulative slip of RE sequences may not release all the accumulated strain from tectonic loading.

The values for α and β that they reported for the Parkfield region were $\sim 2.35 \pm 0.2$ and 0.17 ± 0.001 , respectively. These values have been used for all different tectonic setting to either directly estimate the creep rate at depth or constraining the creep rate models driven by geodetic data (e.g. Igarashi et al., 2003; Schmidt et al., 2005).

Here we used the same Nadeau and Johnson (1998) equation and values for α and β to estimate creep rate at depth from our detected REs (Figure 2.10). We also used the empirical relationship $\log(M_0) = 1.6M_p + 15.8$ of Wyss et al, (2004) to convert local catalog magnitudes to moment.

In using this relationship with our results, care must be taken to account as the recurrence interval for our detected RE families in this region is long (i.e. mean of 7.3 years). Long recurrence interval could be expected for our results based on two main reasons: i) Creep rate in this region is lower than in the Parkfield region, at least based on geodetic surface observations (McFarland et al, 2015; Jin and Funning, 2017), and ii) sparse station coverage in this region results in a higher magnitude of completeness and therefore our detected RE magnitudes are relatively larger compared to the Parkfield region. Considering the 32 year time span of our search (i.e. 1984 to 2016), most of our RE families only have 3 or 4 detected events. If there is temporal clustering of events within an RE family, the estimated creep rates might be significantly biased to faster rates. Nadeau and Johnson (1998) mentioned that such clustering for their cases produced 20% deviation from the mean. As eq 3 is intended to describe a time and slip predictable model, we only apply it to REs whose recurrences had a coefficient of variation (COV) less than 0.4. In the North Bay, 61% of CCpH RE families and 54% of CCO families had a COV less than 0.4.

Fig 10 shows the creep rate estimated from our detected REs with COV less than 0.4. For most of our detected REs, we observe that the creep rates we estimate for these REs based on Eq 3, are similar among closely located RE families. This indicates that our results, in general, are robust for creep rate estimation purposes. However the creep rates that we estimate for the faults in this region using the calibration of Nadeau and Johnson (1998), are 3-4 times greater than creep rates estimated by geodetic measurements (2-8 mm/yr; e.g. McFarland et al., 2015; Murray et al., 2014; Jin and Funning, 2017). Some of the creep rates estimated this way exceed the loading rate estimated for these faults, such as the Bartlett Springs fault at Lake Pillsbury that we estimate 18 mm/yr while estimated geodetic creep rate is 7.7 ± 2.4 mm/yr (Murray et al., 2014). We attribute these discrepancies to the calibration of eq 3, which was calibrated based on REs in the Parkfield region. This calibration might not apply for other regions, which potentially have different fault properties and different loading rates. On the other hand, Chen et al, (2007) showed that the slope of Nadeau and Johnson's relationship between the recurrence interval variation and the moment of REs could be universal, but the intercept may be different for different tectonic settings, and possibly due to differences in the tectonic loading rates.

Here we adopted the suggestion of Chen et al (2007) and calibrate the value of α in eq 3 using a shallow RE family (1.4 km depth; Waldhauser and Schaff (2008) and the shallow creep rate (2 mm/yr) of Jin and Funning (2017) for the Rodgers Creek fault near the epicenter of this RE. The recalibrated creep rates using this procedure are shown in Figure 2.8. Although these creep rates are calibrated using a single RE family on only one fault in the North Bay region, our results agree well with those of McFarland et al, (2015) and Murray et al (2014) for the other nearby faults in these region. We describe the distributions of REs and the creep rates derived from them for each fault in greater detail below.

2.4 Results

Our RE family and pair locations along the three major creeping faults in the region, the Maacama, Rodgers Creek and Bartlett Springs faults are plotted, along with double-difference relocated seismicity (Waldhauser and Schaff, 2008) in cross-section view in Figures 2.8 and 2.9. In the following sections, we will describe these RE locations and the creep rates estimated using their recurrence intervals and magnitudes in greater detail.

2.4.1 Maacama fault

The Maacama fault shows the greatest amount of RE activity of the faults in the region. The along-strike cross-section (profile S1-T1; Figures 2.8 and 2.9), which includes both RE locations and the double-difference relocated seismicity shows that REs are pervasive along the fault. The maximum depth of REs increases, gradually, from south to north, from 5 km near Cloverdale, to 11 km NW of Willits. The majority of these RE families and pairs occur within a prominent band, or ‘streak’ in the relocated seismicity, which also increases in depth along-strike to the northwest. Such streaks of microearthquakes have been identified and associated with creep on other faults (e.g. Rubin et al., 1999).

The density of REs is greater than the average in a couple of areas along the Maacama fault – on the northern part of the fault in the vicinity of Willits (profiles A2-B2 and A3-B3; Figures 2.8 and 2.9) and on the southernmost part of the fault, extending NW from Cloverdale (profiles A5-B5, A6-B6 and A7-B7; Figures 2.8 and 2.9). In these locations, REs are present at shallower depths, as well as located along the ‘microseismic streak’ downdip. In both cases, RE locations are organized into two distinct individual down-dip trends in cross-section. We will describe these in more detail below.

At Willits, the deepest REs are aligned with the NE-dipping trend of microearthquakes that have previously been attributed to the $\sim 60^\circ$ -dipping main surface of the Maacama fault (e.g. Waldhauser and Ellsworth, 2000; profiles A1-B1 to A3-B3; Figure 2.9), suggesting that this structure could be creeping in the depth range 7–10 km. More intriguingly, the shallower REs

in the area, located at depths of 1–5 km, are organized into a subvertical trend that projects to the surface 5 km NE of the main Maacama surface trace, suggesting that there is a subvertical shallow splay fault at this location that may also be creeping (profile A3-B3; Figure 2.9).

This putative shallow subvertical splay at Willits projects to the location of a prominent Quaternary fault scarp on the east side of Little Lake Valley (the name given to the valley containing the city of Willits). This structure, which was covered as part of the GeoEarthScope Northern California LiDAR campaign in 2007 (data set downloadable from <http://opentopo.sdsc.edu/datasetMetadata?otCollectionID=OT.052008.32610.1>), is variously referred to as the ‘East Willits fault’ (e.g. Prentice et al., 2014) or the ‘East Valley fault’ (e.g. Woolace, 2005), and was recognized at least as early as the 1970s (e.g. Simon et al., 1978). Here, for the first time (to our knowledge), we observe a signature of creep in this fault. There may be some support for this idea from previous studies. Murray et al, (2014) reported a discrepancy between their geodetic creep models (9.9 mm/yr) and a nearby alignment array (5.7 mm/yr; McFarland et al., 2015) for this segment of the Maacama fault. Their suggested explanation for this discrepancy was that the alignment array can only capture the surface deformation at the main strand of the Maacama fault, while other active strands such as the East Willits fault might accommodate the additional estimated creep. Intriguingly, the creep rate we estimate for the East Willits fault based on REs detected in this segment is 3-4 mm/yr (profile A3-B3; Figures 2.8 and 2.9) potentially explaining the discrepancy described above.

The second area of structural complexity, in the vicinity of the city of Cloverdale, close to the southern end of the Maacama fault, shows two subparallel dipping structures picked out by RE locations and microseismicity in the 1-7 km depth range, approximately 2–3 km apart (profiles A5-B5 to A7-B7; Figures 2.8 and 2.9). The eastern of the two structures aligns with the mapped Holocene Maacama fault trace at the surface. It is not clear if the western structure has a surface expression, however, there are late Pleistocene and/or undated Quaternary structures mapped in the vicinity (USGS and CGS, 2006). To our knowledge, this is the first evidence that there are two currently active fault segments in this area, and that both are creeping at shallow depths.

Most of the REs whose locations could not be constrained by using S-P difference time and

HypoDD are located on the Maacama fault between Ukiah and Willits, likely an effect of the sparsity of stations in this region (Figure 2.8). The sparsity of seismic network in this region not only affects our ability to relocate REs but also potentially affects the detection of events in the catalog. This may also explain why this segment of the fault has the highest number of aperiodic RE families in this region. Indeed, many of our aperiodic RE families could potentially be RE families that are missing some undetected events.

2.4.2 Rodgers Creek fault

RE activity on the Rodgers Creek fault is almost entirely focused on the segment of the fault NW of the city of Santa Rosa (profiles A8-B8 and A9-B9; Figures 2.1 and 2.6). The same segment has been identified as creeping at the surface at rates of 2–6 mm/yr on the basis of persistent scatterer InSAR data (Funning et al., 2007; Jin and Funning, 2017); these estimates, based upon line-of-sight velocity offsets from fault-perpendicular profiles are only sensitive to creep within the top 2 km of the fault. In contrast, REs within this segment are distributed across a depth range of 2–7 km (e.g. profile A9-B9; Figure 2.9), implying that the creep extends through those depths. The REs define a fault plane that dips steeply ($\sim 80^\circ$) to the NE. In general, there is a good agreement between the along-strike distribution of REs and the along-strike distribution of shallow creep as inferred from InSAR (Jin and Funning, 2017).

RE families detected in this segment of Rodgers Creek fault are the most periodic families in our search area and they are also well constrained by HypoDD (Figure 2.8). This is possibly because of two factors: i) better seismic network coverage with respect to other areas, and ii) the simplicity of the fault segment. Based on our detected REs and background relocated seismicity, the creeping segment of the Rodgers Creek fault is single main strand without the complexities in geometry that we find on other creeping fault segments. We suspect that the creep behavior is less complex and more periodic as a result. While in a complex sub parallel faults the creep is distributed between sub parallel strands and may switch on and off or show more complex behavior.

Our estimated creep rates for this segment of the Rodgers Creek fault are in the range of 2-3 mm/yr, within error of the shallow creep rate estimated from InSAR data (Jin and Funning, 2017), and do not increase significantly with depth (profile S3-T3, Figures 2.8 and 2.9).

2.4.3 Bartlett Springs fault

We identify REs across a wide range of depths (between 1 and 15 km) on the central Bartlett Springs fault, in a zone extending around 20 km NW of Lake Pillsbury (profiles S2-T2 and A4-B4; Figure 2.9). This is a location where both alignment array data and GPS data are consistent with surface creep at around 3–4 mm/yr (e.g. Murray et al., 2014; McFarland et al., 2016). The creep rate that we estimate based on one shallow periodic event in this segment is around 3 mm/yr. This indicates a good agreement with surface deformation measurements.

The distribution of REs implies that creep could be occurring across the full seismogenic width of the fault along this zone that is in agreement with Murray et al., 2014 argument that this segment of Bartlett Springs is possibly creeping on whole seismogenic zone. One other observation that Murray et al., (2014) was made based on their geodetic model of GPS data in this zone that creep rate below 5 km increases to the deep slip rate. Our creep estimation based on REs for four deep (i.e. 10-15 km) RE families is around 5-6 mm/yr, which is almost twice the creep rate estimated for shallow part.

Elsewhere along the fault, the RE families and pairs are more diffuse, making it difficult to make definite statements on the distribution of creep in these areas.

2.4.4 Other faults

We identify four RE groups – two RE pairs and two RE families (one periodic and one non periodic) – on the West Napa fault, source fault of the 2014 M6.0 South Napa earthquake. The periodic family, composed of three repeating events (in 1995, 2000 and 2005) is located on the Browns Valley segment of the fault, 4 km NW of the northern end of the 2014 earthquake rupture zone (e.g. Floyd et al., 2016) and at 6 km depth. We also estimate creep rate of 4.5 mm/yr for this family. The 2014 earthquake showed abundant shallow aseismic afterslip, in-

cluding slip on the southern portion of the Browns Valley segment, however no previous studies had identified any interseismic creep on the West Napa fault (e.g. Funning et al., 2007). The identification of repeating events on the West Napa fault suggests that portions of it may have been creeping prior to the 2014 event, albeit at a rate and depth that may not be detectable at the surface using geodetic data.

2.4.5 Temporal behavior

In order to identify any possible correlations in RE behavior in time, we plot the temporal history of the RE families along the three major faults in Figure 2.9, sorted by their positions along strike. We do not see any obvious synchronicity between sequences, implying that they are not triggered by nearby larger earthquakes (e.g. the 2014 South Napa event), or by transient aseismic slip on any of the major faults.

2.5 Summary

Using a semi automated and multistage algorithm that we specifically developed for detecting REs in regions with sparse network such as our targeted area, we detect 107 RE families and 91 RE pairs in North Bay area. In order to detect REs we divide the North Bay region into 16 large subregions. Although our subregions cover most of the North Bay, we only detect REs near the known active faults. Our results show that some parts of the northern and southern Maacama fault in this region might have subparallel strands that are actively creeping. The detected RE locations along the Rodgers Creek fault corroborate the surface creep signal observed in persistent scatterer InSAR data from previous studies.

We recalibrated the empirical relationship between creep rate and RE magnitude and recurrence interval using a shallow RE family and an estimate of the shallow creep rate from InSAR data. Our creep rates estimated by this method are broadly in agreement with creep rates reported in other studies that measure creep using geodetic data such as InSAR, alignment arrays and GPS for the Rodgers Creek, Maacama and Bartlett Springs faults.

Although we use the full potential of the existing seismic network in this area, our detection results might have biases in the areas that have better station coverage. We suspect that there might be RE sequences whose events were not detected by the NCSN catalog and therefore have not been detected by our method. We think by improving the network coverage in this region and also by using template matching with continuous data we could find many more REs in future. Our method can be used for detecting in any other regions with sparse seismic networks. As our method is less prone to false negatives and false positives, our method also can be used for regions with excellent network coverage such as Parkfield, CA in order to test if we can detect more events.

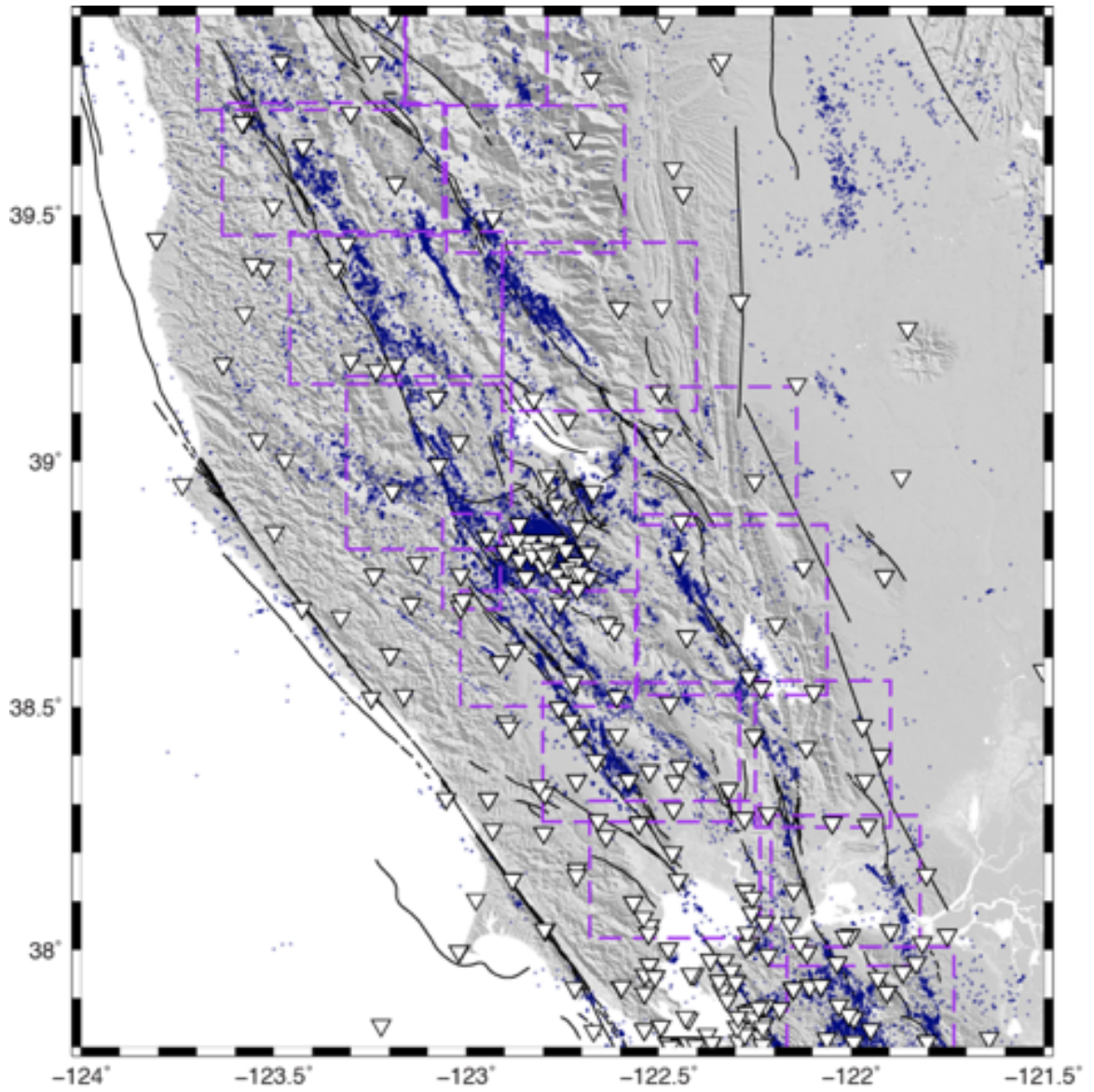


Figure 2.1: Seismic stations and earthquake subregions used in data selection. Over 43,000 events (dark blue circles) in 16 subregions (purple dashed boxes), detected at over 300 stations (white triangles) were used.

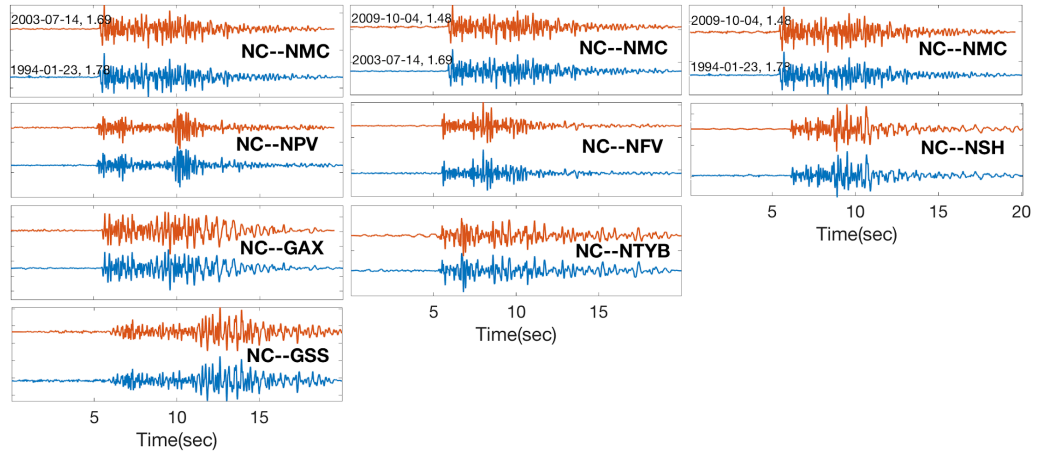


Figure 2.2: Pairwise waveform illustration of an example of a detected RE family on Rodgers Creek fault near north of Santa Rosa, CA. In this family, we detect three sequences occurring in 1994, 2003 and 2009 with local magnitudes of 1.78, 1.69 and 1.48, respectively. For this example, we can see that if we use traditional methods that rely on detecting RE sequences on three or more common stations we were not able to detect this sequence as there is only one qualified station (e.g. not too close and not too far, good signal to noise ratio; in this case NMC station) that recorded all 3 events. Our approach here, however, is a pairwise oriented detection method that links an event to a family if it pairs with other sequences in the family at three or more stations. For this example, the 2009 event pairs with the 2003 and the 1994 events five times at four different stations. (Note that there were more pair detections for the 1994 and 2003 events and for the sake of illustration we show only four stations.)

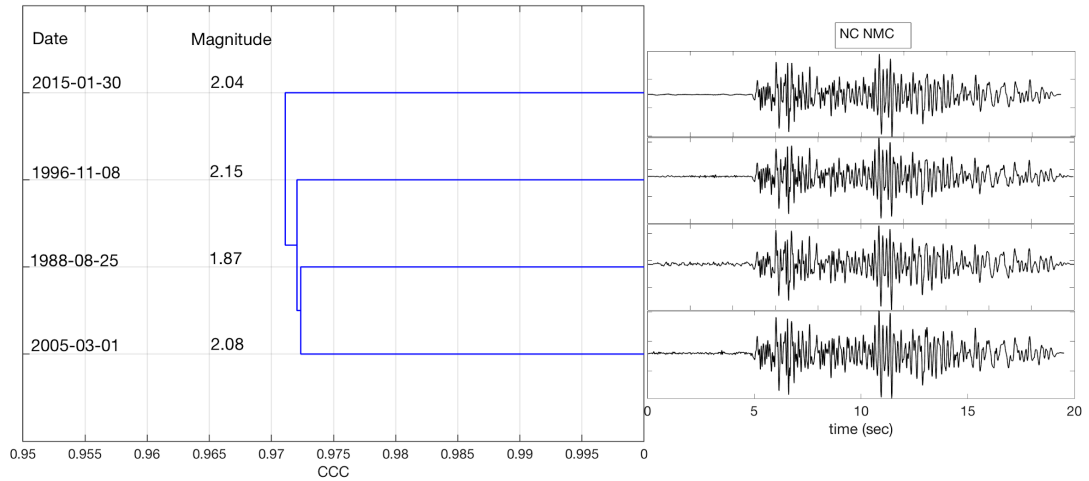


Figure 2.3: Hierarchical dendrogram demonstration for an RE family detected in central Macamma fault, northeast of Cloverdale, CA and correspondent seismic waveforms recorded at NMC station. Using hierarchical visualization we observe that the similarity between family sequences from the average CCC matrix is more than 0.97. This RE family is not connected to any nearby events, meaning that there were no other similar events to this family above our the CCC threshold of 0.8.

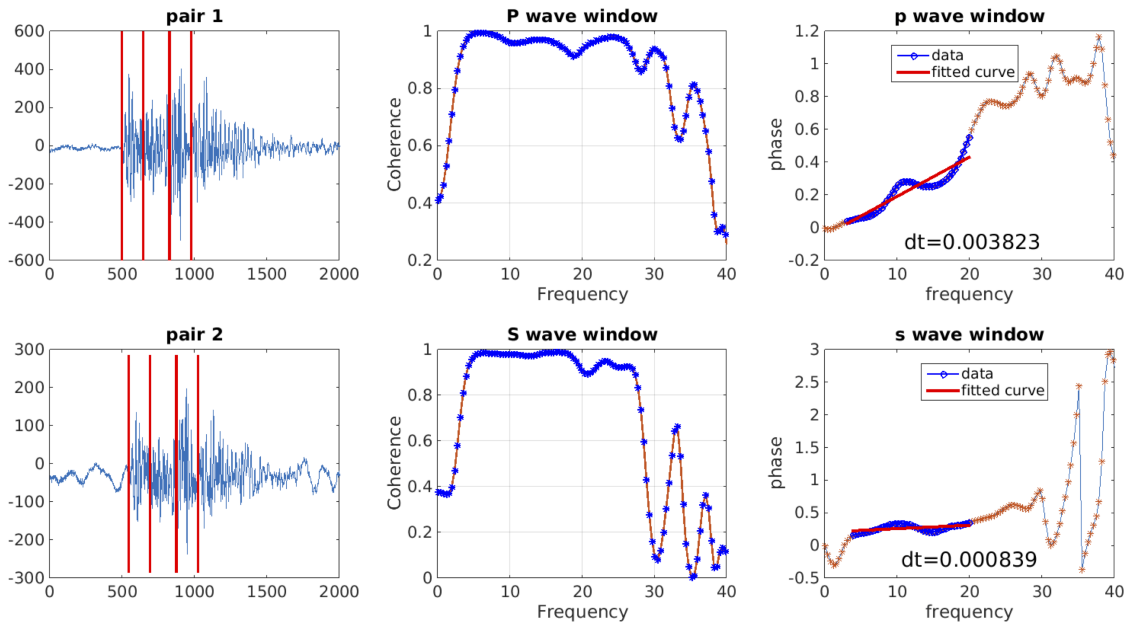


Figure 2.4: The Cross-Spectral approach of estimating relative S-P time for a pair of event waveforms. In this approach we choose one-second window starting with P- wave and a second window starting at the S- arrival or centered on the maximum S-wave amplitude if the S- arrival was not clear (e.g. Schaff 2004) for both events. We then estimate the delay time for both P and S waves based on calculating the best-fitted slope of the phase of the cross-spectrum plot versus frequency (third panel) for the points with coherency above 88% (middle panel). For more information about seismic delay time estimation based on the cross-spectral method see Poupinet et al. (1984) and also Fremont and Malone (1987). We then take the difference between relative P and S delay times as the S-P difference time for this pair – in this case, 0.003 seconds.

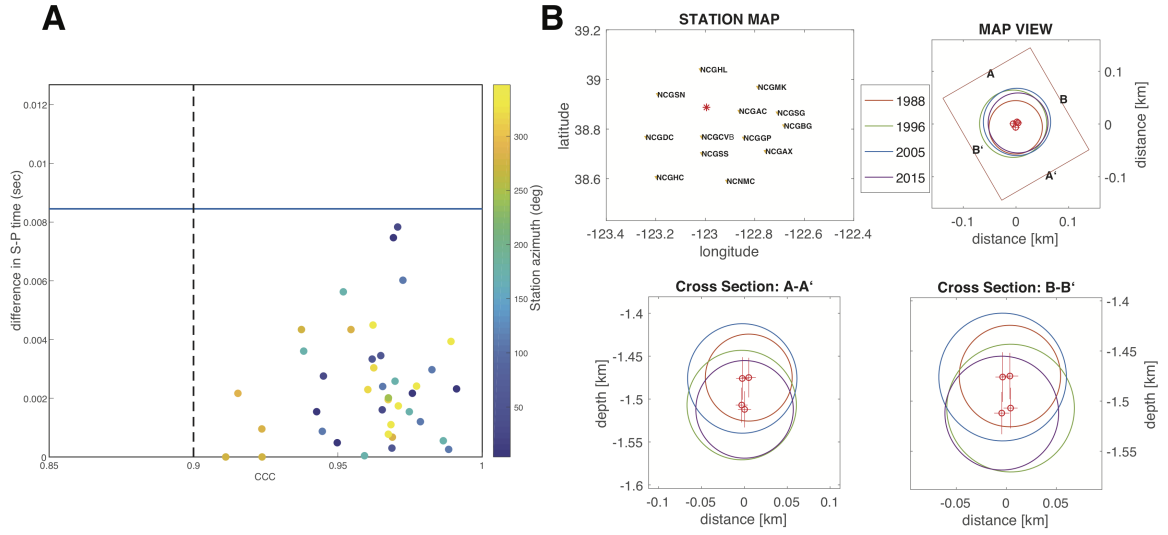


Figure 2.5: A) Same as Figure 2.7 for the example described in Figure 2.3. The S-P time is calculated by the cross-spectrum method (see Figure 2.4) and for all stations distributed in different azimuths for each event pairs. B) Relative location for the same RE family after running HypoDD code. Red crosses and event-based color-coded circles indicate the errors of event locations and the dimensions corresponding to their magnitude assuming a 3 MPa constant stress drop source (e.g. Eshelby 1957). We convert S-P times shown in (A) to relative P and S travel times using the method of Chen et al. (2009). Note that as we are only interested in validating our RE candidates using their relative locations, we did not use any picked phases. and therefore the absolute locations are not accurate. For RE candidate validation we used (B) as a filter and for RE pair candidates we use the results shown in A as a location filter as it was not possible to relocate a pair of events.

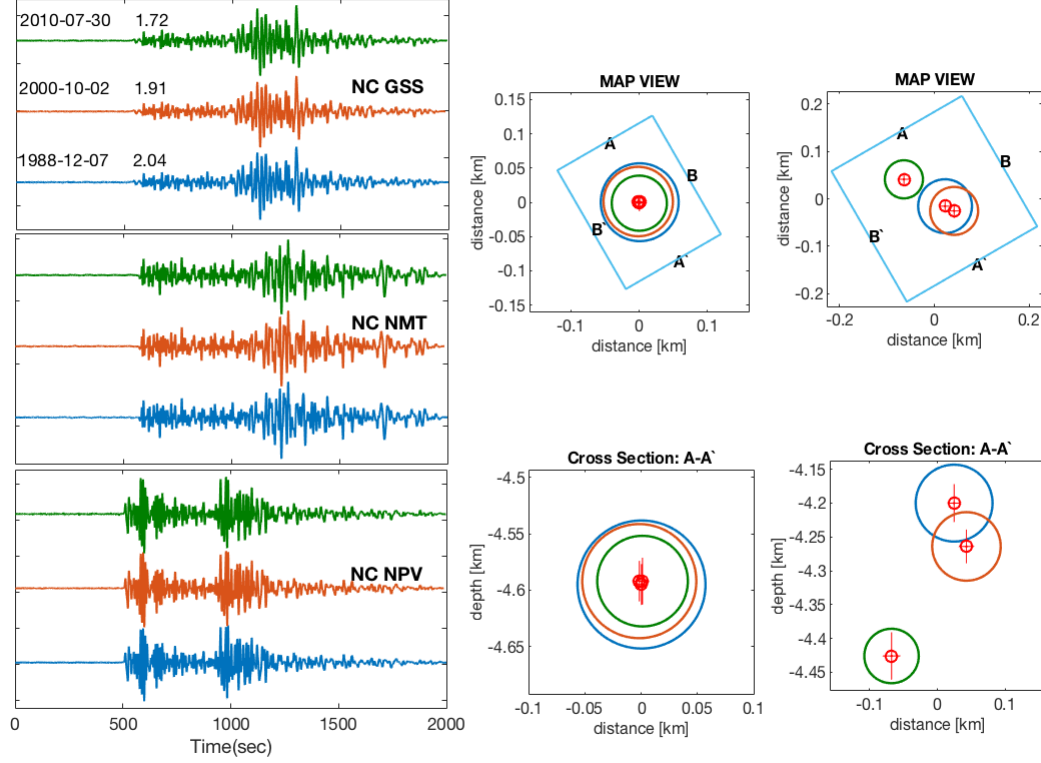


Figure 2.6: Waveforms recorded at 3 common stations (left) and relative location calculated based on our method (middle) and relative locations extracted from the Northern California double-difference earthquake catalog (Waldhauser and Schaff, 2008; right) for one example of detected REs on the Rodgers Creek fault northwest of Santa Rosa. This example was recorded on several common stations with very high-quality data (i.e. high signal to noise ratio) and therefore the waveforms have very high CCCs with each other (see Figure 2.7). Relative locations are only shown for map view and along-strike profile of Rodgers Creek fault. Although the sequences are extremely similar on common stations, we observe a mislocation error in the catalog (especially for the 2010 event). This is not a surprise as we only used relative location but the catalog takes the picked P and S waves into account, and also includes correlations with nearby events as well. We suspect that the 2010 mislocation may have resulted from network evolution over time. This is not the case for the majority of our detected REs, however. In almost 70 percent of cases where RE events were included in the catalog, relative locations from the catalog were in agreement with our results. We also observed the disagreement is geographically dependent. The catalog event relative locations were more similar to ours in the southern part of our study region (e.g. the Rodgers Creek fault) rather than the northern part (e.g. northern Maacama), perhaps resulting from the fast evolution of the seismic network in the southern part.

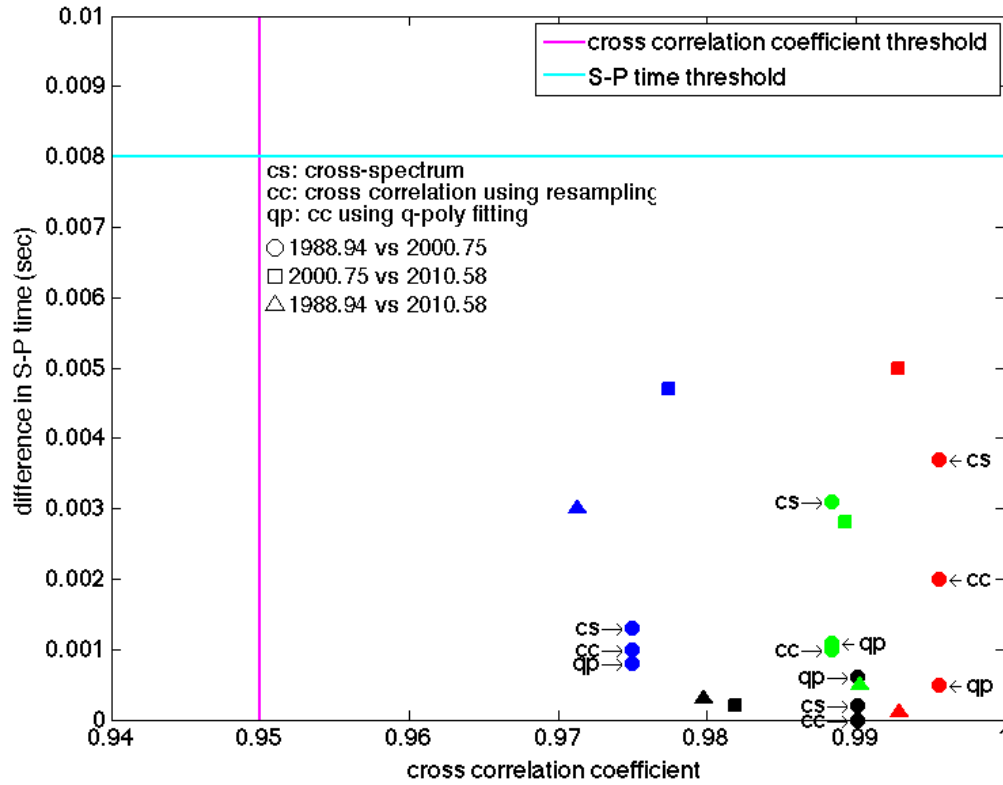


Figure 2.7: S–P time differences for all of the event pairs in a RE sequence (Figure 2.6). Results are color-coded by station (4 stations are shown). Here, we show that our CC coefficient for all pairs and all stations is greater than 0.97, exceeding the detection threshold value of 0.95 (e.g. Nadeau and Johnson, 1998; Chen et al., 2008). Based on the magnitudes of these events, and assuming a backazimuth of 45° , a stress drop of 3.0 MPa, and the velocity model of Eberhart-Phillips (1986), we determined that 0.008 s is the maximum SP time difference that is indicative of a shared source. For event pair 1988.94–2000.75 we also show results from three different estimation methods, cross-spectral (cs), cross-correlation for interpolated waveforms (cc), and fitting a quadratic polynomial to the cross-correlation function (qp). For all of the pairs, methods and stations shown here, the S–P time difference is less than 0.006 s, implying that the earthquakes all share the same source region of the Rodgers Creek fault.

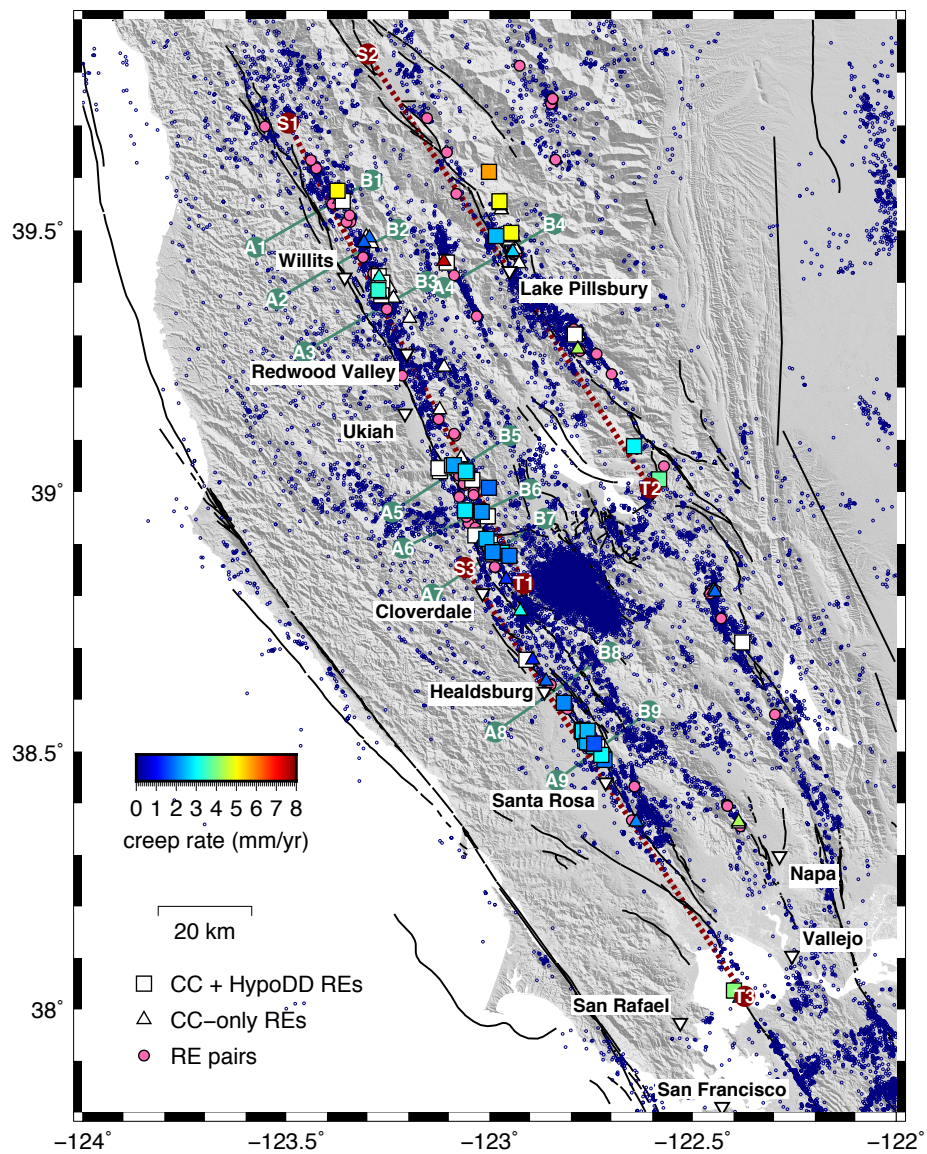
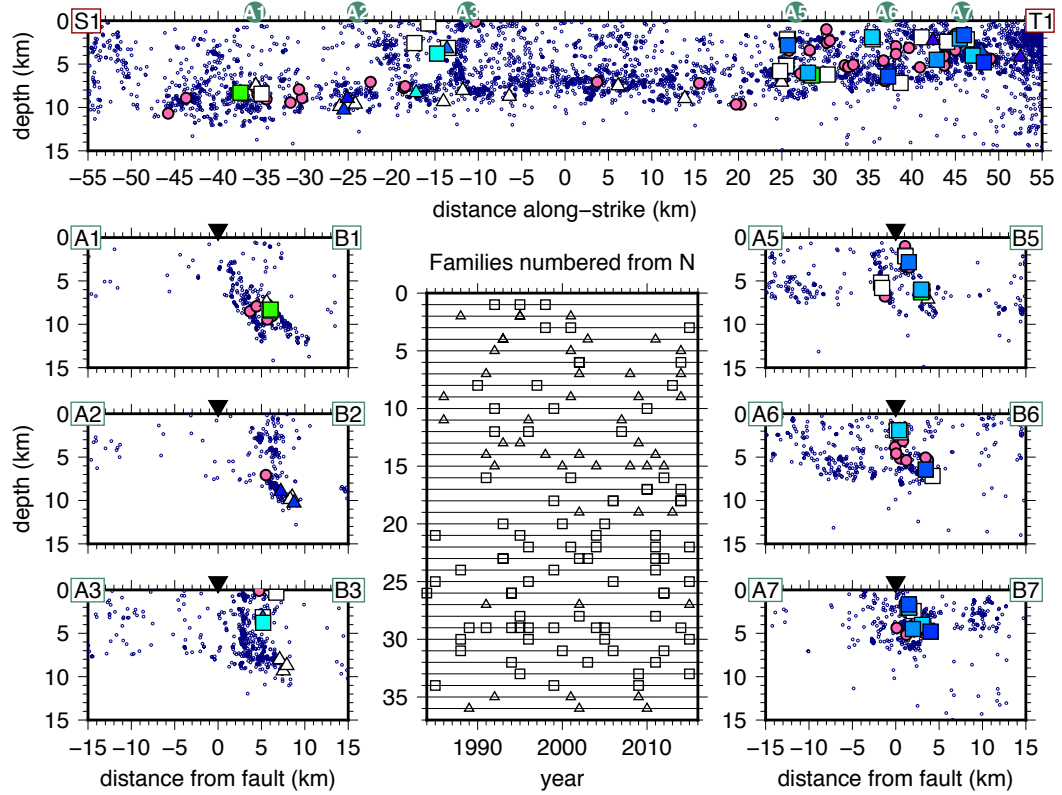


Figure 2.8: (Caption next page.)

Figure 2.8: Seismicity, fault and repeating earthquake (RE) families in the northern San Francisco Bay Area. RE families are shown with different symbols indicating the confidence of detection and the number of family member. RE families with that are shown with squares are detected by their high Cross-Correlation coefficient (CC) between their members and also they are confirmed by HypoDD relocation using their precise S-P times. RE families with triangle symbols are those that have high CC between their members but could not be confirmed by HypoDD as the error of their location where high due to station spatial configurations and converge. The pink circles indicate the location of RE pairs that have high CC between their members and also their locations are validated by precise S-P measurements. RE families except RE pairs are color coded by creep rates estimated by using the Nadeau and Johnson, (1998) empirical relationship recalibrated by using Jin and Funning (2017)'s results for the Rodgers Creek fault. White symbols indicate that the coefficient of variation of those REs are more than 0.4 and therefore they are not periodic enough for creep rate estimation. The creep rates without calibration are shown in Figure 2.10. By looking at the location of REs we observe that the majority of the REs are focused along the Rodgers Creek, Maacama and Bartlett Springs faults, indicating that these faults are likely to be creeping along much of their lengths. Locations of cross-fault (A-B; sea green) and along-strike (S-T; dark red) profiles corresponding to Figure 2.9 are marked. Relocated seismicity, from the near-real time double difference catalog for northern California (Waldhauser and Schaff (2008)) is plotted as dark blue open circles.

Maacama fault



Rodgers Creek fault

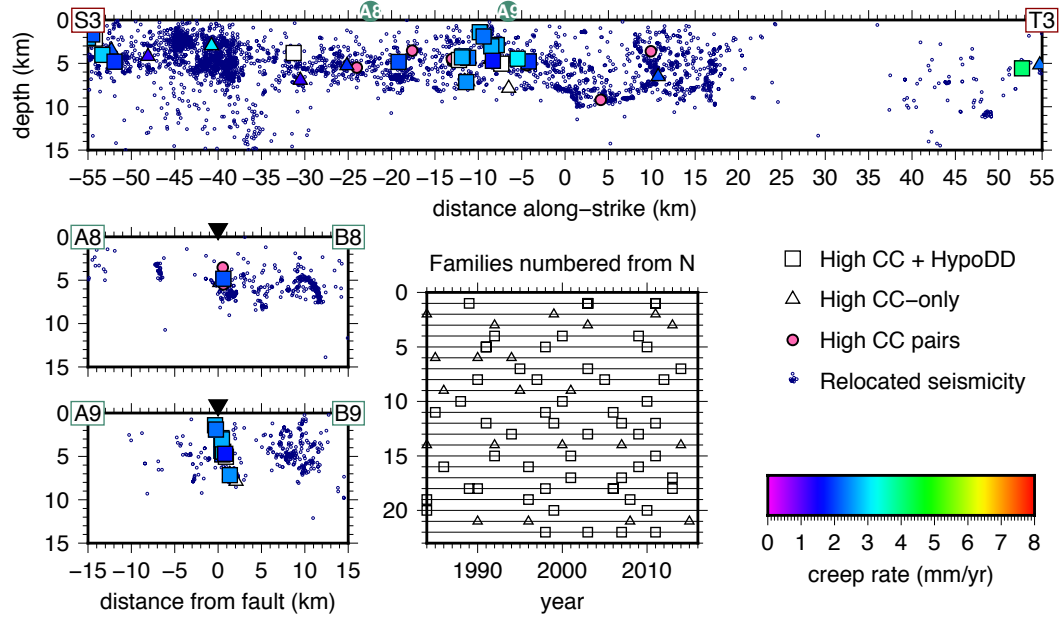


Figure 2.9: (Continued overleaf)

Bartlett Springs fault

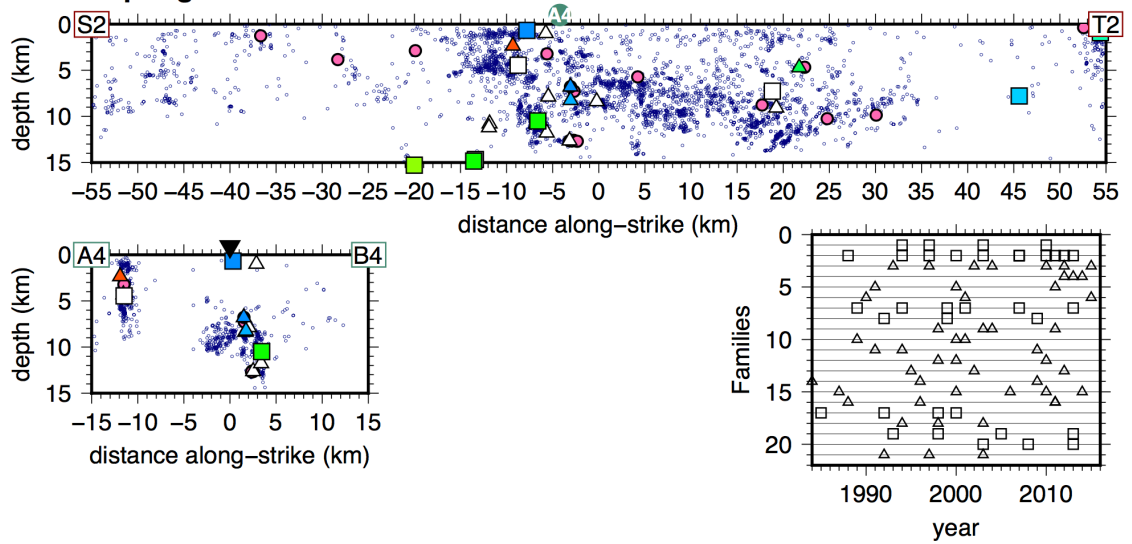


Figure 2.9: Repeating earthquakes (RE) along the major fault systems of the northern San Francisco Bay Area, plotted in cross-section and in time. Both fault-parallel (S-T) and fault perpendicular (A-B) profiles are shown; profile numbers and locations are given in Figure 2.8. We identify clusters of REs on the southern and northern Maacama fault, the central Rodgers Creek fault, and the central Bartlett Springs fault, suggesting that these sections of the fault are likely to be creeping. Time histories for RE families from each fault are arranged and numbered by latitude, from north to south. In general, we see no clear pattern of synchronicity between nearby RE families. More details provided in the main text. Symbols and color codes as for Figure 8.

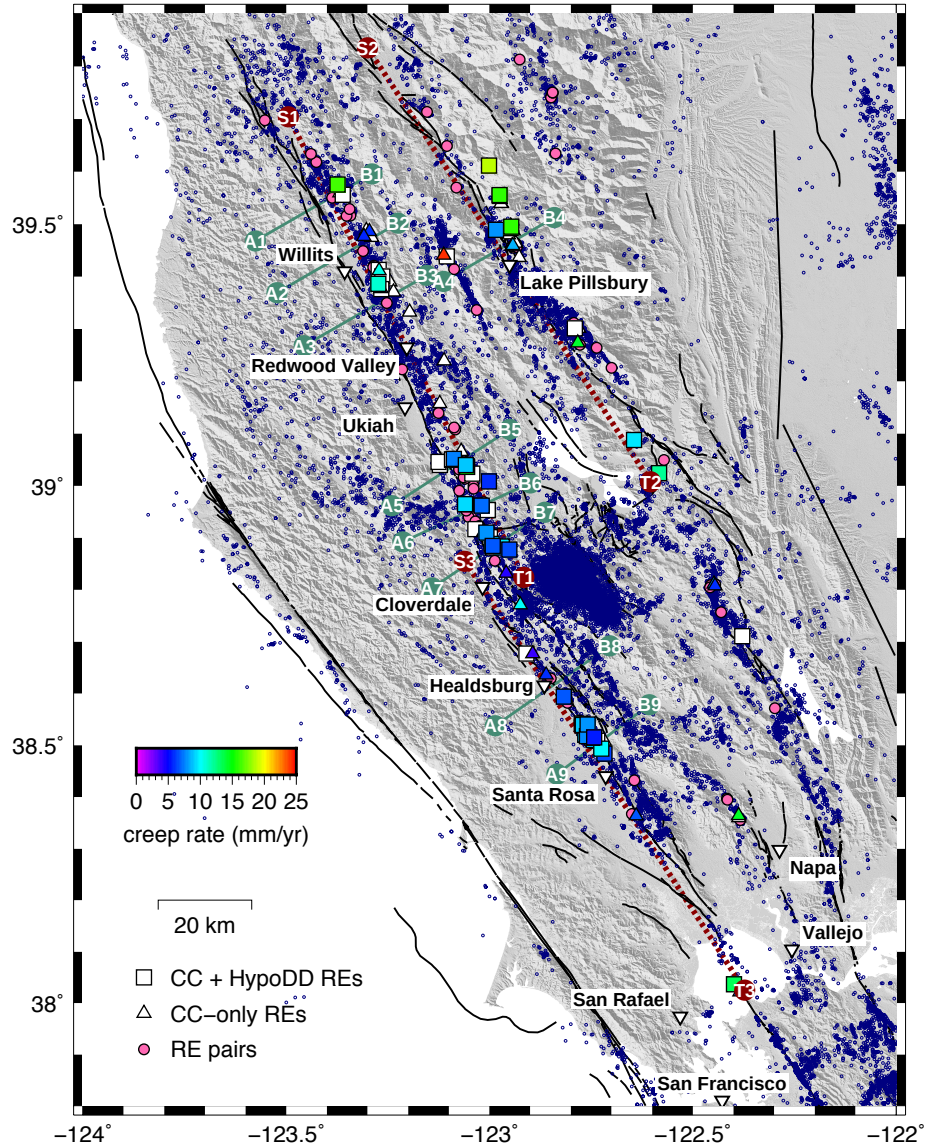


Figure 2.10: Same as Figure 2.8 but creep rates are shown without calibration with a shallow RE on the Rodgers Creek fault. In this case, creep rates are not consistent with the other geodetic observations of McFarland et al, (2015), Murray et al, (2014) and Jin and Funning (2017) for this region. Creep rates are several times higher than for those studies, and for some families exceed the long-term loading rate estimated for these faults.

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Chapter 3

Super-Efficient Cross-Correlation (SEC-C): A Fast Matched Filtering Code Suitable for Desktop Computers

Abstract

We present a new method to accelerate the process of matched filtering (template matching) of seismic waveforms by efficient calculation of (cross-) correlation coefficients. The crosscorrelation method is commonly used to analyze seismic data, for example, to detect repeating or similar seismic waveform signals, earthquake swarms, foreshocks, aftershocks, lowfrequency earthquakes (LFEs), and nonvolcanic tremor. Recent growth in the density and coverage of seismic instrumentation demands fast and accurate methods to analyze the corresponding large volumes of data generated. Historically, there are two approaches used to perform matched filtering; one using the time domain and the other the frequency domain. Recent studies reveal that time domain matched filtering is memory efficient and frequency domain matched filtering is time efficient, assuming the same amount of computational resources. We show that our super-efficient cross-correlation (SEC-C) method—a frequency domain method that optimizes computations using the overlap-add method, vectorization, and fast normalization—is

not only more time efficient than existing frequency domain methods when run on the same number of central processing unit (CPU) threads but also more memory efficient than time domain methods in our test cases. For example, using 30 channels of data with a sample rate of 50 Hz and 30 templates, each with durations of 8 s, SEC-C uses only 2.3 GB of memory whereas other frequency domain codes use three times more and parallelized time-domain codes use $\sim 30\%$ more. We have implemented a precise, fully normalized version of SEC-C that removes the mean of the data in each sliding window, and thus can be applied to raw seismic data. Another strength of the SEC-C method is that it can be used to search for repeating seismic events in a concatenated stack of individual event waveforms. In this use case, our method is more than one order of magnitude faster than conventional methods. The SEC-C method does not require specialized hardware to achieve its computation speed; instead it exploits algorithmic ideas that are both time- and memory-efficient and are thus suitable for use on off-the-shelf desktop machines. Electronic Supplement: Additional figures and MATLAB codes (matched filter algorithm).

3.1 Introduction

Matched filtering, also known as template matching, similarity search, or “query-by-content”, is a commonly used method in seismology. The matched portions of a continuous waveform data set with a template waveform can be identified by calculating normalized correlation coefficients, usually referred to by seismologists as zero-lag cross-correlation coefficients (CCCs). By choosing appropriate thresholds for these CCC values, we can detect similar or repeating patterns in those continuous data. Template matching is often used for detecting seismic events with low signal-to-noise waveforms within large volumes of continuous data. A high-detection capability along with applicability to a wide variety of seismic source types makes template matching a powerful tool for seismologists. For example, template matching can be used to detect seismic events such as foreshocks, aftershocks, icequakes, repeating earthquakes (REs), volcanic earthquakes, geothermal seismic activity, swarms, low-frequency earthquakes (LFEs),

and nonvolcanic tremor to monitor nuclear explosions and to identify seismic triggering (e.g. Nadeau et al., 1995; Gibbons and Ringdal, 2006; Shelly et al., 2007; Peng and Zhao, 2009; Meng and Peng, 2014; Allstadt and Malone, 2014; Skoumal et al., 2015; Kato et al., 2016; Frank et al., 2017).

In addition to the event detection applications explained above, cross-correlation analysis has become an important part of determining event locations and relocations in the last two decades (e.g., Waldhauser and Ellsworth, 2000; Hauksson and Shearer, 2005; Schaff and Waldhauser, 2005). The relative arrival time of seismic phases to seismic stations for each event in a group of nearby events is the main input information for relocation algorithms (e.g., Waldhauser and Ellsworth, 2000; Hauksson and Shearer, 2005) and is traditionally estimated by comparing the picked phase arrival times from earthquake catalogs. The picked phase arrival times usually contain errors due to station noise and uncertainty in the phase picking algorithm or human error. On the other hand, CCC methods can precisely calculate the relative time shift between individual waveforms, as the CCC between them is maximized when two waveforms are aligned. These methods can also be used to precisely detect temporal velocity changes in the Earth's crust (e.g., Poupinet et al., 1984; Schaff and Beroza, 2004; Thomas et al., 2012) or even the Earth's inner core (Tkalčić et al., 2013). Precise information about relative phase arrival times also plays an important role in seismic tomography (e.g., Zhang and Thurber, 2003). Therefore, a fast method for performing template matching in continuous data and for pairwise cross correlations of individual waveforms could potentially lead to computation time improvements in many branches of seismology. For most earthquake detection and (re)location applications (e.g., aftershocks, foreshocks, swarms, event relocations), choosing a waveform template can be straightforward, for example, selecting a well-recorded event within an area of interest (e.g., Shelly et al., 2007; Schaff and Waldhauser, 2010; Meng and Peng, 2014). However, in cases where it is known that a specific type of event repeats over time (e.g., REs or LFEs), but cannot be identified a priori, seismologists have used different techniques such as array processing (e.g., Frank and Shapiro, 2014), pairwise similarity search (also known as “autocorrelation”; e.g., Brown et al., 2008), or careful visualization of seismic data (e.g., Shelly

et al., 2009) to identify templates. The duration of continuous data available for investigation by template matching is of the order of decades (e.g., Shelly, 2017). If, for example, we could reduce the run time of a template matching analysis from 300 to 100 s for each day of seismic data, this would add up to ~ 8 days of computation time savings for one decade of seismic data. In other words, given the power law increase in the volume of waveform data archived in seismic data repositories (e.g., Incorporated Research Institutions for Seismology Data Management Center [IRIS-DMC]; Hutko, et al., 2017), there is a high demand for fast, precise, and user-friendly seismic analysis methods. For a single waveform of continuous seismic data with n samples and a single template with a length of m samples, the time complexity of template matching in the time domain is $O((n - m)m)$, or approximately $O(nm)$ when $n \gg m$. In the frequency domain, the time complexity is $O(n \log n)$ (Lewis, 1995). The normalization of computed CCCs adds an additional delay to the computational run time. The relative computational time complexity between these two methods then can be determined by comparing the size of $\log(n)$ with m . In this article, whenever we talk about time complexity comparisons between the time- and frequency-domain methods, we assume that these two methods are written in a common programming language and use the same computational resources (e.g., a single thread of a central processing unit [CPU]). For seismological applications, a template waveform usually contains several seconds of seismic data (i.e., $m \sim 10 - 1000$ samples) and the data set to be compared to is typically weeks, months, or years of seismic data that are usually stored as daily continuous seismic data files (i.e., $n \sim 10^6 - 10^7$ samples per day). This implies that the frequency domain method should be the faster method unless a template with a short length (e.g., less than a second, for one day of data with 50 Hz sample rate) is used. On the other hand, frequency domain methods, which typically involve the template being padded with zeros at least to the length of the comparison data, require much more memory (e.g., Lewis, 1995; Chamberlain et al, 2018). Despite not being time efficient with respect to frequency domain methods, timedomain template matching is often considered suitable for CPU and graphics processing unit (GPU) parallelization as the implementation is straightforward and memory efficient (e.g., Meng et al., 2012; Mu et al, 2017; Beaucé et al., 2018). Here we demonstrate, using several

algorithmic improvements, a single CPU frequency domain method that we call super-efficient crosscorrelation (SEC-C). It is equivalent in speed to modern CPUparallelized codes running on more than 10 processor cores, and only a few times slower than GPU parallelized codes. Such a code, running on a regular desktop computer with a few processor cores, can be a powerful tool for template matching that in some cases (e.g., long duration of templates, 100 Hz sample rates) is as powerful as GPUparallelized codes without requiring extensive memory or additional hardware. SEC-C is fast, memory efficient, and, for a minimal increase in computation time, can be precise to machine precision. A fully normalized version of the algorithm removes the mean of the data for each sliding window internally and therefore can be used for template matching of raw seismic data (Fig. S1, available in the electronic supplement to this article). Several of the parallelized methods mentioned above require prior operations on the data, or specific conditions or assumptions (e.g., removing the mean from the data, low variability on the amplitude, or using single-precision floating points; Beaucé et al., 2018; Chamberlain et al., 2018; Mu et al., 2017; respectively). Chamberlain et al. (2018) reported that using single-precision floating points for normalization calculations can introduce errors in the CCC results of up to 20% for a large earthquake within low-amplitude noise. Beaucé et al. (2018) tested the removal of the mean from the data from an Mw 7.8 earthquake and showed that the CCC error is 1.2%. SEC-C is capable of outputting both the CCC sum as well as the individual CCC for each channel without introducing extra run time. The latter case is useful when the moveout of P-wave arrivals is not precisely known and when the stations are far from each other (i.e., the moveout is very large), meaning that matched filtering at individual stations is a better option. Our aim in this study is to calculate fast, memory efficient, and precise CCCs for template matching applications in seismology. SEC-C employs a combination of several speed-up techniques such as the fast Fourier transform (FFT), the overlap– add method (Rabiner and Gold, 1975), vectorization tricks, and a fast normalization method inspired by Mueen’s algorithm for similarity search (MASS; Mueen et al., 2015). This method can be coded in any array programming computer language (e.g., MATLAB, see Data and Resources; Fortran 90, R, the NumPy extension to Python). It does not require any special libraries except for the FFT. The SEC-C MATLAB code is provided in the (E)

electronic supplement. The MATLAB code along with a Python version is also available in a GitHub repository (see Data and Resources).

3.2 The algorithm

3.2.1 The traditional time-domain sliding window cross-correlation method

Assume that we have a seismic template waveform X with a length of m samples and a continuous time series Y with a length of n samples. A traditional brute force way of performing template matching is to calculate the CCC of X with a subwindow of Y that has the same length (i.e., of m samples) and repeat this procedure with a sliding subwindow shifted by one sample or some small interval (e.g., 0.02 s; Shelly et al., 2009). Assume that Y^i is the i th subwindow of Y , then the CCC for any subwindow is defined as below:

$$CCC_i = \frac{(X - \bar{X}).(Y^i - \bar{Y}^i)}{\sqrt{((X - \bar{X}).(X - \bar{X}))((Y^i - \bar{Y}^i).(Y^i - \bar{Y}^i))}} \quad (3.1)$$

in which the bar symbol above X and Y^i refers to the mean values for each and the dots indicate scalar (dot) products. For example, $(\bar{X})$ refers to a vector with a length of m in which each component is the mean of X . We assume that the local mean is already removed from the data and templates can thus be reduced to the equation below:

$$CCC_i = \frac{X.Y^i}{(X.X)(Y^i.Y^i)} \quad (3.2)$$

This procedure typically requires looping of this calculation over many subwindows of Y . For most real seismological applications, this needs to be repeated for multiple stations with multiple components and several templates. This becomes time consuming for a long continuous waveform and with the sample rates required for most seismic applications (e.g., usually greater than 20 Hz). For example, calculating CCCs for one day of continuous waveform with a 100 Hz sample rate and sliding for a 0.02 s interval for 10 stations, three components and for 20 templates, requires the evaluation of equation (1) $24 \text{ (hrs)} \times 60 \text{ (min)} \times 60 \text{ (s)} \times$

50 (CC evaluations per second) $\times$ 10 (stations) $\times$ 3 (components) $\times$ 20 (templates) $= \sim 2.6 \times 10^9$ times. For one year of data, the number of calculations increases to $\sim 10^{12}$. The time complexity of equation (1) has a linear relationship with template length (m), and as m increases the total computational time increases proportionately. To tackle the run time problem of computing many nested loops, recent time-domain-based methods have focused on parallelization using either CPU clusters or GPU architecture that can compute this calculation using hundreds to thousands of threads simultaneously (e.g., Meng et al., 2012; Mu et al., 2017; Beaucé et al., 2018). However, performing a real-world case of template matching using a regular desktop machine in the time domain is still a challenge and out of reach. The alternative way of performing template matching is to use the frequency domain to calculate the numerator of equation (2) without looping over sliding windows. Here, we give a brief introduction to frequency domain template matching, using the CCC metric.

3.2.2 The traditional frequency domain cross-correlation method

We first define two vectors with the same length, extended to the next highest power of two:

- 1. $X' = \text{reverse } X \text{ and append } (n + l - m) \text{ zeros to the end,}$
- 2. $Y' = \text{append } Y \text{ with } l \text{ zeros at the end.}$

Here, l is the number of zeros that needs to be added to the Y to make the length of Y a power of two. In the past, the FFT algorithm performed optimally when the length of the data was a power of two. New FFT libraries, however, can calculate the FFT efficiently if the prime factors are small (e.g., the Fastest Fourier Transform in the West (FFTW); Frigo and Johnson, 2005). Therefore, depending on the FFT libraries and n , l can be chosen to be 0 or any number that can make $n + l$ a power of two. Then, the convolution of X' and Y' would produce all the possible numerators of equation (1) (Lewis, 1995):

$$(X' * Y')_i = X.Y^i. \quad (3.3)$$

As mentioned above, subscript i here is referred to the i th sub window. We call this vector the sliding dot product of X and Y , $\text{sdp}(X, Y)$. We can calculate this sliding dot product using the fast Fourier transform (FFT) method as below (Lewis, 1995; Smith, 1997):

- 3. $\text{sdp}(XY) := (X' * Y') = \text{FFT}^{-1}(\text{FFT}(X') \cdot \text{FFT}(Y'))$

The three procedures above allow us to calculate the numerator of (1).

Algorithms for calculating the denominator of eq (2) (i.e. the normalization part) may vary from method to method. As the time complexity of the FFT is $O(n \log n)$, if we assume a normalization with a linear time complexity, then the overall time complexity of the frequency domain method is $O(n \log n)$. If we compare this to the time domain time complexity (i.e. $O(nm)$), when m is greater than $\log n$, the frequency domain approach becomes a better choice of method. For a single day of seismic data, depending on the sample rate (e.g. from 20 to 100 Hz), $\log n$ varies between 14 and 16. This means that the frequency domain approach is more efficient if $m > 16$? corresponding to a template length of 0.32 seconds when a sample rate of 50 Hz is assumed. The exact template length, m , at which the frequency domain becomes more time efficient depends on the hardware and the FFT libraries (Smith, 1997). For most seismic applications, however, template lengths of more than several seconds of data are required, implying that methods that make use of the frequency domain are more time efficient. (Note as we mentioned above our assumption is that both methods use the same amount of CPU resources, e.g. one CPU thread.)

On the other hand, frequency domain methods are not typically memory efficient. During the procedure (1), the template length increases at least to the length of the data (i.e. n if l is assumed to be zero). Our tests (see SEC-C Memory Efficiency section) show that these types of frequency domain methods (e.g. EQcorrscan; Chamberlain et al., 2018) can almost exceed the memory of a desktop computer with 16 GB of RAM in some use cases (e.g. using 40 templates for 10 stations with 3 components with a sample rate of 50 Hz and template length of 8 seconds). Even if a test case includes a small number of channels of data (not 30 channels as above), having a memory efficient method allows the user to perform matching for more

templates at the same time and therefore at a reduced run-time overall. The frequency method memory limitations can be circumvented using algorithmic improvements, however ? below, we describe how our ?Super Efficient? algorithm is efficient both in terms of computation time and memory.

3.3 The SEC-C algorithm

Here, we use several methodological tricks to reduce both the run time and memory usage when calculating CCCs for the multistation and multitemplate case of matched filtering of seismic data using a frequency domain-based method. First, to reduce the run time and memory overhead required, we use a ?block convolution? procedure (also called ?sectioned convolution?; e.g., Rabiner and Gold, 1975) using the ?overlap? add? method (e.g., Rabiner and Gold, 1975) to calculate the sliding dot product using the FFTmethod (i.e., procedure 3). This method is used in signal processing techniques to perform the convolution of a long signal with a finite impulse response filter (e.g., Rabiner and Gold, 1975; Smith, 1997). The main idea is to divide a long signal into small pieces and then perform the FFT convolution for each piece. To ensure accurate calculation of the sliding dot product at the border of two neighboring pieces there should be an overlap of $m - 1$ samples between neighboring pieces. If we assume that the length of each piece is k and if we ignore the recomputation in areas of overlap, the time complexity for a single trace of the data then becomes $O((n/k)(k \log k)) = O(n \log k)$ as we need to compute (3) for $n = k$ pieces. Here, k becomes a tunable parameter that should be carefully chosen for optimal performance. If $k \ll n$ (e.g., comparable in size with m), performing many repetitions (loops) will slow down the process. If k is large and comparable in size with n then calculating the FFT for each piece will be time consuming. The optimal value for k can be determined by trial and error, and depends mainly on hardware aspects (e.g., CPU cache size and clock speed). Using a trial and error procedure that we performed using two different desktop machines, we recommend assigning a power of two for k (e.g., 2^{12} for one day of 20 Hz data or 2^{13} for one day of 50?100 Hz data) for efficient performance. However, in all cases we advise running some

test cases to find values of k to optimize the run time.

One other feature of the overlap-add method is that the template is not required to be padded by zeros to the length of the data, which for large n can require hundreds of MB of memory space. Using the shorter waveform pieces of the overlap-add method reduces this requirement to padding until the length of k (equivalent to tens of KB of memory usage if $k = 2^{13}$). This can result in a large memory savings when multiple stations and templates are used. The k value can also be chosen to be very small to minimize memory usage, although this will come at the expense of increased run times.

The second trick to speed up the template matching is to use vectorized calculations of sliding dot product for all overlap-add pieces instead of looping over these pieces. For example, MATLAB has options for vectorized FFT, dot product, and inverse FFT and therefore the whole procedure of (3) can be vectorized. For the case of multitemplate matched filtering, the FFTs of the templates can also be calculated in a vectorized basis as well.

A third optimization trick is that we apply a very efficient normalization (i.e., denominator of equation 1) inspired by the MASS algorithm (Mueen et al., 2015), which we describe below. $X.X$ is a constant and can be precalculated. For calculating $Y^i.Y^i$, we use the following procedures:

- 1. Calculate the cumulative sum of Y squared and prepend a zero to it as below:

$$C_{k+1} = \begin{cases} \sum_{j=1}^k Y_j Y_j, & (1 \leq k \leq n) \\ 0, & (k = 0) \end{cases} \quad (3.4)$$

- 2. Then, $Y^i.Y^I$ can be calculated as below:

$$Y^i.Y^i = C_{i+m} - C_i \quad (3.5)$$

These will give us the denominator of equation (2) with the time complexity of $O(n)$. Recent versions of MATLAB (2017a and later) include a built-in function, *movsum*, that performs this procedure with a similar time complexity and run time. *movsum* returns

the sliding m -points sums of a vector. We use this function for simplicity in the current version of SEC-C. For other programming languages and older versions of MATLAB, the procedure explained above can be used.

The output of the algorithm we describe above is the sliding CCC for the template X and the continuous waveform Y . The computation has the time complexity of $O(n \log k)$. We then loop over the stations, components, and templates to calculate the various CCCs required in the multichannel and multitemplate cases. Along with these required loops, some of the operations, such as zero padding, reversing, and calculating FFTs of templates, are performed in a vectorized basis. SEC-C can output either the CCC for each channel individually for each template or produce weighted CCC sums of all channels. For the second option, weightings should be provided by the user. For more details of the algorithm, we refer to the MATLAB code provided in the [\(E\)](#) electronic supplement.

SEC-C is a single CPU code that is optimized for seismic data sets with lengths of approximately one day that can handle hundreds of channels of data and templates in an efficient run time. If faster run times are needed, the user can simply parallelize the problem by running SEC-C in parallel for each different day of data on each single CPU core of a multicore desktop machine. A toy example of running SEC-C using the MATLAB parallelized for-loop, `parfor`, is provided in the SEC-C GitHub repository (see Data and Resources).

3.4 The fully normalized version of the SEC-C algorithm

The algorithm explained above is based on equation (2) and includes the assumption that the local mean is removed from the data and templates. This can be acceptable for most cases of seismological applications, but in some cases, for example, when there are sudden large fluctuations in the data, such as instrument spikes or large nearby earthquakes, this assumption can be problematic. Most current approaches based on the assumption that the mean and any spikes are removed from data (e.g., Beaucé et al., 2018; Chamberlain et al., 2018). Beauce et al. (2018) indicate that this assumption can affect the results of CCC calculations for the 2016

Mw 7.8 Kaikōura earthquake by as much as 1.2%; however, this is an extreme case where there are large deviations from the mean in the data. Our experiment on Mount St. Helens seismicity (i.e., a more normal test case) shows the differences between CCCs calculated by equation (1), and the SEC-C method with the zero-mean assumption (equation 2), for a single channel of data are of the order of 10⁻⁴ (Fig. 1e).

Because SEC-C is a versatile algorithm, we can make some simple changes that calculate CCCs based on equation (1) without the need for simplifying assumptions. Here, we briefly discuss this implementation.

First, the mean of the templates can be precalculated and removed. Equation (1) in this case becomes:

$$CCC_i = \frac{X.(Y^i - \bar{Y}^i)}{\sqrt{(X.X)((Y^i - \bar{Y}^i).(Y^i - \bar{Y}^i))}} = \frac{(X.Y^i) - (X.\bar{Y}^i)}{\sqrt{(X.X)(Y^i.Y^i - (2Y^i.\bar{Y}^i - \bar{Y}^i.\bar{Y}^i))}} \quad (3.6)$$

There are two extra terms in this equation with respect to equation (2), $X.\bar{Y}^i$ in the numerator and $(2Y^i.\bar{Y}^i - \bar{Y}^i.\bar{Y}^i)$ in the denominator. Before calculating these two terms, we define S^i as a local sum of Y :

$$S^i = \sum_{j=i}^{i+m} Y_j \quad (3.7)$$

The term $X.\bar{Y}^i$ vanishes as the mean of X is removed. In other words

$$X.\bar{Y}^i = \text{mean}(Y^i)(\text{sum}(X)) = ((S^i)/m)(\text{sum}(X)) = ((S^i))(\text{sum}/m) = (S^i)(\text{mean}(X)) = 0$$

The extra term in the denominator of equation (4) can be calculated as below:

$$2Y^i.\bar{Y}^i - \bar{Y}^i.\bar{Y}^i = 2(S^i)(S^i/m) - m(S^i/m)(S^i/m) = (S^i)^2/m$$

The mean of Y^i is simply S^i/m . S^i can be calculated with a similar algorithm as that described above for $Y^i.Y^i$ or by using the *movsum* function in MATLAB, with a linear time complexity.

After applying these modifications, the run time of SEC-C increases by less than 1.1% of that of the regular SEC-C algorithm and in our heaviest test case the run time is almost the same (Fig. 2a). This is because the cost of computing the mean of the data is borne only once; once the mean is computed, as many templates as desired can be run at no additional cost. Because this fully normalized version of SEC-C removes the sliding mean from the data, it can be used for raw data (e.g., (E) Fig. S1).

3.5 Comparisons with other approaches

We compare SEC-C with other contemporary methods in terms of accuracy, speed, and memory efficiency, the main characteristics of any matched filter method. For the accuracy test, we compare SEC-C with *xcorr*, a built-in MATLAB function for calculating CCCs. To test SEC-C in terms of speed and memory usage, we compare it with two current, recently published methods: EQcorrscan (Chamberlain et al., 2018), a frequency domain-based matched filter method and fast matched filter (FMF; Beaucé et al., 2018), a time domain-based method.

3.5.1 SEC-C accuracy and precision, and the impact of the zero-mean assumption

To test the accuracy and precision of this method, we applied the SEC-C algorithm to the seismicity at Mount St. Helens volcano. We select a template waveform from repeating volcanic earthquake swarms that occurred on 3 December 2005, recorded in the vertical channel of the seismic station YEL (Fig. 1a). The high-seismicity rates on this day are related to the dome building eruption in 2004-2005 at Mount St. Helens. So-called “drumbeat” earthquakes, repeating events that occur at regular, short intervals, occurred every 30-300 s during this eruptive episode (Iverson et al., 2006; Fig. 1b). We calculate the CCC between our template and a 24-hr-long continuous waveform (the whole of 3 December) using both SEC-C and a sliding *xcorr* function over each window calculated with zero lag (Fig. 1c,d). We removed the sliding mean of the data for each sliding window prior to calling *xcorr* for that window. This is a brute force and therefore very slow method, but it is effective as a reference method for calculating

CCCs precisely and accurately. A comparison between the CCC values output by this precise, traditional method, and the SEC-C method on this identical data set show that the differences of the results are on the order of 10^{-4} and 10^{-15} for the regular and fully normalized versions of SEC-C, respectively (Fig. 1e), which implies that the fully normalized version of our method is precise to machine precision and can reproduce the results of traditional methods on the order of machine precision. SEC-C uses double precision for its calculations, and this, along with the option of removing the mean for each sliding window, underpins its capacity for accurate and precise CCC computations.

3.5.2 SEC-C speed

We compare SEC-C with two contemporary codes: one that computes CCCs in the frequency domain, EQcorrscan v. 0.2.7, and one that uses the time domain, FMF, in terms of run time and memory usage. Both the EQcorrscan and FMF methods use routines compiled in C for calculating CCCs, accompanied with multithreaded routines and OpenMP (Dagum and Menon, 1998) loops for parallelization. Both packages have a wrapper for use in Python; FMF also has a wrapper in MATLAB. We use the fastest version of the correlation backend of EQcorrscan that uses the FFTW library (Frigo and Johnson, 2005) for the Fourier transform procedure. We use synthetic data for the comparison test generated by test codes accompanying both software packages. We also use the same synthetic data generated by the FMF test code to test SEC-C. Our tests are run on a desktop machine with an Intel Core i7-4790k CPU processor that includes four cores (eight threads) and 16 GB of memory. This is the intended platform (i.e., a desktop computer) for the current version of the SEC-C method. In contrast, EQcorrscan can take advantage of CPU clusters with large memory capacity, and FMF is designed to take advantage of GPU hardware where available. Therefore, the comparisons stated below do not reflect the capabilities of these methods for their intended cases, rather they show performance of the methods when there are limitations in computation power, memory, or both.

From now on, we demonstrate the matched filter test cases with a vector with six numbers indicating the number of days of seismic data, number of stations, number of components, sam-

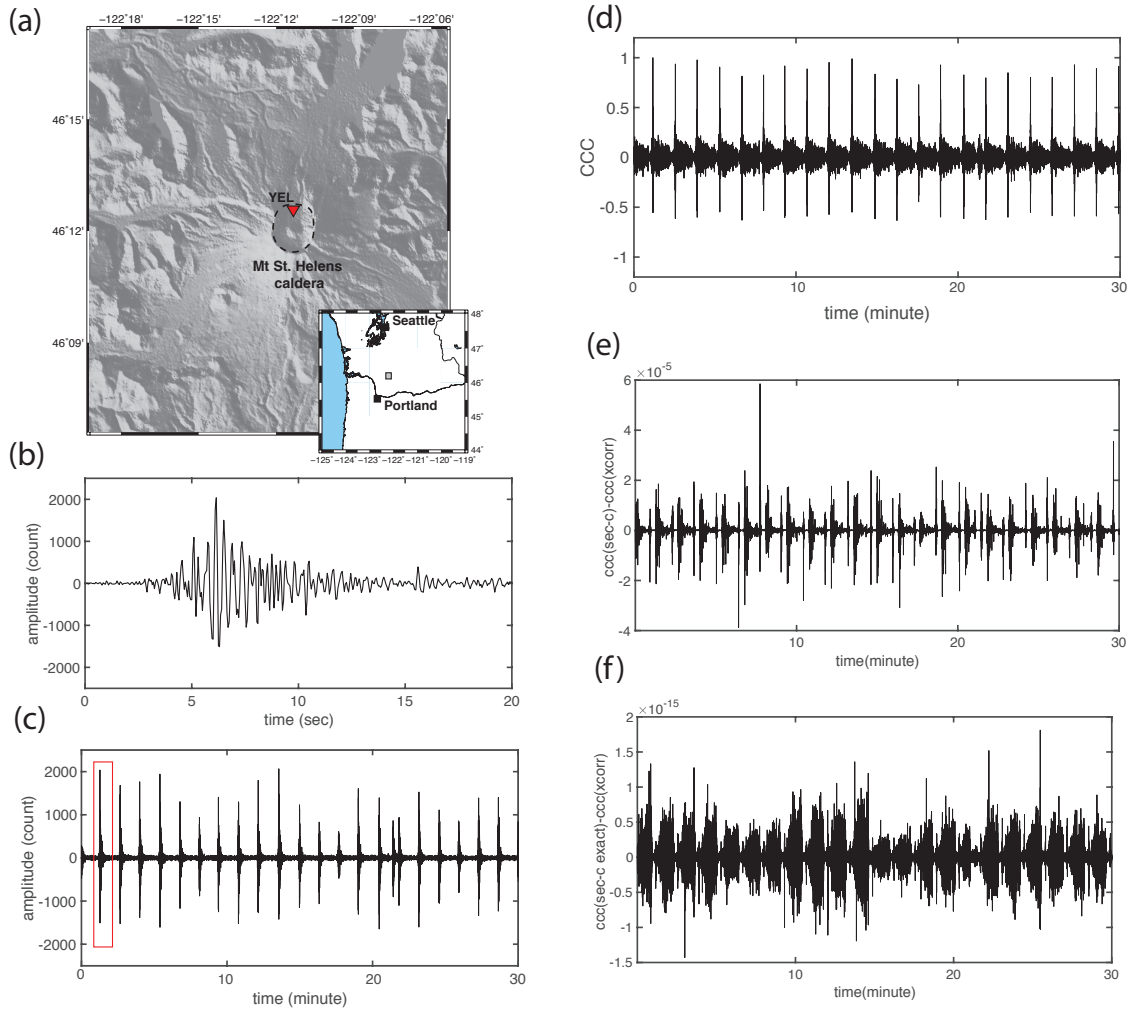


Figure 3.1: (a) A topographic map of the Mount St. Helens volcano area. Inverted triangle shows the location of seismic station YEL. The dashed circle delimits the caldera, the source of drumbeat seismicity. (b) A “drumbeat” earthquake template waveform recorded on the vertical-component channel of station YEL. (c) 30 min of seismic data recorded at the same station on 3 December 2004. Box indicates the template event shown in (b). (d) Cross-correlation coefficient (CCC) function calculated using the traditional sliding window method using the *xcorr* function in MATLAB (with the mean of the sliding window removed) for one day of data, note that in this and subsequent plots we show only a 30 min subset of this CCC function. (e) Difference of CCC calculated with the regular super-efficient cross-correlation (SEC-C) method (sliding window mean not removed) with the CCC from (d). (f) Same as (e) but for the fully normalized version of SEC-C in which the mean is removed from each sliding window. The amplitude of (f) shows that the differences between CCC results are approximately on the order of machine precision (i.e., double precision), indicating the precision of the fully normalized version of the SEC-C method. The color eversion of this figure is available only in the electronic edition.

ple rate in Hz, template length in seconds, and number of templates, respectively. In this case, our test case vector was (1, 10, 3, 50, 8, x). We tried different values of x by varying the number of templates from 1 to 40. We cannot test a greater number of templates as the EQcorrscan code exceeds the available memory on our test machine with more than 40 templates.

To make a clearer comparison between the speed of SEC-C and the speeds of the other codes, we run SEC-C using three different strategies: (1) forcing MATLAB to use only one CPU thread for the computations (hereafter referred to as the single thread case of SEC-C); (2) allowing MATLAB to use multithreading (i.e., the use of multiple CPU threads) for some built-in functions that are optimized for it (the regular case of SEC-C); and (3) running multiple single thread instances of SEC-C independently and simultaneously in parallel (the parallelized case of SEC-C). For strategy (3), if the number of stations is sufficiently small, one day of data can be run per CPU thread; if not, and if memory limitations become an issue, each day of data can be divided by the number of threads into equally sized smaller subsets, with an appropriate overlap that takes moveout into account.

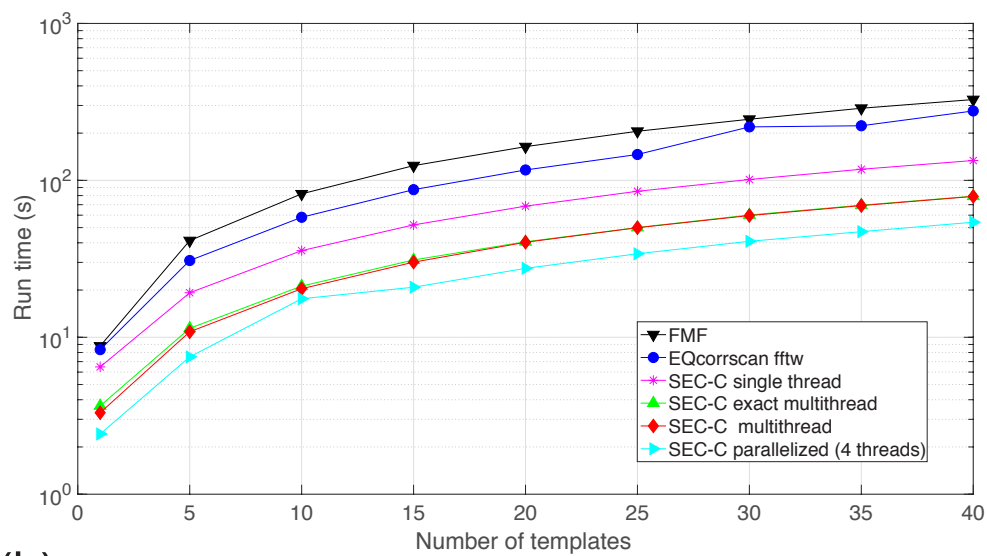
Figure 3.2 demonstrates the results for our speed test. We find that SEC-C's performance is on average ~ 2 , 4, and 6 times faster than FMF for the three SEC-C strategies explained above, respectively. Because FMF makes use of multithreading to gain computation speed, a second test on a machine with an Intel Core i5 processor (four cores, four threads) was 8 times slower than the regular case of SEC-C for the same test vector (Fig. S2). Overall, assuming limited computational resources such as a desktop computer, the strength of the SEC-C algorithm with respect to FMF is when the template length is large (e.g., > 5 s), the number of stations and components is also large (e.g., > 30 channels), and when higher sample rates (e.g., > 50 Hz) are needed. If the use case involves templates with short lengths (e.g., a few seconds) and uses data with lower sample rates (e.g., 20 Hz), then FMF becomes more effective with respect to SEC-C. Also, if the data do not involve higher frequency content, the step feature in FMF, which calculates CCCs at regular sample steps, rather than for every sample, can be used to speed up the computation. However, this comes at the expense of potentially degraded matching performance and/or lower peak CCC values, especially when the step size is bigger than the

shortest period used. As mentioned above, SEC-C can be effectively parallelized by running multiple instances on different CPU threads for enhanced performance, whereas FMF makes use of all CPU resources for a single run.

Although the memory efficiency tweaks that we have made in SEC-C trade-off with computation speed, our run test mentioned above shows that SEC-C runs approximately twice as fast with respect to EQcorrscan when both are using a single thread (Fig. 2a). Memory issues with EQcorrscan did not allow us to perform our test case using the parallelized version of EQcorrscan; however, our tests with fewer templates (less than 5) show that the run time of the parallelized version of EQcorrscan is slightly longer compared with the parallelized version of SEC-C (i.e., strategy 3 mentioned above). Overall, as the number of processes increases (e.g., increasing sample rate, number of stations, number of templates), the speed of SEC-C with respect to EQcorrscan increases.

Here, we give two more examples that show the relative efficiency of SEC-C with respect to other contemporary codes in terms of speed. Beaucé et al. (2018) reported the run time for a matched filter with the test vector (1, 12, 3, 50, 8, 20) while running the test using 24 CPUcores for EQcorrscan and FMF with one sample step (i.e., on all samples). EQcorrscan finished this test in 15.8 s, compared with 55.5 s for FMF. We run the same test using SEC-C on a single CPU thread on the desktop PC mentioned above, completing it in 88 s. This indicates that the single thread case of SEC-C has run times on the order of EQcorrscan and FMF running on multiple threads. The run time of the regular case of SEC-C (i.e., strategy 2 from above) is 49 s for this test. In another study, Mu et al. (2017) reported a test case vector of (1, 1, 1, 100, 2.56, 18) that finished in 2.97 s using the most CPU efficient and parallelized version of their matched filter code (the C2 method) running on 18 processor cores. SEC-C can complete this test case, again using one CPU thread on the same desktop machine mentioned above, in 5.45 s. Both FMF and the method of Mu et al. (2017) are GPU optimized and their GPU implementations can run much faster than their reported runtimes for CPU clusters. However, the examples and tests above highlight the efficiency of SEC-C when the computational resources are limited (e.g., few CPU cores and no available GPU, such as may be available on a desktop computer or laptop).

(a)



(b)

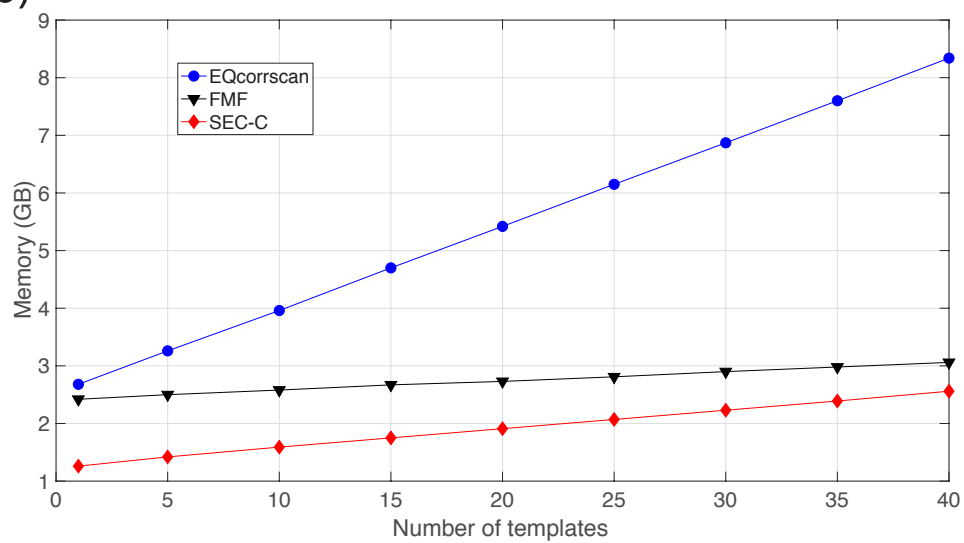


Figure 3.2: (Caption next page.)

Figure 3.2: (Previous page.) (a) Matched filter run time comparison between SEC-C, the fully normalized version of SEC-C, EQcorrscan, and fast matched filter (FMF), performed on a desktop machine with a quad-core (Intel i7-4790) processor. SEC-C run time is reported for three different computation strategies: SEC-C single thread (all computations run on a single central processing unit [CPU] thread), SEC-C multithread (a single instance of SEC-C, but with some MATLAB functions using multithreading in the background) and a parallelized case of SEC-C, in which four single thread instances are run on a quarter of the data set each at the same time. The test case data set includes one day of data for 10 stations, each with three components, with a 50 Hz sample rate and a template length of 8 s. The run time is plotted on a log scale versus the number of templates on a linear scale. We consider only the CCC sum procedure for the comparison and therefore run time does not include the loading of data or preprocessing, such as median absolute deviation (MAD) calculation or detection. The comparison shows that SEC-C would be the best choice to run the matched filter procedure on a desktop computer as it is 2–6 times faster than other contemporary methods, depending on the computational resources used. The speed of the fully normalized version of SEC-C is almost equal to that of regular SEC-C for higher numbers of templates, indicating that in such cases, fully normalized SEC-C would be the better choice as it does not significantly increase the run time. (b) Matched filter peak memory usage comparison between SEC-C, EQcorrscan, and FMF for the same test case in (a). Memory overhead is measured by monitoring the memory usage during each run using the `htop` command. For all of the test cases, SEC-C has the lowest memory usage, using approximately 2–3 times less memory than EQcorrscan, and 20%~30% less memory than FMF. The trend of memory usage with increasing numbers of templates suggests that for large numbers of templates (> 70), FMF will be more memory efficient than SEC-C, as expected for a time-domain code. The color version of this figure is available only in the electronic edition.

3.5.3 SEC-C memory efficiency

The strength of the SEC-C method compared with timedomain CPU codes is the run time speed. However, compared with other frequency domain methods (e.g., EQcorrscan), its strength is its memory efficiency. Here, we test the memory usage of SEC-C with respect to FMF and EQcorrscan while running a test with the case vector of (1, 10, 3, 50, 8, 30). We monitor the memory usage of these three methods using the htop (see Data and Resources) command. We compare the peak of memory usage before and during the runs. We find that the peak memory usage of EQcorrscan was 6.9 GB, compared with 2.95 GB for FMF and only 2.31 GB for SEC-C (Fig. 2b). The memory usage corresponding to the input and output data in this test case adds up to ~ 2 GB. This shows that our memory-based implementation made SEC-C even more efficient than time-domain methods (e.g., in this case FMF uses ~ 0.64 GB more memory than SEC-C). Peak memory usage estimated in this way for a range of numbers of templates (between 1 and 40) is shown in Figure 3.2b. For all of the test cases, SEC-C has the lowest memory usage, using approximately 2–3 times less memory than EQcorrscan, and 20 – 30% less memory than FMF. The trend of memory usage with increasing numbers of templates suggests that for large numbers of templates (> 70), FMF will be more memory efficient than SEC-C, as expected for a time-domain code.

One more example that demonstrates the strength of the SEC-C method with respect to the other methods is when applying a matched filter to a large array of seismic stations, for example, with a test vector of (1, 60, 3, 50, 10, 10). Using a regular desktop or even a small cluster, it is not possible to achieve this efficiently using a time-domain method (e.g., FMF). To avoid memory problems when using a regular frequency domain method (e.g., EQcorrscan), the user must divide the data into smaller subsets with smaller n and loop over those subsets. The additional disk read and write operations when loading data subsets and saving the results could potentially be more time consuming compared with a case where the matched filtering can be completed in one process. SEC-C can complete the example above with the test case mentioned above in approximately two minutes on our test machine. SEC-C can perform matched filtering

of up to a test case of (1, 110, 3, 50, 10, 1) without a memory problem and in a similarly efficient time (i.e., less than a minute) using the same desktop machine.

3.6 Example applications of the SEC-C algorithm

SEC-C is a versatile method that can be used for speeding up detection of any similar seismic events, for example, REs, LFEs, triggered earthquakes, swarms of nonvolcanic or volcanic earthquakes, foreshocks, and aftershock sequences. We show two examples of these applications.

- Detection of LFEs: Here, we present an example to show how this method can help us in the rapid detection of LFEs. We searched for LFEs in waveform data from a tremor burst that occurred on 6 October 2007 on the San Andreas fault near Parkfield, California (Fig. 3a), in which many LFEs were detected by template matching (Shelly et al., 2009). We select an LFE template waveform for each station (Fig. 3b) by stacking matrix profiles (a measure of waveform self-similarity) from 24 hrs of data spanning the tremor burst from three borehole stations of the high resolution seismic network (HRSN) in the Parkfield area. (For full details of this procedure and of the matrix profile method, see Zhu et al., 2016, 2018.)

We then use the SEC-C method to calculate CCC functions for five HRSN stations and sum these CCC functions, aligning them by accounting for the differential arrival time (i.e., moveouts) for the template at each station (i.e., using the S-wave envelope peak). We then use the threshold of eight times of median absolute deviation (MAD, e.g., Shelly et al., 2007, 2009). Figure 3.3c shows the sum of CCC functions for five stations and the threshold. In general, the temporal pattern of detected event origin times (Fig. 3d) is consistent with the results of Shelly et al. (2009; Fig. 2a); any differences in detail can be attributed to the different network configurations used, and the recursive matched filter process used in the earlier study. In this example, the test case vector is (1, 5, 1, 20, 5, 1) and the regular case of SEC-C can complete it in 0.21 s. For the 50 and 100 Hz cases, run time increases to 0.54 and 1.38 s, respectively. Assuming that this computation

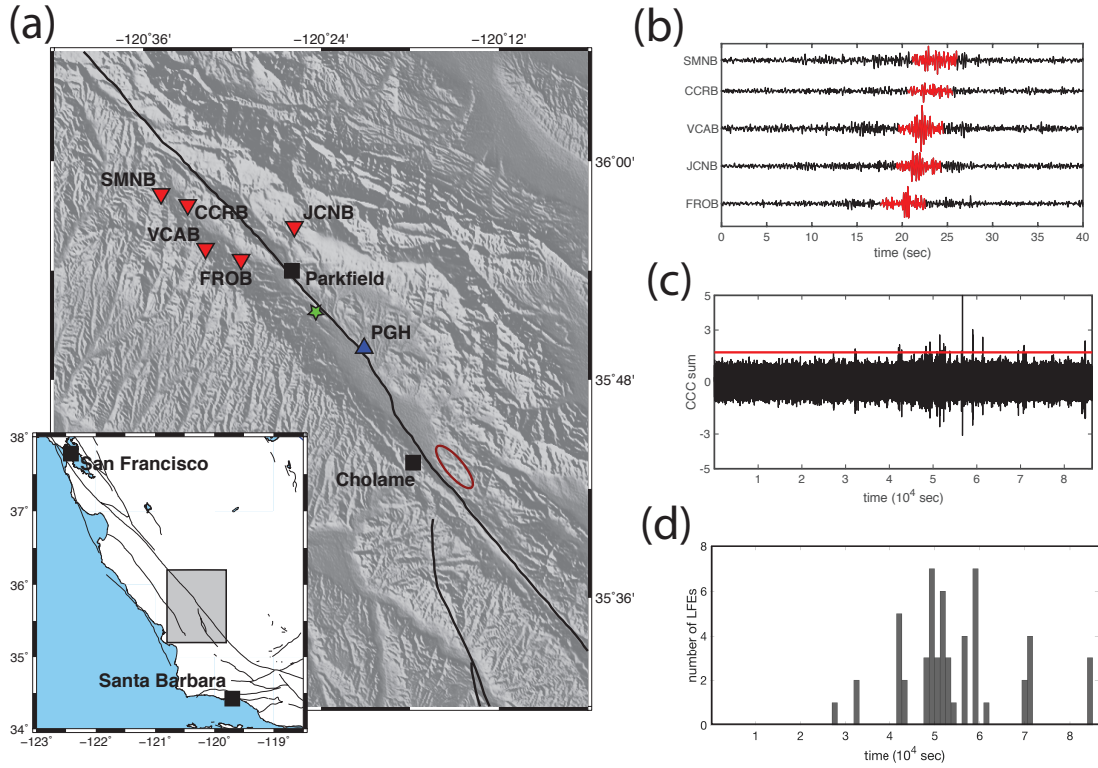


Figure 3.3: (a) A map of the San Andreas fault area near Parkfield, California. Inverted triangles are the locations of Parkfield highresolution seismic network (HRSN) stations that are used in this study to search for low-frequency earthquakes (LFEs), regular triangle is station PGH from the Northern California Seismic Network (NCSN) used to search for repeating earthquakes (REs), the star is the location of a family of REs (see Fig. 3c), and the ellipse shows the approximate locations of the LFEs detected by Shelly et al. (2009). (b) Waveforms from HRSN seismic stations showing our LFE template (indicated by dashed lines). The waveforms are arranged from top to bottom based on their stations' approximate distance to the source (i.e., most to least distant, respectively). (c) Sum of the CCC functions from the five HRSN stations calculated using the template shown in (b) and the SEC-C method, for waveforms from 6 October 2007 (UTC). The horizontal line is the detection threshold we use, eight times the MAD, based on Shelly et al. (2007). (d) A histogram of LFEs detected using the SEC-C method and our template. Although we used a different method, our results (i.e., detection times and number of detections) broadly agree with those of Shelly et al. (2009; their fig. 2). The color version of this figure is available only in the electronic edition.

time would scale linearly with the number of days of data searched, performing the same procedure for one year of continuous data would take between ~ 77 and 504 s depending on the sample rate. To test this hypothesis, we use the parallelized case of SEC-C on 365 days of data, with each of eight CPU threads on our test machine running a single thread instance of SEC-C on one day of data at a time, simultaneously. The run time for this case, including loading data, running SEC-C, and saving the output for the 20 and 100 Hz cases took 81 and 423 s, respectively, using our desktop test machine. This shows how this method could greatly expedite searches for repeating seismic events in continuous waveform data if suitable event templates are known.

- Detection of REs from individual detected catalog events: Along with the acceleration of template matching in continuous seismic data, one main strength of the SEC-C method is that it can be applied to template matching among individual waveforms from previously detected events. Here, we show one example: searching for REs in central California near Parkfield. For this purpose, we compared the performance of SEC-C with that of the `xcorr` function, as the latter in this case is an efficient way of calculating CCC functions (i.e., CCC as a function of lag time) for the individual event waveforms. The maximum lag (in terms of number of samples) that the CCC function needs to be calculated over depends on the errors in the seismogram phase information (e.g., P arrival pick), which are typically of the order of 1–2 s, multiplied by the sample rate. In this section, we use a brute force traditional method using the MATLAB cross-correlation routine `xcorr`, in which individual waveforms are compared with each other one-by-one, via two nested loops, as a comparison to the SEC-C method.

Our run time tests show that the SEC-C method can accelerate the search for REs by up to a factor of 15.5 faster than the traditional method, depending on the number of individual candidate events we start with.

To make use of the SEC-C method to search for REs in a set of individual event waveforms, we must first concatenate these event waveforms together to form one continuous

waveform. The SEC-C method can then be used to compute cross correlations between this continuous waveform and a template waveform as described above. Although SEC-C is fast at computing CCCs, as we demonstrate above, many of the CCCs calculated in this case are not necessary for the detection process. The unnecessary CCC calculations result from our concatenated waveform effectively having a large number of artificial waveforms (or waveform chimeras) composed of parts of pairs of neighboring waveforms. For example, if we have two event waveforms, A and B, and concatenate them, the SEC-C method would calculate the CCC between the template and a waveform window containing the second half of event A and the first half of event B (Fig. 4a). The resulting calculated value would be a scientifically meaningless quantity, and in the traditional method we would not compute it. A great many of the CCCs computed using SEC-C in this setup would be of this unnecessary type. Because we would not expend computing resources to compute these meaningless cross correlations under the traditional method, preferring instead to search for a small range of plausible time shifts within the target waveform, the differential in computation time between the two methods is greatly reduced for this application compared with scanning a continuous waveform, but we still obtain faster run times using SEC-C, as we document below.

Our experiments in searching for REs near Parkfield (Figs. 3a and 4a,b) show that the search for REs using the SEC-C algorithm is more than one order of magnitude faster than the traditional method. We use for this demonstration triggered event data from the Northern California Seismic Network station PGH (Fig. 3a) that has historically high signal-to-noise ratios and also a long period of operation (1987–present). We retrieve event waveforms from this station, targeting events whose catalog locations are within a small area in Parkfield where the occurrence of REs is expected (e.g., Lengliné and Marsan, 2009; Nadeau, 2014). In total, we perform 14,399,661 pairwise CCC calculations for 5366 waveforms that are band-pass filtered between 1 and 15 Hz, with 100 Hz sample rate and with 10 s duration. We find 284 candidate RE families, each having more than three events in a family with CCCs greater than or equal to 0.95 between their

pairs. The family with the largest number of repeats has 49 events in total. Figure 3.3b shows an example of a RE family with 18 recurrences since 1987 detected by SEC-C. The first five sequences of this family reoccurred regularly before the 2004 Mw 6.0 Parkfield earthquake with a recurrence interval of 3.5– yrs. The sequences triggered by the 2004 event had recurrence intervals that were shortened to hours in its immediate aftermath and eventually, following a typical Omori–Utsu law, recovered to their original recurrence intervals from before the 2004 mainshock in a period of ~ 7 yrs.

The new method improves the computation time for searching for REs from around one-and-a-half hours under the traditional approach to less than seven minutes using SEC-C on our desktop test machine. To compare the run times between the two methods, we run multiple tests on each using a series of differently sized random subsets of these waveforms. On average, we find the SEC-C method is 12.1 times faster than the traditional, looped CCC method (see Fig. 4a). The speed-up factor stays above ~ 11 for all the subset sizes we test. We have started to apply the SEC-C code to large scale seismic applications, such as mining a large seismic data set (i.e., including 40000+ events, 300+ stations, 600000+ event waveforms) to search for REs in northern California (Funning et al., 2017). Although a discussion of the results of that work is beyond the scope of this study, we found that the entire process, including data downloading and preprocessing, computation of the waveform comparisons and clustering of the results, could be completed in one week using the same desktop machine.

3.7 Conclusions

We use a combination of different algorithm improvements such as FFT convolution, the overlap–add method, vectorization, and fast normalization to produce an accurate sliding CCC algorithm with zero-lag that is inexpensive to compute for large seismic data sets. This method, which we call SEC-C, is usable for many time series applications that require efficient computation of cross correlations, including various seismological applications such as detecting

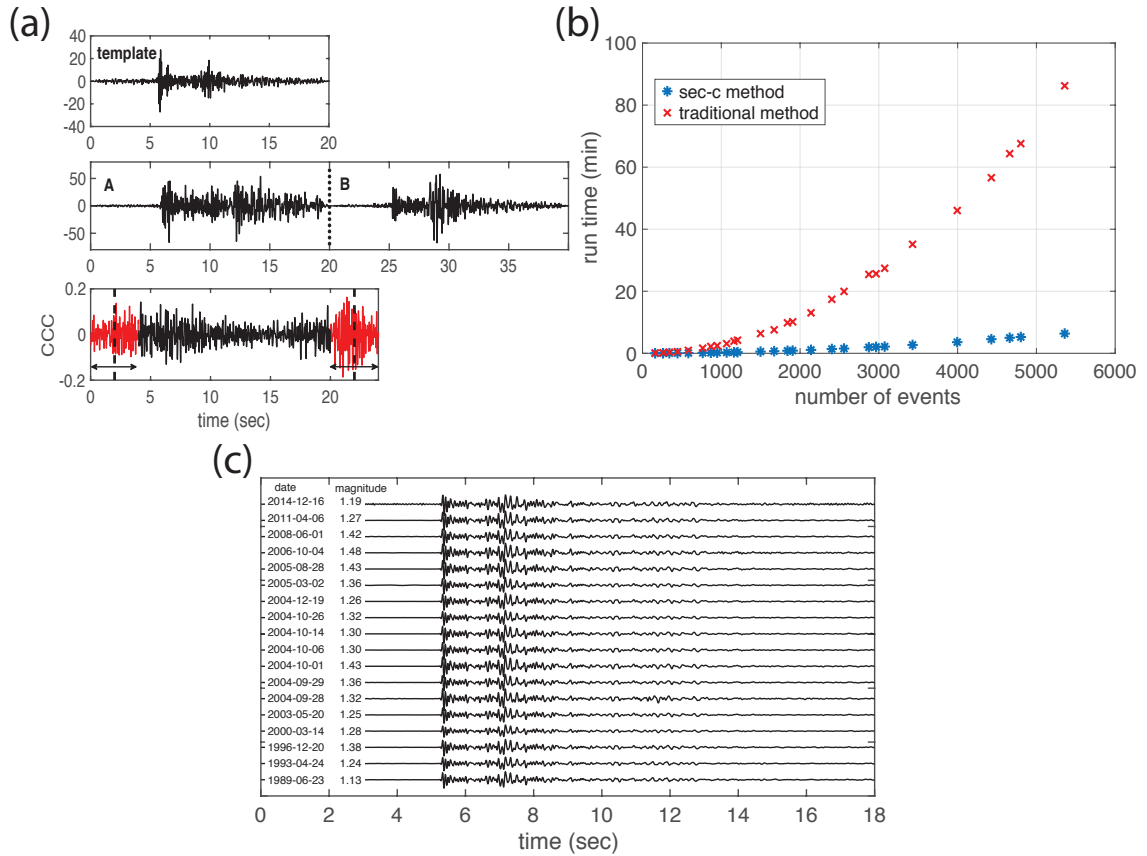


Figure 3.4: (a) An example shows how we use the SEC-C method to calculate CCCs for individual event waveforms. From top to bottom: a template, concatenated waveforms A and B, and CCC between the template and the concatenated waveform. Portions of the CCC function indicated by double-headed arrows are the scientifically useful calculated CCCs and the remainder the unnecessary CCCs calculated in this process. Dashed lines indicate the CCC when the template is aligned with A and B based on P-arrival phase information. The majority of CCC calculations are unnecessary (more than 83%). (b) Computational time comparison between SEC-C method and the traditional method of searching for REs in different data sets containing different numbers of events. Both of these methods show computation time proportional to the square of the number of events, n (i.e., $O(n^2)$). This comparison shows that the SEC-C method is 10.8-15.5 times faster for data sets ranging from hundreds to thousands of events and has a mean improvement of 12.1 times faster in general. (c) One example of a RE family detected by the SEC-C method using waveform data from seismic station PGH (see Fig. 3a for locations of the RE family and PGH). The color version of this figure is available only in the electronic edition.

REs, foreshocks, aftershocks, LFEs, etc. SEC-C is a seismic cross-correlation package that can leverage a regular desktop machine and make it a powerful tool that can handle demanding matched filter projects. The MATLAB code is available in the [Ⓔ](#) electronic supplement and it is also available, along with a Python version, from our GitHub repository. An example of performing template matching that includes retrieving, preprocessing, performing template matching using SEC-C, and postprocessing results is also included in the GitHub repository, for new users with low-computational resources. We test this method on several different seismic data sets at a range of sample rates and compare it with other CPU-based contemporary methods. Our tests reveal that SEC-C is not only accurate to machine precision (i.e., double precision), but also it is the most efficient in terms of speed and memory usage. SEC-C can efficiently calculate the CCC sum and can also save the individual CCCs for each channel without introducing extra cost in terms of speed. Despite calculating many unnecessary CCCs, searching for repeating seismic events in a set of individual event waveforms using the SEC-C method shows a speed improvement of more than one order of magnitude on average for sets of hundreds to thousands of waveforms with respect to regular pairwise CCC calculations. This will reduce the run time required for performing pairwise cross correlation of several thousands of events from hours to minutes using a regular desktop machine.

Our development of the SEC-C method is part of an ongoing effort for speeding up seismic cross-correlation analysis. We plan to continue our time and memory optimization for SEC-C in future through, for example, producing versions in lower level programming languages (e.g., C++) and exploring the possibility of parallelization, both for CPUs and GPUs.

3.8 DATA AND RESOURCES

We retrieved the seismic data for stations near Mount St. Helens and Parkfield from the Incorporated Research Institutions for Seismology Data Management Center (IRIS-DMC) using the IRISFETCH MATLAB software that can be downloaded from <http://ds.iris.edu/ds/nodes/dmc/software/downloads/irisFetch.m> (last accessed July 2018). We managed

the seismic data (e.g., filtering, merging, visualizing, etc.) using the MATLAB signal processing toolbox and Seismic Analysis Code (SAC, <https://ds.iris.edu/files/sac-manual/>, last accessed March 2018). Some figures were made using the Generic Mapping Tools (GMT, <http://gmt.soest.hawaii.edu/>, last accessed March 2018; Wessel et al., 2013; last accessed March 2018). We used EQcorrscan v. 0.2.7 (<https://eqcorrscan.readthedocs.io/en/latest/>; last accessed July 2018) and fast matched filter (FMF; https://github.com/beridel/fast_matched_filter; last accessed July 2018) for our speed and memory comparison tests. GitHub repository is available at https://github.com/Naderss/SEC_C (last accessed September 2018). htop command is available at <https://hisham.hm/htop/> (last accessed October 2018). MATLAB is available at www.mathworks.com/products/matlab (last accessed March 2018).

3.9 ACKNOWLEDGMENTS

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Chapter 4

Towards using InSAR to increase accuracy in long period teleseismic earthquake source inversions and Earth seismic velocity models

Abstract

Historically, teleseismic earthquake source model inversions and Earth seismic velocity model inversions are reliant on each other, as determining each one requires assuming the other. This results from the fact that the seismic data that are the main input for these inversions contain information of both the source and the source-receiver path structural properties. As a consequence, the errors and biases in both sets of model results potentially can propagate between each other, producing a cycle of errors and biases between them. Several recent studies suggest that InSAR can break this cycle as it can provide independent, accurate, in situ locations of earthquakes. On the other hand, using InSAR to derive earthquake source locations and mechanisms is usually much slower (on the order of days) than the seismic case (on the order of hours) and can be applied to a limited set of earthquakes – typically shallow, large continental

events.

Global teleseismic source inversions such as Global Centroid Moment Tensors (GCMTs, Dziewonski et al. 1981; Ekström et al. 2012) historically have not fully accounted for the uncertainties and biases due to lateral heterogeneities of the Earth seismic velocity model and assumptions used in synthetic waveform calculations (e.g. assumptions on seismic wave propagation). However, recent studies show that using 3D Earth velocity models that account for lateral heterogeneities and also using more accurate tools to calculate Green’s functions does not improve the teleseismic source inversions on average with respect to InSAR models. Here in several case studies we investigate this puzzle. We observe that in most cases synthetic seismograms that are produced from InSAR models match the data very well except for a large phase shift (travel time bias) between the two waveforms at some stations. We propose that these phase shifts result from seismic velocity model errors along source-receiver paths. The systematic pattern in phase shifts are very similar for groups of nearby events (10-25 km apart) for several test cases that we examined in southern California, southern Iceland and central Italy. Similar azimuthal patterns of travel time biases observed between nearby events strongly suggest that the biases are correlated regionally and therefore can be used as the basis for regional corrections.

Here we show that these travel time biases are not only the plausible cause of mislocations of GCMT sources with respect to InSAR derived locations, but they are also responsible for miscalculations of the source mechanism. Beside the regional correction scenario, our results overall suggest that constraining global tomography using InSAR results could be viable.

4.1 Introduction, motivation and background

Determining precise earthquake source locations and mechanisms plays a fundamental role in the understanding of global seismic hazard, tectonophysics, Earth’s interior structure and many other applications in solid Earth science. One such effort, the Global Centroid Moment Tensor (GCMT) catalog is derived, via a rapid inversion process, from long-period teleseismic data (e.g. recorded at distances larger than 30 degrees from event source location in periods larger

than 25 seconds) and an assumed Earth velocity model (i.e. model SH8/U4L8 of Dziewonski and Woodward, 1992) as input information and is applicable to any global earthquake with M_w greater than 5 (Ekström et al., 2012). Since the birth of this method, the effects of errors that result from inaccuracies in both the Earth velocity model (e.g., not accounting for lateral heterogeneities) and in wave propagation assumptions remain poorly understood (Hjörleifsdóttir and Ekström, 2010; Ferreira and Woodhouse, 2006), but are likely significant. Ferreira et al., (2011) showed the mislocation of GCMTs in some cases can be of the order of 100 km with respect to accurate locations determined by geodetic methods. Another key question about errors in the GCMT method is whether these errors are unbiased (random errors such as those arising from station noise) or whether they are systematic errors caused, by example, by biases in the Earth seismic velocity model. If we can show that the main source of errors in GCMT method is systematic, we can hope to quantify these biases and increase the accuracy in the method.

Hjörleifsdóttir and Ekström, (2010) tried to evaluate the errors in GCMT method by inverting centroid moment tensor (CMT) solutions and locations from a simulated dataset of waveforms from 50 earthquakes estimated at 150 stations. They calculated the synthetic seismograms from this simulated dataset using the spectral-element wave-propagation package SPECFEM3D GLOBE (Komatitsch and Tromp, 2002a, b; also see method section) and by using two different Earth models – S20RTS (Ritsema et al., 1999) and S362ANI (Kustowski et al., 2008) along with the crustal model Crust 2.0 (Bassin et al., 2000). They applied realistic noise to the synthetic seismograms and then performed an inversion procedure based on the standard GCMT method to solve for source parameters for each case (i.e. CMT location, origin time and mechanism). They interpreted the differences between their input and calculated source parameters as errors in the GCMT method, which were small (e.g. mean of 9.1 and 8.56 km for horizontal mislocation for S20RTS and S362ANI, respectively) on average and indicated biases only in depth (mean of 6.35km) and centroid times (mean of 1.94 seconds). One can argue that the Earth models used in that study themselves were either estimated using input source parameters from the GCMT catalog (Ritsema et al., 1999) or by setting CMT parameters as free parameters and inverting for them as well (Kustowski et al., 2008). So, using these models

to calculate synthetic seismograms might not be an ideal case to show the error in the GCMT method as those synthetics might have biases and errors in them as well.

In this study we aim to improve long-period teleseismic centroid moment tensor (CMT) inversions using information from interferometric synthetic aperture radar (InSAR) as an independent source of information. This might be a novel opportunity to break the cycle of propagation of errors in global tomography and long period teleseismic CMT inversions as mentioned above. InSAR's main strength, with respect to other methods, is finding the accurate location of the best point source, or centroid, for an earthquake. Unfortunately, the number of earthquakes for which we have InSAR data is low, compared with the number of earthquakes recorded seismically. To record an earthquake with InSAR data typically requires a moderate to large magnitude event (i.e. above M5, and more typically above M5.5), with a shallow source depth (typically less than 15 km, and for the smaller detectable events, less than 5 km), in a continental region with low vegetation cover at the ground surface (e.g. Mellors et al., 2004; Lohman and Simons, 2005). In addition to this, earthquake centroid moment tensor inversion (i.e. solving for the location and mechanism of the event) using InSAR data is not yet possible in near-real time, due to the long interval between SAR acquisitions (days to weeks), data processing and also the inversion process itself, and this can take from several days to several weeks, depending on the satellite coverage available and the complexity of the event. On the other hand, seismic methods are fast and can be used for any location and depth, but they are not accurate (up to 60 km; Weston et al., 2011). Here we present our latest results and progress in extrapolating the strengths of InSAR in precisely locating earthquakes to nearby events, using the existing InSAR-based 'ICMT' (InSAR Centroid Moment Tensor) catalog (Weston et al., 2011, 2012). Our results show that it is not only possible to correct and improve long-period CMT inversions for the events with accurate InSAR locations but also it is possible to use these corrections for nearby events. We have tested our method in three different regions (i.e. California, Iceland and Central Italy) and obtained robust results about the success of regional GCMT corrections using the ICMT catalog. We also show how InSAR data can help us to increase the accuracy of relative centroid locations from seismic data.

4.2 The Global Centroid Moment Tensor (GCMT) Method

Digital seismograms have been globally available for seismologists for four decades. In this time a wealth of different models have been developed to invert for source location and source mechanism, each with its own strengths and weaknesses. These methods range in scale from local (e.g., Olson and Apsel, 1982; Hartzell and Heaton, 1983; Beroza and Spudich, 1988) to global (e.g., Aki, 1966; Kanamori, 1970a,b; Langston and Helmberger 1975) and operate either in the time domain (e.g. Dziewonski et al. 1981) or in the frequency domain (e.g., Kanamori and Given 1981; Romanowicz and Guillemant 1984). Among all of these methods, the Global Centroid Moment Tensor (GCMT, formerly Harvard CMT) procedure (Dziewonski et al., 1981) is one of the fastest and most accurate methods. Here we will briefly explain the GCMT method and its strengths and weaknesses. A complete description of this method is presented by Dziewonski and Woodhouse (1983) and also by Aki and Richards (2002). For technical detail aof GCMT see Ekstrom et al., 2012.

The basic idea behind the GCMT method was originally presented by Gilbert (1971), where he developed a formulation for the excitation of the normal modes of the Earth using an earthquake as a source. By following Rayleigh and Routh's work in the 19th Century (e.g. Rayleigh, 1877) on calculation of excitations for a system of N particles, he represented his calculations for the continuum limit. Following this work, Gilbert and Dziewonski (1975) showed that the elastic displacement field due to any source could be written as a superposition of normal modes,

$$u(x, t) = \sum a_k(t) s_k(x) \quad (4.1)$$

where s_k is a complete set of normal mode eigenfunctions and a_k is a function of normal mode eigenvalues, attenuation constants, and time derivatives of the stress glut tensor (Backus and Mulcahy, 1976). By using some approximate assumptions about the source and seismic wave propagation, theoretically the full wavefield for an earthquake can be calculated.

By assuming an earthquake as a source, approximated by a moment tensor acting at a point,

Gilbert and Dziewonski (1975) showed the j th component of displacement at the point (x, t) can be expressed as:

$$u_j(x, t) = \sum_{k=1}^6 G_{jk}(x, x_s, t - t_s) M_k \quad (4.2)$$

which M_k , $k = 1, 2, \dots, 6$ ($M_{rr}, M_{r\theta}, M_{r\phi}, M_{\theta\theta}, M_{\theta\phi}, M_{\phi\phi}$) are six independent components of moment tensor and $G_{jk}(x, x_s, t - t_s)$ – the excitation kernels – are the partial derivatives of the displacement respect to M_k . As this is a linear relationship, $G_{jk}(x, x_s, t - t_s)$ can be calculated as Green's functions of the j th component of displacement at (x, t) responding to a step in moment at (x_s, t_s) , where M_k describes the special tensors

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

respectively, for the sources. This is only because we deal with internal forces for the source which requires conservation of angular momentum and because the moment tensor must be symmetric to ensure no net rotation of the source. Thus, 9 independent components of the moment tensor reduce to 6 independent components (Shearer, 2009). These six tensors are fundamental tensors and all internal sources can be constructed using these six tensors. The step in moment can be represented with a moment rate tensor $\dot{M}(t) = M\delta(t - t_s)$ acting at the source location ($x = x_s$). This is based on our assumption that the whole fault slips instantaneously. This is a reasonable assumption since we are interested in long period data (e.g., >30 s), and this period band is not affected by source complexity (i.e. the period of the seismic waves being used is typically several times longer than the rupture duration of the intermediate earthquake, so the data cannot resolve whether you have instantaneous rupture of a point source or gradual rupture of a more complex source).

If we have a measurement of displacement at several stations (x_n, t_n) , by calculating excitation kernels G_{jk} for these (x_n, t_n) , we would be able to construct a linear inverse problem in order to invert for six components of the moment tensor if we assume a centroid (Eq 2). This

inverse problem can be solved by adjusting these six coefficients in order to achieve the best fit to the data or solution can be found by linear least square method. By assuming a pure double-couple system of equivalent forces for earthquake source, these six parameters can be expressed in terms of strike, dip, rake and seismic moment (Aki and Richards, 2002). The (x_s, t_s) are collectively known as the centroid of CMT and as we saw excitation kernels are functions of them. In the general case, the CMT location and time are unknown and can be estimated by introducing 4 more parameters to the inversion problem (three parameters for location and one for time) and iteratively solving for all 10 parameters (Gilbert and Dziewonski, 1975; Dziewonski et al., 1981; Ferreira and Woodhouse, 2006).

As discussed above, all these assumptions in relationships and formulation are valid as long as source duration and dimension (of the fault that slips) are small relative to the period and wavelength of considered seismic waves, respectively (Dziewonski et al., 1981; Ekström et al., 2012). More information about the Green's function calculation and also solving the CMT inverse problem is provided in method section (see section 4).

4.3 GCMT and global tomography

Among all the potential error sources in the GCMT method (e.g. simplified assumptions on wave propagation calculation, source complexity for large earthquakes, seismic noise and low data quality and coverage), inaccurate Earth structure is the main source that can affect CMT results (Dziewonski and Woodhouse, 1983; Hjörleifsdóttir and Ekström, 2010; Ferreira and Woodhouse, 2006; Ferreira et al., 2011). In the earliest version of the GCMT (Dziewonski et al., 1981) the spherically symmetric Preliminary Reference Earth Model (PREM) of Dziewonski and Anderson (1981) is employed. However this model was simplified and did not account for upper mantle lateral heterogeneity that may significantly affect in surface wave propagation (Ekström et al., 2012, Ferreira and Woodhouse, 2006).

To improve and account for 3D Earth structure, model M84C of Woodhouse and Dziewonski (1984) for the upper mantle and the whole mantle shear-velocity model SH8/U4L8 of Dziewon-

ski & Woodward (1992) have been used in later versions of the GCMT method (Ekström et al., 2012). These 3D Earth structure models are fed, directly or indirectly, by GCMT results. For example for model M84C, Woodhouse and Dziewonski (1984) invert for the 3D distribution of seismic wave velocities simultaneously with source parameters using the GCMT approach for around 2000 seismograms corresponding to 53 events. Existing tradeoffs between GCMT solutions (i.e. source location and time) and Earth structure (i.e. travel time) may produce biases and errors between these two different sets of parameters. Several recent studies focus on errors in GCMT results either by using simulation methods (Hjörleifsdóttir and Ekström, 2010) or by comparing GCMT results with regional earthquake catalogs or InSAR results (Ferreira et al., 2011, Weston et al., 2011, Weston et al., 2012). All of these studies are in agreement that most of these errors in GCMT locations likely result from unmodeled structural heterogeneity. So far none of the existing, more detailed 3D tomographic velocity models tested have had any success in improving on GCMT locations (Figure 4.1; Ferreira et al., 2011) showing a lack of accuracy in current 3D models and suggesting a need to improve the 3D velocity model for Earth.

4.4 InSAR Centroid Moment Tensors (ICMTs)

Not very long after the first European radar remote sensing satellite, ERS-1, successfully launched in 1991, geodesists demonstrated that it was possible to use the Interferometric Synthetic Aperture Radar (InSAR) technique to study earthquakes (Massonnet et al., 1993). This method allows researchers to measure ground displacement (with sub-centimeter precision) at fine spatial resolution ($< 100\text{m}$) covering areas 100 km-wide, or more (See Massonnet and Feigl, 1998, and Brgmann et al., 2000, for comprehensive reviews). Fine spatial resolution and a high level of precision in this method provide a means of measuring Earth surface deformation resulting from earthquakes and can provide accurate, ‘in situ’ locations, completely independent of seismic data and Earth’s velocity model. Through elastic dislocation modeling (e.g. Okada, 1985) the displacement fields measured by this method can be inverted in order to infer earthquake source parameters (e.g. Massonnet et al., 1993; Wright et al., 1999; Funning et al., 2005b).

Since the response of the displacement field to perturbations in many of these parameters is non-linear, this inverse problem must be solved by optimization methods involving repeatedly calculating and adjusting forward models, and assessing their fit to the InSAR data.

Increases in the number of satellite missions that provide data with greater quantity and better quality, along with development in software and methods for processing and modeling InSAR data, have resulted in a large number of earthquakes that have been studied and modeled, primarily in the last decade. At this time, more than 100 earthquakes with magnitude between 4.4 and 9.0 have been studied with InSAR (Funning et al., 2013). The number of events is now large enough to start to identify statistically significant patterns and draw meaningful comparisons with other catalog data. A first attempt at making a catalog of information about source parameters derived by InSAR was undertaken by Weston et al. (2011). They gathered source parameter information from 77 studies, published between 1993 and 2007, for a total of 58 individual earthquakes. By compiling earthquake source parameters from the publications themselves, and/or requesting them from the publication authors, they were able to generate CMT solutions for all these events. Since then, the resulting InSAR CMT, or 'ICMT' catalog has been used for several applications (e.g. earthquake scaling relationships, comparison with other methods, for example GCMT, and more; Funning et al., 2013; Weston et al., 2011, 2012, 2014; Ferreira et al., 2011).

In comparison with other earthquake source parameter inversion methods, InSAR has its own strengths and weaknesses. For example, despite providing robust results on source spatial parameter determination, InSAR does not provide any coseismic temporal information. The common practice of using simplified 1D elastic homogeneous-layered models is another source of error in source parameter determination (e.g. Lohman and Simons, 2005a; Lohman et al., 2002; Hearn and Bürgmann, 2005). InSAR often cannot be used for areas covered by thick vegetation (particularly tropical vegetation, e.g. Funning and Garcia, 2019) or water (e.g. ocean, sea, lakes, river, etc.), and the detection of smaller earthquakes (i.e. $M_w < 5.5$) can be strongly affected by noise from the troposphere (e.g. Mellors et al., 2004; Lohman and Simons, 2005a; Funning and Garcia, 2019).

4.5 Comparison between GCMT and ICMT results

Several studies have focused on comparison and attempted reconciliation between ICMT and GCMT results (Ferreira et al., 2011; Weston et al., 2011, 2012, 2014). These include source mechanism comparisons (i.e. of strike, dip, rake and moment) and also comparisons of centroid location. Significant discrepancies (up to ~ 60 km) in location were identified. On the other hand, moment magnitudes reported in these two catalogs are in good agreement (median difference in M_w of -0.009 and standard deviation of 0.10 magnitude units; Weston et al., 2012). The median of differences in other source mechanism components (e.g. strike, dip and rake) is relatively low (1.0° , 0.0° , -5.5° respectively) compared to the standard deviation of the differences for these parameters (13° , 15° and 16° ; Weston et al., 2012). In our preliminary work for 3 events we found we could significantly reduce discrepancies in source mechanism by accounting for unmodeled travel time biases likely caused by lateral heterogeneities that are not represented in current Earth velocity models (see method section).

The basic idea behind the InSAR technique is the differencing of two images of the ground that span an earthquake – one image acquired prior to the earthquake, and one acquired after the earthquake. Usually the period between the earthquake and the first available post-event data covers days or weeks after the earthquake. It had long been assumed that ICMT solutions should overestimate seismic moment (e.g. Wright et al., 1999; Feigl, 2002; Funning et al., 2007) since, in the period between image acquisitions, InSAR is likely capturing post-seismic surface deformation in addition to the coseismic deformation, especially for those areas that have weak materials near the surface (Floyd et al., 2016). However, recent studies (Weston et al., 2011, 2012) that compare ICMT and GCMT catalogs have shown that there is no resolvable difference in moment for events that appear in both catalogs. There are two different scenarios that can explain such moment comparison results: 1) Prior assumptions of moment overestimation using InSAR data are wrong. 2) The GCMT method is overestimating moment.

4.6 Method

4.6.1 Misfit function analysis

The general form of the GCMT inversion method is based on minimizing differences between synthetic and data by adjusting source parameters. The difference between the forward-modeled seismograms and the data defines a ‘misfit function’. The typical form of a misfit function is (e.g. Dahlen & Baig, 2002; Ritsema et al., 2002)

$$m^2 = \frac{(s - d)^T (s - d)}{d^T d} \quad (4.3)$$

in which d is data vector and s is theoretical seismogram vector and the superscript T indicates the transpose. This form of the misfit function is mostly sensitive to seismogram amplitude and will hereafter referred to as the amplitude misfit function, or ‘AMF’. As explained above, the general form of the GCMT inversion method is based on minimizing differences (a misfit function) between synthetic seismograms and data by adjusting source parameters. Theoretically if we accept that the ICMT method produces accurate source parameters (e.g. Figure 4.1b), the synthetic seismogram that has been produced by these source parameters should fit the data very well, except for any phase shifts (travel time biases) corresponding to unmodeled heterogeneity in the Earth’s 3D velocity structure. As we explain below, we estimate these phase shifts and use them to explore possible Earth model biases. We then investigate the role that these biases play in GCMT mislocations. In order to estimate phase shifts, we develop a semi-automated and routine way of preparing waveform data and synthetic seismograms for a target event. Below we briefly explain these procedures.

4.6.2 Synthetic seismograms

In order to calculate synthetic seismograms using the ICMT source location and source parameters, we start by calculating excitation kernels for each event using their ICMT locations. In general, we follow the procedures used by Weston et al. (2014), to which we refer the reader

for complementary explanations about synthetic seismograms, excitation kernels and station selection.

The first step in the procedure is station selection. To maximize the number of travel time biases we estimate, we use all available stations that recorded our target events and are archived at the Incorporated Research Institutions for Seismology Data Management Center (IRIS-DMC), within a certain angular distance range. We first use the JWEED software (<https://ds.iris.edu/ds/nodes/dmc/software/downloads/jweed/>) to identify which stations were operating at the time of the event. We then use the IrisFetch.m MATLAB software (downloaded from <http://ds.iris.edu/ds/nodes/dmc/software/downloads/irisFetch.m>, last accessed October 2018) to retrieve metadata from those stations. Next, we make input station lists for SPECFEM3D GLOBE, selecting stations with angular distances from 35 to 145 degrees in order to prevent near-source and multiple orbit overlapping (e.g. R1 and R2) effects.

Next, we use the spectral element wave propagation package SPECFEM3D GLOBE (Komatitsch & Tromp 1999) to calculate excitation kernels. SPECFEM3D GLOBE is one of the only software packages that can account for the effects of oceans, Earth ellipticity, topography, gravity, rotation and attenuation on seismic waveform simulations. We then sum these excitation kernels based on Eq (2) and scale them using the ICMT source parameters to calculate the synthetic seismograms. For calculation of the excitation kernels, the centroid latitude and longitude are derived from InSAR data, assuming a fixed centroid depth of 12 km, and the centroid time reported in the GCMT catalog. The 3D Earth model S40RTS (Ritsema et al., 2010) combined with CRUST2.0 (Bassin et al., 2000) was used. We calculate excitation kernels instead of directly computing the synthetic seismograms as we can use them further for inversion purposes. We calculate 120 minutes of synthetic waveforms, filter them with a 25-100 sec bandpass for body waves and a 125-180 sec bandpass for surface waves and select windows around the body and surface wave arrivals. We use the mantle shear velocity model S40RTS (Ritsema et al., 2011) along with the crustal model CRUST 2.0 (Bassin et al., 2000) as the basis for these computations.

4.6.3 Data preparation and phase shift calculations

In order to facilitate our workflow, we developed a semi-automated MATLAB code that can accomplish the following tasks: i) retrieving data two hours before and four hours after the GCMT origin time from the IRIS DMC; ii) removing instrument response and rotating the horizontal components into the radial and transverse directions; iii) bandpass filtering body wave between 25 and 100 seconds and between 120 to 160 seconds for surface wave and also resampling to an appropriate sample rate (1 s); iv) windowing the data around the body and surface wave arrivals (200 and 1000 seconds for body and surface waves, respectively); v) repeating steps ii) to iv) this time for synthetic seismograms; vi) visually checking the similarity between data and synthetic waveforms for quality control (i.e. we remove bad stations); and finally, vii) calculating phase shifts by maximizing the cross-correlation coefficient (CCC). We use only stations and channels that had a maximum cross-correlation coefficient (ccc) more than 0.7 for body waves and more than 0.96 for surface waves. We used polynomial interpolation in the vicinity of the cross- correlation maximum to calculate the phase shifts at sub-sample rate precision (e.g. Schaff et al., 2004).

From all these steps the quality control for data (i.e., low noisy station selection) and windowing for body and surface wave are requires visual inspection. We made these automated mostly by the use of a machine learning approach and based on visual inspection of several events and hundreds of stations. By assigning the synthetics and data similarities high, intermediate and low quality tags for several hundred cases, we were able to explore possible parameter spaces in which these three groups become separated in clusters. We found a clear clustering in a 2D space containing CCC and AMF between the data and synthetics. For example, the cases with the tag of high similarity could be identified by the inequalities $(CCC - AMF > 0.9)$ for surface waves and $(CCC - AMF > 0.85)$ for body waves. The software is now interactive and GUI-based, providing an inspection option for data quality and window choice only for intermediate group. Note that for our method removing stations with low signal to noise ratio is an important factor. High value of CCC-AMF is a signature of that synthetics and

data are highly similar and therefore the signal to noise ratio of the station is high as well.

4.7 Results

Below in several case studies we show how important these phase shifts can be for long period CMT inversions and also how they are indicating the biases in the global Earth model. In the first case study we show these phase shifts not only might be responsible for CMT mislocation problem but also that they sometimes can cause the miscalculation of CMT solutions as well (in this example the dip an event). We then in several case studies targeted several nearby events that were located in range of 10-25km respect to each other. We aim to explore nearby events in order to answer questions such as: i) Is there any systematic pattern of phase shifts respect to azimuth and distances of stations (e.g., indicating the cause might be biases in the Earth model) or not (e.g., indicating the source of phase shifts are random, such as stations noise, random error in the Earth model, etc)? ii) Are these systematic patterns for the nearby events similar to each other? Answering these questions can extremely be helpful for possible future work on increasing accuracy in global earthquake locations and global Earth models.

4.7.1 Case study 1: Large discrepancy between ICMT and GCMT for the dip of the Zarand earthquake

In Februray 22, 2005 a M_w 6.5 earthquake occurred at 02:25 (GMT) in the Kerman province in southcentral Iran that resulted in more than 500 fatalities (Talebian et al. 2006; Rouhollahi et al., 2012). For the Zarand earthquake, a large discrepancy exists between the ICMT source mechanism and seismic inversion results, such as the GCMT result and our own seismic inversion using the long period surface wave (LPS) data (Weston et al., 2014). This difference is particularly large in the dip angle. The estimated dips for ICMT, GCMT, long period body (LPB) and LPS are 63.7° , 46.0° , 55.7° and 24.2° , respectively. This miscalculation of dip angle of the Zarand earthquake in the seismic models is thought to be the reason behind an identified

tradeoff between dip and seismic moment for joint inversion models of that event (Weston et al., 2014).

Here and only for this specific earthquake we used data and excitation kernels obtained from the authors of Weston et al., (2014) instead of calculating them using our method. The main reason for doing this is that we wanted to enable a direct comparison between our methodology versus that of Weston et al., (2014) by avoiding the affect of station and data selections.

Here we first estimate the phase shifts necessary to align the waveform data to synthetic seismograms based on the ICMT source parameters and centroid location, as documented above. When these phase shifts are applied to the waveform data, our LPS inversion indicates a dip of 68° and our LPB inversion, 62° , both close to the ICMT value. In order to investigate that how adding these phase shift could solve the dip discrepancy problem, we plotted the AMF misfit function for LSP versus the dip while the other source parameters were fixed at ICMT values (Figure 4.2). In Figure 4.2 we observe that in general two minima exist for the misfit function versus dip, one near 20° and one near 70° . Before adding phase shifts the global minimum is around 20° while by adding the correction for these phase shifts the global minimum switches to 70° . Note that the (anti-)symmetry of the interferograms of the Zarand earthquake (see Talebian et al., 2006 and Weston et al., 2014) strongly supports the steep dip scenario for this earthquake. By performing this test, our preliminary results suggest that, since adding phase shifts to the theoretical seismograms can solve the discrepancy in dip, the source of this mislocation is an inaccuracy in the 3D Earth velocity model used in the seismic inversions (see Figure 4.2).

4.7.2 Case study 2: 1992 Landers and 1999 Hector Mine earthquakes

To evaluate the consistency of the azimuthal pattern of travel time biases, we analyze two earthquakes that are located close to each other in both ICMT and GCMT catalogs: the June 28, 1992 Landers (M_w 7.3), and October 16, 1999 Hector Mine (M_w 7.1) events. We had several reasons to start with these earthquakes. First, both are well studied using both seismic and InSAR data (e.g. Jonsson et al., 2002; Simons et al., 2002; Fialko, 2004; Salichon et al., 2004). Second, their centroid locations are close (ICMT locations ~ 25 km apart). Third, both events are mislo-

cated by the GCMT catalog with respect to their ICMT locations (a ~ 17 km mislocation for the Hector Mine event and ~ 25 km for the Landers event; Figure 4.3. Finally, their mislocations show a similar northward pattern not only in the GCMT catalog but also in CMT inversions using 4 different 3D Earth models (Ferreira et al., 2011).

Figure 4.3 shows that both earthquakes are similarly mislocated by the GCMT catalog compared to the ICMT catalog (azimuth of 333° for Landers and 358° for Hector Mine). We used the InSAR centroid locations (from Fialko, 2004 and Jonsson et al., 2002, respectively) to calculate synthetic seismograms. For most stations we see a good correlation between synthetics and data (e.g. Figure 4.4).

Here we describe the phase shift patterns with respect to station azimuth and distance for these two events. For the Hector Mine earthquake surface waves we see similar phase shifts for stations with a similar azimuth (Figure 4.5a). For example, stations with azimuths of 10° to 50° have large negative (-10 to -20 seconds) phase shifts while stations distributed from 180° to 250° have positive phase shifts (0 to 10 seconds). Although we have many fewer stations for the Landers earthquake, we observe a similar pattern for the surface waves to that we infer for Hector Mine (Figure 4.5b). For the Hector Mine earthquake body waves we also observe that stations with similar azimuths overall have similar phase shifts. The amplitudes of the phase shifts in this case are slightly less than the surface waves (from 5 to -15 seconds while for surface waves we had phase shifts range of 15 to -20 seconds; see figure 4.5). The amplitudes of the phase shifts for Landers body waves are less than those of the Hector Mine body waves (6 to -8 seconds), perhaps a result of the smaller number of stations available.

If travel-time biases are due to unmodeled mantle heterogeneities in the Earth velocity model we would expect to see similar azimuthal patterns in those biases at distant stations. We find strong similarities in those patterns, especially for surface waves. In both Figure 4.5c and Figure 4.5d we see an interesting inflection at around 320° that seems it might have some coincidence with the Alaska subduction zone (which is located at that azimuth). The body wave biases for Hector Mine around these azimuths reach -15 seconds while in other azimuths the absolute values of phase shifts are not above 5 seconds. The body wave biases show a similar pattern

between the two earthquakes overall but there is a very interesting feature we observe at almost the same azimuth (between $\sim 310^\circ$ and $\sim 330^\circ$). There is a sharp increase in body wave time delay between 310° and 330° for the Hector Mine earthquake that we do not observe for the Landers earthquake (Figure 4.3a and 3c). Detection by several stations suggest it is not due to random error. Comparison for body wave phase shifts at common stations show a pattern that is related to the strike of both events (i.e. 150° ; Figure 4.6a). All the stations on east side of the strike show a negative phase shift differences while the west side of the strike stations show positive values. We do not observe spatial pattern phase shifts for surface waves (Figure 4.6b).

4.7.3 Case study 3: June 2000 South Iceland earthquakes

We similarly compare the travel time biases for a pair of similarly sized and well-characterized earthquakes located close to each other in south Iceland. The two M_w 6.5 events occurred on 17 and 21 June 2000 (i.e. 4 days apart). We calculate synthetic seismograms for these earthquakes using the InSAR source inversion results from Pedersen et al, (2001, 2003) reported in the ICMT catalog (Weston et. al., 2011). The two events had similar strike-slip mechanisms, and occurred on subparallel faults separated by ~ 18 km. Comparing these Iceland events to the Landers-Hector Mine events, we do not see a clear similar pattern in the phase shifts that depends solely on the azimuthal distribution of the stations (see Figure 4.7). In this case, the station distances play as important a role as the azimuths, and we see similar patterns of phase shifts that depend on both azimuth and distance for both events. These differences between the Iceland case and Landers-Hector Mine case can be explained by the sparsity of station coverage for the Landers-Hector Mine case. In that case, there were only a few azimuths where stations at different distances recorded the event. In contrast, for the Iceland events, we had more stations with high-quality data, with a wide sampling of azimuths and distances (see Figure 4.7).

As both of these events detected by many stations we can observe several details by looking at the phase shift pattern respect to station locations. Here we are listing some of these observations: i) For each event, nearby stations (within ~ 10 degrees in azimuth and distance) show similar phase shifts, suggesting that these are caused by biases rather than random errors

in the Earth velocity model. ii) The patterns of phase shifts for both events are very similar to each other, indicating that any inaccuracies in the global model affect both events similarly. As the travel time biases along these source-receiver paths are similar for both earthquakes, the implication is that corrections for one event could be used for the other, raising the possibility of using them to correct events in that region.

We compare the phase shifts for common stations, i.e. stations that recorded both events. We find that phase shifts for both events are similar, overall. However, there are some differences that have an azimuthal pattern and are systematically correlated with the strike of these two events (Figure 4.8). The differences are systematically negative (between 0 and -4 seconds) on the west side (i.e. azimuth 0° to 180°) and positive (between 0 and 3 seconds) on the east side (i.e. azimuths between 180° to 360°). The pattern is consistent with, and divided by, the strike of both events, i.e. $\sim$ north-striking. Note that the amplitude of phase shifts differences is much smaller than the absolute phase shifts. This indicates that the phase shifts are generally similar but there are small differences between them. As these small differences have an azimuthal pattern we suspect that these possibly resulted from small inaccuracies in their InSAR models, in this case most probably the miscalculation of the dip.

4.7.4 Case study 4: 2016 Central Italy earthquakes

In this case study, we target a pair of events that occurred in 2016 in central Italy – the October 26, M_w 5.9 earthquake near the town of Visso, and the October 30, M_w 6.5 event that nucleated below the town of Norcia. Both earthquakes are recorded by more than a thousand stations, and show high similarity between their synthetic seismograms from InSAR and the corresponding waveform data (Figure 4.10).

In order to derive ICMT models of these two events, we use the geodetic models of Cheloni et al., (2017). The models of fault geometry and slip in that study were inverted using InSAR and GPS data and incorporated constraints based on aftershock locations and geological information from the area. We calculated the CMT and best double-couple solutions from these geodetic models using the method of Weston et al. (2011).

Figure 4.10a,b shows the phase shifts associated with the surface waves and body waves. As we find for other pairs of events, the amplitude of body wave phase shifts is much smaller than surface waves (i.e. 15 to -20 and 2 to -5 for surface wave and body wave, respectively; Figure 4.10). Most of the observations we make for the Iceland earthquake pair are valid for these two events as well. The phase shifts are very similar in both body waves and surface waves for these two Italy events. As the Norcia event was larger than the Visso event, we have more stations with high signal-to-noise ratio data for the former, especially for body waves. As with the Iceland case study, we see strong biases in ray paths to stations in North America for both events.

The differential phase shifts between the Visso and Norcia events in this case do not show systematic patterns for the surface waves. As the geodetic model for these events inverted from both GPS and InSAR data along with constraints from seismicity and geologic information, and therefore the source mechanisms were better constrained, this was not a surprise that the error in their ICMT model is minimal. However, we can observe some very small but complicated spatial pattern in phase shift differences for body wave. The strikes of both events are around 150° and the pattern of phase shifts differences for stations between azimuth of -10° to 60° and stations between 150° and 240° are similar to each other. That might result from a combination of source mechanism error or secondary source effects such as directivity.

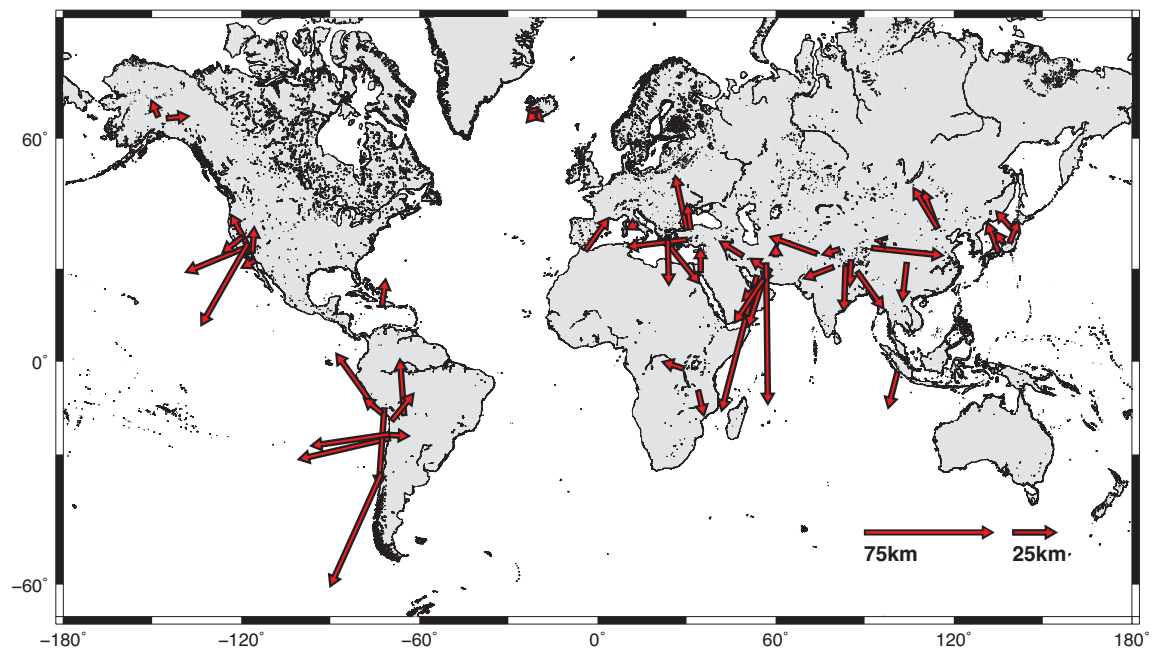
4.8 Conclusion

Using several case studies we investigate whether biases in 3D Earth models, the likely causes of mislocations of earthquake centroids when located using teleseismic long-period waveforms, are similar for nearby events or not. We compare synthetic seismograms that are produced based upon InSAR-derived source models with data. We observe phase shifts, representing unmodeled travel-time biases, between our synthetic and data waveforms that are very similar for nearby events. We show that miscalculations of source mechanism also could be solved were these phase shifts corrected. We observe that these phase shifts are globally systematic and therefore

they indicate biases in the Earth model used.

Observing similar patterns of phase shifts for close-by events indicate that these phase shifts can be calculated for one event with an InSAR source model and applied to other nearby events in order to calculate their locations and mechanisms accurately. Note that by making use of source-receiver reciprocity (e.g. Knopoff and Gangi, 1959), we can estimate the length scales over which such corrections can be usefully applied. In areas with wide and dense receiver coverage, e.g. the continental United States, the length scales over which phase shifts for remote events vary as a function of receiver location will inform us about the length scales over which you would expect the phase shifts to vary as a function of source location – and therefore the size of the region surrounding a well-located event over which you can use the phase shifts derived from it.

(a)



(b)

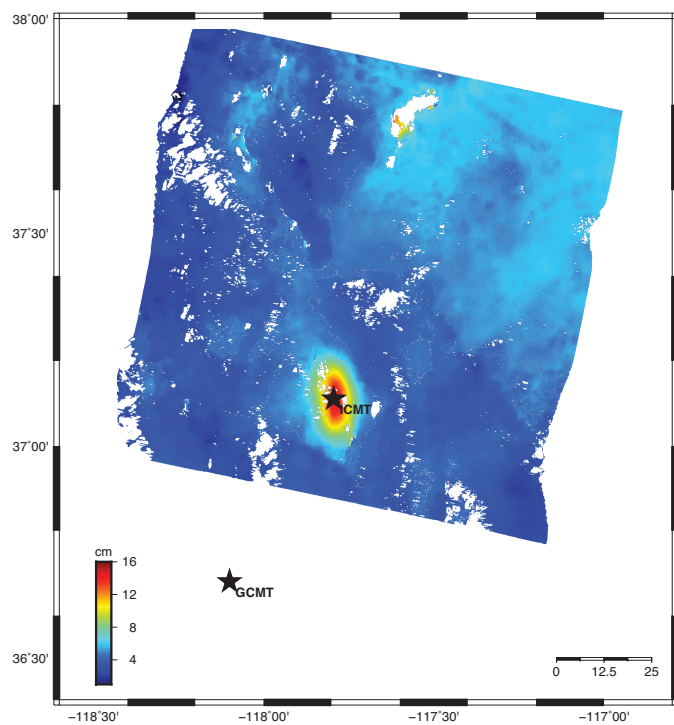


Figure 4.1: (Caption next page.)

Figure 4.1: (a) Mislocation vectors for 58 earthquakes, showing differences between centroid epicentral locations derived from the ICMT and GCMT methods. [Tail of each vector is the InSAR centroid.] (b) Comparison of epicentral centroid locations in the GCMT and ICMT catalogs for the 1993 Eureka Valley, CA earthquake, superposed on the ERS-1 interferogram for the event. Note that the ICMT location is consistent with the maximum line-of-sight deformation in the InSAR data, but the GCMT location is 54 km away, at an azimuth of 210° .

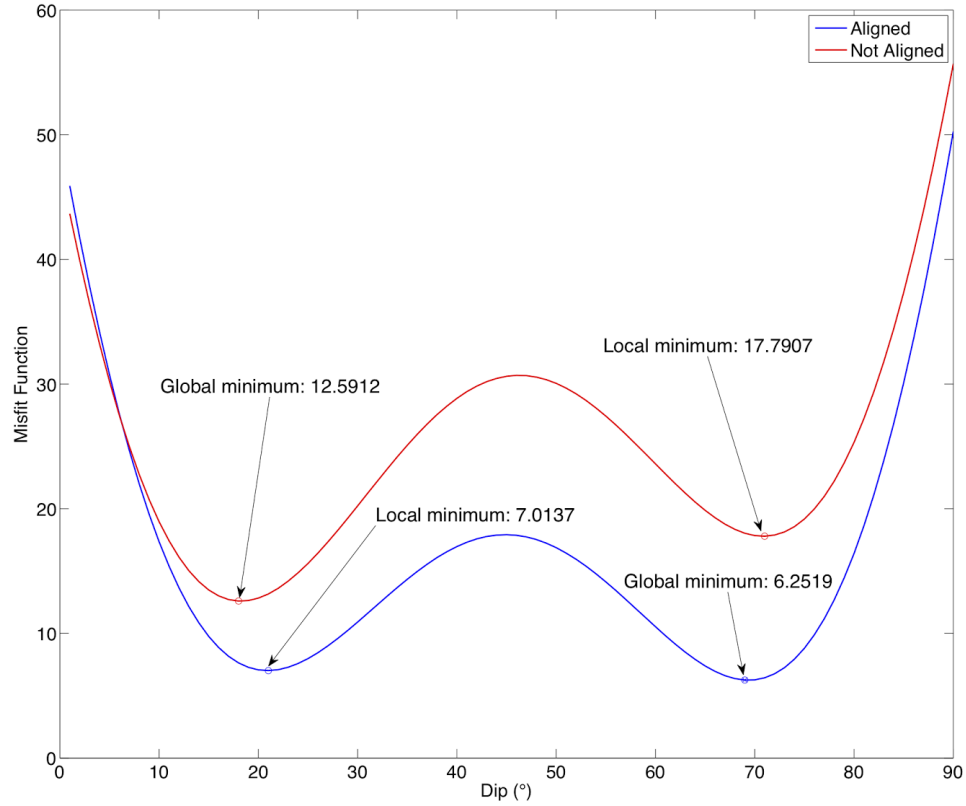


Figure 4.2: : Misfit function (see eq 3) for inversions of long period surface wave recorded at 46 stations, plotted against dip for the 2006 Zarand, Iran earthquake. Red: the regular case where no phase shifts have been added to the synthetic seismograms. Synthetics seismogram are calculated using complied excitation kernels and ICMT parameters from Weston et al., (2014). Blue: the case where phase shifts that align the InSAR Centroid Moment Tensor (ICMT) synthetic seismograms to the data are added to synthetic seismograms before inversion. Adding the phase shifts changes which of two local minima is the global minimum, thus changing the preferred dip from 24° to 68° (close to the ICMT dip of 64°) and demonstrating the effect of travel time biases on the inverted source mechanism. Note that, in addition to the phase shifts producing a dip more similar to the ICMTs, they also reduce the misfit by a factor of ~ 2 .

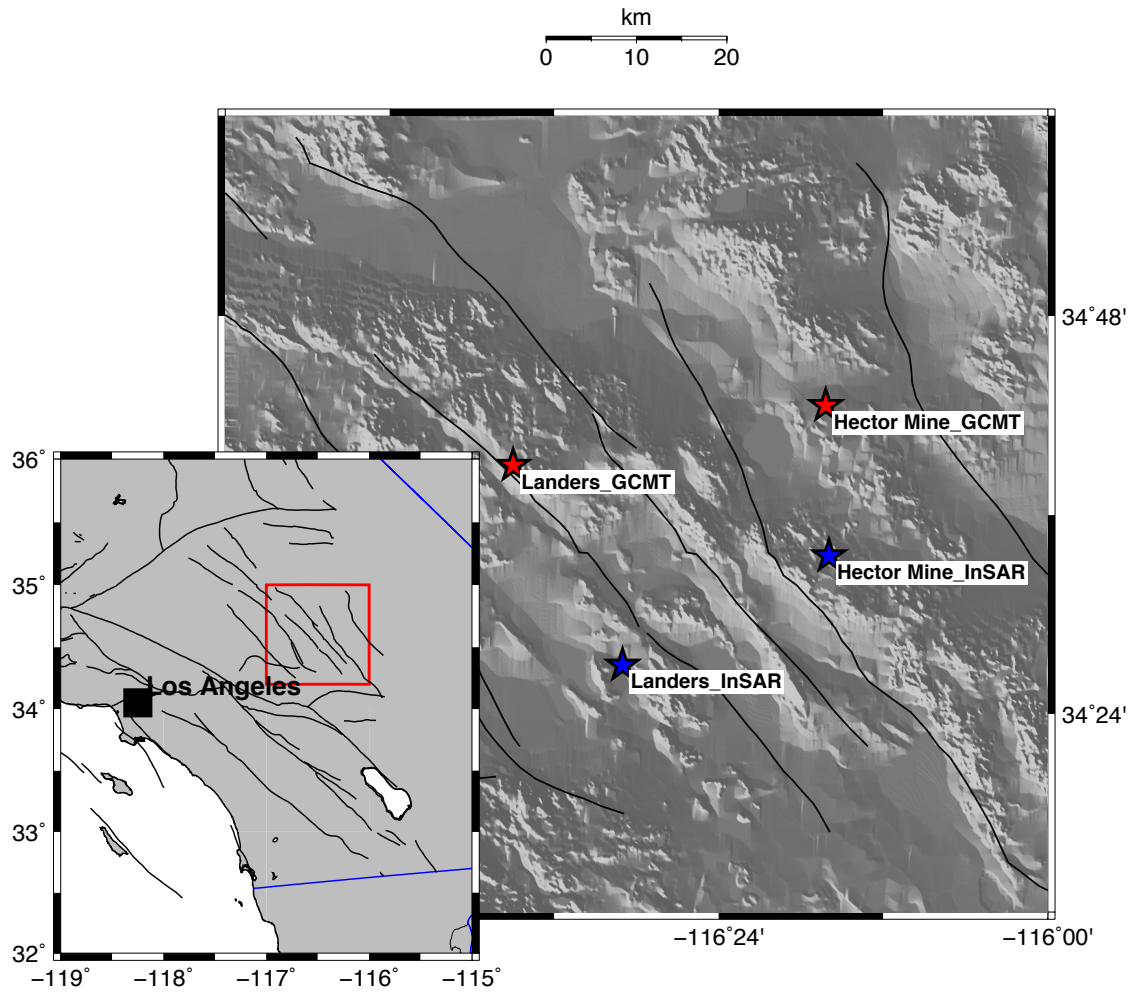


Figure 4.3: Locations of the Landers, 1992, M_w 7.3 and Hector Mine, 1999, M_w 7.1 earthquakes. Blue stars are InSAR-derived centroid moment tensor (ICMT) locations and red stars indicate Global Centroid Moment Tensor (GCMT; Dziewonski et al., 1981; Ekstrom et al., 2012) locations. Landers and Hector Mine ICMT locations are calculated based on the geodetic models of Fialko (2004) and Simons et al. (2002), respectively. By comparing the location of these events we can see that both earthquakes are similarly mislocated by the GCMT catalog, compared to their ICMT locations.

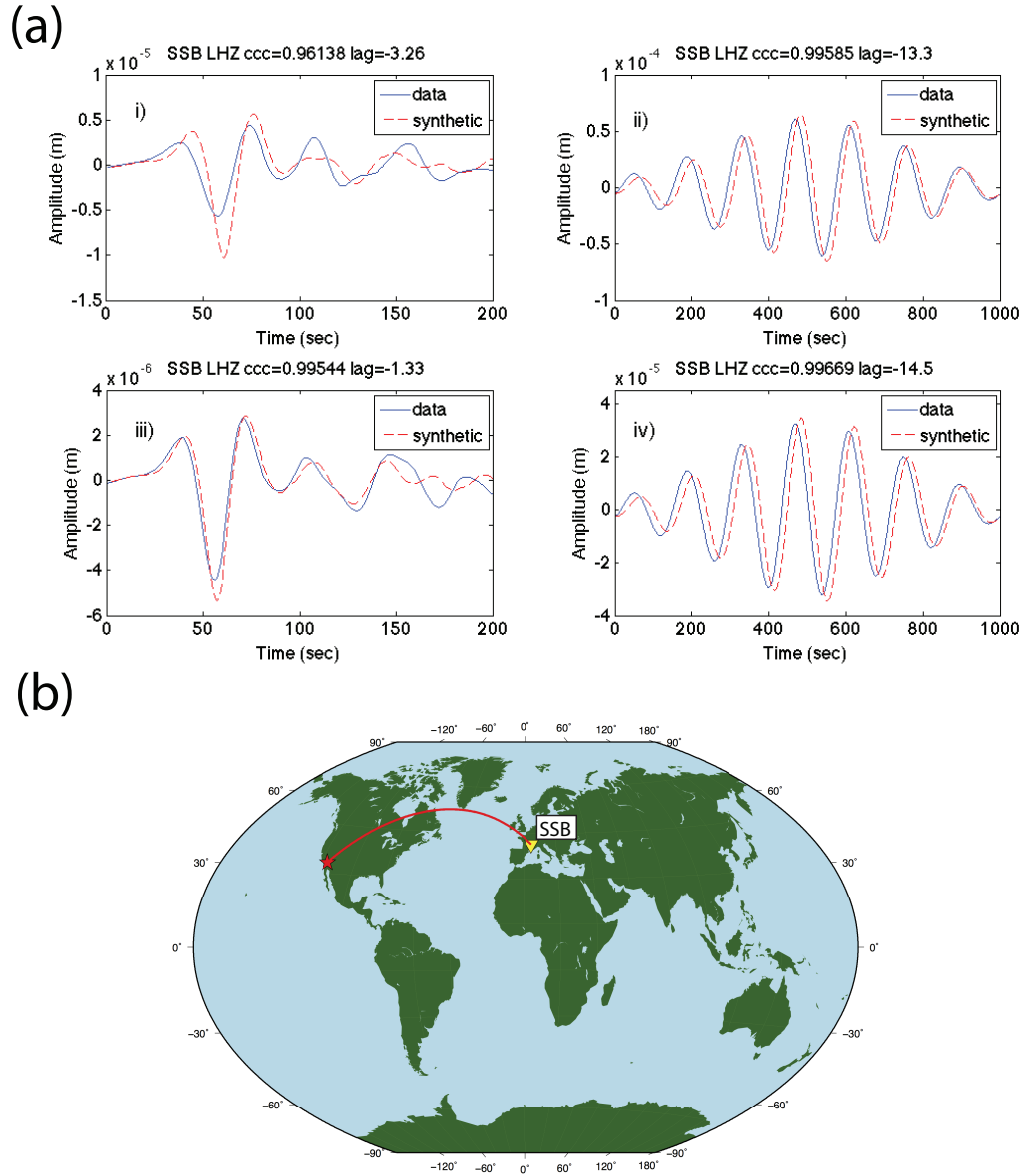


Figure 4.4: Waveform comparisons for different seismic phases at station SSB in France for the 1992 Landers, California and 1999 Hector Mine, California earthquakes. a) Alignment between data (solid blue line) and synthetic seismograms based on InSAR source models (red dashed line) for i) Landers body waves, ii) Landers surface waves, iii) Hector Mine body waves, iv) Hector Mine surface waves. Note how waveform shapes are similar despite requiring large phase shifts (e.g. -13.3 and -14.5 for Landers and hector mine surface waves) to align them, especially for the surface waves. b) A global map that shows the locations of these two events versus the location of SSB station and the great circle path between them.

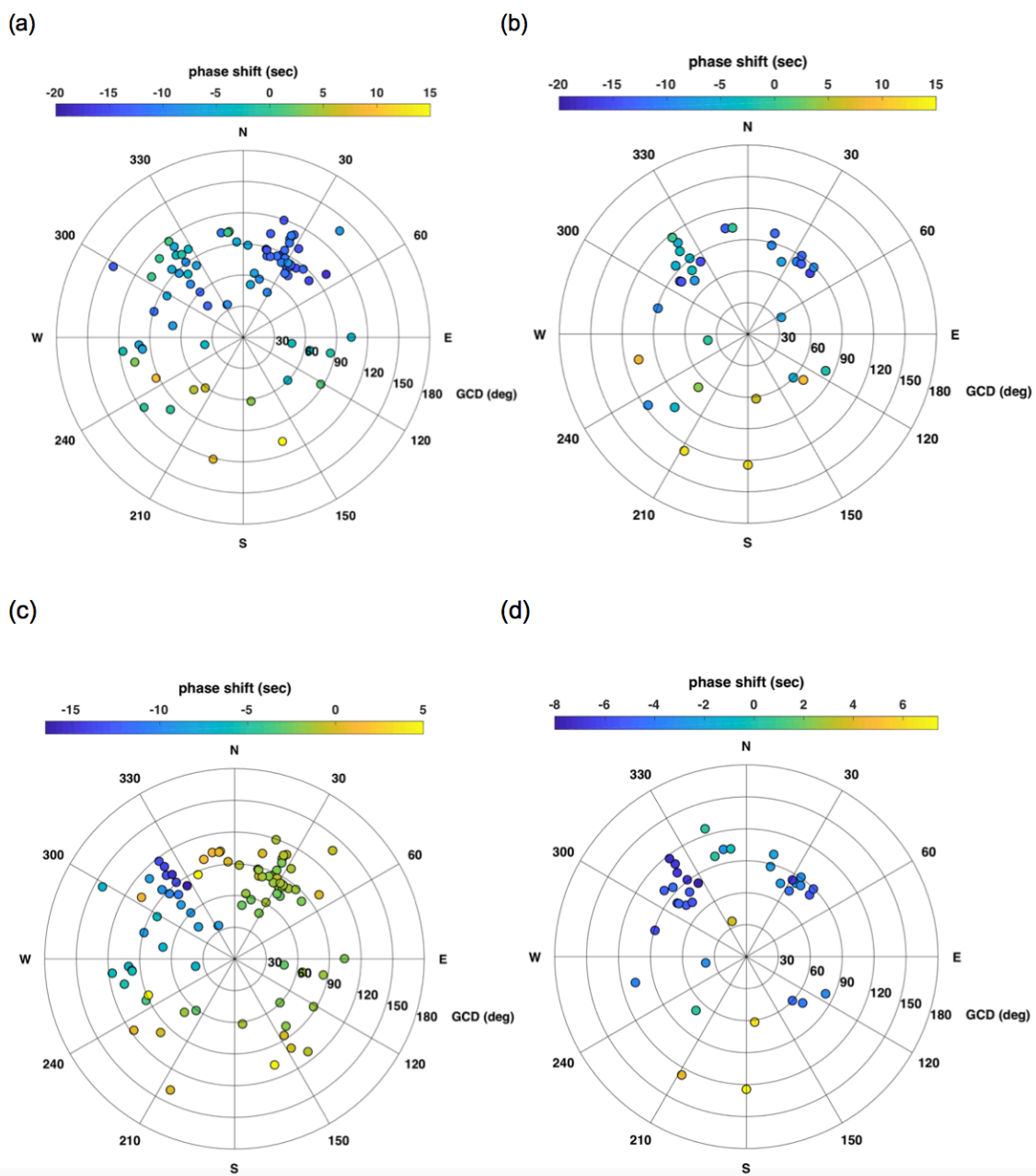


Figure 4.5: (Caption next page.)

Figure 4.5: A polar plot of surface waves phase shifts calculated at stations distributed at 35-145 degree angular distances from the ICMT location for the Hector Mine earthquake. The color bar indicates phase shift values. Note that the negative values represent delayed arrivals of synthetic waveforms with respect to the data and vice-versa. (b) Same as (a) but for the Landers earthquake. (c) and (d) same as (a) and (b) but for body waves. Overall, we see a similar pattern of azimuthal distribution of phase shifts for both events. For example, for surface waves and for stations distributed from the azimuth of $0^\circ - 60^\circ$, we observe large negative phase shifts (up to -20 seconds) for both events.

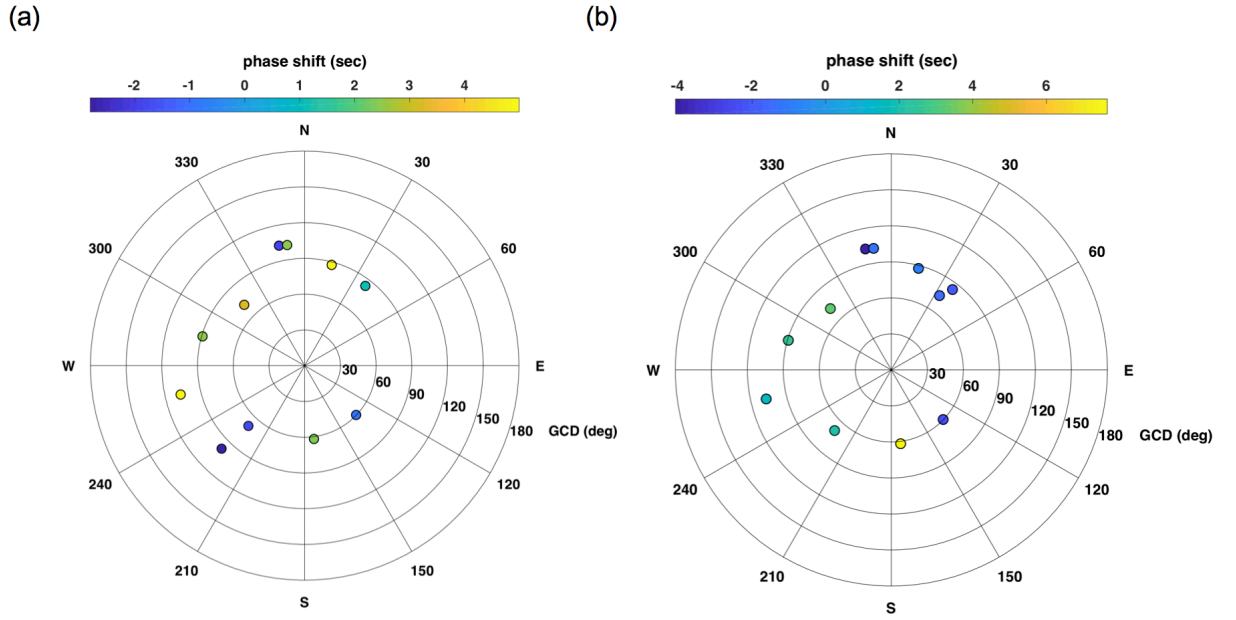


Figure 4.6: : (a) Phase shift differences between Hector Mine and Landers earthquakes for surface waves, i.e. the difference between Figure 5 (a) and (b) at common stations. (b) Same as (a) but for body waves. Comparison for body wave phase shifts at common stations show a pattern that is related to the strike of both events (i.e. 150 degree). All the stations on east side of the strike show a negative phase shift differences while the west side of the strike stations show positive values. We do not observe spatial pattern phase shifts for surface waves. Note that as the earthquakes occurred ~ 7 years apart and therefore there are not many stations are in common.

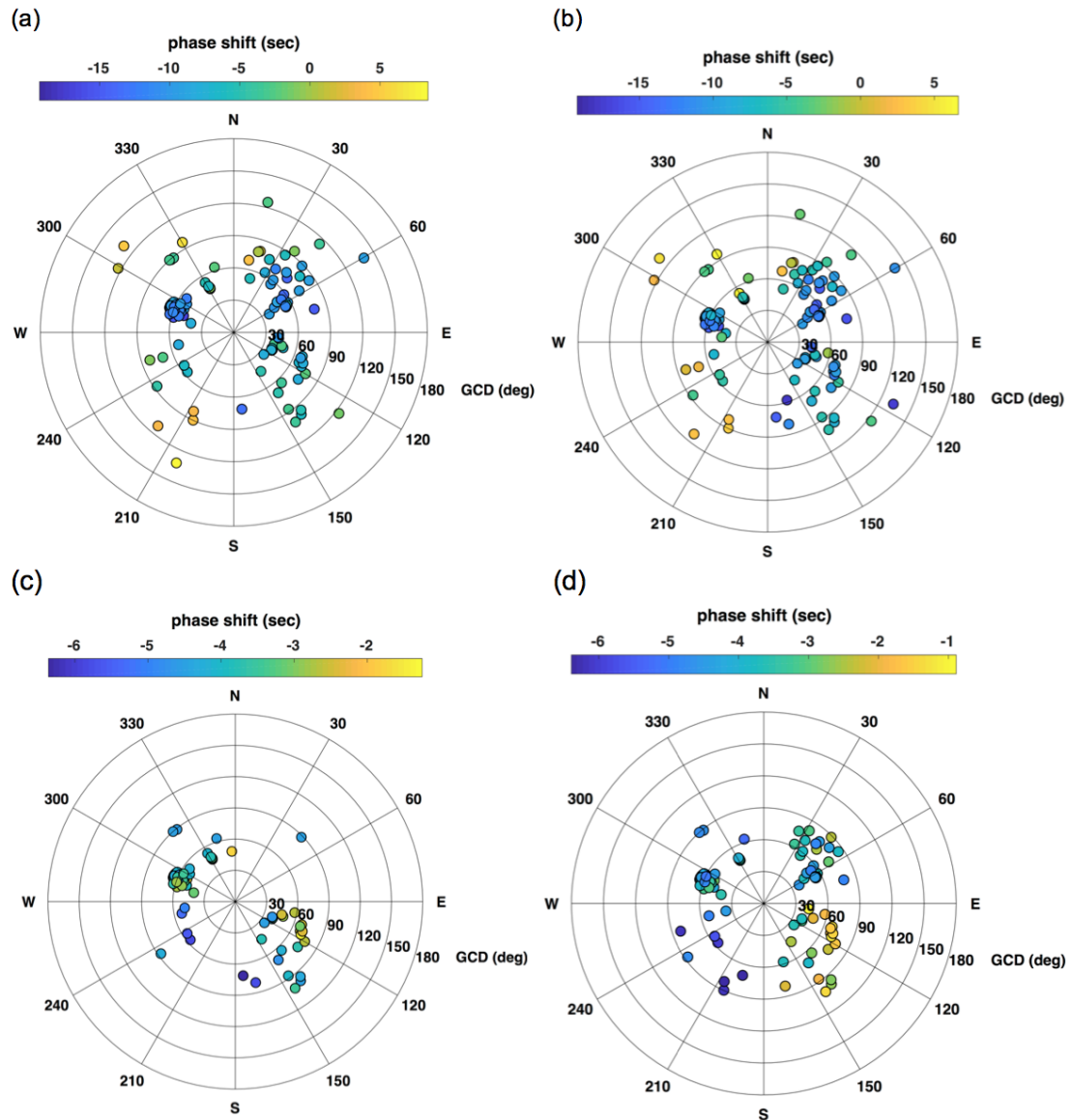


Figure 4.7: (a) A polar plot of surface waves phase shifts calculated at stations distributed at 35-145 degree angular distances from the ICMT location for the 17 June Iceland event. The color bar indicates phase shift values. Note that the negative values represent delayed arrivals of synthetic waveforms with respect to the data and vice-versa. (b) Same as (a) but for the 21 June Iceland event. (c) and (d) same as (a) and (b) but for body waves. Note that there is a similar pattern in the phase shifts and biases for both events and for both body waves and surface waves. The amplitudes of phase shifts are much smaller for body waves, as based on the nature of their ray paths (i.e. diving waves with steep trajectories) they are less prone to be affected by upper mantle lateral heterogeneities. A group of dense stations at azimuth of 290-300 and distance of 50-60 degrees are stations that are located in North America, that seem to have large biases specially for surface waves.

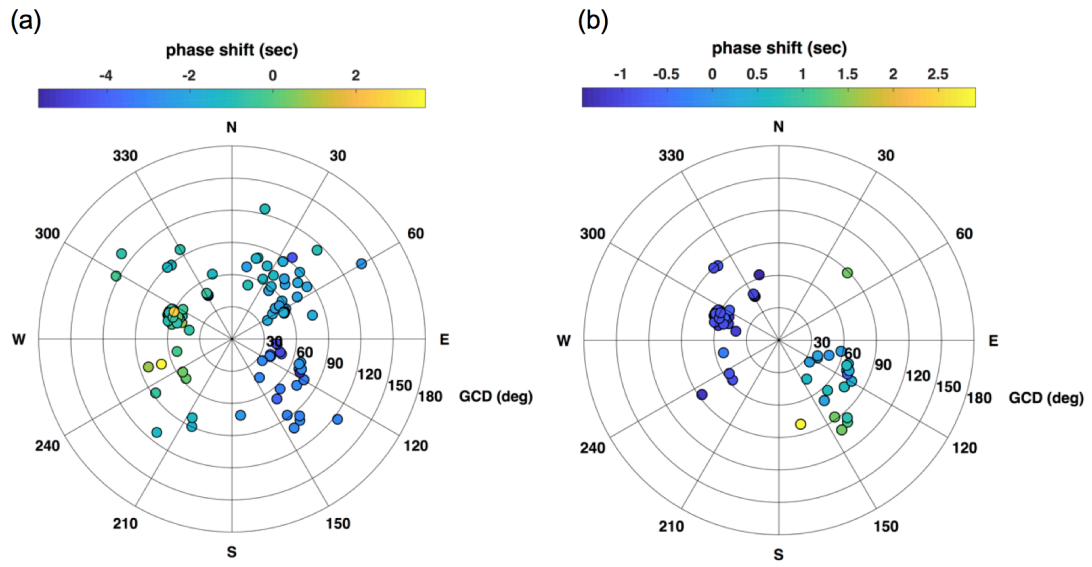


Figure 4.8: (a) Phase shift differences between the 17 and 21 June Iceland events for surface waves, i.e. the difference between Figure 4.7 (a) and (b). The differences are systematically negative (between 0 to -4) on the west side (i.e. azimuth 0 to 180) and positive (between 0 to 3) on the east side (i.e. azimuth between 180 to 360). The pattern is consistent with the strike of both events, i.e. north-striking. (b) Same as (a) but for body waves. The pattern in this case is reverse respect to surface waves.

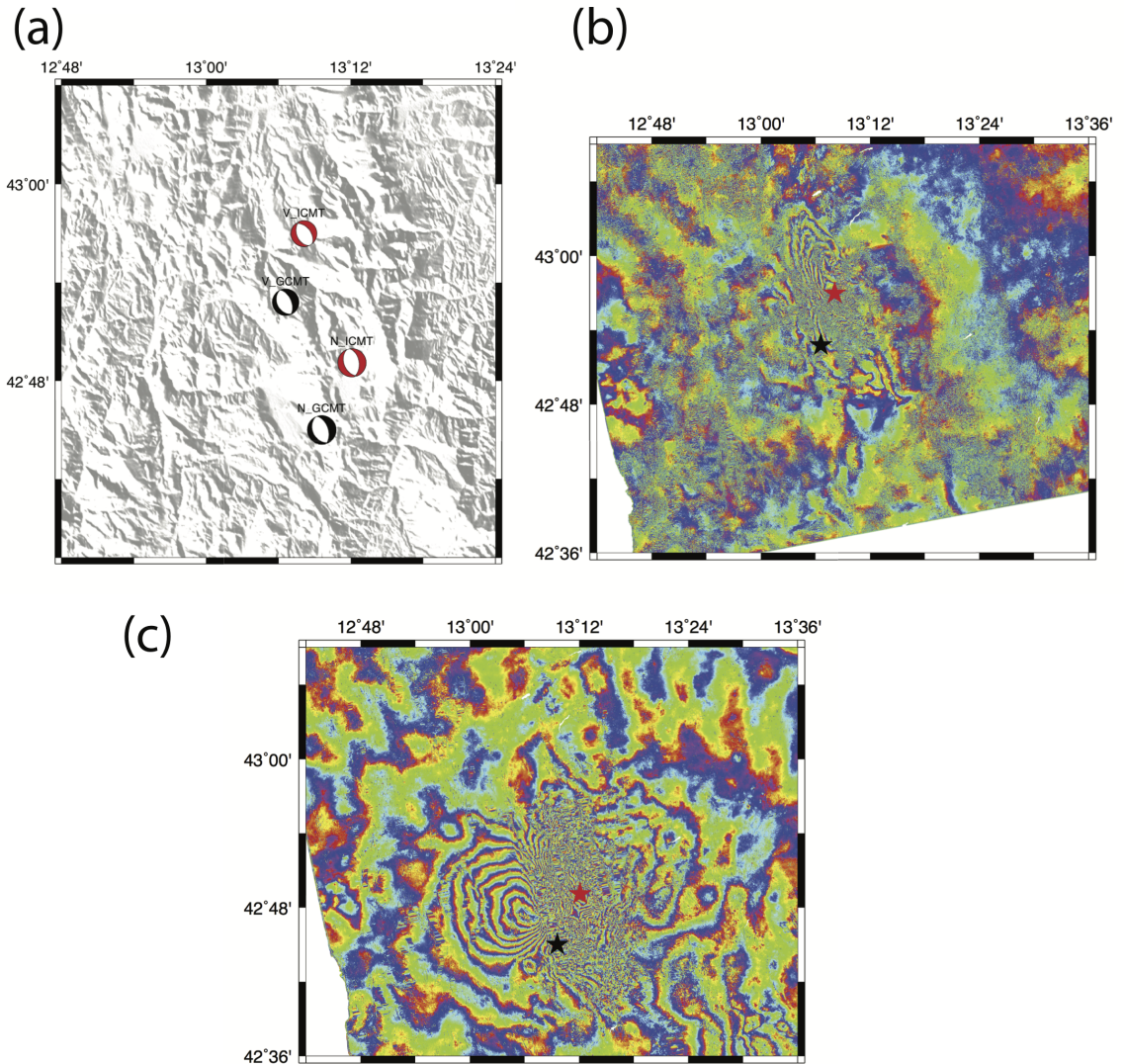


Figure 4.9: (a) A map of area near the 2016 central Italy two main events—26 and 30 October with magnitude 5.9 and 6.5 and that are known by the name of Visso and Norcia, respectively. The CMT location and mechanism are shown for ICMT (red) and GCMT (black) using their beachball representation. Beachball are named based on first alphabet of the event names (i.e. V, N for Visso and Norcia respectively). (b) to (d) are the InSAR interfrogram of Visso and Norcia events. Red starrs show the ICMT locations and black stars show the GCMT location. InSAR intrefrogram of Visso are based on Sentinel-1 wide-swath and from data aquisition dates of 2016/10/21 and 2016/10/27. InSAR intergrogram of Norcia is also from Sentinel-1 wide-swath and the date acquisitions are 2016/10/27 and 2016/11/02.

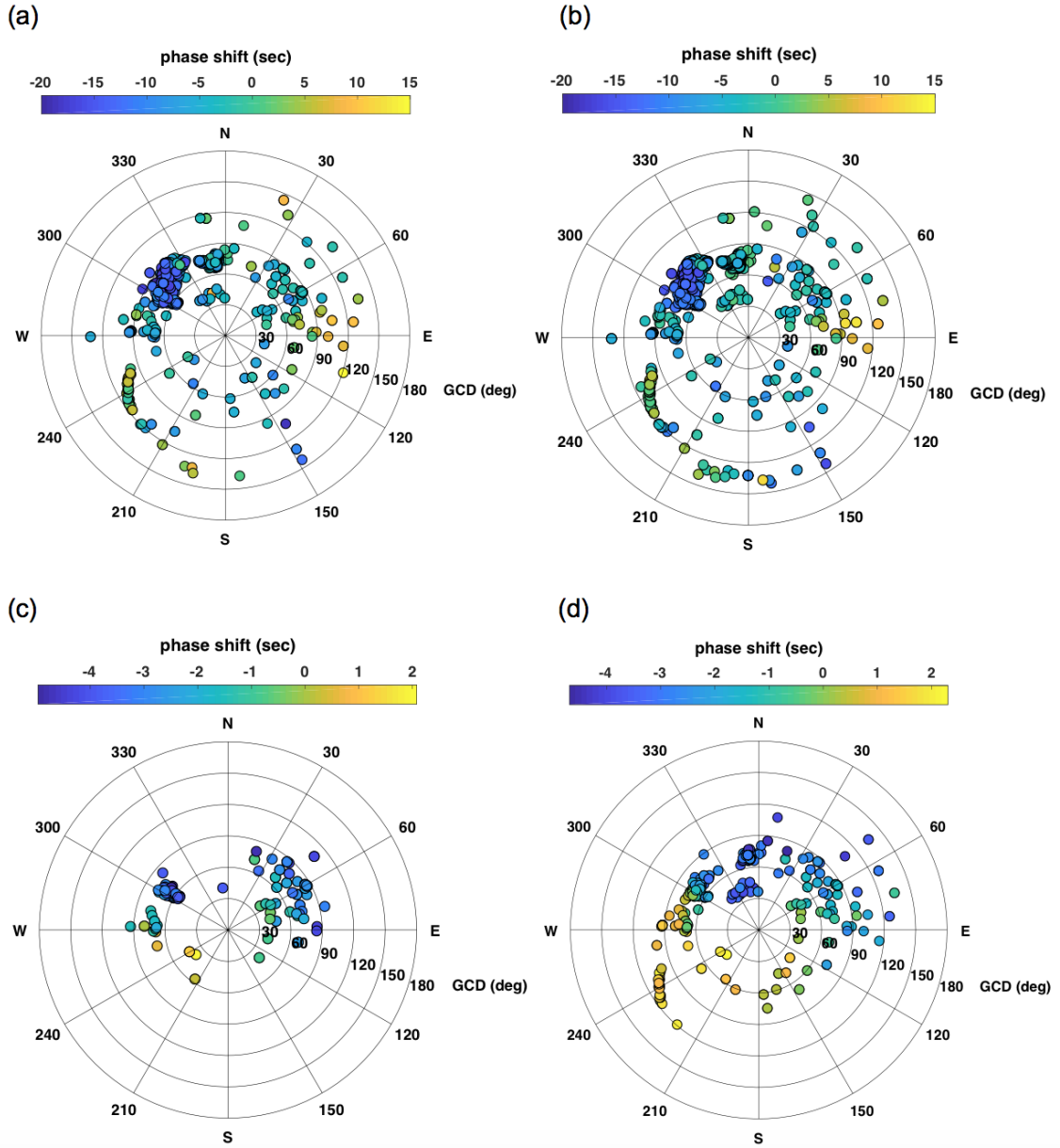


Figure 4.10: (a) A polar plot of surface waves phase shifts calculated at stations distributed at $35^{\circ}\sim 145^{\circ}$ angular distances from the ICMT location for the M_w 5.9, Visso event. The color bar indicates phase shift values. Similar to Figures 5 and 7, the negative values are assigned for delayed arrivals of synthetics respect to the data and positive are assigned for early arriving of synthetics. (b) Same as (a) but for the M_w 6.5, Norcia event. (c) and (d) same as (a) and (b) but for body waves. Overall, again we see a similar pattern for the phase shifts for these two nearby events. The similarity of the patterns is comparable with Iceland events (i.e. Figure 7), but here we have much more stations (i.e. > 1500 versus hundreds for the Iceland events).

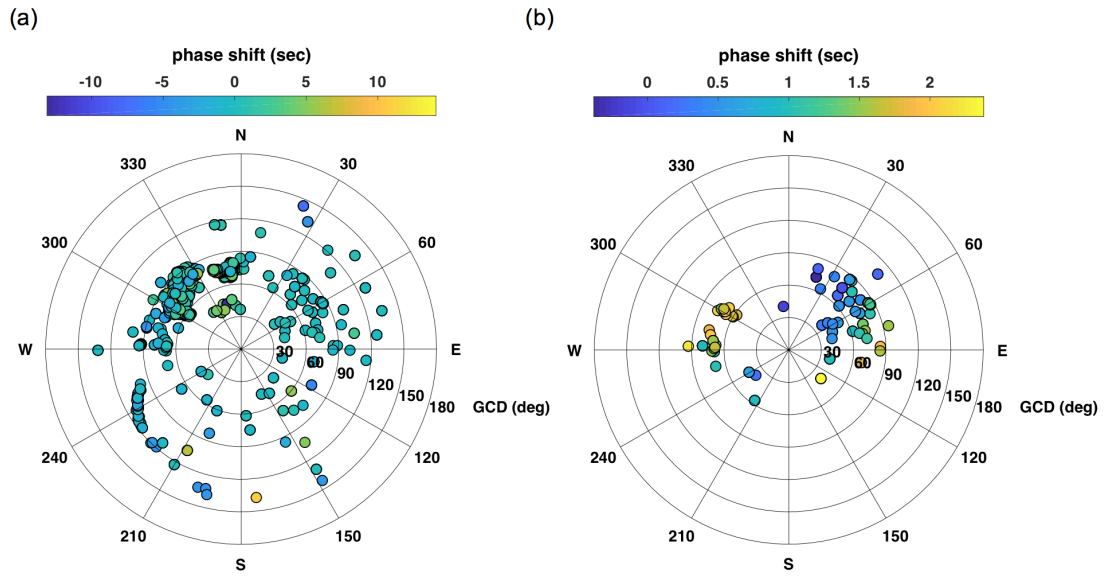


Figure 4.11: (a) and (b) Same as Figure 4.8 (a) and (b) but for Visso and Norcia events in Central Italy. In this case for the surface wave, there is no obvious systematic pattern of phase shift differences for the surface waves. However, body wave phase shift differences show some spatial pattern that seems to have relationship with the second order of event mechanisms (e.g. directivity). Note that strike of events are around 150 degrees and the pattern of phase shifts differences for stations between azimuth of -10° to 60° and stations between 150° and 240° are similar to each other.

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Chapter 5

Conclusions

In two different projects, we combined data and methods from seismology and geodesy to better constrain global earthquake source parameters and regional fault creep behavior. We show that merging these two geophysical sources of information that are measured by independent methods can assist with solving several geophysical problems such as inaccuracies in globally-estimated earthquake centroid locations or the low resolution we have when estimating the fault creep distribution at depth.

5.1 Key findings

In the first project (Chapter 2), we used seismology as a complementary tool to geodesy to increase our understanding of creep behavior in the North Bay. We used recorded seismic data to search for REs in the region. Using a fast, semi-automated and multistage algorithm that we specifically developed for detecting REs in regions with sparse networks, we detect 107 RE families and 91 RE pairs in this region. Our method uses the full potential of the seismic network in this area by constraining all the data and stations available rather than a traditional method that uses few selected stations with high signal to noise ratio and with long operation time.

Our results show that some parts of the northern and southern Maacama fault in this region might have subparallel strands that are actively creeping. To our knowledge, such pervasive

creep along the southern Maacama fault has been not documented before. The detected RE locations along the Rodgers Creek fault corroborate the surface creep signal observed in InSAR data from previous studies (Jin and Funning, 2017). Our detected RE locations along the Bartlett Springs fault are also in agreement with the observation of surface creep from alignment arrays and GPS models. Our estimated creep rates are broadly in agreement with creep rates reported in other studies that measure creep using geodetic data such as InSAR, alignment arrays and GPS.

Some major faults in this area have the potential to produce earthquakes as large as M_w 7. For example seismic hazard analyses suggest a 32% probability of a significant ($M > 6.7$) rupture in the next 30 years in Rodgers Creek fault (UCERF 2; Working Group on California Earthquake Probabilities, 2008). Constraining the depth and the extent of creep on the faults of this region will impact seismic hazard assessments there. Source parameters and locations of our detected REs can be used to update seismic hazard models, by better constraining the areas and rates of the creep on faults in the region (and therefore their loading rates and earthquake nucleation potential), and to improve community models of the fault geometry.

In Chapter 3, we present a new method to accelerate the process of matched filtering (template matching) of seismic waveforms by efficient calculation of (cross-) correlation coefficients. We developed this code specifically to search for REs (Chapter 2), however the cross-correlation method is commonly used to analyze seismic data in many forms, for example, for event detection, earthquake swarms, foreshocks, aftershocks, low-frequency earthquakes (LFEs), and nonvolcanic tremor. We show that our super-efficient cross-correlation (SEC-C) method – a frequency domain method that optimizes computations using the overlap-add method, vectorization, and fast normalization – is not only more time efficient than existing frequency domain methods when run on the same number of central processing unit (CPU) threads but also more memory efficient than time domain methods in our test cases. The SEC-C method does not require specialized hardware to achieve its computation speed; instead it exploits algorithmic ideas that are both time- and memory-efficient and are thus suitable for use on off-the-shelf desktop machines. In case studies using seismic data from Mt St Helens and Parkfield, we show

that SEC-C can reproduce the results obtained by other matched filtering methods, but at significantly faster speeds.

In the final project (Chapter 4) our results address the problem of inaccuracies in rapid global earthquake source models from long period seismology. In previous studies, location systematic errors of long-period seismic source inversions such as GCMT with respect to ‘ground truth’ results from InSAR-derived models are as large as tens of kilometers. Our result shows it is possible to extend and extrapolate the strength of InSAR in accurately locating earthquakes to nearby earthquakes by using existing InSAR-based models. Specifically, we show that synthetic seismograms that are calculated based upon InSAR source models and locations match the data, but are shifted in phase. This shows that inversions of long-period seismic data to rapidly characterize the earthquake source could work well if there were no such phase shifts in the calculated synthetic seismograms. We suggest that these phase shifts are the main reason for GCMT mislocations. In addition to correcting for location biases, our result shows that correcting these phase shifts can also help to identify possible misestimation of the source mechanism by InSAR.

We also test the plausibility of producing regional corrections for long-period teleseismic source inversions, testing regions where InSAR models exist for multiple nearby events (California, southern Iceland, and central Italy). In all three cases, we observe similarities between the pattern of phase shifts, in terms of azimuths and distances to global seismic stations, for pairs of close-by events. This suggests that it is indeed possible to calculate corrections for one event using InSAR and use those corrections to accurately locate other events in the same region using long period seismology. Our results also suggest that the majority of the phase shifts we identify are due to large scale (e.g. regional or continental-scale) biases in our tested Earth model (i.e. S40RTS) rather than local unmodeled features. We arrive at this conclusion as local structure would either affect one event and not the other, or would only affect one station and therefore the nearby events could have all different patterns of phase shifts.

Our results show that travel time biases for surface waves can be as large as 20 seconds for some ray paths for the S40RTS Earth model. Surface waves are the main tool to constrain the

longitude and the latitude of the teleseismic source inversions due to the nature of their ray path and their slow propagation velocities compare to body waves. For example, a small perturbation of 20 km on the horizontal location of the centroid can produce a delay in the surface wave up to 3-4 seconds in certain azimuth while body wave travel time is almost insensitive to this scale of perturbation. This shows that if we have the correction from our method and apply these corrections to routine teleseismic source inversions such as GCMT, we may constrain the source location (at least longitude and latitude) to few kilometers, rapidly. This could have a major impact on rapid response to large and devastating earthquakes, especially in remote areas.

In summary, we use geodetic data to address the earthquake mislocation problem from seismology in one project, and in the other, we use seismological data to address the issue of the low resolution of geodetic data for detecting creep signal at depth. In both projects, our results address important elements in earthquake natural hazard assessment and response. We show that using seismology and geodesy as complementary tools in geophysics can be used to increase our knowledge about fault and earthquake behavior.

5.2 Future studies combining seismology and geodesy

My projects have showed that combining seismology and geodesy has promise for addressing major issues in geophysics studies. In future I plan to extend my project to broader areas and applications. For example our proposed methods in Chapters 2 and 3 were successful at finding REs in a large study area such as the northern San Francisco Bay Area. As our method is mostly automated and can be applied to other areas such as the whole of California, to see just how widespread creep behavior is on faults in the state.

The method developed in Chapter 4 also can be extended to evaluate global Earth models globally using all of the events (over 130 at present) where InSAR models are available. By performing this on the velocity model used in the GCMT project we could potentially improve GCMT location accuracies especially for areas that we have InSAR models. The regional corrections based on our method can be produced for all events in all regions studied with InSAR.

We also can investigate the length scale of regional corrections, e.g. by making use of source-receiver reciprocity (Knopoff and Gangi, 1959) as we have many stations recording recent large earthquakes such as Central Italy (see Chapter 4). The ultimate goal of this method would be to perform surface wave tomography using all of the InSAR based models that we have. The numbers of these InSAR-studied events are increasing at an every greater rate (e.g. Funning and Garcia, 2019) as as result of the improved coverage of newer InSAR satellite missions such Sentinel-1 and ALOS-2. With hazard-focused future missions such as NISAR due to launch in the next few years, soon we will have enough InSAR-studied events to perform such tomographic inversions.

5.3 REFERENCES

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