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Multiscale Surface Deformation in Northern California from L-Band InSAR

by

Danielle Marie Pilaar Lindsay

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Earth & Planetary Science

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Roland Bürgmann, Chair

Professor Micheal Manga

Professor Nicholas Sitar

Fall 2025

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Danielle Marie Pilaar Lindsay

Abstract

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University of California, Berkeley

Professor Roland Bürgmann, Chair

This dissertation investigates multi-scale surface deformation across Northern California using advanced InSAR techniques, focusing on ALOS-2 ScanSAR data to constrain regional-scale velocity fields, characterize surface creep rates along the Maacama and Rodgers Creek faults, and examine triggered accelerations of slow-moving landslides.

In Chapter 2, we utilize L-band InSAR data from the ALOS-2 satellite to capture surface deformation across Northern California from 2015 to 2024. Our analysis spans spatial scales, from slow-moving landslides to tectonic processes around the Mendocino Triple Junction. By validating InSAR observations with GNSS velocities and time series, we establish robust regional velocity fields and address the challenges associated with detecting long-wavelength deformation. Our new vertical velocity field encompasses the region north of San Francisco to the Oregon border, nearly spanning the width of the state. Our observations reveal significant aquifer subsidence in 2022 during the last year of record drought, subsidence at the summit of Medicine Lake Volcano, and seasonal landslide acceleration. This chapter highlights the ability of L-band InSAR to maintain coherence in vegetated regions and detect subtle seasonal deformation, laying the groundwork for future observations with the upcoming NISAR mission.

Chapter 3 aims to resolve creep variability along the Maacama and Rodgers Creek Faults. Understanding where creep occurs and how creep rates change through time is integral to determining seismic potential and constraining future earthquake scenarios. We utilize an updated repeating micro-earthquake catalog and surface creep rates from radar satellite-based and terrestrial measurements to identify decadal-scale changes in fault behavior on the Rodgers Creek and Maacama faults. We examine the distribution of creep within the seismogenic zone, as inferred by the presence of CREs, and surface creep, measured by InSAR and alignment arrays. We analyzed 20 years of alignment array measurements to examine temporal changes in creep rates along the northern Maacama Fault. The time series reveal a notable creep event in 2002, followed by a multi-year suppression in surface creep that is

mirrored by a reduction in CRE productivity. We find seasonally modulated surface creep in both the alignment array and InSAR time series. This work contributes to refining seismic hazard assessments by characterizing decadal-scale changes in fault dynamics.

Chapter 4 documents the kinematic evolution of slow-moving landslides in Northern California, influenced by precipitation and earthquake shaking, between July 2021 and March 2024. During our study period, slow-moving landslides in Northern California experienced increased precipitation and earthquake shaking (M_w 6.2, December 20, 2021; M_w 6.4, December 20, 2022). The seasonal accelerations of slow-moving landslides induced by precipitation are well established; however, the combined effect with earthquake shaking is less well understood. We apply a systematic approach to extracting and cleaning InSAR displacement time series for over 400 slow-moving landslides. By grouping landslides with similar acceleration responses following the 2022 earthquake, we find that spatial clustering correlated with the region of highest shaking in the larger 2022 earthquake. These landslides cluster in the direction of rupture propagation of the 2022 earthquake, exhibiting an immediate onset of sliding and subsequent decay. The kinematic response of these slides is well-fitted with a piecewise model (linear + exponential), indicating that landslides return to within 90% of their pre-event rates in approximately 16 months. We suggest that the directivity of the 2022 earthquake contributed to the spatial clustering of the triggered landslides, while the shaking preconditioned further-field slides, and decreased the delay time between the onset of precipitation and seasonal sliding.

Drawing on a nine-year ALOS-2 ScanSAR record and supporting observations, this dissertation shows that L-band InSAR—integrated with GNSS, alignment arrays, and repeating-earthquake catalogs—can coherently resolve deformation from hillslope to plate-boundary scales. At a broader level, the work illustrates why space geodetic observations using InSAR of actively deforming systems matter: We link the slow, regional accumulation of tectonic strain to week-to-month-long accelerations on faults and slopes, providing a continuous view across spatial and temporal scales that seismology or field measurements alone rarely capture. By making dense, repeatable measurements of the real world, future modeling efforts can test frictional and hydrologic models, evaluate when stable sliding persists, and identify conditions that tip systems toward shear failure. These capabilities address enduring questions—Which faults host shallow creep, and how stable are they over time? Where are landslides slipping slowly, and what processes drive some into catastrophic motion? They also serve practical goals: earlier detection of transient deformation, better constraints on time-varying hazard, and more targeted monitoring where risk is highest. Ultimately, this work serves as a demonstration of L-band InSAR capabilities at the dawn of the NISAR (NASA-ISRO Synthetic Aperture Radar) era. L-band data preserves long-wavelength deformation, while also providing high temporal and spatial resolution of localized features. Integrating detailed observations enhances our scientific understanding of the mechanisms and systems driving the evolution of the Earth’s surface, and consequently improves our ability to prepare communities for fault and slope hazards.

To Jackson

You can do hard things too.

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Chapter 1

Introduction

Our understanding of the fundamental processes driving various slip-driven transient deformations and the transition to catastrophic failure—such as pore fluid pressure, shear zone dilatancy, and rate-and-state friction—is limited, in part, by our capacity to observe and characterize these behaviors comprehensively (Finnegan & Saffer, 2024; Lau et al., 2020). The potential for earthquakes along faults reflects a dynamic, time-dependent process driven by strain accumulation changes over short time scales (e.g., creep pulses (Materna et al., 2024)) and long time scales (e.g., interseismic (W. Xu et al., 2018)), thereby influencing hazard assessment (Elliott et al., 2016). Similarly, the hazard posed by landslides escalates due to external factors such as precipitation (Handwerger et al., 2013), earthquake shaking (Lacroix et al., 2015), or glacial retreat (Svennevig et al., 2024). Kinematic changes in the rate or spatial extent of landslide sliding can precede catastrophic failure and indicate an increase in the risk to people and infrastructure (Handwerger, Huang, et al., 2019; Handwerger et al., 2025). At a larger scale, transient deformation is underpinned by tectonic forces that load fault systems through repeated cycles of failure, generating topography and causing landslide erosion. Constraining large-scale strain accumulation and making localized observation of spatial and temporal changes in transient deformation features can help resolve the underlying mechanics controlling the spectrum of steady-slip to failure, and inform our understanding of the associated hazards.

This thesis investigates multiscale deformation across northern California using a unique ALOS-2 ScanSAR L-band dataset. This dataset spans 9 years, including regular 14-day acquisitions from July 2021 to March 2024. The long observation period allows for the constraining of low-rate, long-wavelength deformation, while the high temporal sampling allows for the characterization of time-dependent deformation. The L-band signal maintains coherence over historically challenging terrain for geodetic imaging, enabling continuous mapping in highly vegetated and seasonally snow-covered regions. Chapter 2 establishes the limits of the data and validates the measurements against independent observations, producing regional-scale velocity fields. Chapter 3 then focuses on creeping faults, constraining the spatiotemporal history of the Maacama and Rodgers Creek Faults. Finally, through careful temporal analysis, Chapter 4 examines landslide kinematics in response to earthquake

shaking and precipitation, identifying slow-moving landslides triggered by the 2022 M_w 6.4 earthquake. These observations are spatially grounded within northern California and utilize the same ALOS-2 ScanSAR dataset, demonstrating the diversity of deformation targets from a single SAR platform within a central study region. This work is timely, as the NASA-ISRO SAR (NISAR) Mission successfully launched on July 30, 2025, and will usher in a new era of publicly available, global L-band observations.

1.1 Tectonic History

In northern California, the Pacific, North American, and Juan de Fuca plates meet at the Mendocino Triple Junction (MTJ) (Figure 1.1a). To the north, convergence is accommodated by the Cascadia Subduction Zone (CSZ), where the Juan de Fuca plate subducts beneath the North American plate at 30 mm/yr (DeMets et al., 2010). South of the MTJ, the San Andreas Fault (SAF) system accommodates approximately 40 mm/yr of right-lateral slip, distributed across three major sub-parallel fault strands (Freymueller et al., 1999). The oceanic Mendocino Fault Zone (MFZ), which slips right-laterally at 47 mm/yr, separates the Juan de Fuca and Pacific plates (DeMets et al., 2010; Materna et al., 2018). The MTJ has undergone significant tectonic reconfiguration over the past 30 Myr. Between 29-27 Ma, the spreading ridge separating the Pacific and Farallon plates subducted below the North American plate, establishing the present-day configuration of the SAF and CSZ systems (Atwater, 1970). Since its inception, the MTJ has migrated northward to its present location at a rate of ~ 50 mm/yr (Atwater, 1970; Sella et al., 2002). High heat flow, volcanism, and north-south variations in crustal thickness in central and northern California have been interpreted as imprinted signatures resulting from the passage of the MTJ and associated slab-window (Beaudoin et al., 1996; Furlong & Schwartz, 2004; Zandt & Carrigan, 1993). Uplift rates from marine terraces (Merritts & Bull, 1989), reorganization of drainage capture (Lock et al., 2006), and migration of knickpoints (Willenbring et al., 2013) can be attributed to the passage of ephemeral uplift associated with MTJ migration.

The long-term tectonic history of the US West Coast imprints and governs the surface deformation observed across many spatial scales in the present day. On the scale of hundreds of kilometers, strain accumulation is driven by the current tectonic plate configuration, manifesting as low-amplitude, long-wavelength deformation. The subtleties within the deformation field at smaller spatial scales often mirror the inherited crustal structures and geology. For example, in California, the distribution of surface fault creep is often associated with the presence of Serpentine (Moore et al., 2018). The faults themselves are often reactivated structures associated with past subduction (Melosh et al., 2024; McLaughlin et al., 2012). Similarly, the distribution of slow-moving landslides in northern California is associated with the mechanically weak Franciscan mélangé (Y. Xu et al., 2021) and the presence of aseismic creep (Scheingross et al., 2013).

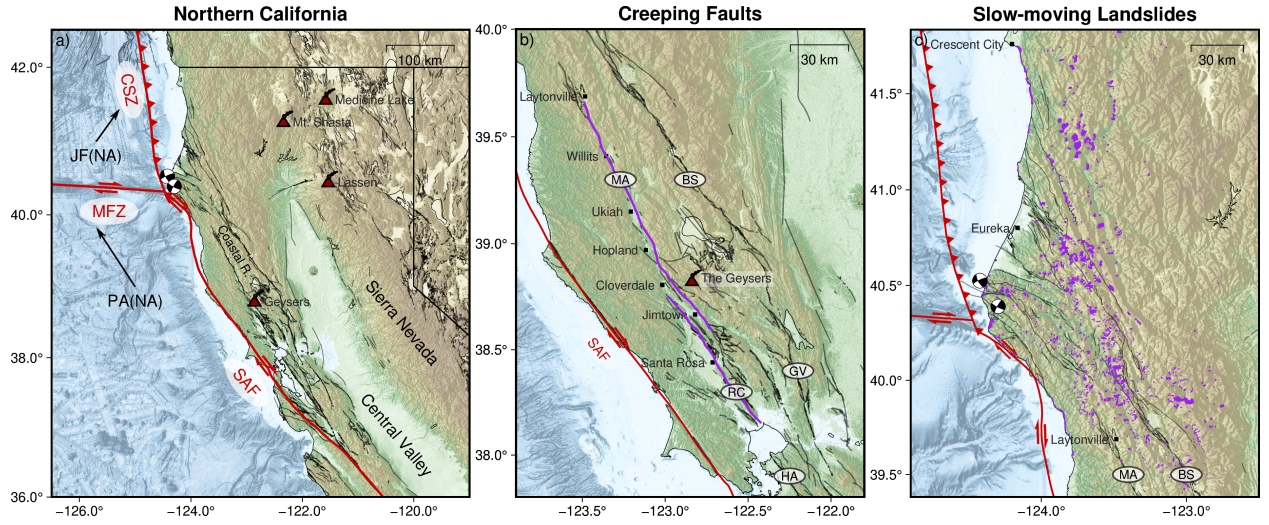


Figure 1.1: a) Tectonic setting in northern California, regional focus for Chapter 2. b) Location of creeping faults in Chapter 3. c) Location of slow-moving landslides, focus of Chapter 4 (Y. Xu et al., 2021).

1.2 Creeping Faults

Fault creep is the gradual, aseismic sliding of rocks along a fault plane, which releases elastic strain accumulated over the seismic cycle (Avouac, 2015). When a fault releases strain more slowly than its tectonic loading rate, a moment deficit can develop, increasing the likelihood of rupture along a fault segment. In contrast, when creep occurs at or near the tectonic loading rate, the seismic hazard posed by that fault segment is reduced (Avouac, 2015). Accurately measuring deformation to understand the temporally variable component of seismic hazard is crucial in assessing the slip deficit that remains to drive large earthquakes (Harris, 2017). Typical interseismic rates of fault creep on strike-slip faults range from millimeters to tens of millimeters per year. More broadly, slow slip events, of which creep events are a subset, can occur on the scale of seconds to years and accumulate millimeters to meters of slip (Bürgmann, 2018).

Creeping faults are found throughout California, most notably the central SAF and the Hayward Faults. Along the central section of the SAF, between San Juan Bautista and Parkfield, lies a 150-km-long central creeping zone, where the majority of the 32 ± 5 mm/yr right-lateral motion is accommodated through aseismic slip (Savage & Burford, 1973; Khoshmanesh et al., 2015). The Hayward-Calaveras fault zone diverges northeastward from the SAF, extending sub-parallel to the SAF along the East Bay. Both faults have documented temporally and spatially variable fault creep (e.g. Turner et al., 2015; Shirzaei & Bürgmann, 2013; Chaussard, Bürgmann, Fattahi, Johnson, et al., 2015; Y. Li et al., 2023). The northern Hayward fault connects to the Rodgers Creek faults, and the combined fault zone could

rupture as a magnitude-7 earthquake (Watt et al., 2016; Harris et al., 2021).

North of San Pablo Bay, plate boundary deformation is distributed across the width of the Pacific Coastal Ranges on sub-parallel strands, including the SAF, Rodgers Creek-Maacama faults, and Green Valley-Bartlett Springs faults (Figure 1.1b). The Rodgers Creek fault extends 80 km northwest, with evidence of surface creep through Santa Rosa (Funning et al., 2007; McFarland et al., 2023). The Maacama fault extends ~ 170 km, with the southern portion adjacent to the subsiding Geysers geothermal field and evidence of multiple active strands along the Cloverdale and Willits sections (Shakibay Senobari & Funning, 2019; Shelly et al., 2023). The Maacama fault has evidence of both deep fault creep, as evidenced by repeating earthquakes (Shakibay Senobari & Funning, 2019; W. Xu et al., 2018; Waldhauser & Schaff, 2021), and surface creep (Jin & Funning, 2017; Tong et al., 2013; W. Xu et al., 2018; McFarland et al., 2023). In contrast to the central SAF and Hayward fault, the northern extension of this system remains less well characterized in terms of a continuous along-strike estimate of surface creep and temporal variability in creep rates.

1.3 Slow-moving landslides

Slow-moving landslides can persist for months to centuries, moving at rates of centimeters to meters per year, slowly transporting material downslope and carving the landscape, with the potential for catastrophic failure (Lacroix et al., 2020). Slow-moving landslides primarily threaten infrastructure; however, the catastrophic failure of slow-moving landslides has claimed lives (Wartman et al., 2016). External driving mechanisms for landslide acceleration include rainfall, snowmelt, earthquakes, river incision, and human activities that reduce the effective normal stress or increase shear stress on the sliding plane, promoting sliding (Lacroix et al., 2020). As the climate continues to change, more extreme weather events are expected, heightening the risk of landslide failure (Gariano & Guzzetti, 2016). In California, the velocity of these landslides is primarily modulated by precipitation (Terzaghi, 1950) while their spatial distribution is strongly associated with lithology (Y. Xu et al., 2021). The kinematics of individual slides (e.g., Nereson & Finnegan, 2019) and basin-scale populations (e.g., Roering et al., 2009) have been closely studied for decades. As slow-moving landslides are typically mapped manually through fieldwork or remote sensing (Roering et al., 2009; Zhao et al., 2012; Y. Xu et al., 2021), automated mapping and detection of accelerations are essential for scaling analysis.

Creeping faults and slow-moving landslides are transient deformation features characterized by stable sliding and have the potential for sudden failure, such as earthquakes and rapid landslides. These features share structural and kinematic similarities, such as heterogeneous lithology, the coalescing of slip onto a single plane with the maturity of the sliding, and frictional controls on sliding velocity that external stress perturbations can drive. Both landslides and faults pose significant risks to essential infrastructure, such as water, transportation, and energy systems, disrupting economies and threatening lives.

1.4 Interferometric Synthetic Aperture Radar

Interferometric Synthetic Aperture Radar (InSAR) has revolutionized our understanding of interseismic and transient deformation by providing high-resolution, sub-centimeter accuracy observations of surface deformation (Bürgmann et al., 2000). A single interferogram measures the phase difference between acquisitions from a similar vantage point at different times (e.g. Massonnet et al., 1993). In calculating stacks of interferograms, we can map deformation through time from a single vantage point (e.g. Schmidt & Bürgmann, 2003). When integrating observations from multiple vantage points and satellites, 3D motion can be constrained, with limited accuracy in the north-south direction (e.g. Fialko et al., 2001). Currently operating SAR satellites carry radar sensors with wavelengths (2π) around 3 cm (X-band), 6 cm (C-band), and 23 cm (L-band) that propagate varying degrees into a medium, with L-band able to scatter within vegetation such as scrub and forest canopies. The spatial coverage of the deformation is limited by phase correlation, where pixel decorrelation occurs when the phase change exceeds π , due to a range of contributors including the vantage point changing too much (geometric limit), high deformation gradients between neighbouring pixels (phase aliasing), and temporal changes in the biomass in vegetated region, snow cover, flooding, or ground disturbance (temporal decorrelation).

We first focus Synthetic Aperture Radar (SAR) images into single-look complex (SLC) images, which contain phase and amplitude information for each pixel in the range and azimuth imaging planes. The ‘phase’ measurement (ϕ_1, ϕ_2) is a two-way range measurement of the number of cycles completed between the radar and the surface and back again (ρ_1, ρ_2). The ‘amplitude’ measures the magnitude of the returned signal and depends on the amount of scattered energy reflected to the receiver. Rocks, vegetation, and urban structures are examples of scatterers; they each reflect the energy differently, depending on the wavelength of the incoming radar signal and the azimuth and look-angle of the satellite. The interferometric phase is obtained by multiplying, pixel by pixel, the phase of the first SLC image (ϕ_1) with the complex conjugate of the phase of the second image (ϕ_2) (Massonnet & Feigl, 1998). In calculating the interferometric phase (ϕ_I), the common phase components cancel, leaving only the phase difference due to changes in the differential path delay ($\delta\rho$):

$$\phi_I = \phi_1 - \phi_2 = \frac{4\pi}{\lambda}(\rho_2 - \rho_1) = \frac{4\pi}{\lambda}\delta\rho \quad (1.1)$$

Each interferogram contains contributions from surface displacement, topography, tropospheric delays, ionospheric advances, systematic and processing errors, changes of surface or subsurface scattering mechanism, and phase noise, which must be mitigated during processing (Massonnet & Feigl, 1998; Bürgmann et al., 2000). By calculating co-registered stacks of interferograms, we can determine the displacement history, observing changes in the deformation field on timescales ranging from days to months and years across various spatial scales (Schmidt & Bürgmann, 2003). We can derive horizontal and vertical deformation fields by integrating InSAR from multiple observation geometries with GNSS (Wright et al., 2004). Recent C-band InSAR advances have demonstrated the ability to detect

both large-scale vertical deformation and small-amplitude, temporally variable deformation associated with creeping faults and landslides, providing valuable insights into transient deformation processes. Examples include state-wide vertical velocity maps (Govorcin et al., 2025), strain localization before catastrophic failure of a landslide (Handwerger, Huang, et al., 2019; Handwerger et al., 2025), post-seismic response of slow-moving landslides (Cao et al., 2023), and temporal variability in surface fault creep (Y. Li et al., 2023; Jolivet et al., 2023). However, the same utility of L-band time series has not yet been explored.

1.5 Motivation

This dissertation aims to resolve surface deformation across spatial scales, with a particular focus on vegetated regions that have historically been challenging to resolve with shorter-wavelength SAR. The scope, ranging from landslide to plate boundary scale deformation, is resolvable within the ALOS-2 ScanSAR dataset, owing to its large scene footprints. The frequent 14-day acquisitions allow for the quantification of time-dependent signals. The long wavelength maintains coherence with temporal separation, allowing it to bridge across seasonal snowfall, with less sensitivity to changes in vegetation, compared with shorter-wavelength platforms. We now have a dataset and computational resources to consider fundamental questions about surface deformation in northern California, including:

- **Plate Boundary Scale:** What is the vertical velocity field around the MTJ? Where is strain accumulating in the crust?
- **Fault Creep and Earthquake Cycles:** Where are faults creeping to the surface? How do their rates change over the seismic cycle?
- **Landslide Acceleration and Failure:** Did earthquake shaking trigger landslide acceleration? To what extent do previous seasonal conditions influence the likelihood of a landslide accelerating following earthquake shaking?

These broad questions all address why multiscale surface deformation measurements are important; earthquake and landslide hazards pose a significant risk to people and infrastructure. By providing quality observations, we can enhance our fundamental understanding of the mechanisms controlling shear failure and its driving forces, and subsequently better prepare for and mitigate the effects of these hazards. This dissertation is structured as three stand-alone studies. Chapter 2 presents a regional-scale velocity field derived from ALOS-2 ScanSAR to evaluate vertical and horizontal deformation across northern California, with a focus on validating against independent observations. Chapter 3 builds on this, focusing on the spatial-temporal variability of fault creep along the Maacama and Rodgers Creek Faults using InSAR and microseismic catalogs. Chapter 4 utilizes the 14-day repeat intervals to investigate kinematic changes in slow-moving landslides under co-occurring precipitation and seismic forcing. Each chapter is formatted for submission as a peer-reviewed journal article, followed by a concluding synthesis.

Chapter 2

Nine-Year L-band InSAR Time Series of Tectonic and Non-tectonic Surface Deformation in Northern California

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Key Points

- We produce nine-year ALOS-2 ScanSAR time series and velocity maps for northern California and validate them with GNSS and Sentinel-1.
- 14-day L-band time series resolves time-dependent aquifer subsidence and landslide accelerations in vegetated terrain.
- Mitigating ionospheric noise remains a key limitation, affecting coastal, low-coherence regions and sparse interferogram networks.

Abstract

L-band InSAR preserves coherence in vegetated regions and has been successfully used to constrain static displacements, yet its application for measuring time-dependent deformation remains more limited. This study demonstrates the capabilities of L-band time series produced with JAXA’s ALOS-2 ScanSAR data for measuring tectonic, volcanic, hydrologic, and geomorphic processes across the heavily vegetated northern California. We derive long-term rates using data spanning 2015–2024, and a subset from 2021 onward (with 14-day repeat intervals) is used to examine time-dependent deformation. We validate long-term velocities against Global Navigation Satellite System (GNSS) data (RMSE 2.1–2.9 mm/yr) and, for time-dependent signals, compare ALOS-2 and Sentinel-1 time series with GNSS (RMSEs of 1.5 and 2.0 cm, respectively). At Medicine Lake Volcano, we provide a spatially continuous map of subsidence with peak rates of 10–15 mm/yr. In the Sacramento Valley, we quantify aquifer-related subsidence, with total vertical displacement exceeding 20 cm along the Tehama–Colusa Canal during 2022. To demonstrate small-scale sensitivity, we examine the kinematic changes associated with earthquake shaking and precipitation at two slow-moving landslides: the Graham Landslide Complex and the Boulder Creek earthflow. Attempts to constrain low-amplitude, long-wavelength deformation features are hindered by residual ionospheric noise, phase decorrelation, and temporal sampling limitations. To our knowledge, this study is among the first to focus on extracting time-dependent deformation signals from ALOS-2 ScanSAR. As access to L-band SAR data increases with the NISAR and ROSE-L missions, these results highlight the utility of L-band time series for reliable geodetic imaging in historically challenging settings.

2.1 Introduction

Understanding three-dimensional (3D) crustal deformation in both space and time is crucial for advancing our knowledge of Earth’s dynamic systems and for monitoring and responding to geohazards, such as earthquakes, ground subsidence, and landslides. However, mapping long-term and transient deformation in vegetated regions using Interferometric Synthetic Aperture Radar (InSAR) remains challenging. We map deformation across northern California using L-band ScanSAR (wide-swath) data from the Japan Aerospace Exploration Agency’s (JAXA) Advanced Land Observing Satellite-2 (ALOS-2), hereafter referred to as ‘ScanSAR’. ScanSAR data provide large scene footprints that maintain coherence in vegetated terrain over long periods, allowing for the study of interseismic and transient features in the densely forested and frequently snow-covered regions of northern California. We process a nine-year dataset (2015–2024) to constrain long-term deformation rates, focusing on a particularly dense three-year subset (2021–2024) with near 14-day repeat intervals to investigate time-variable deformation signals. We compare our results with Global Navigation Satellite System (GNSS) and Copernicus Sentinel-1 InSAR observations to validate the capability of our ScanSAR dataset to resolve deformation features across a range of spatial scales

and rates. We present case studies that demonstrate ScanSAR’s enhanced spatiotemporal capability to resolve both long-term 3D deformation and transient displacement signals in vegetated regions. With the anticipated expansion of publicly available L-band data from the NISAR (NASA–ISRO Synthetic Aperture Radar) and ROSE-L (Radar Observing System for Europe in L-band) missions, it is crucial to understand the current and future utility of L-band InSAR for constraining interseismic deformation and actively monitoring geohazards.

The largest publicly available archive of L-band InSAR data comes from the ALOS-2 satellite, operated by JAXA. This dataset provides critical observations for hazard monitoring, including earthquakes, landslides, volcanoes, and floods. ALOS-2 acquires SAR data in three modes: Spotlight (highest resolution, smallest footprint), Stripmap (medium resolution, medium footprint), and ScanSAR (lowest resolution, largest footprint). To date, most geodetic applications of ScanSAR have focused on mapping large co-seismic displacements, where its broad swath enables deformation mapping from the fault trace to the far field in a single image (e.g., Lindsey et al., 2015; Hamling et al., 2017). Liang, Liu, Fielding, and Bürgmann (2018) first demonstrated the potential of ScanSAR time series for measuring interseismic velocities and anthropogenic deformation in Southern California, using 17 scenes acquired over three years. Chong et al. (2025) applied ScanSAR time series to quantify the uplift of anticlines above the Rakhine–Bangladesh megathrust using a dataset of 50 scenes spanning seven years. Wegmüller et al. (2024) demonstrated the utility of ScanSAR for landslide monitoring in alpine environments, mapping slow-moving landslides in Switzerland using 15 scenes acquired between 2015 and 2021. Despite these successes, ALOS-2 ScanSAR’s ability to resolve temporally variable deformation at high spatial resolution, such as seasonal, episodic, or transient signals, remains largely unexplored.

Northern California provides an ideal natural laboratory for investigating both interseismic tectonic deformation and time-dependent signals related to volcanic, anthropogenic, and geomorphic processes (Figure 2.1). The North American, Pacific, and Juan de Fuca plates meet at the Mendocino Triple Junction (MTJ). The Cascadia Subduction Zone accommodates convergence between the Juan de Fuca and North American plates, while right-lateral shear occurs along the San Andreas Fault system and the Mendocino Fault Zone. These plate-boundary interactions result in the accumulation of strain over hundreds of kilometers, which is well-constrained by GNSS observations (e.g., Zeng, 2022). The region includes the southern extent of the Cascade Volcanic Arc, where surface deformation has been documented at Lassen Volcanic Center and Medicine Lake Volcano (MLV) (Dzurisin et al., 1991; Poland et al., 2006; Parker et al., 2014, 2016). Subsidence in the Central Valley, driven by sustained groundwater withdrawal that intensifies during drought periods, is well-documented in California (Smith et al., 2021; Carlson et al., 2024; Ojha et al., 2018). Northern California also hosts numerous slow-moving landslides, whose spatial distribution is controlled by local geology and whose velocity is modulated by seasonal precipitation (Handwerger et al., 2022; Y. Xu et al., 2021). Together, these deformation features span a wide variety of spatial scales and deformation rates, making northern California an ideal location to explore the breadth and depth of the applications of ScanSAR InSAR for resolving steady and time-variable deformation.

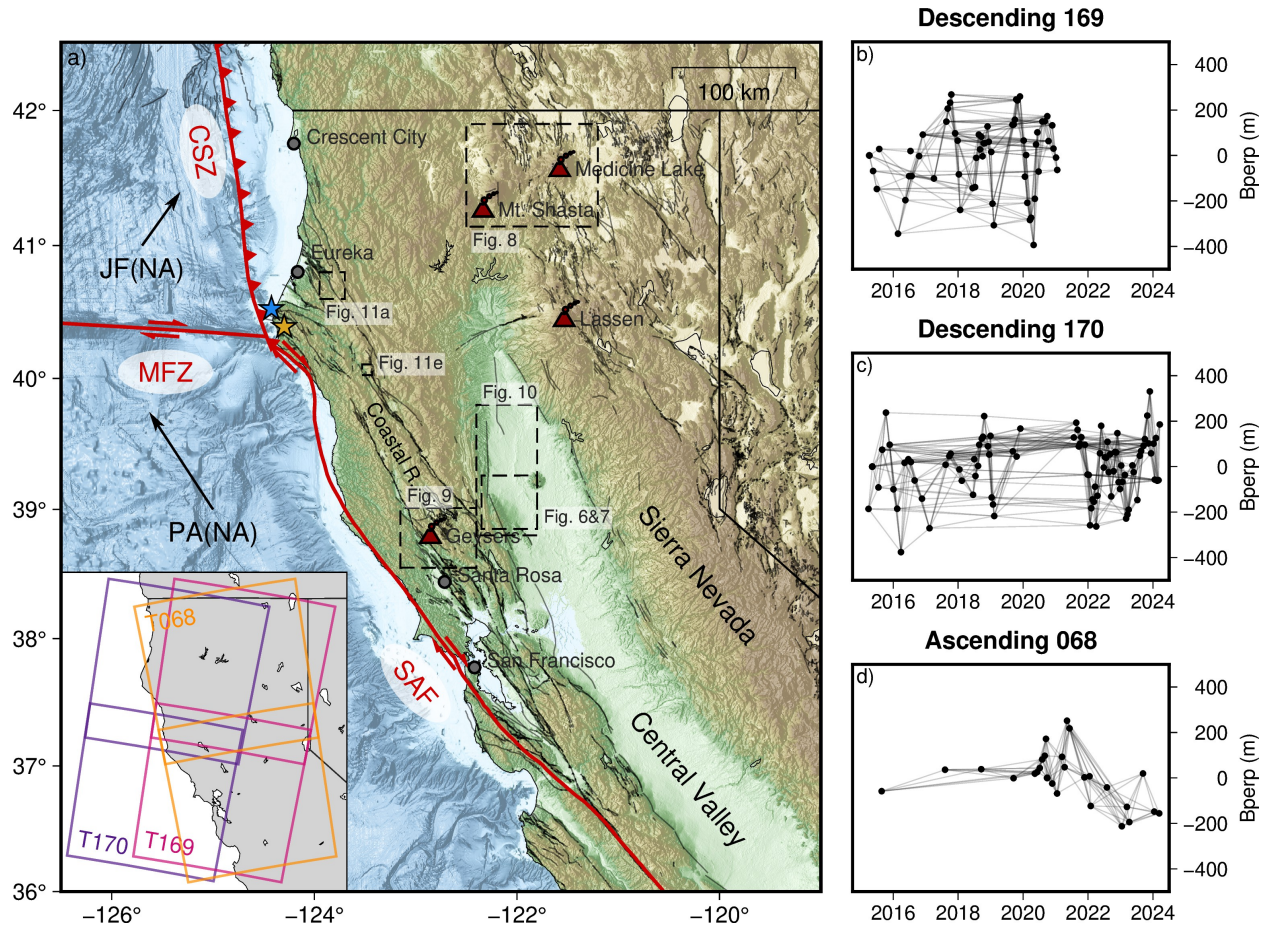


Figure 2.1: (a) Northern California tectonics: the North American (NA), Pacific (PA), and Juan de Fuca (JF) plates meet at the Mendocino Triple Junction. Convergence between JF and NA is accommodated by the Cascadia Subduction Zone (CSZ). Right-lateral shear is accommodated between the NA and PA along the San Andreas Fault (SAF) and between the PA and JF along the Mendocino Fault Zone (MFZ). Locations of 2021-12-20 M6.2 (yellow) and 2022-12-20 M6.4 (blue) earthquakes. ALOS-2 ScanSAR footprints are outlined in the inset. (b–d) Interferogram networks for each track, plotted as acquisition time versus perpendicular baseline (Bperp); note irregular sampling and data gaps.

Research motivation and aims

Traditional geodetic methods, such as GNSS and C-band InSAR, have limited ability to resolve the complete range of surface deformation features in space and time. Continuous GNSS (cGNSS) networks accurately measure large-scale, low-rate horizontal deformation, but their spatial resolution is fundamentally limited by station density. As a result, they

are unable to resolve deformation features smaller than 10–20 km in dimension. Resolving broad-scale vertical deformation with GNSS at the mm/yr level also continues to be challenging (C. W. Johnson et al., 2021). C-band InSAR, such as with Sentinel-1, offers dense spatial coverage and is well-suited for measuring low-rate deformation over both localized and regional scales (e.g., Materna et al., 2024; Wright et al., 2023). However, rapid deformation and changes to the scattering surface due to snow or vegetation can lead to decorrelation and phase unwrapping errors, limiting the accuracy of C-band InSAR in resolving fast subsidence or landslide accelerations (Goldstein et al., 1988; Zebker & Villasenor, 1992). Additionally, unwrapping errors and decorrelation limit the ability to estimate and remove ionospheric phase contributions; therefore, long-wavelength tectonic motions are more challenging to constrain with C-band InSAR (Liang et al., 2019). L-band ScanSAR offers a complementary dataset to GNSS and C-band InSAR. Its longer wavelength maintains coherence in vegetated terrain, even under rapidly changing surface conditions. In addition, its wide footprint enables regional mapping of deformation over hundreds of kilometers. As a result, ALOS-2 ScanSAR is uniquely suited to bridging the observational gap between broad-scale tectonic processes and localized, transient deformation features.

In this study, we evaluate the performance of L-band ALOS-2 ScanSAR time series across a range of deformation processes in Northern California. Using adaptive processing strategies, we address the challenges of large-scene interferometry and validate our results against independent GNSS and Sentinel-1 observations. The following research questions guide our work:

1. How well do ScanSAR observations validate against Sentinel-1 interferometry and GNSS data through space and time?
2. Can ScanSAR, independent of GNSS, constrain vertical deformation features with amplitudes of 1–2 mm/yr over hundreds of kilometers?
3. Can ScanSAR resolve localized time-dependent deformation with rates ranging from 0.5 to 30 cm/yr from features on scales of hundreds of meters and greater?
4. What observations, previously limited by spatial coherence or high deformation rates, are now possible with this new dataset?

We first outline the datasets and ALOS-2 ScanSAR processing workflow. We describe the construction of the interferogram networks, time series inversion, and the correction strategies employed to isolate surface displacements. We validate the velocity fields and displacement time series against GNSS and Sentinel-1 to test spatial accuracy and assess the time series’ ability to capture temporal deformation signals. We evaluate the internal consistency between ALOS-2 tracks by comparing overlapping regions. We present case studies—tectonic, volcanic, hydrological, and geomorphic—that highlight the utility of L-band InSAR for resolving low-amplitude, long-wavelength features and monitoring time-dependent deformation. Finally, we discuss the limitations and strengths of our ScanSAR dataset, providing context for future L-band applications.

2.2 Geodetic Data

Synthetic Aperture Radar (SAR) sensors emit pulses of energy at microwave frequencies, with X-band (~ 2 cm), C-band (~ 6 cm), and L-band (~ 23 cm) wavelengths commonly used for deformation mapping. In a radar interferogram, the interferometric phase contains contributions from surface displacement, topography, tropospheric delays, ionospheric advances, systematic and processing errors, changes of surface or subsurface scattering mechanism, and phase noise (Massonnet & Feigl, 1998; Bürgmann et al., 2000). A key limitation of L-band is its increased sensitivity to the ionosphere, which introduces a dispersive phase shift that must be corrected during the processing of each interferogram (Yunjun et al., 2022). Changes in ground scattering properties lead to phase decorrelation, which is more severe in vegetated and seasonally snow-covered terrain. The longer wavelength of L-band SAR withstands greater surface changes, maintaining coherence over longer time intervals than shorter wavelengths (Wei & Sandwell, 2010). Phase unwrapping becomes challenging when the line-of-sight (LOS) displacement between neighboring pixels approaches $\pm\pi$, and impossible beyond $\pm\pi$ (Goldstein et al., 1988). Thus, L-band InSAR is more tolerant of steeper deformation gradients than shorter wavelengths, making it well-suited for capturing localized, rapid signals.

L-band ALOS-2 ScanSAR

We analyze full-aperture L-band ALOS-2 ScanSAR data acquired by the Japan Aerospace Exploration Agency (JAXA). Images are acquired in the wide-swath ScanSAR mode, consisting of five sub-swaths, with a total width of ~ 350 km. The most common ALOS-2 ScanSAR mode has a 14 MHz range bandwidth, which yields ~ 17 m range and ~ 80 m azimuth ground resolution (note that the JAXA full-aperture single-look-complex (SLC) products for ScanSAR are highly oversampled from the true resolution). Orbits are tightly controlled, with perpendicular baselines usually ≤ 300 m. The reference frame of the SAR is tied to that of the orbits, which is the International Terrestrial Reference Frame (ITRF, version unknown). We process 58, 91, and 27 acquisitions for tracks 169, 170, and 068, respectively (Figure 2.1b–d). The dataset begins in 2015; track 169 ends in 2021, while tracks 170 and 068 extend to early 2024. ScanSAR acquisitions are typically sporadic through time; however, since July 2021, JAXA acquired data along track 170 with a consistent 14-day repeat cycle for a NASA-JAXA collaboration project. We process Level 1.1 SLC products using the ScanSAR stack processor (Liang, Liu, Fielding, & Bürgmann, 2018; Liang & Fielding, 2017) within ISCE-2 (Rosen et al., 2012), and generate time series with the Miami InSAR Time-series software in Python (MintPy) (Yunjun et al., 2019) (details in section 2.3).

C-band Sentinel-1 TOPS

For comparison with ALOS-2, we analyze C-band Copernicus Sentinel-1 data operated by the European Space Agency (ESA). Sentinel-1 operates in TOPS (Terrain Observation by

Progressive Scans) mode, which merges three sub-swaths into 250 km frames. Like ALOS-2, the platform maintains a well-controlled orbital tube. Sentinel-1A began 12-day imaging in August 2014. The launch of Sentinel-1B (April 2016–December 2021) reduced the revisit interval to 6 days; after its failure, the interval returned to 12 days. Interferograms are generated with the Hybrid Pluggable Processing Pipeline (HyP3) GAMMA on-demand system provided by the Alaska Satellite Facility (ASF) (Hogenson et al., 2025), applying a filter strength of 0.6 and multilooking by factors of 4 in azimuth and 20 in range, resulting in an ~ 80 m pixel resolution. To validate temporal signals imaged during the period of dense observations along track 170, we construct our interferogram network by connecting four nearest-neighbor pairs between July 2021 and March 2024. The resulting time series is computed with MintPy.

GNSS

We utilize daily position solutions from the Nevada Geodetic Laboratory (NGL) to validate InSAR results and derive input fields for vertical velocity decomposition (Blewitt et al., 2018). NGL daily solutions in the IGS14 reference frame are corrected for tropospheric delays and ionospheric advances, as well as for solid-Earth, pole, ocean, and ocean-pole tides, but omit adjustments for plate motions, permanent tide, and non-tidal loading (Blewitt et al., 2018). We retain stations with $\geq 70\%$ data coverage per track and drop those with long gaps. We visually inspect each station’s time series and exclude those with substantial increasing scatter or instability, which may be due to vegetation growth, monument instability, or snow cover. We correct time series for all equipment-related offsets documented in NGL metadata and remove additional steps not associated with earthquakes when their magnitude or timing suggests instrumentation issues. We do not remove steps or transients associated with earthquakes, as these are not removed from the InSAR time series. For LOS validation, we compute linear GNSS velocities for each track window: 2015-03-30 to 2024-03-18 (170), 2015-04-08 to 2021-01-20 (169), and 2015-08-25 to 2024-03-12 (068). Linear velocity fields are corrected for plate motion following Stephenson et al. (2022) to maintain reference frame consistency between GNSS and InSAR solutions. East, north, and up components are projected into the SAR LOS using the spatially variable radar incidence and heading angles. All IGS14 GNSS velocities are differenced relative to the co-located reference station P345, near Redding at the top of the Central Valley. For July 2021–March 2024, InSAR time-series validation in the Central Valley, LOS-projected GNSS displacements are shifted to local reference station P208. To estimate a continuous vertical velocity field from the GNSS data, east and north GNSS components are interpolated with VISR in the Strain-2D toolbox (Shen et al., 2015; Materna & Maurer, 2023; Maurer & Materna, 2023). We restrict the interpolation distance in VISR through a weighting threshold of 10 to preserve high spatial gradients within the GNSS network.

2.3 InSAR Processing

Section 2.3 details the co-registered interferogram stacks, section 2.3 the ionospheric corrections, section 2.3 the parameter adjustments for different deformation targets, section 2.3 summaries time-series corrections (solid-Earth tide, troposphere, DEM) and velocity-domain corrections (plate motion, GNSS ramp), and section 2.3 compares three approaches to derive vertical velocities.

Interferogram network and ionospheric correction

For each track, we generate co-registered interferograms through (1) co-registration of SLC images, (2) interferogram formation, (3) ionospheric phase correction, (4) phase unwrapping, and (5) filtering and multi-looking (Rosen et al., 2012; Liang, Liu, Fielding, & Bürgmann, 2018). The topographic phase is removed from each interferogram with the Shuttle Radar Topography Mission (SRTM) one arcsecond (30 m) Digital Elevation Model (Farr et al., 2007). For tracks 169 and 170, we use four nearest-neighbor pairs, as well as multi-year pairs that connect similar seasons across years (Figure 2.1). Long-temporal pairs stay within ± 50 m perpendicular baseline and span 1 to 5 years within a ± 2 -month window. The relatively low perpendicular baseline limit was chosen to minimize computational and storage requirements. Ascending track 068, acquired sporadically, is linked with five nearest-neighbor pairs. The final networks contain 319, 579, and 125 interferograms for tracks 169, 170, and 068.

Ionospheric phase correction

Ionospheric phase results from the spatial-temporal variations of the Total Electron Content (TEC) in the upper atmosphere. The dispersive nature of the ionosphere introduces a phase shift that is proportional to the radar wavelength squared, representing a significant error for longer-wavelength InSAR, such as L-band. We use the range split-spectrum method of Liang, Liu, Fielding, and Bürgmann (2018) to estimate and remove ionospheric phase advance from individual interferograms (Figure S1). Using two sub-band interferograms, we can separate the dispersive component caused by the ionosphere and the non-dispersive component in the InSAR measurement. We first generate subband SLCs by band-pass filtering the spectrum, forming the corresponding lower- and upper-band interferograms, and removing the topographic contribution from each. Each interferogram is heavily multi-looked (80 in range and 448 in azimuth) to suppress decorrelation noise and subsequently unwrapped. The ionospheric phase is calculated with Equation 4 in Liang, Liu, Fielding, and Bürgmann (2018), and a Gaussian filter is applied. We solve for ionospheric phase estimates on a per-date basis using a least-squares inversion across all available interferograms. The redundancy across multiple interferogram pairs enables us to identify and exclude poor estimates of ionospheric phase resulting from unwrapping errors or residual filtering artifacts. This improves the stability of the ionospheric corrections while maintaining a well-connected network.

Adaptive processing strategy

We adapt our processing strategy based on the spatial and temporal characteristics of the targeted deformation signal to optimize results across diverse targets. For the regional velocity fields, which aim to resolve broad-scale, long-term deformation such as interseismic strain accumulation, we prioritize spatial coverage and noise reduction by using longer temporal baseline interferograms and larger multilooking. We apply a multilook factor of 10 in range and 56 in azimuth, resulting in a ground pixel size of $85.8 \text{ m} \times 160.4 \text{ m}$. For time-variable or highly localized deformation targets, such as landslide acceleration or aquifer subsidence, we prioritize temporal resolution and preserve smaller pixel sizes. We apply a multilook factor of 5 in range and 28 in azimuth, resulting in a ground pixel size of $42.9 \text{ m} \times 80.2 \text{ m}$. In these cases, we include only the four nearest-neighbor interferograms to reduce temporal decorrelation and avoid phase unwrapping errors in rapidly deforming areas.

Displacement time series and velocity inversion

We apply the Small Baseline Subset (SBAS) method in MintPy to estimate the displacement time series using a weighted least squares approach, where weights are assigned based on phase variability (Yunjun et al., 2019; Berardino et al., 2002; Guarnieri & Tebaldini, 2008). We use the GNSS station P345 near Redding as the reference point for the regional velocity field, located on the North American Plate. To minimize unwrapping errors, we iteratively refine the interferogram network through manual quality control. We begin by visually inspecting spatial coherence maps, connected component maps, and unwrapped interferograms to identify low-quality interferograms, which are then excluded from the network. We then apply unwrapping error corrections using both bridging and phase-closure approaches to the remaining interferograms and evaluate the performance of these corrections by examining non-zero phase closure distributions (Section 3 Yunjun et al., 2019). We iteratively modify the input network to improve the result until we reach a point of diminishing returns. Despite testing several automated alternatives, we found that manual quality control is the most effective strategy for retaining signal and minimizing noise.

In the time series domain, we correct for residual phase contributions from solid Earth tides, stratified tropospheric phase delay, and DEM error; in the velocity domain, we also correct for the impact of rigid plate motions (Figure 2.2). Solid Earth tides are removed using PySolid (Yunjun et al., 2022), and stratified tropospheric phase delay is corrected using ERA5 climate model outputs as implemented in PyAPS (Jolivet et al., 2011, 2014). For localized landslide examples, we find better performance applying the height correlation method of Doin et al. (2009) to correct the stratified tropospheric phase delay. DEM errors are corrected by exploiting their proportionality with the perpendicular-baseline time series (Fattahi & Amelung, 2013). We exclude noisy acquisition dates and solve only for the linear velocity during the 9-year observation period, as the irregular sampling is insufficient to constrain annual and semi-annual terms. We correct the linear velocity field for the impact of rigid plate motions by estimating and removing the range-dependent LOS signal introduced

by incidence angle sensitivity across each frame, following the method of Stephenson et al. (2022) for stable North America (Altamimi et al., 2017). Inspection of the residuals between GNSS-derived and InSAR-derived LOS velocities reveals that ramp-like features are present in all three ScanSAR tracks, primarily aligned in the range direction. Excluding GNSS stations with vertical velocities less than -5 mm/yr, we minimize these GNSS-InSAR residuals by fitting a quadratic ramp, thereby tying the InSAR velocity field to GNSS and removing a substantial portion of the remaining noise field.

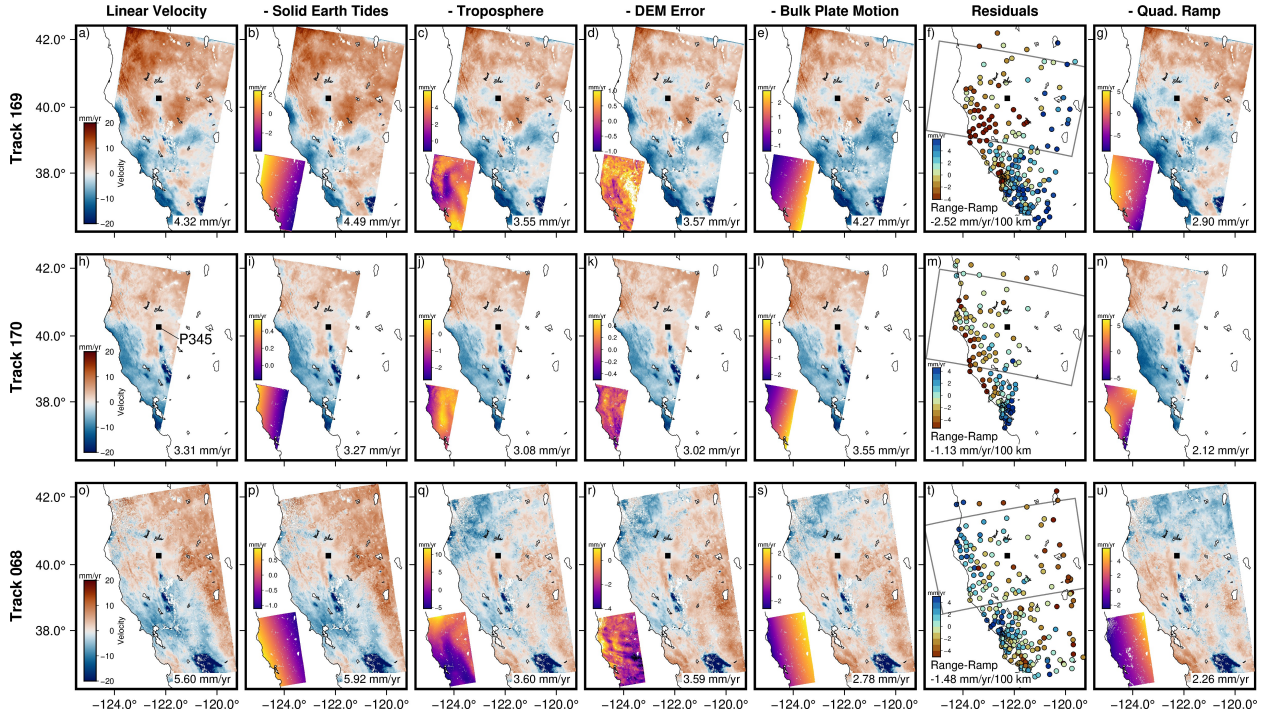


Figure 2.2: Velocity-field corrections for tracks 169 (a–g), 170 (h–n), and 068 (o–u) with applied corrections in the inset of each subfigure and GNSS–InSAR LOS RMSE values. From left to right: raw velocity, then sequential removal of solid-Earth tides, stratified troposphere delay, DEM error, bulk plate motion, GNSS residuals, and a quadratic ramp. Panels f, m, and t report the mean residual and range-direction ramps (mm/yr per 100 km) for stations within the box. Final products are g, n, and u.

Realization of vertical velocity field

We test three methods for deriving a vertical velocity field from the full ScanSAR archive (Figure S2). (i) Semi-vertical: project interpolated GNSS east and north velocities into LOS and subtract from ascending/descending InSAR LOS rates (e.g., X. Xu et al., 2021). (ii) InSAR-only: use paired ascending/descending LOS velocities to solve for east and vertical

components, assuming negligible contributions from north-south motions (Wright et al., 2004; Fialko et al., 2001). (iii) Joint InSAR–GNSS: integrate ascending and descending InSAR data with interpolated GNSS east and north velocities to solve for east, north, and up components (e.g., Ou et al., 2022). Method details appear in the Supplement and Figure S2. Each method is benchmarked against a common set of vertical GNSS velocities using the median InSAR value within 0.004° (~ 445 m $\times$ 330 m) of every station. Results from all methods agree well, with the joint InSAR–GNSS solution producing the lowest Root Mean Square Error (RMSE) with the vertical GNSS velocities (1.82 mm/yr) and the InSAR-only method the highest (2.74 mm/yr). We adopt the joint InSAR–GNSS vertical solution, reverting to the InSAR-only product in northeastern California, where sparse GNSS limits the interpolation between large inter-station distances.

2.4 Validation

We validate our InSAR results by comparing them with independent GNSS and Sentinel-1 observations, as well as assessing the internal consistency between the overlapping InSAR tracks. Our datasets are in global reference frames (IGS14 for GNSS; and an unspecified ITRF version for ALOS-2) referenced locally to P345. Both velocity fields are corrected for troposphere, ionosphere, solid-Earth tides, and plate motion, and InSAR LOS velocity fields are tied to GNSS with a quadratic ramp. For each test, we compare GNSS velocities projected into LOS to the median of InSAR pixels within 0.004° radius of the station. We adopt the sign convention that positive LOS indicates motion toward the satellite.

Performance assessment of correction layers

To evaluate how each successive error-correction step reduces error, we compare intermediate InSAR LOS rates to GNSS (Figure 2.2). After removing solid-Earth tides, stratified troposphere, DEM error, and plate motion, the RMSEs are 4.27, 3.55, and 2.82 mm/yr for tracks 169, 170, and 068. Although the performance of individual correction layers varies between tracks, we apply the full suite uniformly for consistency. Figure 2.2 (f, m, t) shows the residuals between GNSS and InSAR LOS: residuals center on zero with means of 0.96, -0.42, and 0.01 mm/yr for tracks 169, 170, and 068. For the nearest stations to the reference point (gray box in Figure 2.2 f, m, t), a linear range-direction ramp of 8.8, 3.9, and 5.5 mm/yr across a 350 km wide frame explains 43%, 12%, and 38% of the variance for tracks 169, 170, and 068. Applying the quadratic ramp provides significant improvements, lowering RMSEs to 2.90, 2.12, and 2.28 mm/yr, representing improvements of 32%, 40%, and 19%, respectively. The ramp corrections for tracks 169 and 068 correct a large component of the range-dependent residuals. For track 170, the quadratic ramp exhibits a dome-like pattern, with the largest correction applied to the San Francisco Bay area. For track 068, the DEM-error layer also suppresses noise from ionospheric scintillations (Figure 2.2r). The deramping step corrects for long-wavelength residuals not captured by physical models, such as errors

from orbits, uncorrected contributions from the ionosphere or troposphere, and processing artifacts, including unwrapping errors or swath misalignment.

GNSS velocity-field comparison

We compare InSAR LOS velocities with GNSS-projected LOS velocities to quantify long-term agreement across the study area (Figure 2.3). We utilize the full archive, spanning 2015-2024 for tracks 170 and 068, and 2015-2021 for track 169, with GNSS LOS velocities corresponding to the same period as the respective tracks (see Figure 2.1 b-d). For a common set of GNSS stations, the RMSEs are 3.2, 2.0, and 2.2 mm/yr for tracks 169, 170, and 068, respectively. To assess whether error increases with distance from the reference pixel, we color-code each point by its distance from the reference station and find robust agreement beyond 400 km (Figure 2.2d, e, f). The residuals follow near-Gaussian distributions, with 48%, 70%, and 65% of the residuals falling within ± 2 mm/yr, R^2 of 0.78, 0.85, 0.92, and near-unity slopes. The RMSE values of our LOS velocity field represent a modest improvement over comparable L-band ScanSAR studies. Liang and Fielding (2017) projected three GNSS components to LOS and reported an RMSE of 4.4 mm/yr from GNSS-independent processing. Chong et al. (2025) found RMSEs of 6.6 mm/yr before and 3.0 mm/yr after tying the InSAR field to GNSS. Although not fully independent, comparing InSAR and GNSS linear velocities provides a robust measure of LOS accuracy, giving us confidence that our regional fields accurately capture regional deformation in a single, contiguous map as well as localized features that are not captured in GNSS-derived velocity fields.

GNSS and InSAR time series comparison

During the period of dense acquisitions along track 170 from July 2021 to March 2024, we test our ability to capture transient signals by comparing ALOS-2 and Sentinel-1 time series to differential GNSS velocities across baselines in a subsiding area. We target a rapidly subsiding area in the Sacramento Valley that exhibits time-dependent, predominantly vertical deformation, as confirmed by near-identical horizontal GNSS velocities (Figure 2.4). We first examine the spatial agreement between ALOS-2 and Sentinel-1 LOS velocity fields for the period from July 2021 to March 2024. Velocity profiles reveal broad agreement, but along the eastern portion of profile X-X' we observe noise amplification of the L-band ALOS-2 over challenging ground cover (Figure 2.4c,d). To explore temporal agreement, we examine the baseline changes between pixels located at GNSS stations P208 (outside the basin) and P270 (within the basin). The GNSS daily positions are resampled to match the InSAR acquisition interval by averaging positions within a 6-day window of each satellite pass. We compare both LOS displacement (Figure 2.4 e) and vertical deformation (Figure 2.4 f) by projecting GNSS to LOS and InSAR LOS to the vertical. ALOS-2 measurements agree more closely with GNSS for both projections (LOS: RMSE 1.5 cm, Up: RMSE 1.8 cm) than Sentinel-1 (LOS: RMSE 2.0 cm, Up: RMSE 2.5 cm). Both datasets capture the spatial pattern of the

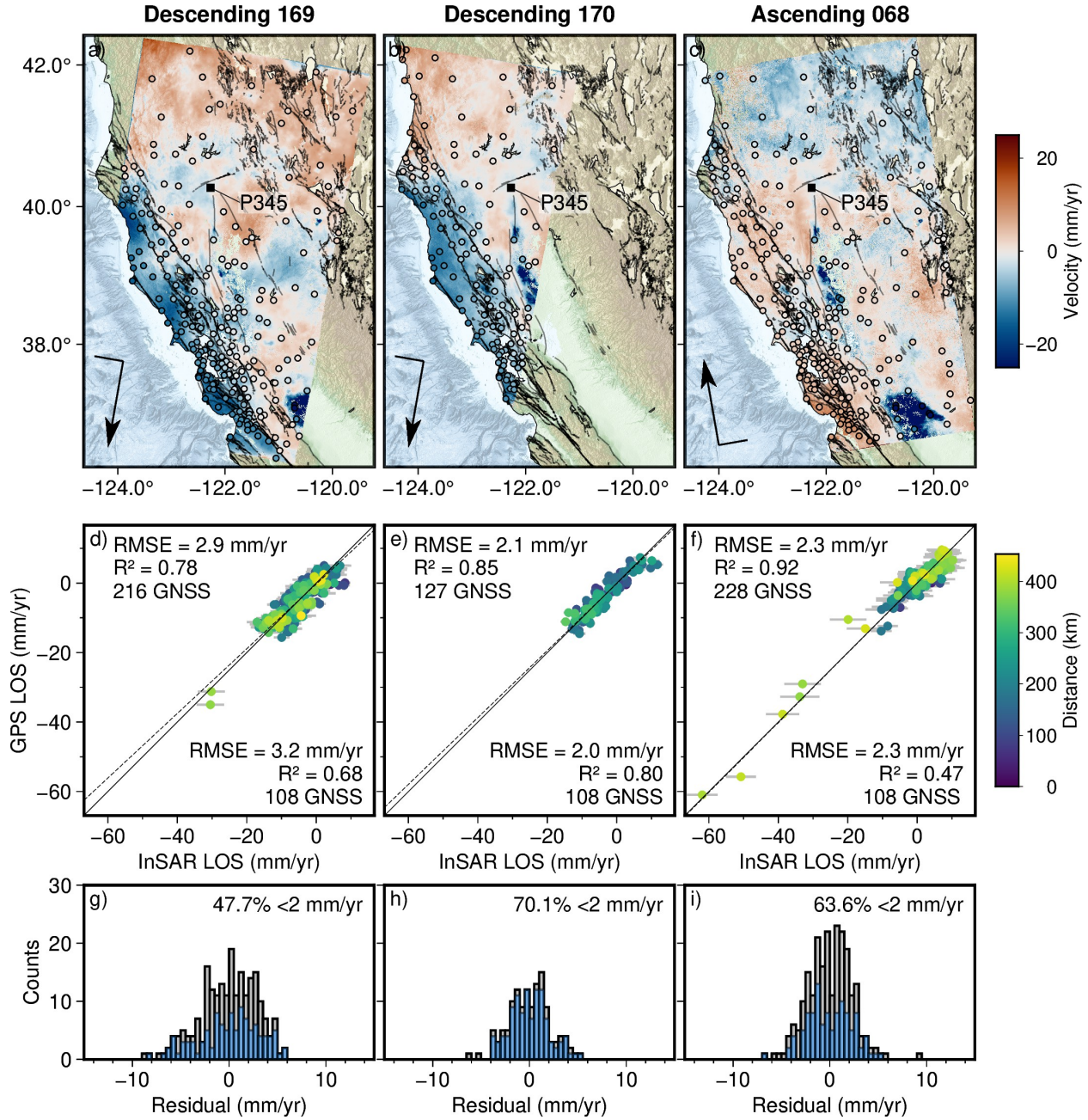


Figure 2.3: Line-of-sight (LOS) velocity maps for tracks 169 (a), 170 (b), and 068 (c). InSAR and LOS GNSS (circles) are referenced to P345. Scatterplots (d–f) show GNSS versus InSAR with a 1:1 line (grey), best-fit regression (dashed), and points colored by distance to P345; statistics for all stations appear upper-left, and for a common subset lower-right. Histograms (g–i) display residuals for all stations (grey) and the common subset (blue), with the fraction within ± 2 mm yr/yr annotated. Negative LOS values indicate motion away from the sensor.

deformation field and resolve the amplitude and timing of deformation in the GNSS baseline time series.

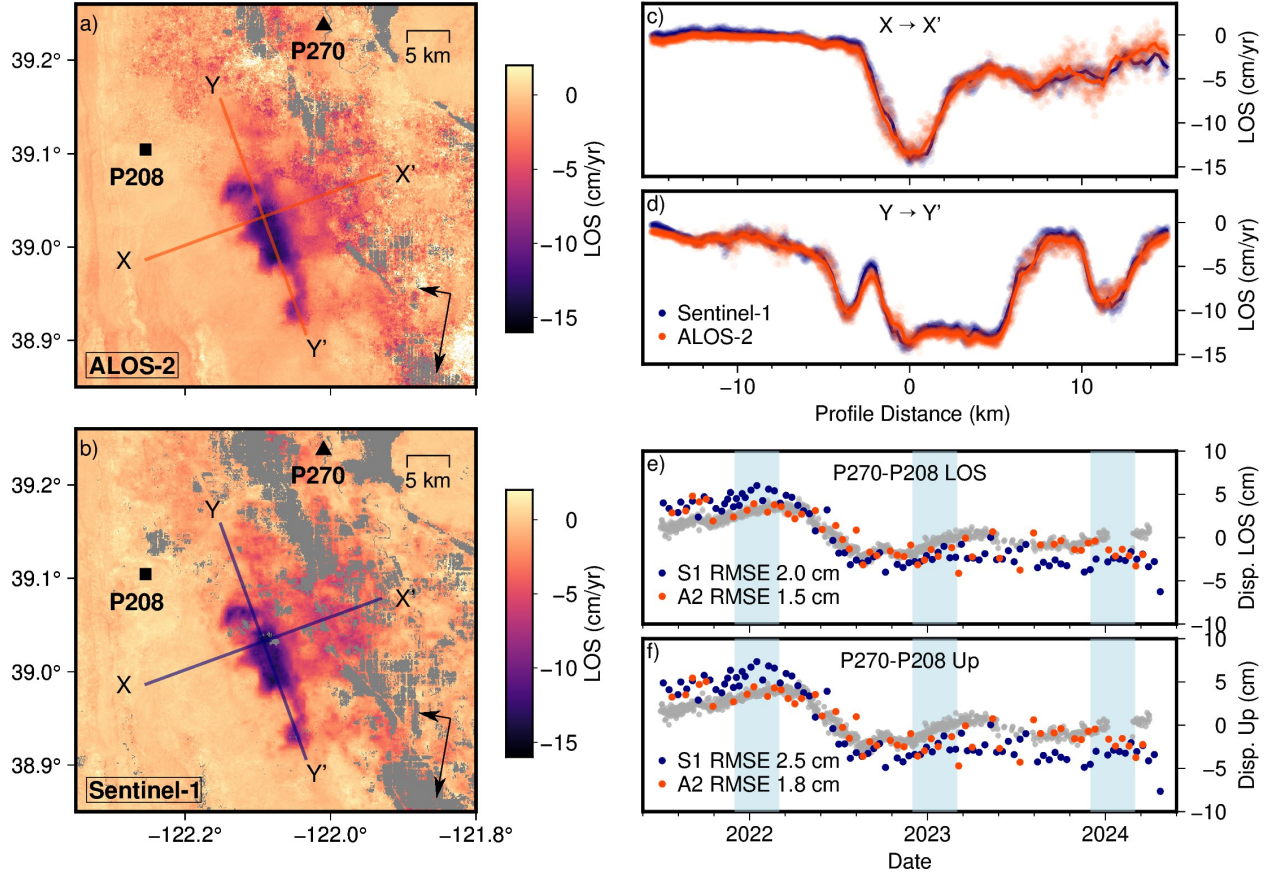


Figure 2.4: Comparison of 2021-2024 ALOS-2 and Sentinel-1 data and validation of InSAR time series with GNSS in the Sacramento Valley Basin. LOS velocity maps for (a) ALOS-2 (track 170) and (b) Sentinel-1, for July 2021 - March 2024. (c) X-X' and (d) Y-Y' velocity field profiles. P270-P208 baseline comparison with (e) GNSS (grey dots) in east, north, and up projected to LOS and (f) InSAR projected to up.

Internal consistency between overlapping tracks

We assess internal consistency by differencing overlapping ScanSAR tracks, highlighting broad-scale noise patterns and sampling effects. Ascending track 068 and descending track 170 sample the Sacramento Valley with different geometries and network densities over the same period, 2015-2024. Assuming predominantly vertical motion viewed with similar incidence angles (170: 28° , 068: 37°), the projected velocity fields agree well (RMSE 6.7 mm/yr,

$R^2 0.94$; Figure A.4a–c). The final velocity field of track 068 comprises 22 acquisitions and 83 interferograms, while track 170 comprises 89 acquisitions and 364 interferograms, highlighting the robustness of the agreement despite the reduced sampling in the ascending track. Differencing the overlapping portions of descending tracks 169 and 170 (Figure A.4d–f) exposes broad-scale residuals with amplitudes of ± 5 mm/yr; likely resulting from unmodelled ionospheric and tropospheric noise in track 169. Residuals are evident in the Central Valley, where accelerated subsidence in 2022 appears in track 170 but not in track 169, which ends early in 2021. When comparing the same period from 2015 to 2021, during which track 170 had similarly limited data, both tracks exhibit spatially coherent anomalies and measure a similar magnitude of subsidence in the Central Valley (Figure S3). Overall, despite differences in viewing geometry, acquisition density, and observation periods, the ScanSAR time series yield broadly consistent velocity fields in overlapping regions.

2.5 Results

Using the nine-year L-band ScanSAR dataset integrated with interpolated cGNSS velocity fields, we constrain long-term regional deformation rates and examine short-term time-dependent deformation (2021–2024). We present a series of case studies demonstrating the dataset’s capability to resolve low-amplitude, long-wavelength features and time-dependent signals in heavily vegetated terrain. The densely forested region of northern California is an environment where traditional C-band InSAR often struggles to image, and cGNSS inter-station distances can be as much as 50 km. Our results capture long-wavelength tectonic loading with superimposed short-wavelength signals associated with MLV, Central Valley aquifer withdrawal, and slow-moving landslides.

Regional deformation across northern California

Figure 2.6 presents our final 3D deformation realization, derived from our integrated GNSS–InSAR inversion. We extend the spatial extent of earlier Sentinel-1 (X. Xu et al., 2021; Govorcin et al., 2025) and ALOS-1 (Tong et al., 2013) regional velocity fields, providing spatially continuous measurements in densely vegetated areas, notably along the coastline and within the north Coastal Ranges. The cGNSS anchors the long-wavelength horizontal field, resolving distributed deformation across the San Andreas Fault and the Cascadia Subduction Zone. Short-wavelength horizontal signals (e.g., slow landslide motion) and the vertical velocity field derive solely from InSAR, thus reflecting its characteristic noise structure. The results include two distinct regions of subsidence, in the Central Valley (see Section 2.5) and at The Geysers geothermal field (with maximum rates of -16 mm/yr). Maximum uplift aligns with the flanks of the Central Valley, which have limited GNSS control. We detect subsidence along Humboldt Bay leveling lines near Eureka (Patton et al., 2023) and coastal uplift at Crescent City (P783), with InSAR–GNSS residuals ≤ 0.5 mm/yr. At Point Reyes,

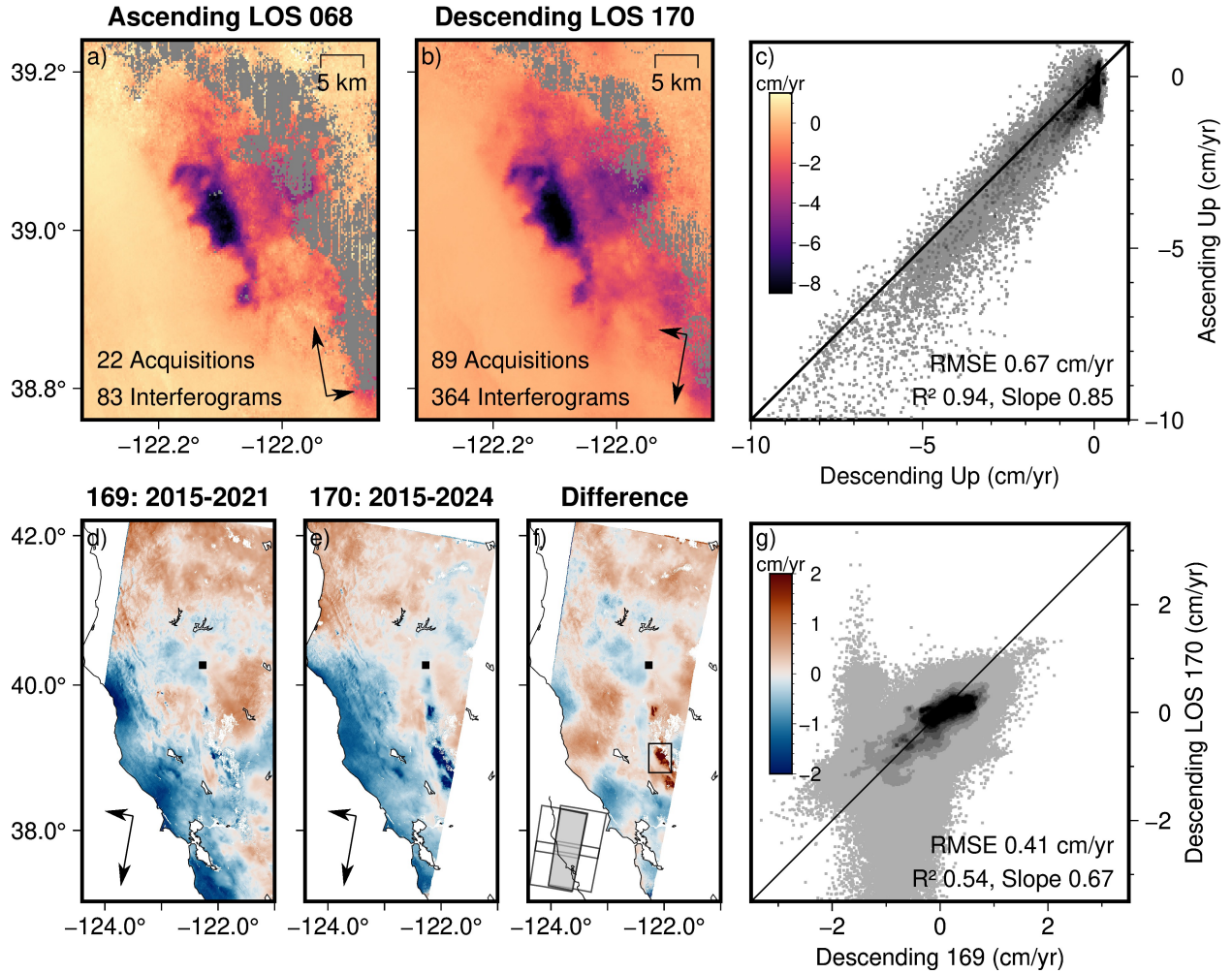


Figure 2.5: Independent InSAR validation. (a-c) Comparison of vertical projection of ascending and descending observations for the period 2015–2024 in the area of dominantly vertical aquifer deformation. (d-g) Comparison of overlapping line-of-sight (LOS) observations from descending tracks 169 and 170. The velocity field of track 169 spans 2015–2021, while 170 spans 2015–2024. Central Valley aquifers experienced accelerated subsidence in 2021 and 2022, which is not captured by track 169. Long-wavelength noise in f) is attributed to errors in the ionosphere or troposphere corrections.

where the San Andreas Fault extends offshore, subsidence reaches 6 mm/yr, consistent with Govorcin et al. (2025).

Comparison with vertical GNSS reveals excellent agreement in the greater San Francisco Bay Area, but poorer performance along the coast onshore from the MTJ. The Bay Area has many examples of robust InSAR results (e.g., Ferretti et al., 2004; Chaussard, Bürgmann,

Fattahi, Nadeau, et al., 2015; Y. Li et al., 2023), due to low vegetation cover and dense GNSS. Vertical velocities in the Bay Area exhibit lower GNSS–InSAR residuals, with vertical RMSE values of 1.2 mm/yr within the dashed box (Figure 2.6c), compared to 1.88 mm/yr across the whole domain (Figure S2). The spatial pattern of the vertical velocity within the Bay Area aligns well with Govorcin et al. (2025), with both results including many locations of localized subsidence along the shoreline. By contrast, the most significant residuals occur along the coast and inland of the MTJ (red labels in Figure 2.6d). These spatially coherent errors likely stem from poor ionosphere estimates and residual tropospheric noise (Sections 2.4 and 2.6). Broad-scale InSAR noise remains a key limitation in recovering long-wavelength, low-amplitude deformation, for which GNSS-only solutions continue to outperform InSAR results (Lau et al., 2020; Hammond et al., 2016). Due to the lack of temporal sampling along track 068, we experience phase decorrelation in the northwest part of our study region, which limits the spatial resolution of the vertical velocity field.

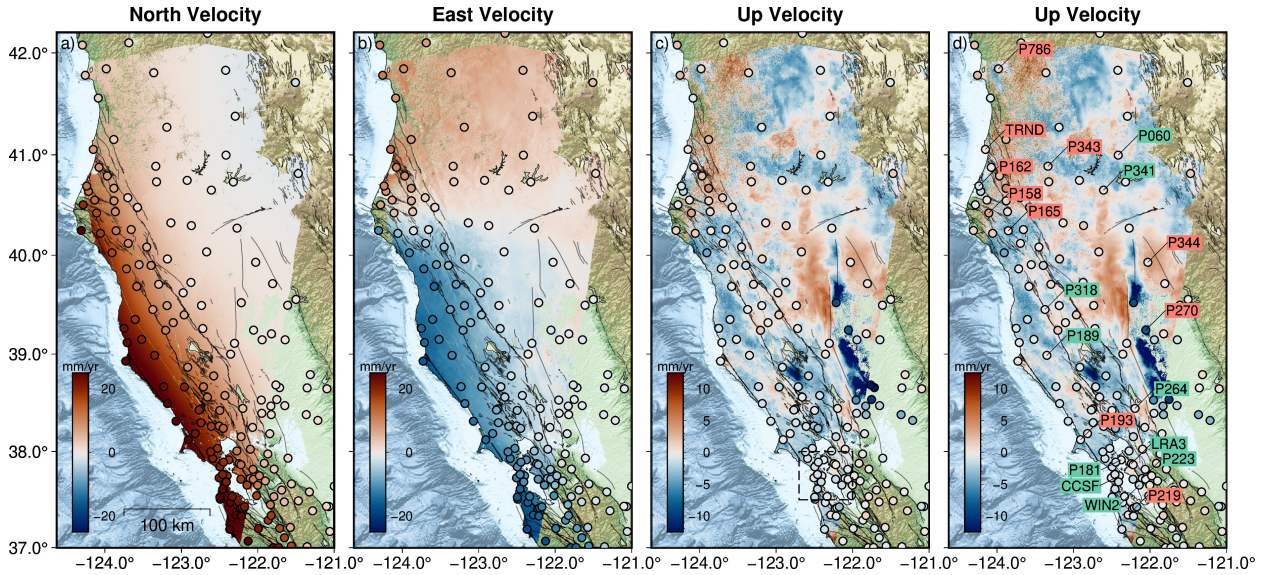


Figure 2.6: (a) North, (b) East, and (c) Up velocities from our integrated InSAR and GNSS decomposition. (d) GNSS stations with the smallest vertical-velocity residuals (± 0.3 mm/yr, green) and largest residuals (± 3.3 -5.2 mm/yr, red). The dashed box in (c) outlines the San Francisco Bay area, where five of the best-fitting stations are located.

Subsidence at Medicine Lake Volcano

This case study demonstrates that our data effectively resolves low-rate deformation, even in the presence of seasonal snow and dense vegetation. We map localized subsidence within the caldera of MLV along with a broad band of subsidence that trends southwest to Mount

Shasta (Figure 2.7). We select a local reference pixel at GNSS station P784, and present the InSAR-only vertical velocity field from the full 2015–2024 archive. L-band coherence enables longer temporal interferograms that span the snowy season (November–May), substantially increasing the areal extent of reliable measurements compared to C-band InSAR. To check for elevation bias, due to remaining errors caused by the stratified troposphere, we first mask out the area of peak subsidence (the white circle of 20 km radius in Figure 2.7b) and compute the correlation between elevation and vertical velocity. Beyond 20 km from the caldera center, the correlation is weak ($r^2 = 0.04$), ruling out elevation-dependent bias in the peripheral region. In contrast, within the 20 km caldera zone, the relationship is stronger ($r^2 = 0.50$), probably reflecting deformation processes that actively shape the topography of MLV.

The subsidence at MLV forms a region with radial symmetry within the caldera rim of MLV, characterized by steeper gradients on the southern and western flanks and a broad lobe of subsidence extending southwest toward Mount Shasta. Mount Shasta itself lacks a clear subsidence signal, though its north-west flank shows slope movement (Figure S4). Profiles of vertical velocities across MLV extend ± 30 km from the caldera center, revealing peak subsidence of 10–15 mm/yr, which returns to baseline beyond 20 km. Historical leveling between 1954 and 1989 recorded subsidence rates of up to 8.6 ± 0.9 mm/yr at MLV (Dzurisin et al., 1991). Stacked ERS-1/2 interferograms from 1993–2000 mapped ~ 10 mm/yr in LOS at the caldera, tapering to zero over ~ 15 km on the northeast flank (approximately from the center to Y', Figure d) (Poland et al., 2006). ALOS-1 and Envisat studies through 2011 reported peak subsidence rates of ~ 8 mm/yr (Parker et al., 2014). Most recently, a Sentinel-1 velocity field spanning 2017–2021 observed peak rates of 14 mm/yr, which is in agreement with our estimate of peak subsidence on the northeastern flank (Bussard, 2024). Rate discrepancies may reflect sampling coverage: the leveling lines traverse the western and southern flanks, where the gradient is modest in the region of subsidence extending to the southwest, and thus miss the steeper gradient to background rates on the northeastern side. Overall, we extend the deformation history, corroborating a generally steady subsidence trend since the 1950s, and provide far denser spatial coverage.

Aquifer-driven subsidence in the Sacramento Valley groundwater basin

For this case study, we present new time series observations that capture the deformation associated with the transition from drought conditions in 2021–2022 to record precipitation in 2023, and provide displacement rates for where the Tehama-Colusa Canal intersects with localized subsidence. In the Sacramento Valley, we resolve two 20 by 10 km subsidence patches along the basin’s eastern margin near Greenwood and Arbuckle (Figure 2.8, partly the same as Figures 2.4 and A.4). Displacement time series are derived from track 170 (July 2021–March 2024) at ~ 80 m resolution referenced to station P208 and projected to vertical. We measure a drastic increase in subsidence during 2022 within the Sacramento

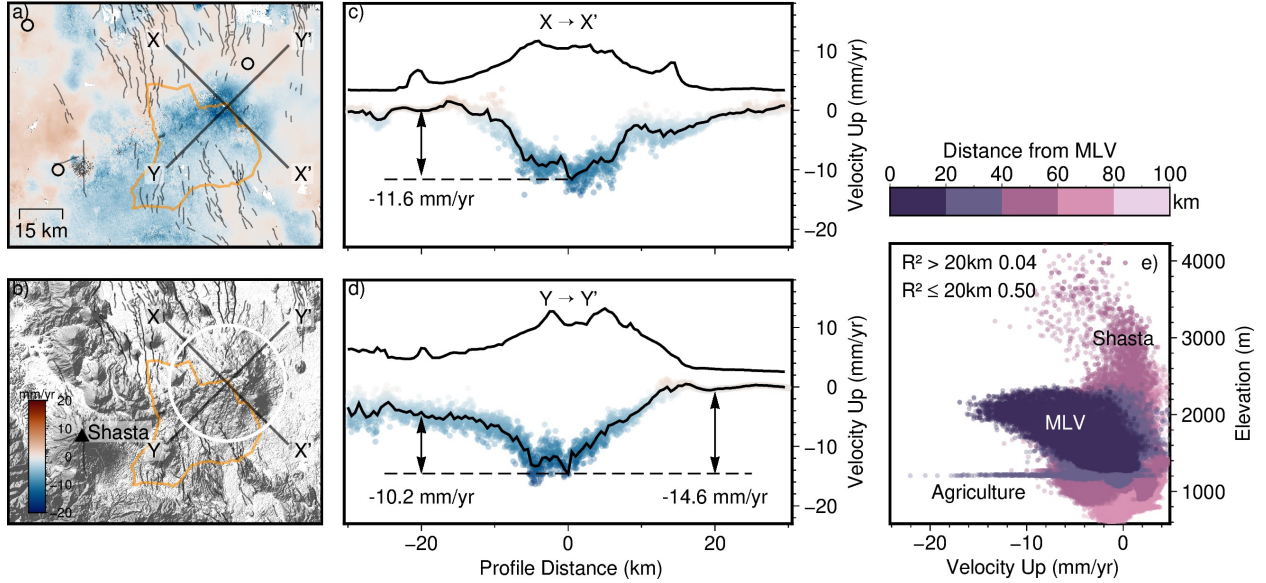


Figure 2.7: (a) Vertical velocity field from InSAR-only decomposition for Medicine Lake Volcano (MLV) between 2015 and 2024, and GNSS vertical velocities in colored circles (see color scale in (b)). (b) Corresponding DEM, fault locations, leveling survey line (orange), and region that was masked out in elevation-dependent testing (white circle). (c) and (d), vertical velocity (colored points, black line is mean value) and elevation profiles ranging from 1300 to 2100 m (plotted with vertical exaggeration) (e) Comparison of velocity and elevation colored by distance from the center of the Caldera.

Valley Groundwater Basin (Figure 2.8 c, d). Near Greenwood, we observed vertical rates of -28.5 ± 2.6 cm/yr in 2022, which decreased to -4.3 ± 1.4 cm/yr in 2023. Similarly, near Arbuckle we find -31.3 ± 1.6 cm/yr in 2022 and -0.9 ± 1.0 cm/yr in 2023. During the most rapid period of subsidence from May to September of 2022, peak vertical rates reached -57.6 ± 6.6 cm/yr and -50.0 ± 5.2 cm/yr for Greenwood and Arbuckle, respectively. For comparison, long-term ALOS-1 rates (2007-2011) were only 2–3 cm/yr at both sites (Smith et al., 2021; Ojha et al., 2018). More recently, Arbuckle subsided at ~ 8 cm/yr during 2019-2021 (Carlson et al., 2024). Despite record 2023 rainfall, we do not see a recovery from the subsidence experienced during 2022, implying inelastic compaction from groundwater having reached a new low stand in 2022 (Chaussard & Farr, 2019). The Tehama-Colusa Canal crosses both localized features and subsided 20 cm near Greenwood and 21 cm near Arbuckle during 2022. This single-year subsidence is similar to that reported by Miller et al. (2020), along a localized section of the California Aqueduct. Monitoring subsidence along water transport infrastructure is crucial for maintaining water-delivery efficiency, planning repairs, and mitigating hazards.

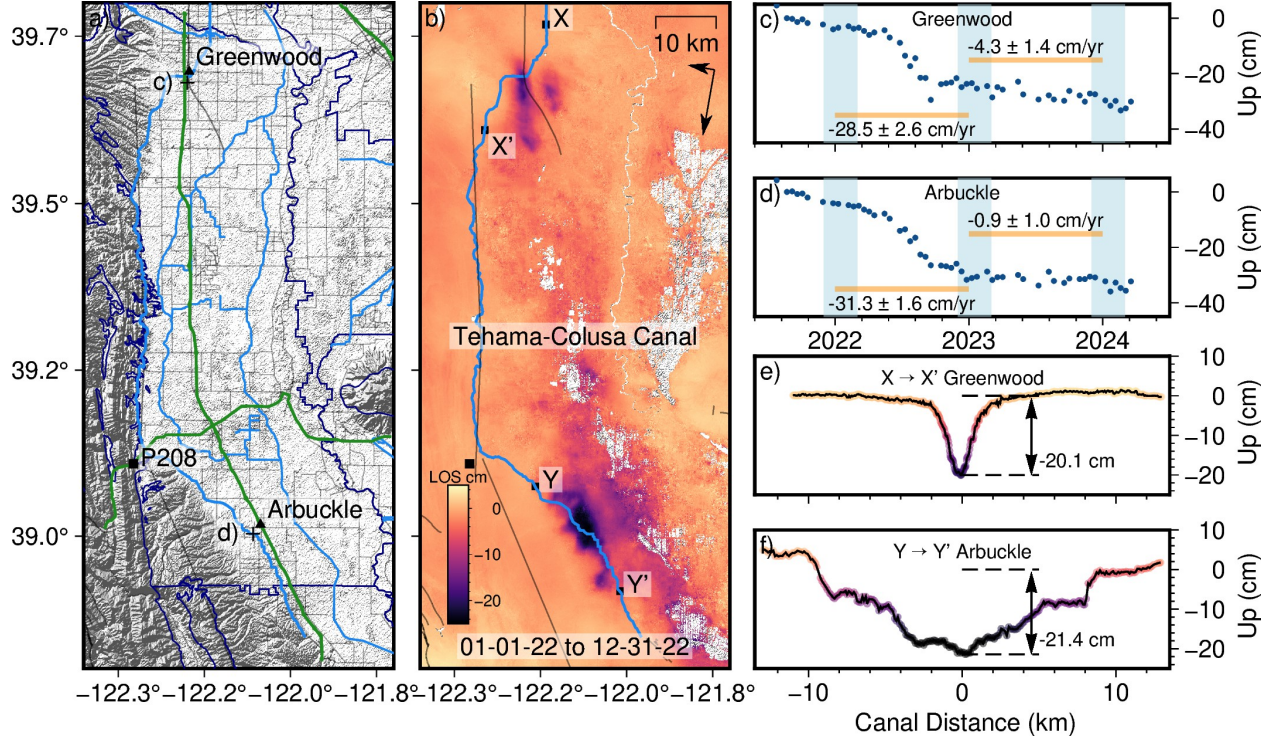


Figure 2.8: (a) Location map of the Sacramento Valley Basin with aquifer boundaries (navy), canals (blue), major roads (green), and time series locations (+). (b) Line-of-sight (LOS) cumulative displacement field for 2022, showing the location of profiles along the Tehama-Colusa Canal (X-X' and Y-Y'). Vertical displacement time series at (c) Greenwood and (d) Arbuckle. (e) and (f) cumulative vertical displacement during 2022 along canal profiles for X-X' near Greenwood and Y-Y' near Arbuckle (California Department of Water Resources, 2025).

Slow-moving landslides

To illustrate the ability of our dataset to reveal landslide dynamics at a regional scale, this case study presents two examples of landslide acceleration located in heavily vegetated terrain. While catastrophic landslides move at rates of tens of meters per second, slow-moving landslides creep slowly at rates of up to meters per year and have the potential to transition to catastrophic failure (Handwerger, Huang, et al., 2019; Lacroix et al., 2020). In northern California, the majority of slow-moving landslides are located within the mechanically weak Franciscan Melange (Y. Xu et al., 2021). Their velocities are primarily modulated by precipitation, with annual accelerations initiating during the wet season (Handwerger et al., 2022). Slow-moving landslides are also known to occasionally exhibit accelerations and catastrophic failure associated with earthquake shaking (Lacroix et al., 2020). Our time series records

landslide responses to the 2021 and 2022 earthquakes, as well as the abrupt transition from drought to above-average rainfall in 2023 (Figure 2.9). We derived displacement time series for the Graham landslide complex and the Boulder Creek earthflow from track 170 (July 2021–March 2024, ~ 80 m pixels).

We compare LOS steady sliding rates during the driest months (roughly April through November) and find striking contrasts between our selected examples (Figure 2.9). On the Graham landslide complex, Point c was static through 2022, while Point d moved at 4.0 ± 1.1 cm/yr. Following the 2022 quake and heavy rains, both accelerated to ~ 11.5 cm/yr LOS during the 2023 dry season. Boulder Creek slid steadily until late 2022, then paused. Coincident with the onset of precipitation and the 2022 earthquake, steady sliding resumed but at slower dry season rates, dropping from 12.2 to 6.8 cm/yr at Point g and 6.0 to 4.1 cm/yr at Point h. These results are in agreement with InSAR-derived estimates of Handwerger, Fielding, et al. (2019), who reported approximately 8 cm/yr between April 2016 and February 2018 in the UAVSAR LOS and higher Handwerger et al. (2022) that reported 4.75 cm/yr in the downslope direction for 2015 - 2020 from Sentinel-1 InSAR. Together, the two sites highlight how a single, high-resolution ScanSAR dataset can track landslide kinematics in space and time over large, forested areas.

2.6 Discussion

Motivated by the research aims outlined in section 2.1, we evaluate time series results from L-band ALOS-2 InSAR acquired in ScanSAR mode across Northern California. To address research aim 1, we performed extensive validation using GNSS, Sentinel-1, and independent ScanSAR observations. We find that 50-70% of residuals between long-term InSAR and GNSS-derived LOS rates are within ± 2 mm/yr (Figure 2.3), comparable performance to Sentinel-1 in retrieving temporally variable signals (Figure 2.4), and robust cm-scale deformation retrieval in overlapping ScanSAR regions regardless of acquisition count, interferogram number, or orbit direction (Figure A.4 a-c). In pursuit of research aim 2, we attempted to recover broad-scale (hundreds of kilometers), low-amplitude (~ 1 – 2 mm/yr) vertical signals from ScanSAR; however, enduring noise challenged these efforts, especially in coastal regions. We observe ± 5 mm/yr broad-scale noise—attributed to unmodeled atmospheric noise and phase noise from low coherence—that masks low-amplitude regional signals (Figure A.4 d-g). We evaluate our ScanSAR datasets’ ability to resolve localized, rapid deformation (research aim 3) and find the dataset to be highly effective. We demonstrate that ScanSAR resolves localized, time-dependent deformation (0.5–30 cm/yr) on hundred-meter scales, as evidenced by subsidence in the agricultural Central Valley and detailed landslide kinematics in heavily vegetated coastal ranges. Finally, relating to research aim 4, we present new observations enabled by this dataset: spatially continuous subsidence mapping of MLV (Figures 2.7); documentation of accelerated subsidence, likely inelastic deformation, associated with drought conditions in 2022 and lack of recovery in 2023 (Figure 2.8); and the first time series for the Graham Landslide Complex, underscoring active geohazard monitoring opportunities with

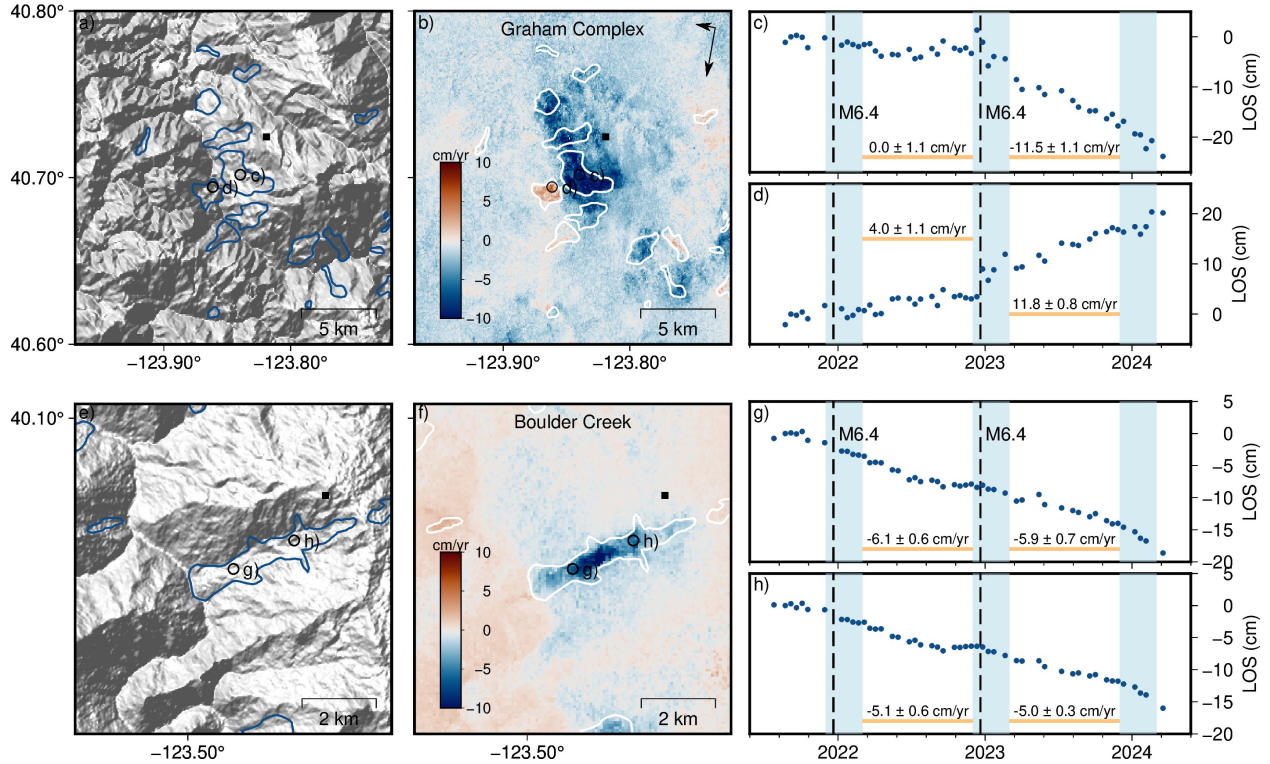


Figure 2.9: Location map for (a-d) Graham landslide complex and (e-h) Boulder Creek Landslide. (left) DEM and location of other InSAR mapped slow-moving landslides (Xu et al., 2021), (b, f) LOS velocities from track 170, for March 2021 to July 2024, and (c, g) LOS displacement time series. Light blue panels illustrate typical periods of peak precipitation, and orange lines show the timing of the M6.4 2022 and M6.4 2023 earthquakes near the MTJ (see Figure 1 for locations).

L-band InSAR (Figure 2.9). The following subsections discuss the limitations and highlight the strengths of the dataset, new observations, and the utility of L-band InSAR for future deformation monitoring.

Limitations of the dataset

The largest persistent challenge in L-band InSAR is mitigating phase contributions from the ionosphere. Studies of data from L-band missions with narrow swaths (e.g., ALOS-1, ~ 70 km) could approximate ionospheric effects with a simple linear or quadratic ramp in most cases (e.g., Lindsey et al., 2015); in contrast, we find examples of very heterogeneous ionospheric structure in the ALOS-2 widewidth data (Figure S1). The split-spectrum method has proven very effective in mitigating such ionospheric phase advances; however, it encoun-

ters challenges due to low coherence, unwrapping errors, and small range bandwidth (Liang, Liu, Fielding, & Bürgmann, 2018). Despite our best efforts, residual biases of up to 5 mm/yr persist along the coastline, most clearly near Point Reyes (P193) and Eureka (P162) (Figure 2.6 d). Their peninsular settings leave too little coherent land for stable estimation, and the algorithm especially struggles when the ionospheric gradient aligns with the coast (Figure S1e). To reduce error from ionospheric estimation, we recommend (1) masking disconnected regions before ionosphere estimation, (2) applying stricter quality control for interferograms used for the per-date inversion, and (3) testing multiple filtering and multilooking parameters for low-coherence regions to mitigate artifacts. We note that more recent software releases include more robust handling of the phase difference between subswath subband interferograms in the ionospheric phase estimation, and this may remediate ramp-like features. Because (ScanSAR) ionospheric correction in time-series analysis remains relatively under-explored, standardized approaches for diverse conditions are lacking; further refinement is needed to reduce user intervention and support future L-band applications.

The remaining noise field manifests differently in each track because several error sources act at once. Range-direction ramps, which dominate 068, appear weaker on 169 and 170, and may in part result from sub-swath misalignment due to phase differences between subband interferograms. Alignment of sub-swaths is dependent on coherence, which is low in the more densely vegetated northern Coastal Ranges and Sierra Nevada. Spatially coherent anomalies (~ 5 mm/yr over tens of kilometres) are consistent with residual atmospheric noise and are prevalent along tracks 068 and 169 (Figure A.4f). Only 068, acquired closer to peak daily TEC, shows ripple-like streaks, attributed to ionospheric scintillations that vary faster than filtering and unwrapping algorithms can resolve when estimating the ionospheric phase (Figure 2.2r) (Yunjun et al., 2022). Across all tracks, short-wavelength noise is introduced by changes in the scattering properties of the ground surface, which cause phase errors due to decorrelation. In northern California, processes that alter scattering properties include seasonal snow cover, soil moisture, and wildfire. Because only a small portion of each scene may have snow cover, we chose to include these scenes despite introducing phase noise in small regions, in order to maintain temporal resolution for the dataset as a whole. A further source of error may be the application of the bulk plate motion correction, designed for stable interiors, to the diffuse San Andreas-Cascadia plate boundaries.

Our ability to remediate the error sources listed above is substantially limited by computational capacity. Each raw ScanSAR frame is ~ 66 GB, and duplicating the data during resampling, alignment, and ionospheric estimation pushes a single re-processing run into tens of terabytes of temporary storage and many CPU-days. To conserve resources, we delete raw data once SLC alignment is complete and discard resampled stacks after interferogram formation. However, these savings restrict the number of parameter tests we can perform, particularly for ionosphere estimation. Given these constraints, we adopt a pragmatic final step in our workflow: we solve for and remove a best-fit quadratic ramp tying InSAR to GNSS, minimizing residuals and yielding the most reliable velocity field with the present data. Sensitivity tests show that, after deramping, excluding winter interferograms, adjusting masking thresholds, or shifting the reference pixel changes the final RMSE by only a few

tenths of a millimetre per year and leaves the residual distribution essentially unchanged. Our final displacement time series resolves centimetre-scale, localized deformation independently; yet, our velocity fields still require a GNSS tie to suppress long-wavelength noise and reliably recover interseismic tectonic signals. While independently processing InSAR without GNSS is advantageous (e.g., Chaussard et al., 2016), our results examine some of the long-wavelength noise sources in L-band ScanSAR and underscore the benefit of incorporating GNSS early in the workflow (e.g., X. Xu et al., 2021). Continued work characterizing long-wavelength noise sources in L-band InSAR is integral for expanding interseismic deformation studies beyond locations with dense GNSS coverage.

Strengths of ALOS-2 ScanSAR

Northern California’s forested, snow-prone terrain has historically presented a challenge for geodetic imaging, especially for InSAR time series of displacement. Our ALOS-2 ScanSAR time series resolves both subtle and rapid deformation, producing spatially continuous velocity fields in regions that de-correlate with C-band sensors. To our knowledge, this is one of the first studies to focus specifically on time-dependent deformation using ALOS-2 ScanSAR data. Validation efforts demonstrate that where ScanSAR acquisitions are regular and frequent (July 2021 to March 2024), L-band results achieve centimeter-level accuracy on a monthly scale, matching C-band performance while extending coverage into previously incoherent zones. Our 14-day repeat time series with L-band InSAR over northern California opens new opportunities for studying signals with semi- and annual-scale time dependence. Our time series in the Central Valley is the first to document the unprecedented, localized acceleration of subsidence exceeding 20 cm during 2022 within the Sacramento Valley Groundwater Basin (Figure 2.8). Two regions of significant subsidence intersect with critical infrastructure: the Tehama-Colusa Canal, which supplies water to 17 different water districts in four counties, and Interstate 5 (I-5), the main north–south Interstate Highway through the Central Valley. The time series for both locations, Figures 2.8c and d, illustrate that the aquifer did not recover in the post-drought period of 2023, indicating that water withdrawal reached a new record low and likely led to inelastic deformation. We present the first detailed time series from the Graham Landslide Complex, illustrating a pronounced acceleration in early 2023 following intense precipitation and earthquake shaking (Figure 2.9). The time series from the Graham and Boulder Creek landslides are examples of the detailed kinematic behavior that can be similarly extracted and analyzed for hundreds of previously mapped slow-moving landslides within our unique, region-wide ScanSAR dataset (Y. Xu et al., 2021). The large scene footprints, improved spatial coherence from the L-band wavelength, and regular 14-day repeat intervals make ScanSAR an excellent tool for monitoring time-dependent deformation in heavily vegetated regions.

L-band InSAR for future deformation monitoring

Deformation transients originating from landslides, subsiding aquifers, and faults pose significant risks to essential infrastructure—water, transportation, and energy systems—and can disrupt economies and threaten lives. Although the ALOS-2 ScanSAR time series offers new opportunities, only a few locations globally currently benefit from frequent 14-day repeats, and the application of ionospheric corrections remains challenging. We expect many of the issues of ALOS-2 ScanSAR to be mitigated by the NISAR mission, which is expected to facilitate significant improvements in monitoring transient deformation. NISAR’s regular acquisition schedule (12-day repeat) and enhanced spatial resolution (3–10 m) are expected to enable more precise measurements of rapidly deforming, localized features. NISAR’s dedicated frequency band for ionospheric correction is expected to eliminate the persistent ionospheric noise and broad-scale anomalies identified in our ScanSAR data, thereby improving the reliability of regional deformation mapping. With NISAR’s well-controlled orbits and rigorous validation program, the long-wavelength noise field is expected to be thoroughly characterized, alleviating dependence on GNSS networks for studies of deformation targets larger than the scene footprint. Importantly, open access to NISAR data will enable the community to maximize its potential and contribute to the development of processing and analysis tools that advance our field, providing a basis for new scientific discoveries.

2.7 Conclusions

This study is among the first to use ALOS-2 L-band InSAR acquired in ScanSAR mode to measure time-varying deformation across northern California’s densely vegetated, seasonally snow-covered terrain. By retaining coherence where C-band decorrelates and delivering dense, wide-area coverage beyond the point sampling of GNSS, ALOS-2 ScanSAR bridges a critical observational gap, capturing deformation across a full spectrum of rates and spatial scales. Extensive validation demonstrates centimeter-level accuracy for local, time-dependent signals and, when integrated with GNSS, enables reliable imaging of low-rate deformation over more than 400 km from the reference pixels. Residual long-wavelength atmospheric noise—primarily due to imperfect ionosphere estimation—remains the primary obstacle to fully independent mapping of distributed interseismic deformation and regional uplift fields with this dataset. Our time series extends the geodetic record of deformation at Medicine Lake Volcano, providing improved spatial coverage and temporal context. We also document unprecedented subsidence in the Sacramento Valley Groundwater Basin during 2022, which notably did not rebound in 2023, despite record precipitation, indicating non-recoverable compaction following a new low stand. We present time series from two slow-moving landslides that illustrate what wide-swath L-band InSAR can now deliver: routine, high-fidelity geohazard monitoring across vegetated terrain that was previously inaccessible. As access to L-band SAR expands, our results provide a timely examination of the dominant noise sources and highlight new observations that were previously unobtainable due to coherence

loss. Upcoming L-band missions, specifically NISAR—with shorter revisit times, finer pixels, and a dedicated frequency for ionospheric corrections—will further advance these capabilities, enabling routine, high-resolution deformation monitoring worldwide.

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Open Research

Original ALOS-2 ScanSAR Level 1.1 SLC products are publicly available and can be searched and downloaded via JAXA’s G-Portal (Japan Aerospace Exploration Agency (JAXA), Earth Observation Research Center (EORC), 2025), and many are now available from the NASA Alaska Satellite Facility (ASF) Distributed Active Archive Center and Japan Aerospace Exploration Agency (JAXA) / EORC (2024). Data from 2015-2021 are also archived with the Western North America InSAR (WInSAR) Consortium (2025). Interferograms were produced with ISCE-2 (ISCE-2 Development Team, 2025) and analysis and plotting tools can be found at Lindsay (2025a). Sentinel-1 data were processed with the ASF cloud-based HyP3 service (Hogenson et al., 2025). Time series and velocity results used in this study are archived on Zenodo (Lindsay, 2025d).

Competing interests

The authors have no competing interests.

Chapter 3

Spatiotemporal Creep Distribution on the Rodgers Creek and Maacama Faults: Decade-long creep suppression and seasonal modulation

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Key Points

- We map surface creep along the Rodgers Creek–Maacama faults using L-band InSAR, alignment arrays, and repeating earthquakes.
- A 2002 creep event on the Maacama Fault was followed by a decade-long suppression in surface and seismogenic creep rates.
- Fault creep is not steady but varies seasonally to decadal, shaping how we understand time-dependent seismic hazard.

Abstract

The Rodgers Creek–Maacama (RC–MA) fault zone in northern California hosts fault creep that remains undercharacterized, limiting understanding of its role in the earthquake cycle. To address this gap, we integrate ALOS-2 and Sentinel-1 InSAR, alignment arrays, and characteristic repeating earthquakes (CREs) to characterize spatial and temporal variability. We find that surface creep along the Maacama Fault reaches 4–8 mm/yr, correlating with shallow CREs and the base of the seismogenic zone, while the Rodgers Creek Fault creeps more modestly at 3–4 mm/yr near Santa Rosa. Alignment array records reveal a 5–10 mm creep event on the northern Maacama Fault in 2002, followed by a sustained period of suppressed surface creep. This deceleration is mirrored in reduced seismogenic creep rates inferred from CREs and in a decrease in background seismicity. Seasonal modulation of creep is evident in both InSAR and alignment array records, though expressed differently between sites and datasets. These findings highlight that fault creep is not steady but varies over seasonal to decadal timescales, shaped by evolving stress and internal fault properties, with implications for understanding the temporal variability of seismic hazard.

3.1 Introduction

Aseismic creep—the gradual sliding of one fault block past another without generating detectable seismic waves—plays a crucial role in the seismic hazard associated with a given fault. Tectonic forces continuously load faults, and the amount of strain released through fault creep directly influences the amount of energy remaining in the system to drive large earthquakes (Avouac, 2015). Creeping fault segments pose a lesser seismic hazard than fully locked faults by increasing the interval between large earthquakes or reducing the magnitude of potential events (Field et al., 2014; Harris, 2017). Creeping patches may act as barriers to rupture propagation, imposing a geometric limit on the magnitude of a possible earthquake (Kaneko et al., 2010), or may also host ruptures that propagate into the creeping zone (Noda & Lapusta, 2013). Accelerating creep increases stressing rates on adjoining asperities and may at times indicate precursory earthquake behavior (Mazzotti & Adams, 2004; Mavrommatis et al., 2015; Dascher-Cousineau & Bürgmann, 2024).

Changes in the rate of fault creep reflect the state of stress acting on and the strength of the aseismically slipping portion of that fault over short (e.g., seasonally pore fluid infiltration), median (e.g., static stress change from earthquakes) and long (e.g., viscous relaxation) time scales, and therefore reflect the evolving seismic hazard associated with a fault throughout the seismic cycle. Static and dynamic stress changes from earthquakes influence creep rates by temporally enhancing (e.g., Shelly & Johnson, 2011) or suppressing creeping regions (e.g., Lienkaemper et al., 1997), or triggering pulse-like creep events (e.g., Tymofeyeva et al., 2019). Precipitation can modulate the pore fluid pressure, where increased fluids in the fault surface can lower effective normal stress and promote seasonally modulated creep events (Roeloffs, 2001; S. Schulz et al., 1983; Khoshmanesh & Shirzaei, 2018). For the shal-

lowest portion of the fault, seasonal soil swelling may also generate a cyclic clamping and unclamping of the fault (Bilham et al., 2004). Understanding where creep occurs and how creep rates change through time is integral to determining seismic potential and constraining future earthquake scenarios (Field et al., 2014).

We categorize creep as ‘deep creep’ below the seismogenic zone, ‘shallow creep’ within the seismogenic zone, and ‘surface creep’ observable at the surface trace of the fault. Geologic slip rates are assumed to average across multiple seismic cycles and, therefore, represent the closed system of the seismogenic portion of the crust, which also represents long-term deep creep rates. Geodetic slip rates from GPS model inversions fit present-day geodetic observations and infer the time-averaged slip rate. Observations far from the fault constrain deep creep rates within these inversions, while observations from nearer stations inform us about the shallow creep within the seismogenic zone. Surface creep rates can be estimated from within the closest few kilometers of a fault trace, using offset cultural markers, alignment arrays, creepmeters, image correlation, or synthetic aperture radar interferometry (InSAR). Complimenting surface observations, we use the spatial distribution of characteristic repeating earthquakes (CREs) to infer the location of shallow creep (e.g., Uchida & Bürgmann, 2019) and recurrence intervals of CRE families to estimate shallow creep rates (Nadeau & Johnson, 1998). The difference between persistent deep creep below the seismogenic depth, which loads the system, and shallow creep, which gradually releases strain, creates a moment deficit that defines the amount of stored energy we expect to be relieved by future earthquakes (Avouac, 2015). In the temporal domain, we describe a creep event as a discrete step in our timeseries and an acceleration as a gradual change in rate. A continuous creep acceleration can be an aggregate of multiple creep events that occur more frequently or with larger amplitudes. Both phenomena are classes of slow slip events reflecting a fault patch that slips over minutes to decades (Bürgmann, 2018). The grouping or splitting of events and subevents is dependent on both the temporal resolution of the dataset and the user’s choice.

Northern California’s faults

In northern California, the boundary between the Sierra Nevada-Great Valley microplate and the North American Plate distributes deformation across three sub-parallel fault zones: the San Andreas Fault, the Hayward-Rodgers Creek (RC)-Maacama (MA) Faults, and the Green Valley-Bartlett Springs Faults. The 100 km width of the deformation zone accommodates ~ 40 mm/yr of slip, with the majority accumulating elastically and released in earthquakes while a smaller portion releases as aseismic creep throughout the seismic cycle (Freymueller et al., 1999; Murray et al., 2014). The northwest-southeast dextral RC-MA zone is characterized by a sequence of right-stepping restraining bends and step-overs with seismicity distributed across multiple fault strands and structures (McLaughlin et al., 2012; Melosh et al., 2024; Shelly et al., 2023). The RC fault dips northeast $75\text{--}80^\circ$ while the northernmost section of the MA shallows with a dip between $50\text{--}75^\circ$ (Castillo & Ellsworth, 1993). The southern section of the RC fault lacks seismicity, while the northern RC and south MA host seismicity

to depths of 8-10 km. Seismicity along the MA fault deepens from 7 km near Clear Lake and the Geysers geothermal field to 12-15 km near Laytonville and Willits in the north (Castillo & Ellsworth, 1993; Waldhauser & Schaff, 2008). The most recent large earthquake on the RC fault is likely to have occurred between 1715 and 1776, with a minimum estimated dextral slip of 2.2 m (Hecker et al., 2005), equivalent to a magnitude 6.8 to 7.4 event. The MA hosts infrequent large events, with 2-3 large earthquakes identified since 1180 cal BP in the Ukiah Valley (Prentice et al., 2014).

The RC-MA zone cuts through the Franciscan terrane, a melange of accreted subduction rocks containing lenses of serpentinite, a hydrothermally altered, mechanically weak material with a low friction coefficient associated with fault creep (Upp, 1989; Moore & Rymer, 2007; Wakabayashi, 2015). Early field mapping from (Pampeyan et al., 1980) notes specific sites where the fault contact is between serpentinite and other Franciscan rocks. The faults are interpreted as often reactivating inherited structures within the Franciscan terrane and reorganizing with successive slip events to orientations more suited to the present-day stress field (Upp, 1989; McLaughlin et al., 2012). Slip along the RC and MA initiated around 7 Ma and 3.2 Ma, in the wake of the adjacent northward progression of the Mendocino Triple Junction (McLaughlin et al., 2012). There is a clear surface expression of both faults until the northernmost section of the Maacma fault, reflecting its shorter slip history (Upp, 1989; Castillo & Ellsworth, 1993). Over the past 500 years, a moment deficit sufficient for an M_w 7.0–7.2 has accumulated on the MA fault (Murray et al., 2014; Lienkaemper et al., 2014). The RC is also coming to the end of its seismic cycle and has accumulated moment sufficient for an M_w 7.1 (Lienkaemper et al., 2014; Schwartz et al., 2014; Field et al., 2014).

The RC-MA zone has evidence of both shallow fault creep (Shakibay Senobari & Funning, 2019; W. Xu et al., 2018; Waldhauser & Schaff, 2021) and surface creep (Funning et al., 2007; Jin & Funning, 2017; Tong et al., 2013; X. Xu et al., 2021; McFarland et al., 2017). The first evidence of surface creep on the RC-MA zone came from (Simon et al., 1978), who identified offsets in cultural markers (Pampeyan et al., 1980; Upp, 1989). RC geological slip rates of 6.4–8.6 mm/yr (Prentice et al., 2014) are in agreement with geodetic estimates of 7–11 mm/yr (d’Alessio et al., 2005; McCaffrey, 2005; K. M. Johnson et al., 2022). InSAR-derived surface creep estimates range from 1.9–6.7 mm/yr, with the most coherent signal around Santa Rosa (Jin & Funning, 2017; Funning et al., 2007; W. Xu et al., 2018). (Shakibay Senobari & Funning, 2019) CRE catalog suggests surface creep extends to depths of 1.4–7.0 km along the 30 km section northwest of Santa Rosa. The 9–13 mm/yr geodetic slip-rate estimates along the MA fault (Freymueller et al., 1999; Murray et al., 2014; K. M. Johnson et al., 2022; Evans, 2022) are higher than the geologic rates in the range 6.4–8.6 mm/yr (Prentice et al., 2014). InSAR-derived surface creep rates from (Swiatlowski, 2020) estimate the northern MA section creeps at 1–7 mm/yr while the southern MA section creeps at 4.2–11 mm/yr. The alignment array in Willits (MWIL) and Ukiah (MUKI) measure average creep rates of 5.06 ± 0.08 mm/yr and 4.18 ± 0.05 mm/yr (McFarland et al., 2017). CREs follow seismicity along the MA, and are located on three sub-parallel structures near Hopland and east of the main trace near Willits (Woolace, 2005; Shakibay Senobari & Funning, 2019; Melosh et al., 2024). Previous InSAR studies with C-band have implemented Persistent Scatterers processing to

extract velocities for the most stable features, which trades off spatial coverage for precision (Jin & Funning, 2017; Funning et al., 2007; Swiatlowski, 2020). The L-band effort of (Tong et al., 2013) demonstrated the higher spatial coverage of the longer-wavelength platform; however, surface creep estimates are provided at increments of 10 km along the fault and include negative (sinistral) rates. Existing studies also focus on constraining long-term rates, whereas the temporal aspect of surface creep remains underexplored using InSAR imaging.

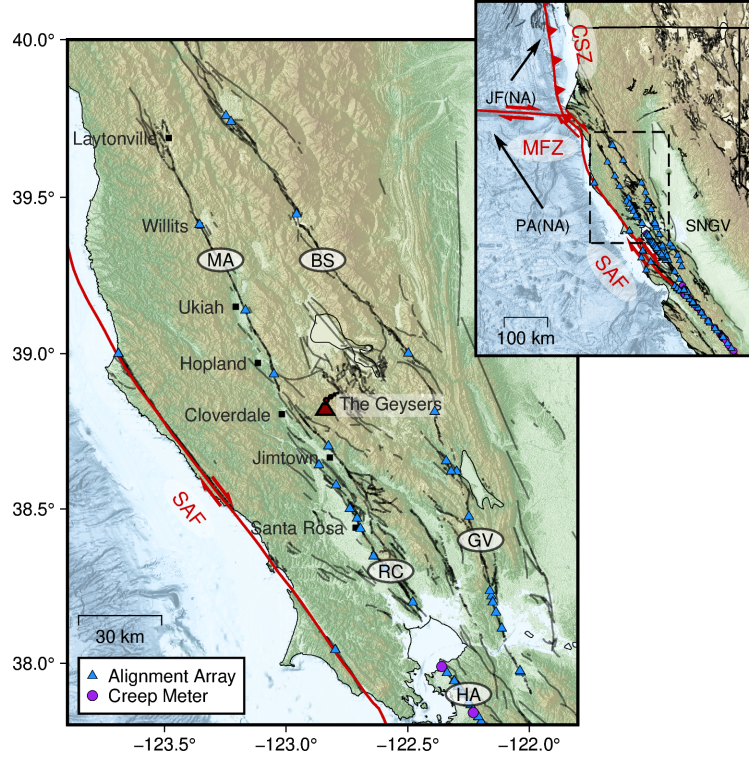


Figure 3.1: Plate boundary deformation in northern California is distributed across three parallel structures: the San Andreas Fault (SAF), Hayward (HA)-Rogers Creek (RC)-Maacama Faults (MA), and the Green Valley (GV)-Bartlett Spring (BS) Faults. The insert shows the tectonic setting where the North American (NA), Pacific (PA), and Juan de Fuca (JF) plates meet at the Mendocino Triple Junction. Convergence between JF and NA is accommodated by the Cascadia Subduction Zone (CSZ). Right-lateral shear is accommodated between the Sierra Nevada–Great Valley Block (SNGV) and PA along the San Andreas Fault (SAF) and between PA and JF along the Mendocino Fracture Zone (MFZ)

Motivation and research questions

The RC-MA fault zone poses a significant seismic hazard in northern California and hosts relatively under-characterized aseismic creep. Most existing surface creep measurements

along the RC-MA system focus on populated areas that host alignment arrays and produce coherent C-band InSAR data. However, much of the fault zone lies in vegetated regions, where coherence challenges have limited previous InSAR studies; additionally, there are no creep meter installations along either of the fault zones. By utilizing InSAR from the ALOS-2 satellite — an L-band sensor capable of maintaining coherence through vegetation — we aim to provide spatially continuous estimates of surface creep along the entire fault zone (Lindsay et al., 2025). We combine observations from InSAR (Sentinel-1 and ALOS-2), terrestrial alignment arrays, and characteristic repeating earthquake (CRE) catalogs to achieve an integrated view of creep’s spatial and temporal evolution.

We address the following key questions:

1. **Spatial Distribution:** Which sections of the RC-MA zone exhibit active creep, and what is the magnitude of creep along the length of the fault? How does its spatial variability correlate with fault geometry, lithologic contrasts, and proximity to the Geysers geothermal field?
2. **Temporal Variability:** Do creep rates vary over seasonal to decadal timescales, and what mechanisms (e.g., hydrological loading, static or transient stress changes) drive these variations?

We first describe our data sources and methodologies for measuring creep using CREs, InSAR, and alignment arrays. Spatial distribution of creep rates, CREs, and seismicity is summarized to provide a comprehensive view of shallow and surface creep. We examine temporally variable creep rates within the sensitivity of our dataset and discuss the mechanisms driving seasonal and multi-annual changes in creep rates.

3.2 Data and Methods

We compute surface creep estimates from Sentinel-1 and ALOS-2 InSAR time series for 2015–2024. While previous InSAR studies have provided regional creep rates with sparse sampling (e.g., Tong et al., 2013; W. Xu et al., 2018), this project aims to deliver densely sampled creep rates that account for localized noise sources. In addition, we present a new CRE catalog that builds upon previous efforts by expanding the study regions northward and extending the temporal coverage (Shirzaei & Bürgmann, 2013; Y. Li et al., 2023).

InSAR surface creep estimates

We use SAR data from the Sentinel-1 and ALOS-2 satellites. Sentinel-1 operates at C-band (~ 5.6 cm wavelength), while ALOS-2 operates at L-band (~ 24 cm wavelength). Sentinel-1 offers higher precision and more frequent temporal sampling, while ALOS-2 retains better coherence in vegetated regions. Combining both datasets enables us to more effectively

constrain time-dependent deformation in populated areas and preserve coherence in vegetated areas. Given the orientation of the faults, the descending tracks are better suited for measuring fault-parallel deformation. For Sentinel-1, where two observation orientations are available, integrating ascending data improves vertical deformation estimates and helps isolate fault-parallel creep rates where possible.

For ALOS-2 ScanSAR data, we generate co-registered stacks of interferograms connecting one date to the following four and include multi-year pairs using the ISCE-2 processing software (Rosen et al., 2012). We correct for ionospheric delays and unwrapping errors for each interferogram (Liang, Liu, Fielding, & Bürgmann, 2018; Yunjun et al., 2019). We apply a Goldstein-Werner filter with a strength of 0.6 and a multilook factor of 10 in range and 56 in azimuth, resulting in a ground pixel size of $85.8 \text{ m} \times 160.4 \text{ m}$. We invert for the displacement time series and weight the least squares with the inverse of the phase variability using MintPy software (Yunjun et al., 2019). In the time series domain, we correct for tropospheric delay (Jolivet et al., 2014, 2011), solid earth tides (Yunjun et al., 2022), and DEM error (Fattahi & Amelung, 2013). We mask pixels with temporal coherence less than 0.7. These data span from 2015 to 2024, with 91 and 27 acquisitions for descending track 170 and ascending track 068, respectively. Ascending track 068 is irregularly sampled with year-long intervals at a time. Descending track 170 was irregularly sampled between 2015 and 2020. After a year-long hiatus, acquisitions resumed at regular 14-day intervals starting in July 2021. See Lindsay (submitted) for more details on processing methods and validation.

We utilize the Alaska Satellite Facility’s Hybrid Pluggable Processing Pipeline (Hyp3) on-demand processing tool to generate Sentinel-1 interferograms, connecting one date to at least the next four (Hogenson et al., 2016). The interferograms are processed with Gamma software, have a Goldstein-Werner filter with a strength of 0.6 applied, and are multilooked by factors of 4 in azimuth and 20 in range, resulting in an $\sim 80 \text{ m}$ pixel resolution. For time series analysis, we apply the same weighting scheme and corrections as those used in ALOS-2 ScanSAR to generate displacement time series. The ascending data comprises 232 acquisitions from January 3, 2019, to April 30, 2024, while the descending data consists of 227 acquisitions from December 13, 2016, to November 13, 2024. These data have regular repeat intervals of 6 to 12 days.

We calculate surface creep rates for three subregions, selecting appropriate reference pixels for each based on average spatial coherence and away from regions with seasonal deformation. We remap the fault traces to a single continuous strand with a variable local strike, informed by the qfaults traces and identified steps in the InSAR velocity fields (U.S. Geological Survey & California Geological Survey, 2019). We apply a similar approach to (Y. Li et al., 2023; Dalaison et al., 2021) to estimate fault creep. At 250 m increments along the trace, we extract 500-m-wide fault-perpendicular profiles (using local strike), select pixels within 500 m and 1500 m of the trace, and ensure there are at least 10 valid pixels on each side of the fault.

For the ALOS-2 time series for which we only have dense sampling for the descending orbit, we project the line-of-sight (LOS) into the fault parallel direction. We extract the time series for the selected pixels by calculating the median value from each date in the cumulative

displacement time series. For the time series on each side of the fault, we project the LOS displacement (d_{LOS}) onto the fault-parallel ($d_{\text{fault_parallel}}$) direction using the satellite's local incidence (θ_{inc}) and azimuth angles (θ_{azi}) and the local strike of the fault geometry (strike θ_{strike}).

$$d_{\text{fault_parallel}} = \frac{d_{\text{LOS}}}{-\sin(\theta_{\text{inc}}) \cos(\theta_{\text{azi}} - \theta_{\text{strike}})} \quad (3.1)$$

We subtract the fault-parallel displacement time series from one side of the fault from the other, thus removing common noise (primarily from tropospheric and ionospheric phase contributions) and providing a cleaned time series of relative fault-parallel displacements. This projection assumes negligible vertical deformation, with the outcome of any vertical source being mapped into the fault-parallel time series. Finally, we calculate the velocity at each increment; due to the irregular sampling of the ALOS-2 data, we only solve for the linear term and not the seasonal components. Our sampling aperture of 1500 m means this estimate is sensitive to creep within the top 1500 m from the surface (Savage & Lisowski, 1993).

For the Sentinel-1 data, where time series of both ascending and descending observations are available, we linearly interpolate the time series to a common set of dates and then decompose the fault-parallel and vertical displacement components at each time step. Each LOS direction (d_{asc} d_{des}) is modeled as a linear combination of vertical (U) and fault-parallel (FP) unit vectors, expressed as:

$$\begin{pmatrix} d_{\text{asc}} \\ d_{\text{desc}} \end{pmatrix} = \begin{pmatrix} \cos(\theta_{\text{inc,asc}}) & -\sin(\theta_{\text{inc,asc}}) \cos(\theta_{\text{azi,asc}} - \theta_{\text{strike}}) \\ \cos(\theta_{\text{inc,desc}}) & -\sin(\theta_{\text{inc,desc}}) \cos(\theta_{\text{azi,desc}} - \theta_{\text{strike}}) \end{pmatrix} \begin{pmatrix} U \\ FP \end{pmatrix} \quad (3.2)$$

We solve this equation for U and FP using a least-squares inversion:

$$\begin{pmatrix} U \\ FP \end{pmatrix} = (G^T G)^{-1} G^T \begin{pmatrix} d_{\text{asc}} \\ d_{\text{desc}} \end{pmatrix} \quad (3.3)$$

Where G is the projection matrix derived from the satellite geometry and local fault strike. This framework assumes negligible fault-perpendicular motion between the sampled locations on either side of the fault trace. We fit the Sentinel-1 relative displacement time series data with a combined linear and seasonal model of the form:

$$d(t) = d_0 + d_1 t + a_1 \sin(2\pi t) + b_1 \cos(2\pi t) \quad (3.4)$$

Using a least squares optimization, we calculate the creep rate velocity as $d(t)$, where t is time in years and d is the fault parallel relative displacement time series, and a_1 and b_1 are the seasonal coefficients.

CRE upper crustal estimates

The location, magnitude, and recurrence interval of repeating earthquake sequences can be used to infer the spatial and temporal distribution of deep aseismic slip at seismogenic

depth, e.g., (Nadeau & McEvilly, 1999). Where we have a CRE in an otherwise aseismically creeping section of a fault, an asperity is continually loaded and repeatedly fails. When recorded at the same station, the waveform for each event is almost identical. The degree of similarity suggests that the same patch along a fault slipped, and the path between the source and the receiver remains constant over time (Nadeau et al., 1995). Their average recurrence intervals generally vary in proportion to the inverse of the creep rate on the fault where the repeating earthquakes are located. (Nadeau & Johnson, 1998) documented an empirical scaling relationship between the cumulative aseismic slip indicated by a recurring CRE sequence and seismic moment for the Parkfield section of the SAF. Subsequent studies corroborated the empirical relationship with independent measurements of fault creep (Chen et al., 2007; Khoshmanesh et al., 2015). In effect, the sequences can act as creepmeters at seismogenic depths. When the recurrence interval is periodic, the system is thought to be in a near-steady state. At the same time, transient slip activity can drive burst-like seismicity accelerations (e.g., Shaddox & Schwartz, 2019) or periods of relative quiescence (e.g., Materna et al., 2018). We use the presence of CREs to infer fault slip at depth and to probe changes in the fault strength and stress state (Nadeau & McEvilly, 1999).

To search for CREs and their respective families along the RC-MA for the period 1984–2020, we assemble seismic waveforms for individual earthquakes listed in the northern California Seismic System (NCSS) catalog (NCEDC, 2014). As the magnitude of completeness in our target area is close to 1.0 (Tormann et al., 2014), our waveform analysis focuses on earthquakes with a magnitude larger than 1.0. A total of 71297 earthquakes are analyzed. Our CRE detection is based on waveform coherency following (Shirzaei & Bürgmann, 2013; Taira et al., 2014). We assemble seismic waveforms in the vertical component collected at stations located within 35 km from each earthquake location (epicenter) to measure a waveform similarity for a pair of two earthquakes. To enhance seismic signals from local earthquakes, all waveforms are bandpass filtered at a frequency of 8-24 Hz. A time window for the coherence analysis is 10.24 s from the direct P wave, and this window will ensure that both direct S-wave and coda waves are included. This frequency band and time window are selected to suppress false CRE detections. We compute CRE families for coherency thresholds of 0.95, 0.96, 0.965, and 0.97. At the 0.95 coherency threshold, we detected 429 CREs within 184 families, compared to 220 CREs and 95 families with the 0.97 coherency threshold.

We estimate the inferred slip (d , in cm) for each event based on its magnitude (M_w). First, we convert magnitude to seismic moment (M_0 , in dyne-cm) using the empirical relationship from (Hanks & Kanamori, 1979):

$$\log_{10}(M_0) = 1.5M + 16.1 \quad (3.5)$$

We then compute slip from seismic moment using the empirical scaling from (Nadeau & Johnson, 1998):

$$\log_{10}(d) = -2.36 + 0.17 \log_{10}(M_0) \quad (3.6)$$

Combining these two equations yields a direct magnitude-to-slip relationship:

$$\log_{10}(d) = 0.255M + 0.377 \quad (3.7)$$

We then calculate the cumulative fault slip across individual fault sections. Following (Nadeau & McEvilly, 2004), we sum the inferred slip inferred from all CREs within a defined region and divide it by the number of families. The cumulative slip with time reflects the productivity of the repeating earthquakes across many families. With steady creep rates, the cumulative slip is expected to increase linearly with time. In the case of a regional stress change, the loading of asperities should be proportional; therefore, averaging across fault segments provides insight into the broad shift in behavior beyond the change in repeat intervals of individual families. Due to the variable fault width in map view, we mask the catalog with polygons that include CREs that we interpret as fault-related and exclude those related to the Geysers (5 km east of MA) and the Lake Pillsbury fault (20 km east of MA) (Thomas et al., 2013) and include the eastern strand of the MA (8 km east of MA) (Woolace, 2005).

Alignment arrays

The alignment array measurements collected over the years by USGS and San Francisco State University and available through the USGS (McFarland et al., 2023) provide the longest record of surface fault creep (McFarland et al., 2017). A theodolite measures the change in angle between three fixed cross-fault points, enabling confident detection of creep greater than 1–2 mm (McFarland et al., 2017). Along the RC-MA zone are 11 alignment array locations, two of which are particularly useful for this study, MWIL and MUKI. MWIL in Willits accumulated 158 mm of fault-parallel displacement between 1991 and 2022, while MUKI in Ukiah had a cumulative displacement of 125 mm between 1993 and 2021. Both sites were occupied 4 to 5 times yearly before 2008, and subsequently reduced to annual measurements. We identify candidate creep events based on the slip between occupations. We perform linear regression on each station’s cumulative displacement and inter-event periods to estimate the fault creep rate and the associated standard error. For stations MWIL and MUKI, we differentiate the cumulative displacement to yield an approximate instantaneous velocity, representing the rate of change between each time interval. We solve for a harmonic model, excluding data points within 0.25 years of a step, with least-squares fitting to determine whether the variation in velocity is seasonally modulated. Here, $y(t)$ is the modeled velocity at time t_0 , v_0 is the mean velocity, and a_1 and b_1 represent the seasonal amplitudes:

$$y(t) = v_0 + a_1 \sin(2\pi t) + b_1 \cos(2\pi t) \quad (3.8)$$

The seasonal peak is reported as a fraction of the year (e.g., 0.25 = early April), and its uncertainty reflects the standard deviation of the propagated phase error, assuming normally distributed residuals. The phase uncertainty is computed using first-order error propagation applied to the $\arctan 2(b_1, a_1)$ transformation.

3.3 Results

Fig.3.2 presents maps and fault-parallel cross-sections that integrate InSAR, CREs, background seismicity, and alignment-array estimates to provide a fault zone-wide view of creep on the RC and MA faults. We present evidence of a creep event associated with multi-annual changes in surface and shallow creep along the MA, as shown in alignment array time series and fault slip rates inferred from CREs (Figs. 3.3 & 3.4). We explore seasonality within the alignment array and InSAR datasets, and determine temporal relations with precipitation (Figs. 3.2 & 3.5). Broadly, our results are in agreement with previous studies, lending confidence to these findings (Funning et al., 2007; Shakibay Senobari & Funning, 2019; Melosh et al., 2024). Our results provide an integrated view of the spatiotemporal history along the MA and RC, within the resolution of the available data.

Spatial distribution of creep

Rodgers Creek Fault

Surface creep along the RC initiates south of Santa Rosa, remains uniform at 3-4 mm/yr, and ceases northward near the RCBP alignment array (Fig. 3.2 d,f). The descending LOS velocity field from ALOS-2 InSAR shows a discrete step along the RC trace near alignment array RCMW in Santa Rosa (Fig. 3.2 d). The southernmost section of the fault does not host seismicity; the seismic quiescence is attributed to the rupture extent of a large earthquake in 1715 (Hecker et al., 2005). From Santa Rosa (RCSM) northward, seismicity and CREs are present at depths shallower than ~ 10 km, with the shallowest CREs at approximately 2 km. We find that the location of the shallowest CREs correlates with the peak slip rates estimated by the alignment array RCMW, as well as ALOS-2 and Sentinel-1 InSAR.

Maacama Fault

Surface creep along the MC initiates north of Jimtown and the MSKP alignment array, varies between 4-8 mm/yr, and ceases north of Willits (Fig. 3.2 c,e). The most prominent feature of the LOS velocity map is the subsidence related to the Geysers geothermal field (Fig. 3.2 b). The clearest location of fault creep appears adjacent to The Geysers, between Jimtown and Cloverdale. Clear surface creep is also evident between Ukiah and Willits along the main fault trace (Fig. 3.2 b). The peak creep rates broadly agree with the long-term rate measured with alignment arrays; however, the InSAR creep rates at the specific locations of both MWIL, MUKI, and MAMR are lower. Estimates of creep are challenged by the presence of slow-moving landslides within our sampling aperture of 1.5 km from the fault trace. Landslide motion is observed in the LOS map as strong negative values between Cloverdale and the MAMR alignment array (Y. Xu et al., 2021). This is evident in the creep estimate, where the estimate rapidly decreases from 6-8 mm/yr to near zero where landslides are present. The filtered surface creep estimate provides a more accurate representation of

the overall pattern, which smoothly increases towards peak rates of 6-8 mm/yr parallel to The Geysers.

Seismic activity is observed throughout the entire span of the fault, with depths decreasing from around 10-12 km at either end to about 6 km near Cloverdale. Along the northern MA seismicity and repeating earthquakes are offset from the main fault trace by up to 8 km, aligned with the eastern strand of the fault (Fig. 3.2 a) (Prentice et al., 2014). The shallowest CREs in our catalog relate to the location of the 2020 swarm activity on the eastern strand, south of Willits' (Shelly et al., 2023). We find no evidence of surface creep along the eastern strand where the seismicity is concentrated. The CREs and seismicity between Cloverdale and Ukiah do not focus on the main fault trace, but are distributed and delineate multiple active structures within a pull-apart basin, as previously noted by (Shakibay Senobari & Funning, 2019; Melosh et al., 2024). In this section, the CREs extend from the surface to a depth of 8 km. Notably, CREs are sparse south of Jintown, where no surface creep is recorded. We find broad agreement between surface creep, the location of CREs, and the depth of the seismogenic zone (inferred from the 90th and 95th percentile contours on Fig. 3.2g); where the surface rate peaks near Cloverdale, the seismicity is also the most shallow, and where we observe surface creep, we also find CREs.

Temporal distribution of creep

As noted along many continental strike-slip faults, surface creep can exhibit variability on time scales ranging from minutes to weeks and years (e.g., Dalaison et al., 2021; Jolivet et al., 2023; Y. Li et al., 2023). The extended observation period of the alignment arrays in Willits and Ukiah allows for the examination of multi-annual changes in rates. While the temporal resolution alignment arrays for the period 1992-2008 and Sentinel-1 InSAR data from 2019 to 2024 can resolve seasonal deformation. Seasonally modulated creep can be a response to near-surface processes such as pore fluid pressure changes from precipitation entering the fault slip surface and from the rising water table (Roeloffs, 2001). Changes in normal stress acting on the fault may occur due to the seasonal swelling of shallow, clay-rich sediments, broad-scale patterns of hydrological surface loading from drought cycles, or the horizontal contraction signal associated with adjacent subsiding features (Fig. S10).

Cumulative displacement time series from the alignment array in Willits (MWIL) slowed relative to the long-term average following a creep event in early 2002 (epoch: 2002-03-20 to 2002-06-02) (Fig.3.3a) (Lienkaemper et al., 2014). The linear rate over the entire observation period is 5.1 ± 0.1 mm/yr ($R^2 = 0.975$). The time series is punctuated by three steps in early 1994, late 1996, and early 2002, with magnitudes of 6.6, 4.8, and 5.7 mm, respectively. The inter-event rates before the 2002 step, 4.08 ± 0.65 mm/yr, 4.98 ± 0.57 mm/yr, and 5.28 ± 0.19 mm/yr, remained close to the long-term average. In contrast, the linear rate from 2002.3 to 2014.0 decreased to 3.65 ± 0.09 mm/yr, representing a 28% reduction in surface creep compared with the long-term average. The alignment array in Ukiah (MUKI) 32 km to the south experienced a step of 8.1 mm in the epoch following the 2002 step at MWIL (step epoch: 2002-06-02 to 2002-08-31) and a modest rate change from 4.4 ± 0.2 mm/yr to

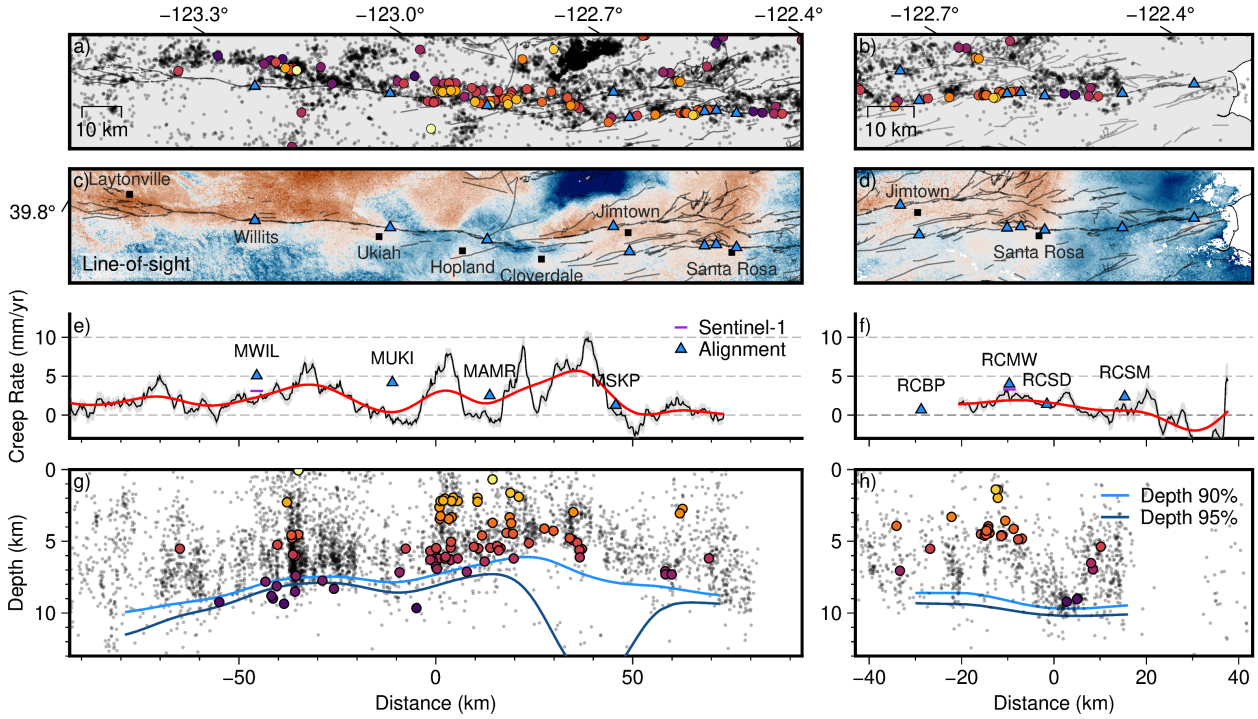


Figure 3.2: (left) Maacama and (right) Rodgers Creek faults. Maps of (a,b) CREs and background seismicity, (c,d) line-of-sight (LOS) velocity field. (e,f) Surface creep estimates from ALOS-2, Sentinel-1, and alignment arrays. (g,h) Along fault cross-sections with background seismicity, CRE's and depth of 90% and 95% of seismicity.

3.4 ± 0.2 mm/yr (Fig.3.3b). The detrended displacement time series emphasizes both the steps in the timeseries and the rate change following the 2002 step (Fig.3.3c,d). Fig. 3.3e,f) presents the instantaneous velocity for each station and a harmonic model to resolve the seasonality of the signal. Creep rates peak around December 20 (± 11 days) each year, with the amplitude of the seasonal response varying over time. The delay between the modeled peak and the 2002 step is ~ 146 days, indicating a period of lower creep rates preceded the 2002 event — a possible transient suppression of creep before the event.

We investigate the correlation between seasonal modulation at MWIL and precipitation (Fig. 3.3h). The cumulative precipitation over the whole observation window remains steady, despite the fluctuations associated with drought cycles. We see no broad-scale change in cumulative precipitation associated with the 2002 step. The mean annual onset of precipitation is October 26 (± 14 days), and the modeled precipitation rate peaks on January 19 (± 2 days) (Fig. 3.3h). The peak velocity rate at MWIL precedes peak precipitation by ~ 44 days, while the delay between the onset of rain for the season and the peak velocity rates is 42 days. This suggests that surface creep is more sensitive to the onset of precipitation rather than peak annual precipitation.

To examine whether changes in surface creep are reflected at depth, we consider background seismicity (Waldhauser & Schaff, 2008), along with the CRE catalogue from this study and (Shakibay Senobari & Funning, 2019) and (Waldhauser & Schaff, 2021). The background seismicity within ± 40 km of MWIL along the fault zone, including MUKI, reveals no earthquakes larger than M4.5 within the selected range and no moderate earthquakes associated with the 2002 step (Fig. 3.3). We do, however, note a subtle change in the rate of cumulative moment, whereby the trend reduced by 20% when comparing the 1.5 years before and after the 2002 event. While subtle, we do observe a change in background seismicity associated with the 2002 change in surface creep rates.

The change in interval time before CRE can be used to infer creep at seismogenic depths; however, where loading rates are lower, repeat intervals are longer, and therefore, establishing a long-term creep rate is more challenging. Given the low loading rates, each family experiences only a few repeating earthquakes during the observation period; therefore, the average cumulative fault slip per fault segment is a better representation of the multi-year changes in behavior. For each of the three independent CRE catalogues, we find the cumulative fault slip within each fault segment from CREs, and fit linear terms to the ± 12 years of the 2002 step (Fig. 3.4). Along the northern MA we find 49%, 46%, and 51% reductions in slip rate the catalogs from this study, (Shakibay Senobari & Funning, 2019), and (Waldhauser & Schaff, 2021), respectively. The southern MA and RC faults do not exhibit as coherent a pattern, with the three catalogs deviating in their response across the 2002 time step. From this, we infer that shallow creeping, within the seismogenic zone, along the northern NA does experience a suppressed creep rate following the 2002 step; however, this does not extend to the southern MA or RC sections.

To determine whether InSAR and alignment arrays observe similar seasonal modulation, despite their differing temporal resolutions and observation periods, utilize the Sentinel-1 time series. We decompose the ascending and descending time series from 2019 to 2024 into vertical and fault-parallel components and solve for both the long-term rate and seasonal phase and amplitudes (Fig. 3.5) using the local strike value. We calculate a fault parallel creep rate of 3.1 mm/yr from the InSAR near MWIL; this is comparable to the post-2002 creep rate at the site of 3.7 mm/yr and lower than the long-term rate of 5.1 mm/yr (Fig. 3.5a-d). For the RC in Santa Rosa, we calculate a creep rate of 4.1 mm/yr, which is in agreement with 4.3 mm/yr measured at the nearest alignment array site, RCMW. In both cases, the vertical time series show a near-zero linear trend and seasonal amplitudes of approximately 1.4 mm. The fault parallel time series exhibits seasonality with very low amplitudes of 0.3 mm and 0.73 mm for Willits and Santa Rosa, respectively. In map view, surface creep is very apparent in the fault-parallel direction where a step in the rate coincides with the fault trace (Fig. 3.5f,h). In comparison, the vertical velocity fields remain smooth over the fault trace (Fig. 3.5e,g). The vertical velocity field at Willits includes subsidence in the basin between the main and eastern fault traces.

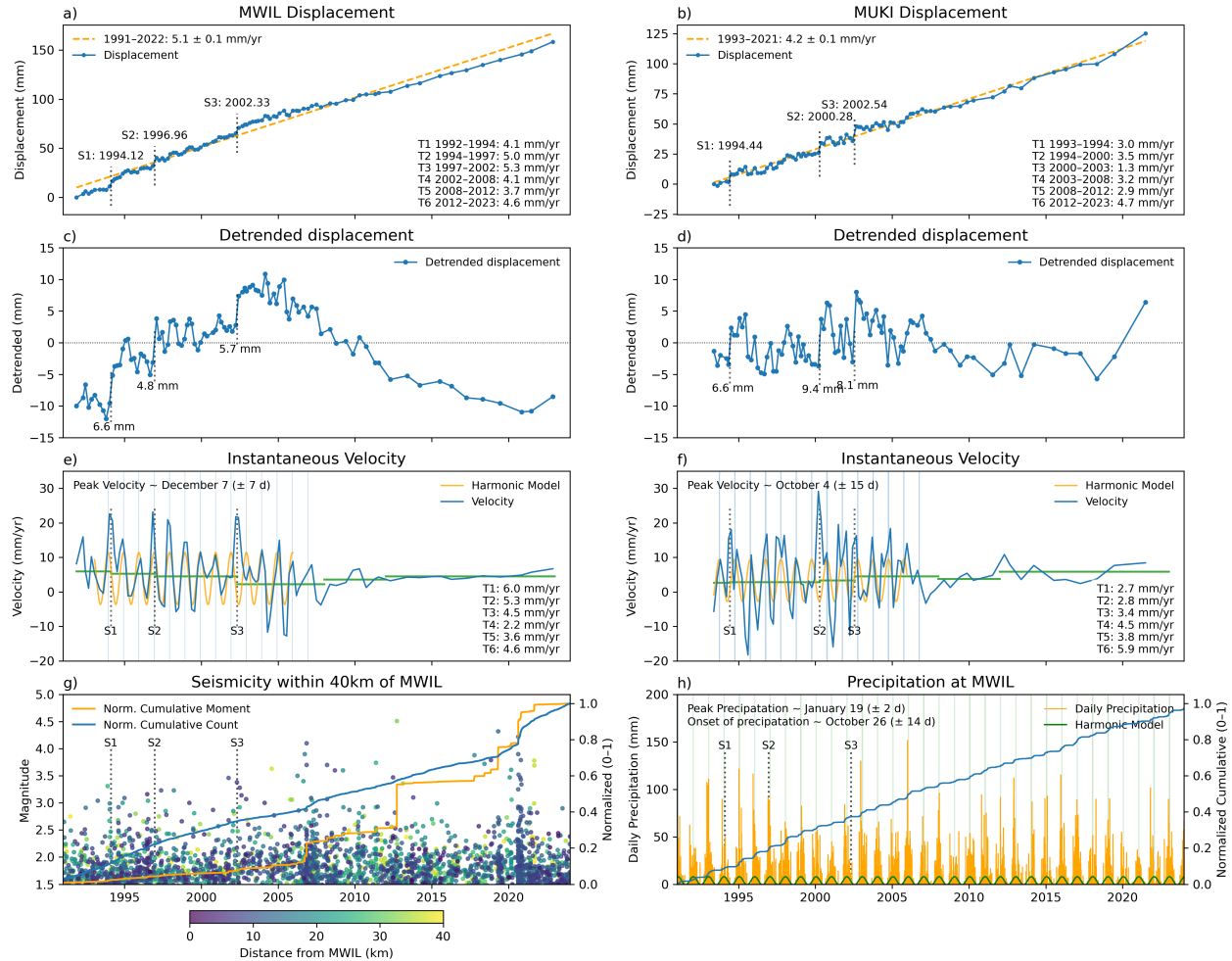


Figure 3.3: Alignment array time series from Willits (MWIL, left) and Ukiah (MUKI, right)(McFarland et al., 2017). (a,b) Displacement time series, with linear velocity, location of identified steps, and interval velocities. (c,d) Detrended displacement time series highlighting creep events and for MWIL a sustained period of creep suppression following the 2002 event. (e,f) Instantaneous velocity with a harmonic model highlighting the seasonality of surface creep rate and mean instantaneous velocity for each segment. (g) Background seismicity within ± 40 km of MWIL along the fault zone, with normalized cumulative moment and count (Waldhauser, 2009). Note activity related to the 2020 swarm (Shelly et al., 2023). (h) Cumulative and daily precipitation data, along with a harmonic model of daily rainfall, (*prism2014*, n.d.).

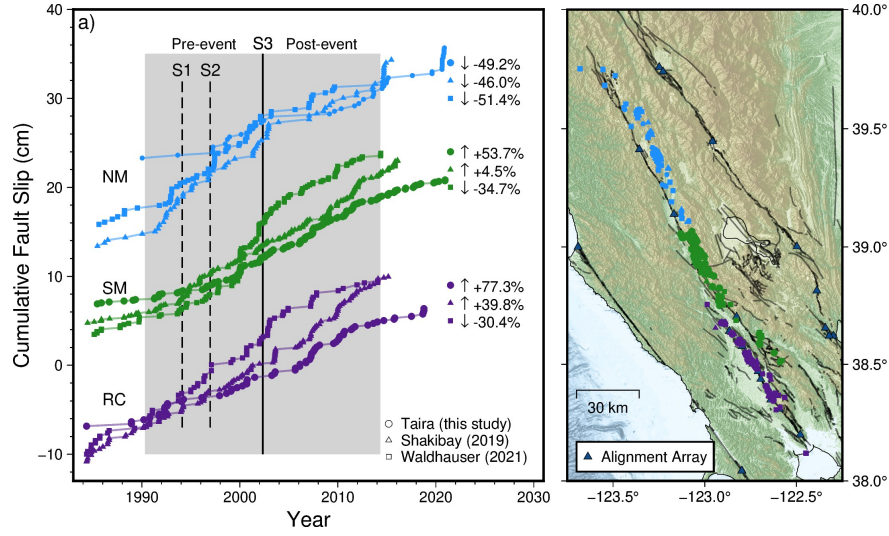


Figure 3.4: (a) Cumulative fault slip inferred from Characteristic Repeating Earthquake (CRE) for the north Macaama (NM), south Maacama (SM), and Rodgers Creeks (RC) faults. We compile data from this study, as well as Shakibay Senobari and Funning (2019) and Waldhauser and Schaff (2021). The grey box denotes the pre- and post-event periods over which linear rates are calculated, and the percentage change in rate is noted for each dataset and fault segment. (b) Location of CREs used for each fault segment.

3.4 Discussion

InSAR studies, creepmeter records, and alignment array data collectively have demonstrated the variability in fault creep rates across California and that these observations represent a physically meaningful aspect of the earthquake cycle (e.g., Y. Li et al., 2023; Langbein et al., 2024; Shirzaei & Bürgmann, 2013; Jiang & Lapusta, 2016; Jiang et al., 2021; K. M. Johnson et al., 2022). As earthquake rupture scenarios now consider multi-fault events and the role of fault creep, it is important to understand the spatiotemporal characteristics of creep on these faults (Harris et al., 2021; Field et al., 2014). The spatiotemporal distribution of aseismic creep influences possible rupture barriers and moment deficit calculations. In this study, we examine the variability in creep along the RC and MA faults using multiple geophysical datasets. We document the long-term spatial distribution of creep rates, characterize individual creep events, identify multi-year changes in creep rate, and analyze evidence of seasonal modulation. While these phenomena are not novel in themselves, our results contribute to a growing body of work that emphasizes fault creep as a dynamic, evolving process over a wide range of spatial and temporal scales. Our work differs from others in that the loading rates on these faults are significantly lower than those on the creeping San Andreas (Turner et al., 2015), Chaman (Dalaison et al., 2021), and North Anatolian Faults (Jolivet et al., 2013). Additionally, we are limited by historical data, as we lack detailed creep meter

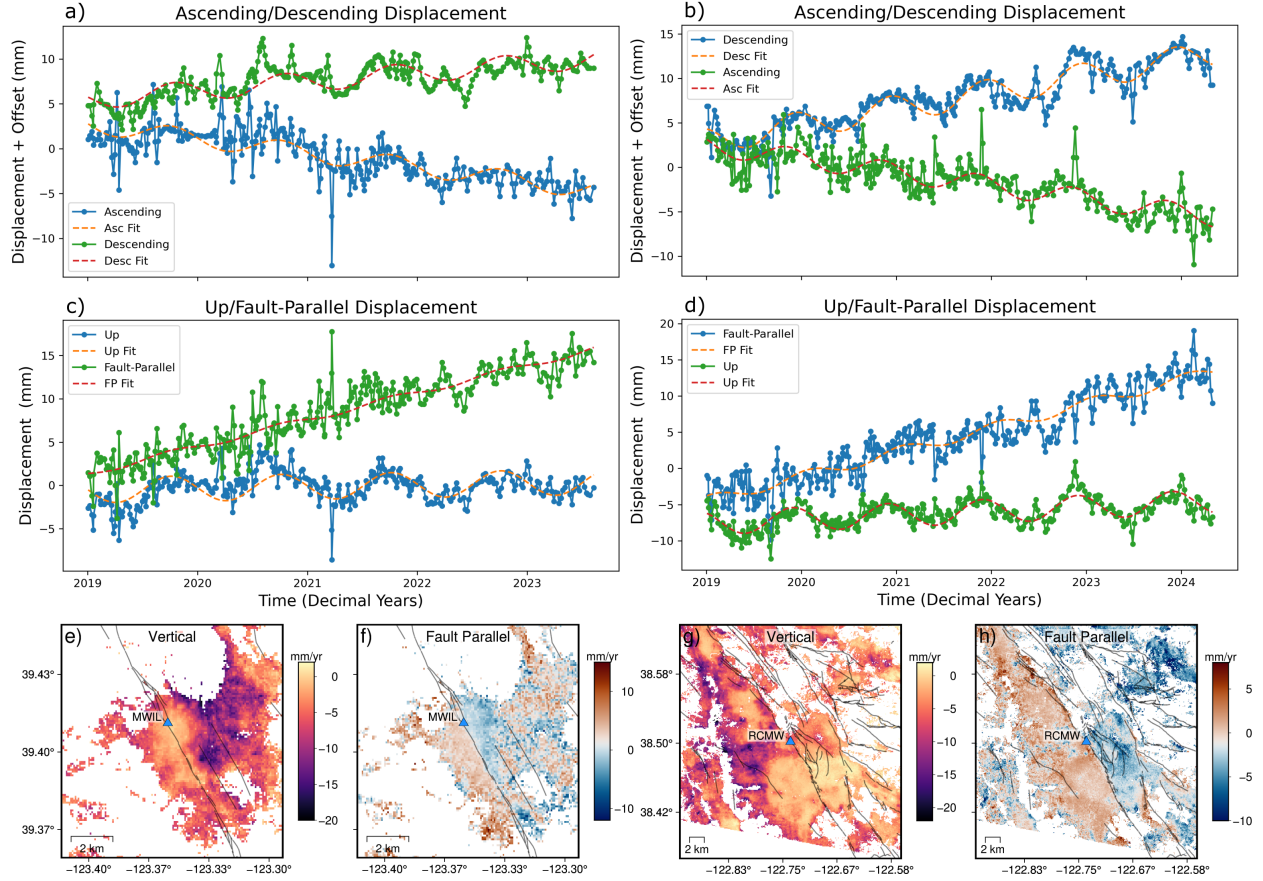


Figure 3.5: Seasonal analysis for Willits (left) and Santa Rosa (right) from Sentinel-1. (a,b) Displacement time series of relative ascending and descending cross-fault motion. (c,d) Decomposed time series showing relative vertical and fault parallel motion through time. (e,g) Vertical and (f,h) fault parallel velocity maps. The subsidence in (f) is in the Little Lake Basin.

time series, and face a challenging environment for InSAR imaging. We now discuss in more detail our interpretation of the 2002 creep event and the subsequent period of suppressed creep, including an exploration of the triggering mechanisms and the possibility of spontaneous slip. We discuss similarities and differences in the seasonal modulation of surface creep between datasets. And finally, the correlation between surface creep and variations in seismogenic depth in the unique context of The Geysers geothermal field.

2002 creep event

We have three lines of evidence to suggest that the 2002 step in the alignment array time series is related to a significant creep event. Firstly, the time scale of the decay following the 2002 step exceeds that of seasonal and drought cycles, suggesting a tectonic origin. Secondly, the step in the creep event occurs at both MWIL and MUKI, albeit separated by one epoch, and both sites experience subsequent creep suppression. Thirdly, both the CREs and background seismicity experience coincident rate changes; for the CRE, three independent catalogs experience decreases (46-52%) in cumulative slip rate. Taken together, we interpret the step in the MWIL displacement time series as a creep event of a spatial scale greater than 30 km, the interstation distance between MWIL and MUKI, with a decay that recovers to near background rates over 5-8 years. With this interpretation, we now examine potential triggering causes for the 2002 creep event and consider the possibility of spontaneous initiation of the event. Creep or slow-slip events on strike-slip faults are known to be either triggered, most often by seismicity or precipitation, or can be a spontaneous process (Tymofeyeva et al., 2019; Roeloffs, 2001; S. Schulz et al., 1983). We focus our search on the interval bracketed by alignment-array occupations at MWIL (March 30–June 2, 2002). We evaluate the seismic and hydrologic influences on surface creep around the time of the largest measured creep event(s) on the RC-MA, which also coincided with the prominent change in creep rate on the fault.

We examined the consideration of both local and global dynamic triggering candidates but did not find an obvious relationship. Assessment of local seismicity reveals that no earthquakes of magnitude $\geq$ Mw 4 occurred within a 50 km radius of the MWIL site, and no events of magnitude $\geq$ Mw 5.5 occurred within 1000 km. The closest seismic event (Mw 3.38, depth 7.7km, distance 6.8 km) was too small and too distant to induce meaningful static-stress changes. During the interval between the occupations of the alignment arrays, two large earthquakes (both Mw 7.1) occurred in Taiwan and Guam. Due to the temporal resolution of the array, we are unable to establish whether global events had any dynamic triggering effects and infer that the expected static stress change imposed by local events is likely negligible.

Next, we examine the role of hydrological effects, considering both the cumulative annual precipitation and changes in the precipitation rate (Fig. 3.3e) (Roeloffs, 2001). Precipitation records indicate average rainfall levels during 2002, suggesting that the total rain accumulation was unlikely to produce near-surface fluid pressure or surface loading changes beyond the typical range. The daily precipitation rate during the epoch is lower compared to winter

rates, indicating that a single intense rainfall event did not trigger the event. We do not consider hydrological effects a triggering mechanism for the 2002 event.

Finally, we consider the hypothesis that the Willits creep event and the subsequent reduction in creep rate are indicative of a spontaneous slow-slip event (SSE) rather than a seismically triggered or superficial hydrologic process. While surface creep is strongly seasonally modulated in Willits (Fig. 3.3e), the winter preceding the event saw peak creep rates remain near zero. And the expected annual peak did not occur until 146 days after the modeled peak time. This may indicate a transient locking period preceding the actual creep event. This threshold-type behavior, where delayed failure results in larger slip, aligns with prior observations from (S. Schulz et al., 1983). The event itself was initially measured at the MUKI alignment array and subsequently at the MUKI array in the following epoch, which could indicate two events or temporal propagation (e.g., (Materna et al., 2024)). The slow decay after the event is reminiscent of the type of decay associated with post-seismic processes, suggesting the presence of mechanisms such as fault healing or pore fluid diffusion. Without geodetic data with high spatial and temporal resolution for this time period, our interpretations remain speculative and propose intriguing considerations.

Seasonality of creep rates

We observe clear seasonal modulation of fault-creep signals in both InSAR and alignment array datasets. Seasonal modulation of fault creep may result from precipitation-induced increases in pore-fluid pressure, which reduces effective normal stress on the fault and thus promotes slip (Roeloffs, 2001). Conversely, seasonal soil swelling adjacent to the fault can inhibit creep by increasing normal stress and clamping the fault plane (W. H. Schulz et al., 2018). Where subsidence due to elastic aquifer deformation related to changes in the water table occurs, a corresponding horizontal contraction likely exists (Fig. S10). We have two such subsiding regions adjacent to the MA; The Geysers (Fig. 3.2) and the Little Lake Basin east of Willits (Fig. 3.5e). Where ground subsidence occurs adjacent to the fault, the corresponding horizontal contraction acts to reduce the normal stress on the fault plane itself and may further enhance aseismic slip. Overall, hydrological effects can act to both enhance or inhibit surface creep, depending on the local fault conditions.

While both InSAR and alignment arrays measure seasonal deformation, the two techniques are sensitive to different components of displacement and do not necessarily measure the same thing. Alignment arrays record only horizontal angular changes between monuments, making them insensitive to vertical displacements. As a result, the observed seasonal signal in alignment array data reflects a real and consistent fault-parallel component of creep. InSAR, by contrast, provides LOS measurements that are sensitive to both vertical and horizontal deformation. Our decomposition reveals that the seasonal signal in the LOS time series is primarily driven by vertical motion, which encompasses both sensor-related effects, such as changes in vegetation and soil moisture, as well as ground deformation processes. The latter may reflect differential responses to elastic sediment deformation across the fault, driven by variations in sediment thickness or groundwater levels. For example, the

RC lies west of the Santa Rosa basin, and the MA bounds the east side of the Little Lake Basin—both settings that promote asymmetric subsidence. These findings emphasize the importance of utilizing at least two viewing geometries when interpreting InSAR time series for fault creep analysis, as vertical deformation—if unaccounted for—can be misinterpreted as fault-parallel deformation and lead to inaccurate surface creep rate estimates.

Surface creep rate and depth of the seismogenic zone

Interestingly, the envelope of surface-creep rates broadly follows the base of the seismogenic zone along much of the MA zone, indicating the deep locking depths could influence the surface expression of creep (Fig.3.2i). Creep analysis along the MA offers a unique opportunity to examine the relationship between surface creep rates and the depth of the seismogenic zone, often referred to in geodetic frameworks as the lower locking depth. This relationship is well described by the 2D crack formulation of Savage (1993), which relates surface creep and deep slip rates to the dimensions of a locked zone separating shallow and deep creep on a fault. In this framework, for a given deep slip rate, the stressing rate on the shallow portion of the fault increases as the deep locking depth shallows, and therefore, the surface expression of creep also increases. This relationship has been applied widely, including recent examples along the North Anatolian Fault and along Californian faults (e.g., Dalaison et al., 2021; K. M. Johnson et al., 2022; Jolivet et al., 2023).

Along the MA, we observe a pattern similar to that described by (Jolivet et al., 2023), who found a correlation between surface creep rates and shallowing of the lower locking depth along the Northern Anatolian Fault. However, unlike that study, we can identify a physical mechanism for this shallowing in northern California. The presence of the Clear Lake volcanic field and the adjacent Geysers geothermal field results in locally elevated geothermal gradients, which raise the brittle–ductile transition and reduce the depth of the seismogenic zone. Our smoothed creep-rate envelope reveals a clear correlation between zones of peak creep rate and these areas of reduced seismogenic depth. Together, these findings support a physically consistent model linking thermal structure, fault geometry, and surface creep behavior, which warrants further investigation.

3.5 Conclusions

The Rodgers Creek fault creeps at a surface rate of 3-4 mm/yr between Santa Rosa and Jintown, with the location of Characteristic Repeating Earthquakes (CREs) correlated with the expression of surface creep. The Macaama Fault exhibits surface creep between Jintown and Cloverdale, and again between Ukiah and Willits, rates are in the range of 4-8 mm/yr in agreement with the alignment array estimate. Seismicity and CREs highlight complexities in the fault structure, which contribute to the challenge of extracting meaningful surface creep estimates from InSAR. The alignment array data from MWIL in Willis and MUKI in Ukiah provide the longest record of creep. Within this dataset, we find seasonal modulation of creep

as well as individual creep events. Following a creep event in 2002, the fault experienced a multi-year period of suppressed creep. We find no clear seismic or hydrological triggering mechanism and speculate about the scenario of spontaneous fault creep. We observe seasonal modulation of creep rates in InSAR time series and discuss the mechanisms driving horizontal and vertical seasonal variations. Finally, we note that the Maacama Fault is uniquely suited to explore the relationship between variations in seismogenic depth and surface expression of creep. Together, our results contribute to the growing body of research highlighting the temporal variability in fault creep, which is crucial for understanding the evolution of seismic hazards throughout the entire seismic cycle.

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Open Research

Original ALOS-2 ScanSAR Level 1.1 SLC products are publicly available and can be searched and downloaded via JAXA's G-Portal (Japan Aerospace Exploration Agency (JAXA), Earth Observation Research Center (EORC), 2025), and many are now available from the NASA (Alaska Satellite Facility (ASF) Distributed Active Archive Center & Japan Aerospace Exploration Agency (JAXA) / EORC, 2024) (NASA Earthdata, 2025). Data from 2015-2021 are also archived with the (Western North America InSAR (WInSAR) Consortium, 2025). Interferograms were produced with ISCE-2 (ISCE-2 Development Team, 2025), and analysis and plotting tools can be found at (Lindsay, 2025a). Sentinel-1 data were processed with the ASF cloud-based HyP3 service (Hogenson et al., 2025). Code for the final analysis and figures is available at (Lindsay, 2025b). Time series and velocity solutions are available at (Lindsay,

2025c). The CRE catalog is available at (Taira, 2024). Data from Theodolite Measurements of Creep Rates on San Francisco Bay Region Faults, California, is available at (McFarland et al., 2023). For plotting and creep rate comparisons, we use the double-difference seismic catalog from the Northern California Earthquake Data Center (NCEDC) from 1984 to 2024 and include all events greater than M1 (Waldhauser & Schaff, 2008; Waldhauser, 2009).

Competing interests

The authors have no competing interests.

Chapter 4

Earthquake Triggering of Slow-Moving Landslides in Northern California: Insights from 14-day L-band InSAR Time Series Analysis

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Key Points

- Extract landslide time series in vegetated terrain from 14-day ALOS-2 ScanSAR L-band InSAR.
- Population-scale landslide kinematics: 437 time series across a $\sim 300 \times 400$ km region (≤ 150 km from earthquakes).
- Subset accelerates after 20 Dec 2022 and clusters in high-PGA zone, implicating pulse-like rupture.
- Piecewise (linear+exp) fits capture triggered kinematics; $\sim 90\%$ recovery in 16 months.

Abstract

We quantify slow-moving landslide kinematics across northern California using a 14-day L-band ALOS-2 ScanSAR InSAR time series spanning July 2021–March 2024. The record captures responses to precipitation and two moderate earthquakes: M_w 6.2 (December 20, 2021) and M_w 6.4 (December 20, 2022). After systematically extracting and cleaning the displacement time series, we analyze deformation of 437 landslides across a $\sim 300 \times 400$ km area and group time series by relative velocity changes to identify anomalously fast motions. We test associations with external drivers (PGA, precipitation) and landslide attributes (slope, aspect ratio, area); shaking from the 2022 event shows the strongest association with faster sliding rates. For slides that experienced higher PGA and increased velocities, a piecewise model (linear pre-event trend + exponential post-event decay) yields recovery to within $\sim 10\%$ of pre-event rates in ~ 1.3 years. The localization within the high-PGA footprint, along with the immediate onset and exponential decay, favors a seismic trigger. This work quantifies regional landslide responses to precipitation and earthquake shaking, providing a detailed analysis of triggered events. Using two earthquakes of similar magnitude and location, we demonstrate that rupture dynamics shape the spatial distribution of triggering and supply rare regional constraints on onset and recovery.

4.1 Introduction

Rapid landslides are movements of a mass of rock, debris, or earth down a slope, often at velocities of meters per second. In contrast, slow-moving landslides creep at rates ranging from millimeters per year to tens of meters per year, and they can continue to slide for hundreds of years (e.g., Slumgullion (Hu et al., 2020)), or in more rare cases, accelerate to catastrophically fail (e.g., Mud Creek (Handwerger, Huang, et al., 2019)). Slow-moving landslides, which include large earthflows, deep-seated slides, and other coherent slope movements, are distributed globally in mechanically weak, clay-rich lithologies (Lacroix et al., 2020). They have been extensively documented in the western United States, New Zealand, northern Italy, the European Alps, and China, among others (Lacroix et al., 2020). When slow-moving landslides do transition to runaway failure, they pose an immediate hazard to human life and infrastructure (e.g., Handwerger, Huang, et al., 2019; Handwerger et al., 2025; Lacroix et al., 2023). The recent evacuation of the village of Blatten before the devastating May 28, 2025 landslide demonstrates that detection of precursory accelerated motion can provide critical lead time for successful evacuations (Islam et al., 2025; Dai et al., 2020). Monitoring and characterizing slow-moving landslides is therefore crucial both for hazard mitigation in a changing climate, where activity is expected to increase, and for advancing our understanding of the forcings and mechanisms that govern shear failure (Gariano & Guzzetti, 2016; Finnegan & Saffer, 2024).

The motion of slow-moving landslides can be described with increasing complexity, from simple Coulomb failure to hydromechanical and rate-and-state frameworks that account for

evolving frictional properties (Terzaghi, 1950; Iverson, 2000; Lacroix et al., 2020; Handwerger et al., 2016). In Coulomb failure, sliding initiates once shear stress exceeds shear strength, where shear strength is reduced when effective normal stress decreases, often due to elevated pore-fluid pressure following rainfall (Iverson & Major, 1987; Iverson, 1997), while driving stresses can rise through added mass or removal of resisting forces at the toe (Mackey & Roering, 2011). To explain the characteristic seasonal accelerations and decelerations of slow-moving landslides, 1D pore-pressure diffusion models have been applied, in which lag times between rainfall and acceleration scale with landslide depth and hydraulic diffusivity (Iverson & Major, 1987; Handwerger et al., 2013). More complex frameworks incorporate evolving frictional and hydromechanical properties of the shear zone. Proposed stabilizing mechanisms include shear-induced dilatancy, in which grain rearrangement increases porosity and lowers pore-fluid pressure, temporarily strengthening the sliding surface (Iverson, 2005). However, once critical-state porosity is exceeded, dilatant strengthening is lost and failure can ensue. Rate-and-state friction models, adapted from earthquake mechanics, describe how friction on a basal sliding surface evolves as a function of slip velocity and the time-dependent state of grain contacts. In this framework, velocity-strengthening behavior promotes stable creep, whereas velocity-weakening behavior promotes instability if the sliding patch exceeds a critical nucleation size (Handwerger et al., 2016). Together, these models provide a hierarchy for interpreting how external forcings modulate landslide velocity and the conditions under which slow-moving landslides stabilize, accelerate, or transition to catastrophic failure.

Characterization of slow-moving landslide kinematics through in situ instrumentation, optical imagery, LiDAR, DEM analysis, and satellite radar observations demonstrates that precipitation and earthquakes are key external drivers of motion (Lacroix et al., 2020). Precipitation-driven accelerations are well established in California, where seasonal rainfall increases pore-water pressure, reduces effective normal stress, and promotes sliding (Terzaghi, 1950; Handwerger et al., 2013). Landslides typically accelerate weeks after the onset of rains, with lag times of about 40 days observed in the Eel River catchment and Berkeley Hills (Handwerger et al., 2013; Cohen-Waeber et al., 2018). Seasonal decelerations follow as pore-fluid pressures dissipate during dry months, and sliding can slow to a halt (Handwerger et al., 2013). Longer-term hydrologic conditions also modulate behavior: during the 2016–2017 wet year, the number of active landslides in the Eel River basin more than doubled compared to the preceding drought year (Handwerger, Fielding, et al., 2019). At Mud Creek, California, a rapid transition from drought to heavy rainfall in 2017 triggered slip localization and catastrophic failure (Handwerger, Huang, et al., 2019; Handwerger et al., 2025). Precipitation-driven responses of slow-moving landslides are well established and represent a primary driver of seasonal and interannual deformation.

Earthquake shaking is another important driver of slow-moving landslide motion, capable of producing both catastrophic failures and sustained accelerations. These responses can persist for days to years after shaking and may be influenced by internal feedbacks within the landslide body. In Peru, coseismic shaking induced widespread slope failures and accelerated motion of pre-existing slow slides, in some cases persisting for months to years (Lacroix et al., 2014; Bontemps et al., 2020). In New Zealand, 21 slow-moving landslides triggered by

the 2016 M_w 7.8 Kaikōura earthquake accelerated from millimeters to several centimeters per year, with velocities that decayed exponentially toward background rates over years (Cao et al., 2023). Seismic and geodetic observations from Bontemps et al. (2020) show that coincident rainfall and seismic shaking produce greater displacement than either driver alone, and they infer that elevated rates of small earthquakes during wet conditions suppress healing and maintain a weakened state. These observations suggest that the mainshock is not the sole control on kinematic response, that elevated microseismicity in the weeks to months following an event, especially under wet conditions, can prolong or amplify sliding. While precipitation-driven accelerations are well documented, the role of earthquake shaking—and its interaction with hydrologic conditions and internal landslide structure—remains poorly constrained, motivating further investigation.

The influence of earthquake shaking on slow-moving landslides has yet to be systematically evaluated in Northern California, which provides a unique natural laboratory. Two moderate earthquakes (M_w 6.2, 20 December 2021; M_w 6.4, 20 December 2022) occurred within the same coastal region near Cape Mendocino and Ferndale (Figure 4.1a) (Yoon & Shelly, 2024; Yeck et al., 2023; Shelly et al., 2024). Both events generated strong ground shaking with epicenters approximately 5 kilometers from previously mapped slow-moving landslides (Figure 4.1c,d). The 2022 event was followed by a succession of intense atmospheric rivers that delivered exceptional rainfall and flooding across the region (Figure 4.1e,f). The earthquake occurred against the backdrop of dry-to-wet conditions, from drought in 2021–2022 to the intense storms of early 2023. Using near-regular 14-day L-band InSAR coverage from ALOS-2 from July 2021 to March 2024, we monitor landslide kinematics across northern California, including in densely vegetated regions. Our regional approach compares landslides at varying distances from the earthquake epicenters, providing a direct control for seismic shaking and enabling an assessment of spatial variability in responses. This rare combination of seismic and hydrologic forcing allows us to test whether earthquake shaking amplifies rainfall-driven accelerations, acts independently, or leaves no detectable signal. Motivated by this setting, we explore:

1. How do precipitation and earthquake shaking individually and jointly influence the kinematics of slow-moving landslides in northern California?
2. To what extent do landslide responses vary spatially, particularly with distance and azimuth from the earthquakes?
3. What insights can a regional, population-scale analysis provide compared to single-site case studies for understanding landslide triggering and stability?

Study region

Northern California’s Coast Ranges host a dense population of slow-moving landslides, whose distribution is largely controlled by the mechanically weak Franciscan mélange (Figure 4.1a) (Y. Xu et al., 2021; Zhao et al., 2012). These landslides are typically large, deep-seated

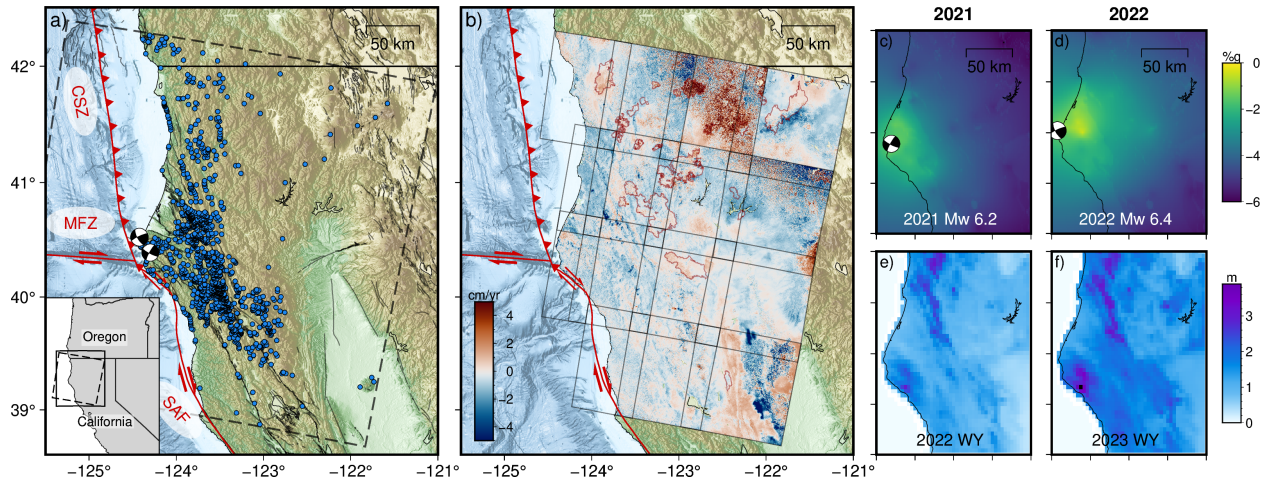


Figure 4.1: Study area in northern California at the junction of the Cascadia Subduction Zone (CSZ), Mendocino Fault Zone (MFZ), and San Andreas Fault (SAF). (a) Collated inventory of slow-moving landslides (circles), InSAR frame perimeter (dashed line), and focal mechanisms for the Mw6.2, 20 December 2021, and Mw6.4, 20 December 2022 earthquakes. (b) InSAR LOS velocity field with subregions for time-series analysis outlined (overlapping black boxes). Subregions are defined so that no landslide is located more than approximately 80 km from a reference pixel, reducing noise in displacement time series. Red polygons show wildfire perimeters (greater than 5000 acres) active during the InSAR observation period (CAL FIRE, 2024). (c,d) PGA maps for each earthquake (U.S. Geological Survey, 2025). (e,f) Cumulative precipitation for each water year (PRISM Climate Group, 2025).

earthflows that deform coherently over years to decades, making them well-suited for long-term observation and modeling (Roering et al., 2015). The region’s Mediterranean climate delivers most precipitation between November and April, producing strong seasonal forcing on hillslope hydrology and kinematics (Figure 4.1e,f) (Handwerger et al., 2013). The coastal ranges receive snowfall during winter, but it does not persist throughout the entire season at lower elevations. Slow-moving landslides in the Eel River catchment, in particular, have been the focus of detailed mapping and monitoring for more than four decades, providing a benchmark for understanding precipitation-modulated deformation cycles (Iverson, 1997; Handwerger, Fielding, et al., 2019). The tectonic influence of the northward-migrating Mendocino Triple Junction has been linked to patterns of uplift, river incision, and landslide distribution, situating these landslides within the broader context of Coast Range landscape evolution (Bennett, Miller, et al., 2016).

4.2 Methods

InSAR processing

Using Interferometric Synthetic Aperture Radar (InSAR), we interfere the phase returns from SAR collected on two dates and produce maps of how the ground surface has changed through time. SAR emits pulses at microwave frequencies, with the signal able to scatter more deeply through foliage, soil, and snow as the wavelength increases. Active satellite missions acquire X-band (~ 2 cm), C-band (~ 6 cm), and L-band (~ 23 cm) SAR data at regular intervals and are commonly used for deformation mapping. The X- and C-band data decorrelate more quickly than L-band due to changes in ground scattering properties, which are more severe in vegetated and seasonally snow-covered terrain (Wei & Sandwell, 2010). Phase decorrelation also occurs when deformation gradients exceed $\pm\pi$ between adjacent pixels (Goldstein et al., 1988). Longer-wavelength SAR is available in the P-band (67–139 cm), which is acquired using UAVSAR (Uninhabited Aerial Vehicle Synthetic Aperture Radar). P-band’s utility has been demonstrated for landslide detection with the longer wavelength maintaining coherence and resolving rapid deformation gradient; however, its temporal sampling is sporadic (Y. Xu et al., 2023). Satellite L-band InSAR is well-suited for capturing localized, rapid signals in vegetated terrain, as the data is more tolerant of changes in ground scattering properties and steeper deformation gradients, and can be acquired at regular intervals.

L-band data from the Advanced Land Observing Satellite-2 (ALOS-2) of the Japan Aerospace Exploration Agency (JAXA) has been instrumental in observing hazards such as earthquakes, landslides, volcanoes, and floods. ALOS-2 operates in three modes: Spotlight, which offers the highest resolution with the smallest coverage area; Stripmap, which provides medium resolution and coverage; and ScanSAR, which delivers the lowest resolution but covers the largest area. In northern California, ALOS-2 regularly acquires descending-orbit ScanSAR data, along with irregular ascending and descending Stripmap acquisitions, as well as ascending ScanSAR data. Since July 2021, descending ScanSAR data have been collected every 14 days as part of a NASA–JAXA data-sharing agreement (NASA Earthdata, 2025). Two key advantages exist for the L-band ScanSAR dataset in Northern California. Firstly, the large scene footprint is useful for determining temporal relations, as all features in the study area are images on the same day. Secondly, due to the JAXA-NASA data-sharing agreement, observations are acquired regularly, with the 14-day frequency not previously available with an L-band sensor.

ALOS-2 ScanSAR data are processed using the Jet Propulsion Laboratory (JPL) Interferometric Synthetic Aperture Radar Scientific Computing Environment (ISCE) (Rosen et al., 2012). Our data are from descending track 170, frame 2800, acquired in wide swath mode (WD1), producing a single scene with a 350 km wide swath. These data span the period from July 2021 to March 2024, during which the repeat interval was 14 days. These data were made available via a data-sharing agreement between JAXA and NASA, with the scenes now publicly available from the Alaska Satellite Facility (ASF). We use the ALOS-2 stack processor to generate co-registered stacks of interferograms connecting one date to

the following four, totaling 234 interferograms from 54 acquisitions (Liang, Liu, Fielding, & Bürgmann, 2018). We implement the range split-spectrum method of Liang and Fielding (2017) to estimate and remove ionospheric phase advance from individual interferograms. We correct the topographic phase with a 1 arc second (30 m) Digital Elevation Model (DEM) (NASA Shuttle Radar Topography Mission (SRTM), 2013). We apply a Goldstein-Werner filter with a strength of 0.6 and a multilook factor of 5 in range and 28 in azimuth, resulting in a ground pixel size of $42.9 \text{ m} \times 80.2 \text{ m}$.

To mitigate noise and reduce the influence of isolated decorrelated areas on the broader region, we divide the large frame into 16 overlapping subregions for time series analysis (Figure 4.1b). This approach ensures that all landslide candidates fall within 80 km of a reference pixel, thereby reducing spatially correlated noise. In regions affected by seasonal snow cover, we exclude specific dates within subregions while preserving coverage across the rest of the study area. By including 56-day interferograms, we maintain a fully connected network even when excluding dates with snow cover. For each subregion, we visually inspect the interferograms, coherence maps, and connected component maps, and we exclude individual interferograms or dates as needed. We choose reference pixels based on connected components and spatial coherence, favoring stable, high-coherence locations near landslides, such as bedrock exposures or ridge tops. This approach maximizes usable data across diverse conditions, enabling robust time series analysis even in regions with seasonal decorrelation.

We generate displacement time series using the Miami INsar Time-series software in Python (MintPy), applying a weighted least squares inversion based on the inverse of phase variability (Yunjun et al., 2019). We correct unwrapping errors for each interferogram using first bridging and then phase-closure methods Yunjun et al. (2019). We correct each date in the time series for tropospheric delay (Jolivet et al., 2014, 2011), solid Earth tides (Yunjun et al., 2022), and DEM error (Fattahi & Amelung, 2013). To focus on localized deformation and suppress long-wavelength noise, we remove a quadratic ramp from each date. Within each subregion, we use RMSE values from a linear fit to guide selection of the reference pixel, correction layers, and weighting scheme. We then calculate the linear velocity field and mask pixels with temporal coherence below 0.7. See Lindsay et al. (2025) for additional processing details and validation.

Collation of landslide inventory

We compile a unified landslide inventory by combining five previously published catalogs with newly mapped candidates, applying spatial clustering to merge overlapping entries. We identify additional features using ALOS-2 velocity fields, Google Earth imagery, and digital elevation models (DEMs), mapping 53 new coastal and 261 inland landslide candidates. We reproject all landslide polygons to a common coordinate system and retain only those with centroid locations within the InSAR frame and areas $\geq 10000 \text{ m}^2$. Where polygons overlap by $\geq 30\%$ and lie within 500 m of each other, we cluster them into single entries, retaining the largest polygon. For each landslide, we compute geometric descriptors including centroid coordinates, area, perimeter, compactness, axis ratio, orientation, short-axis length,

and convex-hull maximum diameter. The final inventory contains 1403 landslide candidates derived from Bennett, Miller, et al. (2016) (N=756), Handwerger et al. (2015) (N=36), Handwerger, Fielding, et al. (2019) (WY2017, N=306), Mackey and Roering (2011) (N=104), Y. Xu et al. (2021) (N=318), and 312 new landslides identified in this study (Figure 4.1a).

Time series extraction

We design a pixel-selection method to extract and ‘clean’ landslide time series (Figure 4.2). We aimed to reduce user input into decision-making and generate a population of landslide time series with uniform threshold parameters across the dataset. Our method statistically defines the transport zone based on a histogram of pixel velocities and spatial clustering of the fast-moving pixels. Based on the findings of Handwerger et al. (2015) that the fastest moving regions of landslides remain stable over time, we use the linear velocity map for the whole time period to identify the representative fastest moving pixels.

For each landslide in the inventory, we first define the ‘landslide’ and ‘background’ regions (Figure 4.2 left). We define the region of interest as a $12 \text{ km} \times 12 \text{ km}$ box centered on the landslide centroid, classifying pixels based on their geodesic distance from the centroid. We define landslide area as all pixels within a radius of either 500 m or equal to half the maximum diameter of the polygon, whichever is larger, and background area as all pixels at a distance greater than a buffer threshold of 4 km. We assume the background represents a stable area and define the uncertainty based on the standard deviation (σ_{bg}) within this region. We reject candidates where the $\sigma_{bg} \geq 1.5 \text{ cm/yr}$. We screen for landslides located along the frame edge, rejecting those with less than 80% valid data points within the landslide region.

For each landslide, we retain pixels above background noise levels by discarding values within $\pm 2\sigma_{bg}$, and reject candidates with fewer than 40 pixels (Figure 4.2 center). We determine the direction of motion—whether the displacement time series predominantly increases or decreases in LOS—based on the sign of the median pixel value. We compute the 75th and 95th percentiles and select the subset based on a minimum requirement of 10 pixels. The region determined to represent the fastest-moving part of the landslide, therefore, has a minimum area equivalent to a square approximately 185 m by 185 m ($\sqrt{(42.980.210)}$). We qualify the compactness of the pixel cluster by calculating the mean nearest-neighbor distances and scale this by an ideal nearest-neighbor (where all pixels are neighbors of each other). We set a threshold of 2, allowing the 95th percentile clusters to revert to the 75th percentile cluster if the clustering threshold is not met. For each cluster, we extract the slope, aspect, height, and satellite incidence and azimuth related to the specific pixel cluster from a 1 arc second (30 meter) DEM (NASA Shuttle Radar Topography Mission (SRTM), 2013). We estimate the surface area of the cluster based on the number of pixels in the subset and calculate the distance and azimuths to the reference pixel and the epicenter of large earthquakes.

For each epoch in the time series, we calculate the median of the pixel cluster and the median of the background. We subtract the background from the landslide at each epoch to remove common-mode noise, effectively placing the landslide time series relative

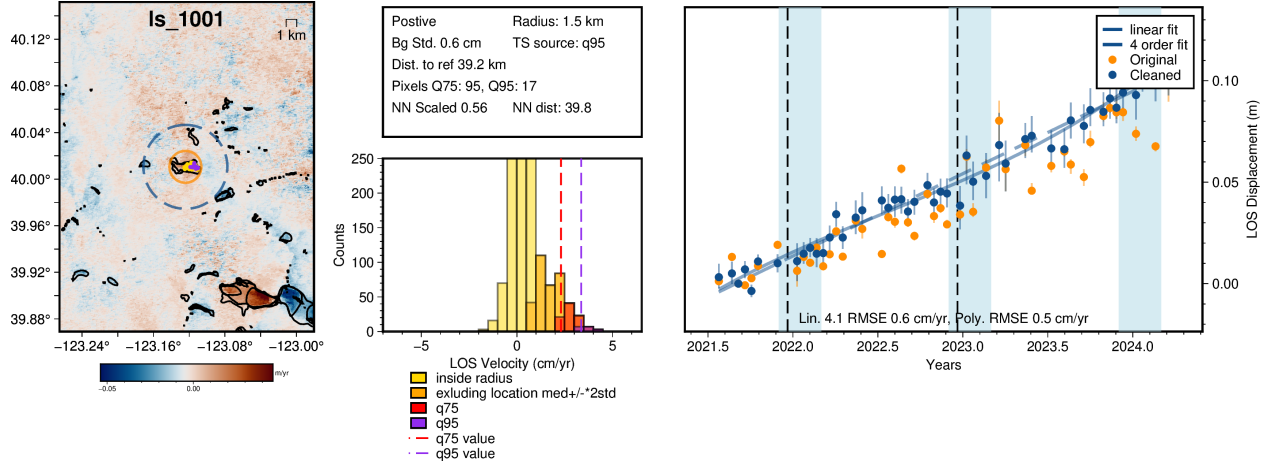


Figure 4.2: Example of time series extraction. (left) Line-of-sight (LOS) velocity, landslide area defined within the purple circle, and background between the green circle and the frame. Location of pixels above the 75th percentile (yellow) and above the 95th percentile (purple). Polygons included for visualization purposes only from Bennett, Miller, et al. (2016); Handwerger et al. (2015); Handwerger, Fielding, et al. (2019); Mackey and Roering (2011); Y. Xu et al. (2021). (middle) Histogram of LOS velocity inside the radius (yellow), above the background noise threshold (orange), above the 75th percentile (red), and above the 95th percentile (blue). (right) LOS time series of the original (orange) and cleaned (blue). Dashed lines indicate earthquakes, and blue denotes typical wet months.

to the ‘stable’ region surrounding it (Figure 4.2 right). This step removes common residual ionosphere or troposphere noise that is similar over short distances between the landslide and the immediate surroundings. We propagate uncertainties based on the inter-quartile ranges of the pixels within the landslide cluster and background. As we iterate through the 16 InSAR subregions with varying reference pixel locations, individual landslides may be sampled multiple times, resulting in duplicate time series. We resolve duplications by selecting the candidate time series with the lowest error-aware outlier fraction, defined as the proportion of epochs whose residual from a robust rolling-median trend exceeds three times the larger of the interquartile uncertainty $(\text{errhigh} - \text{errlow})/2$ or the MAD-scaled residual scatter. Finally, we visually inspect each time series to remove any remaining duplicate candidates. The resulting dataset includes 437 time series from individual landslides across a 300×400 km region (Section 4.3).

Time series normalization

For part of the analysis, we choose to normalize the LOS displacement time series, rather than project motion into the downslope direction, to focus on relative changes in amplitude

through time. Previous work shows that time series from InSAR and optical pixel tracking often capture the same key temporal features, such as the onset of acceleration. However, where the landslide dramatically accelerates, the absolute magnitude of displacement differs, with InSAR typically underestimating downslope motion (Handwerger et al., 2025; Handwerger, Fielding, et al., 2019). Additionally, downslope projection requires assumptions about slope and aspect, which can vary within a single landslide and may not accurately represent the fastest-moving region, especially in larger slides. To avoid introducing these additional uncertainties, we normalize the LOS displacement time series. Each landslide is mean-centered and direction-aligned using the slide’s sign, and then rescaled using a min–max scaling to a value between zero and one. Per-date distributions are summarized by the raw median, which is also smoothed with a five-sample rolling mean. This approach allows us to compare temporal patterns across landslides without relying on potentially inaccurate magnitude estimates and avoids the introduction of projection errors.

Complementary datasets

For each landslide, we compile shaking and rainfall metrics to complement the displacement time series. We use the USGS ShakeMaps of peak ground acceleration (PGA) and search for earthquakes within 300 km of each centroid that produce $\text{PGA} \geq 0.001 \text{ g}$ at the site (a threshold between *Not Felt* [0.0005 g] and *Weak* [0.003 g]) (U.S. Geological Survey, 2025). We compute cumulative PGA and cumulative earthquake count for each landslide and down-sample both to 14-day intervals to align with the SAR record. Although the largest events dominate the cumulative PGA, we also capture aftershock sequences, including the $M_w 5.4$ aftershock 45 days after the 2022 $M_w 6.4$ mainshock. Because microearthquake frequency may influence landslide healing (Bontemps et al., 2020), we also consider the event counts alongside PGA. We extract daily precipitation for each landslide from the PRISM Climate Group (2025) precipitation model and compute cumulative precipitation and down-sample to the same 14-day intervals.

Kinematic grouping and driver tests

We first group landslides by their kinematic response, defined by velocity ratios computed across post-mainshock windows of 3, 6, and 12 months, as well as across water years (October 1–September 30), to form observational categories of accelerated, stable, or slowed motion. This approach is agnostic to assumptions about external drivers and provides a basis for testing associations with shaking and rainfall. To evaluate associations with external drivers, we use two complementary summaries. (i) For groupwise contrasts, we estimate a nonparametric bootstrap (10,000 iterations; percentile 95% confidence interval; significant if the CI excludes zero) of the difference in medians between *Much Faster* and *Slower* among slides that remained active. (ii) For continuous trends, we compute Spearman’s rank correlation (coefficient ρ) between the velocity ratio ($V2/V1$) and each covariate. We then intersect kinematic groupings with PGA and precipitation ratio-based classifications to iden-

tify subsets of landslides that share both a displacement response and a forcing condition (e.g., accelerated motion coincident with high shaking). PGA and precipitation ratios are defined as cumulative values over the water year (October 1–September 30). Because both vary smoothly in space, they serve as effective spatial filters. Thresholds for kinematic and forcing categories are summarized in Table 4.1. We define earthquake-triggered landslides as those that exhibit faster sliding rates after a mainshock and experience relatively higher shaking than the surrounding areas. This two-step approach—first grouping by displacement kinematics, then filtering by external forcings—enables systematic comparisons while remaining observationally grounded.

Table 4.1: Thresholds used to group landslides by velocity, PGA, and precipitation ratios of water years 2023 and 2022.

Category	Velocity Ratio (V2/V1)	PGA Ratio (WY23/WY22)	Precipitation Ratio (WY23/WY22)
Much Slower / Lower	$r < 0.2$	$r < 0.6$	No Data
Slower / Lower	$0.2 \leq r < 0.83$	$0.6 \leq r < 0.83$	No Data
Similar	$0.83 \leq r \leq 1.2$	$0.83 \leq r \leq 1.2$	$r \leq 1.1$
Faster / Higher	$1.2 < r \leq 5$	$1.2 < r \leq 3$	$1.1 < r \leq 1.5$
Much Faster / Higher	$r > 5$	$r > 3$	$r > 1.5$

Modeling

For landslides we identify as triggered, we model the stacked, normalized displacement median $y(t)$ using a piecewise function with a linear pre-event trend and an exponential post-event decay, a similar approach as Cao et al. (2023):

$$y(t) = \begin{cases} k(t - t_0) + b, & t \leq t_1, \\ C - A e^{-\beta(t-t_1)}, & t \geq t_1, \end{cases} \quad (4.1)$$

where t_1 is the earthquake time, k is the pre-event slope, and C and β govern the post-event decay. We estimate a turning time t_1 by grid-searching within ± 3 months of the 2022 earthquake date. Continuity at t_1 gives

$$A = C - [k(t_1 - t_0) + b]. \quad (4.2)$$

Parameters $\theta = \{k, b, C, \beta\}$ are estimated by ordinary least squares on the unfiltered group-median series: we fit the linear term to the 12 months between the 2021 and 2022 earthquakes and the exponential term to all post-2022 earthquake data ($t \geq t_1$), enforcing the continuity condition above. From β we report the characteristic decay time

$$t_{90} = \frac{\ln 10}{\beta} \quad (4.3)$$

which is the time since t_1 for the normalized post-event velocity to decay to within 10% of its initial value. Uncertainty is quantified via a slide-level bootstrap: we resample the N

landslides, recompute the stacked median, refit θ , and take the 2.5–97.5th percentiles for t_{90} and t_1 , estimated by grid search.

4.3 Results

This study is one of the first to utilize regular 14-day acquisitions with L-band InSAR, enabling the resolution of time-dependent landslide behavior over nearly three years. We perform time series analysis on 437 slow-moving landslides to provide a spatially comprehensive analysis that extends beyond a single watershed and to provide a detailed response of all landslides in the region to significant weather and seismic events.

Inventory overview

After collating a common inventory and applying geometric filters, we evaluate 1,403 individual landslide candidates and extract displacement time series for 437 slides (overall retrieval rate of 31%) (Figure 4.3). The Bennett, Roering, et al. (2016) inventory detection fractions were 25% for active (53/212), 16% for debris (43/277), and 19% for dormant (50/217) landslides. This indicates continued motion for landslides mapped as debris and possible reactivation of dormant candidates. From the Handwerger, Fielding, et al. (2019) inventory from water year 2017, a high rainfall year, we recover 22% (67/305). We recover the highest fraction from Handwerger et al. (2015) at 61% (22/36), and we recover 37% (119/318) from Y. Xu et al. (2021). The extraction rate for newly mapped candidates is 68% (212/312); the higher recovery rate is likely because both mapping and time-series extraction were performed on the same dataset. Our newly mapped candidates cluster along the coast and in regions that experienced strong ground shaking, as well as within the Eel, Mad, and Trinity River watersheds, where landslide mapping is already extensive.

Building on the original Mackey and Roering (2011) earthflow inventory and the reanalysis by Bennett, Roering, et al. (2016), our study is the third to assess detectability and similarly finds that fewer slides are now detectable. Our recovery from the Mackey and Roering (2011) subset is 14% (14/104). This is comparable to Bennett, Roering, et al. (2016), who analyzed 98 Mackey and Roering (2011) earthflows and found $\sim 25\%$ were undetectable by 2009–2012, and an additional $\sim 50\%$ of those still active became undetectable by 2012–2014. The motion of the earthflows in the Mackey and Roering (2011) inventory was mapped using a combination of LiDAR (light detection and ranging) and orthorectified historical aerial photographs between 1944 and 2006. In comparison to this dataset, the spatial resolution is much higher for Mackey and Roering (2011), and the motion represents long-term motion over decades, in contrast to the snapshot provided by the nearly 3 years of our dataset. Overall, inter-catalog differences reflect both genuine temporal changes in activity (from active to dormant) between different observation periods and inherited limitations and differences in mapping techniques from the original inventories.

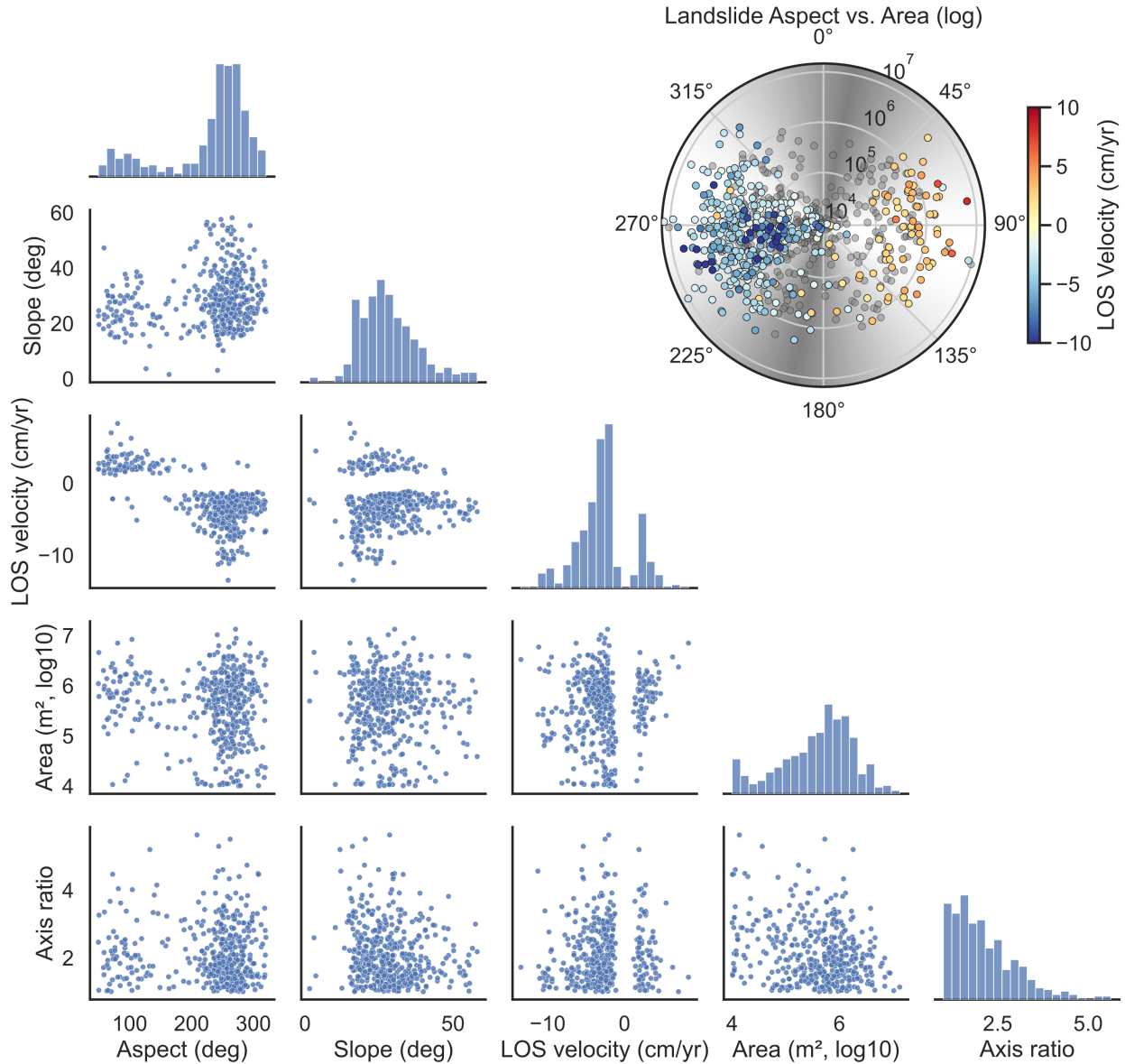


Figure 4.3: (bottom left) Multi-variable scatter plot showing distributions of aspect, slope, linear line-of-sight (LOS) velocity July 2021 - March 2024, area of mapped polygon, and axis ratio (long vs short axis ratio). (top right) Landslide aspect (directional axis) and logarithmic landslide area in m²(radial axis). We present the distribution of the full 1,403 inventory (grey circles), 437 linear LOS velocities from July 2021 to March 2024 (color circles), and InSAR sensitivity (gray shading). The shaded areas indicate where InSAR is least sensitive to landslide motion based on the satellite azimuth direction.

Of the 437 landslides we extract time series for, 87% of the slopes are dominantly west-oriented (circular mean 255.4°); slope gradients range $2\text{--}58^\circ$, elevations span $0\text{--}3357$ m, and polygon areas range $0.01\text{--}13.35$ km² (Figure 4.3). We interpret the westward skew primarily as a consequence of hillslope orientation, which itself is skewed toward east–west aspects. Additionally, the SAR descending-orbit viewing geometry is more sensitive to downslope motion directed away from the look direction (i.e., westward). Figure 4.3 (top) presents the directional distribution, which reveals that we do not recover small eastward sliding candidates or those in the satellite’s azimuth direction. Coastal landslides, which make up 10% of the inventory, are steeper, with a median slope of 36.7° compared with inland slides, with a median of 26.3° (Figure S1). For the inland slides, we find 21.6% of the slopes are shallow ($\leq 20^\circ$), 21.3% are moderate ($20\text{--}25^\circ$), 38.6% are steep ($25\text{--}35^\circ$), and 18% are very steep ($\geq 35^\circ$) (Figure 4.3). We set the landslide sign (positive/negative LOS) based on the cumulative displacement and find 3.7% with the opposite sign to that expected from the slope aspect. Based on the aspect-ratio criteria of Handwerger et al. (2021), the inventory comprises 69% slumps, 28% earthflows, and 3% complexes. The centroids of 19.3% (93/483) of landslides are within 500 m of a road, which is important for monitoring and hazard assessments. Overall, the bulk of the landslide time series represents westward motion on moderate to steeply sloping terrain across a 300 km x 400 km region of northern California.

Kinematic grouping of slow-moving landslides

To assess landslide kinematic responses, we compare changes in the linear rate of the landslides over increasing post-seismic time periods (Figure 4.4). Because the earthquakes occurred exactly a year apart on 20 December 2021 and 20 December 2022, we can compare post-seismic periods after each earthquake and examine the relative changes in linear velocity rates over 3-, 6-, 9-, and 12-month post-earthquake periods. Landslides are grouped by velocity ratio for each period into: *Much faster* ($>4\times$), *Faster* ($1.2\text{--}5\times$), *Similar rate* ($0.83\text{--}1.2\times$), *Slower* ($0.2\text{--}0.83\times$), and *Much slower* ($<0.25\times$). In the three months following the 2022 earthquake, 21.1% of landslides were classified as Much Faster. For the 6-, 9-, and 12-month windows, the fractions classified as Much Faster were 4.8%, 6.5%, and 10.9%, respectively. Comparing between the 2022 and 2023 water years, 57% moved Faster, and a further 13% were Much Faster. For the 43 slides that were Much Faster in the 12-month window, the median LOS rate increased from 1.5 cm/yr after the 2021 earthquake to 11.5 cm/yr for the 2022 earthquake, nearly an 8-fold increase in sliding rate. Figure 4.5 compares linear velocities for the intervals 0-3 months, 3-6 months, 6-9 months, and 9-12 months following each earthquake. The broad pattern reveals elevated rates between 0-3 months, with 47% of slides being faster in 2022 during the 3-6 month interval and 61% for the 6-9 month interval. The most prominent feature is a slowing of rates in the 9-12 month interval with 66% in the ‘Slower’ or ‘Much slower group’ (Figure 4.5d).

The normalized stacked timeseries for the 9-month windowing of the velocity ratios grouping illustrate how the kinematic response of these landslide populations differs (Figure 4.6). Most prominently, the Much Faster group exhibits steady rates through 2022, rapidly accel-

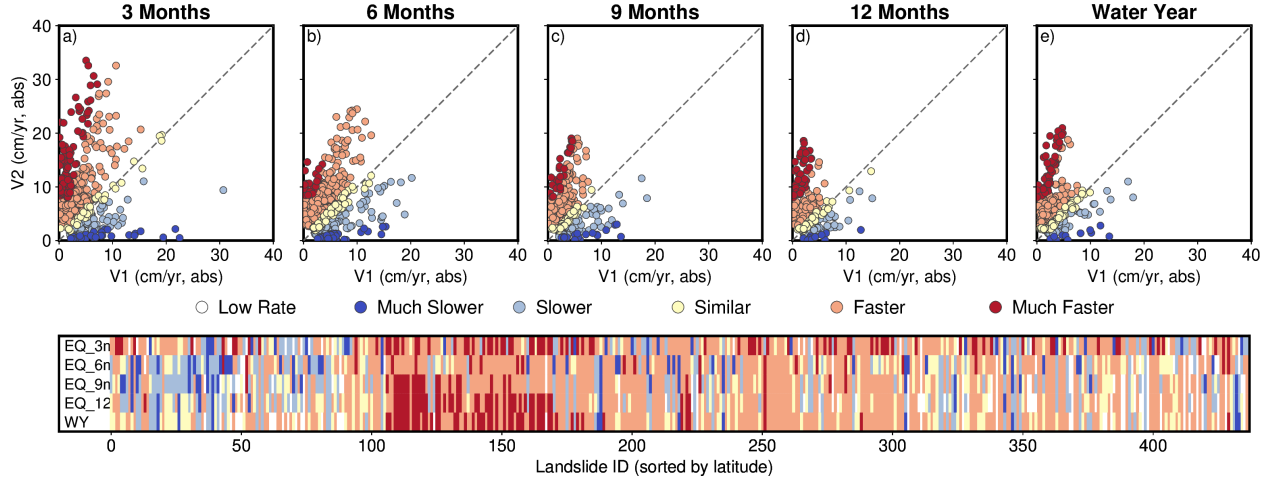


Figure 4.4: (top) LOS velocity for post-2021(V_1) and post-2022 (V_2) earthquakes for five windows: 3, 6, and 12 months after the earthquake, the whole water year (beginning October 1st). Panels (a–e) plot initial velocity (V_1 , x-axis) versus subsequent velocity (V_2 , y-axis), with a 1:1 dashed line. The ratio classifies V_2/V_1 into “Much Slower,” “Slower,” “Similar,” “Faster,” and “Much Faster”; extreme classes use a $4\times$ multiple (i.e., $(V_2/V_1) \geq 4$ or $\leq 1/4$). Landslides with both V_1 and $V_2 < 2$ cm/yr are excluded as *Low Rate*. (Bottom) Heat map of relative change for each landslide (columns; sorted by latitude) across the five time windows (rows); a continuous red vertical stripe denotes a landslide that is faster in all windows relative to its rate in the corresponding period in the previous year.

erates entering a new sliding regime around the time of the 2022 earthquake, and decays to lower rates over the subsequent year. All time series reveal an acceleration during 2022, with the Faster and Slower groups including a clear delay between the onset of precipitation (and the 2021 mainshock) and excess sliding. For the Faster sliding group, the 2022 acceleration slows to a halt by mid-2022, with accelerations returning with the late-2022 mainshock and onset of precipitation, with no clear delay time. Sliding tapers off by mid-2023, but remains active through the remainder of the water year. For the Similar group, there is no distinct change in rate around the 2022 earthquake, and sliding remains near linear through 2023. The Slower group maintains similar rates throughout both water years, with the primary difference being the timing of the acceleration onset, which is clearly earlier in 2023. Finally, the Much Slower group is smaller and exhibits more scatter. These slides mirror the response of the Much Faster group, with steady sliding through 2022 that declines considerably during 2023. Figure 4.6f illustrates the systematic differences in the medians, with kinematics deviating from early 2022 to mid-2023, and then returning to near agreement.

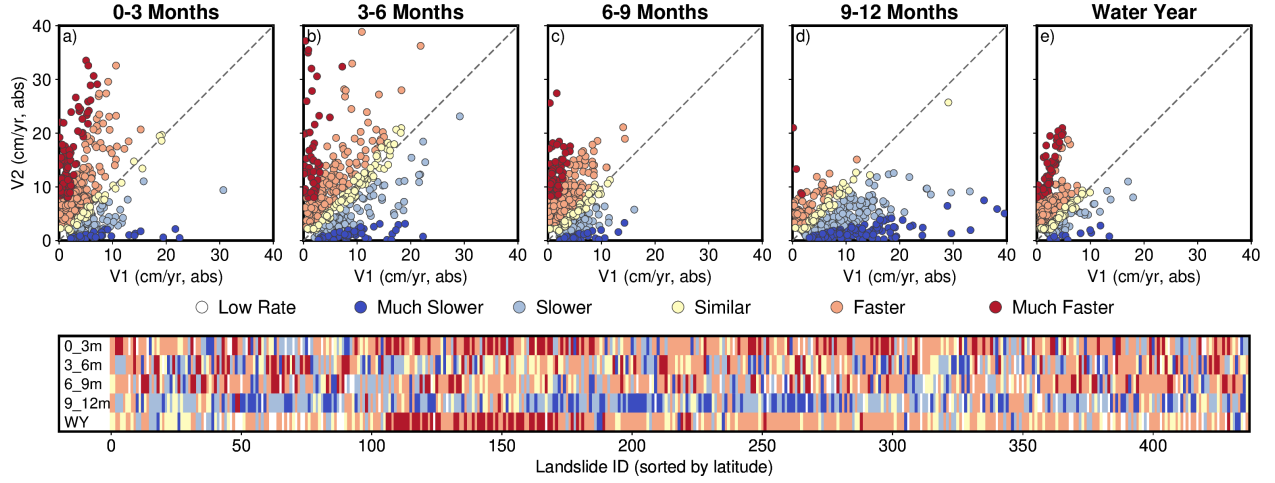


Figure 4.5: (top) LOS velocity for post-2021(V_1) and post-2022 (V_2) earthquakes for five time intervals: 0-3, 3-6, 6-9, and 9-12 months after the earthquake, the whole water year (beginning October 1st). Points are colored by their velocity ratio grouping. Panels (a–e) plot initial velocity (V_1 , x-axis) versus subsequent velocity (V_2 , y-axis), with a 1:1 dashed line. The ratio classifies V_2/V_1 into “Much Slower,” “Slower,” “Similar,” “Faster,” and “Much Faster”; extreme classes use a $4\times$ multiple (i.e., $(V_2/V_1) \geq 4$ or $\leq 1/4$). Landslides with both V_1 and $V_2 < 2$ cm/yr are excluded as *Low Rate*. (Bottom) Heat map of relative change for each landslide (columns; sorted by latitude) across the five time windows (rows); a continuous red vertical stripe denotes a landslide that is faster in all intervals relative to its rate in the corresponding period in the previous year.

Association of landslide motion with shaking, precipitation, and morphology

In the 9-month post-quake window, earthquake shaking is associated with higher 2023 sliding rates (Figure 4.7a-c). Both the cumulative PGA ratio (WY23/WY22) and the event-count ratio are higher in *Much Faster* than *Much Slower* among active slides and exhibit positive monotonic trends, with the median PGA ratio between the groups showing larger separation (Δ median = 1.64 [0.01, 2.45]). Treating the velocity ratio as continuous, Spearman ρ is positive for both shaking metrics. In contrast, the median precipitation ratios for the *Much Faster* than *Much Slower* are similar (Δ median = 0.04 [−0.13, 0.25]). The association of relative sliding rate and landslide morphology, including slope, axis ratio, and area, offers limited separation in medians between end-member groups (Figure 4.7d-f). Because apparent size effects can depend on data resolution and mapping conventions, we consider the area of the time-series footprint as a less subjective proxy for relative size, rather than mapped polygon area. Overall, stronger shaking corresponds to faster 2023 sliding, while rainfall differences appear inconclusive in this framing (Figure 4.7).

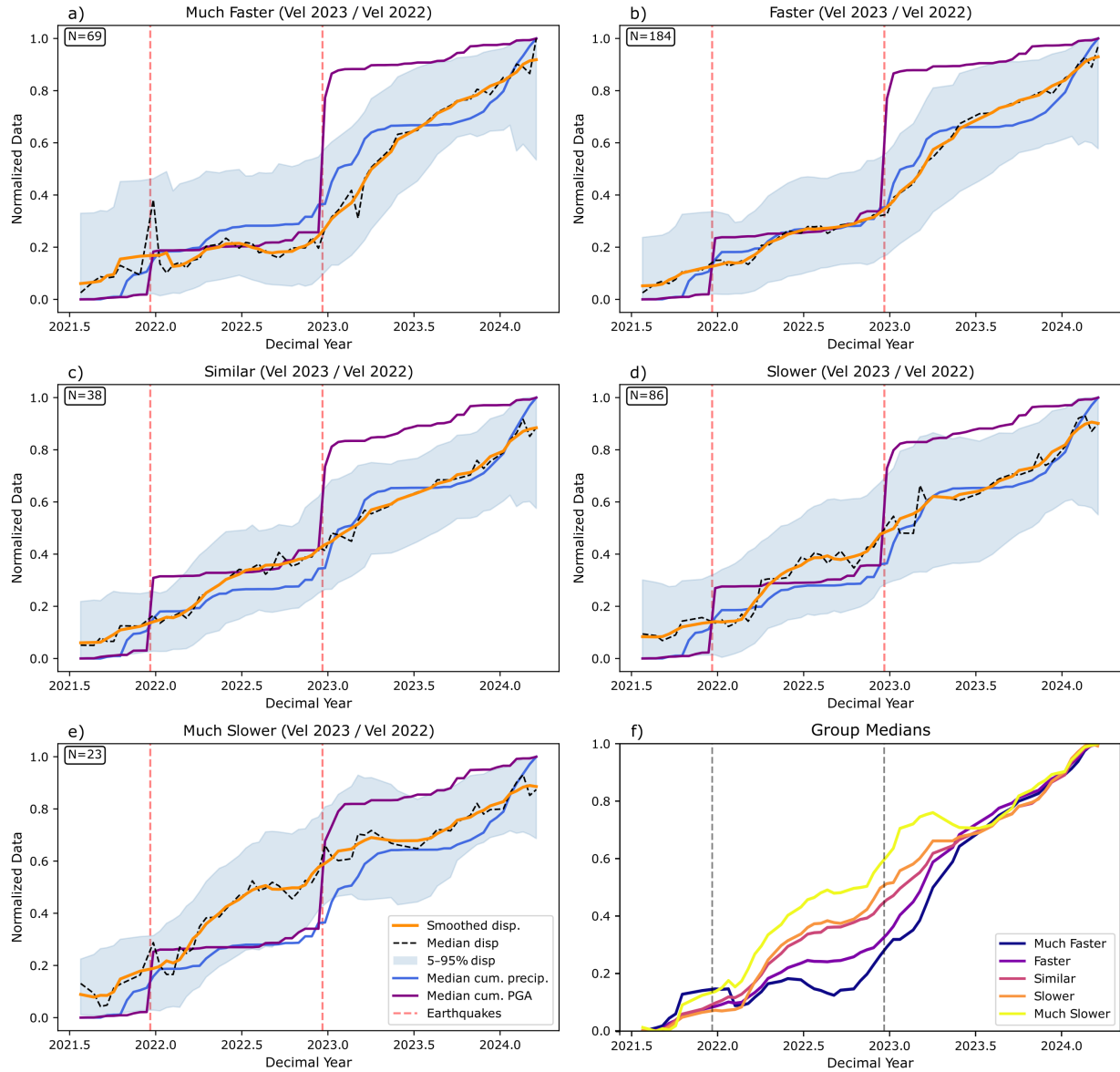


Figure 4.6: Normalized LOS displacement time series grouped by velocity ratio for the 9-month window following the 2021 and 2022 earthquakes, grouped by Much Faster, Faster, Similar, Slower, and Much Slower. The raw (black dashed) and smoothed median displacement (orange) illustrate the time-dependent differences between groups and their relationships to the median cumulative PGA (purple) and precipitation (blue). Vertical dashed lines denote the 2021 and 2022 earthquakes. (f) The smoothed median from all groups highlights the systematic post-2022 acceleration compared to the prior year. Low-rate slides (both periods less than 2 cm/yr) are excluded from all aggregates.

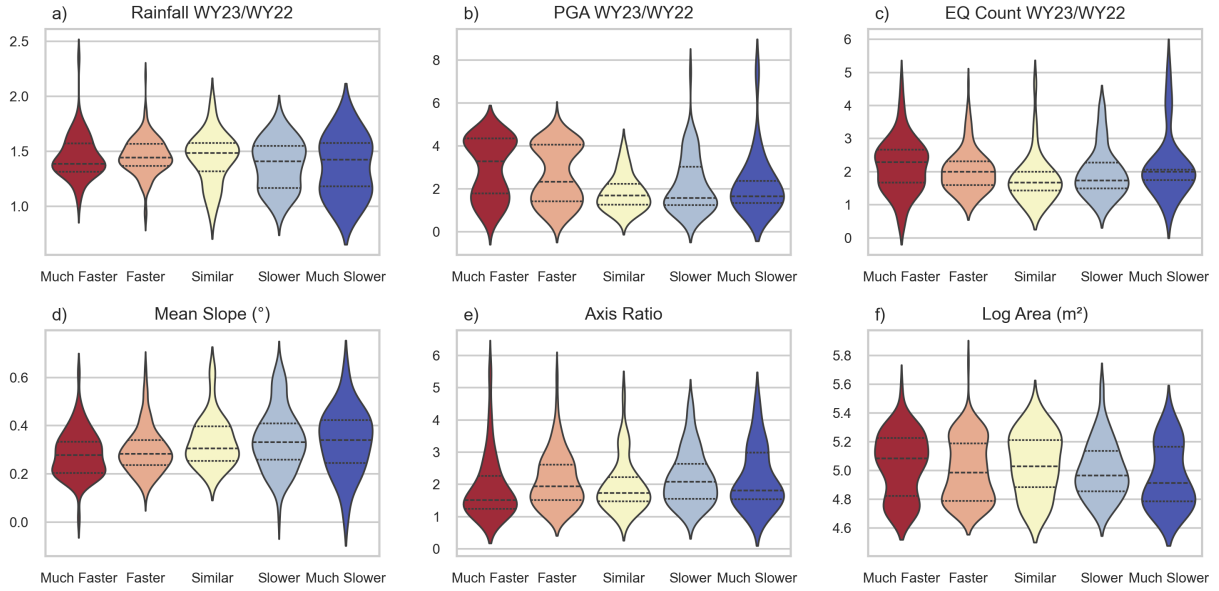


Figure 4.7: Distributions of covariates by velocity–ratio group for the 9 months post-quake. Violin plots display kernel density with quartiles and median. The variables include the ratio of WY23 to WY22 for rainfall, cumulative PGA, earthquake count, and the mean slope, axis ratio, and $\log_{10}$ area (m²) of the pixels used for time series extraction.

We find that the 9-month velocity ratio is spatially coherent: *Much Faster* slides cluster ~ 50 km northeast of the epicenters, whereas *Slower/Much Slower* slides cluster north of 41° N (Fig. 4.8a). Along the coast, sites south of the epicenters move faster on average in 2023 than in 2022, whereas northern coastal sites tend to slow. Peak WY23/WY22 cumulative PGA ratios occur northeast of the epicenters and spatially coincide with the *Much Faster* cluster. The inset (Fig. 4.8h) highlights this region of accelerated sliding within the high-shaking corridor. This alignment is consistent with the positive PGA–velocity association and the larger median separation. Precipitation ratios increase southward and are near year-to-year parity north of 42° N; this gradient shows limited correspondence with the kinematic groupings, consistent with the small, negative precipitation effect size. The 2023 vs. 2022 LOS-velocity scatter shows separation for PGA-grouped points—with the fastest-moving landslides in 2023 grouped as *Much Higher* PGA—and only modest separation for precipitation-grouped points. Overall, these spatial relations reinforce the independent tests of drivers and illustrate the relationship among epicentral distance, peak ground shaking, and slow-moving landslide triggering.

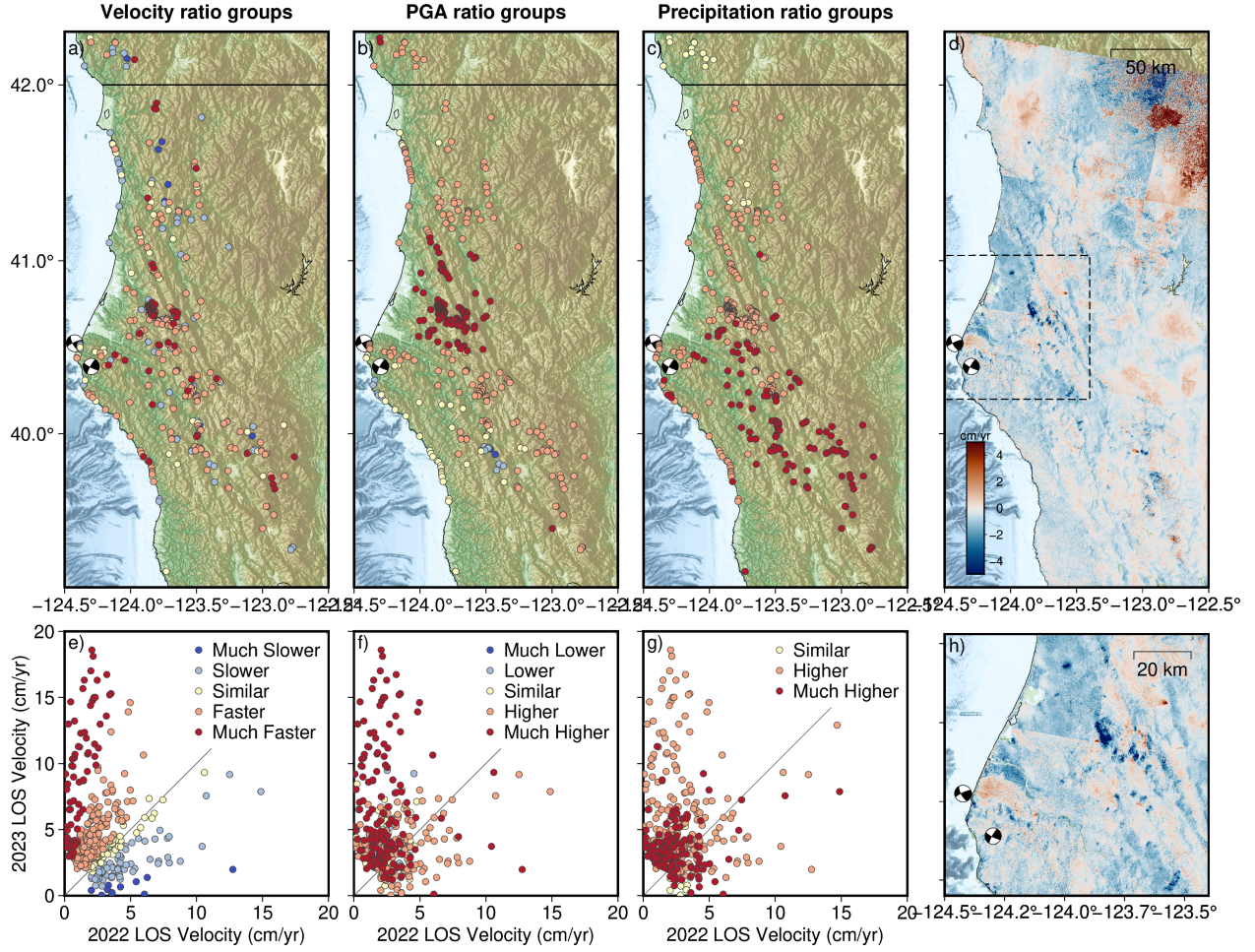


Figure 4.8: (a-c) Spatial distribution and (e-g) scatter of velocity, PGA, and precipitation ratios for the 12-month post-quakes. (d) Line-of-sight linear velocity map for July 2021 to March 2024 with (h) zoom in of epicentral region and triggered landslides.

Landslides triggered by the 2022 earthquake

We analyze the subset of landslides that are both *Much Faster* by velocity ratio and *Much Higher* by PGA ratio, clustering sites with similar kinematics while spatially filtering for the strongest shaking. 71 slides experienced *Much Faster* velocities in the 9 months after the 2022 earthquake, compared with the 9 months after the 2021 earthquake. We fit a linear term to the 12 months between the 2021 and 2022 earthquakes to define a background or pre-event sliding rate, and then fit an exponential decay to the remaining time series to determine the time it takes for the slide to return to the pre-2022 earthquake sliding rate. For the 38 slides that experienced both *Much Faster* sliding rates and *Much Higher* PGA, the sliding rate returned to 10% of the pre-2022 earthquake rates in 16 months ($\tau_{90} = 1.43$

yr). The best-fitting transition from linear rates to exponential decay occurred on January 9, 2023 ($t_1 = 2023.022$), 20 days after the earthquake, and aligns with the second post-quake acquisition. Allowing t_1 to vary improves the model fit, reducing RMSE from 0.083 to 0.076 (8.4% reduction). Given the 14-day temporal resolution, the earthquake date and the onset of sliding are well aligned. 33 slides experienced *Much Faster* sliding rates and were located outside of the *Much Higher* PGA region. These landslides began sliding 6 weeks later, around February 27, 2023 ($t_1 = 2023.137$), and returned to within 90% of the pre-2022 earthquake rate in 14 months ($\tau_{90} = 1.16$ yr). Spatially, the *Much Faster* and *Much Higher* subset cluster ~ 60 km northeast of the 2021 and 2022 epicenters in a $\sim 30 \times 40$ km area within the Franciscan Complex. At its center is the Graham Landslide Complex, in the peak shaking regions of the $M_w 6.4$, 20 December 2022 earthquake and spanning a 6×10 km zone (Figure 4.9b,c). Inspection of Planet optical imagery (PBC, 2023) shows no evidence of catastrophic failure within the Graham complex between 2021 and 2024. We interpret these results as evidence that the slides in the high-PGA region experienced stronger shaking and thus a larger co-seismic perturbation, which triggered immediate post-earthquake sliding with higher initial acceleration and a longer decay period. Slides that accelerated away from the highest-PGA zone showed a delayed onset, experienced lower peak accelerations, and returned to background rates more quickly.

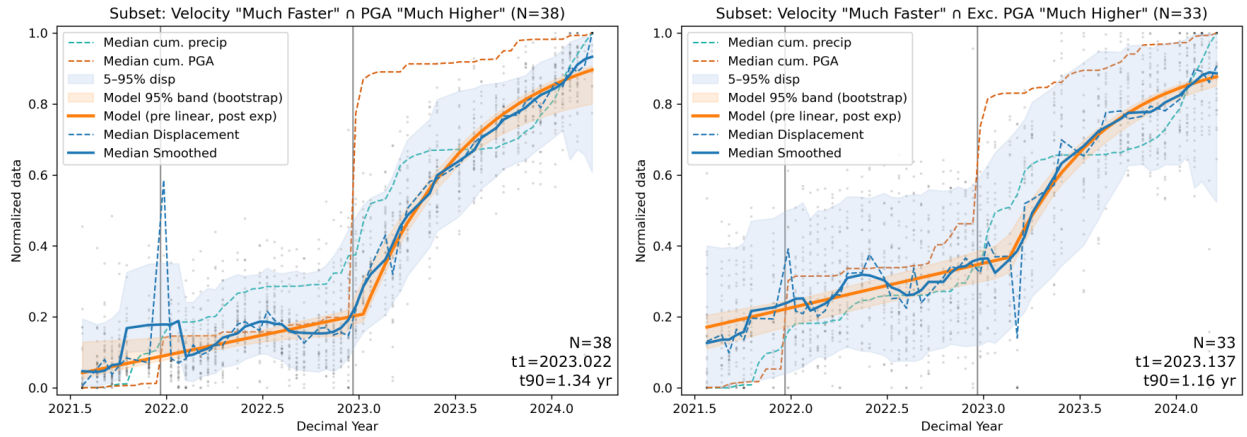


Figure 4.9: (left) Subset of 38 landslides classified as *Much Faster* (velocity ratio) inside the *Much Higher* PGA region and (right) subset of 33 landslides classified as *Much Faster* (velocity ratio) outside the *Much Higher* PGA region. Normalized time series per landslide (grey dots), smoothed median (blue) with 5th and 95th percentile bounds (light blue). The normalized cumulative precipitation (dashed teal) and normalized cumulative PGA (dashed dark red). The solid orange curve represents the fitted piecewise model (linear pre-event, variable onset time, exponential post-event) with a 95% bootstrap confidence band. Vertical gray lines mark the 2021 and 2022 earthquakes.

4.4 Discussion

Using a 14-day L-band (ALOS-2 ScanSAR) InSAR time series over northern California from July 2021 to March 2024, we quantify the kinematics of slow-moving landslides after two moderate earthquakes that occurred a year apart: The M_w 6.2 earthquake on 20 December 2021 and the M_w 6.4 earthquake on 20 December 2022 (Figure 4.1c,d). We compile an inventory of 1,403 candidate landslides from five prior studies and 312 new features by unifying overlapping polygons through spatial clustering (Figure 4.1a). We extract high-quality displacement time series for 437 landslides using a systematic and statistically robust extraction and cleaning pipeline, enabling consistent, population-scale comparisons (Figures 4.2, 4.3). These time series cover approximately 300×400 km, with sites located up to 150 km from the earthquake sources (Figure 4.8). We group the landslides by relative rate changes across fixed 3-, 6-, 9-, and 12-month windows, testing the associations with various forcings (cumulative PGA, earthquake counts, precipitation) and attributes (slope, aspect, area) (Figures 4.4, 4.6). We find that faster rates post-2022 are associated most strongly with cumulative PGA (Figure 4.7).

The subset of landslides that accelerated following the 2022 earthquake and experienced strong shaking shows steady pre-event rates, a sharp step-like acceleration immediately after the earthquake, and a subsequent decay (Figure 4.9). A simple piecewise model (linear pre-event + exponential post-event) captures this behavior, suggesting a return to within 10% of pre-event rates in approximately 16 years. The model also determines the onset of accelerated sliding (t_1), which occurs 20 days after the 2022 main shock, on January 9, 2023. Our analysis of kinematic grouping and forcing associations suggests that the 2022 earthquake triggered this subset, leading to a notable rate increase from 2022 to 2023. The location of this subset along the rupture-propagation corridor with highest PGA, immediate post-quake acceleration, and longer decay time support the conclusion that a seismic trigger, rather than rainfall, influenced the landslide activity (Figure 4.8). Below, we discuss our results in the context of : (i) earthquake-triggered accelerations, (ii) why the landslide response differed between the 2021 and 2022 earthquakes in terms of source mechanics and rupture directivity, and (iii) the sensitivity of InSAR for tracking landslide motions.

Earthquake-triggered accelerations

Earthquakes can trigger slow-moving landslides via the passage of seismic waves, which temporarily increase shear stress on the sliding surface, sometimes leading to rapid failure or accelerated motion (Lacroix et al., 2014). In regions closest to the earthquake epicenter, which experience the greatest shaking, landslides typically fail rapidly, and the density of failure decays with distance from the fault trace (Meunier et al., 2007; Lin et al., 2008). Triggering of slow-moving landslides has been observed at greater distances from the epicenter, where the shaking is sufficient to perturb but not overwhelm basal strength (Lacroix et al., 2015). Our results align with this pattern: we detect triggered slow slides away from the peak-shaking zone. The kinematic response of our triggered landslides also mirrors ob-

servations of seismic landslide triggering—an instantaneous acceleration at the time of the earthquake, then a relaxation over weeks to months, with those that experienced greater shaking experiencing greater acceleration (Figure 4.9) (Lacroix et al., 2014; Bontemps et al., 2020; Cao et al., 2023). The slides with the greatest accelerations are clustered in the 2022 rupture propagation direction and coincide with the region with higher shaking (Figure 4.8). Together, the localization of responses within the high-PGA region, the immediate initiation and exponential decay, and the lack of near-field triggering of slow-moving landslides favor a seismic trigger.

Beyond transient dynamic stresses, earthquake shaking leaves lasting hydro-mechanical changes that persist after the shaking has stopped. Shaking can modify the permeability and rigidity of landslide bodies by generating or widening fractures and fissures, thereby altering the hydraulic conditions within the landslide body. New or enlarged crack networks create preferential flow paths that recharge the basal sliding surface and promote sliding—provided the fissures do not extend far enough to drain the shear zone (Krzeminska et al., 2013). Bontemps et al. (2020) inferred changes in the rigidity of the landslide following earthquakes based on an observed drop in dv/v immediately after earthquakes, followed by recovery that mirrored the landslide’s deformation response, which showed an initial acceleration followed by slowing. These earthquake-induced changes in permeability and rigidity can precondition landslides to respond more readily to subsequent forcings Lin et al. (2008). We suggest that this preconditioning may explain the difference in onset time between precipitation and excess sliding across the two years. While we observed a clear delay across all slides between the onset of precipitation in late 2021 and the onset of sliding in early 2022, the onset of sliding initiates across all groups at the very end of 2022, exhibiting no or much shorter delays (Figure 4.6). Within the *Much Faster* subset, the onset of sliding within the highest PGA region was nearly coincident with the 2022 earthquake, while at distances from peak shaking, the slides began accelerating approximately 6 weeks after the earthquake, a delay still shorter than expected from precipitation alone (Figure 4.9). We suggest that the observed change in timing of the seasonal acceleration may be attributed to this conditioning mechanism, in conjunction with higher rates of precipitation that act globally across the dataset (Figure 4.4 bottom).

Differences in landslide response to the 2021 and 2022 earthquakes

Although the two earthquakes were similar in magnitude and separated by only 20 km, their rupture processes were distinctly different. The 20 December 2021 sequence comprised two subevents separated by ~ 10 s (offshore initiation followed by a deeper onshore rupture) (Yeck et al., 2023; Hellweg et al., 2025). In contrast, the 20 December 2022 earthquake ruptured a single fault plane with predominantly unilateral northeastward propagation (Shelly et al., 2024; Hellweg et al., 2025; Yoon & Shelly, 2024). These source differences are evident in the ground motions: the 2021 moment-rate function is multi-peaked and longer (~ 20 s), while the 2022 function is shorter (~ 12 s) and pulse-like (Yeck et al., 2023; U.S. Geological Survey, 2022). Consistently, stations near our study area (e.g., BJES, 20 km SE of

the Graham Complex) recorded substantially larger dynamic displacements in 2022 than in 2021 (Hellweg et al., 2025). Figure 4.1c and 4.1d highlight the differences in the distribution of PGA, with the 2021 event producing more diffuse shaking across the region, while the map of the 2022 event includes a concentrated region with elevated PGA to the northeast of the epicenter aligned with the rupture propagation direction. The landslides we identify as triggered cluster within this corridor, implicating the focused, pulse-like motions associated with directivity. This interpretation is consistent with prior results showing that pulse-like ground motions and directivity increase landslide triggering probability (Z. Li et al., 2024). Since both events occurred during the same time of year and regional precipitation anomalies were relatively uniform, we suggest that directivity and the associated velocity-pulse characteristics, along with the larger magnitude, were primary factors influencing the much larger accelerations observed in 2022. We also recognize that prior hydrologic conditions and the 2021 earthquake contributed to making the land more susceptible to sliding.

InSAR sensitivity and limits on measuring slow-moving landslide motion

Our ability to constrain landslide motion is limited by factors inherited from the observation platform, terrain, land cover, and the displacement rates of the landslide. A primary control on sensitivity to landslide motion is the azimuth, or fly direction, where there is no sensitivity parallel to the azimuth direction, meaning we cannot retrieve information regarding landslide motion in the near north-south orientations (Figure 4.3). Furthermore, geometric distortions occur due to the geometry between the steepness of the satellite’s line-of-sight (LOS) and the local topography (Hanssen, 2001; Wasowski & Bovenga, 2014). For steep slopes facing the satellite, the returned signal from a large ground resolution cell may be compressed into a single InSAR pixel, or the returned signal may not arrive back at the radar in the correct order and be attributed to the wrong part of the ground resolution cell (layover). For steep terrain when the slope faces away from the satellite, the slope angle may exceed the incidence angle, resulting in a shadow zone where no signal is returned (shadow). For a median incidence angle of this dataset of 40° [Range: 30° to 45°], the shadowing affects slopes steeper than 50° . Within our dataset, the median slope angle is 27° [Range: 2° to 58°], including 29 slides with mean slopes greater than 45° , and 17 greater than 50° , which are primarily located along the coastline (Figure S1). Based on the observation geometry, we expect to confidently retrieve displacement histories from the majority of landslides within the study region without the effects of geometric distortions.

The land cover affects decorrelation, where the surface scattering properties change rapidly between acquisitions, and the phase signal no longer correlates. In our study region, this is primarily due to seasonal snow cover, deforestation, and wildfires. Most notably, we see a region of positive LOS within the bounds of the 2022 McKinney wildfire in northern California (Figure 4.1b, 42° , -122.8°). The land cover of the landslide itself also influences the strength of the returned signal; InSAR depends on the presence of persistent scatterers (i.e.,

large rocks, buildings, cliff faces) that have higher amplitudes of the returned signal than the surrounding areas. When the landslide cover is homogeneous, there are fewer features to track the relative change in phase and accurately capture the full displacement history within each InSAR pixel.

Finally, phase aliasing occurs when the rate of displacement between neighboring pixels exceeds a quarter of the wavelength. Beyond this limit, continuous unwrapping of the interferogram is not possible, and errors are introduced, which may contribute to an underestimate of the total displacement. For our data set with a wavelength of ~ 23 cm, and using up to 56-day interferograms (the longest temporal baselines in this dataset), we can theoretically resolve displacement gradients of 12 cm per 56 days (78 cm/yr) between each 40 m pixel. Within our dataset, we do not observe displacement rates approaching the theoretical limit: peak rates for the 3 months following the 2022 earthquake peak at approximately 35 cm/yr (Figure 4.4). While InSAR is an incredibly useful technique for measuring surface changes, given its global coverage and regular acquisitions, the limitations of the method must be at the forefront when designing a study, measuring the signal, and finally interpreting the results.

4.5 Conclusions

In a northern California region densely populated by slow-moving landslides, two similar-magnitude earthquakes—20 December 2021 (Mw 6.2) and 20 December 2022 (Mw 6.4)—occurred one year apart in near-coincident locations. This unique situation provides a natural experiment to test concurrent drivers (precipitation and earthquake shaking) on landslide behavior. Our systematic region-wide workflow, utilizing ALOS-2 ScanSAR L-band time series collected every 14 days from July 2021 to March 2024, enabled the comprehensive quantification of slow-moving landslide kinematics across an area of roughly 300 by 400 kilometers. We compile 1,403 candidates from five prior studies plus 312 newly mapped features and extract high-quality time series for 437 landslides, with sites up to 150 km from the earthquake sources. A distinct subset of these landslides accelerated immediately after the December 20, 2022, earthquake. A piecewise model (linear pre-event, exponential post-event) effectively captured the triggered kinematics, including the initial acceleration and subsequent decay to 90% of the pre-event rates within 16 months. While the regional precipitation patterns were spatially uniform, the PGA was strongly heterogeneous across the region and between the two quakes. The spatial clustering of slides with greater accelerations within the region of peak PGA from the 2022 earthquake suggests that seismic forcing, rather than rainfall, was the primary driver of the accelerated movements following the 2022 earthquake. Differences in source mechanism and shaking distribution between the two earthquakes—especially the unilateral 2022 rupture—suggest that rupture directivity is a key contributor to the triggering of slow-moving slides. These results provide regional-scale observations of how slow-moving landslides respond to earthquakes and precipitation, providing empirical constraints for future hydro-mechanical and rate-and-state modeling of

landslide responses.

Chapter 5

Conclusions

This dissertation demonstrates the capability of L-band InSAR time series for imaging surface deformation across spatial scales. Through careful validation with independent observations in Chapter 2, we illuminate tectonic, volcanic, and hydrologic deformation at scales of hundreds of meters to hundreds of kilometers. This chapter presents, to our knowledge, the first 14-day time series from ALOS-2 ScanSAR data. Chapter 3 details the spatial and temporal distribution of fault creep along the Maacama and Rodgers Creek Faults, finding evidence for temporal variations from seasonal to multi-annual scales. These results resolve millimeter-scale deformation, with complementary observations corroborating the InSAR-derived measurements. Finally, Chapter 4 presents evidence of earthquake-triggered landslides derived from the careful extraction of time series for 437 individual landslides within a 300 km x 400 km region. This work exploits the large scene footprint and regular observations to determine population-scale responses to external forcings. These careful observations of the natural world can inform future modeling efforts and advance our understanding of the underlying mechanics and governing laws.

5.1 Limitations of the Dataset

While the ALOS-2 ScanSAR dataset has clear advantages over currently available C-band and X-band datasets, significant challenges still arise. These are explored in Chapter 2, with challenges stemming from (i) the irregular sampling between 2015 and 2021, limiting our capacity to resolve time-dependent deformation during this period, (ii) the implementation of ionosphere correction, which has limited performance in regions with low coherence and introduces broad-scale errors in our results, and (iii) the land cover of the study region remains challenging, despite retaining better spatial coherence compared with shorter wavelength platforms, decorrelation does exist and introduces noise scaled by the wavelength. For Chapter 3, which focuses on relative fault displacements at very localized scales, the ALOS-2 ScanSAR pixel size remains a limitation for resolving fault creep within the closest 200 m of the trace. The compounding effect of larger pixels and subsequent spatial filtering

smooths the deformation across the fault trace more so than sensors with higher spatial resolution (e.g., Sentinel-1). Our interpretation of earthquake-triggered slow-moving landslides in Chapter 4 was limited to the durations of high-frequency measurements, which meant we could not establish background rates of seasonal deformation before the earthquakes. Our results suggest that we are likely underestimating landslide deformation, as our observed rates do not approach the theoretical limit of deformation gradients. The lower rates indicate that, while we are sensitive to relative changes over time, we are likely not capturing the true ground displacements. The analysis in this dissertation not only highlights weaknesses and areas for improvement but also sets the stage for refining methodologies in L-band InSAR applications, ultimately enhancing our ability to quantify surface deformation.

5.2 New Observations and Future Research

Chapter 2 presents specific case studies of deformation across volcanic, hydrologic, and geomorphic deformation in California. Our observations of deformation at Medicine Lake Volcano confirm the continued subsidence within the Caldera, and the extended spatial coverage reveals a region of subsidence that spans between Medicine Lake and Mount Shasta Volcanoes. Although the subsidence of Medicine Lake Volcano is effectively modeled using a volumetric point source (Mogi model) (Parker et al., 2014), further investigation into the role of thermal contraction as a driving mechanism for volumetric changes and subsequent surface subsidence would enhance our understanding of the processes occurring beneath the edifice. The region of subsidence between Medicine Lake and Mount Shasta Volcanoes also warrants further investigation regarding the potential connectivity between the two structures.

The rapid subsidence event in the Sacramento Basin in 2022 underscores the importance of continuous monitoring of aquifer subsidence. The displacement time series shows that subsidence did not rebound in 2023, despite record precipitation, indicating a new lowstand with the basin experiencing non-recoverable compaction. Both the impact of deformation on the water-transporting infrastructure (i.e., cracks in canals resulting from rapid localized subsidence) and the long-term management of water resources (reducing losses) are essential motivations for this research. With the imminent increase in L-band SAR availability from the NISAR mission, near-real-time monitoring with higher spatial and temporal resolution will become possible at the aquifer scale.

Chapter 3 provides an update on long-term surface creep rates of the Rodgers Creek (3-4 mm/yr) and Maacama (4-8 mm/yr) Faults. We also present evidence of a creep event in 2002, which extended at least 20 km along the fault and to seismogenic depths, as well as seasonal modulation of surface creep. The exploration of the 2002 creep event emphasizes the importance of long-term, repeatable measurements, without which identifying long-term changes in rates over the seismic cycle is not possible. The discrepancies between the alignment array and the InSAR-derived seasonal modulation of surface creep indicate that further research is required to fully quantify these observations, with subsequent modeling of the near-surface structure to better understand surface modulation under changing climatic con-

ditions. The relationship between time-variant subsidence in the Geysers and surface creep also warrants further review; however, the noise level within the ALOS-2 ScanSAR time series dataset precludes this analysis.

In Chapter 3, we begin discussing the relationships between surface creep rates and the seismogenic depth. The Maacam Fault is uniquely suited for this exploration, with the high heat flow associated with the Geysers, which raises the seismogenic depth. Further to this, extending the analysis south to the Hayward Fault, where repeating earthquakes and previous InSAR have identified asperities that act similarly, decreasing the fault width over which creep can occur, allows another testing ground for this relationship. With the increased density of measurements possible in higher coherence urban areas, we can also explore the propagation of surface creep events and validate these against point measurements at alignment arrays and creep meters. The results detailed in Chapter 4 contribute to the growing body of research emphasizing the temporal variations in fault creep, which is crucial for understanding fault evolution and behavior throughout the seismic cycle.

In both Chapters 2 and 4, we present displacement time series for slow-moving landslides, illustrating what wide-swath L-band InSAR can now deliver: large-scale, high-fidelity monitoring of landslides across vegetated terrain that was previously geodetically challenging. We suggest that the 2022 M_w 6.4 Ferndale Earthquake triggered slow-moving landslide accelerations, within a coherent region coinciding with the rupture propagation direction. These landslides began to slide at approximately the same time as the earthquake and then decayed towards background rates, returning to 90% in 16 months. Open questions remain that are best addressed with rate-and-state modeling regarding the effect of rupture directivity and preconditioning on landslide triggering. Was it the more pulse-like shaking of the 2022 earthquake that triggered these landslides? How did the presence of microearthquakes and multiple moderate-magnitude events precondition the slides for subsequent drivers? These findings provide regional insights into the kinematic response of slow-moving landslides in relation to seismic activity and rainfall, offering empirical conditions for advancing models of landslide behavior.

The mapping and change detection monitoring of both linear infrastructure (aquifers, dams, roads) and geomorphic features (slow-moving landslide) is prime for the application of machine learning detection models for near-real-time alerting to mitigate risk and hazard. The large-scale time series analysis, as completed in Chapter 4, provides a high-quality training dataset for such endeavors. To fully utilize the global scale of NISAR L-band InSAR, automation must be implemented, and the results from such scaling allow for the exploration of forcings across various climate and geological conditions. With more observations of the failure of both creeping faults and landslides, we can better improve our understanding of the transitions from stable to catastrophic failure, as well as the nuances of tipping points and triggering conditions.

5.3 Final Remarks

With the increasing availability of L-band SAR, this dissertation provides timely contributions to our understanding of the limitations and primary noise sources within large-scale L-band InSAR analysis. We demonstrate the range of observations possible with the dataset and emphasize the expanded utility of L-band in the NISAR era for surface deformation monitoring. Our results contribute to our understanding of spatial and temporal variability in surface creep rates as well as earthquake-triggering of slow-moving landslides. Upcoming L-band missions, specifically NISAR—with shorter revisit times, finer pixels, and a dedicated frequency for ionospheric corrections—will further advance observational capabilities, enabling routine, high-resolution deformation monitoring worldwide.

Appendix A

Supplement for ‘Nine-Year L-band InSAR Time Series of Tectonic and Non-tectonic Surface Deformation in Northern California’

Contents of this file

1. GNSS Projection to LOS
2. Decomposition Methods
3. Figure S1: Ionosphere correction examples
4. Figure S2: Decomposition Realizations
5. Figure S3: Internal Validation for 2015-2021
6. Figure S4: Mount Shasta landslide time series

GNSS Projection We project GNSS east (V_e), north (V_n), and up (V_u) components into the LOS vector for each track using the corresponding pixel incidence (θ_{inc}) and azimuth angles (θ_{az} , measured from the east with anti-clockwise direction as positive). Finally, we reference the GNSS solutions to the InSAR reference location by subtracting the LOS velocity at the reference station from all others.

$$GNSS_{LOS} = V_e \sin(\theta_{inc}) \sin(\theta_{az})(-1) + V_n \sin(\theta_{inc}) \cos(\theta_{az}) + V_u \cos(\theta_{inc}) \quad (\text{A.1})$$

With error propagation:

$$\sigma_{LOS} = \sqrt{(\sin(\theta_{inc}) \sin(\theta_{az}))^2 \sigma_{V_e}^2 + (\sin(\theta_{inc}) \cos(\theta_{az}))^2 \sigma_{V_n}^2 + (\cos(\theta_{inc}))^2 \sigma_{V_u}^2} \quad (\text{A.2})$$

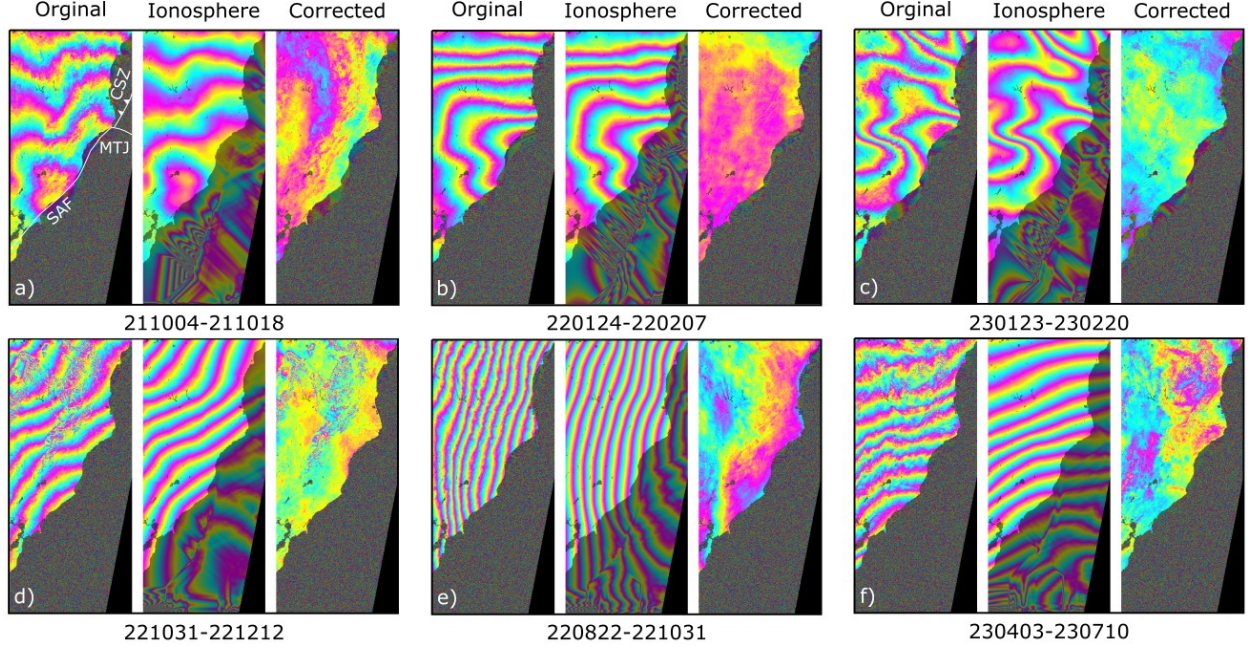


Figure A.1: Uncorrected, estimated ionospheric correction, and corrected interferograms for six examples on track 170, displayed in radar coordinates. (a-c) show examples that a linear or quadratic ramp cannot well approximate, and (d-f) have high ionospheric gradients. In (a), the approximate location of the plate boundary is shown. In (e), the gradient runs nearly parallel to the coastline, leading to reduced correction performance. The residual signal in the corrected interferogram in (f) includes a large storm event that caused widespread flooding across northern California on April 3rd, 2023. Erroneous ionospheric estimations frequently occur along both the northern coastline and the San Francisco Peninsula due to low coherence and limited land areas.

Decomposition methods

1) Semi-vertical. We interpolate the GNSS horizontal velocities, project to the LOS, and subtract their projected contributions from the InSAR LOS velocity in ascending and descending. Specifically, the GNSS LOS velocity $v_{gnss,LOS}$ is computed using the relation

$$v_{gnss,LOS} = -v_{gnss,east} \sin(\phi) \sin(\theta) + v_{gnss,north} \sin(\phi) \cos(\theta), \quad (\text{A.3})$$

where $v_{gnss,east}$ and $v_{gnss,north}$ denote the east and north velocity components where ϕ and θ are the incidence and azimuth angles, respectively. The projection is completed for ascending and descending and subtracted from the corresponding observation geometry. The resulting velocity field captures vertical motion and short-wavelength deformation features that GNSS measurements may not resolve, such as creeping faults and slow-moving landslides. This method is effective when only one observation orientation from InSAR is available, and a sufficiently dense GNSS network allows the interpolation of the horizontal velocity field.

2) InSAR-only inversion. We utilize two observation orientations to decompose a horizontal and vertical component using least-squares inversion. We define the horizontal component in the east direction, assuming that the northward contribution to the LOS velocity is negligible. We perform a least-squares inversion to estimate the eastward v_E and vertical v_U displacement components from the ascending v_{asc} and descending v_{des} line-of-sight (LOS) measurements using the following system:

$$\begin{bmatrix} -\sin(\theta_{asc}) \sin(\phi_{asc}) & \cos(\phi_{asc}) \\ -\sin(\theta_{des}) \sin(\phi_{des}) & \cos(\phi_{des}) \end{bmatrix} \begin{bmatrix} v_E \\ v_U \end{bmatrix} = \begin{bmatrix} v_{asc} \\ v_{des} \end{bmatrix}, \quad (\text{A.4})$$

where θ_{asc} and θ_{des} are the ascending and descending azimuth angles, and ϕ_{asc} and ϕ_{des} are the corresponding incidence angles. The least-squares solution to this system is given by

$$\begin{bmatrix} v_E \\ v_U \end{bmatrix} = (\mathbf{G}^T \mathbf{G})^{-1} \mathbf{G}^T \begin{bmatrix} v_{asc} \\ v_{des} \end{bmatrix}, \quad (\text{A.5})$$

where $\mathbf{G}$ denotes the design matrix defined above. This method is valid when one component of horizontal deformation is near zero; here, we assume this to be in the north direction.

3) GNSS-InSAR joint inversion. We perform a least-squares inversion to solve for the velocity field’s east v_E , north v_N , and up v_U components using interpolated GNSS east $v_{gnss,east}$ and north $v_{gnss,north}$ velocities, along with ascending v_{asc} and descending v_{des} observations, using the following system:

$$\begin{bmatrix} -\sin(\theta_{asc}) \sin(\phi_{asc}) & \cos(\theta_{asc}) \sin(\phi_{asc}) & \cos(\phi_{asc}) \\ -\sin(\theta_{des}) \sin(\phi_{des}) & \cos(\theta_{des}) \sin(\phi_{des}) & \cos(\phi_{des}) \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} v_E \\ v_N \\ v_U \end{bmatrix} = \begin{bmatrix} v_{asc} \\ v_{des} \\ v_{gnss,east} \\ v_{gnss,north} \end{bmatrix}, \quad (\text{A.6})$$

where θ_{asc} and θ_{des} denote the ascending and descending azimuth angles, and ϕ_{asc} and ϕ_{des} are the corresponding incidence angles. The least-squares solution to this system is given by

$$\begin{bmatrix} v_E \\ v_N \\ v_U \end{bmatrix} = (\mathbf{G}^T \mathbf{G})^{-1} \mathbf{G}^T \begin{bmatrix} v_{asc} \\ v_{des} \\ v_{gnss,east} \\ v_{gnss,north} \end{bmatrix}, \quad (\text{A.7})$$

where $\mathbf{G}$ denotes the design matrix defined above. The resulting horizontal deformation fields are similarly smooth as the input GNSS data, with some shorter wavelength features, such as slow-moving landslides. The vertical component is constrained entirely by the input InSAR velocity fields.

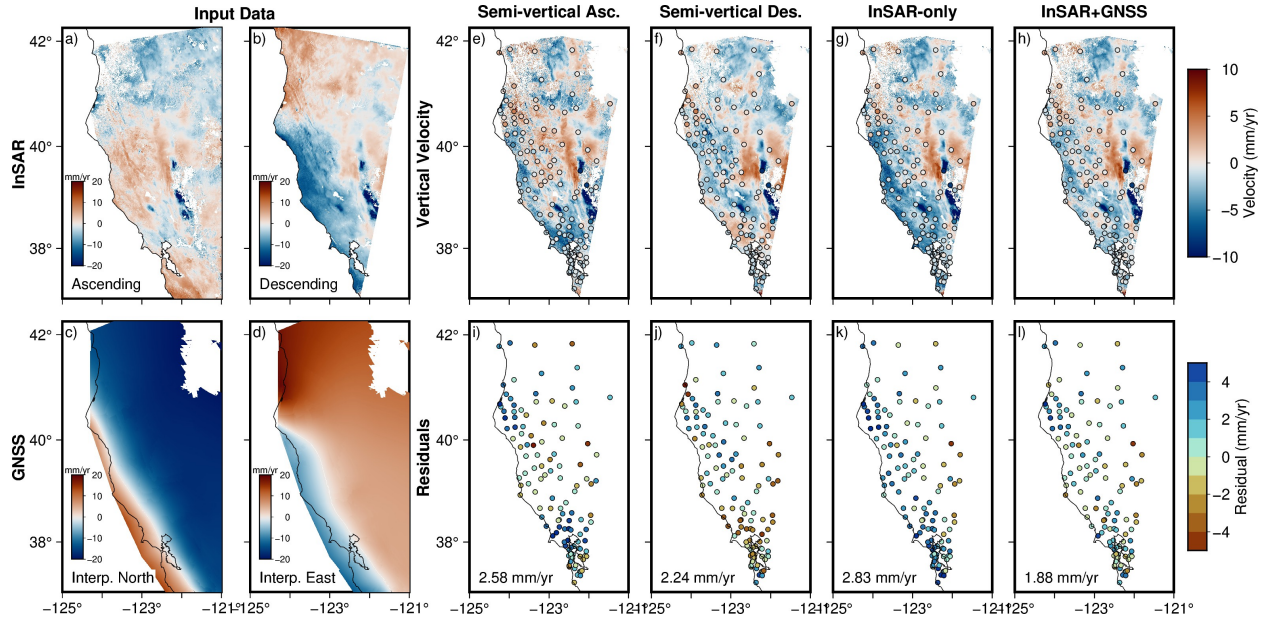


Figure A.2: Comparison of vertical velocity realization. (a-d) Input InSAR and GNSS data, (e-h) results from different decomposition methods, and (i-l) residuals between vertical velocity fields and GNSS. Positive residuals mean that the GNSS velocity (observed) is larger than the InSAR velocity (predicted). Note a) and b) are the same as Figure 3 subplots g), n), and u).

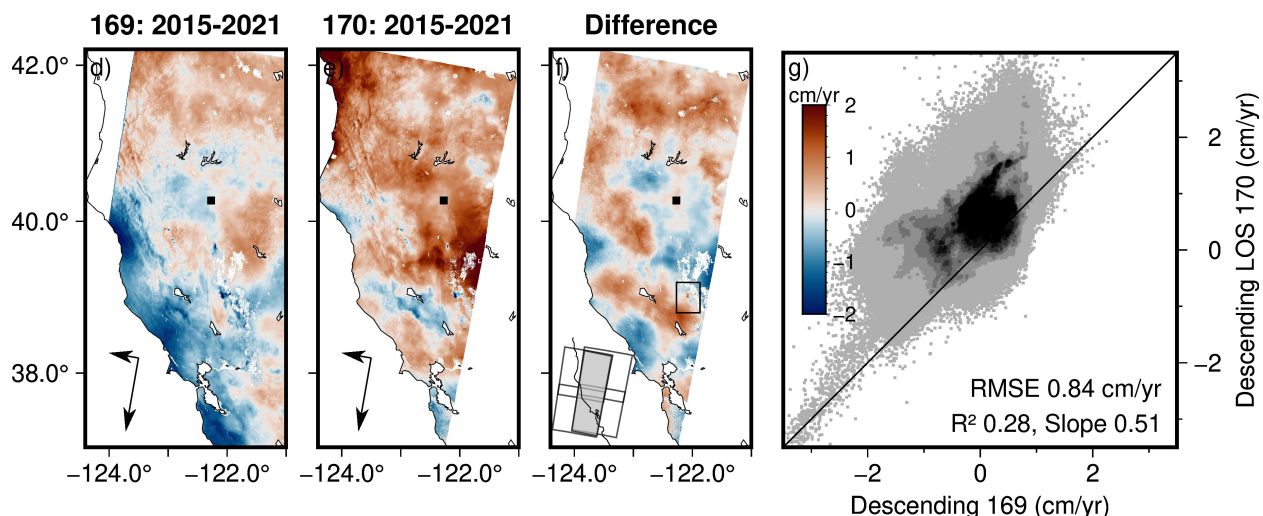


Figure A.3: For the same time period. 2015 - 2021. (d-g) Comparison of overlapping descending tracks for 169 and 170. The velocity field of track 169 spans 2015–2021, while 170 spans 2015–2024. Central Valley aquifers experienced accelerated subsidence in 2021 and 2022, which is not captured by track 169. Long-wavelength noise in f) is attributed to errors in the ionosphere or troposphere corrections.

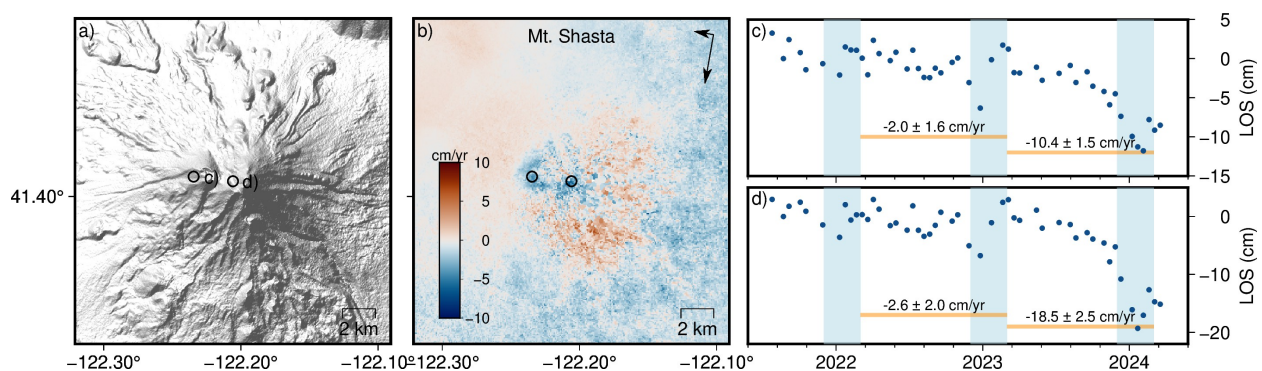


Figure A.4: (a) DEM for Mt. Shasta with time series locations labels, (b) Line-of-sight (LOS) velocities from track 170, for March 2021 to July 2024, and (c,d) LOS displacement time series with annual displacement rates on Shastina (c) and Mt. Shasta (d).

Appendix B

Supplement for ‘Spatiotemporal Creep Distribution on the Rodgers Creek and Maacama Faults’

Contents of this file

1. Cross section of seismicity and CREs on multi-strand Maacama Fault.
2. Cumulative displacement for all InSAR tracks.
3. Contraction signal across The Geysers geothermal field.

Because the MA fault comprises many active strands, differences between geological, surface, and geodetic rates can be partially reconciled by recognizing that each method samples different apertures of the fault zone. Within the restraining bend at Ukiah (Melosh et al., 2024), modeled three active fault splays – Ukiah Valley Fault, the Cow Mountain-Mill Creek Fault, and the Willow Creep Fault – as all host CREs they are candidates for hosting some portion of creep and therefore in this region strain could be distributed across these structures. The presence of seismicity, CREs, and swarms on the eastern strand of the MA (or Little Lake Valley Fault) and the clear surface creep expression of the western strand of the MA fault indicate both structures are active, and there strain may also be distributed in this region too (Pampeyan et al., 1980; Shelly et al., 2023; McFarland et al., 2017). Along the eastern strand both our CRE catalog and that of (Shakibay Senobari & Funning, 2019), do not reach the surface and InSAR does not indicate surface creep, leading to the conclusion that the shallowest portion of the eastern strand maybe frictionally locked. The absence of repeating earthquakes on the western strand does not imply that the fault is not creeping, we know from geodetic inversion it is being loaded at a slower rate so expect longer inter-event intervals and smaller magnitudes. With the lower station density around the northern Maacama Fault compared with the Hayward fault, the magnitude of completeness is likely higher compared so our results are less likely to be sensitive to small changes in creep rates.

Creep partition has been well documented between the Hayward and Calaveras Faults (e.g., Y. Li et al., 2023), and may be present between the RC and MA faults and within step-over structures along the MA fault. Over the 40 km of overlap between the RC and MA faults, surface creep diminishes along the Healdsburg fault segment at the northern RC and initiates along the MA fault.

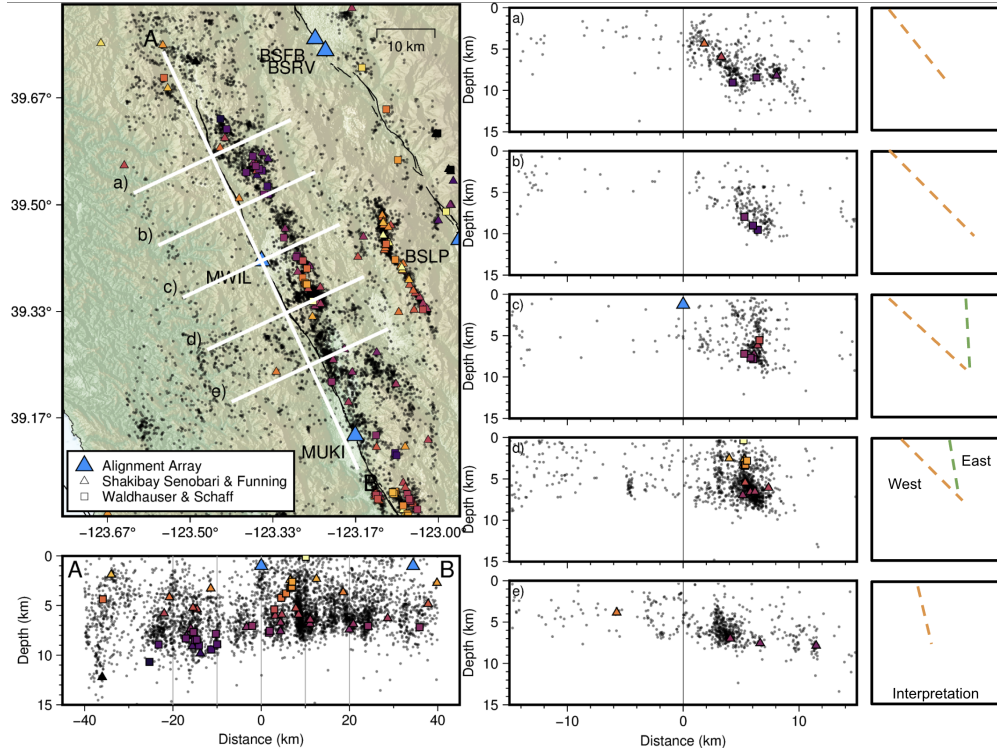


Figure B.1: Cross Sections through seismicity and repeating earthquakes to highlight the complexity of the structure in the region. CRE catalog from this study (circles), (Shakibay Senobari & Funning, 2019) (triangles) and (Waldhauser & Schaff, 2021) (squares). Blue triangle denotes the location of the MWIL alignment array, which measures 5 mm/yr surface creep. Profile (a) highlights the dip of the northern sections of the Maacama Fault; this lineation disappears further south. Profile (c) shows offset in the location of surface creep on the western strand and seismicity and repeating earthquakes on the western strand. Profile (d) includes the most shallow repeating events in the catalog from the 2020 swarm documented by (Shelly et al., 2023). The profile from A-B, parallel to the fault, again presents the shallowing of seismicity and CREs southward.

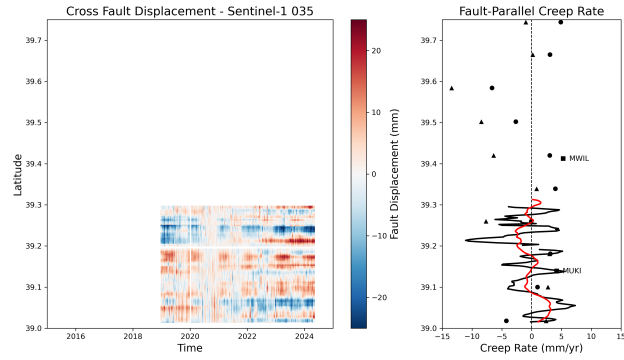


Figure B.2: North Maacama Fault, Sentinel-1 track 035

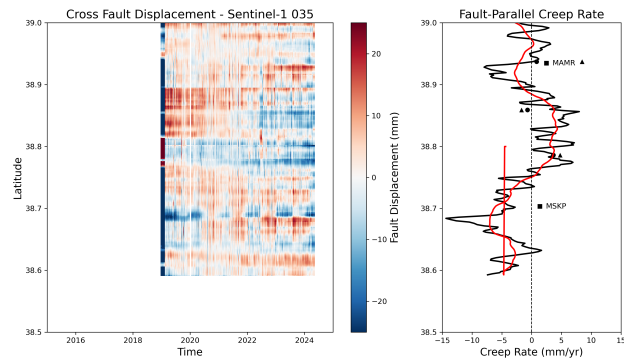


Figure B.3: South Maacama Fault, Sentinel-1 track 035

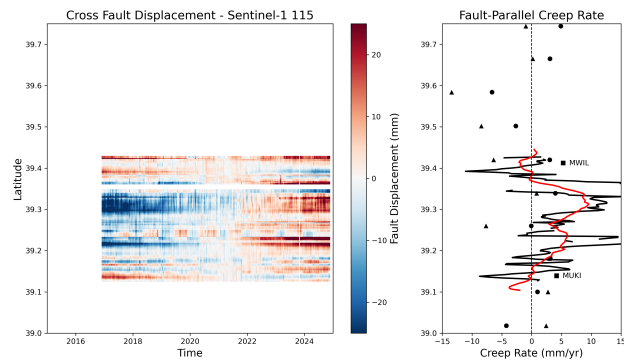


Figure B.4: North Maacama Fault, Sentinel-1 track 115

APPENDIX B. SUPPLEMENT FOR ‘SPATIOTEMPORAL CREEP DISTRIBUTION92

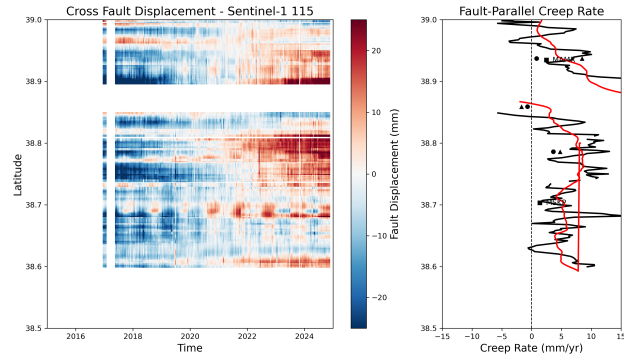


Figure B.5: South Maacama Fault, Sentinel-1 track 115

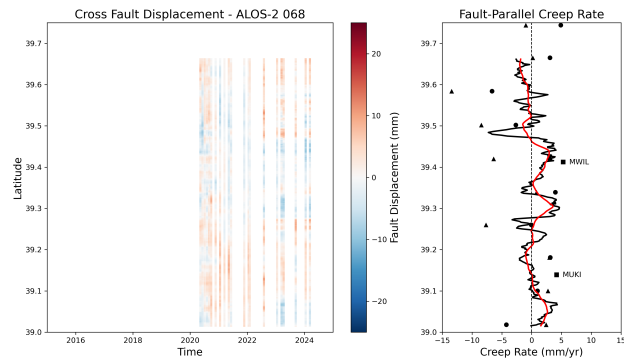


Figure B.6: North Maacama Fault, ALOS-2 track 068

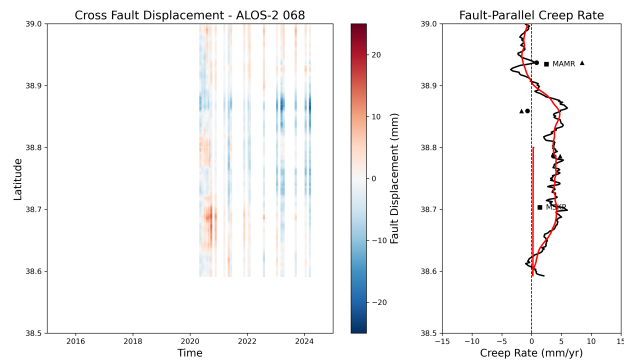


Figure B.7: South Maacama Fault, ALOS-2 track 068

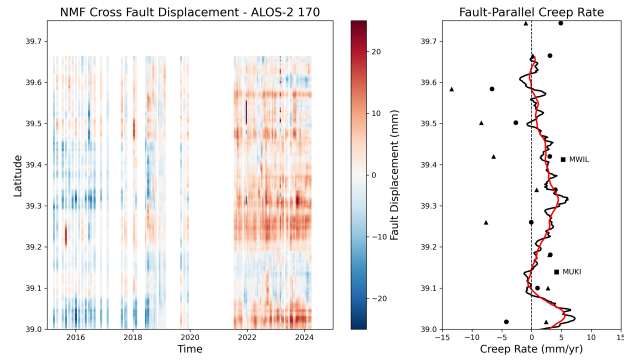


Figure B.8: North Maacama Fault, ALOS-2 track 170

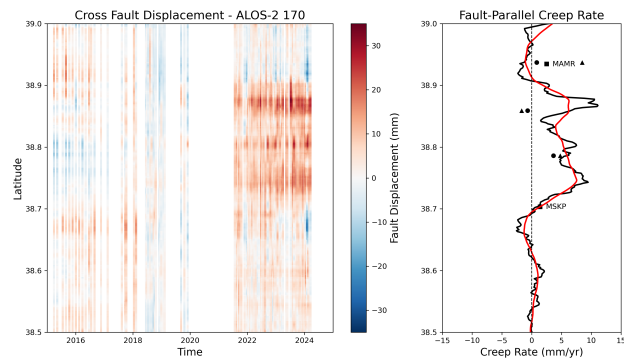


Figure B.9: South Maacama Fault, ALOS-2 track 170

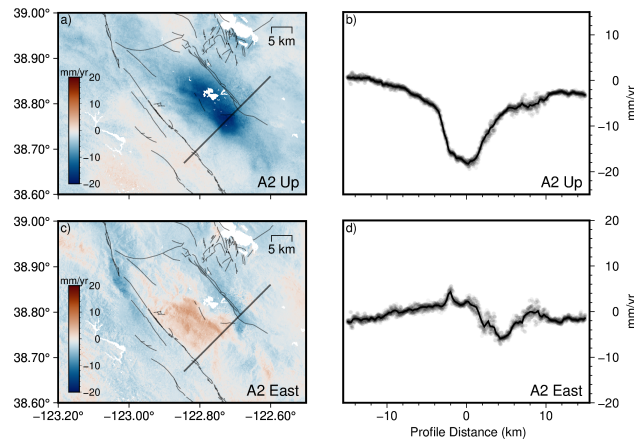


Figure B.10: (a) Vertical and (c) east velocities for The Geysers geothermal field from ALOS-2 ScanSAR velocity field for the period 2015 to 2024. Corresponding velocity profiles (b,d) highlight the constriction signal across the most rapidly subsiding regions of the Geysers geothermal field.

Appendix C

Supplement for ‘Triggering of Slow-Moving Landslides in Northern California: Insights from L-band InSAR Time Series Analysis of the 2022 Ferndale Earthquake’

Contents of this file

1. Additional Inventory Characterization
2. Velocity Ratio Statistics
3. Kinematic Grouping Statistics

Additional Inventory Characterization

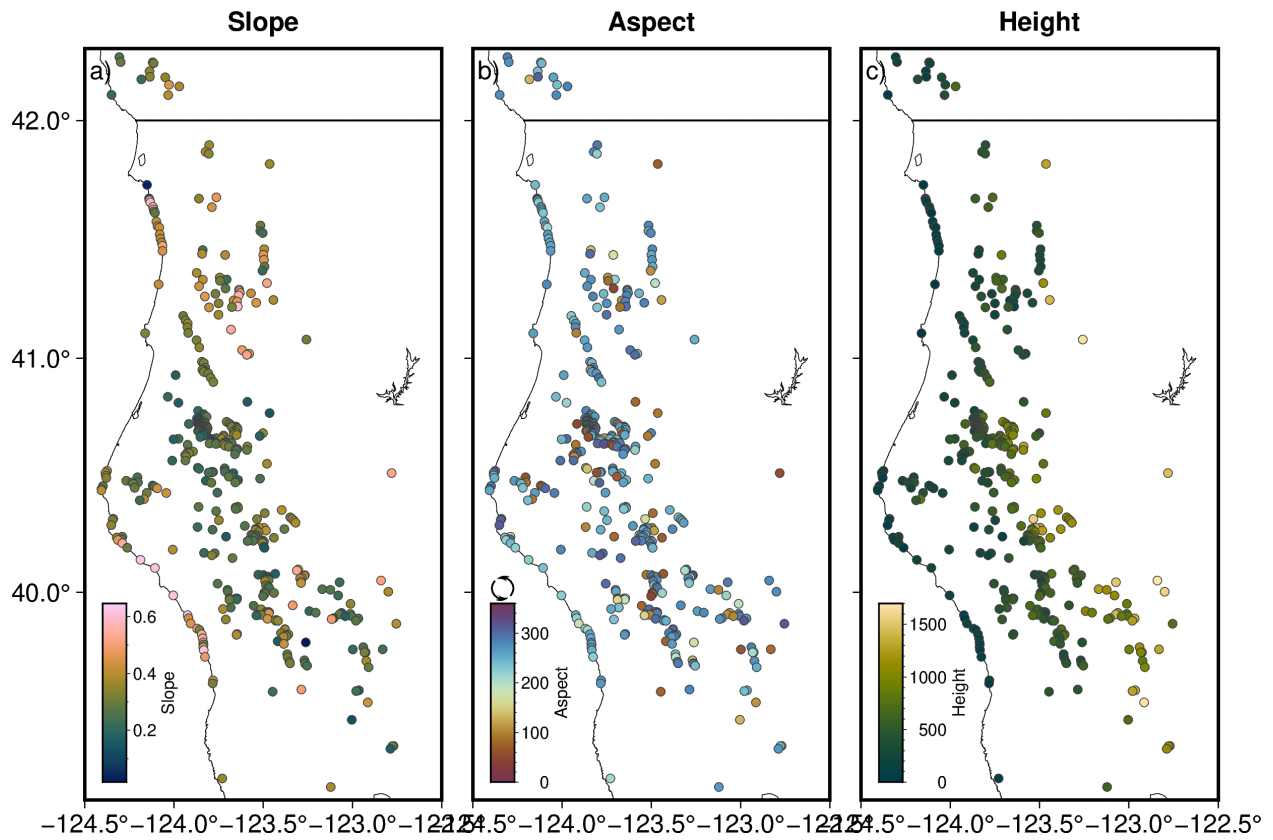


Figure C.1: Map of aspect, slope, height of landslides for time series analysis.

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(n.d.).

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