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Spatiotemporal Patterns of Seasonality in Landslide Deformation from InSAR and GPS

By

Julien Francois Cohen-Waeber

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

Doctor of Philosophy

in

Engineering – Civil and Environmental Engineering

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Nicholas Sitar, Co-Chair
Professor Roland Bürgmann, Co-Chair
Professor Jonathan D. Bray
Professor William E. Dietrich

Spring 2018

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Abstract

Spatiotemporal Patterns of Seasonality in Landslide Deformation from InSAR and GPS

by

Julien Francois Cohen-Waeber

Doctor of Philosophy in Engineering – Civil and Environmental Engineering

University of California, Berkeley

Professor Nicholas Sitar, Co-Chair
Professor Roland Bürgmann, Co-Chair

High-resolution characterization of landslide deformation and its spatiotemporal response to external triggering mechanisms is a first step toward improved hazard forecasting. Slope instability in the San Francisco East Bay Hills (EBH), including the Lawrence Berkeley National Laboratory (LBL), has been a prevalent problem since development of the area began. The EBH are home to a number of very slowly moving (~ 20 mm/yr), earth and rock flow-type landslide complexes whose activity has been shown to vary spatiotemporally in response to seasonal precipitation and seismic activity. Advanced technologies such as Interferometric Synthetic Aperture Radar (InSAR) and continuous Global Positioning Systems (cGPS) are well suited for monitoring these types of processes, as they allow for remote detection and characterization of ground surface displacements with sub-centimeter precision and accuracy. Relying on InSAR and cGPS, two time histories of ground deformation with exceptionally high spatial and temporal resolution are produced for the EBH. The spatiotemporal patterns of variability in each of these signals are identified and related to different ground deformation mechanisms.

After careful evaluation of nearly 50 inventoried landslide deposits, a network of 6 autonomous cGPS landslide monitoring stations was instrumented across four select sites. Established in 2012, the network is set to continue monitoring ground deformation at high rates (1Hz and 20Hz) through the foreseeable future. The methodology for this field instrumentation effort is described and the resulting time series are examined. The data reveals seasonally modulated shrink/swelling cycles of the surficial soils and downslope velocities indicative of landslide deformation.

Relying on TerraSAR-X satellite images (2009-2014) and an improved data processing algorithm (SqueeSARTM), InSAR time series analysis produces a record of ground deformation over the same study area, with exceptionally dense spatial coverage. Through the use of functional curve fitting, and Principal and Independent Component Analyses the data reveals four distinct spatial and temporal surface deformation patterns which relate to different geo-mechanical processes. Two components of time-dependent landslide deformation isolate continuous motion and motion driven by precipitation-modulated pore-pressure changes controlled by annual seasonal cycles and multi-year drought conditions. Two components capturing more widespread seasonal deformation separate precipitation-modulated soil swelling from annual cycles that may be related to groundwater level changes and thermal expansion of buildings.

*To my family:
Your support and encouragement made this endeavor possible.
I am grateful beyond measure.*

*Nothing is simple
Nothing is what it seems to be
Nothing stays the same
In the fullness of time...
-Edmund W. Medley*

Acknowledgements

If there is one thing that has truly marked me about the University of California at Berkeley, it is the incredible caliber of its faculty, staff, students and alumni. During my undergraduate studies at UCLA, I took a special interest in geoengineering in large part because of Prof. Jonathan Stuart (Cal PhD) who remains to this day one of my favorite professors. When I started as a staff geologist, Dr. Leonard Evans Jr. (Cal PhD) taught me everything he knew in a soils laboratory. He was my first Mentor. After my Masters degree (at Cal), my first supervisor Dr. Edmund Medley (Cal PhD) took me on wild geological engineering adventures and soon became my mentor. Of course, the list doesn't stop there and it is no wonder I've ended up where I am today.

Today, I am again humbled by the quality of my Berkeley entourage, "la mafia" so to speak. I am forever grateful to my advisors Prof. Roland Bürgamnn and Prof. Nicholas Sitar, who patiently gave me the freedom and support to make this experience truly unique. I am also honored by the rest of the Berkeley Geosystems and Earth and Planetary Science faculty and staff. The caliber of experience and education you have brought me, makes "Phinishing" bittersweet. I am especially thankful to those faculty with whom I've had the extreme pleasure to work with both in the classroom and lab: Prof. William E. Dietrich, Prof. Jonathan D. Bray, Prof. Michael Riemer, Prof. Steven Glaser, Prof. Raymond B. Seed and Dr. Paul Henshaw. Of the Civil Engineering Staff, Shelley Okimoto and Joan Chamberlain, I can't possibly thank you enough for all of your help.

As Dr. Medley might point out, "It's all about the money!" Indeed, my work would not have been possible without generous financial support. I gratefully acknowledge the financial support from the Lawrence Berkeley National Laboratory, Earth Science Division Director's Fund, the National Aeronautics and Space Administration (NASA) through grant NNX12AQ32G, and the Civil and Environmental Engineering department and Cahill Chair at the University of California Berkeley. Equally valuable were the data contributions to my work. TerraSAR-X data were provided through a user license by the German Space Agency (DLR). cGPS data for this study come from the Bay Area Regional Deformation Network (BARD), doi:10.7932/BARD, operated by the UC Berkeley Seismological Laboratory, which is archived at the Northern California Earthquake Data Center (NCEDC), doi: 10.7932/NCEDC. Additional waveform data, metadata, or data products for this study were accessed through the Northern California Earthquake Data Center (NCEDC), doi:10.7932/NCEDC. Precipitation data for this study was provided by the Lawrence Berkeley National Laboratory (LBL) by personal communication from Patrick Thorson. In the Berkeley earth Science department, I owe so much to Prof. Estelle Chaussard, Prof. Manoochehr Shirzaei, Dr. Mong-Han Huang, Dr. Ingrid Johanson and Dr. Mario Aranha, who all made significant contributions to my work.

On a more personal note, I want to recognize my Civil Engineering cohort who I am honored to call my friends. Your friendship, support and collaboration over the years has made this experience worth every moment. When you've been involved with the university as long as I have, the list of people you are grateful for becomes a bit unmanageable, but a number of people stand out. In no particular order: Dr. Robert Lanzafame, Dr. Diego Cobos-Roa, Dr. Matthew Over, Dr. Mike George, Dr. Roozbeh Mikola, Michael Gardner, Dr. Josh Zupan, Dr. Justin Hollenback, Dr. Joseph Weber, Dr. Tonguc Deger, Dr. Hamed Hamedifar, Dr. Juan Perri, Dr. Nathaniel Wagner, Dr. Roberto Luque, Dr. Chukwuebuka Nweke, Dr. Gabriel Candia, Maggie Parks. I am so grateful to have you in my life and I look forward to many more years of your friendship.

There are a very few who's love and support I cherish more than anything. Dr. Edmund Medley, without your encouragement, advice, honesty and friendship, I really would not be here today.

Your mantras strike a special note in my heart. Pascal Palancade, Carolina Alvarado-Palancade, Guillaume Fornerod and Lalaina Rideout, I consider you family. Dawn O'Brien, PhDs are known to destroy relationships, we met at my worst and you stuck around. That means the world to me. To my extended family, you've always been my biggest supporters, I cannot describe how grateful and honored I am to have you in my life.

Most overall, I am grateful to my sister Jane Cohen-Waeber and my parents Deborah Cohen and Alain Waeber. Simply put, you are my best friends.

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Chapter 1. Introduction

1.1 Overview

In an ever-expanding urban environment, we opt to live with the risk of catastrophic natural hazards (e.g. earthquakes, flooding, landslides), through a perceived safety net of building codes and engineering solutions. Unfortunately, our concern for these hazards is often focused on their immediate impact to our every-day lives and does not account for imperceptible processes that may become significant over decades in time. Notoriously, some landslides slowly and continuously deform, ultimately causing costly unpredicted damage to homes, lifelines and other infrastructure. Recent advances in satellite technology allow accurate measurement of these long-term movements, tracking where and when they occur.

Beyond the scientific interest in characterizing these small deformations, there is also a considerable need to develop the use of new remote sensing capabilities in the Geo-Science and Engineering fields as a whole. Where traditional field investigations fall short of capturing the complete spatiotemporal behavior of geologic processes both large and small, remote sensing technologies thrive. Advanced technologies such as Interferometric Synthetic Aperture Radar (InSAR) and continuous or real time Global Positioning Systems (GPS) are the exact type of improvements these fields require, and in order to justify their expense they must be vetted. Hence, the objective of this research to monitor and characterize the spatiotemporal patterns of small seasonally modulated landslide deformation from InSAR and GPS.

The San Francisco East Bay Hills (EBH) offers an ideal setting for this research. Slope instability in the EBH, including the Lawrence Berkeley National Laboratory (LBL), has been a prevalent problem since development of the area began. In particular, the EBH are home to a number of very slowly moving (~ 20 mm/yr), earth and rock flow-type landslide complexes whose

activity has been shown to vary spatiotemporally in response to seasonal precipitation and seismic activity (Hilley et al., 2004; Kropp & Lettis, 2002; Quigley et al., 2010). Persistent landslide activity has also led to significant geologic field investigation efforts, through which the local geologic setting has been well characterized. Thus, drawing on extensive site knowledge, careful InSAR observation and continuous GPS (cGPS) monitoring programs were developed to study seasonal ground deformation patterns. Through different signal processing methods, the collected data sets reveal four independent components of ground motion and their spatiotemporal relationship with seasonal precipitation.

1.2 Objectives

The development of this research project was largely experimentally based and reliant on the extensive collection and analysis of remote sensing data sets. The intent being to develop concrete observations of otherwise theoretical assumptions on the mechanisms of landslides. It aims to improve the fundamental understanding of seasonally modulated deformation of very slow moving earthflow type failures, through advanced sensing technology. This research generally focuses on the following key objectives:

- Establish a landslide monitoring network of autonomous near-real time high-rate cGPS stations to monitor landslide creep behavior.
- Perform an extensive InSAR time series analysis applying new algorithms for higher resolution data to explore the spatiotemporal intricacies of landslide deformation.
- Identify dominant modes of deformation processes through signal processing methods.
- Compare the InSAR and cGPS monitoring results.

1.3 Outline

The location of the study area in a heterogeneous regional geologic setting, required careful background and geologic research in order to focus the field instrumentation and remote sensing portions of the project to a limited number of relatively well understood and active landslides. The majority of the most relevant reports on previous investigations were made available by the Lawrence Berkeley National Laboratory and local engineering consultants, in particular Alan Kropp and Associates and A3GEO. The details of the geologic setting are presented in Chapter 2, followed by a more detailed description of the landslides included in this research. In addition, the landslides triggering mechanisms that were considered in order to form a context for the ground deformation measurements are reviewed as well.

The core analysis in this work was aimed at identifying different seasonal and long-term transient spatiotemporal patterns of ground surface deformation using SAR and GPS time series analyses through different signal processing methods. In most cases, field observations of landslide displacement throughout the study area include an accurate record of the landslide deposits and their average velocities at the ground surface, occasional measurements and estimates of deformation profiles with depth, and marginal groundwater profiles. To compare those available field observations with the spatiotemporal trends isolated in the remote sensing data, downslope velocities, average depths of sliding and precipitation driven transient pore pressure profiles were estimated from first order models. Chapter 3, provides a description of the data and signal

processing methods used to identify and extract the spatiotemporal patterns of ground deformation recorded in the InSAR and GPS time series. Then, the first order models are used to reconcile the remotely sensed trends with geomorphic processes and actual field observations

Chapter 4 encompasses the application and results from the signal processing methods applied to the InSAR displacement time series. The controls of observed time-dependent landslide deformation were investigated through a combination of signal processing methods. Using functional curve fitting (FCF) and principal component analyses (PCA), four modes of temporal and spatial variability were identified in the observed surface ground motions, which are tied to annual and multi-year precipitation cycles. Independent Component Analysis (ICA) allowed optimal separation of the four spatiotemporal patterns and their contributions to the original signal. The utility of these methods is evaluated by relating the observed patterns of ground motion to the underlying driving mechanisms of slope displacement, specifically isolating precipitation-correlated landslide deformation that is directly linked to time dependent pore-pressure changes. Finally, the applicability of these methods to the most active and well documented landslide in the study area, the Blakemont landslide (BLS), is addressed and related to observations at the remaining landslides in the study area.

Though Global Positioning Systems (GPS) seems to have become common place, it is not used for a fraction of its capabilities. At the time that this research effort was undertaken, satellite GPS technology had already reached a degree of accuracy in the measurement of ground surface processes that matches highest quality terrestrial surveying methods. In particular, the technology lends itself to the application of real-time monitoring systems, and specifically for hazard prediction. With the intent to evaluate landslide hazard through an extensive monitoring program, an automated and autonomous, near-real time continuously streaming GPS monitoring network was established on existing landslides throughout the study area. Special attention was given to the Lawrence Berkeley National Laboratory (LBL) campus, which has been afflicted by a long history of landslide activity and stands at great risk with the development of its state-of-the-art facilities. Chapter 5 provides an overview of the experimental model and methodology applied to developing this landslide monitoring network. It summarizes over five years of monitoring results, and discusses the advantages and shortcomings of the process in terms of efficacy of monitoring small landslide deformation over time, as well as its applicability in combination with InSAR.

In conclusion, the results of each of the monitoring methodologies are summarized and revisited in terms of the general the general research objectives. These include a discussion of the advantages and disadvantages of InSAR and cGPS monitoring specifically in terms of capturing small deformations and the ability to isolate the different signal modes observed. Finally, based on the results and experience gained in this research thoughts on potential areas of future work are presented.

Chapter 2. Site Characterization and Data

The location of the study area in heterogeneous a regional geologic setting, required careful background and geologic research in order to focus the field instrumentation and remote sensing portions of the project to a limited number of relatively well understood and active landslides. The majority of the most relevant reports on previous investigations were made available by the Lawrence Berkeley National Laboratory and local engineering consultants, in particular Alan Kropp and Associates and A3GEO. The details of the geologic setting are presented in Chapter 2, followed by a more detailed description of the landslides included in this research. In addition, the landslides triggering mechanisms that were considered in order to form a context for the ground deformation measurements are reviewed as well.

2.1 Geologic Setting

The study area for this project is located along the western flank of the San Francisco East Bay Hills (EBH), California. The regional geologic setting is the product of an approximately 360 million year old accretionary process during which the North American plate margin transitioned from subduction (Japanese and Andean Type plate margin) of the Farallon Plate to a transform boundary (California Type margin) against the Pacific Plate (Dickinson, 1981). Known as the San Andreas Fault system, tectonic activity along the plate margin presently accommodates approximately 38 mm/year of right-lateral relative displacement (Argus & Gordon, 2001; d'Alessio et al., 2005), with continued uplift of approximately 1-2 mm/year (R Bürgmann et al., 2006; Gilmore, 1993).

Hence, several orogenies and accreted terranes are responsible for what is now a northwest trending and low lying mountain range. As illustrated in Figure 2-1, the EBH are an uplifted block of Jurassic to Tertiary sedimentary, volcanic, and metamorphic rocks, folded in a synclinal form during regional transpression (David L. Jones et al., 1994) related to the active plate margin, beginning 1-2 million years ago (Russell W. Graymer, 2000). The area is particularly renowned for its Franciscan Complex Mélange, a regional scale jumble that makes up about one third of the

bedrock in the central and northern Coast Ranges of northern California (Bailey et al., 1964; McLaughlin et al., 1982). Now largely overlain by Quaternary colluvial and alluvial deposits, this highly fractured, intensely weathered, moderately soft rock is prone to landsliding (Beatty, 1956; David L Jones & Curtis, 1991).

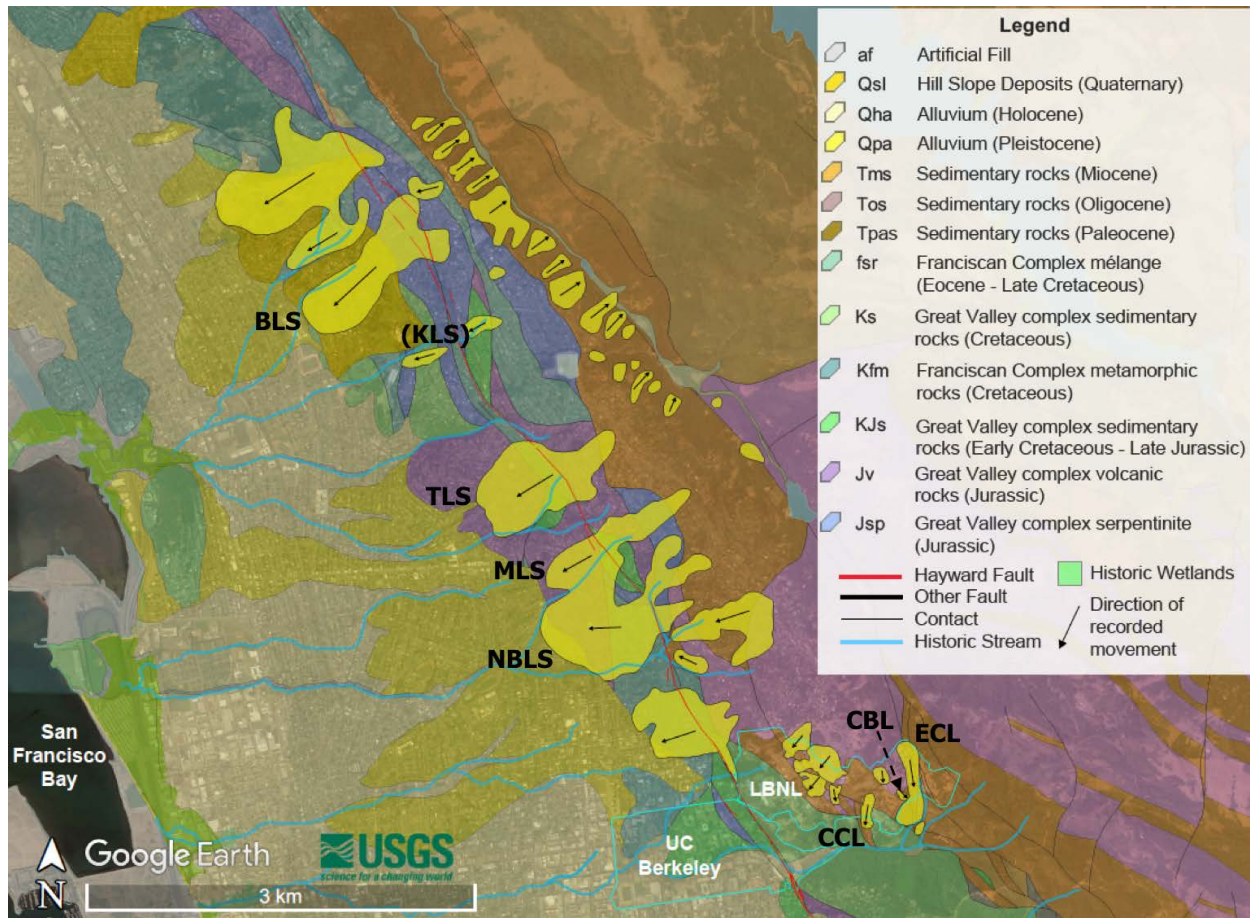


Figure 2-1. Geologic map of the San Francisco Bay region (R. W. Graymer et al., 2006), updated with relevant geomorphic features, including mapped significant landslide deposits (Kropp, 1995; Kropp & Lettis, 2006).

In addition to providing the geologic setting of our study area and the relevant geologic formations throughout, Figure 2-1 presents an inventory of all local landslides relevant to this study, with their sense of motion. The map also depicts the Hayward Fault (HF), a significant source of local seismic activity, which plays an active role in the mechanics of the larger landslides in our study area. A general description of the relevant geologic formations is presented in Table 2-1.

Table 2-1. Stratigraphic summary of relevant geologic formation in the study area.

Period	Name	Age	Type	Description
<i>Quat.</i>	Deposits	Holocene (11Ka)	Colluvial Alluvial	Chaotic deposits of source rock, overlain by colluvial sediment. Generally unconsolidated material with varying sized blocks in fine grained matrix.
	Moraga	L. Miocene (~9-10.2 Ma)	Volcanic	Terrestrial Basalt flows (10) and one Rhyo-Dacite Tuff.
<i>Tertiary</i>	Orinda Fm.	L. Miocene (~9.5-13 Ma)	Sedimentary	Non-Marine Pebble conglomerate, sandstone and mudstone, containing rounded Franciscan Complex clasts.
	San Pablo Grp.	M. Miocene (~10-20 Ma)	Sedimentary	Marine Claystone, siltstone and fine sandstone.
	Claremont Fm.	M. Miocene (~13-16Ma)	Sedimentary	Silicious shale and chert interbeds.
<i>Mesozoic</i>	Great Valley Grp.	M. Jurassic to L. Cretaceous (~66-175 Ma)	Sedimentary	Arc-related accreted and deformed Jurassic oceanic crust overlain by turbidites (marine shales and sandstones with interbedded claystones).
	Franciscan Complex	M. Jurassic to Paleocene (~60-175 Ma)	Metamorphic Volcanic Sedimentary	Intermixed Mélange, basalt, serpentinite, sandstone and shale.

2.2 Landslide Activity

The objective being to gain insight into the spatial and temporal seasonal behavior of landslides, the first task was to identify sites that would be most promising candidates for the application of Interferometric Synthetic Aperture Radar (InSAR) satellite imaging and continuous Global Positioning System (cGPS) tracking. Hence, the evaluation of potential points of interest included the feasibility for using these technologies, beyond a general understanding of the local geology and landslide activity. This section describes those points of interest and the basis for identifying them, then summarizes the relevant information upon which we will later base much of our research and analysis.

2.2.1 General

The geomorphic expression of geologic formations is a direct manifestation of the strength of those materials, their resistance to weathering, and their history of tectonic deformation. Landslide activity is a product of these conditions, driven by the steepness of the landscape and the quality of their underlying materials. They are also a result of external triggering mechanisms, where precipitation, seismic activity or even human effects are often the source.

Slope instability in the EBH is a prevalent problem, where landslides of all types (Varnes, 1978) have been disruptive and costly since development in the area began in the early 20th century. Of particular note, the EBH are home to a number of active, deep-seated (>15m) and very slowly moving (~20 mm/yr), earth and rock flow-type landslide complexes (Cruden & Varnes, 1996). Pre-development era imagery exhibits their presence and activity well through the visible expression of head scarps, toe bulges, slumps, seeps and hummocky topography (Figure 2-2)

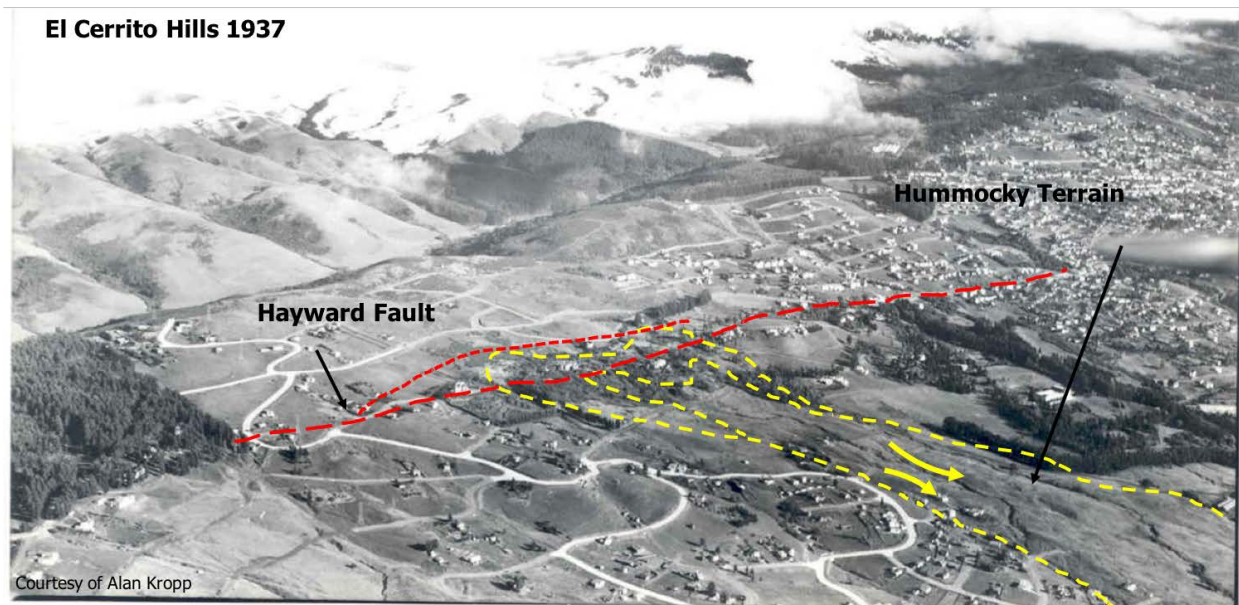


Figure 2-2. 1937 pre-development aerial photo of the East Bay Hills (El Cerrito, CA.), annotated to highlight the locally known Blakemont Landslide with clear hummocky terrain.

To date, these slide deposits have been extensively developed and their potential for large deformation presents a significant hazard. Fortunately, beyond the systematic damage caused by their constant deformation, there is no record of sudden large-scale failure of these slide masses. In fact, a careful comparison of development landmarks in historical air photos suggests between 3 and 5 m of accumulated downslope displacement from persistent creep over the last 100 years (Kropp, 2010). These rates (3-5 cm/yr) are consistent across a number of local landslide investigations and using different sensing methods.

Beyond a characterization of general displacement rates, the inventory of local landslides is also largely based on a thorough analysis of historical imagery (Kropp, 1995), and local site knowledge from an extensive history of geologic and geotechnical field investigations. At least 50 significant landslides were identified throughout the study area, barring failures of less than 2000-3000m² in area.

Based on a general understanding of landslide activity and the availability of site investigation data, two areas of interest within the EBH were identified:

- the five principal EBH landslides (largest and most active)
- landslides within the Lawrence Berkeley National Laboratory (LBL) campus

Within these areas, the active landslides having significant site investigation data that would best lend themselves to our monitoring methods were:

- Blakemont landslide (northernmost end of the EBH)
- Chicken Creek, Centennial Bridge and East Canyon landslides (southeast LBL campus)

In the remainder of this section, the relevant details regarding each of these landslides are addressed. A summary of the relevant information is presented in Table 2-2 and Figure 2-3, including the locations of relevant rain gauges, GPS monitoring stations and historical seismicity discussed later.

Table 2-2. East Bay Hills Landslide Summary.

Landslide	Area (m²)	Aspect Ratio	Depth (m)	Rate (cm/yr)	Water Depth (m)
<i>Blakemont</i>	172,602	0.23	3-30	3	3-9
<i>Chicken Cr.</i>	21,440	0.34	21-25	2	4.5-6
<i>Centennial Br.</i>	4,819	0.5	6-19	1.3	4.5
<i>East Cyn.</i>	88,087	0.3-0.5	12-20	NA	1.5-11

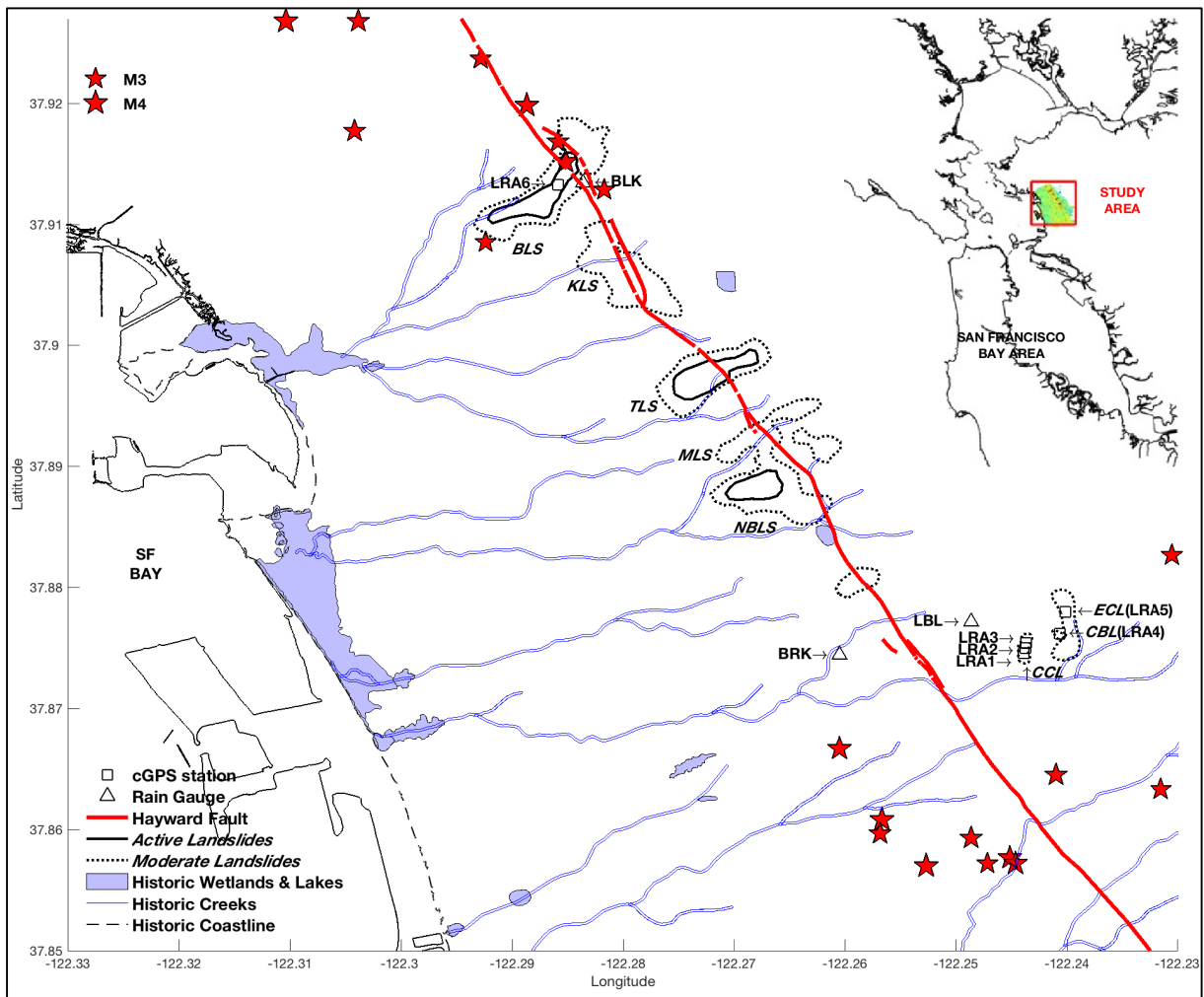


Figure 2-3. Site Location map with study area, landslides (Hilley et al., 2004), fault lines, historic earthquake epicenters (>M3 since 1992), historic creeks, original coastline, existing and historic water bodies and Rain Gauge Station locations.

2.2.2 East Bay Hills Landslides

The five principal EBH landslides were identified based on their size and demonstrated activity. A landslide map of the Berkeley Hills (Kropp, 1995), not only identifies landslide deposits, but also their activity. The largest landslide deposits immediately stand out as also being the most active. A subsequent study of landslide activity using early InSAR sensing technology (Hilley et al., 2004), largely confirms these landslide deposits and their activity. For the purpose of this research these five principal EBH landslides are (North to South):

- Blakemont landslide (BLS)
- Kensington Landslide (KLS)
- Thousand Oaks Landslide (TLS)
- Marin Landslide (MLS)
- North Berkeley Landslide (NBSL)

Of these landslides, the BLS was by far the most well documented and, therefore, considered to be best suited to figure as a research point of interest.

Blakemont Landslide

The Blakemont Landslide is well defined from previous field studies (C. C. Bishop et al., 1973; Dibblee Jr, 1980; Russell W. Graymer et al., 1994; Kropp & Lettis, 2002; Seidelman & Deane, 1994). It is composed of highly expansive clays and sandy clays to depths of approximately 3 m, underlain by gravels, clays, and clays with rock fragments. Deeper landslide debris (8 to ~22 m) are composed of mixtures of hard blocks from the Franciscan Complex bedrock within a weaker sheared matrix of clay and shale. The active slide mass exhibits typical hummocky topography and springs in predevelopment air photos from the 1930s (Figure 2-2). Over time, development progressively spread across the BLS and today, it affects nearly 135 property parcels, causing structural damage to homes and regularly disrupting underground utilities (Figure 2-4).

Subsurface investigations performed by Kropp and Lettis (Kropp & Lettis), show that on average, active deformation within the BLS is distributed within the upper 10 m of the slide mass with a majority of the displacement known to occur along distinct shear zones near the ground surface (up to 1.5 m depth), at depths of 5 to 10 m, and as deep as 15 m. From borehole inclinometer data, they indicate a record of downslope (southwest) movement between 2000 and 2001 of up to 33 mm/year at 6-7 m depth and up to 3 mm/year to depths of approximately 15-19 m.

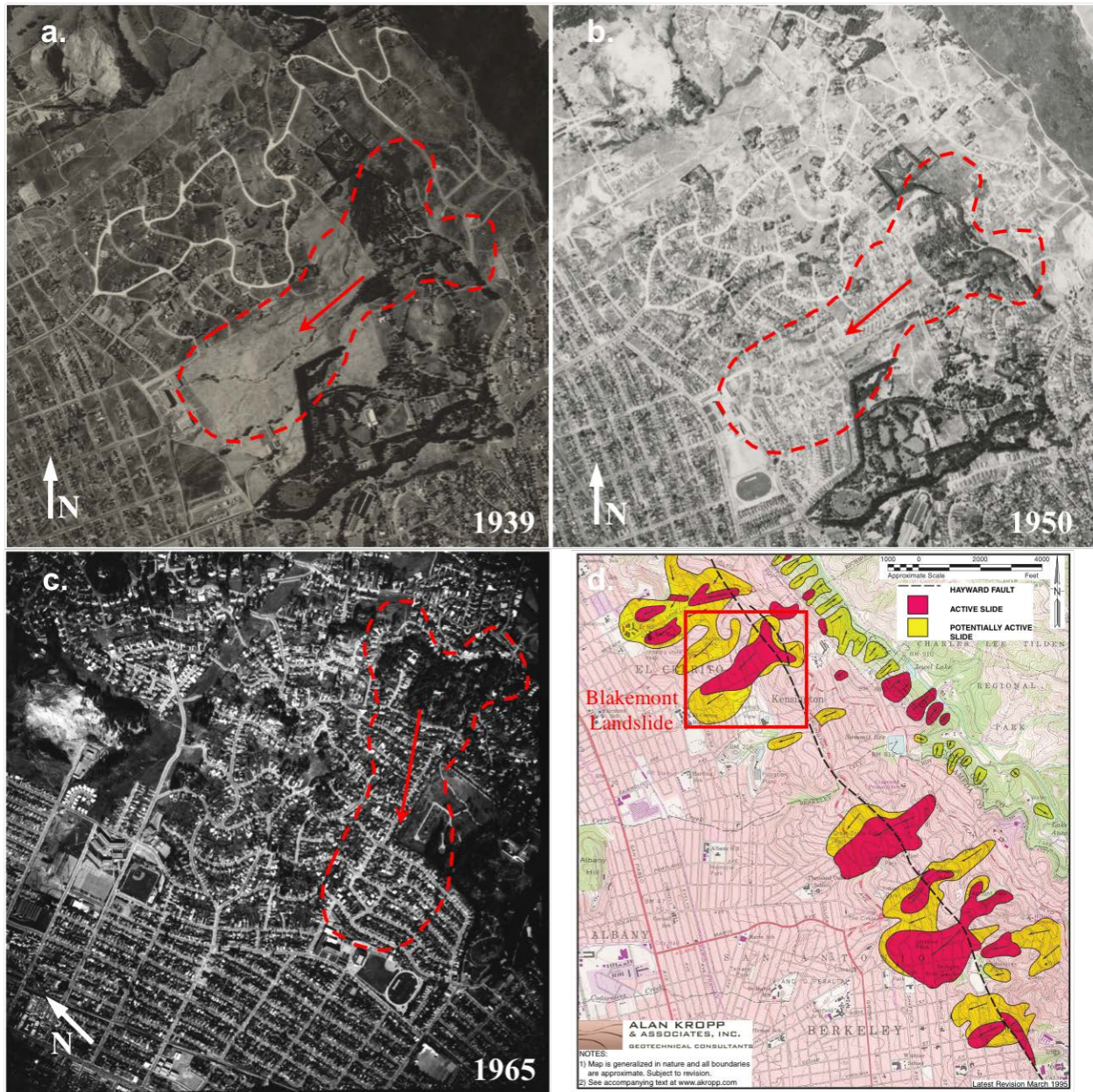


Figure 2-4. Historic air photo panel of the BLS illustrating development of the area. (a) Clear signs of surficial mobility are visible across the BLS in the predevelopment 1939 frame, with stream beds and hummocky terrane. (b) Development of the active slide area began around 1950 and (c) it was fully developed by 1965. (d) The BLS is highlighted in the map of known landslides in the Berkeley hills (Kropp, 1995).

Using datasets from different satellites over several time periods between 1992 and 2006 (Hilley et al., 2004; Lei & Bürgmann, 2010; Lei et al., 2010; Quigley et al., 2010), previous InSAR analyses over the EBH confirm these field observations. They resolve average downslope displacement rates of 25-39 mm/year for measurement points across the same spatial extent as the BLS. These studies also reveal accelerated rates of displacement are tied to seasonal precipitation.

Other Relevant Landslide Data

Subsurface investigation data across the remaining four principal EBH landslides is limited, but suggest that their geologic composition is similar to that of the BLS. Also, borehole inclinometer data collected at the NBLs from 2005-2008 recorded slightly shallower active displacement depths between 3-6m and with rates of ~20mm/yr. Average surface velocity rates for the NBLs from the same suite of InSAR studies (Hilley et al., 2004; Lei & Bürgmann; Lei et al., 2010; Quigley et al., 2010) confirm these values. Generally, what data is available for these landslides indicates that after the BLS the remaining 4 landslides ranked in order of decreasing activity are NBLs, TLS, MLS and KLS.

2.2.3 Lawrence Berkeley National Laboratory Landslides

The Lawrence Berkeley National Laboratory site has had a long history of disruption due to landslide activity. The result of which, has led to an abundance of geological and geotechnical investigation reports documenting each failure. In a majority of the cases, some form of mitigation has been adopted, to maintain the safe and continuous function of LBL. In several cases, monitoring of those deposits has been determined sufficient due to limited impact of failure and prohibitive mitigation costs. The focus of this research were the remaining landslides at LBL which have the benefit of some degree of exploration, are well constrained, and are either known or suggested to be active.

Chicken Creek Landslide

The Chicken Creek Landslide (CCL) owes its name to the chicken farm which occupied the area before LBL. Pre-1920 historical air photos of the area show a clear paleo-landslide deposit and hummocky topography. With post-1920 development of the area, the slide deposit underwent grading and construction but is still visible in 1935 air photos (Figure 2-5). Now part of the LBL campus, desired development of the site has led to a number of geological investigations (Kropp & Lettis, 2009). The CCL has been characterized as an earthflow type failure, with a combination of nested translational and rotational features (Figure 2-5 cross section), and is believed to be part of a larger (inactive) Plio-Pleistocene deposit. Based on geophysical transections of the deposit, the CCL is aligned with a bedrock depression along Chicken Creek, generally oriented toward the southwest.

Borehole and piezometer data show the slide thickness is up to 25 m with a groundwater table that varies between 4.5 and 6m below the ground surface. An LBL monitoring well (MW31-97-18) located on the edge of the slide mass confirms that the groundwater table remains consistently at an average depth of ~6m with seasonal fluctuations of ~1.5m. Borehole data also characterize the landslide deposit as being composed of highly expansive clays and sandy clays with gravels and rock fragments derived from the sedimentary Orinda Formation and Great Valley Group.

The CCL also exhibits signs of creep, though not coherently across the deposit. Pavement distress along access roads at the top and bottom of the landslide are evident and seasonally progressive (Figure 2-5), and manual measurements suggest a rate of ~20mm/yr. A short retaining wall within the bottom of the landslide is also failing. Unfortunately, no other measurements of ground deformation rates at the CCL have been reported, and coverage from previous regional InSAR studies at this location are poor.

Though no history of measured displacement at the CCL are available, it was deemed a good candidate for instrumentation and remote sensing analysis. The deposit is relatively clear of vegetation, shows signs of activity and benefits from good investigative data. Based on these observations, the site was instrumented with three cGPS stations (Figure 2-5).

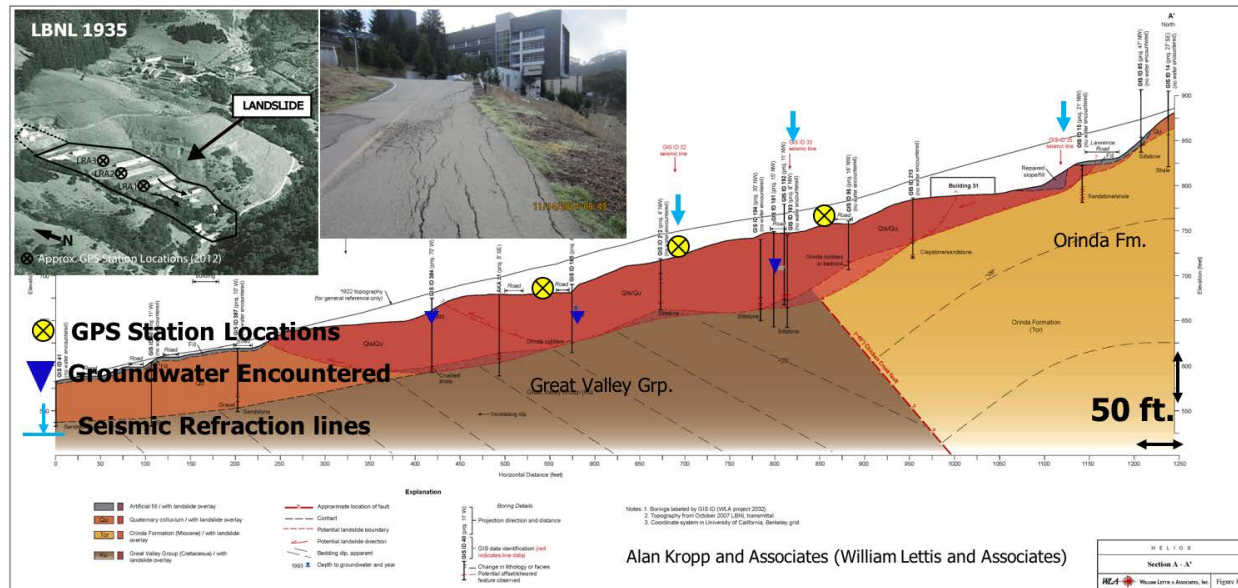


Figure 2-5. Geologic cross section of the Chicken Creek Landslide (Kropp & Lettis, 2009) illustrating the landslide depth and morphology. A 1935 historical air photo shows the paleo landslide deposit. The second photo shows pavement distress in 2014 due to landslide activity.

Centennial Bridge Landslide

Centennial drive is one of few direct access roads connecting both sides of the Berkeley hills, without having to pass through a tunnel or take a significant detour. This is a significant consideration in case of a large seismic event, and particularly in terms of emergency response. Where Centennial drive crosses part of LBL in an overpass, that overpass is constructed on the CBL. Though the slide is relatively small ($\sim 4800\text{m}^2$), it has shown consistent activity over the last 40 years and stands to cause significant disruption.

In 1978, ground deformation caused a significant deflection of the overpass West abutment, which was immediately mitigated. In 1982, movement in the toe of the CBL then caused failure of the eastern overpass abutment. As part of its repair, the toe of the CBL was removed and replaced. The remaining portion of the slide which remains today was instrumented with several inclinometers (SI-8) which have recorded up to 13 mm/yr downslope displacement from 1982-1983 and at depths of 6-19m (Dare & King, 1984). Since the failure of the East abutment, the western abutment has continued to show deflection from landslide related ground deformation. It has been periodically mitigated with temporary tie backs and continues to be actively monitored (Figure 2-6).

Due to its history of activity, the CBL has been well studied and its extents are well constrained. It has been characterized an earthflow type failure, and is composed of highly expansive clays and sandy clays with gravels and rock fragments derived from the sedimentary Orinda Formation. For

the purpose of this research, the historic instrumentation at this site made it an ideal candidate for a cGPS installation, though InSAR coverage was expected to be poor from vegetation cover.

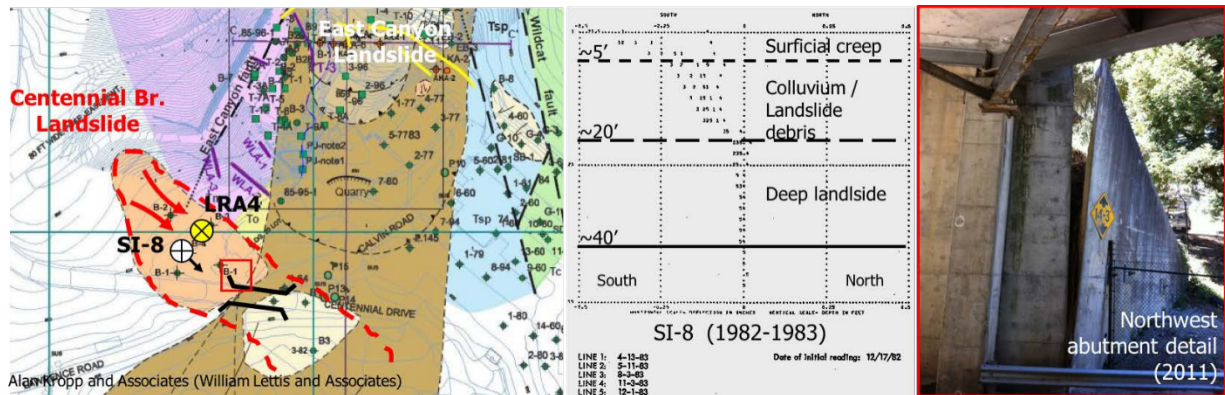


Figure 2-6. (left) Geologic map (Kropp & Lettis, 2009) of the Centennial Bridge Landslide with the location of cGPS station LRA4. (middle) Inclinometer deformation time history for SI-8 (Dare & King, 1984) showing depths of active surficial creep and landslide movement between 1982 and 1983. (right) 2001 photo of active ground deformation causing deflection of overpass abutment wall.

East Canyon Landslide

Much as for the CBL, stability of the ECL is of concern due to a large power transmission tower within the upper part of the deposit and a recoded failure of the slope beneath due to construction activity. Otherwise, no recent investigations of the site report active ground deformation. Of the three LBL landslide study sites however, the ECL is the least well constrained. The slide mass is significantly larger ($\sim 880000\text{m}^2$) and there is some question as to whether it is in fact a composite of two adjacent landslides. Still, pre-development (1906) historical air photos show a clear image of the paleo-landslide deposit and hummocky topography (Figure 2-7). Borehole data characterize this earthflow type deposit as being composed of highly expansive clays and sandy clays with gravels and rock fragments derived from the sedimentary Orinda Formation, between 12 and 20m thick and with a highly variable groundwater table (1.5-11m). Interest in instrumenting and studying this site stems from access to better InSAR coverage, and the potential for future failure of the locally step slopes.

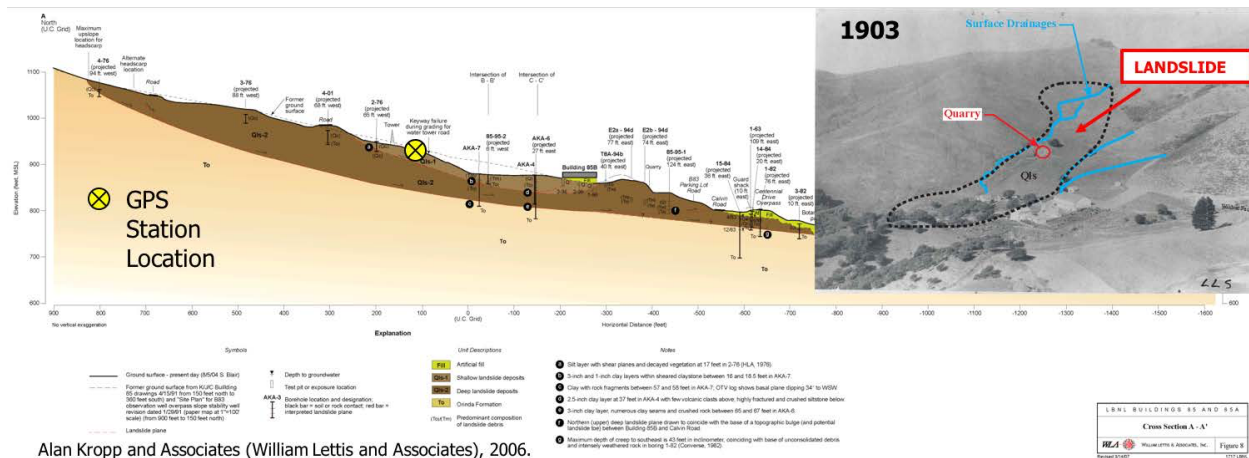


Figure 2-7. Geologic cross section of the East Canyon Landslide (Kropp & Lettis, 2006) illustrating the landslide depth and morphology and the location of LRA5. A 1903 historical air photo shows the paleo landslide deposit.

2.3 Landslide Triggering Mechanisms

To analyze the spatiotemporal behavior of the landslides within this study, it was necessary to carefully compare the transient activity with major triggering mechanisms: seismicity and precipitation, as discussed next.

2.3.1 Seismic Triggering

Seismic shaking from nearby faults can be expected to trigger accelerated landslide displacements (Keefer & Johnson, 1983; Lacroix et al., 2014). As part of the greater San Francisco Bay region, the EBH are no exception to the potential for strong seismicity. The right-lateral strike slip Hayward Fault (HF), which traverses the EBH and the head scarps of the EBH landslides has the potential for a Mw 7.0 event (Chaussard et al., 2015; Field & 2014-WGCEP, 2015). Although a clear relationship between seismicity and landslide activity has yet to be established in the EBH, Hilley et al. (2004) suggest that a HF Mw 3.9 event in December 1998 induced downslope displacements at the BLS. After a HF Mw 4.0 event in March 2012, located only 2 km northwest from the previous event, the cGPS captured the seismic waveform, though no evidence of seismically induced landslide displacements could be determined in any of the time series analyses. Furthermore, there was no evidence of accelerated landslide displacements documented due to any of the large historic earthquakes in the region, since 1868. This point is illustrated by plotting the epicenters for all HF seismic events greater than M3 (since 1992) near our study area (Figure 2-3).

2.3.2 Precipitation

Pore pressures within any slide mass are a primary driving factor of landslide motion (Terzaghi, 1950). Seasonally, surface hydraulic load conditions produce transient increases in pore pressures at depth. The duration of precipitation events controls the depth to which pore pressures are affected. Depending on the slide mass properties and antecedent moisture conditions, precipitation induced rising pore pressures may only cause landslide motion after lag times ranging up to months (Iverson & Major, 1987). Without sufficient characterization of subsurface conditions to create a

reliable pore pressure diffusion model, our interest lies in characterizing the effects of seasonal and long-term changes in precipitation on ground motion.

Landslide mobility in the EBH is primarily driven by a wet microclimate from local orographic precipitation (Beaty, 1956; Gilliam, 2002). Precipitation rates are strongly seasonal, with little rainfall between May and October (Nilsen & Turner, 1975). As the area of study for this project is inherently large and orographic precipitation patterns can vary with topography, we look to analyze precipitation modulated ground deformation based on precipitation records relevant to each site. By virtue of the EBH being so well developed, a number of precipitation and weather stations are available throughout the area (Figure 2-3), with relatively complete data records reaching as far back as 1898.

Records from a total of 4 rain gauges were collected and compared to establish what differences might be observable within the precipitation patterns across the study area and what data should be used for our analysis. Of these stations, two were located at or near the head of the landslides at the northern and southern-most ends of the study area. The first at Blakemont Landslide in the University of California Blake Garden (BLK), the second in the middle of the Lawrence Berkeley National Laboratory Campus (LBL), respectively. For comparison, data from two stations located at the foot of the EBH in the cities of Oakland (OAK) and Berkeley (BRK) were also collected. Historic data for OAK and BRK was retrieved from the National Oceanic and Atmospheric Association (NOAA, 2017) while BLK and LBL data were made available by the University of California College of Environmental Design and the Lawrence Berkeley National Laboratory. Table 2-3 summarizes the data collected at each station and the station location.

Table 2-3. East Bay Precipitation Station Summary.

Station	Lat. (deg)	Lon. (deg)	Elev. (m)	Start Date²	% Comp.
<i>Lawrence Berkeley National Lab. (LBL)</i>	37.877133	-122.248629	274	1974/10/01	100
<i>UC Blake Garden (BLK)¹</i>	37.913419	-122.283599	177	1965/07/01	100
<i>Oakland Museum (OAK)</i>	37.79833	-122.26417	94.5	1970/10/01	94
<i>Berkeley (BRK)</i>	37.8744	-122.2605	9.1	1893/01/01	93

Notes:

¹Manually collected data

²Dates are in YYYY/MM/DD format

Given their similar position with respect to the landslides of interest (similar elevations near the landslide head scarps), the LBL and BLK precipitation time series were compared to determine what difference the distance between these two sites (~6km) might make. In general, while the precipitation event times of their historic records match well, the LBL site experiences slightly higher amounts of precipitation on average (Figure 2-8). While this may be an effect of orographic

differences or systematic differences in local weather patterns, it may also be due to the use of automatic rain gauges at LBL vs a manual tipping gauge at BLK. Similar comparison of the LBL and BLK stations against a combination of the OAK and BRK stations (to fill data gaps) shows that the data match reasonably well.

Based on these comparisons, the LBL precipitation time series across was used in all of analyses. The average seasonal precipitation based on records since 1974 is 76.5 cm, but it was above average during the winter months of 2010 and 2011 with 84 and 94 cm, respectively. During the period of 2012-2014, California experienced extreme drought conditions (Bennett et al., 2016; Seager et al., 2015), reflected in cumulative precipitation of only 48 cm during the winter season of 2013/2014. 2015 and 2016 saw a steady drought recovery with 59 and 70 cm respectively while 2017, was one of the wettest years in recent record with 120cm.

Data Set 1 (DS1) is the daily precipitation data collected from LBL since October 01, 2008 through September 31, 2017 (LBNL meteorologist Patrick Thorson, personal communication). The data file header information is summarized in Table 2-4.

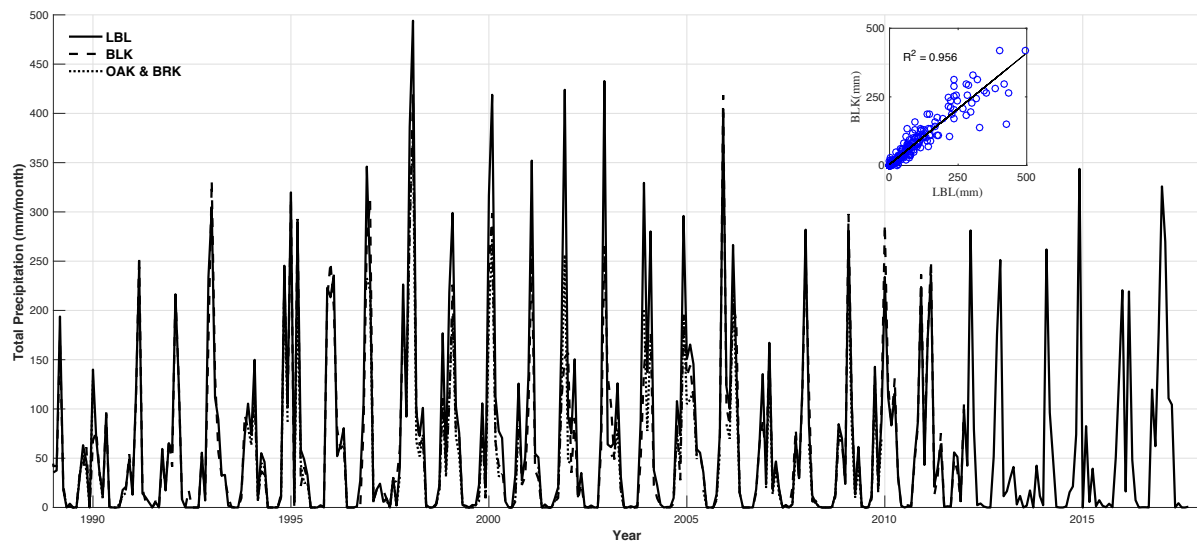


Figure 2-8. A comparison of historic precipitation records at monitoring stations near and within the EBH shows very good agreement. Shown here are monthly precipitation totals at the Lawrence Berkeley National Laboratory (LBL) station, the University of California Berkeley Blake Garden (BLK) station and an averaged record of the Oakland Museum (OAK) and Berkeley (BRK) stations. Subset is a comparative graph showing a linear fit between BLK and LBL indicating that differences in local weather patterns bring slightly higher precipitation to LBL.

Table 2-4. Precipitation data file format.

Header	Explanation
<i>Year</i>	Year of data collection
<i>Julian Day</i>	Julian Day calendar date
<i>Date(MM/DD/YY)</i>	Date of data collection (MM/DD/YY)
<i>Daily(mm)</i>	Total daily precipitation (mm)
<i>Daily(in)</i>	Total daily precipitation (in)

2.4 Monitoring Data Sets

2.4.1 InSAR

InSAR time series are a record of change in radar signal return phase over time, reflecting the change in distance between the ground surface and, in our case, a satellite based radar platform (range-change). The strength of the return signal for each radar pulse is dependent of the physical properties of the target (or scatterer). Where distinct structures (curbs, rocks, buildings, etc.) will return a persistent strong signal, less prominent surfaces (roads, fields, etc.) will return lower intensity distributed signals and noise. Among others, the two principal types of InSAR time series analysis methods are thus known as Permanent Scatterer (PS) or Distributed Scatterer (DS) analysis methods (respectively). The first accounts only for PSs while the second accounts for a combination of PSs and DSs.

The most significant limitations of InSAR are its temporal resolution, the orientation of ground displacement with respect to the satellite, the radar wave length and its prohibitive cost. Temporal resolution corresponds to the sampling frequency which is limited by the satellite orbit times, measured in days or months. The viewing geometry of the satellite also make it impossible to detect movement that is parallel to its flight path. Different radar wavelengths are better suited for different ground surfaces. Shorter wavelengths will provide significantly greater measurement point (MP) densities but perform poorly over vegetated surfaces. Ultimately, this is still a prohibitively expensive technology. Space agencies can charge hundreds of dollars for a single recent image to academic research institutions. The cost to private agencies is tenfold. Fortunately, satellite radar imagery is on the way to becoming a much more cost effective (if not free) method of remote sensing.

InSAR time series analysis allows for remote detection and characterization of ground surface displacements with sub-centimeter precision and accuracy and tens of meters spatial resolution (Roland Bürgmann et al., 2000), making it particularly suitable for the study of active landslides (Colesanti & Wasowski, 2006; Tofani et al., 2013; Wasowski & Bovenga, 2014). Its application has been shown to successfully track landslide deformation in the EBH, using datasets from different satellites over several time periods between 1992 and 2006 (Hilley et al., 2004; Quigley et al., 2010). The German Space Agency (DLR) TSX satellite data acquisitions from 2009-2014 is used in the research presented herein.

1992-2001 Time Series of ERS

Hilley et al (Field & 2014-WGCEP) use 46 European Space Agency ERS-1 and ERS-2 satellite data acquisitions from 1992-2001 to perform a PS analysis of the EBH. They are the first to have shown the application of InSAR time series analysis for landslide tracking, producing ground displacement time series for known landslides across the EBH. Over this period, their data indicate landslide related downslope surface displacement rates of 27 to 38 mm/yr. They illustrate that periods of landslide acceleration closely related to seasonal precipitation with a lag of up to 3 months. Additionally, Hilley et al. (2004) suggest seismic related landslide displacement occurred ensuing a HF $M_w 3.9$ on December 4, 1998. Though the temporal resolution of their time series could not directly document the seismically triggered deformation, they observed unexpectedly high InSAR displacement measurements relative to the amount of precipitation during the same period.

2001-2006 Time Series of RadarSAT-1

Quigley et al. (2010) examined seasonal precipitation-related landslide displacement in the EBH, supplementing the same ERS data set (Hilley et al., 2004) with Canadian Space Agency RADARSAT-1 acquisitions from 2001 to 2006. Landslide displacement rates were shown not only to be of same magnitude, but clearly seasonal and sensitive to variations in rainfall patterns, with the same 1 to 3 month displacement response lag time.

2009-2014 TerraSAR-X

Lei et al. (2010) use German Space Agency (DLR) TerraSAR-X (TSX) data acquisitions from 2009-2010 to perform PS analyses of the same EBH area, finding consistent results as for the previous studies and with significantly higher MP density. This research expands on that work using 119 TSX data acquisitions from 05/2009-05/2014. The data were provided through a user license by DLR and the time series analysis was performed by TRE ALTAMIRA using their SqueeSARTM algorithm (Ferretti et al., 2011) discussed in the following Chapter. They produce a line-of-sight (LOS) deformation time series for the EBH which we include as Data Set 2 (DS2). The data file header information is summarized in Table 2-5. All data follows a sign convention such that positive movement is toward the Satellite. We also include the TRE ALTAMIRA processing report in Appendix A.

Table 2-5. InSAR data file format.

Header	Explanation
<i>X, Y</i>	Longitude, Latitude (Decimal Degrees)
<i>Z, HEIGHT</i>	Height (m)
<i>VEL(mm/yr)</i>	Velocity (mm/yr LOS)
<i>H_STDEV, V_STDEV</i>	Standard Deviation of Height and Velocity
<i>COHERENCE</i>	Coherence Value
<i>EFF_AREA</i>	Area of distributed scatterer estimation
<i>D20090510 – D20140521</i>	LOS deformation (mm LOS) at Date ('D'YYYYMMDD)

2.4.2 Continuous GPS Monitoring Network

The continuous GPS data collected through this study was automatically stored and processed by the Berkeley Seismology Lab (BSL) as part of the Bay Area Regional Deformation (BARD) network (<http://earthquakes.berkeley.edu/bard/>). BARD is a network of continuous GPS stations established to monitor crustal deformation across the Pacific-North America plate boundary, and evaluate earthquake hazard in the greater San Francisco Bay Area region. Receiver data was archived and is available at the Northern California Earthquake Data Center (NCEDC), as raw 24-hour IGS-standard RINEX ("Receiver Independent Exchange" format) files. The data stored are the phase and pseudorange for both L1 and L2 band GPS frequencies, at high (1Hz) and low (0.03-0.06 Hz) rates. A detailed discussion of the relevant background and data collections methods is presented as a part of Chapter 5.

Chapter 3. Methods of Analysis

To compare those available field observations with the spatiotemporal trends isolated in the remote sensing data, downslope velocities, average depths of sliding and precipitation driven transient pore pressure profiles were estimated from first order models. This section, provides a description of the data and signal processing methods used to identify and extract the spatiotemporal patterns of ground deformation recorded in the InSAR and GPS time series. Then, the first order models are used to reconcile the remotely sensed trends with geomorphic processes and actual field observations

3.1 Data Processing Methods

3.1.1 GPS Data Processing Method

Processing of the collected GPS data is performed as part of an automated processing chain at the BSL, using the GAMIT (Herring, King, et al., 2015) and GLOBK (Herring, Floyd, et al., 2015) software packages developed at the Massachusetts Institute of Technology and the Scripps Institution of Oceanography. The GPS data is first processed through GAMIT, which estimates the 3D relative positions of the stations and satellites. The method includes standard correction models for satellite radiation pressure and tropospheric delay to correct for orbit and atmospheric errors. The data is further corrected by Double Differencing (DD) the carrier phases (L1 and L2) to account for the effects of variations in the satellite and receiver oscillators. Each of these correction models are then combined and smoothed using a Kalman filter approach, implemented through GLOBK. To average errors, white noise (2mm/yr horizontal and 5mm/yr vertical) is added, and “benchmark wobble” is corrected using Markov process noise ($1\text{mm}/\sqrt{(\text{yr})}$). Final solutions are provided as daily averages in precise NAD83 reference frame coordinates, based on orbital adjustments performed by the California Spatial Reference Center, in partnership with the National Geodetic Survey.

The Nevada Geodetic Laboratory (NGL) at University of Nevada Reno (www.geodesy.unr.edu) also implements an automatic GPS processing chain to all available data from the BSL. Here, a separate software package is applied, GIPSY-OASIS II in Precise Point Positioning (PPP) mode (Zumberge et al., 1997), developed by the National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory (JPL). While the NGL and BSL GPS processing methods are fundamentally similar, the software packages apply different positioning algorithms and strategies. Where station positions are estimated from DD and network adjustments in GAMIT/GLOBK, GIPSY/OASIS uses PPP. Ultimately, both methods provide high-precision daily solutions, with no appreciable differences. This work was performed on data processed at BSL.

3.1.2 InSAR Data Processing Method

The high spatial resolution of InSAR, particularly that of X-band imagery in urbanized environments, makes it a valuable tool for monitoring the details of mm-scale surface deformation of slow moving (< 20 mm/yr) landslides (Wasowski & Bovenga, 2014). InSAR time series represent a record of change in radar signal return phase over time, mostly reflecting the change in Line Of Sight (LOS) distance (or range) between the ground surface and the radar platform. Persistent or permanent scatterer (PS) InSAR time series analysis techniques are based on finding pixels whose amplitude and/or phase properties are stable through time (Ferretti et al., 2001; Hooper et al., 2012). We produce InSAR time series with substantially improved temporal resolution and an enhanced analysis algorithm (SqueeSARTM) to capture the full spatiotemporal response patterns of ground deformation to annual precipitation cycles and multi-year drought conditions for landslides in the East Bay Hills.

The algorithm SqueeSARTM (Ferretti et al., 2011) relies on a statistical test (two-sample Kolmogorov-Smirnov) to partition image pixels into PSs with stable amplitude properties and coherent signal phase, and additional phase-stable distributed scatterers (DSs). Here, the PSs are processed in the manner described in Ferretti et al. (Ferretti et al.), and the DSs are integrated in the same processing chain taking into account their different statistical behavior (Ferretti et al., 2011), thus increasing the measurement point (MP) density (6228.1 MP/km²) by roughly one order-of-magnitude (Figure 3-1) from that shown in Hilley et al. (2004).

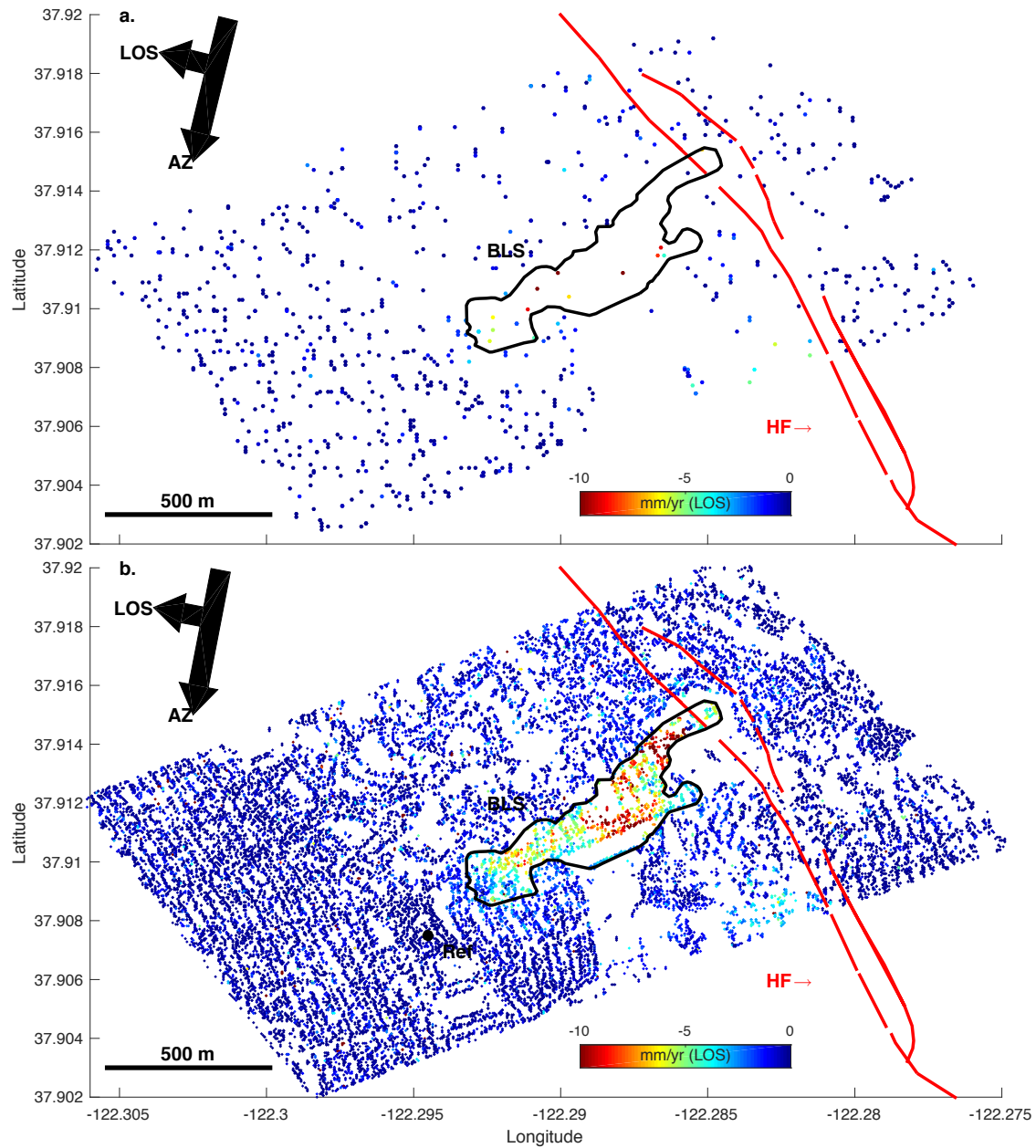


Figure 3-1. Map of Blakemont landslide (black outline) and surrounding area illustrating the spatial coverage and LOS velocities from (a) PSInSAR analysis of 1992-2001 ERS data, and (b) SqueeSARTM analysis of 2009-2014 TSX data (including the analysis reference point 'Ref'). Negative LOS velocities (see color scale) are produced by subsidence and westward motions

For each MP, a deformation time series is produced from the 119-scene data stack, using 118 interferograms with respect to a central reference image (Figure 3-2) and a stable reference point (Figure 3-1), located southwest of the BLS on the roof of a large three-story building (Lat: 37.90747°, Lon: -122.29453°). While the reference point was selected in an area that is consistently stable with low amplitude signal throughout the time series, the measured signal in all

MPs inherently includes its background temporal variability. Atmospheric and other noise sources were mitigated as described in Ferretti et al. (2001).

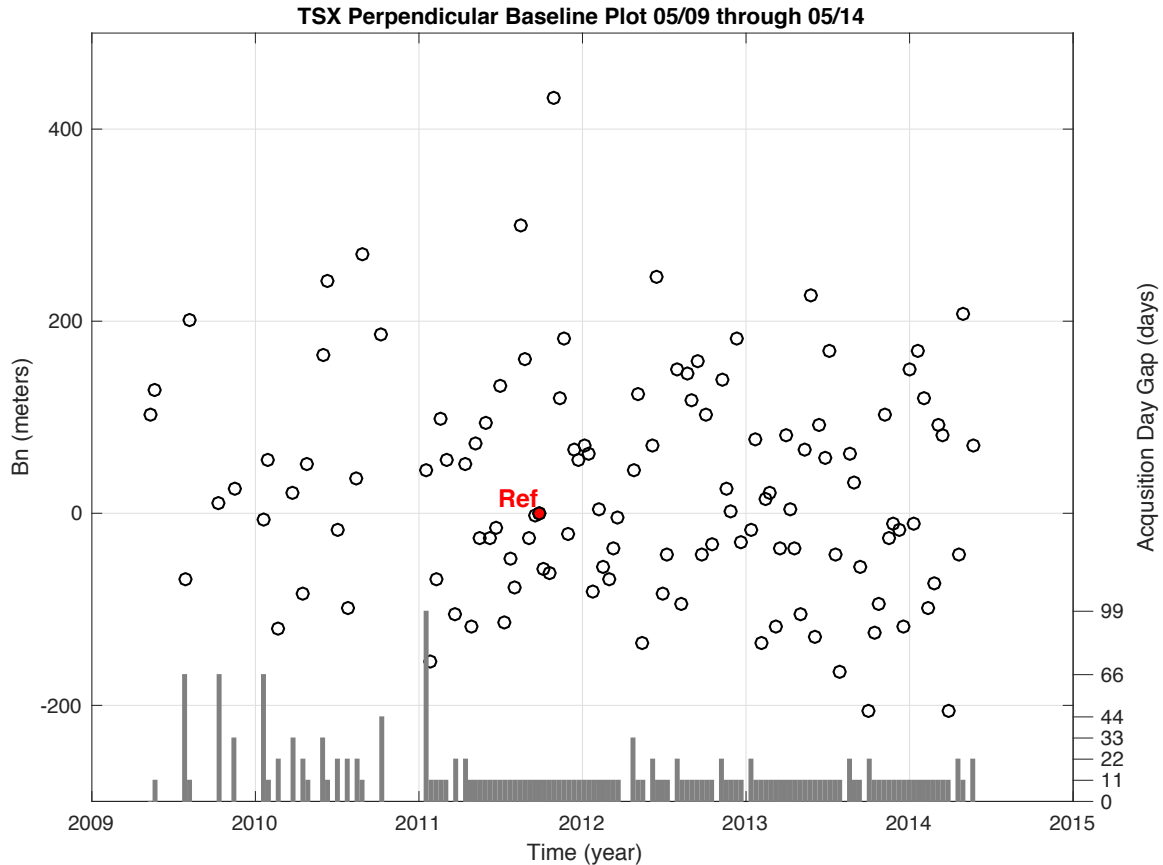


Figure 3-2. Satellite perpendicular baseline (Bn) as a function of time for the 119 TSX data acquisitions from 2009-2014 (open dots), used in the SqueeSARTM analysis. The reference image is shown in red and the TSX temporal coverage, defined by the gap in days between acquisitions, is shown with the grey bars at the bottom of the plot. Prior to January 2011 the acquisition intervals range between 11 and 99 days, due to tasking and maintenance issues related to the recently launched TSX satellite. After January 2011, tasking of TSX consistently included the study area except for several scenes with 22-day gaps and one 33-day gap. While the baseline distances are not of concern in our analysis, a majority of baselines are short (<250m), only one is greater than 400m.

3.2 Signal Processing Methods

3.2.1 Functional Curve fitting

For a first order estimate of transient temporal patterns and their spatial distribution, we rely on traditional curve fitting of representative functions. We apply the linear sum of several a-priori functions to fit measurement point (MP) time series produced from continuous GPS stations and

InSAR scatter points within and around known landslide masses. A linear trend accounts for average landslide velocity, a squared term accounts for long-term acceleration, and a combination of sinusoidal functions with periods of 0.5 and 1 year represent cyclic seasonal deformation. Equation (3-1) describes the functional form used and the coefficients are solved for by a least squared inversion.

$$H(t) = \sum_{n=2}^3 \left[a_n \cdot \sin\left(\frac{2^n \pi t}{2}\right) + b_n \cdot \cos\left(\frac{2^n \pi t}{2}\right) \right] + ct^2 + dt + e \quad (3-1)$$

where H defines the relative deformation at each MP as a function of time t , c and d are coefficients that describe the curvature and slope, respectively, a_n and b_n describe the amplitudes of the sinusoidal functions at each period, and e is an error term. While Functional Curve Fitting (FCF) can provide a reasonable measure of temporal trends and spatial differences in phase between MPs, it does not successfully isolate spatiotemporal difference in the data into statistically independent signals. To separate the spatial patterns of dominant long-term, seasonal and other common-mode variations in the surface deformation field without assuming functional forms of their time-dependence, we apply Principal and Independent Component Analyses (PCA and ICA).

3.2.2 Principal and Independent Component Analyses

Of the different modes of PCA that exist (Richman, 1986), we use the temporal mode (T-mode) to isolate spatial deformation patterns over time, which allows characterization of temporal and spatial variability without a-priori constraints. T-mode PCA (TPCA) has been successfully applied to GPS, electronic distance measurements, and InSAR data (Chaussard et al., 2014; Ji & Herring, 2011; Savage, 1988). In this study, the number of GPS stations is insufficient to produce any reliable spatial deformation patterns from TPCA or ICA, so we apply it to our InSAR data set only.

To perform the TPCA analysis, we create an m by n matrix $\mathbf{X}$ populated by the displacement values of the m MPs considered at each of their n time steps. The matrix $\mathbf{W}$ is the orthogonal linear transformation that maximizes the variance between the rows of the resulting component matrix $\mathbf{U}$ such that:

$$\mathbf{W}^T \mathbf{X} = \mathbf{U} \quad (3-2)$$

The TPCA method (illustrated in Figure 3-3) isolates different spatio-temporal patterns into individual components relying on this linear transformation from a set of inter-correlated variables into a new set of uncorrelated variables. The result is a set of successive Principal Components (PCs) that explain the data projected along orthogonal basis vectors, ordered by the percentage of variance explained. The method maximizes variance of the data projected along orthogonal directions, then removes the contribution of that component and iterates. The first coefficient contains the maximum variance, and so on, each with decreasing variance and uncorrelated to the rest.

While PCA captures the variance most efficiently, it is also limited by its orthogonal basis and may miss and mix some part of the data trends. To identify all significant trends within our data set, we consider the complete set of PCs determined by the number of acquisitions (in this case $n = 119$ radar acquisitions). Using the scree plot and slope change tests (Cattell, 1966; Cattell &

Jaspers, 1967; Jackson, 1993), we then determine the number of PCs with significant contributions to the variance (greater than 0.25%). This reduces the number of dimensions in the data set while preserving most of its characteristics (Lischeid, 2009; Manly, 1986; Tabachnick et al., 2001; Wackernagel, 1988). With an understanding of the underlying geologic and geomorphic mechanics of the study area, we can then determine the number and rank of significant components necessary to best describe the signal and its spatial distribution.

The ICA uses the same generalized form presented in equation (3-2), where $\mathbf{W}$ is now a non-linear transformation that minimizes the statistical dependence between rows of $\mathbf{U}$. Much like for the PCA, the ICA iterates after removing the contribution of each component. In contrast to the PCA, instead of maximizing the variance explained by each orthogonal component, ICA maximizes the independence of the components based on the number of components allowed, and without an order of importance. The ICA is therefore sensitive to the number of components imposed on the analysis, such that one component too many might feature mostly noise and one component too few might mix the desired independent signals together. Combining both methods in a complimentary fashion, we are able to determine the number and rank of necessary components (by PCA) and then optimally describe the data's spatiotemporal patterns (by ICA).

The component analysis outputs are eigenvalues and eigenvectors of each PC/IC and the score at every measurement point of each PC/IC. For the PCA, eigenvalues correspond to the variance explained by each component, as the diagonal values of the correlation matrix $\mathbf{W}$. For the ICA, the eigenvalues correspond to the independence of the components. Eigenvectors represent the temporal variability of each PC/IC and correspond to the magnitude of the contribution at each time step. The scores represent the spatial variability of each component and correspond to the contribution of the original data at each pixel in the domain defined by each PC/IC. The scores are presented as spatially distributed amplitude maps of each component alongside its corresponding eigenvector time series.

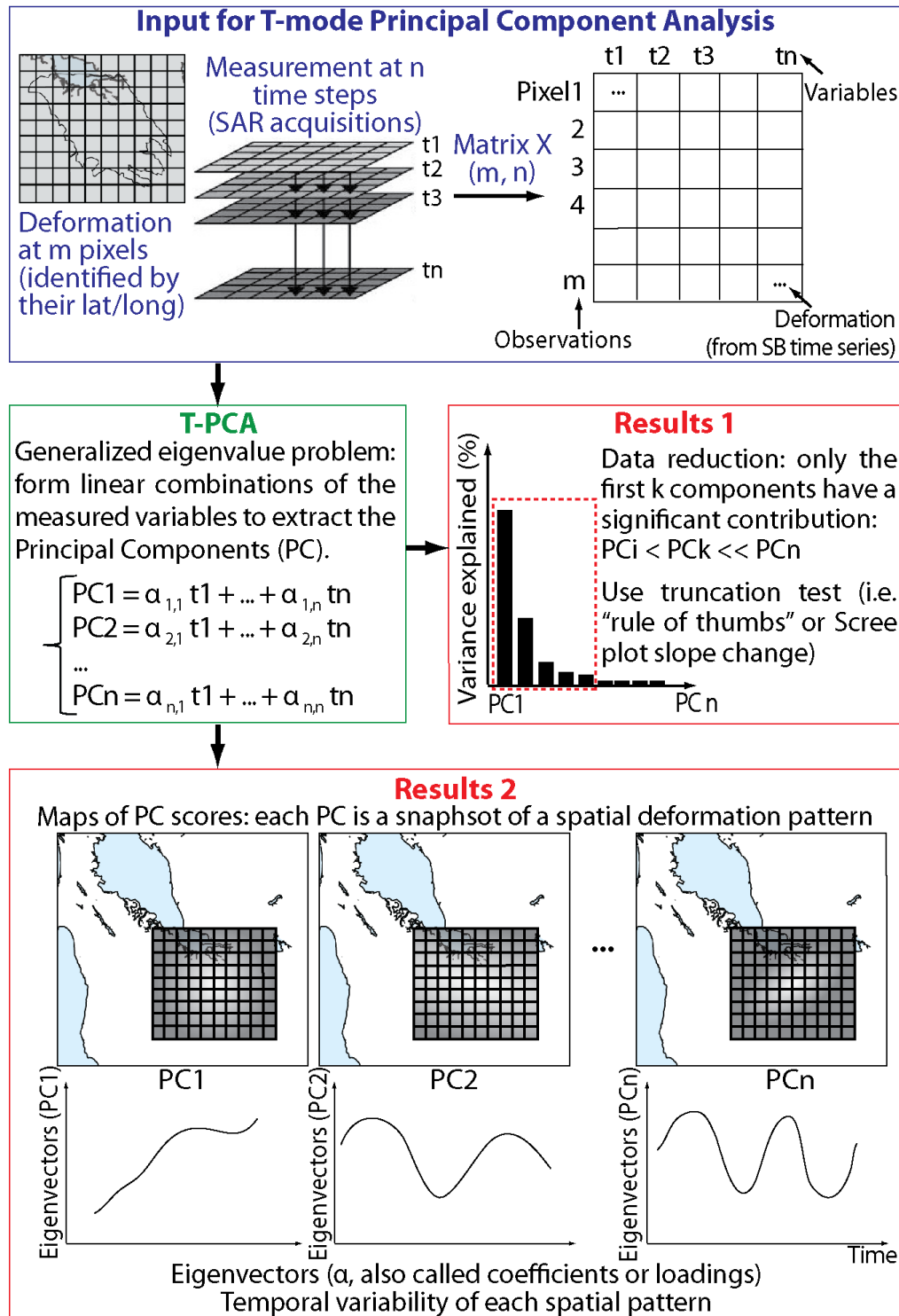


Figure 3-3. TPCA work flow illustration as applied to InSAR time series (Chaussard et al., 2014).

3.3 First Order Estimation Models

3.3.1 Estimation of 3D Velocity Field from InSAR Time Series

Where GPS time series provide a continuous and three-dimensional sense of motion for a single MP, InSAR time series are limited by the satellite observation frequency and its look geometry. Without at least three independent satellite LOS observations, it is not possible to remotely resolve the 3D sense of landslide motion (Delbridge et al., 2016). However, an estimate of the magnitude of actual ground displacement can be made if the downslope orientation of landslide motion is known. To convert measured LOS velocities to approximate downslope velocities, a unit vector is projected in the downslope direction onto the unit vector in the satellite look direction following Hilley et al. (2004) and using the equation:

$$S = 1/\mathbf{v}^T \mathbf{u} \quad (3-3)$$

Here, $\mathbf{v}$ and $\mathbf{u}$ are vectors representing the downslope and satellite look directions, respectively, defined by their [x y z] components in a positive-up, right handed coordinate system. S is the amplification factor by which the satellite measured range-change rate is multiplied to obtain the downslope velocity. Using this first order estimation of the 3D velocity field to compare with actual ground observations of landslide displacement rates to verify the veracity of our InSAR measurements. As the slope, orientation and general landslide displacement orientation varies significantly across the EBH, our work is primarily performed in terms of LOS displacements.

3.3.2 Landslide Depth-Area Relationships

Multiple first order models exist for estimating landslide volume and depth based on remotely sensed 3D surficial data (Aryal et al., 2015; Hu et al., 2018). In most cases, the models simplify the landslide geometry to a single circular or planar failure surface and won't account for nested or sinuous failure mechanisms as are the case for the landslides in our study area. Still, they provide a useful framework to compare surficial observations with subsurface field data. The balanced cross-section model (K. M. Bishop, 1999) for example, uses this common structural geology method (Woodward et al., 1989) to determine the depth of sliding from the ratio of the depressed zone of depletion area and observed displacement. Similarly, a balance thickness model for determining glacier thickness (Morlighem et al., 2011), can be applied to determining landslide thickness using the depth-averaged mass conservation equation (Booth et al., 2013; Delbridge et al., 2016; Huang et al., 2017).

Without an accurate record of 3D surface deformation, we look to estimate sliding depths from a simplified depth-area relationship, developed for large slow moving landslides world-wide with similar morphology to ours. Depth-area and volume-area relationships for landslides and rock falls alike have been shown to follow a power law distribution (Dussauge et al., 2003; Fuyii, 1969; Simonett, 1967). The depth-area relationship is:

$$Z = \alpha A^\gamma \quad (3-4)$$

where Z is landslide depth, α is a fit parameter, A is the landslide area (m^2), and γ is a power-law exponent. Based on global landslide data sets, previous studies suggest wide ranges for the fit

parameter and power-law exponent, where $\alpha \sim 0.066$ to 0.08 and $\gamma \sim 0.42$ to 0.44 (Larsen et al., 2010; Simoni et al., 2013). A similar relationship developed specifically for large slow moving landslides as those in our study area suggests $\alpha \sim 0.46$ and $\gamma \sim 0.29$ (Handwerger et al., 2013). A range of slide depths is estimated from a complete range of these parameters and find that they match reasonably well (Figure 3-4). This is an estimate of maximum landslide deposit depth, active sliding likely occurs along shallower nested slide planes.

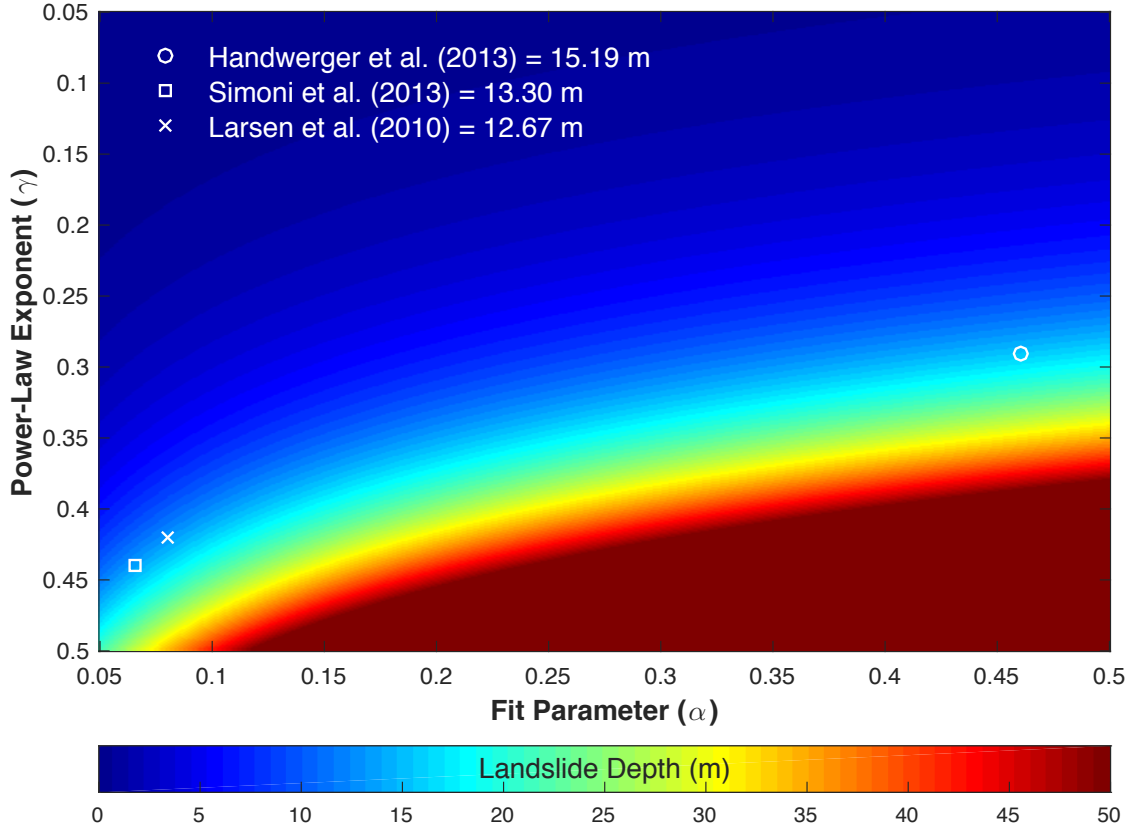


Figure 3-4. Landslide depth estimates for the Blakemont landslide using Depth-Area relationships finds reasonably similar first-order results.

3.3.3 Transient Pore Pressure Model

Seasonal landslide rate changes modulated by precipitation which drives transient pore-pressure increases at depth (Iverson & Major, 1987), with lag times dependent on the subsurface properties. The standard diffusion equation gives a first order estimate of transient pore-pressures we look to, following the method used in Handwerger et al. (2016), where the change in pore-pressure (P) over time (t) can be described as a function of effective hydraulic diffusivity (D) and depth (z):

$$\frac{dP}{dt} = D \frac{d^2 P}{dz^2} \quad (3-5)$$

Assuming that the rate of precipitation (R) controls the surface boundary condition for pore-pressure, we can describe a pore-pressure time series in function of the precipitation rate time series and an empirical scaling factor (s), as:

$$P(t, z = 0) = sR(t) \quad (3-6)$$

Then we can define a one-dimensional solution for the diffusion equation as:

$$P(z, t) = \int_{t_0}^t \frac{z}{\sqrt{4\pi D(t-t')}} \exp\left[\frac{-z^2}{4D(t-t')}\right] P(t', z = 0) dt' \quad (3-7)$$

which we solve for in the Fourier domain, with F as the Fourier transform, by:

$$F(t) \sim \frac{z}{\sqrt{4\pi D(t-t')}} e^{\frac{-z^2}{4D(t-t')}} \quad (3-8)$$

$$G(t') \sim \mathcal{F}[P(t, z = 0)] \quad (3-9)$$

$$P(t, z) \sim \mathcal{F}^{-1}(F \cdot G) \quad (3-10)$$

Calculating the residual (Root-Mean-Square Error) between this solution for transient pore-pressure changes and InSAR measured landslide velocity, a grid-search of depth and diffusivity is performed (Figure 3-5). A first order value of diffusivity (D) is estimated based on the range of landslide depths from the Depth-Area relationship. This value is used to create a profile of transient pore-pressures with depth over the precipitation time history (Figure 3-6) and compare the depth varying pore-pressure with the measured surface velocities. In doing so, we identify by cross-correlation analysis at what depth precipitation-modulated transient pore-pressure and measured landslide velocity are positively correlated with zero lag and compare the results with field observations of subsurface slide activity.

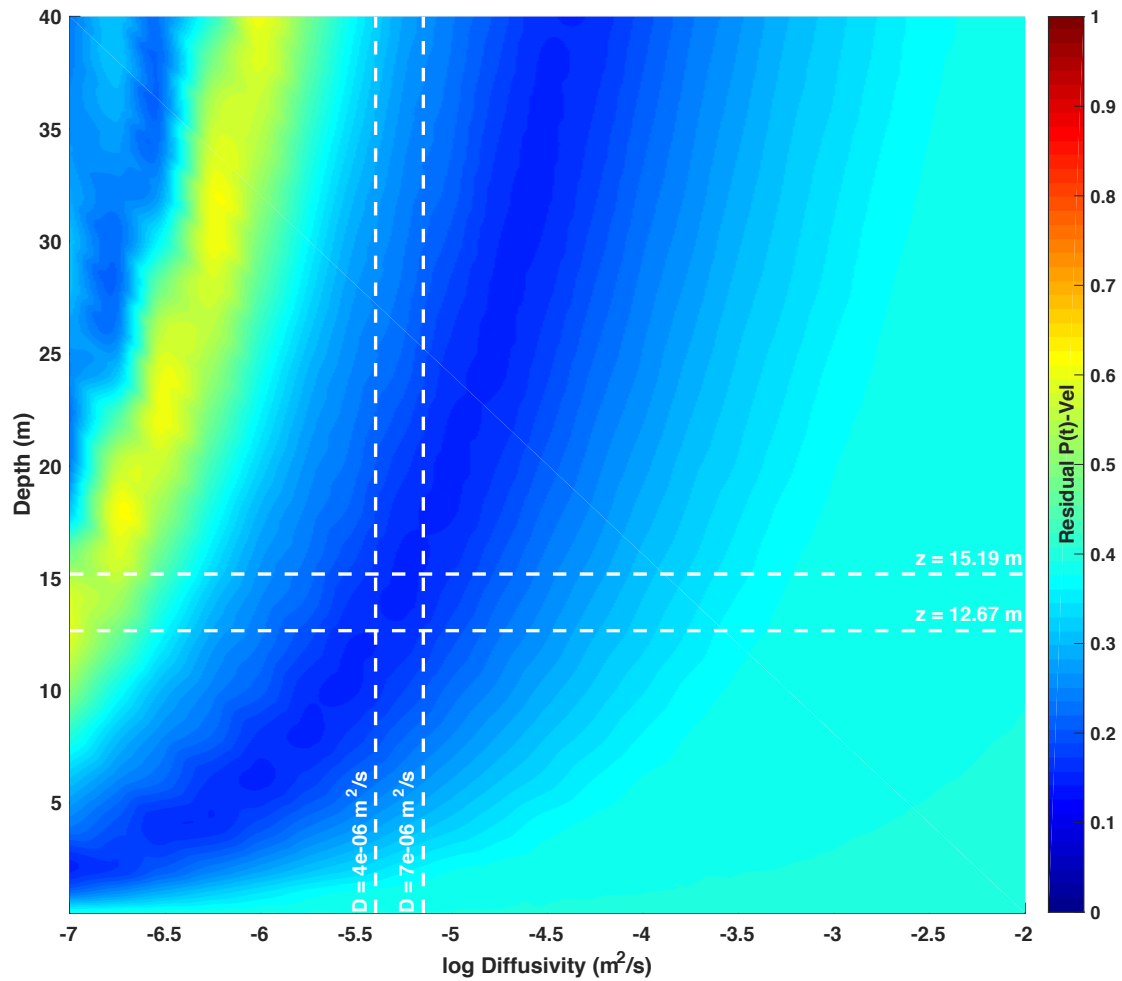


Figure 3-5. RMSE residual between transient pore-pressures calculated from a simple 1-D diffusion model and measured TSX landslide velocity illustrating the time series misfit with changes in depth and diffusivity at Blakemont landslide. Based on a sliding depth of approximately 12-15 meters, we estimate a first order value of diffusivity.

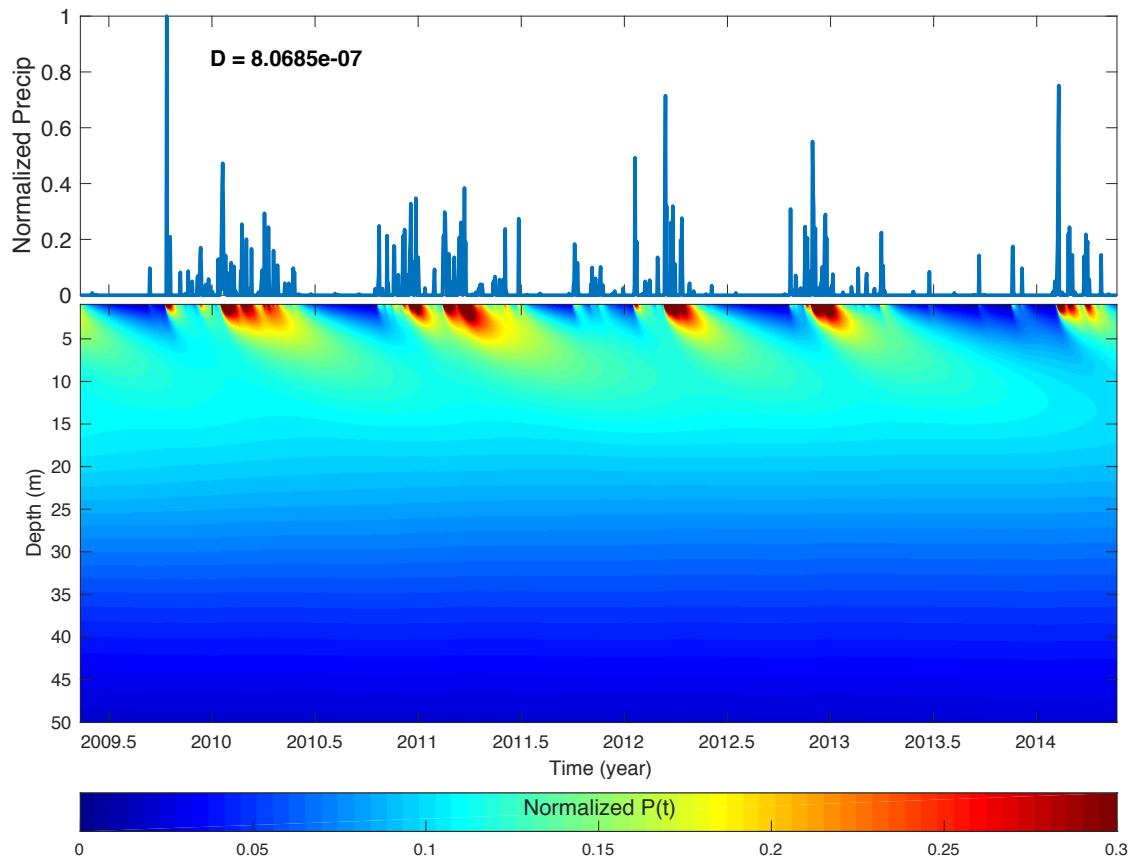


Figure 3-6. Profile showing the transient component of pore-pressure with depth in response to precipitation rates, using a diffusivity of $8 \times 10^{-7} \text{ (m}^2/\text{s)}$ for the Blakemont landslide

Chapter 4. InSAR Deformation Tracking

This section encompasses the application and results from the signal processing methods applied to the InSAR displacement time series. The controls of observed time-dependent landslide deformation were investigated through a combination of signal processing methods. Using functional curve fitting (FCF) and principal component analyses (PCA), four modes of temporal and spatial variability were identified in the observed surface ground motions, which are tied to annual and multi-year precipitation cycles. Independent Component Analysis (ICA) allows optimal separation of the four spatiotemporal patterns and their contributions to the original signal. The utility of these methods is evaluated by relating the observed patterns of ground motion to the underlying driving mechanisms of slope displacement, specifically isolating precipitation-correlated landslide deformation that is directly linked to time dependent pore-pressure changes. The applicability of these methods to the most active and well documented landslide in the study area, the Blakemont landslide (BLS), is addressed first and then related to observations at the remaining landslides in the study area.

4.1 InSAR Analysis Results

4.1.1 Velocity field and background signals

Previous analyses of InSAR datasets from different satellites over several periods between 1992 and 2006 (Hilley et al., 2004; Quigley et al., 2010) focused on defining the spatial extent of known active landslides, resolving consistent average downslope displacement rates ($\sim 25\text{-}39$ mm/year), and revealing the average time lag between maximum winter precipitation and peak landslide velocity ($\sim 1\text{-}3$ months). Using data from the German Aerospace Center TerraSAR-X (TSX) satellite, the previous work is expanded and used to produce InSAR time series (Chapter 3) with substantially improved temporal resolution and an enhanced analysis algorithm (SqueeSARTM). In doing so, the full spatiotemporal response patterns of ground deformation to annual precipitation cycles and multi-year drought conditions for five large slow moving landslides in the East Bay

Hills (EBH), including the Blakemont landslide (BLS) is captured. Figure 4-1 illustrates the average line-of-sight (LOS) velocities of half of the 463,373 MPs across the EBH with respect to the reference point. The data reveal the active portions of historically mapped landslides, ~ 5 mm/yr of shallow aseismic slip along the NW-trending Hayward fault (Chaussard et al., 2015; Shirzaei & Bürgmann, 2013), and settlement of man-made landfill along the San Francisco Bay coastline to the west. Using the LOS velocity field, we determine the spatial extent of active EBH landslides (Figure 4-2) by clusters of MPs (≥ 10 MPs/100m²) with velocities exceeding the mean velocity of the study area by one standard deviation (≤ 2 mm/yr LOS). While the resulting active slide areas generally match previously mapped slide masses (Hilley et al., 2004; Kropp, 1995; Quigley et al., 2010), the improved MP density resolves the landslide boundaries and displacement fields in much greater detail (Figure 4-3).

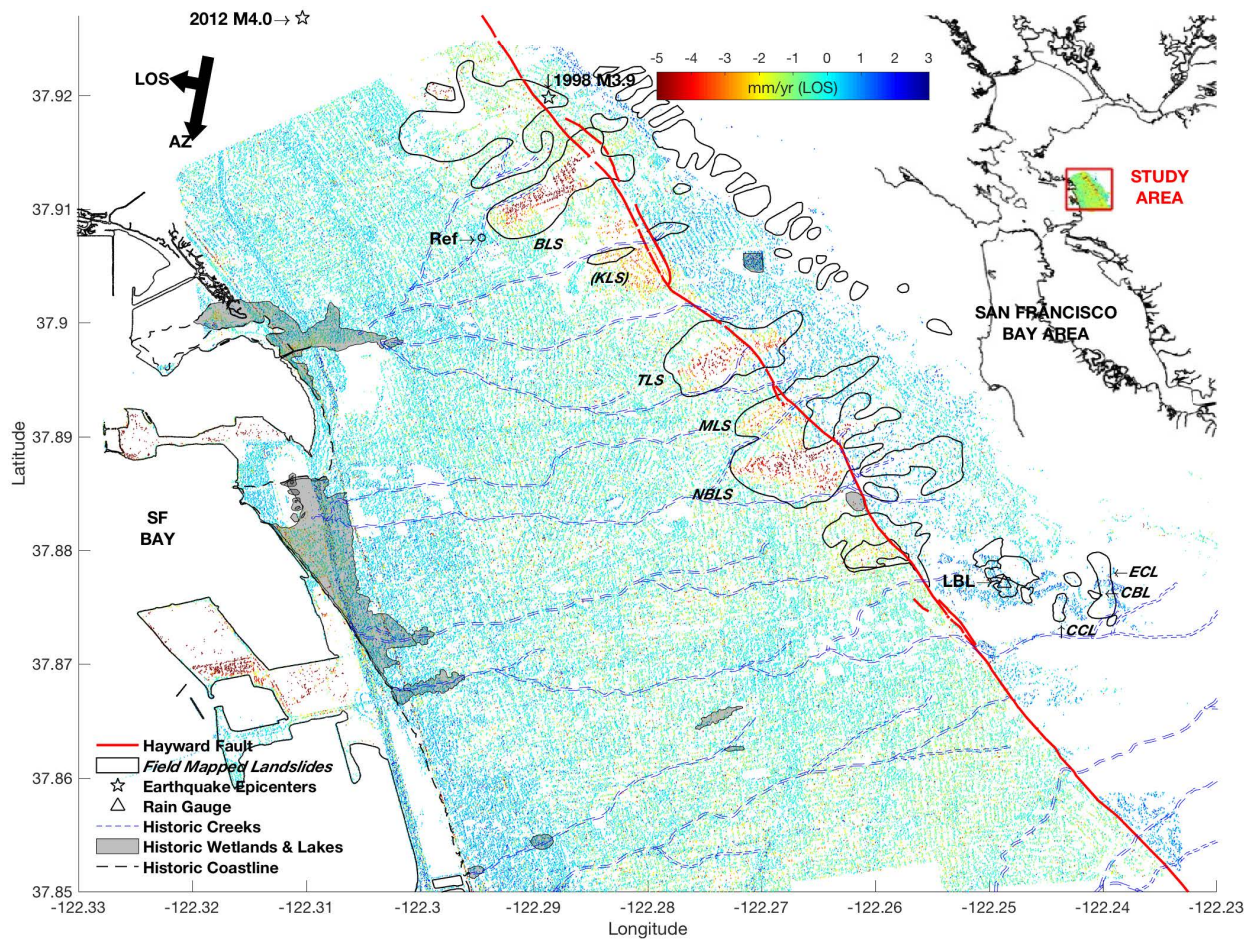


Figure 4-1. TerraSAR-X mean LOS range-change velocity map of the EBH area obtained from the SqueeSARTM analysis, showing motion relative to the reference point (Ref). Positive values (blue colors) show motion towards the satellite (i.e. uplift or eastward movement), and negative values (red colors) show motion away from the satellite (i.e. subsidence or westward movement).

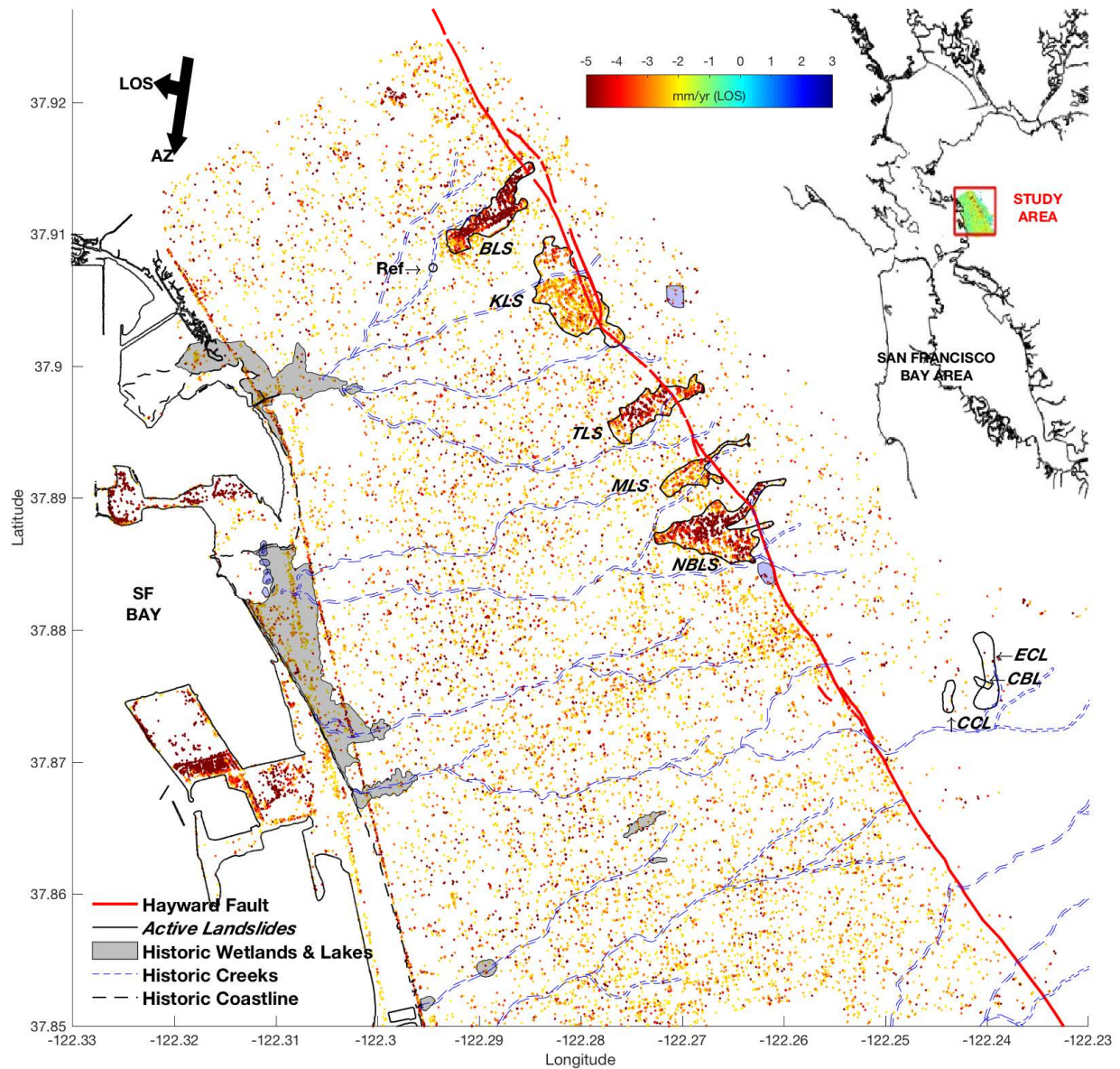


Figure 4-2. Re-sampling of all measurement points, as illustrated in Figure 4-1, showing velocities exceeding the mean velocity of the study area by one standard deviation ($<-2\text{mm/yr LOS}$) and the resulting active landslide outlines from our TSX data set.

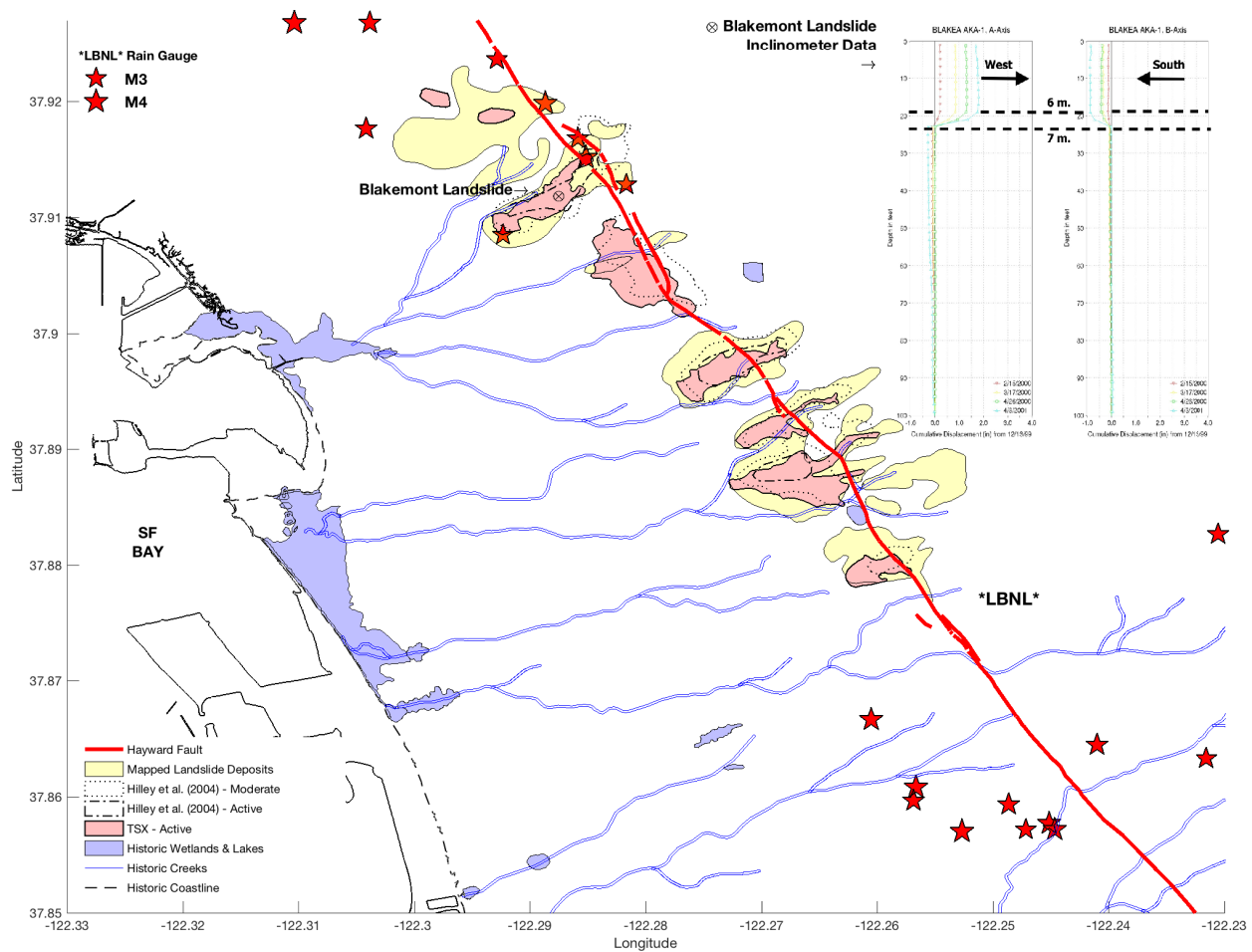


Figure 4-3. Site map of the EBH highlighting mapped landslide deposits (yellow) by Kropp (1995) with the outlines of “moderately active” (dotted) and “highly active” (dashed) slide masses defined by Hilley et al. (2004), compared with the highlighted (red) active slide areas defined in this study. An inclinometer record of ground displacement at BLS from 12/1999 through 4/2001 (Kropp & Lettis, 2002) is included in the upper right. The general direction of displacement indicated by the inclinometer data is downslope toward the southwest. The precipitation data used in this paper are from rain gauge located at LBL. Red stars indicate M 3-4 earthquakes.

4.1.2 Limitations of InSAR Analysis and Mapping

Importantly, there are visible differences in mapped historic, moderately active and active landslide deposits from Figure 4-3. Each effort to identify these landslide deposits used different data sets over different time periods. Therefore, slide margins were determined with varying degrees of certainty depending on the resolution and accuracy of each data set, and do not account for changes in landslide behavior or ground use over time.

The most comprehensive record of landslide deposits in our study area (Kropp, 1995) is a result of careful manual mapping of historic landslide deposits, based on historical air photo analyses, geologic field mapping (Russell W. Graymer et al., 1994), and decades of local geotechnical and geological consulting experience. These mapped landslide margins can be considered reliable to within tens of meters accuracy. In comparison to the two subsequent records of landslide activity

mapped by InSAR in Hilley et al. (2004) and for this study, we find that the Kropp (1995) record is for the most part complete. Both iterations of InSAR mapped slide deposits fall within the mapped historic deposits with few exceptions. The main discrepancy between each of these three iterations is the Kensington landslide, where InSAR mapping clearly shows a large, moderately active landslide deposit in an area where Kropp (1995) shows two small deposits. Also, one smaller landslide deposit was mapped as part of our work, at the North end of the study area (approximately Lat: 37.92 Lon:-122.3), which had not otherwise been observed. This speaks to the utility of InSAR mapping where ground use (residential development) likely impeded both field and air photo observations of landslide induced ground distress, or the extent of these landslide deposits were simply not visible through field and air photo observation. However, while InSAR is clearly a useful tool for remotely characterizing large scale ground deformation, this comparison also underlines some of its shortcomings:

- The necessity for active ground deformation.
- The direction of ground deformation.
- Signal limitations from ground cover and processing algorithms.

The most significant limitation of InSAR is the necessity for active ground deformation. This is made apparent through Figure 4-3 where active ground deformation primarily falls within the historic record of slide deposits (Kropp, 1995), while many of the historic slide deposits show little to no deformation in the InSAR time series. Without active deformation, InSAR will not identify historic landslide deposits which may be otherwise apparent in a geomorphic sense. The same can also be said for the opposite, where ground deformation between two scenes may be too great to resolve from InSAR. Since InSAR is a record of Radar phase shifts, it is limited by a maximum detectable phase gradient and loses coherence with large gradient deformation (Liu et al., 2014).

For slide deposits known to be active, their direction of movement speaks to the second limitation of InSAR, the satellite geometry. Radar satellites are limited to measuring range changes in the direction of their source beam, otherwise known as their 'Line-Of-Sight' or 'Look' direction. Ground deformation parallel to the satellite flight path will not result in as strong a signal and thus the need for multiple satellites to resolve complete and 3-dimensional ground displacement vectors (Delbridge et al., 2016). This is apparent from several landslide deposits located within the LBL campus at the southern end of our study area, for which InSAR time series show little to no deformation though they are known to be active (Figure 4-2). This is in part due to a lack of MP coverage.

Poor MP density illustrates the question of signal limitations. Ground cover significantly affects the Radar return signal depending on its wavelength. Shorter signal wavelengths provide better MP densities in areas with steady targets, but loose coherence over smooth and vegetated surfaces. This is evident throughout the study area from gaps in MP coverage which correspond to fields and parks in an otherwise urban environment (Figure 4-1) as well as the difference in MP density between this and previous studies (Figure 3-1). In addition to better coverage from a shorter Radar wavelength, InSAR processing algorithms such as the one used in our analysis (SqueeSARTM) significantly improve the MP density through spatial averaging of low-intensity return signals. A large part of the differences in active landslide mapping between the two InSAR iterations (Figure 4-3) can be attributed to an improvement in mapping accuracy from increased MP coverage. Qualitatively, these differences further suggest that landslide deformation is likely varying spatially over time. Such behavior within a larger historic landslide deposit is well recognized, in that the activity of nested failures should vary both spatially and temporally with

some sections more active than others, depending on transient pore pressure conditions, differential mobility and progressive failures.

4.2 Downslope Velocity and Landslide Depth Estimates

4.2.1 Downslope Velocity Estimates

Without at least three independent LOS observations, it is not possible to resolve the 3-dimensional sense of landslide motion (Delbridge et al., 2016). Thus the rest of the analysis is performed in terms of LOS. However, an estimate of the magnitude of actual ground displacement can be made by assuming a downslope orientation of landslide motion (Chapter 3). Overall, the estimated TSX downslope velocities are similar to previous studies. While there are few quantitative measurements of motion prior to the 1990s, it also appears that the landslides have moved at comparable rates for many decades. A detailed review of streets and property lines from historical air photos and land surveys suggest 3-5 m of downslope displacement over the last 100 years (Kropp, 2010). Inclinometer data has recorded 3-4 cm/yr of surficial displacement (Kropp, 2010; Kropp & Lettis, 2002).

Hilley et al. (2004) estimate average downslope velocities of 27-38 mm/yr for the major EBH landslides, based on ERS LOS velocities of 5-7 mm/yr at the North Berkeley and Thousand Oaks landslides, measured between 1992 and 2001. They resolved these downslope velocities using the ERS LOS configuration and determine an amplification factor of 5.5 based on an average slope geometry for the entire EBH. Using the same method and slope geometry, Lei and Bürgmann (2010) estimate downslope rates on the order of 10-30 mm/yr for data from three separate TSX acquisition modes, covering the same short period between 2008 and 2010. Quigley et al. (2010) estimate similar average downslope displacement rates of between 10 to 25 mm/yr by resolving 2-dimensional slope displacements from the ERS 1992-2001 data and RADARSAT-1 data collected between 2001 and 2006. Table 2-2 and Table 4-2 summarize the different satellite and slope configurations, and their corresponding vectors.

Expanding on one of the Lei and Bürgmann (2010) TSX data sets, this study considers data from 2009 through 2014. First, we find average LOS velocities within the most active portions of each of the five large EBH landslides. Applying the same method and EBH slope geometry as Hilley et al. (2004) (Table 4-2), the average downslope velocities are resolved for each using an amplification factor of -3.9 (Table 4-3). Figure 4-4 presents the estimates of downslope velocities at the BLS. Based on average LOS velocities of -7 to -10 mm/yr, the downslope velocities estimates are between 27 and 39 mm/yr. These estimates of downslope velocity appear consistent with the those previously estimated for the EBH landslides, regardless of the acquisition satellite, period of interest and processing method. They are also consistent with the limited in-situ inclinometer data reported by Kropp and Lettis (2002) for the BLS (Figure 4-3).

Table 4-1. Satellite parameters and their corresponding transformation vectors used to obtain landslide downslope velocities from satellite LOS velocities.

Satellite Acquisition Geometry	Flight Path Azimuth (0°)	Look Angle (δ°)	Vectors (x: East, y: North, z: Height)		
<i>TSX</i>	190.82	22	0.368	-0.07	0.927
<i>ERS 1&2</i>	193.8	23	-0.23	0.06	-0.97
<i>RADARSAT-1</i>	8.6	34	-0.55	0.08	0.83

Table 4-2. Slope parameters and their corresponding transformation vectors used to obtain the amplification factor and landslide downslope velocities from satellite LOS velocities.

Slope	Azimuth (degrees)	Dip (degrees)	Vectors (x: East, y: North, z: Height)			TSX Amplification Factor (S)
<i>EBH</i>	222	4	-0.66	-0.75	0.07	-3.9

Table 4-3. Summary of average downslope landslide velocities (mm/yr) for all EBH studies.

Source	Satellite	Date Range	BLS	KLS	TLS	MLS	NBLS
<i>Hilley (2004)</i>	ERS	1992-2001	[27-38]	[20-25]	27-38	[20-25]	27-38
<i>Quigley (2010)</i>	ERS/RADARSAT	1992-2006	-	-	10	-	25
<i>Lei (2010)</i>	TSX	2008-2010	[20-30]	[10-15]	[15-25]	[10-15]	[20-30]
<i>This study</i>	TSX	2009-2014	27-39	8-16	16-20	8-16	23-35

Notes:

[] bracketed numbers were approximated from figures, not explicitly stated in text.

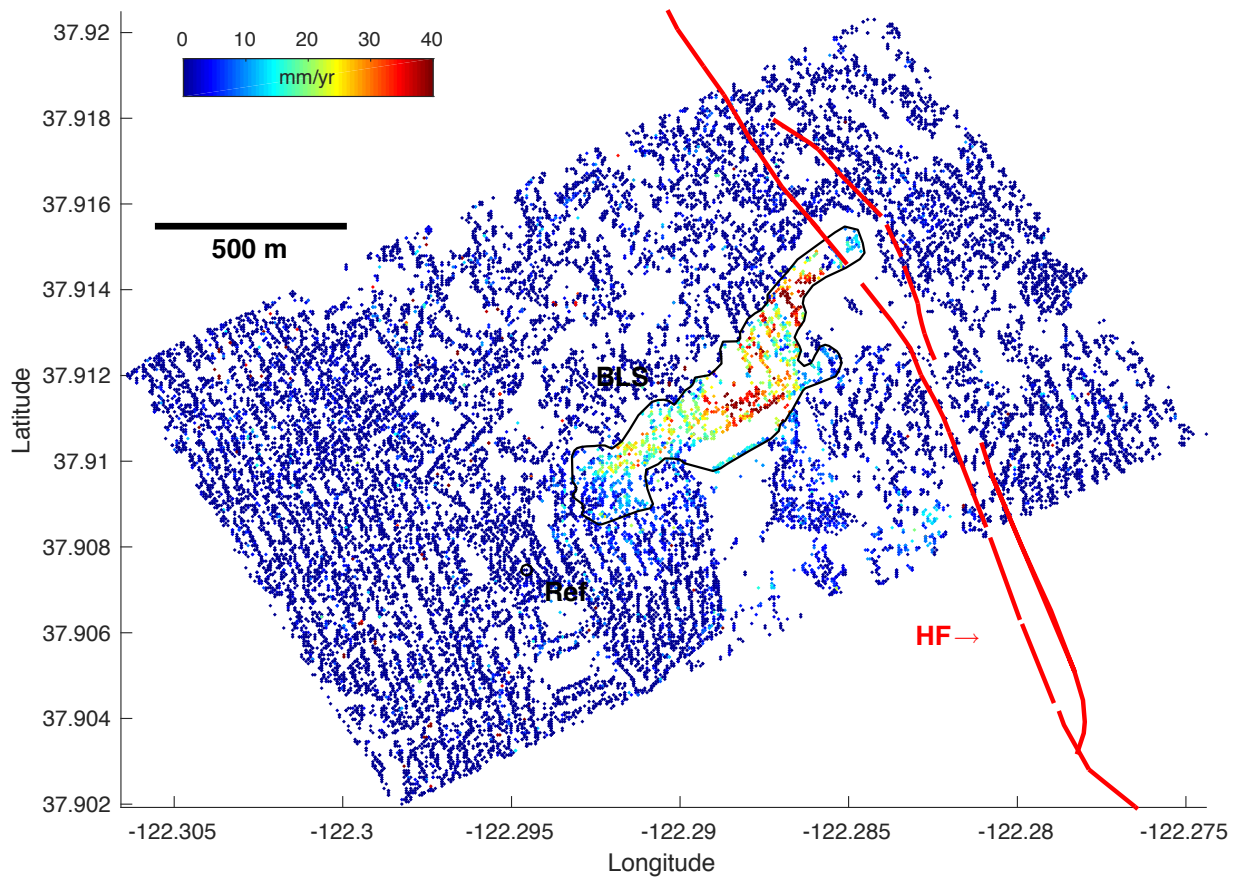


Figure 4-4. Map of Blakemont landslide and surrounding area illustrating downslope velocities calculated from TSX LOS velocities and the estimated EBH landslide orientation from Hilley et al. (2004). Downslope velocities shown here are from transformed LOS velocities using an amplification factor $S = -3.9$ to reflect subsidence and westward motions as positive (see color scale).

4.2.2 Landslide Depth Estimates

While ground surface deformations provide an overall sense of motion, without some knowledge of the subsurface it is difficult to draw any conclusions on the mechanics of that deformation. Fortunately, the urban development throughout the study area has led to numerous geologic investigations, although the extent of those investigations is generally limited to understanding of only a small subset of what is a much larger and complex geologic setting. However, the data is limited in depth since data collected from beyond 10-15 m depth is sparse.

Local studies suggest that active mass wasting due to seasonal shrink/swell cycles of clay-rich materials are likely constrained to within the upper 1 to 2 m of the subsurface (Fleming, 1972). Measured surface deformation within landslide deposits, is therefore a combination of mass wasting and deeper ground movement. Based on limited borehole and inclinometer data, the landslides within our study area exhibit active ground displacement heterogeneously distributed within the upper 6 to 8 m of the subsurface and as deep as 30 m. The most significant record of subsurface deformation within our entire study area is data from a single inclinometer located within the BLS and maintained for one year (2000-2001). The record (Figure 4-3) clearly indicates

a one meter thick shear zone from 6-7 m, with distributed landslide deformation above and a minor creep deformation extending a deep as 30 m. The record also confirms minor surficial soil activity within the upper 1-2 m.

For lack of reliable landslide depth measurements, the total landslide deposit thickness is estimated based on a first order Depth-Area relationship (Chapter 3). These estimates are summarized in (Table 4-5), with illustrated solutions included in Appendix B. A summary comparison of these estimates with available field observations confirms that they are generally realistic and consistent.

Table 4-4. Estimated landslide deposit depths from different depth-area relationships.

Landslide Depth (m)	Larsen et al (2010)	Simoni et al (2013)	Handwerger et al (2013)
<i>BLS</i>	13	13	15
<i>KLS</i>	17	18	18
<i>TLS</i>	12	13	15
<i>MLS</i>	10	10	13
<i>NBLS</i>	16	17	18

4.3 Time-dependent surface displacements from FCF

4.3.1 FCF Analysis of Blakemont Landslide

The first order estimate of the temporal periodicity and amplitude of the controlling modes within the observed time series is obtained using the Functional Curve Fitting (FCF) analysis (Chapter 3). The linear sum of several a-priori functions is used to fit each InSAR MP time series. The FCF analysis identifies three first order trends, showing seasonally precipitation-modulated accelerations of landslide displacement with a measurable lag, a multi-year deceleration in landslide deformation caused by the onset of regional drought conditions in 2012 (Bennett et al., 2016), and a notably cyclic background seasonal signal in all MP time histories.

The LOS velocity map (Figure 4-1) defines the spatial extent of active EBH landslides. Isolating each landslide, we produce average displacement time series for all points ‘on’ and ‘off’ the active slide mass and compare deformation to total cumulative precipitation. In each case, there is cyclic deformation both ‘on’ and ‘off’ of the landslides which is closely correlated with seasonal cycles in precipitation. The motion of points off the landslides is primarily cyclic with no cumulative deformation, while points on the landslide show both. To extract purely landslide driven average deformation, removing the average ‘off-slide’ seasonal motion from each ‘on-slide’ MP time series produces a ‘clean’ (or ‘corrected’) time series. The cyclic behavior is analyzed using model time histories using the FCF analysis of each MP by solving for the coefficients in Equation 3-1 (least squares inversion).

Figure 4-5 illustrates these results through a closer look at the BLS. It shows (Figure 4-5 a.) the FCF analysis results fit to the average displacement time histories for MPs ‘ON’ the landslide (black circles), ‘OFF’ the landslide (blue circles) and the ‘clean’ (‘COR’) landslide displacement time history (red circles). The modeled curves (dashed lines in corresponding colors) fit the displacement time series well ($R^2 > 93\%$) and when compared to total cumulative precipitation (solid black line), there is a clear association between the seasonal precipitation cycles and annual

cycles in ground deformation both on and off the BLS. Also, the onset of local drought conditions in 2012 clearly causes the average velocity of BLS to slow by as much as 75%. This analysis reveals how displacement rates increase following the onset of precipitation, reach their peak near the onset of each dry season, then slow down during the dry summer months, and are sensitive to long term (multi-year) climatic conditions.

Comparing monthly ground deformation rates for each MP to the average annual monthly precipitation rates over the study period, further reveals a first order sensitivity of landslide deformation to precipitation (Figure 4-5 b.). Plotting phase and normalized amplitude of peak displacement rates for ‘off-slide’ MPs (blue) and clean ‘on-slide’ MPs (red), against average monthly precipitation rates, shows that peak seasonal landslide rates occur between March and June, with a ~30-40 day lag to peak seasonal precipitation rates, which occur in February-March. In contrast, MPs off the landslide are clearly tied to the onset of seasonal precipitation, reaching their peak between October and January, and on average (in November-December) 60-90 days after the onset, and 100-120 days before peak landslide rates.

Mapping the maximum coefficient amplitudes for each modeled MP time history, also reveals first order spatial trends in landslide behavior (Figure 4-6 a.-d.). The amplitude of acceleration (Figure 4-6 a.) suggests a decrease in the LOS velocities over our period of study, a long-term deceleration that is directly correlated to the onset of severe regional local drought conditions in 2012. The spatial distribution of the average velocity term (Figure 4-1 b.) suggests heterogeneous motions across the body of the landslide, typical of earthflow-type failures. The sinusoidal functions in Equation 3-1, used to describe seasonal variations, suggest that displacements are governed by a strong annual cycle (Figure 4-6 c.), with a modest semi-annual amplitude (Figure 4-6 d.).

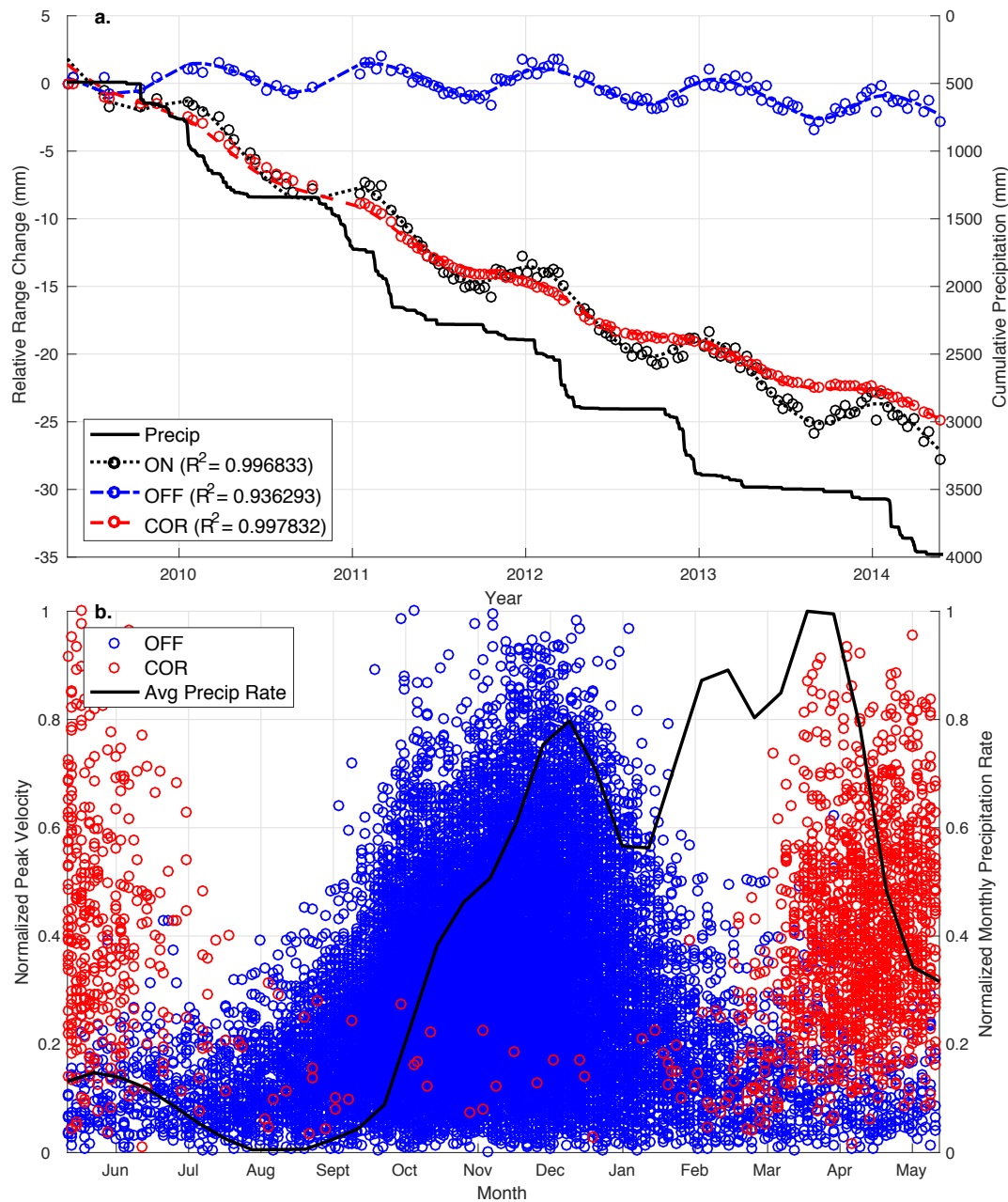


Figure 4-5. (a) FCF results fit to the average BLS displacement time histories for ‘ON’ landslide (black circles), ‘OFF’ landslide (blue circles) and corrected (‘COR’) landslide (red circles). Precipitation (solid black lines) is shown in (a) as total cumulative and in (b) as an average annual normalized monthly rate over the study period. (b) Phase and normalized amplitude of peak seasonal corrected velocity ‘on’ (red circles) and ‘off’ (blue circles) the BLS. Peak velocities within the BLS occur primarily between March and June, with an average 30-40 day lag passed the peak seasonal precipitation rates. Peak velocities of MPs points outside the BLS are tied to the onset of seasonal precipitation, occurring on average around November and December, approximately 100-120 days before peak landslide velocities.

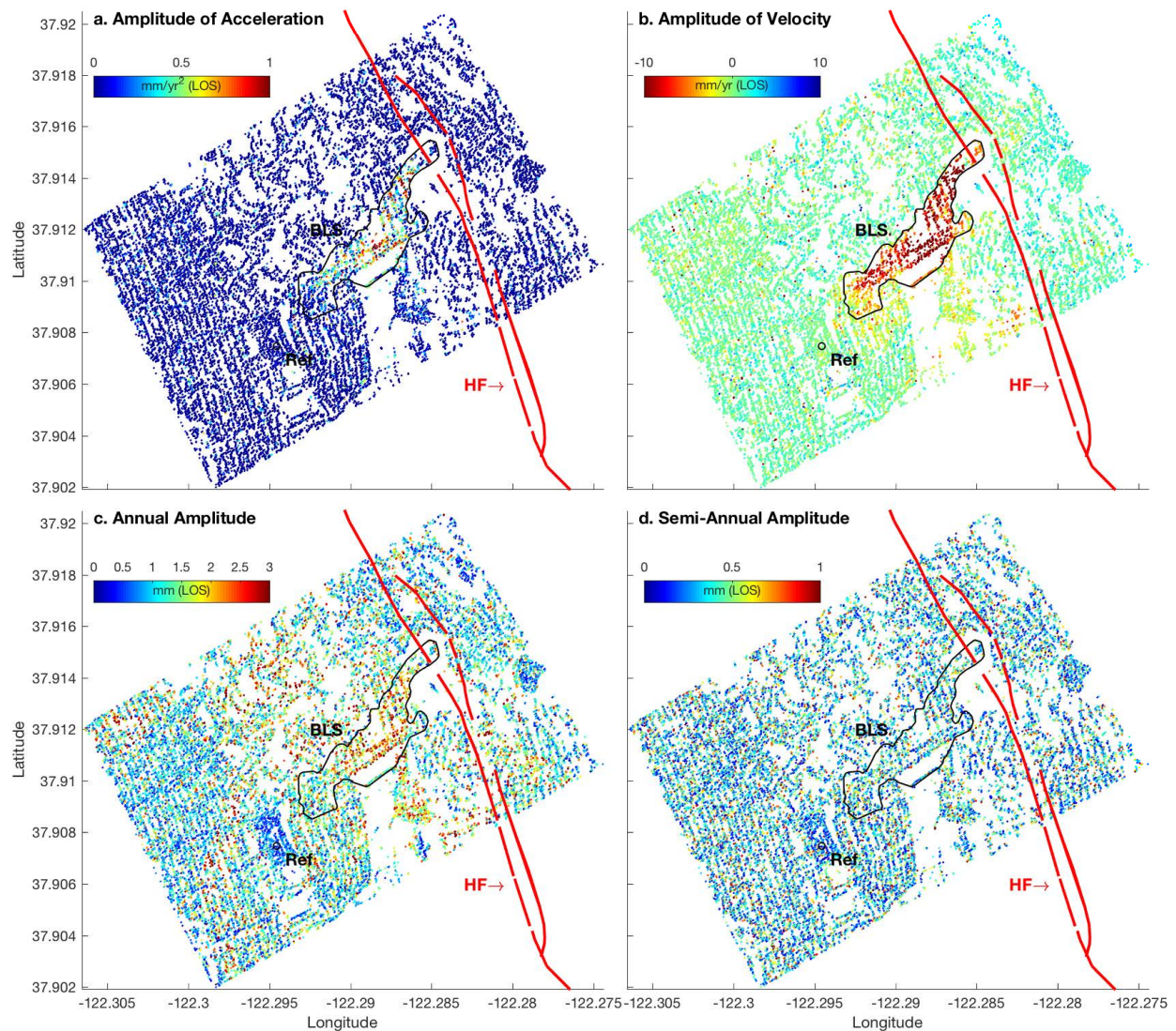


Figure 4-6. Spatial distribution and amplitude of the coefficients for each term in eq. 3.1 of the FCF. **(a)** Coefficient of acceleration, illustrating the effects of drought onset in 2012. The fastest portions of the BLS are most affected as the earthflow slows under drier conditions. Positive acceleration amplitudes reflect a decrease in measured velocity (see scale). **(b)** Coefficient of velocity illustrating the general westward movement (away from the satellite) of the BLS, in contrast with the surrounding stable slopes. **(c)** Coefficients of the annual sinusoidal term, illustrating that MPs located on the BLS have higher sensitivity to the effects of annual precipitation cycles than surrounding areas. **(d)** Coefficients of the semi-annual sinusoidal term, illustrating that there is little to no amplitude at a 6-month period.

4.3.2 FCF Analysis of the East Bay Hills Landslides

The FCF analysis results for each of the remaining four EBH landslides are consistent with those from the BLS (Figure 4-7 a.). Though each landslide exhibits a different degree of activity and sensitivity to seasonal precipitation (all lesser than the BLS), the OFF-landslide time histories

are consistent throughout. The corrected time histories (red points and fitted curves) also support that while the amplitude of peak deformation rates in response to seasonal precipitation varies significantly, the response phase is equally consistent (Figure 4-7 b.). Over the period of study, the average peak landslide deformation rate for each landslide in the study area occurs annually between March and June, between 30 and 60 days after peak seasonal precipitation rates and approximately 180 days after the onset of seasonal precipitation.

Expanding on observations of spatial trends across the BLS (Figure 4-6), the maximum coefficient amplitudes for each modeled MP time history across the remaining landslides are mapped in Figure 4-8 a.-c. The maps reveal the same spatio-temporal processes but with greater heterogeneity. After the BLS, the NBLs and the TLS show the most consistent activity, with a measurable deceleration from the onset of drought conditions within their most active areas, an active and spatially heterogeneous velocity profile, and a visible response to seasonal cycles in precipitation. In contrast, the KLS and MLS show significantly lower amplitudes of velocity, and are evidently less seasonally sensitive. Regardless of amplitude, the peak rate phase for all MPs located on the landslides, clearly illustrate that all of the EBH landslides follow the same precipitation modulated seasonal trend (Figure 4-8 d.), with landslide mobility beginning approximately two months after the average period of peak seasonal precipitation and six months out of phase with the surrounding areas which are correlated with the onset of seasonal precipitation. The individual amplitude maps for each of the remaining landslides are included separately as part of Appendix B.

The FCF analysis clearly reveals strong first-order spatiotemporal patterns of ground deformation tied to precipitation both on and around the EBH landslides. It provides a reasonable approximation of ground movement sensitivity to precipitation, and is suggestive of well-known geomechanical processes. On one hand, we know that the duration and intensity of precipitation drive an increase in transient groundwater pore-pressures (Handwerger et al., 2016; Iverson & Major, 1987) which in turn trigger landslide mobility (Terzaghi, 1950). The lag time between peak periods of precipitation and maximum landslide deformation rates is indicative of the diffusive properties of the slide mass and its state of equilibrium. As for the hillslopes surrounding the landslides, the immediate increase in peak rates tied to the onset of seasonal precipitation is an indication of soil activity (Skempton, 1953). The fine grained surficial soil deposits throughout our study area experience annual shrinking and swelling cycles which reach their maximum activity within three months and their full swelling potential within six months of the seasonal precipitation onset.

These observations equally portray the shortcomings of the FCF analysis in successfully isolating these different trends both temporally and spatially. The method is not able to distinguish between continuous landslide deformation or ‘creep’ (Terzaghi, 1950) and seasonally modulated deformation (Iverson & Major, 1987). Furthermore, slight shifts between the different average OFF-landslide motions (Figure 4-7 a.) suggest there may be more than one background signal, which cannot be identified through FCF.

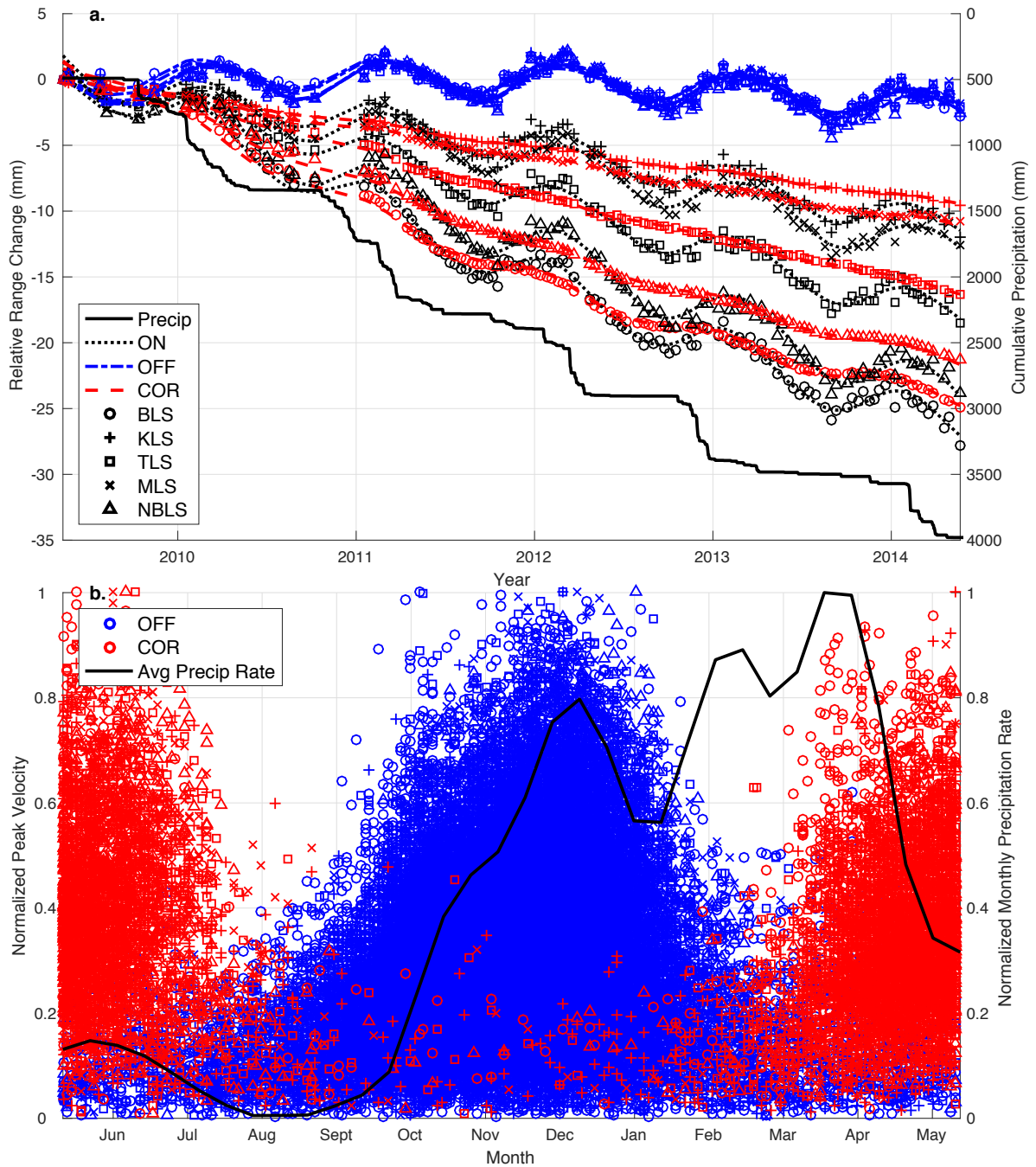


Figure 4-7. FCF analysis results for the BLS (circles) as presented in Figure 4-5 including those for the other four EBH landslides included in our study (KLS 'plus', TLS 'square', MLS 'x' and NBLs 'triangle'). (a) Though each landslide shows different degrees of activity and sensitivity to seasonal precipitation, the OFF landslide time histories are consistent throughout. (b) The phase of each landslide's peak seasonal rate is equally consistent.

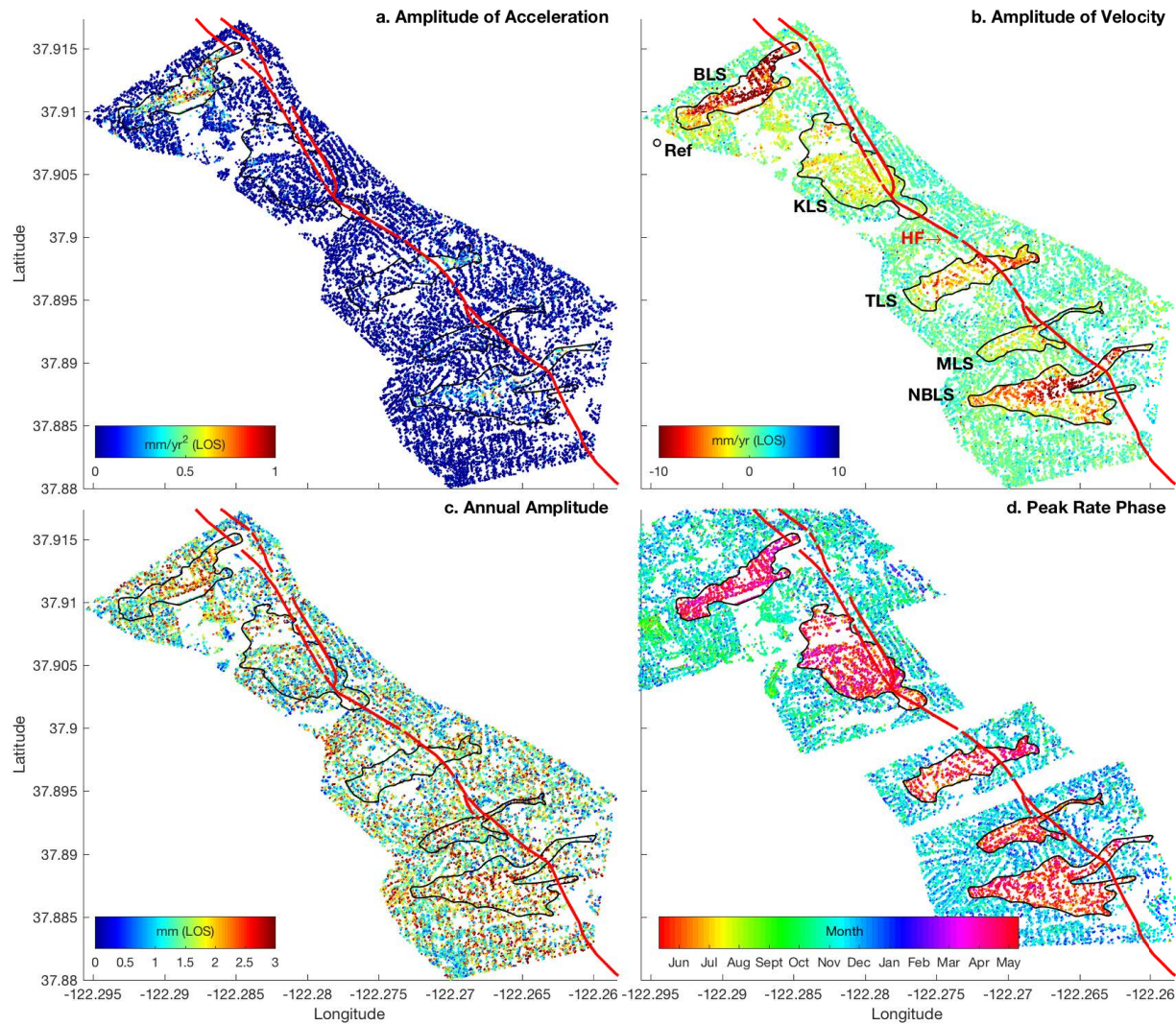


Figure 4-8. Spatial distribution and amplitude of the coefficients of (a) acceleration, (b) velocity and (c) annual cycle of the FCF for all five EBH landslides in our study area, as previously illustrated in Figure 4-6 for the BLS. (d) Illustrates the spatial distribution of phase for the peak annual rate at each MP within and around each of the EBH landslides. Landslide mobility clearly reaches its peak between March and June, six months out of phase with the surrounding areas.

4.4 Time-dependent surface displacements from PCA

To better relate the first order trends revealed through FCF to spatiotemporally uncorrelated signals within the data set, a Temporal-mode PCA (TPCA) is used with focus on the most seasonally sensitive example, the BLS. A TPCA of the BLS area reveals that the most distinct spatial and temporal patterns are captured by the first four PCs (Figure 4-9) which account for ~91% of the signal variance (Figure 4-10). While some temporal variability also exists within the next four components (Figure 4-11), they account for less than 0.25% (each) of variance and are likely

associated with atmospheric effects. The remaining 110 components account for a combined 8% of the signal variance and likely capture only noise.

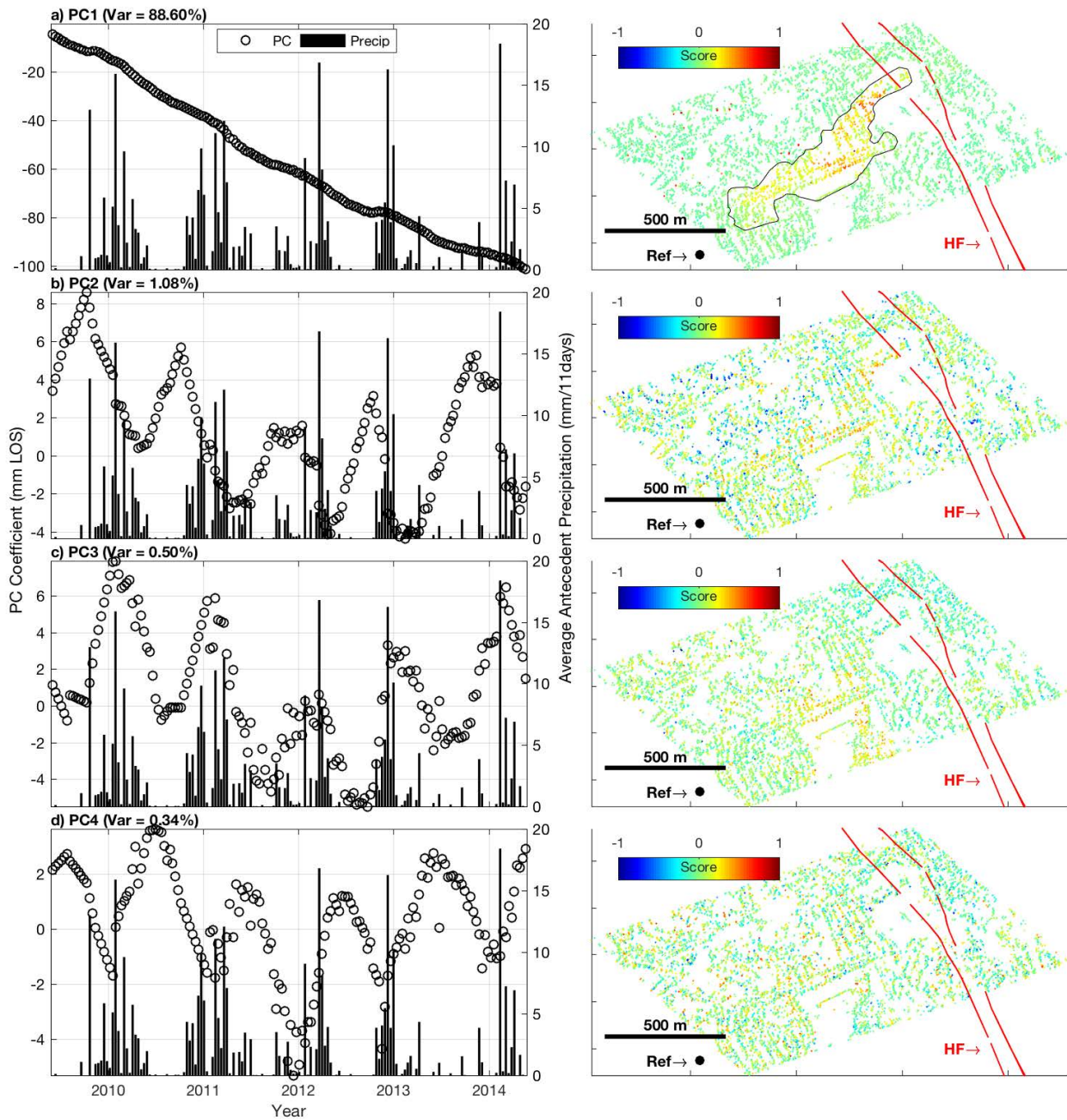


Figure 4-9. Time series of eigenvectors and score maps from TPCA analysis for PC1-PC4. (a) PC1 illustrates relatively steady westward displacement of the BLS with some seasonal acceleration. (b) PC2 represents purely seasonally driven surface displacements within the BLS. (c) PC3 and (d) PC4 reflect seasonally driven surface displacements on and off the BLS. Histograms in (a) – (d) show 11-day precipitation values.

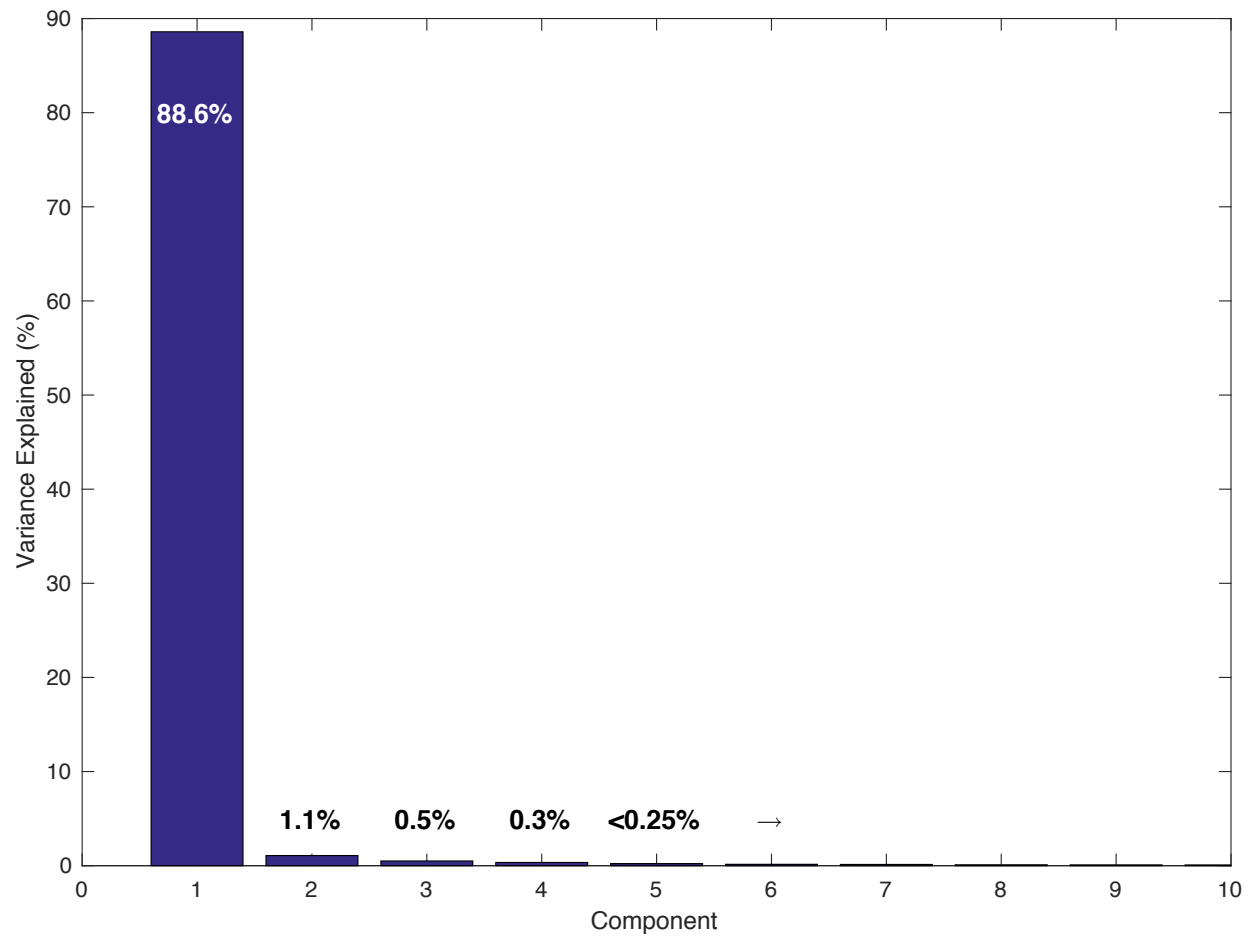


Figure 4-10. Percentage of variance explained in the first 10 components of the TPCA. The first four principal components account for 90.5% of the signal variance. The remaining 115 components each account for less than 0.25% of the signal variance (approximately 9.5% total) and are likely associated with atmospheric effects.

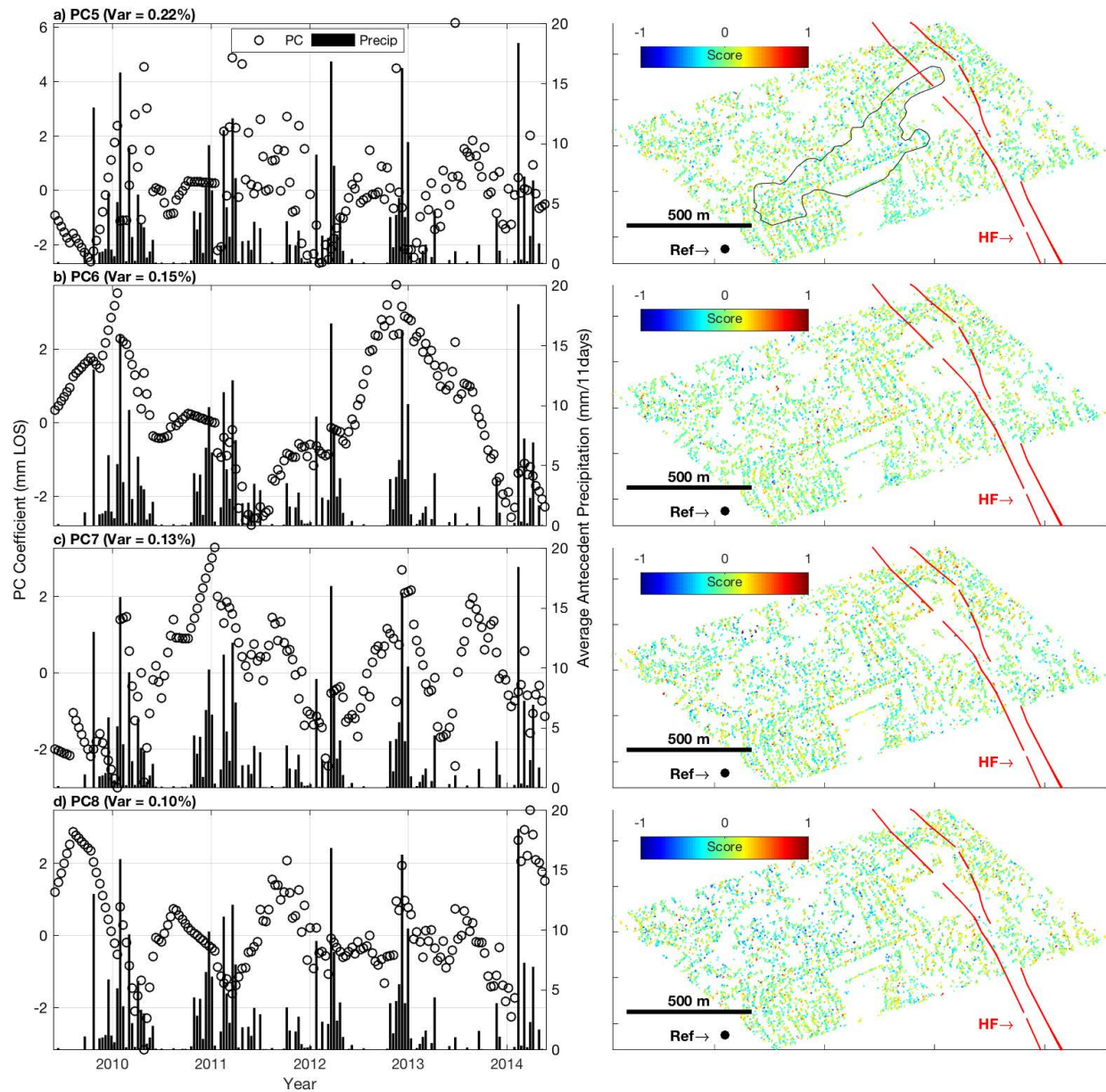


Figure 4-11. Time series of eigenvectors and score maps from TPCA analysis for PC5-PC8 (a-d). We do not observe any significant spatial or temporal trends in these or the remaining components.

The first PC (PC1), which accounts for nearly 89% of the signal variance, is representative of long-term deformation with a nearly linear eigenvector time series. The PC1 score plot (Figure 4-9 a.) indicates that this component is spatially tied to the landslide, with generally positive scores observed across the BLS footprint. The negative slope of the eigenvector time series corresponds to the negative LOS displacements, consistent with downslope movement of the slide mass. Annual fluctuations associated with seasonal precipitation are visible in the eigenvector time series and a multi-year deceleration is caused by the onset of severe regional drought conditions in 2012 (Bennett et al., 2016). The areas surrounding the BLS exhibit nearly no contribution to this component.

The following three PCs (PC2-4) correspond to different spatial distributions of varying temporal deformation, with oscillating eigenvector time series generally following an annual seasonal cycle, superimposed on a rate change associated with the drought conditions starting in 2012. PC2 (Figure 4-9 b.), which accounts for approximately 1% of the signal variance, describes a negatively correlated sense of motion with respect to precipitation that is highly sensitive to the peak period of precipitation. This is evident in steps in the time series (subsidence or westward motion for positive score values) coinciding with the largest 11-day precipitation values. The score map illustrates that the motion described by this component is spatially tied to the BLS area with an opposite sense of motion in the areas surrounding the landslide. Similarly, PC3 (Figure 4-9 c.), which accounts for approximately 0.6% of the signal variance, describes a sense of motion that is generally tied to the BLS area (as well as large vegetated areas neighboring the slide), with a low amplitude and opposite contribution from the other areas surrounding the landslide. However, the PC3 eigenvector time history is positively correlated to the rate of precipitation. Finally, the signal component described by the PC4 (Figure 4-9 d.) eigenvector time history, which accounts for approximately 0.4% of the signal variance, describes a seasonal sense of motion opposite to that of PC3 (negatively correlated with the rate of precipitation), though with half the amplitude and a generally incoherent spatial distribution. In each case, the onset of regional drought conditions in 2012 significantly affects the eigenvector time histories causing their longer-term slopes to reverse.

Building on observations from the FCF analysis, the TPCA reveals that there are not three but four relevant trends in the recorded signal, as well as their order of importance. A generally linear landslide ground motion dominates the signal, followed by a seasonally modulated landslide ground motion. The two remaining components describe different parts of the background seasonal motion observed in the FCF analysis. While the TPCA clearly improves our understanding of the relevant signal trends, the presence of both short and long term seasonal variability in each component suggests a certain degree of mixing within the signal.

4.5 Time-dependent surface displacements from ICA

4.5.1 ICA of the Blakemont Landslide

ICA is used to optimize the four spatiotemporal patterns from the TPCA into statistically independent ICs. Figure 4-12 summarizes the results of the ICA for BLS, using four components (IC1-IC4), which optimally isolate the major spatial and temporal trends underlying the deformation time series. For relevance, the FCF analysis results are shown in Figure 4-12 (a.) along-side a velocity map of BLS. The remaining panels in Figure 4-12 (b.-e.) describe the ICA results for the BLS, showing eigenvalue time series for each IC (left, circles) plotted against precipitation (left, solid lines) and their corresponding score maps (right). For clarity and comparison, each score map has been normalized by its relative maximum and factored into the eigenvector (IC) time series. The time series have also been corrected for the percentage of data explained (~95.7%). As such, the product of the MP score values and their corresponding eigenvalues (IC Coefficients) in Figure 4-12, will return the contribution of each component in deformation units (mm). Using less or more components, shows that parts of the different signals are either superimposed or result in less distinct time series and featureless score maps in the extra components.

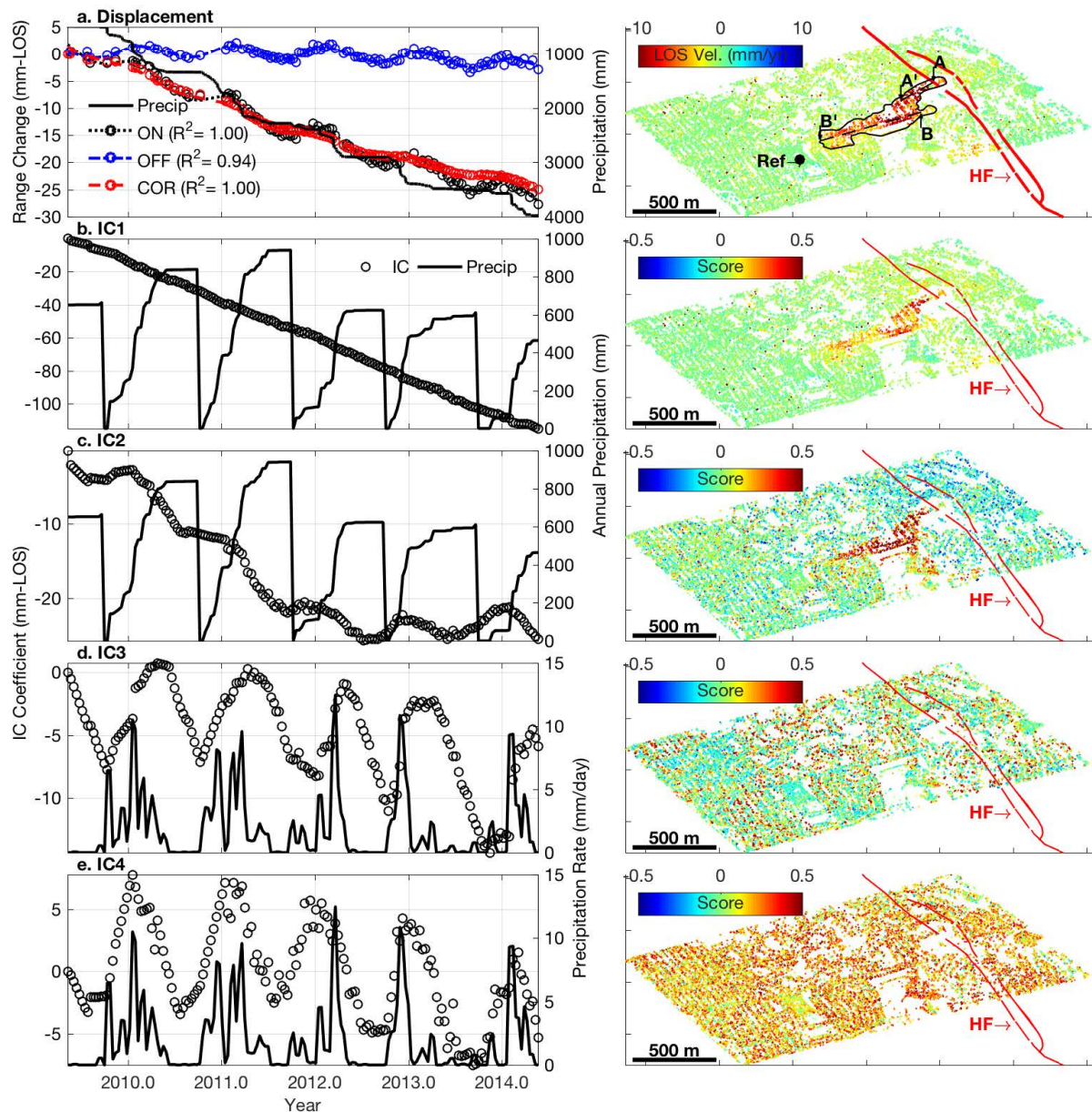


Figure 4-12. (a) (Left) FCF results for the BLS of average ‘ON landslide’ (black circles), ‘OFF landslide’ (blue circles) and ‘CORrected (ON – OFF) landslide’ (red circles) displacement time histories. (Right) LOS velocity map of the BLS area with the ‘active’ BLS deposit defined by MP velocities $< -2\text{mm/yr}$. (b-e) ICA results for the BLS showing eigenvalue time series for each IC scaled by the percent non-zero eigenvalues retained (left, circles) and their corresponding score maps (right). Precipitation (solid black lines) is shown in the left panels as total cumulative (a), water-year cumulative (Oct-Sep) (b,c) or daily rates (d,e).

IC1 and IC2 (Figure 4-12 b. and c. respectively) show positive scores on the BLS, indicating downward and westward displacements (negative eigenvector slope), with negligible contribution from points outside the BLS footprint. IC1 describes a nearly linear deformation time history with

no seasonal variability, while IC2 describes seasonal accelerations directly correlated to peak seasonal precipitation rates and a reduction in displacement rate with the onset of the drought in 2012. The combination of these two components and their score maps returns the same average displacement time series describing precipitation-modulated landslide motion as the “Corrected” (red circles) curve from the FCF analysis (Figure 4-12 a.).

To better illustrate both spatial and temporal seasonal variation in the BLS velocity field, a plot the velocity time history along a 100-m-wide swath (Figure 4-12 a, right) against the rate of precipitation is presented in Figure 4-13. Variations in the velocity field along the cross section show which portions of the slide remain active throughout (e.g., ~320 m), while others slow or stop. Figure 4-13 also captures the response time of displacement to precipitation for different parts of the landslide (with ~40 days lag) and the significance of drought effects since 2012, with shorter periods of landslide activity sometimes slowing to a halt (e.g., 500 to 600 m along section A-A'-B-B'). This is further illustrated through a velocity time history map of the BLS in Animation S1 (and Animation S2 for the entire study area), plotting two month average velocities over time for the combined IC1+IC2 displacement time histories at each MP on and around the BLS. The animation reveals internal strain deformation of the slide mass with the spatial extent of activity within the upper and middle portions of BLS, and a velocity pulse from top to bottom as the lower portions of the slide accelerate late each season. The effects of drought beginning in 2012 are also made more visible as the entire slide can be observed coming to a complete halt during the dry seasons.

The IC3 and IC4 score maps describe a broadly distributed signal, both on and off the BLS (Figure 4-12 d. and e. respectively). The eigenvector time series describe seasonal deformation with precipitation-modulated ground displacements, where positive slopes (in combination with the positive score values) describe uplift/eastward motion (towards the satellite). While the eigenvector time series in IC3 shows a positive correlation to seasonal precipitation that is highly sensitive to the peak periods of precipitation, IC4 shows a positive correlation to the rate of precipitation with a phase lag from IC3 of approximately 3-4 months.

It becomes evident that while the processes in IC3 and IC4 are best described by the phase and amplitude of their seasonal deformation with precipitation rates, IC1 and IC2 are landslide processes controlled by transient pore-pressures acting within the slide body and best described by their rates of change. Assuming that the rate of precipitation controls the surface boundary condition for pore-pressure, we define a one-dimensional solution for the diffusion equation (Handwerger et al., 2016) as a function of depth and time. As described in Chapter 3, the estimated first order value of diffusivity ($9 \times 10^{-7} \text{ m}^2/\text{s}$) at the BLS is based on an approximate depth of sliding (~12-15 m. at BLS from the Depth-Area relationship) and the recorded velocity time series (Figure 3-5 and Figure 3-6).

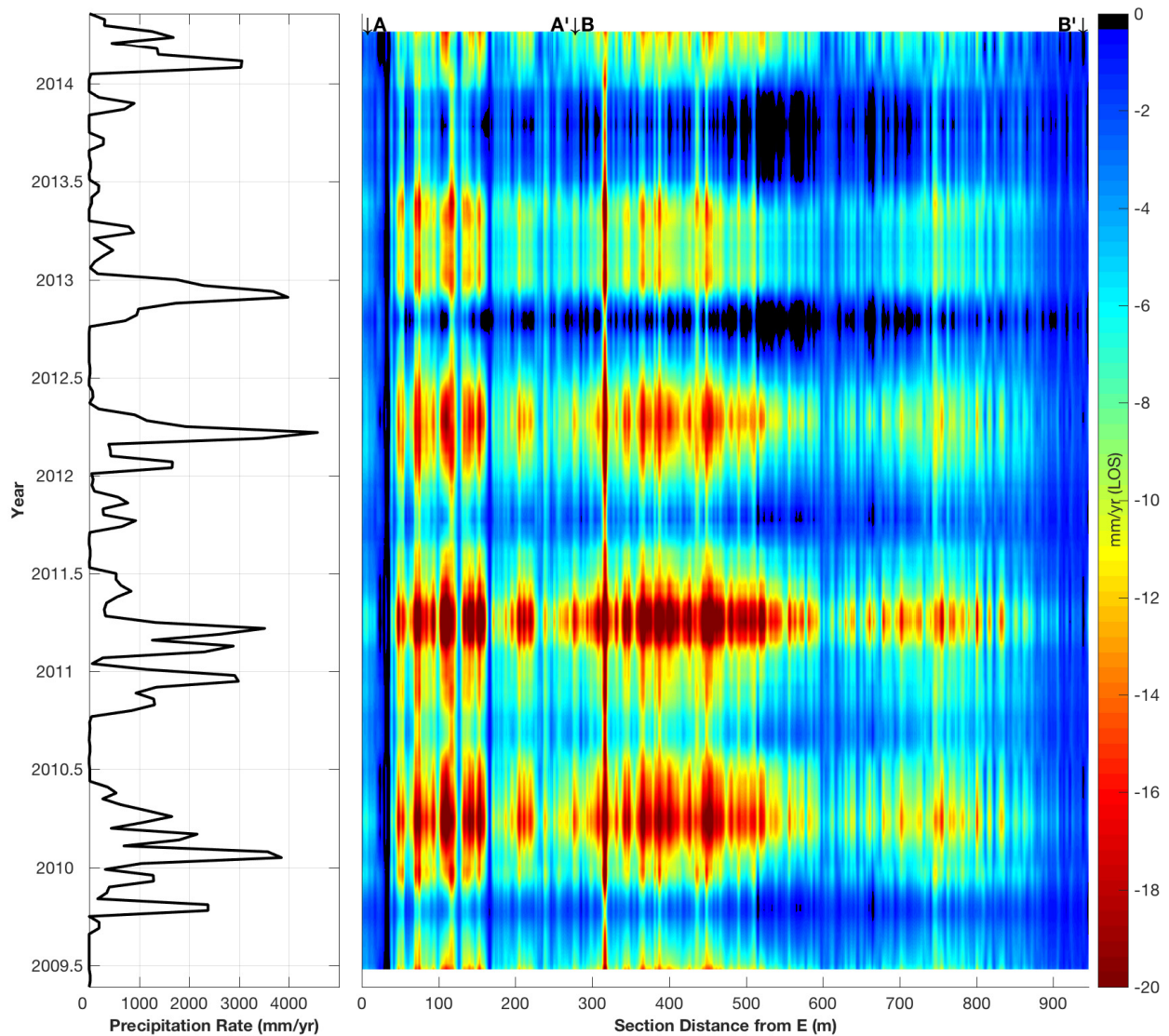


Figure 4-13. Time series of spatial variability in the velocity field along a 100 m-wide swath from top to bottom (Figure 4-12 a, right) of the BLS, reconstructed from IC1 and IC2. Supplemental Animation S1 shows the velocity time history for all MPs on the BLS.

A cross-correlation analysis of the IC eigenvector time series with precipitation rates and transient pore-pressures quantifies the observed seasonal effects on surface deformation (Figure 4-14). Combining IC1 and IC2, allows the reconstruction of a landslide deformation time series and a comparison of the rate of surface deformation with transient pore-pressure at ~5.3m (Figure 4-14 a.) and the rate of precipitation (Figure 4-14 b.). The cross-correlation between the rate of IC1+IC2 and modeled pore-pressure is positive with zero lag. The cross-correlation between the rate of IC1+IC2 and the rate of precipitation illustrates the delayed seasonal response of landslide displacement, with a positive lag of 44 days. Due to its sensitivity to peak precipitation events, the correlation between the rate of IC3 deformation and the rate of precipitation (zero lag) masks its underlying behavior. Cross-correlating the IC3 eigenvector time series with precipitation (Figure 4-14 c.) reveals that it is also strongly correlated to seasonal onsets with upward movement

occurring as long as precipitation persists, followed by a drawn-out recovery through the dry season. The ~ 77 day lag coincides well with the onset of the dry season approximately 2-3 months after peak seasonal precipitation. IC4, on the other hand, reveals a positive correlation to precipitation with only an 11-day lag, suggesting it is more directly tied to the timing and amount of precipitation (Figure 4-14 d.).

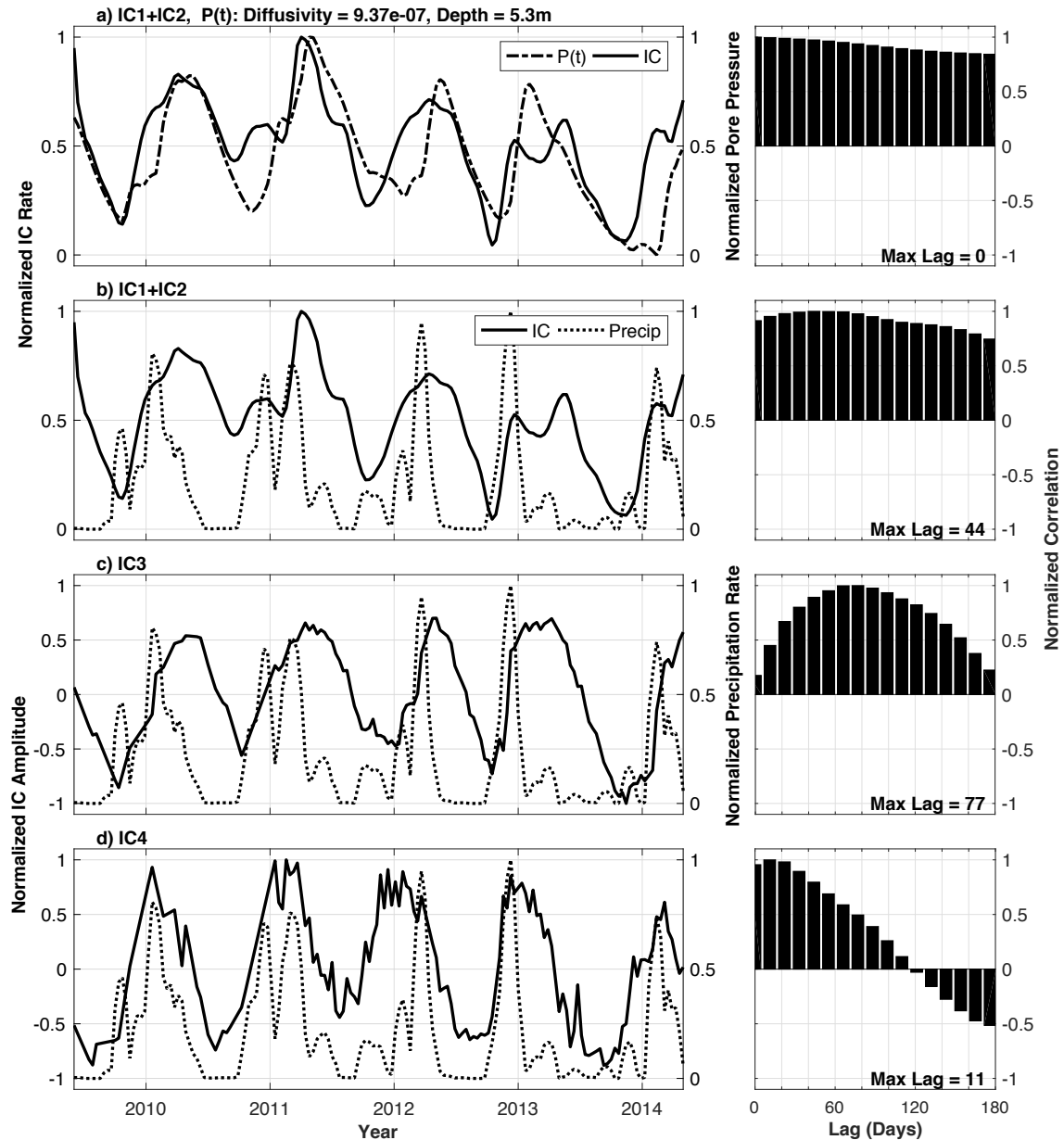


Figure 4-14. Results of the cross-correlation (right, bars) between the IC eigenvector time series (left, solid), transient pore-pressures $P(t)$ (left, dashed) and precipitation rates (left, dotted). The rate of IC1+IC2 describing changes in landslide velocity is (a) positively correlated to transient pore-pressures with zero lag and (b) positively correlated to precipitation with a 44-day time lag. Deformation described by (c) IC3 is positively correlated to seasonal precipitation with a 66-77 day lag and (d) IC4 is positively correlated to precipitation with an 11-day lag.

4.5.2 ICA of the East Bay Hills Landslides

As for the FCF analysis, the ICA at BLS are extended to the remaining EBH landslides. To capture differences in landslide behavior, the analysis is first performed separately for each landslide (included in Appendix B), then in comparison, for the study area as a whole (Figure 4-15). In each case, the FCF analysis results are included along-side a velocity map to help visualize average ‘ON’, ‘OFF’ and clean (‘COR’) landslide motion. In Figure 4-15 (a.) the displacement time histories, their fitted curves and average velocities are for all ‘ON’ and ‘OFF’ landslide areas combined. The comparison illustrates the spatial variability in slide activity where the BLS and NBLs are most active in comparison to the rest. The remaining panels in Figure 4-15 (b.-e.) describe each of the four ICs analyzed over the entire study area and plotted against precipitation as a proxy for transient pore pressures. Again, the time series have been corrected for the percentage of data explained (~94.9%). As such, the product of the MP score values and their corresponding eigenvalues (IC Coefficients) in Figure 4-15 (b.-e.), will return the contribution of each component in deformation units (mm) and add up to the averaged displacement time histories in Figure 4-15 (a.).

IC1-IC4 evaluated over the entire study area are consistent with those evaluated for each individual slide. The IC1 and IC2 (Figure 4-15 b. and c.) produce positive score maps across each slide mass with negligible contribution from the surrounding MPs and where their eigenvalue time histories capture landslide related continuous and seasonal deformation patterns (respectively). IC1 and IC2 also support the differences in landslide seasonal activity and sensitivity observed in part from the FCF analysis. The BLS and NBLs both show strong signal contributions in IC1 and IC2, in contrast to the low amplitude (albeit present) contributions from the KLS and MLS. The TLS also provides a good example of spatial heterogeneity within the slide mass and between components where boundary conditions around the Hayward Fault result in the eastern half of the TLS to be less continuously active (IC1) and more seasonally active (IC2).

Where variability in landslide behavior is made apparent by IC1 and IC2, IC3 and IC4 describe broadly distributed background signals with remarkable consistency. The eigenvalue time histories for IC3 and IC4 evaluated for each individual landslide as well as the entire study area describe the same seasonal deformation with precipitation-modulated ground displacements. These results are particularly underlined by the cross correlation analyses for each scenario (summarized in Table 4-5. Summary of cross-correlation analyses for each landslide.). For each landslide, based on the approximate total deposit depth (Table 4-4) and its average velocity time history (from FCF), a value of diffusivity and a transient pore pressure profile with depth can be calculated from the record of precipitation. Solving for the depth at which the velocity time history (from IC1+IC2) has zero lag with peaks in transient pore pressures defines the active depth of sliding. Correlation between the IC1+IC2 velocity and precipitation rates shows that landslide activity follows the peak seasonal rate of precipitation by approximately 33-44 days (i.e. April). Finally, in each case the seasonal ‘off-slide’ signal consistently lags precipitation rates by ~77 and 11 day (IC3 and IC4, respectively).

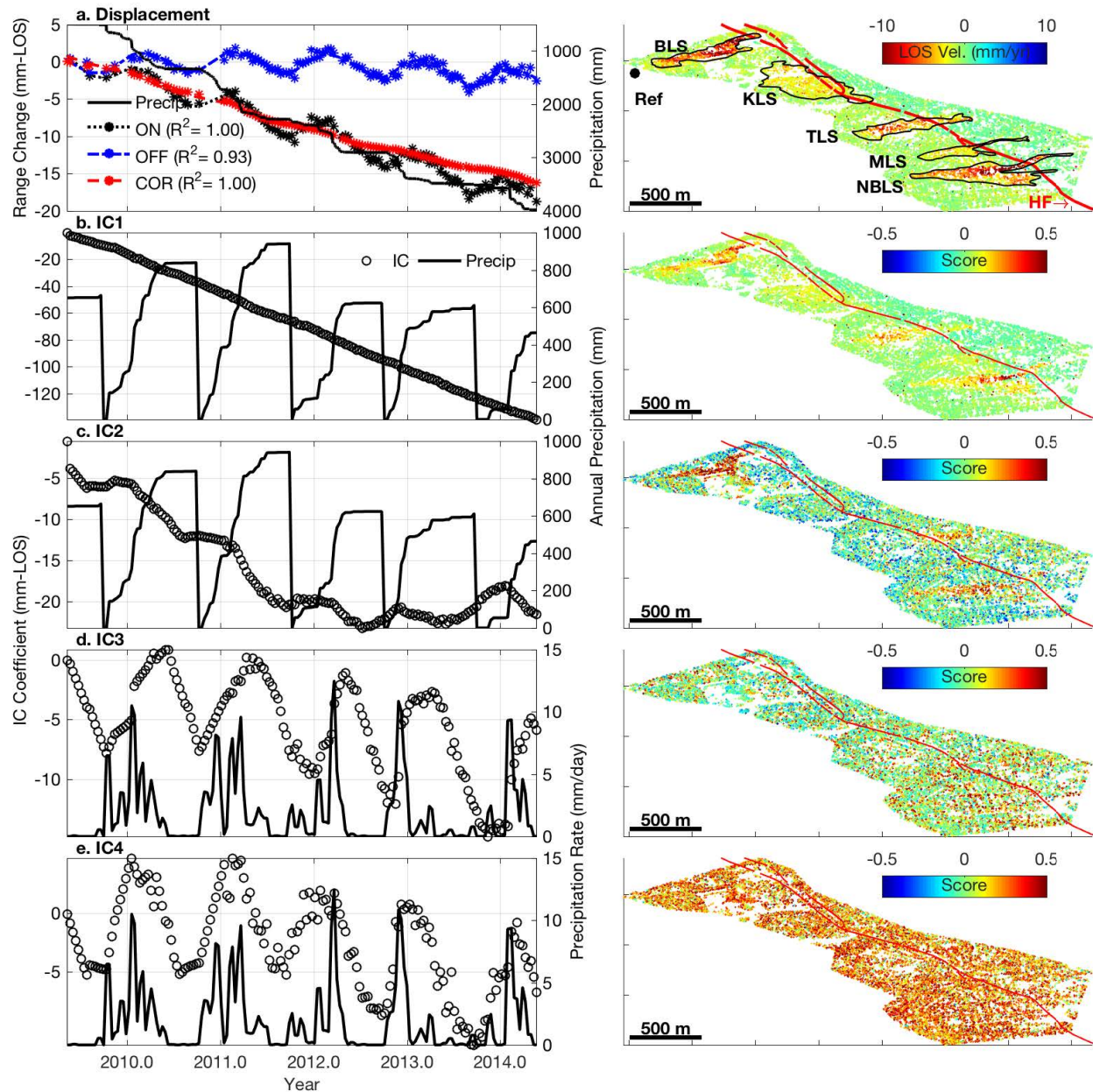


Figure 4-15. (a) (Left) Average FCF results for all EBH landslides showing average ‘ON landslide’ (black circles), ‘OFF landslide’ (blue circles) and ‘CORrected (ON – OFF) landslide’ (red circles) displacement time histories. (Right) LOS velocity map of the study area with the ‘active’ deposits defined by MP velocities $< -2\text{mm/yr}$. (b-e) ICA results all EBH landslides showing eigenvalue time series for each IC scaled by the percent non-zero eigenvalues retained (left, circles) and their corresponding score maps (right). Precipitation (solid black lines) is shown in the left panels as total cumulative (a), water-year cumulative (Oct-Sep) (b,c) or daily rates (d,e).

Table 4-5. Summary of cross-correlation analyses for each landslide.

Landslide	Diffusivity (m ² /s)	Depth (m)	Lag (days)			
			IC1+IC2 Rate vs P(t)	IC1+IC2 Rate vs Precip Rate	IC3 vs Precip Rate	IC4 vs Precip Rate
<i>BLS</i>	9.37e-07	5.3	0	44	77	11
<i>KLS</i>	7.87e-07	5	0	55	77	11
<i>TLS</i>	1.05e-06	5	0	44	88	22
<i>MLS</i>	2.50e-07	3	0	11	77	11
<i>NBLS</i>	8.30e-07	4.5	0	33	77	11

4.6 Discussion

The goal is to separate the spatial and temporal patterns of dominant long-term, seasonal and other common-mode variations of displacement and isolate the responsible processes. In general, the seasonal precipitation and geologic conditions are the primary factors in modulating deformation. Anthropogenic changes in land use (i.e. new construction) play only a minor role in MP variability and show no significant spatial correlation.

The dense SqueeSARTM MP coverage in the study area accurately documents several surface deformation features in the EBH including the spatial extent of active landslides (Figure 4-1 and Figure 4-3). The goal is to separate the spatial and temporal patterns of dominant long-term, seasonal and other common-mode variations of displacement and to isolate the responsible processes. This objective is accomplished by first performing a FCF analysis for a first order estimation of spatial and temporal trends. The FCF reveals two spatial patterns of deformation, one relating to landslide processes, the other relating to wide-spread seasonal cycles of mass-wasting. The FCF also reveals two temporal patterns of deformation, one relating to short and long term seasonal fluctuations, the other relating to continuous landslide creep deformation.

To identify a number and importance of signal patterns of statistical significance a TPCA is applied. This allows characterization of temporal and spatial variability without a-priori constraints. The results show that four components are necessary to explain over 90% of the variance in our data, and that the remainder do not represent any coherent signal. Much like in the FCF analysis, there is a combination of two spatial patterns of deformation ('ON' and 'OFF' landslide), and two temporal patterns of deformation (linear and seasonal), with the added understanding of their relative contribution to the signal. Also, while TPCA provides useful information, it does not succeed in fully isolating those different spatiotemporal patterns.

The ICA does this by maximizing the independence of components such that they must represent different spatiotemporal patterns. The results show that seasonal precipitation is the primary factor in modulating deformation on and off the BLS, as well as the remaining EBH landslides. The spatial distribution of motions across the landslide bodies vary (Figure 4-13 and Animations S1, S2), illustrating the heterogeneous nature of the slide mass, supporting its characterization as an earthflow type slide complex and capturing its spatially variable response to precipitation-modulated transient pore-pressures in IC1 and IC2.

The broadly variable spatial distribution of IC3 and IC4 (Figure 4-12 d. and e.) suggests that their seasonal signal is tied to general soil and hydrological deformation processes. We propose that IC3 is primarily tied to shrink-swell cycles of surficial soils that are sensitive to both the

amount and occurrence of precipitation (Ng et al., 2003; Rosenbalm, 2013). A reversal in surface deformation is tied to the end of each wet season, when evapo-transpiration begins to drive progressive shrinking. In contrast, the eigenvector time history in IC4 illustrates ground surface deformation directly correlated to the rate of precipitation with a short lag time and little variability during dry months (Figure 4-14 d.). While we have no concurrent groundwater level data for the observation period, groundwater levels in the EBH can fluctuate by several meters (Kropp & Lettis, 2002; Seidelman & Deane, 1994) and we interpret this component as the poro-elastic response to shallow precipitation-driven groundwater-level changes (Chaussard et al., 2014). Alternatively, IC4 is also strongly anti-correlated with seasonal temperature variations. Thermal expansion of buildings, including the reference point, during warm summer months may contribute to this component, but is likely to be small.

The TSX deformation time series reveal the direct response of landslide motion to short-term, seasonal and multi-year changes in precipitation. While their processes are mechanically related, IC1 and IC2 (Figure 4-12 b. and c.) isolate the sensitivity of landslide related ground displacements to these climate driven cycles. We observe three distinct temporal trends. First, IC1 (Figure 4-12 b.) reflects continuous creep deformation unaffected by seasonal variations at an average LOS rate of -3.5 mm/yr. Next, IC2 (Figure 4-12 c.) demonstrates both longer-term and seasonal landslide velocity changes. A distinct reduction in the average IC2 velocity occurs in 2012, quantifying the effects of drought conditions on slide displacement (Bennett et al., 2016). As EBH seasonal precipitation decreases from ~90 cm to ~60 cm, average LOS rates slow by ~2 mm/yr (~75%). IC2 also quantifies the sensitivity of the BLS to seasonal precipitation, where precipitation enhanced LOS rates reach -8 mm/yr during peak wet seasons and slow or stop during peak dry seasons. Combined, IC1 and IC2 closely match the corrected 'on-slide' time series (Figure 4-12 a.), with parts of the landslide coming to a halt during the fall of 2012 and 2013 (Figure 4-13). We find that a simple model of time-dependent pore-pressure diffusion can explain the non-linear relationship between precipitation and seasonal deformation captured by IC1 and IC2 in the ICA of the TSX time series.

Chapter 5. GPS Deformation Tracking Network

Though Global Positioning Systems (GPS) seems to have become common place, it is not used for a fraction of its capabilities. At the time that this research effort was undertaken, satellite GPS technology had already reached a degree of accuracy in the measurement of ground surface processes that matches highest quality terrestrial surveying methods. In particular, the technology lends itself to the application of real-time monitoring systems, and specifically for hazard prediction. With the intent to evaluate landslide hazard through an extensive monitoring program, an automated and autonomous, near-real time continuously streaming GPS monitoring network was established on existing landslides throughout the study area. Special attention was given to the Lawrence Berkeley National Laboratory (LBL) campus, which has been afflicted by a long history of landslide activity and stands at great risk with the development of its state-of-the-art facilities. This section provides an overview of the experimental model and methodology applied to developing this landslide monitoring network. It summarizes over five years of monitoring results, and discusses the advantages and shortcomings of the process in terms of efficacy of monitoring small landslide deformation over time, as well as its applicability in combination with InSAR.

5.1 Overview

The focus of this research was first and foremost to establish whether a network of continuous GPS (cGPS) monitoring stations had the capacity to provide high accuracy real time landslide driven ground deformation time series. Conceptually, high frequency time series of a single point are practical for large scale deformation processes as tectonic deformation, seismic events and block-type ground displacements, where the magnitude of displacement outweighs measured noise and the data can be extended by inference to the surrounding areas. In contrast, the intent of real time hazard monitoring is to measure normally imperceptible ground deformation behavior to

predict larger, sometimes catastrophic, failure. The particularity of slow-moving earthflow type failures is their heterogeneous nature, resulting in spatially incoherent ground displacement, which makes hazard monitoring by cGPS a difficult task and particularly at our scale of interest. This is further compounded by ubiquitous surficial slope-related processes such as mass wasting, making it difficult to separate natural soil creep from deeper landslide processes. Careful consideration was given to these questions in building a robust experimental station model to mitigate these effects. Ultimately, the high temporal frequency and poor spatial capacity of 3-dimensional cGPS time series is complementary to 1-dimensional ground deformation tracking from InSAR which provides high spatial coverage at a significantly reduced frequency. We look to gain insight into the mechanisms driving these earth flow type failures by combining the collected cGPS time series with the InSAR time series discussed in Chapter 4.

5.2 Previous Studies

The use of GPS campaigns for 3-dimensional landslide deformation tracking is by no means new, though very few autonomous cGPS landslide monitoring networks exist. Limitations due to prohibitive costs, difficult site access, data collection/transmission systems, and the often-ephemeral necessity for such sites are in part the reason. This work draws on several recent and concurrent studies discussed here.

5.2.1 cGPS in the EBH

Though well studied, landslide activity in the East Bay Hills (EBH) has been monitored by cGPS only once before this project (Quigley et al., 2010). Between 2007 and 2009 a temporary cGPS receiver was installed in a residential garden within the North Berkeley Landslide (NBL) which had been shown to be active from recent InSAR analyses (Hilley et al., 2004). The station location was determined on the basis of local site knowledge (Kropp, 1995, 2010), and benefitted from the proximity of two current inclinometers (Figure 4-1 a.). During the winter (wet) season of 2007-2008, the receiver was set to collect 1Hz data for an antenna mounted on a ~2.5 m rod driven half way into the ground. For the remainder of the study period, data was only collected at a rate of 0.03 Hz. Due to the brevity of the study period and below average precipitation, results of the study failed to show conclusive evidence of seasonally modulated ground deformation through inclinometer reading did indicate movement at depth (Figure 4-1 b.-c.). Nevertheless, this work helped in understanding the potential magnitudes of displacement in the study area given below-average precipitation and the design basis for the network installations.

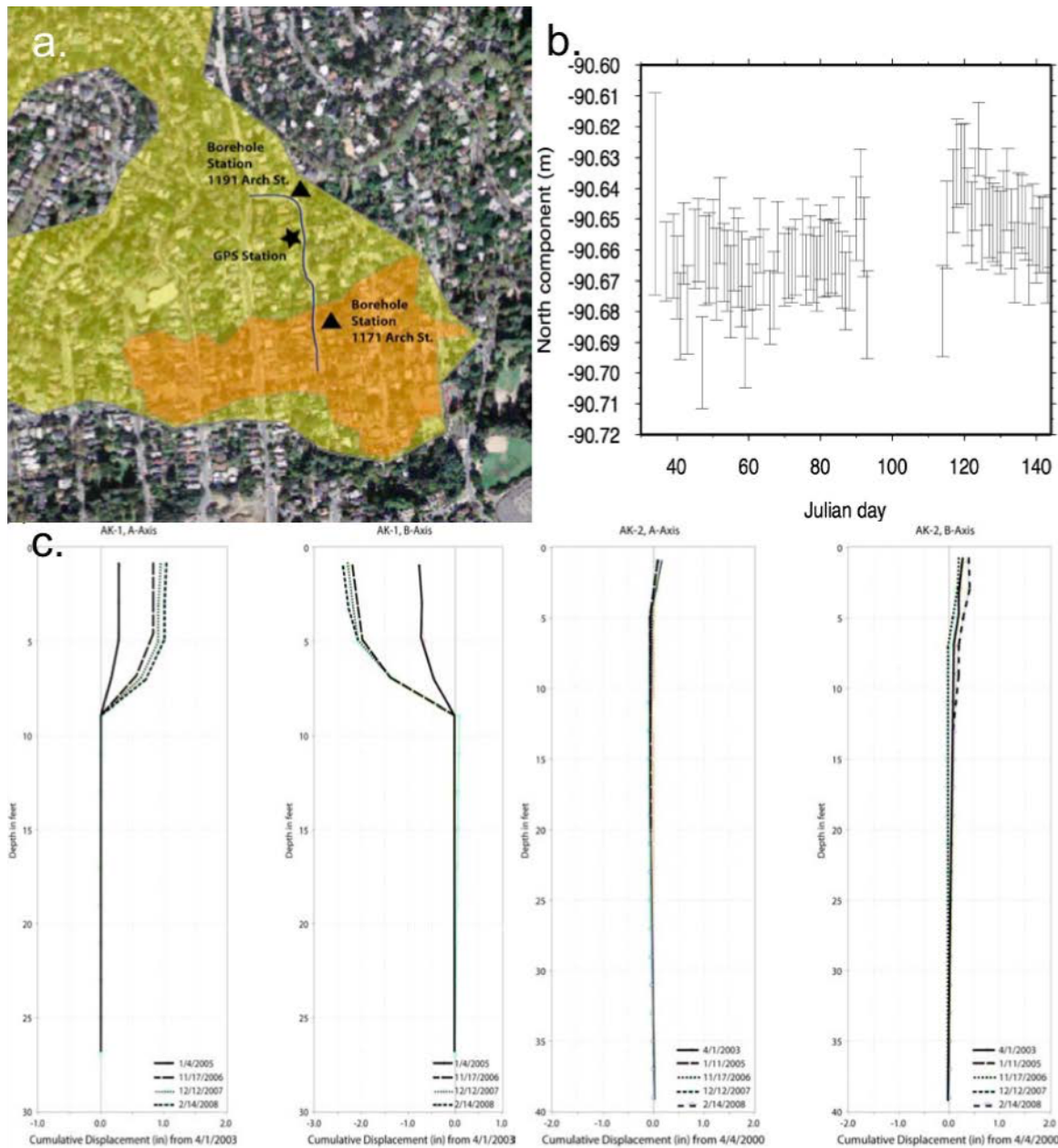


Figure 5-1. cGPS study results from 2007-2009 (Quigley et al., 2010). (a.) NBLs study area with showing GPS station and inclinometer locations. (b.) 2008 cGPS time series results. (c.) 2005-2008 borehole inclinometer results for AK-1 at 1191 Arch st. and AK-2 at 1171 Arch st.

5.2.2 Recent GPS Landslide Monitoring Studies

A great deal of concurrent landslide research applies GPS technology for ground deformation tracking. Two studies in particular, make successful use of semi-continuous (Hu et al., 2018) and campaign (Delbridge et al., 2016) GPS time series in conjunction with InSAR to characterize active landslide deformation in 3-dimensions. In both cases, however the methods are applied to landslides with significantly higher rates of ground deformation by one to two orders of magnitude

(respectively). Delbridge et al. (2016) use campaign GPS to validate 3-dimensional InSAR velocity measurements from NASA-JPL's application of Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) at the Slumgullion landslide (Colorado, USA) which is known to be moving ~1-2 cm/day. Here, campaign GPS time series at several measurement points support that spatial variability in ground deformation within the same "slow-moving" earthflow-type failure are significant.

As discussed in Chapter 4, Hu et al. (2018) used InSAR time series constrained by the ground surface aspect to characterize seasonal spatiotemporal deformation of the Crescent Lake Landslide (Washington, USA) and estimate the geometry of its basal failure surface. They used a single semi-permanent cGPS installation to verify their quasi-3-dimensional landslide deformation time series, and record pre-cursory subsidence to seasonal deformation. In this case, the Crescent Lake Landslide is also a "slow moving" earthflow-type landslide with average surface deformation rates of 15-20 cm/yr and the cGPS receiver is founded on a large rock (presumably "float") within the landslide body. While it was not an extensive period of study with some significant temporal gaps in GPS coverage, this work is a good example of how well a single cGPS time series can be used to complement InSAR by verifying approximated 3-dimensional ground displacements with the added value of revealing local surface processes through high temporal sampling.

5.3 Instrumentation Methodology

The first phase of this project was to establish a network of cGPS stations for high rate tracking of landslide deformation throughout the EBH, with the potential for eventual real-time tracking. This involved the instrumentation of individual landslides with autonomous, continuously streaming GPS stations specifically designed to capture landslide displacement at depth and over an indefinite period of time with minimal required maintenance. In January 2012, 5 such stations (LRA1-LRA5) were established at LBL on three separate landslides (Chicken Creek, Centennial Bridge and East Canyon) and one at the University of California Blake Garden on the BLS at the North end of the study area (LRA6). Being in close proximity to the Hayward fault, the BLS site was additionally instrumented with a USGS seismometer. Each installation required careful consideration for the following points:

- Antenna Location
- Antenna Monument
- Ancillary Equipment and Monument
- Data Collection and Management

A significant resource in establishing our station design was the University NAVSTAR Consortium (UNAVCO) knowledge base.

5.3.1 Antenna Location

The measurement point of a GPS station is the centroid of its antenna. Each position estimate is subject to error from a number of sources (Combrinck & Schmidt, 1998; Dana, 1997) which cause scatter in consecutive point estimates (Noise), or more systematic offsets in those estimates (Bias and Blunder). While noise error is dealt with in the post-processing stages of GPS data management, bias and blunder are a direct effect of the antenna's environment. Bias is error due to the number of satellites involved in each point estimate, while blunder is a result of multipath

error (signal obstruction). Therefore, the first and most important consideration in an antenna's location is satellite visibility, free from signal obstruction.

To avoid signal bias, each site was analyzed for satellite presence based on the flight path geometry of the constellation. Only the American GPS constellation (33 satellites) was used and each antenna location was evaluated such that it had a minimum of 7 satellite 'views' at all times. Since landslide deposits typically occupy geomorphic depressions, this is an important consideration. In this study the antenna locations had to be optimized within each landslide deposit to achieve the most un-inhibited visibility of the southwestern sky and as close to the horizon as possible.

To avoid signal blunder, minimizing any kind of obstruction to satellite view was the most obvious consideration. However, multipath error can also be a problem if the antenna is located too close to the ground surface or any large, massive neighboring objects. A general rule of thumb is that the antenna be placed at least 1 m. above ground, and as far from a large structure as it is tall. Each antenna location was once again optimized to minimize the effects of multipath error to the extent possible, and the antennas were generally constructed within 1.5 to 2 m. above ground.

Additional considerations in urbanized environments include future development, site security and significant radio and power sources. While it may be difficult to predict future site use, other progressive sources of error such as growing vegetation (specifically trees) should be considered, and especially where the satellite field of view might already be restricted. Site security is equally important, as equipment tampering can be an issue. Finally, high voltage power transmission lines and radio broadcast towers can also be a significant source of signal error.

5.3.2 Antenna Monument

In addition to its location, a major issue in site selection was the feasibility of constructing a reliably robust antenna monument. Typical monument design requires a sturdy immovable base upon which to fix the antenna and measure the surface processes of the medium it is fixed to. Hu et al., (Hu et al.) achieve this with a large "float" rock which primarily capture landslide displacement without the interference of other processes. However, some secondary surface processes may be unavoidable. Large concrete and steel structures for example, are problematic due to daily and seasonal effects of material heat expansion. To the same extent, monitoring active earthflow deformation requires a sturdy foundation that will capture active ground deformation without being affected by unrelated differential displacements. In this case, measuring actual deep seated landslide deformation will likely be affected by seasonal shrink/swell cycles of surficial clays as well as general slope mass wasting processes.

For soil sites, few solutions exist for a solid antenna base which will capture deeper landslide deformation processes without the effect surficial processes. Where the antenna cannot be founded in rock, general recommendations are to construct the monument as either a drilled and grouted "tripod" frame or a concrete pillar monument (Figure 5-2). With the expectation of differential movement from seasonal shrink swell cycles as deep as 1-2 m (Fleming, 1972), we believe that multiple tripod legs may in fact be worse. To limit the effects of surficial disturbance, each antenna monument was constructed as a single 30 cm diameter reinforced concrete pier, drilled to a minimum depth of 2 m vertically into the slope, with an imbedded stainless-steel pipe rising 1.5-2 m above ground as the antenna mount (Figure 5-2 and Figure 5-3).



Figure 5-2. **(left two)** Tripod antenna installation examples from UNAVCO. **(right two)** Concrete pillar antenna foundation design for this research. We use Trimble Zephyr Geodetic 2 antennas.

5.3.3 Ancillary Equipment and Monument

The key to designing a robust system that can stand the test of weather and time is simplicity. In addition to the GPS receiver, the basic requirements for each station included access to local wireless internet, a wireless transmitter, a solar array with photovoltaic controller and storage batteries for power, a circuit breaker, and in one case, a seismometer. As illustrated in the construction plan (Figure 5-3), a 150W solar array was angled at 60 degrees from horizontal and oriented to the south. An Automatic Sequencing Charger photovoltaic charge controller was placed in series between the array and a minimum of two 100Ahr 12V solar batteries (mounted in parallel). This ensured that the batteries received a constant charge until they reached capacity and then regulated input from the array as necessary. The batteries fed the appropriate power to a receiver, transmitter and seismometer through 1A fuse circuit breakers. Both the GPS receiver (Trimble NetR9) and seismometer (USGS Netquake) were set to store and back log data as it was remotely accessed and automatically downloaded through the transmitter., we Simple wireless bridges as transmitters (TRENDnet TEW-640MB) were used where the strength and consistency of the available wireless signal was good. Where a reliable wireless signal was not available, directional antennas (LARSEN YAGI 4 element 8dBi 890-960MHz) and radio receive/transmitters (FREEWAVE FGR2-IOS-CE) were used. The equipment was housed in weatherproof metal and fiberglass enclosures with all wiring connected through liquid tight conduit and each station ancillary monument was embedded on a minimum 30 cm thick concrete foundation. The station that included the seismometer was additionally founded on a 20 cm thick reinforced concrete slab that is coupled to the ground with a 30 cm diameter, 1.5 m deep reinforced concrete pier. The construction sequence of station LRA6 at the BLS is illustrated in Figure 5-4 and Figure 5-5. Including the cost of equipment, installation of each station amounted to approximately \$15,000.

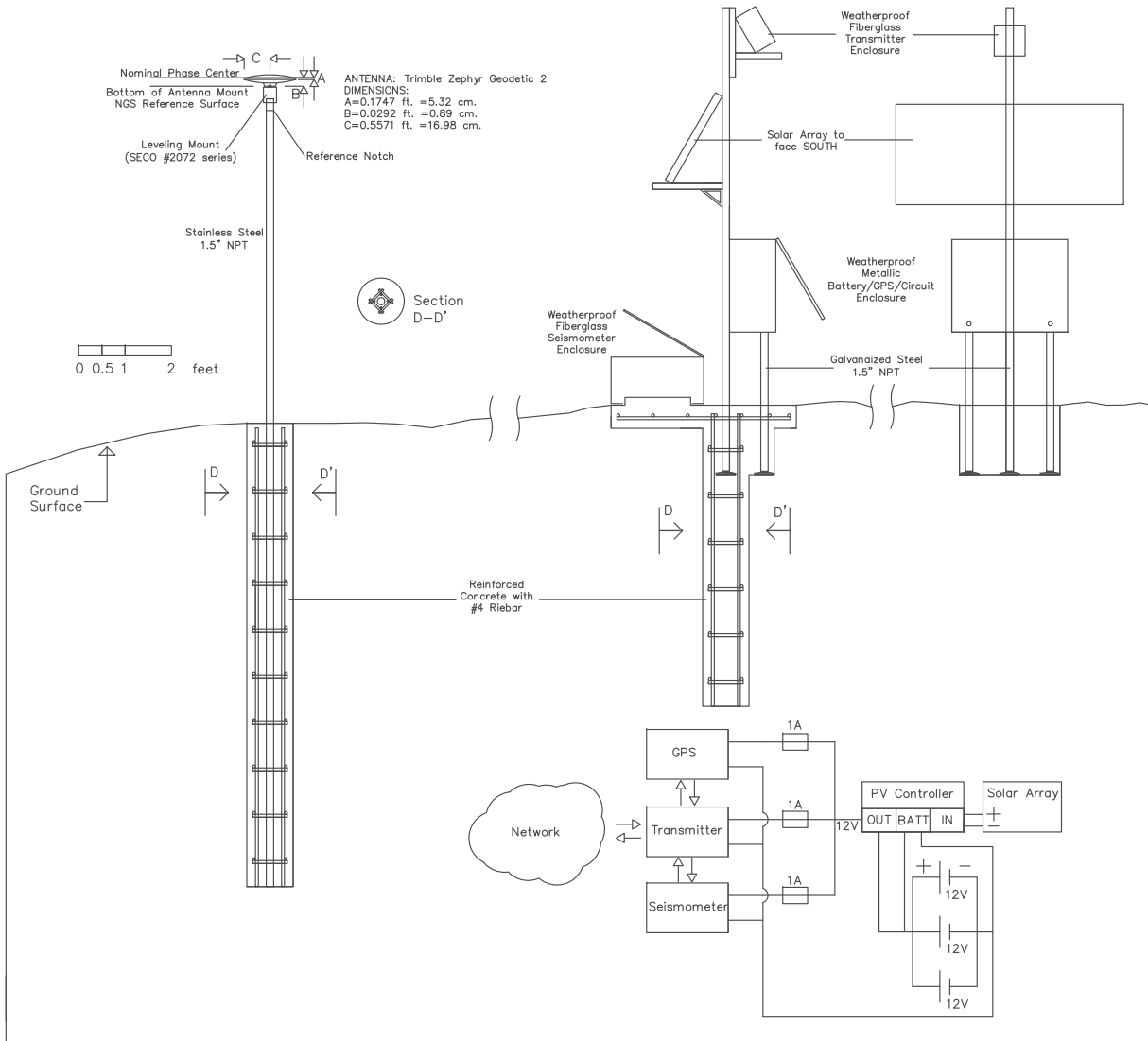


Figure 5-3. cGPS station plans including **(left)** antenna monument, **(right)** ancillary monument, and **(bottom)** electrical chart.



Figure 5-4. cGPS station construction sequence at LRA6 showing (left to right) drilling and excavation, reinforced concrete foundation installation for ancillary monument and reinforced concrete foundation installation for antenna monument.



Figure 5-5. cGPS station equipment and setup at LRA6.

5.3.4 Data Collection and Management

As detailed in Chapter 3, the data collected at each of the six landslide monitoring stations was (and still is) remotely collected, stored and processed by the Berkeley Seismology Lab (BSL). The LRA network (LRA1-LRA6) is set for pseudo-range code tracking of the Coarse Acquisition (C/A) and Precision (P) codes on the L1 and L2 carrier phases of the American GPS constellation only. Though the network also has the capacity to track the GPS L5 carrier phase as well as the Russian GLONASS and European GALILEO constellations, the current setting provides the precision and accuracy required for our study (mm-scale) and the automated processing chain is not yet equipped for those other signals. All data collected by the BSL including the site logs are stored at the Northern California Earthquake Data Center (NCEDC).

Each station is presently programmed to record and backlog two independent data sets. The first records point estimations at a rate of 1Hz which is then stored in a local backlog on the receiver's internal memory. Each receiver is remotely accessed on a daily basis by the BSL and the newly acquired 1Hz raw data is downloaded for storage and processing. The internal backlog of data allows the BSL to backfill any corrupted or missing data dating back as much as 5 months. Beyond that point, the receiver backlog is set to overwrite once it's memory allocation is full. While average daily solutions produced from the BSL processing chain are used, the entire LRA network 1Hz data set (with minor gaps) is publicly available through the BSL.

A second set of very high rate (20Hz) data is also collected and stored internally on each of the network receivers, though it is not set to be automatically downloaded or processed. The purpose of this data set is to capture time histories of displacement in case of seismicity. In this case, the desired data can be accessed remotely by BSL staff or physically downloaded from each station before the internal backlog overwrites. Due to its high rate, the internal memory allocated to this data set allows a backlog of only 10 days. During the period of this study, only one seismic event occurred which was large and close enough for consideration, a M4 event on March 5 2012, with epicenter just 2km North of the BLS.

5.4 LRA Network cGPS Site Location Overview

Beyond the technical requirements discussed above, LRA network site locations were carefully chosen based on their potential for activity, accessibility, and security. Owing to the litigious nature of landslide activity in the EBH, all potential site locations located on residential property were ignored. While consideration was given to property owned by school, water and utility districts, the resulting data set could have become proprietary and these sites were avoided. Conversely, public property is notoriously insecure for such expensive installations, and access to wireless signals can be difficult. At a great advantage to this research, the University of California owns two properties in our study area with sites of interest (LBL and the University of California Blake Estate) which are secure public sites with accessible free wireless connectivity.

Landslide activity at LBL is of significant concern as high-end research facilities are continually being developed and maintained across the campus. The US Department of Energy which is its primary source of funding, takes this investment seriously and periodically requires thorough hazard assessments of the site. Given its history of disruption due to landslide activity, LBL maintains a current inventory of landslides (Figure 5-6), associating a risk level to each deposit based on the potential severity of damage due to disruption. Beyond public safety and disruption

to critical infrastructure, the process takes into consideration the environmental and financial cost due to impacted laboratory facilities. Research at LBL involves the use highly sensitive equipment and environmentally hazardous materials, the disturbance of which can be costly. Development of the LRA network at LBL was therefore welcome.

After review of a considerable amount of geological and geotechnical investigation data, and in consideration of planned development projects, 3 landslides within the south end of the LBL campus showed most promise for instrumentation. As such, three stations (LRA1-LRA3) were installed within the Chicken Creek Landslide (CCL, highlighted as the focus area in Figure 5-6), one station (LRA4) was installed within the Centennial Bridge Landslide (CBL) East of the CCL and one station (LRA5) was installed within the East Canyon Landslide (ECL) East of the CBL. Also illustrated in Figure 5-6 is the location of a future reference station to be installed on the roof of the Lawrence Hall of Science (LHS) and the location of a temporary station used to monitor movement of the Wilson Landslide during active failure in 2013.

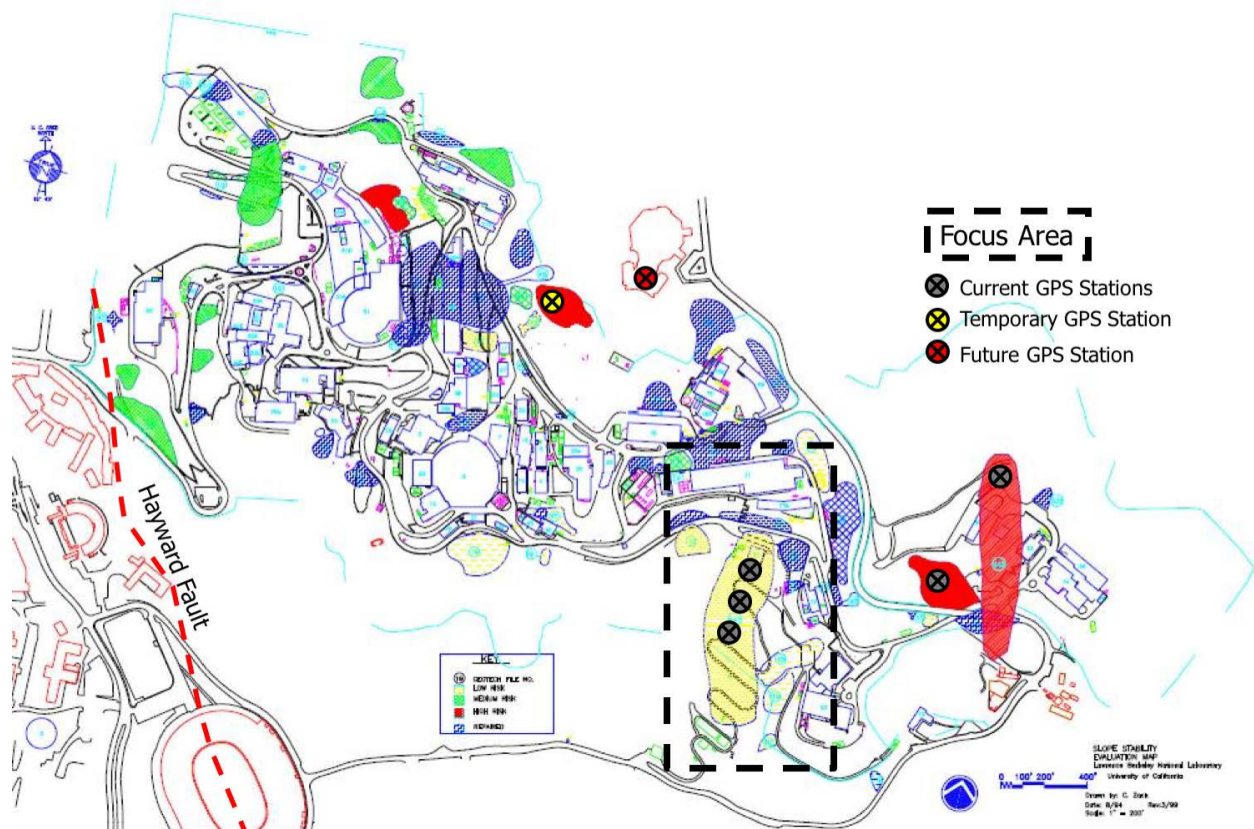


Figure 5-6. Landslide inventory map of the LBL campus illustrating risk associated with impact due to catastrophic slope failure. Green, yellow and red indicate (respectively) low, medium and high severity due to landslide disruption. Blue indicates landslide deposits that have been stabilized or removed. Current and future LRA network cGPS station locations are shown and the Chicken Creek landslide is highlighted as our focus area at LBL.

A sixth and final station LRA6 was installed within the University of California Blake Estate, known as Blake Garden, in Kensington, California. Previously location to the private home of the

University of California presidents, the site is now an active landscape and architecture learning center, managed by the University of California College of Environmental Design. The site is also located within the Blakemont Landslide (BLS) at the northern end of our study area, which as shown in Chapter 4 is highly active and benefits from high density InSAR coverage. Unfortunately, the parts of Blake Garden which show most landslide activity are also heavily wooded. The LRA6 site was installed within the moderately active part of the BLS and nearest the active landslide as possible.

5.5 Results

At this time the LRA network has been in operation for over six years. The results obtained from the landslide monitoring network are evaluated and presented as follows:

- Data Completeness and significant sources of Error
- Regional Deformation Setting (BARD Network and BAVU Project)
- Landslide Time Histories
- Recorded Seismicity
- cGPS vs InSAR Landslide Monitoring
- Active Failure Case History (Wilson Landslide)

5.5.1 Data Completeness and Multipath Error

The measures of data completeness and error are an important indication of the quality of data. Data completeness is the percentage of recorded point estimations per observation period with respect to the number of observations expected. Lower percentages are indicative of data loss due to any number of reasons, including receiver power cycles, excessively excessive noise or poor satellite visibility. Multipath error refers to the effect of multipath reflection from the ground or nearby objects on the L1 and L2 signal phases, which can be estimated by parameters for L1 and L2 (Estey & Meertens, 1999). It is reported as the RMS and maximum RMS of daily recorded multipath error on both acquisition codes (RMS code and Max RMS code) in meters. Table 4-5 summarizes these statistics for our entire data set to date. We note the effects on quality of data at LRA1, LRA4 and LRA6 which are most impeded by vegetation and nearby objects

Table 5-1. Summary of data completeness and multipath error estimates.

Station	Landslide	% Complete	RMS code (m)	Max RMS code (m)
<i>LRA1</i>	Chicken Creek	92.7	1.09	1.40
<i>LRA2</i>	Chicken Creek	95.7	0.75	1.08
<i>LRA3</i>	Chicken Creek	95.0	0.65	0.90
<i>LRA4</i>	Centennial Bridge	76.9	1.05	1.51
<i>LRA5</i>	East Canyon	95.4	0.77	1.04
<i>LRA6</i>	Blakemont	85.0	1.02	1.53

5.5.2 Average Regional Slide Displacement

The BSL manages a number of seismic and GPS networks across Northern California and the San Francisco Bay Area, which primarily focus on tracking tectonic deformation and seismicity.

Bay Area Regional Deformation (BARD) is a network of 32 permanent cGPS stations (the BARD ‘backbone’) which track crustal deformation across the tectonic margin between the Pacific and North America plates. This Transform margin is best known for the San Andreas fault and the BARD network serves to enhance rapid earthquake response assessment and earthquake hazard reduction studies. The LRA network and a number of other local GPS networks managed by the BSL owe a significant part of their accuracy to the BARD backbone sites, which serve as a network of stable reference stations in the differential post-processing stages at BSL.

The Bay Area Velocity Unification (BAVU) project (d'Alessio et al., 2005) gathered GPS velocities for all sites across the greater Bay Area region (including BARD) to compare tectonic deformation across the San Andreas fault margin. The project successfully reveals velocity trends across the transform plate boundary, where the entire region is moving North with the Pacific Plate. Re-centering the data around a central reference station (LUTZ) reveals a differential shift across the margin where the easternmost stations are, in a relative sense, moving South with the North-American plate. While the LRA network stations move along these same trends within the North American data frame, they include a significant landslide motion component. This is made evident by plotting the LRA network data against the BAVU data referenced around LUTZ, this is evident.

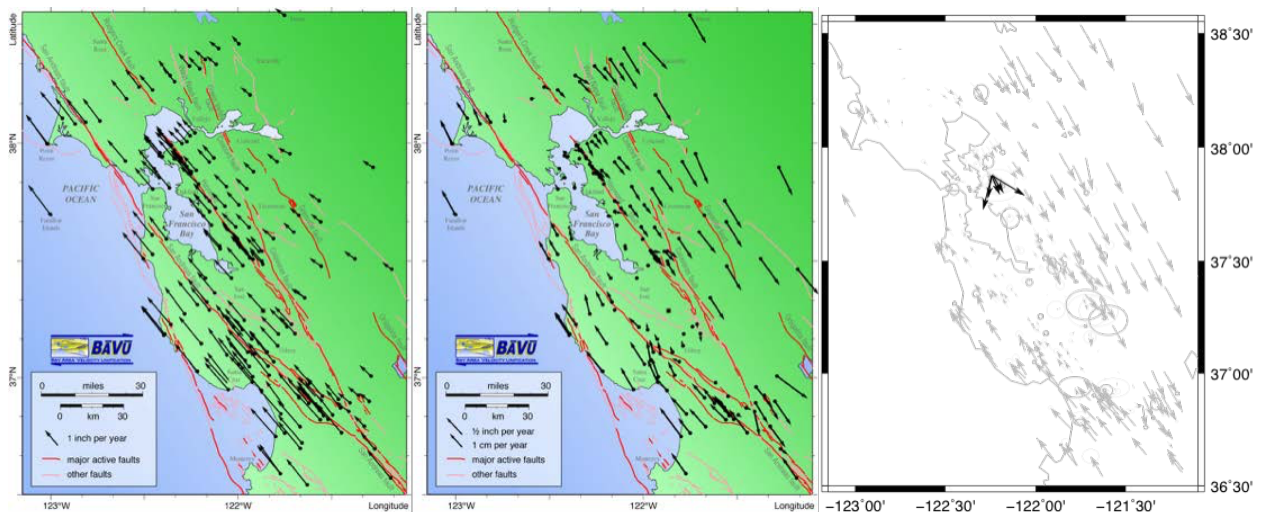


Figure 5-7. **(left and middle)** BAVU cGPS velocity map in North-American data frame and referenced to LUTZ (d'Alessio et al., 2005). **(right)** LRA network referenced to LUTZ with BAVU backdrop.

5.5.3 Landslide Time Histories

Daily solutions for the 6 LRA network cGPS stations have been recorded since their installation in January 2012 through the present. For practical purposes, we analyze data collected through September of 2017, before the beginning of the 2017-2018 water year. In order to remove the most possible atmospheric noise and tectonic deformation bias, each station is referenced to a nearby BARD backbone site, the closer the reference station the better (hence the necessity for a future cGPS station at the LHS). LRA1-LRA5, located East of the Hayward fault are referenced to station P224 approximately 3 km to the south. LRA6, located West of the Hayward fault is referenced to SRB1 approximately 5km to the south. We highlight here the Chicken Creek Landslide at LBL

which is instrumented with three stations LRA1-LRA3, focusing on the results of LRA1. The results for the remaining stations and landslides are included in Appendix C

The CCL has been subject to extensive geological, geophysical and geotechnical investigations (Kropp & Lettis, 2009). The extents of the deposit are thus reasonably constrained and the ground surface shows signs of active heterogeneous deformation (Chapter 2) typical of an earthflow-type failure. Stations LRA1-LRA3 were installed (from bottom to top) along the approximate center-line of the deposit, with the intent to capture differential displacements in addition to their individual deformation time histories. Each 3-dimensional deformation time series is presented as a cumulative differential displacement, in terms of the station's North, East and South baselines, where northward, eastward and upward displacement is positive (Figure 5-8).

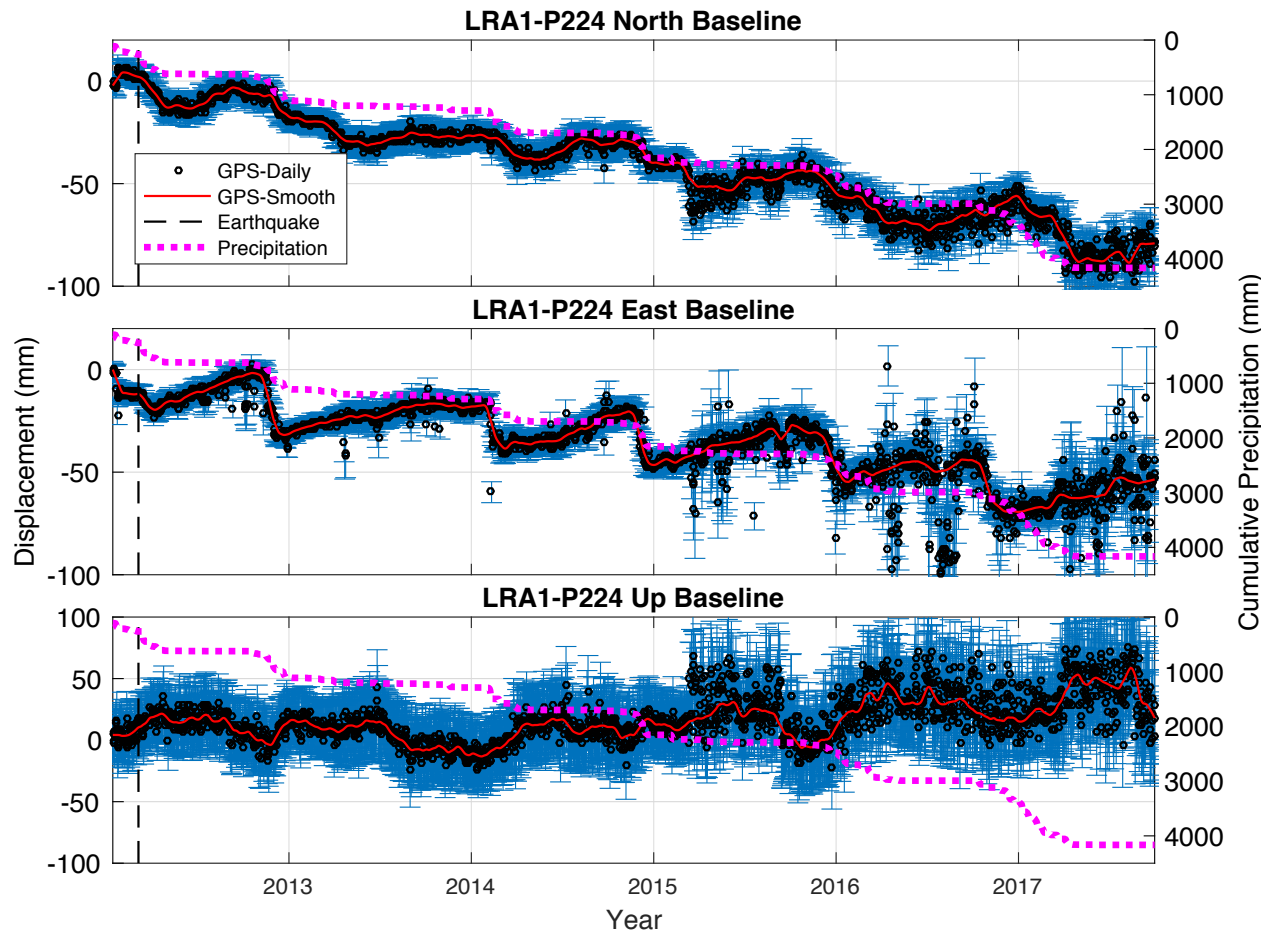


Figure 5-8. Three-dimensional differential displacement time history at landslide monitoring station LRA1 (Chicken Creek Landslide, LBL) with respect to reference station P224. Each data point (black circles) represents a daily average of 1Hz cGPS point estimations and includes a range in error (blue error bars). An average time history (red solid line) is estimated using an 'rlowess' smoothing function. Each series is plotted against total cumulative precipitation (magenta dashed line), measured at LBL.

For each station, as illustrated for LRA1 (Figure 5-8), the displacement time series (black circles) is plotted in cumulative differential displacement, based on daily averages of the collected 1Hz

GPS point estimation time series. Error bars (blue) indicate the uncertainty as a result of the post-processing and daily averaging stage. Scatter within the data points is primarily a result of multipath error from vegetation growth or temporary equipment storage near the station antenna. An average time series (red lines) over a span of 10 to 30 points (depending on the amount of data noise) is estimated using a robust locally weighted scatter plot smooth function (rlowess) which is resistant to outliers.

Each time series is also plotted against total cumulative precipitation (magenta dashed line), measured at LBL. As shown in Chapter 4, precipitation is the driver for seasonal ground surface deformation due to shrink/swell cycle of soils and is a proxy for transient pore pressure increases which drive landslide displacement. In each case, the cGPS time series are clearly sensitive to seasonal precipitation. Significant differential displacement occurs in all baseline directions with little visible lag.

While baseline deformation time series are practical in describing the complete sense of 3-dimensional motion and its temporal sensitivity to precipitation, the sense of spatial deformation is better visualized by plotting the time series in two dimensions, as well as projected along its vector of displacement in the downslope direction (Figure 5-9). In this view, the processes driving displacement become apparent. While LRA1 is clearly moving downslope at an average rate of approximately 2 cm/yr, surficial soil activity and differential deformation along the antenna foundation drive a seasonally cyclic pattern of deformation. This same pattern of deformation was observed in each of the LRA network stations. The best interpretation is that this is apparent antenna ‘wobble’ due to the combined effect between seasonal soil shrink/swell cycles and actual landslide deformation at depth. With the onset of seasonal precipitation, the antenna exhibits movement in the downslope direction which progressively reverses as seasonal soil swelling begins to tilt the antenna in an upslope direction. In combination with this upward swelling movement, a downslope translational motion driven by deeper (presumably landslide related) deformation drags the toe of the antenna downslope, tilting the antenna yet farther back. At the end of each period of seasonal precipitation, a downslope tilt of the antenna occurs as surficial soils progress through their shrinking phase.

To the same extent the spatiotemporal behavior of landslide activity can be compared between each of the three CCL stations (Figure 5-10). Differencing the baseline displacements between LRA1, LRA2 and LRA3 and plotting them in 2-dimensional deformation plots, a sense of differential landslide deformation is apparent. The observed downslope velocity of LRA1 is twice that of LRA2 and LRA3, indicating that the lower portion of the slide is more active than the upper portion over our period of study. The sense of seasonally cyclical motion in LRA2 and LRA3 is also consistent with a clockwise wobble, while the wobble in LRA1 is consistently counterclockwise.

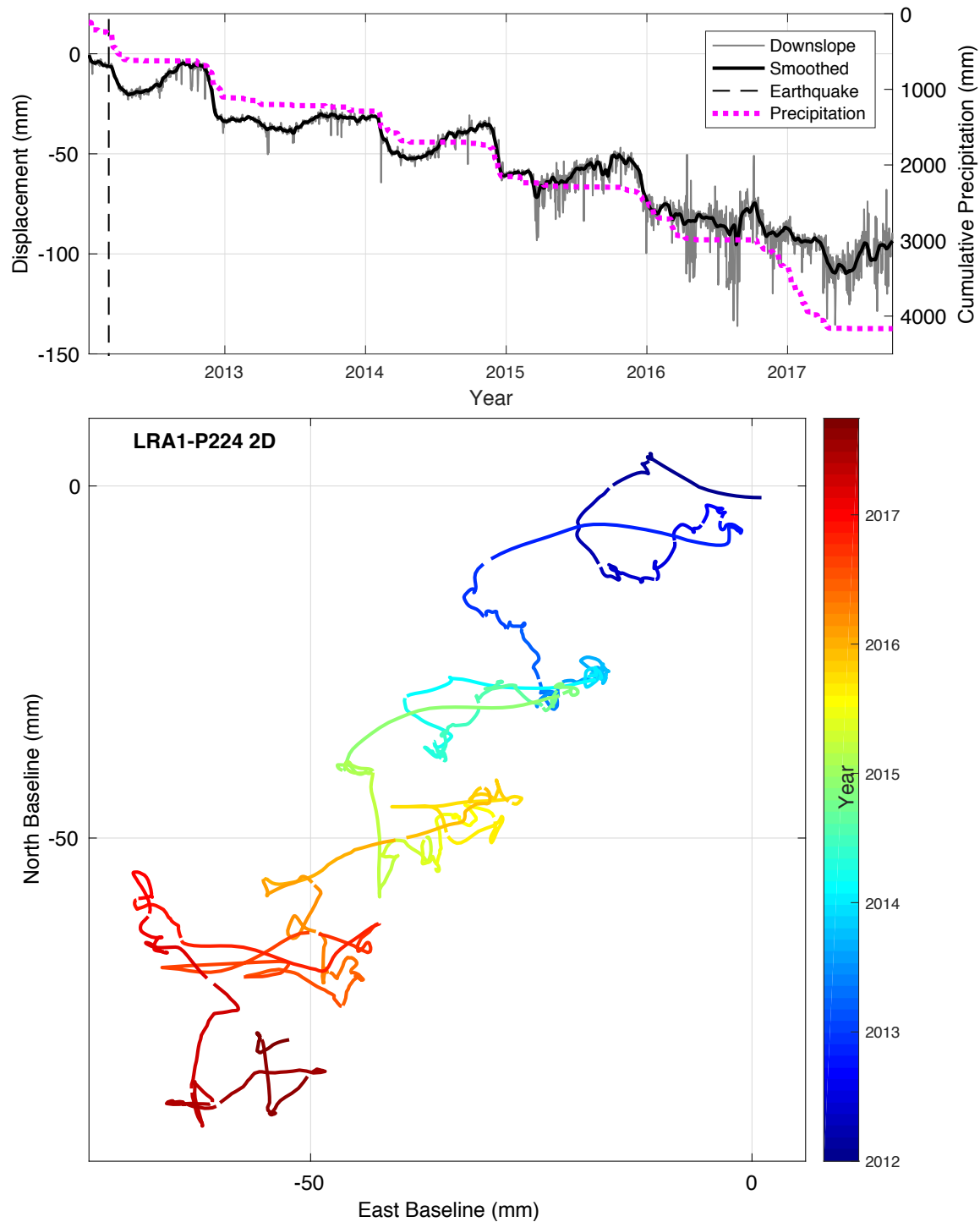


Figure 5-9. Deformation time series of LRA1 illustrating **(top)** projected downslope deformation and **(bottom)** two-dimensional displacement.

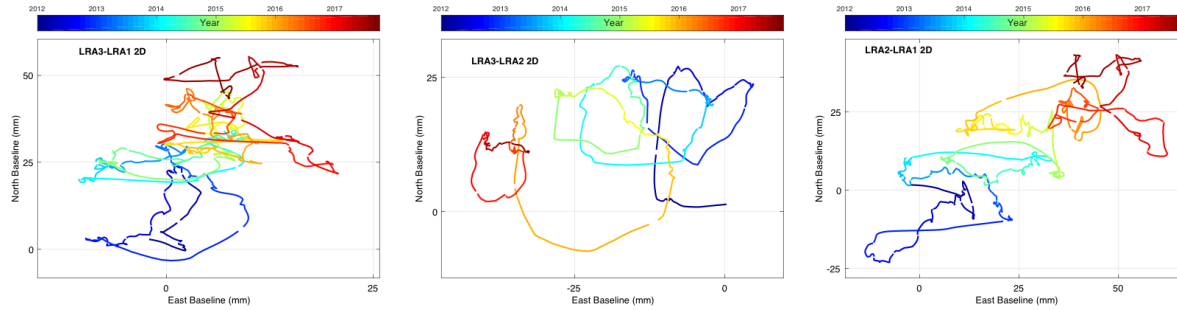


Figure 5-10. Differential deformation time series between LRA1 LRA2 and LRA3 on the CCL.

While these 2-dimensional displacement plots illustrate well the spatial behavior of each station in relation to seasonal soil and landslide activity, the projection of baseline displacements into the downslope direction provides a better sense of their temporal behavior. Overall, the comparison between total cumulative precipitation and the downslope deformation time history (Figure 5-9) confirms the previous observations on antenna wobble. With the onset of precipitation, a strong and immediate downslope motion occurs, which reverses at the height of each wet season when soil swelling reaches its peak and landslide activity should be at its highest. Through each dry season, the upslope motion then slows and eventually reverses with the onset of the next wet season.

Similarly to the comparison between ICA eigenvectors and precipitation (Chapter 4), an estimate can be made of the time series of the rate of downslope deformation and compare to the rate of precipitation. A cross correlation analysis of these two time series shows they are positively correlated with nearly no lag. In Table 5-2, we summarize the cross correlation analysis results for each of the LRA network time series, illustrating a consistently low lag time (1 to 5 days). In doing so, however, cross correlating daily precipitation rates with the raw deformation rate time series does not provide reliable results due to the underlying levels of scatter between point estimations. Instead, we perform the cross correlation analysis using a linear fit curve, estimated with a smoothing function over the smallest possible sample of points (Figure 5-11, Appendix C).

Table 5-2. Summary of LRA network station velocities and cross correlation lag times between the rate of displacement and the rate of precipitation.

Station	Landslide	Velocity (mm/yr)	Disp-Precip Lag (days)
<i>LRA1</i>	Chicken Cr.	19	1
<i>LRA2</i>	Chicken Cr.	9	3
<i>LRA3</i>	Chicken Cr.	11	2
<i>LRA4</i>	Centennial Br.	16	4
<i>LRA5</i>	East Cyn.	7	5
<i>LRA6</i>	Blakemont	4	1

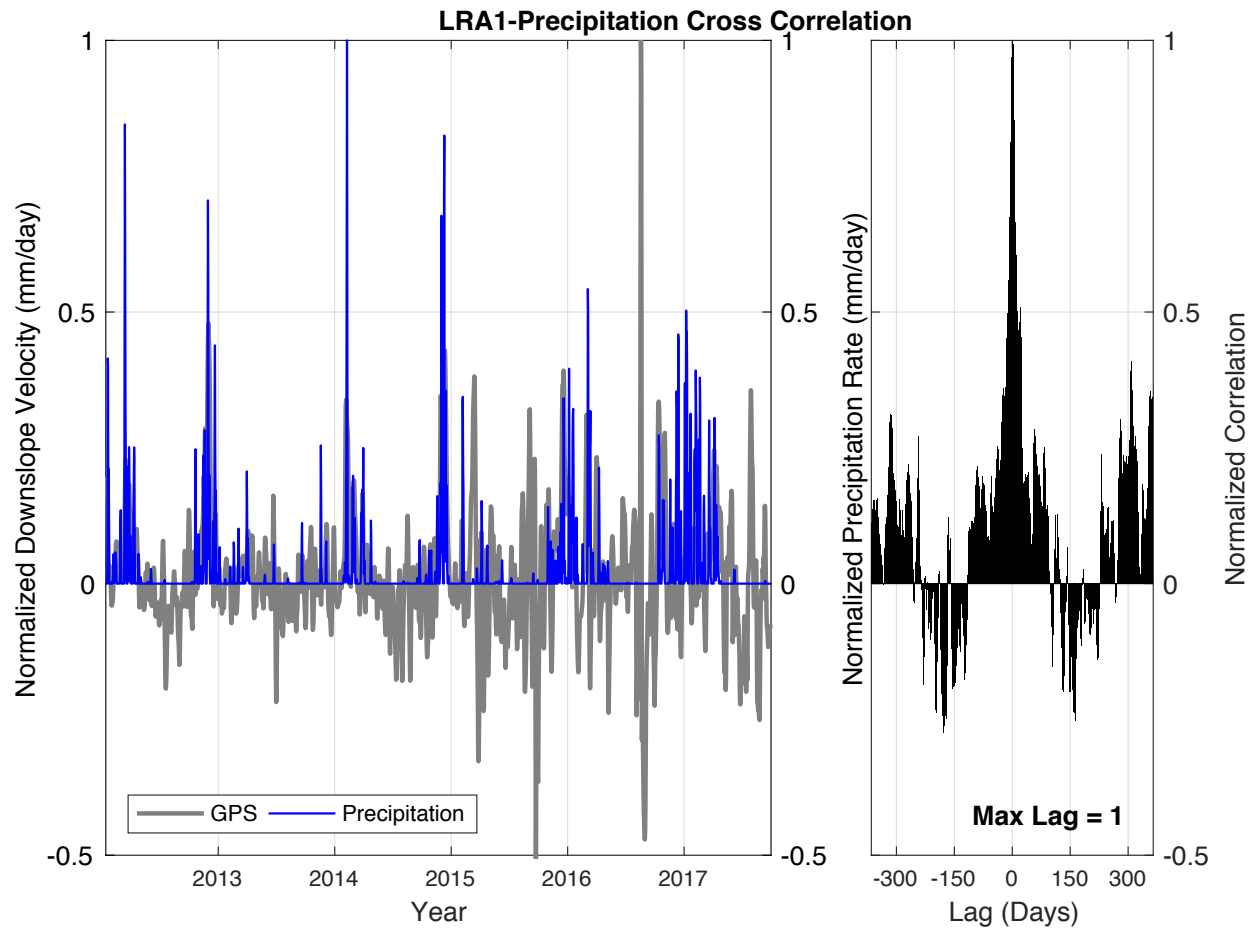


Figure 5-11. Cross correlation analysis results between displacement rate at LRA1 and rate of precipitation.

5.5.4 Recorded Seismicity

The LRA network was equipped to gather 20Hz deformation time series in the case of seismicity. To date, only two seismic events have occurred that may have induced landslide displacement and that would have been recorded by the LRA network. On August 24, 2014 a M_w 6 event occurred on the West Napa fault, approximately 40km North of our study area. Due to the dry time of year and its distance, no meaningful waveforms or seismic displacements were recorded.

On March 5, 2012, a M_w 4 seismic event occurred along the Hayward Fault (HF) at a depth of approximately 8km and with epicenter approximately 2km northeast of the BLS (Figure 5-8 and Figure 5-9). This event is of particular interest since Hilley et al. (2004) suggest that a M_w 3.9 HF event in December 1998 located just north of the BLS induced downslope displacements. However, due to the temporal resolution of their time series they were not able to quantify this. The most significant difference between these two seismic events are the climatic conditions surrounding them. The 1998 event occurred in the height of a wet season following the notably wet 1997-1998 El Niño season. As noted in Chapter 4, the 2012 event did not induce landslide displacement, but that it does coincide with the onset of one of the most severe droughts in the last 100 years. Since

pore pressures are the major driving force behind slope deformation, the extreme drought conditions may be the reason for not having observed landslide displacement.

Figure 5-12 shows that, in fact, stations LRA1, LRA5 and LRA6 all captured a visible waveform from the 2102 event. The event consisted of two earthquakes in sequence (denoted by the two vertical lines), the first a M3.4, the second a M4, located beneath LRA6 and approximately 5-6km northwest of LRA1 and LRA5. Two processing runs are shown, one with LRA1 as reference (top rows) and one with LRA5 (bottom rows). In each case, LRA6 shows different waveforms, which may be due to the different reference site motions. Also, the LRA network 20Hz seismic event buffer had not yet been programmed and this event was sampled at a rate of only 5Hz. Due to its proximity to the epicenter, LRA6 may have been subject to higher frequency motions that the sampling rate was not sensitive to. Ultimately, the stations recorded no seismically induced permanent ground deformations or increase in landslide displacement rates, while they did record precipitation induced activity only several days later.

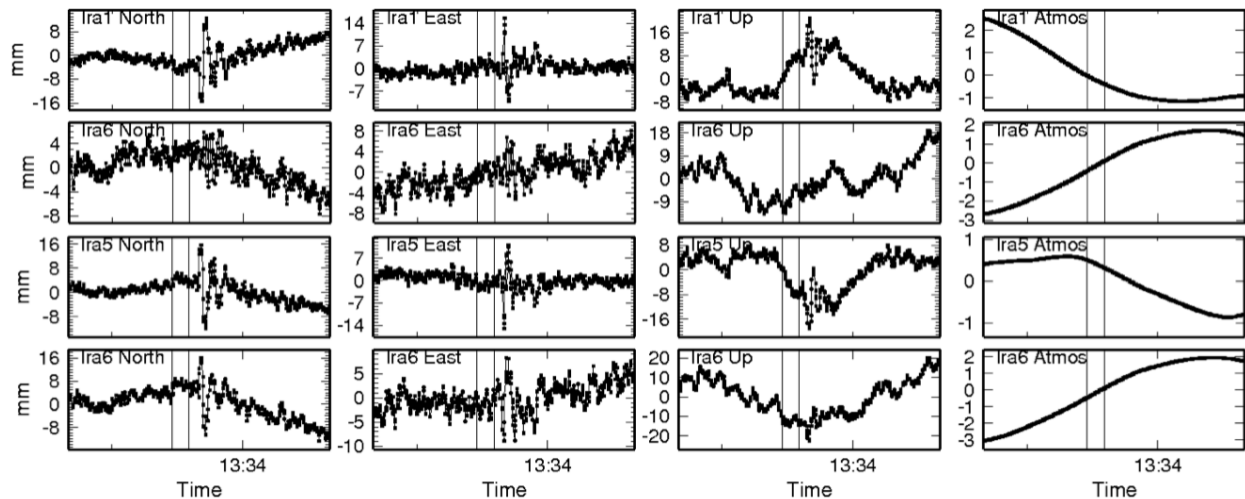


Figure 5-12. Displacement time histories of seismic waveforms at LRA1, LRA5 and LRA6 due to the M4 2012 event. (**top rows**) Seismic wave forms with LRA1 as reference. (**bottom rows**) Seismic wave forms with LRA5 as reference.

5.5.5 cGPS vs InSAR Landslide Monitoring

The original intent of this research was specifically to combine cGPS and InSAR time series. In the development of the LRA network it became apparent that this would likely be a difficult task. The best options being either to instrument an area with good InSAR coverage but uncertain ground activity (LRA6 at BLS), or instrumenting a relatively active site with poor InSAR coverage (LRA1-LRA3 at CCL). Each case is illustrated in Figure 5-13, showing the BLS and LRA6 on the left, and the CCL with LRA1-LRA3 on the right. As discussed in Chapter 4, the spatiotemporal coverage of the InSAR time series allows unique insight into the seasonal behavior at BLS. The site would greatly benefit from a cGPS station which might provide the additional temporal resolution necessary to determine the landslide's response to precipitation and seismic triggering events. LRA6 holds promise that it might detect more movement in the future, though it is currently located on the edge of the active body, and has yet to record any clear landslide deformation. Conversely, the CCL exhibits relatively active ground deformation through LRA1-LRA3 but has

poor measurement point coverage from InSAR. This is clear from the relatively incoherent ‘on’ and ‘off’ landslide motions illustrated in Figure 5-13 (right). Improvement at this site would require an extended InSAR analysis over the LBL campus and possibly with multiple Satellite points of view. Similarly to the CCL, it is difficult to draw a meaningful comparison of cGPS and InSAR results at the CBL and ECL (Appendix C). While LRA4 provides a good record of landslide movement, InSAR coverage of the CBL cannot likely be improved upon due to significant cover of vegetation. The opposite is true of LRA5 and the ECL, where InSAR coverage is reasonable but landslide activity is minimal.

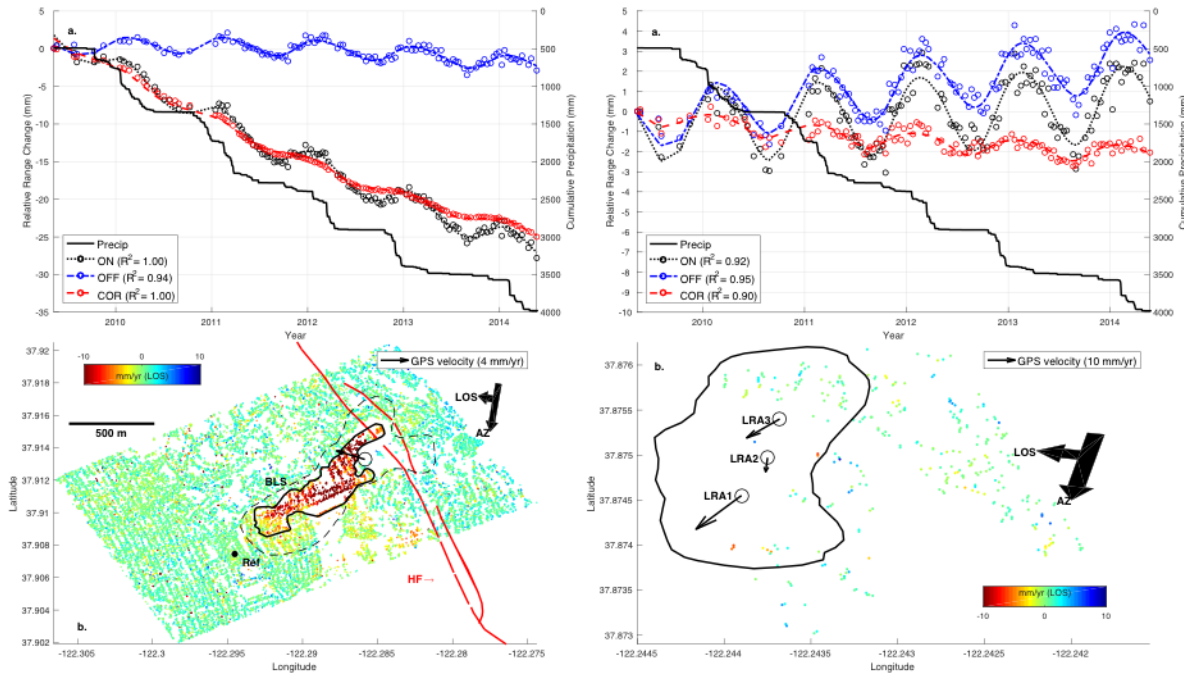


Figure 5-13. **(left)** Comparison of InSAR displacement time history and velocity field with LRA6 at the BLS. LRA6 is located within the larger moderately active slide deposit (dashed black lines) and on the edge of the active slide deposit (solid black line). **(right)** Comparison of InSAR displacement time history and velocity field with cGPS velocity data from LRA1, LRA2 and LRA3 at the CCL.

5.5.6 Active Failure Case History (Wilson Landslide)

While none of the LRA network instrumented landslides exhibited significant modes of failure during our period of study, one landslide at LBL did. Though relatively small (30x15 m), Wilson landslide is perched above an approximately 20 m tall road cut, and across a small road from large scientific research facilities. Should the slide mobilize and flow over the top of the road cut, the runout would likely cause severe infrastructural damage and with the potential for loss of life.

A review of historic landslide activity at the site reveals that active deformation of this same earth flow had been recorded on four separate occasions since 1958, each generally coinciding with years of above average seasonal precipitation. Though precipitation totals between 2012 and 2014 were historically low due to local drought conditions (Bennett et al., 2016), a period of above average precipitation occurred in late 2012. Following a 30 to 40 day period of approximately 5mm/day average rainfall, a large storm event (exceeding 20mm/day precipitation) in December

2012 triggered the incipient failure. Over the course of several days, as much as 2m of cumulative ground displacement were recorded.

This case offered the rare opportunity to monitor landslide related surficial ground deformation of a heavily instrumented slide mass. In an effort to carefully monitor the slide mass before it could be mitigated, two inclinometers were installed as well as several surficial survey points (Figure 5-14). The slide mass was also remotely surveyed using LiDAR and air photogrammetry. A temporary cGPS station was also installed at the site, using stainless steel pipe driven 1m into the slide mass as an antenna monument. Figure 5-15 presents a summary of the monitoring results for a period of 2 months between January and March 2013, comparing the collected cGPS time series with survey and inclinometer measurements over the same period with remarkably consistent results. The data show a clear period of active creep in early January at 15 mm/day, then slowing to approximately 0.7 mm/day once dewatering wells had been installed in mid-January.

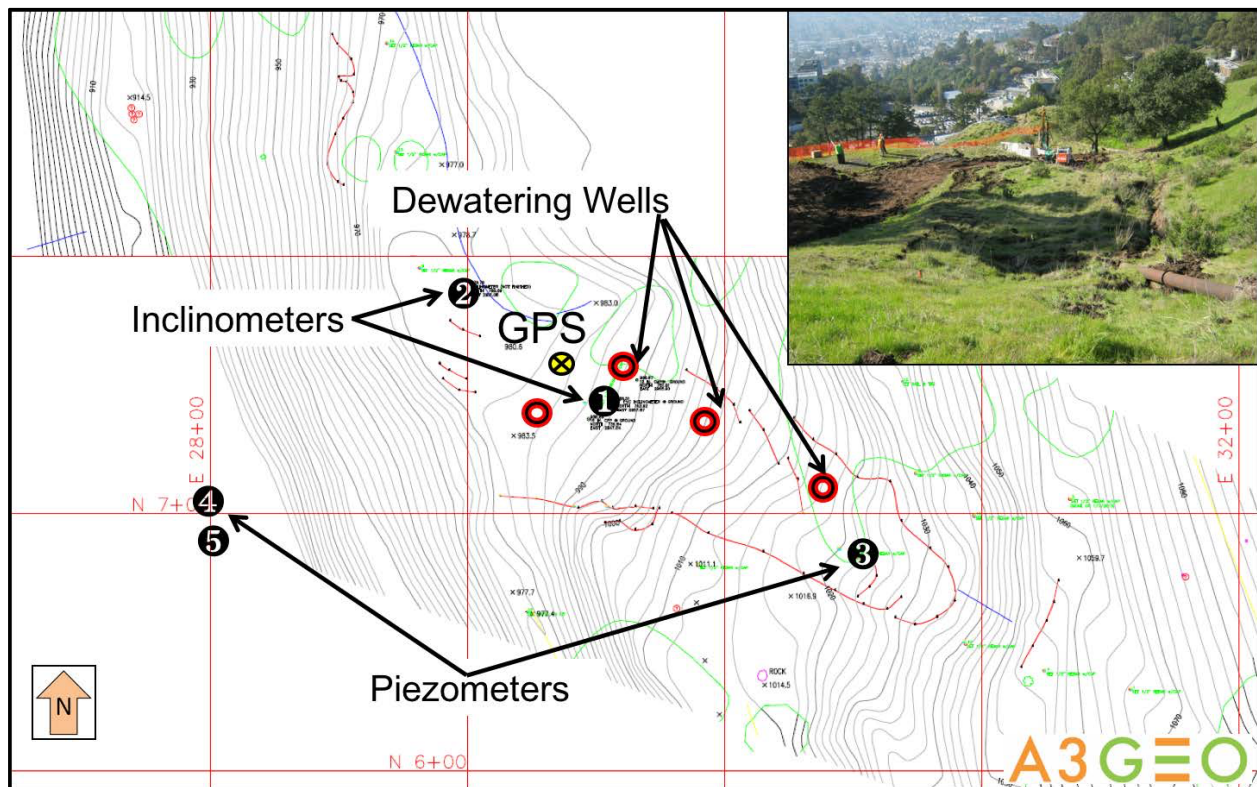


Figure 5-14. Detailed topographic survey of Wilson Landslide showing instrumentation locations (Magnusen & Baldwin, 2013).

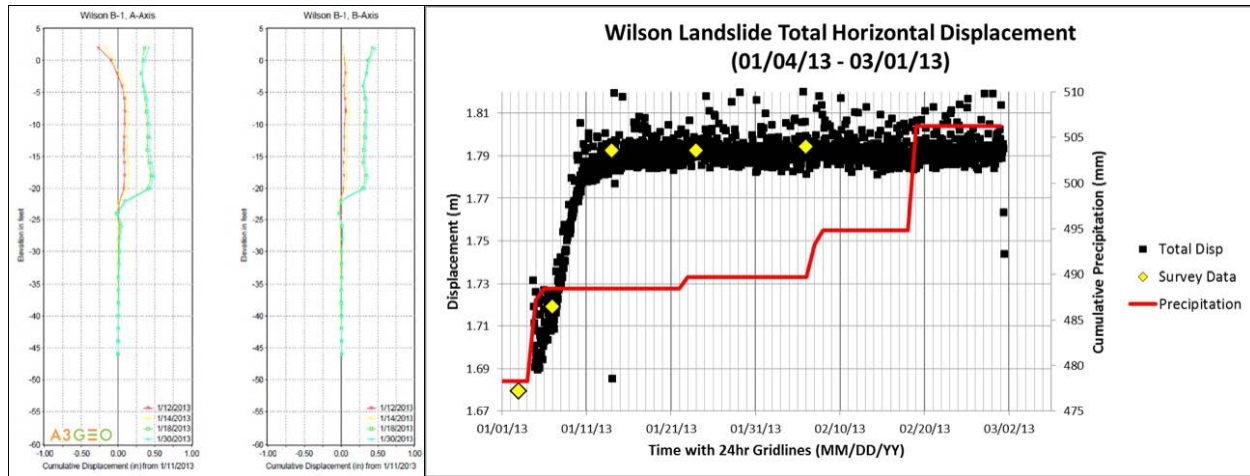


Figure 5-15. **(right)** Record of displacement at Wilson Landslide between January and March 2102 showing very good agreement between the cGPS time series (black squares), periodic survey data (yellow diamonds), and **(left)** inclinometer deformation (Magnusen & Baldwin, 2013).

5.6 Summary

The results presented above reveal many of the advantages and shortcomings of establishing a landslide monitoring network using cGPS. In a first part, they show that cGPS monitoring of very small ground deformations is meaningful and accurate provided the appropriate site, equipment and installation are possible. The experience collected in the course of this study provides a reasonable (though not exhaustive) framework for establishing such a network, by drawing on previous and concurrent examples. After six years of data collection, the good quality of the data set is a testament to a successfully robust installation, which could be improved on, and eventually made into a true real-time hazard monitoring system.

The extensive data set also illustrates some of the difficulties in its interpretation. Monitoring such small deformations and at such high rates lends itself to issues relating to noise and multipath error. Though it was not possible to quantify a lower limit of observation, the deformation range of interest for this project is close to it. Between a combination of point estimate scatter and error, it can be difficult to distinguish what are actual trends in surface deformation.

In addition, having some form of concurrent deformation measurement is crucial. For example, it is possible that with a record of antenna tilt, the observed wobble in each signal might be better understood. This would also allow filtering of that portion of the signal, to better isolate the deeper landslide displacements. In an attempt to do so, periodic manual measurements of antenna tilt and orientation were collected. Unfortunately, these measurements were far too inaccurate at the scale of interest to produce any reportable data. The effort would have required a precise inclinometer and data logger to collect a continuous time history of antenna inclination, as well as the distribution of subsurface deformation, though these were not planned for in our budget.

Chapter 6. Conclusion

6.1 Overview

High-resolution characterization of spatiotemporal patterns in very small surface deformations of landslides is a first step toward improved hazard forecasting. The intent of this work was to improve the fundamental understanding of seasonally modulated deformation in very slow moving earthflow type failures, through advanced sensing technology. The primary objectives were to:

- Establish a landslide monitoring network of autonomous near-real time high-rate cGPS stations to monitor landslide creep behavior.
- Perform an extensive InSAR time series analysis applying new algorithms for higher resolution data to explore the spatiotemporal intricacies of landslide deformation.
- Identify dominant modes of deformation processes through signal processing methods.
- Compare the InSAR and cGPS monitoring results.

To accomplish these objectives, an extensive field investigation program was developed to establish a robust network of cGPS landslide monitoring stations at select sites across the Lawrence Berkeley National Laboratory and greater San Francisco East Bay Hills. An extensive signal processing analysis of an unusually comprehensive InSAR time series was also performed. In each case, a detailed record of spatiotemporal surface deformation patterns was found to be insightful and several modes of slope deformation processes were identified.

6.2 Seasonal Behavior of Landslide Motion

A review of independent InSAR time series analyses of the EBH from satellite acquisitions over different time intervals from 1992-2011, shows remarkable consistency. Each study confirms mean landslide velocities measured in the field (~20-30 mm/yr) and documents precipitation modulated ground deformation. The data acquired in the course of this project produces similar conclusions through an extended analysis of InSAR (2009-2014) and cGPS (2012-present) time series. It shows the duration and amount of seasonal precipitation and associated water pressure changes determine how fast the landslides move and how recent drought conditions have slowed

their advance. The satellite data allow landslide deformation to be distinguished from normal seasonal changes in unaffected areas, giving greater predictability of this hazard.

A series of signal processing methods (ICA, PCA and FCF) performed on the InSAR time series provides unique insight into the mechanisms driving observed ground surface displacements. Through FCF analysis, mean seasonal deformation observed away from the landslides can be identified and removed, revealing an underlying trend of annually accelerated landslide displacements. Through PCA and ICA, four independent spatiotemporal components of the deformation are separated, illustrating different geo-mechanical processes on and around the landslide. The first two components capture the sensitivity of landslide deformation rates to annual and long-term climate conditions. These reveal a slowdown of landslide movement associated with the onset of severe drought conditions in 2012, and seasonal precipitation-modulated landslide deformation with an approximately 44-day lag. The correlation of landslide motion and precipitation at variable time scales is well explained by a simple model of time-dependent pore-pressure diffusion. Two additional components on and off the landslide characterize broadly distributed and spatially heterogeneous seasonal deformation, associated with the shrink/swell cycle of near-surface soils and a combination of annual groundwater heave processes and thermal expansion of structures. The ability to differentiate and quantify these processes to the extent illustrated is a significant advancement toward predicting the magnitude and spatiotemporal distribution of seasonal ground deformation in slow-moving landslides.

After nearly six years of continuous monitoring, the LRA landslide monitoring network, has also measured well-defined precipitation triggered slope movement. Though the data provides a temporally comprehensive record of surface displacement it was not possible to meaningfully isolate landslide related movement from other surficial processes. Additionally, a clear seismic waveform was recorded from a nearby $M_w = 4$ earthquake, though it did not trigger any measurable landslide deformation. Overall, the system has demonstrated its capability to record very small scale ground deformation and at high sampling rates reliably.

The original intent of this research was specifically to combine cGPS and InSAR time series. Given the constraints discussed it was not possible to obtain the necessary combination between instrumentation feasibility and proper InSAR coverage for a direct comparison. Fortunately, with the planned longevity of the LRA network, if the landslide deposit beneath LRA6 were to increase in activity and if further InSAR studies can be improved upon across the LBL campus, a meaningful comparison might yet be possible. Still, in both cases, records of landslide related surface displacement have comparable down-slope velocities, with periods of increased activity modulated by precipitation, and seasonal shrink/swell cycles are identifiable.

6.3 Lessons Learned for Future Work

The instrumentation of landslide sites across the EBH with a network of permanent and autonomous cGPS monitoring stations is an improvement for landslide hazard forecasting and opens the path toward future research. In a more immediate sense, it has provided a useful record of very small ground motions at a high sampling rate. Installation and data processing efforts also underline some of the important considerations required for establishing this kind of network, and interpreting its results.

Specifically, the LRA cGPS network illustrates the importance of proper site selection and establishing proper secondary control measures. More than any other consideration, the

importance of site selection is paramount. Of the six installations, only one has not recorded measurable landslide deformation. LRA6 missed the most active ground deformation at the Blakemont landslide by only a few meters. Conversely, if this station begins to record deformation of the landslide on which it is installed, that data will provide invaluable information on the triggering thresholds of large, deep seated paleo-landslide deposits.

Additionally, at each of the LRA cGPS network stations a common mode of seasonally cyclic ground behavior was recorded (antenna ‘wobble’), which measures a secondary mode of surface deformation behavior. Although tracking of the GPS antenna tilt was attempted, the result was inconclusive, and a better method of measuring the stations’ response to seasonal cycles in shrink/swell cycles of surficial soil is needed. A comparison between the cGPS and InSAR time series may be capable of explaining the observed surficial processes. Unfortunately, the spatiotemporal data available for this research did not sufficiently overlap to perform this comparison.

With respect to the difficulties encountered from the LRA cGPS network, the InSAR time series analysis performed as part of this work is a testament to the benefits of this technology. It allowed a meaningful spatiotemporal analysis of ground deformation processes over a very large area, with uncommonly dense coverage and at a frequency that is not easily attainable in satellite based radar technology. The analysis also speaks to the necessity for longer time series, and evaluation over a larger area. Understanding trends in climatic effects require longer periods of study. In this case, the onset of drought and its effects on ground mobility produced interesting observations and would require a longer record to reveal the long term seasonal effects suggested herein.

The InSAR coverage area would benefit by expansion over a larger area of study and with different processing reference points. To provide a meaningful comparison with previous studies, this research was performed over a specific area which also benefits from considerable site knowledge (i.e. the EBH landslides). As a result, some areas of interest were found to be lacking in InSAR coverage as was the case with the LRA network stations at LBL. Otherwise, the direct comparison cGPS and InSAR time series for a given location might have provided additional insight to landslide mechanics, owing to their similarities in sampling frequency and spatial coverage.

Regardless of their overlap, each of these technologies significantly advances the general understanding of spatiotemporal landslide deformation through interpretation of large data sets. This research highlights how the use of signal processing methods are beneficial in characterizing these ground motions, the application of which has historically been uncommon simply due to a lack of data. With the advancement of high rate and high density remote sensing technologies, this work provides a practical framework in handling the resulting datasets to identify common signal modes and their relation to surface processes.

6.4 Recommendations for future study

This research is the first step in a larger long term effort to characterize landslide hazard. It provides a framework for infrastructure installation and data processing methods which will improve insight for landslide mechanics as the data sets grow and analysis quality is increased.

As the next step, InSAR analysis of the EBH should be expanded spatially and temporally. Expanding the analysis to a larger area might reveal surface processes that have otherwise gone

undetected. Expanding the time series through present would also result in a better understanding of long term seasonal conditions affected by climate change.

While this research effort focuses on the topic of landslides, two other areas of interest were deserve to be studied in more depth. First, a clear time series of landfill subsidence is observed along the San Francisco Bay margin. The effects of sea level rise and climate change are likely to have a measured effect on this process and should be investigated. Second, a record of pipe and transmission line breaks shows a strong correlation to seasonal landslide deformation. A more complete analysis of these occurrences, in relation to pipe materials and sizes is warranted.

LRA monitoring network was established to enable a long-term and near-real time data set. In hopes that it is maintained, the cGPS time series should be revisited to gain insight on long-term surface deformation behavior. It also stands to provide valuable information in the event of a large seismic event, should the 20Hz data set and seismometer data (at LRA6) be retrieved. The opportunity to combine cGPS and InSAR data sets before and after an earthquake would produce an important contribution to the study of seismically triggered, climate driven land movement.

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Appendix A – *SqueeSARTM Processing Report*

TRE ALTAMIRA SqueeSARTM Processing Report

Note: TRE report pages 3 and 9 were blank.



SqueeSARTM Processing Report

Area name: **Berkeley**
Report number: **I1528A15**

For the attention of: Stefano Cespa
Contract number:
Report date: 24-Jul-2014

TRE
Ripa di Porta Ticinese, 79
20143 Milan, Italy
Tel: +39 02 4343 121
Fax: +39 02 4343 1230
info@treuropa.com

TRE Canada
Suite #410 475 W. Georgia Street
Vancouver, BC V6B 4M9 Canada
Tel: +1 604 331 2512
Fax: +1 604 331 2513
info@trecanada.com

www.treuropa.com

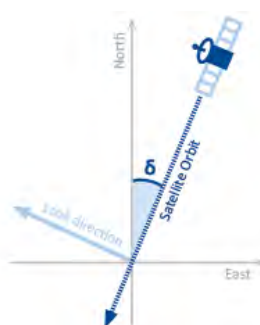
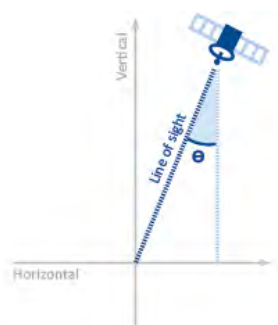


Satellite info

Satellite	Wavelength	Satellite geometry	Sensor mode	Satellite track
TSX	3.11 cm	DESCENDING	SM003	38

Acquisition geometry

Line of sight angle	θ :	22°	δ :	10.82°		
Line of sight versors	H:	0.927	N:	-0.07	E:	0.368

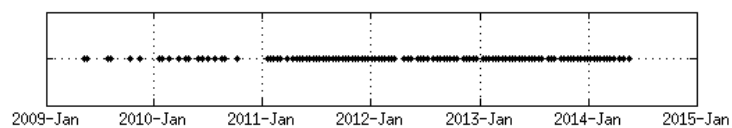




Dataset

Time range	10-May-2009 21-May-2014
Number of scenes	119

Temporal distribution of acquisitions



List of images

Date	Acquisition time	Sensor
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21-May-2009	14:23:39	TSX1 SM003
26-Jul-2009	14:23:42	TSX1 SM003
06-Aug-2009	14:23:43	TSX1 SM003
11-Oct-2009	14:23:48	TSX1 SM003
13-Nov-2009	14:23:48	TSX1 SM003
18-Jan-2010	14:23:43	TSX1 SM003
29-Jan-2010	14:23:43	TSX1 SM003
20-Feb-2010	14:23:43	TSX1 SM003
25-Mar-2010	14:23:44	TSX1 SM003
16-Apr-2010	14:23:45	TSX1 SM003
27-Apr-2010	14:23:45	TSX1 SM003
30-May-2010	14:23:47	TSX1 SM003
10-Jun-2010	14:23:47	TSX1 SM003



02-Jul-2010	14:23:47	TSX1 SM003
24-Jul-2010	14:23:48	TSX1 SM003
15-Aug-2010	14:23:50	TSX1 SM003
26-Aug-2010	14:23:51	TSX1 SM003
09-Oct-2010	14:23:55	TDX1 SM003
16-Jan-2011	14:23:48	TSX1 SM003
27-Jan-2011	14:23:47	TSX1 SM003
07-Feb-2011	14:23:47	TSX1 SM003
18-Feb-2011	14:23:47	TSX1 SM003
01-Mar-2011	14:23:47	TSX1 SM003
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24-Aug-2011	14:23:54	TSX1 SM003
04-Sep-2011	14:23:54	TSX1 SM003
15-Sep-2011	14:23:53	TSX1 SM003
26-Sep-2011	14:23:54	TSX1 SM003



07-Oct-2011	14:23:54	TSX1 SM003
18-Oct-2011	14:23:54	TSX1 SM003
29-Oct-2011	14:23:55	TSX1 SM003
09-Nov-2011	14:23:54	TSX1 SM003
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23-Dec-2011	14:23:51	TSX1 SM003
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14-Jan-2012	14:23:50	TSX1 SM003
25-Jan-2012	14:23:49	TSX1 SM003
05-Feb-2012	14:23:49	TSX1 SM003
16-Feb-2012	14:23:50	TSX1 SM003
27-Feb-2012	14:23:50	TSX1 SM003
09-Mar-2012	14:23:50	TSX1 SM003
20-Mar-2012	14:23:50	TSX1 SM003
22-Apr-2012	14:23:51	TSX1 SM003
03-May-2012	14:23:52	TSX1 SM003
14-May-2012	14:23:53	TSX1 SM003
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16-Jun-2012	14:23:55	TSX1 SM003
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01-Sep-2012	14:23:57	TSX1 SM003



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23-Sep-2012	14:23:58	TSX1 SM003
04-Oct-2012	14:23:58	TSX1 SM003
15-Oct-2012	14:23:58	TSX1 SM003
06-Nov-2012	14:23:59	TSX1 SM003
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25-Jun-2013	14:24:00	TSX1 SM003
06-Jul-2013	14:24:01	TSX1 SM003
17-Jul-2013	14:24:01	TSX1 SM003



28-Jul-2013	14:24:02	TSX1 SM003
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30-Aug-2013	14:24:04	TSX1 SM003
10-Sep-2013	14:24:04	TSX1 SM003
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13-Oct-2013	14:24:05	TSX1 SM003
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04-Nov-2013	14:24:05	TSX1 SM003
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16-Mar-2014	14:24:01	TSX1 SM003
27-Mar-2014	14:24:02	TDX1 SM003
18-Apr-2014	14:24:02	TSX1 SM003
29-Apr-2014	14:24:03	TSX1 SM003
21-May-2014	14:24:04	TSX1 SM003

Discarded images

Date	Acquisition time	Sensor	Motivation
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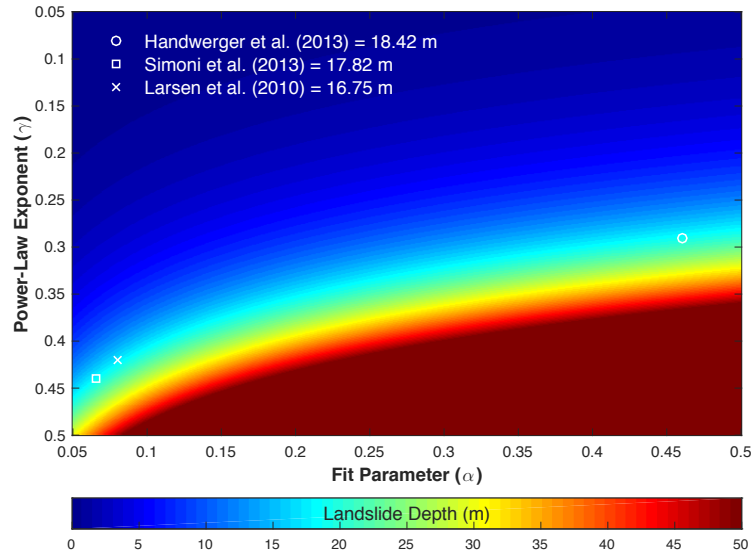
Results

Number of measurement points (MP)	463373
Area	74.4 sq km
Measurement point density	6228.1 MP/sq km
Coordinate reference system	WGS 1984
Georeferencing data layer	Microsoft Bing Maps
Reference point	Code: AE3T2 X coordinate: -122.2945306 Y coordinate: 37.9074728
Product list	BERKELEY_TSX_T38_D_I1528A1S-REF.shp BERKELEY_TSX_T38_D_I1528A1S-TSR.shp BERKELEY_TSX_T38_D_I1528A1S.xml BERKELEY_TSX_T38_D_I1528A1S.pdf

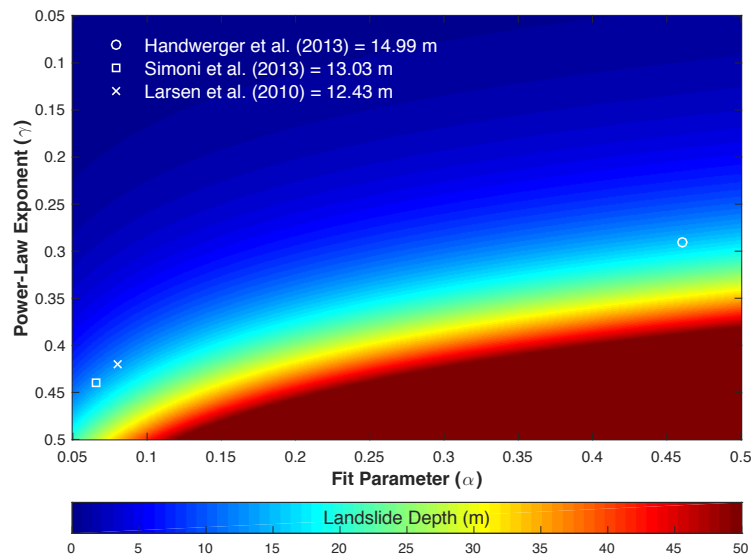
Appendix B – *InSAR Analysis Supplemental Figures*

Depth-Area Relationship

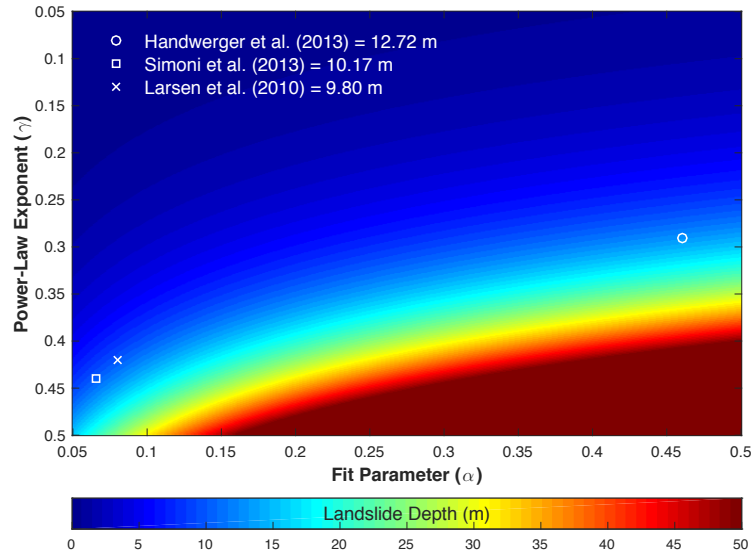
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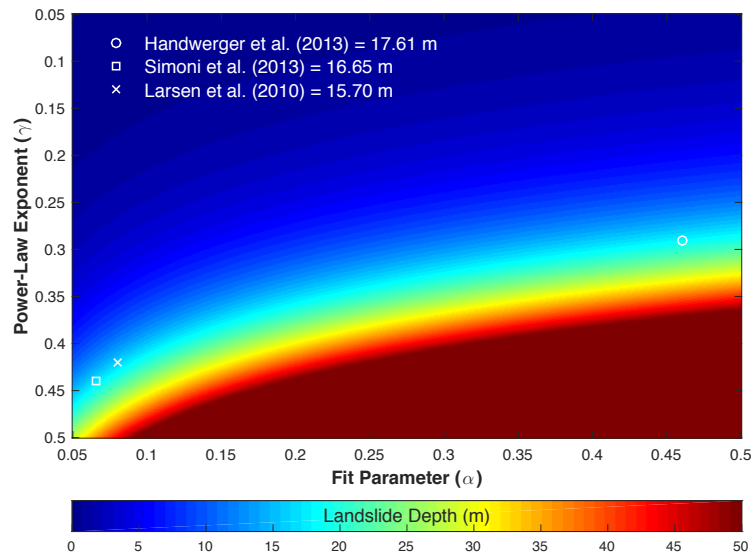
Thousand Oaks Landslide:



Marin Landslide:

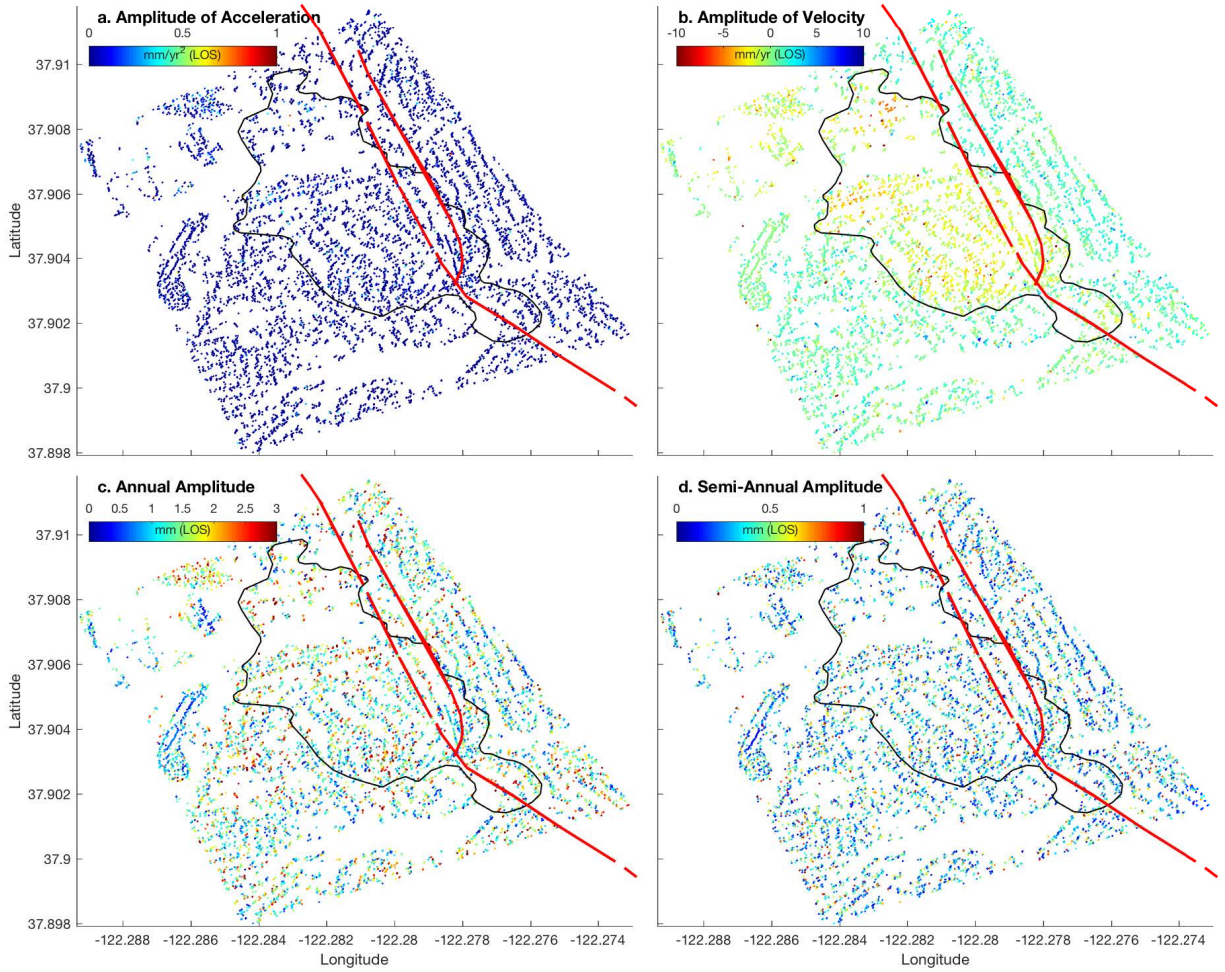


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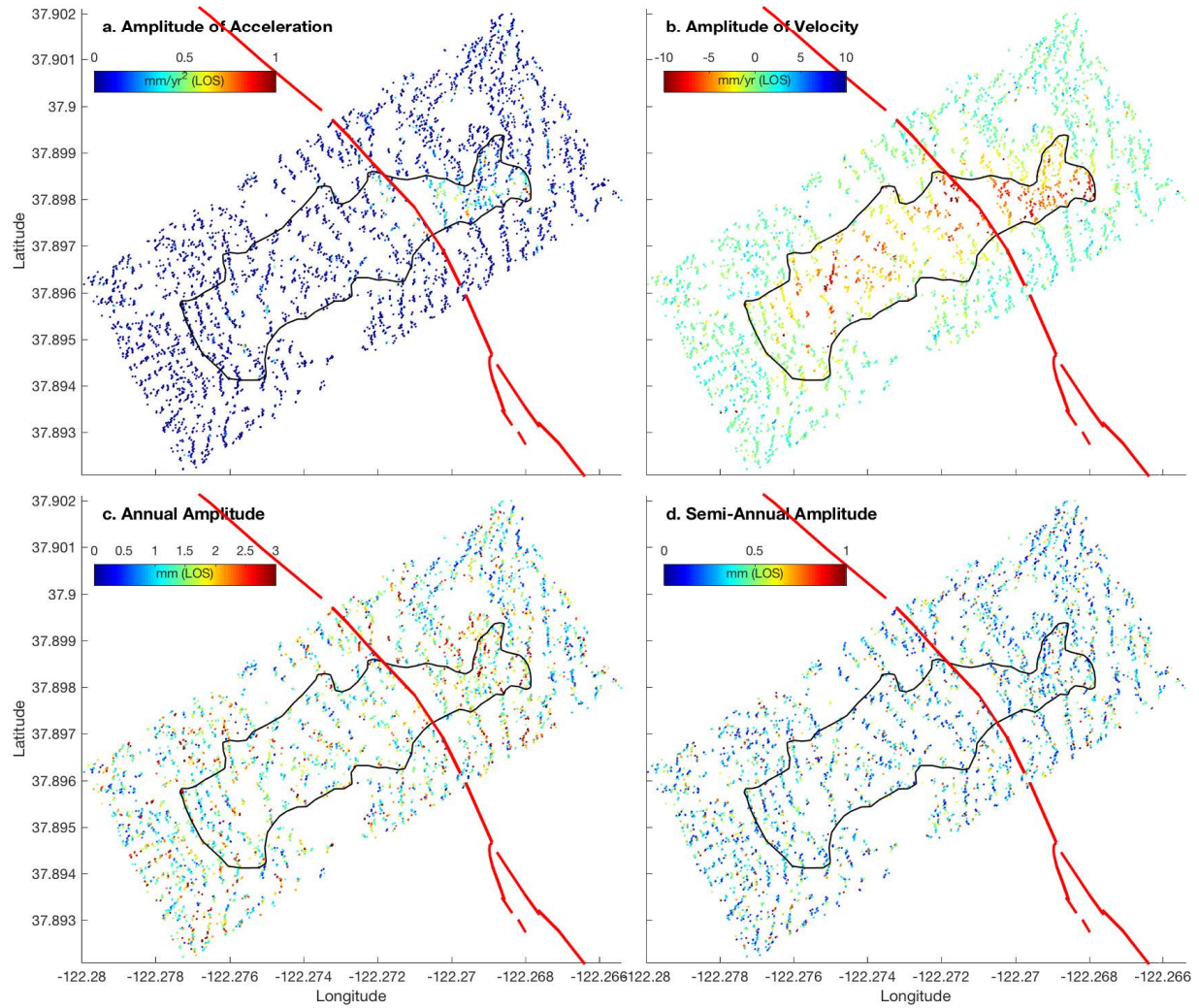


FCF Amplitude Maps

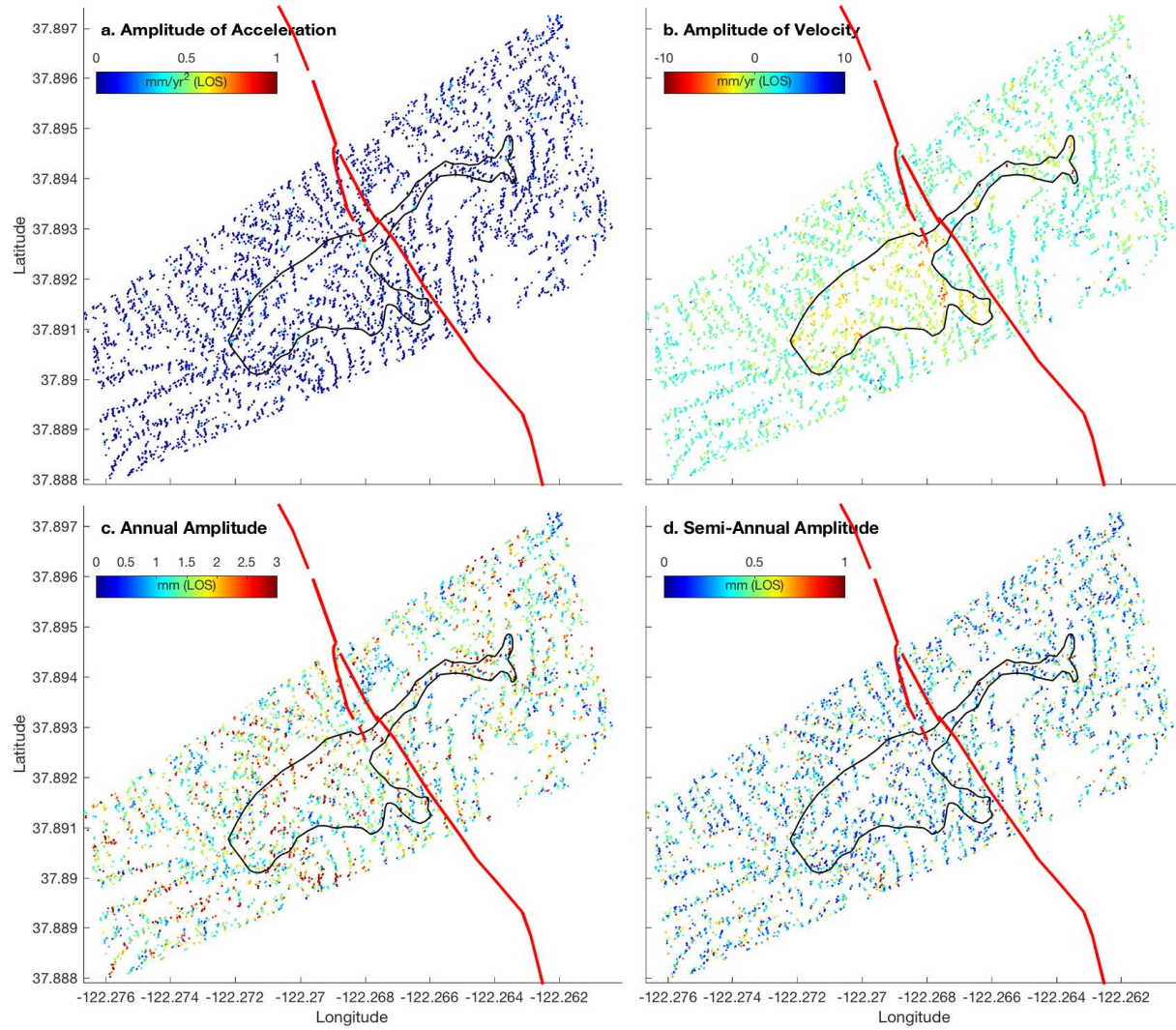
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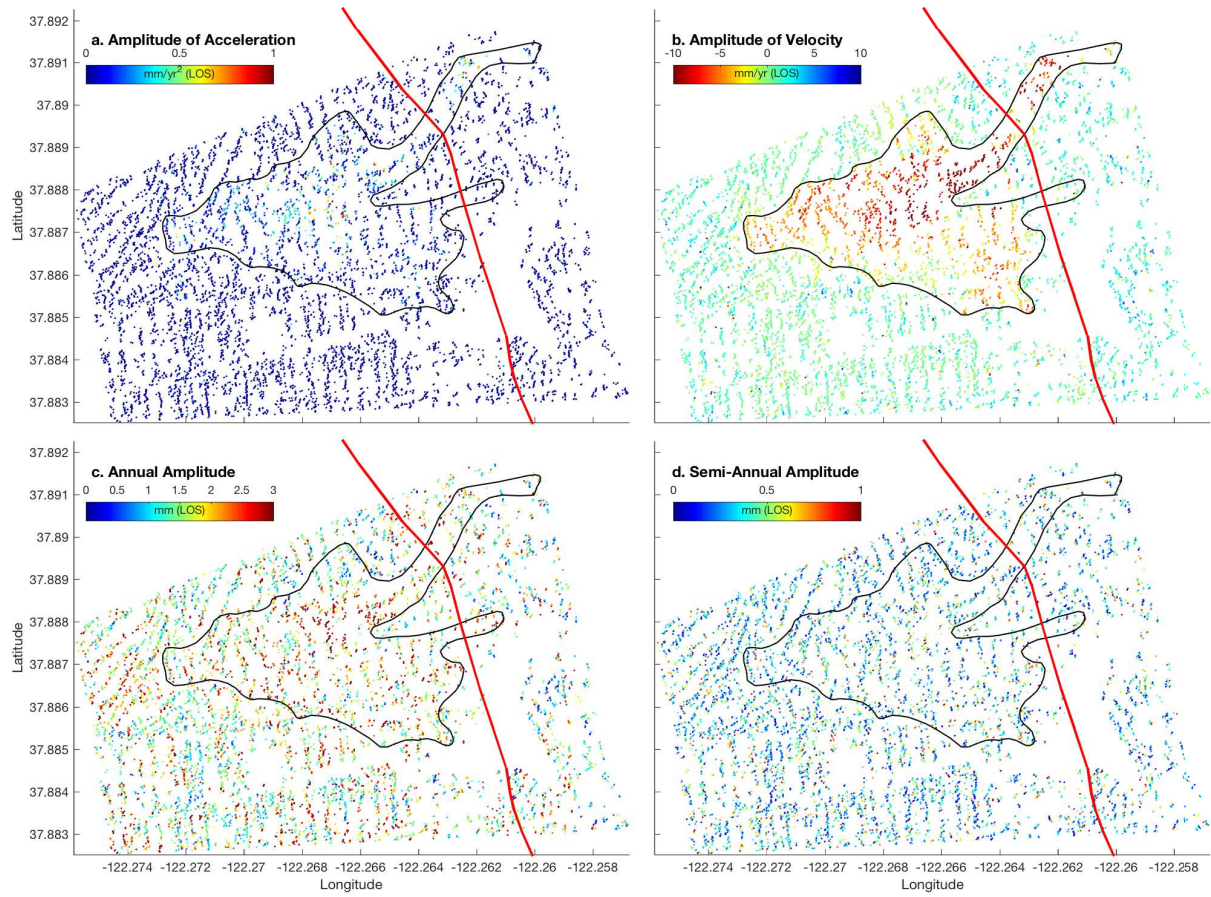
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Marin Landslide:

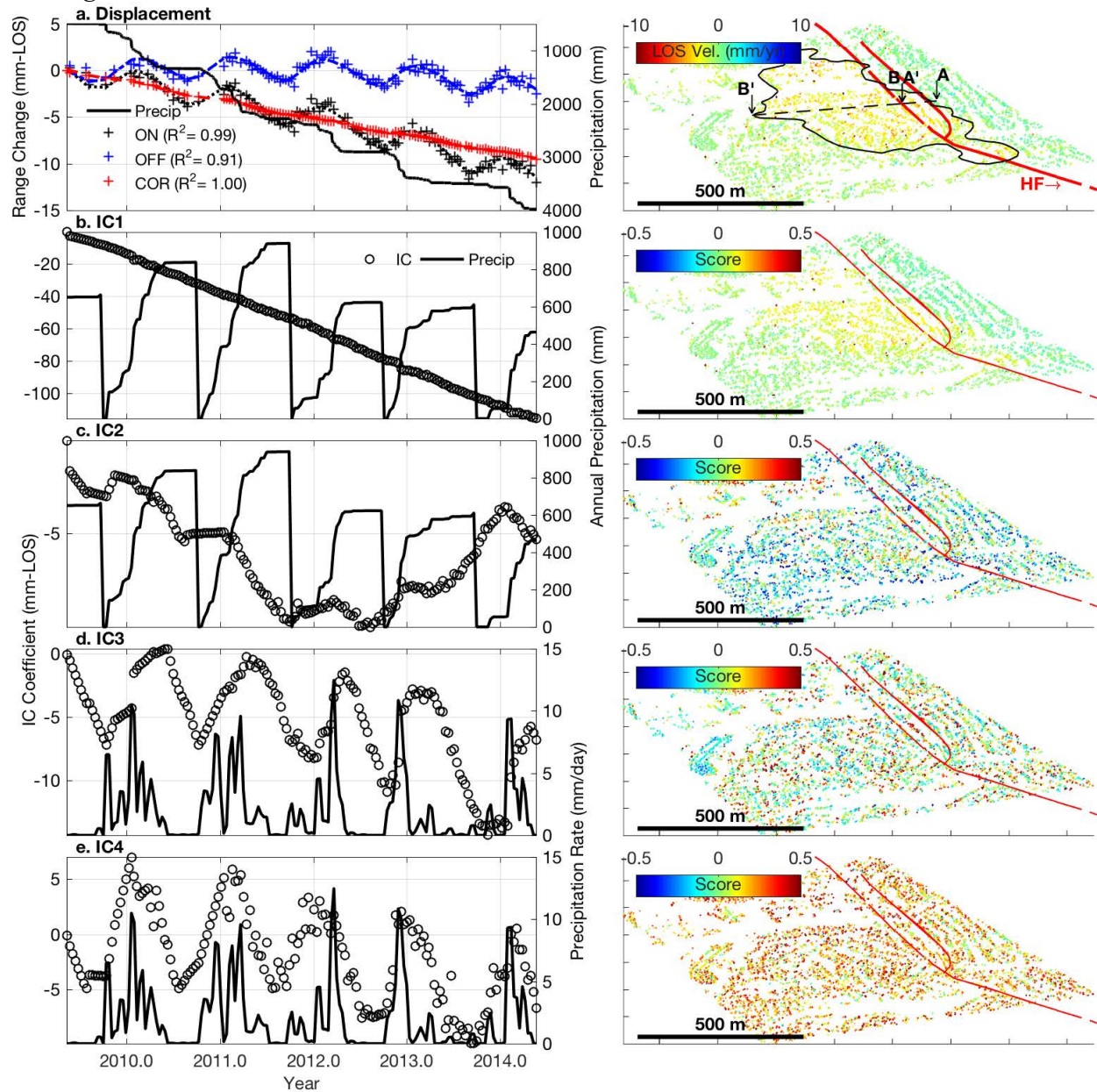


North Berkeley Landslide:

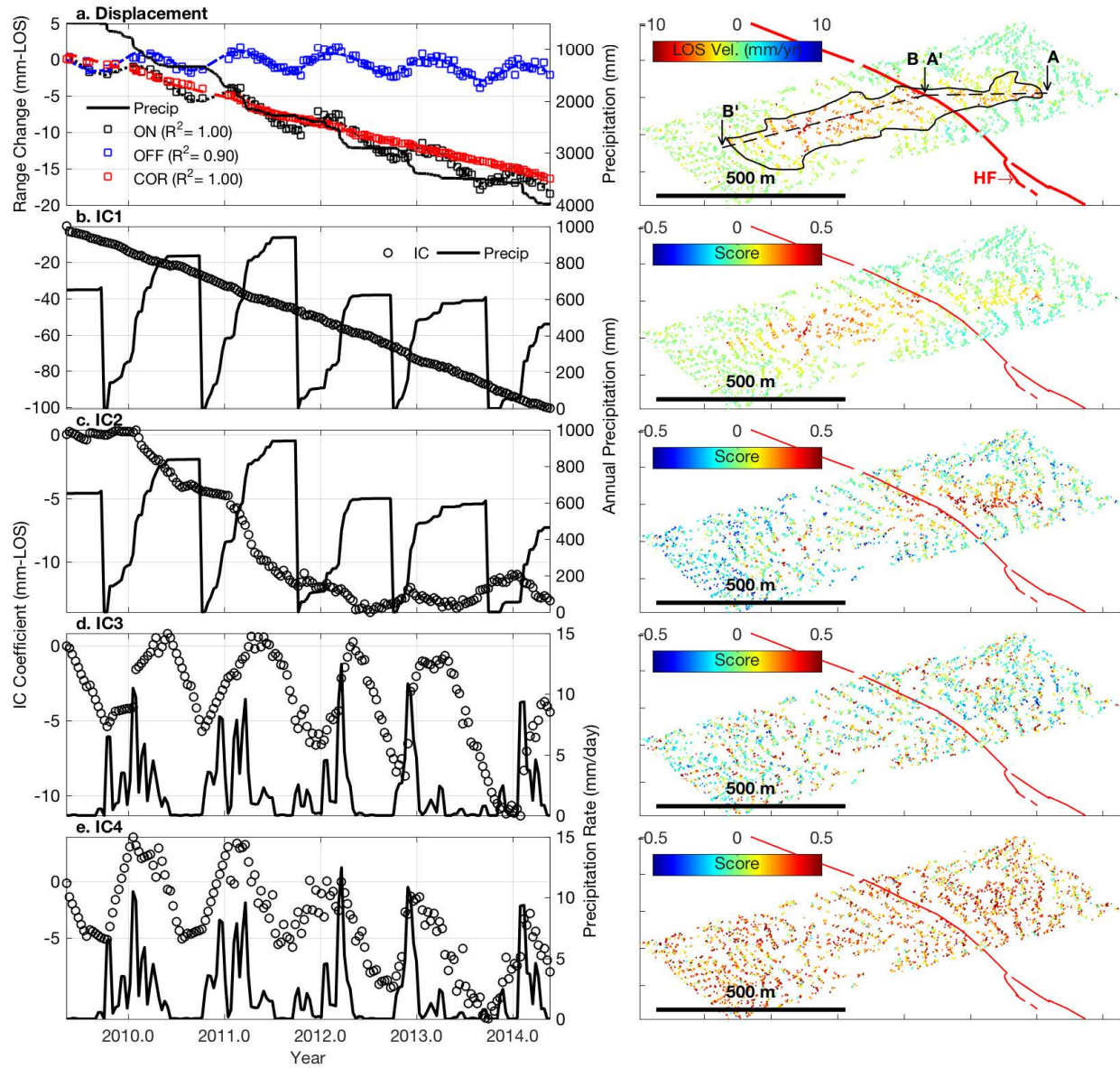


ICA Summary Figures

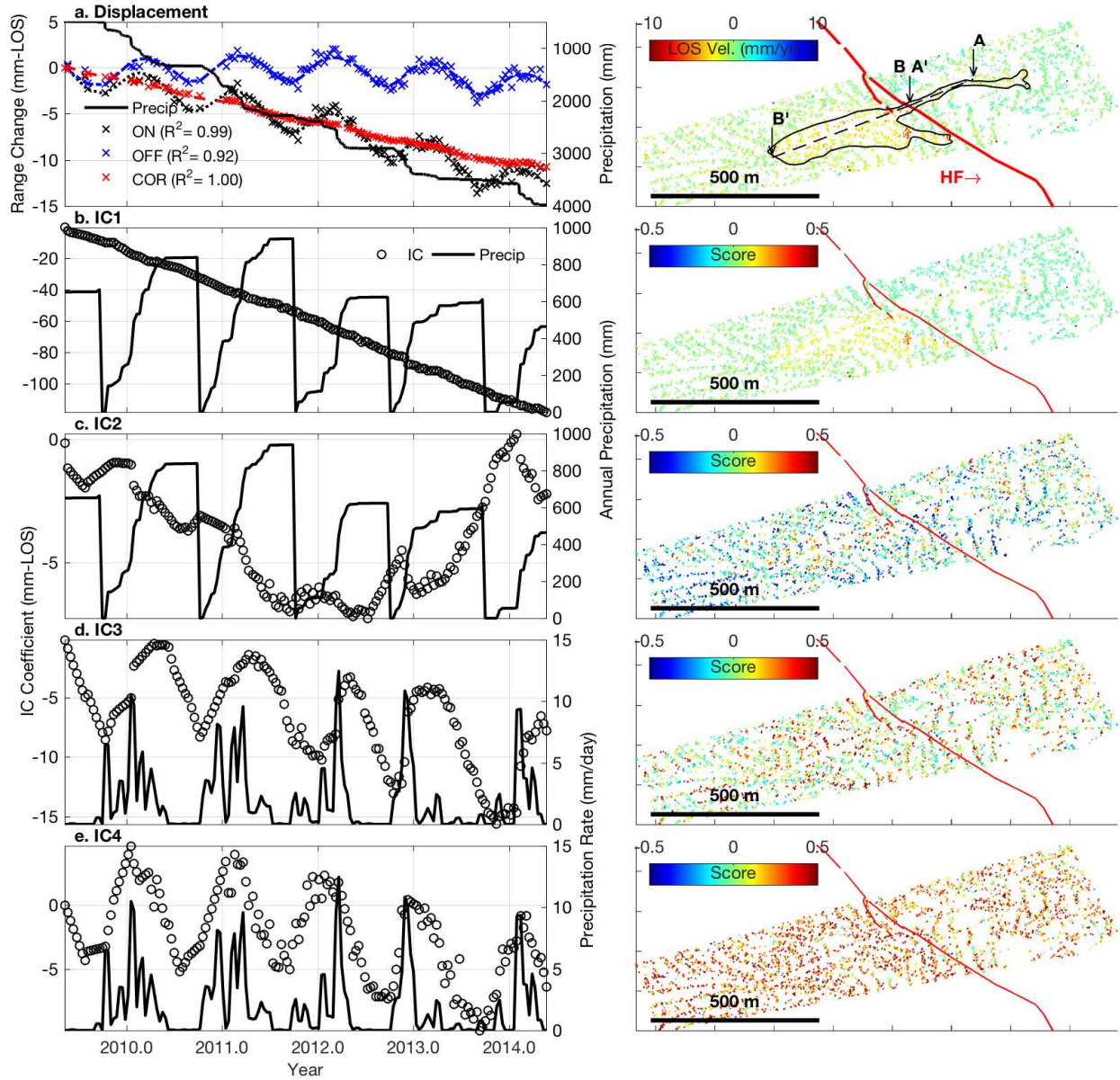
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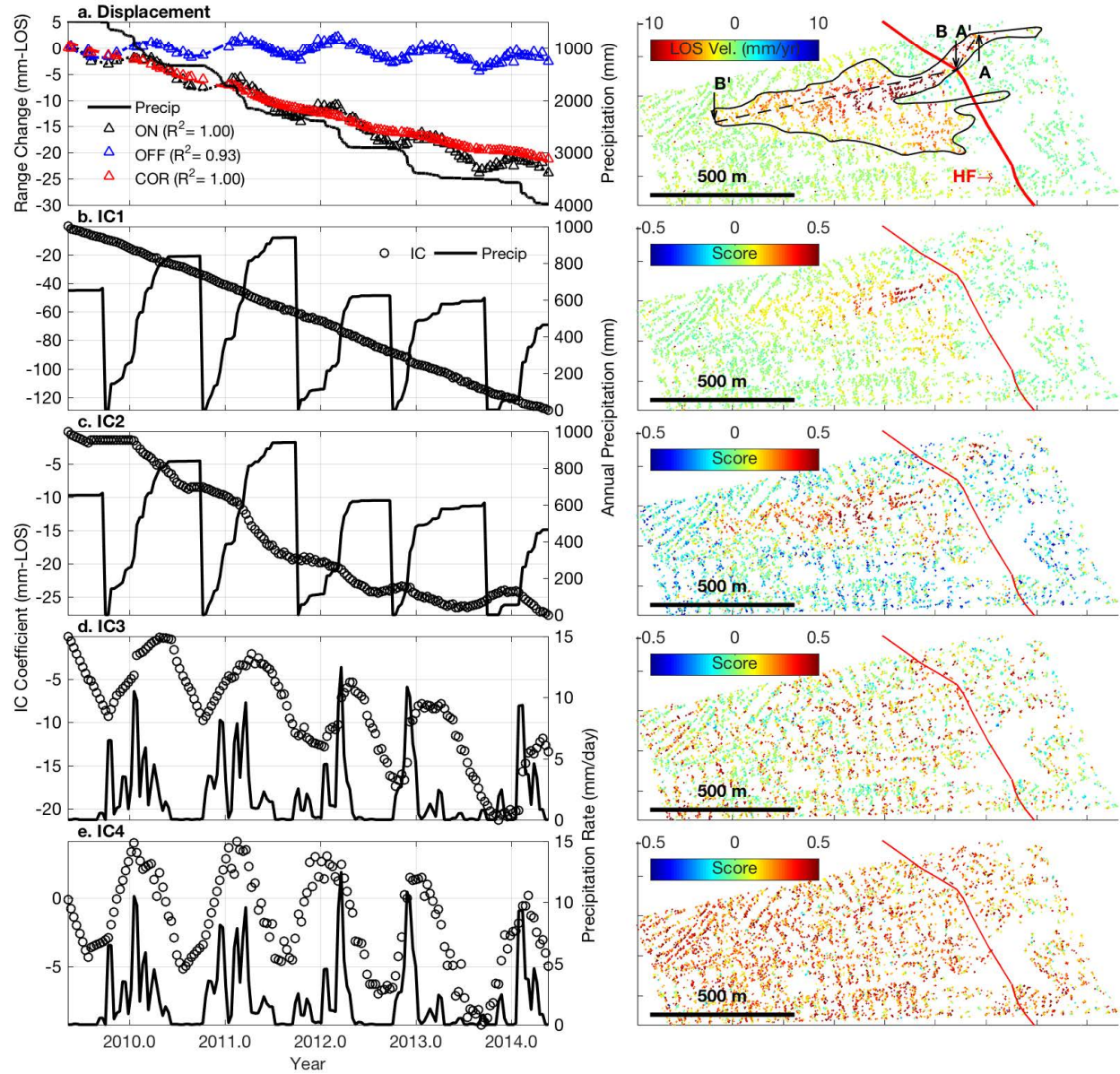
Thousand Oaks Landslide:



Marin Landslide:

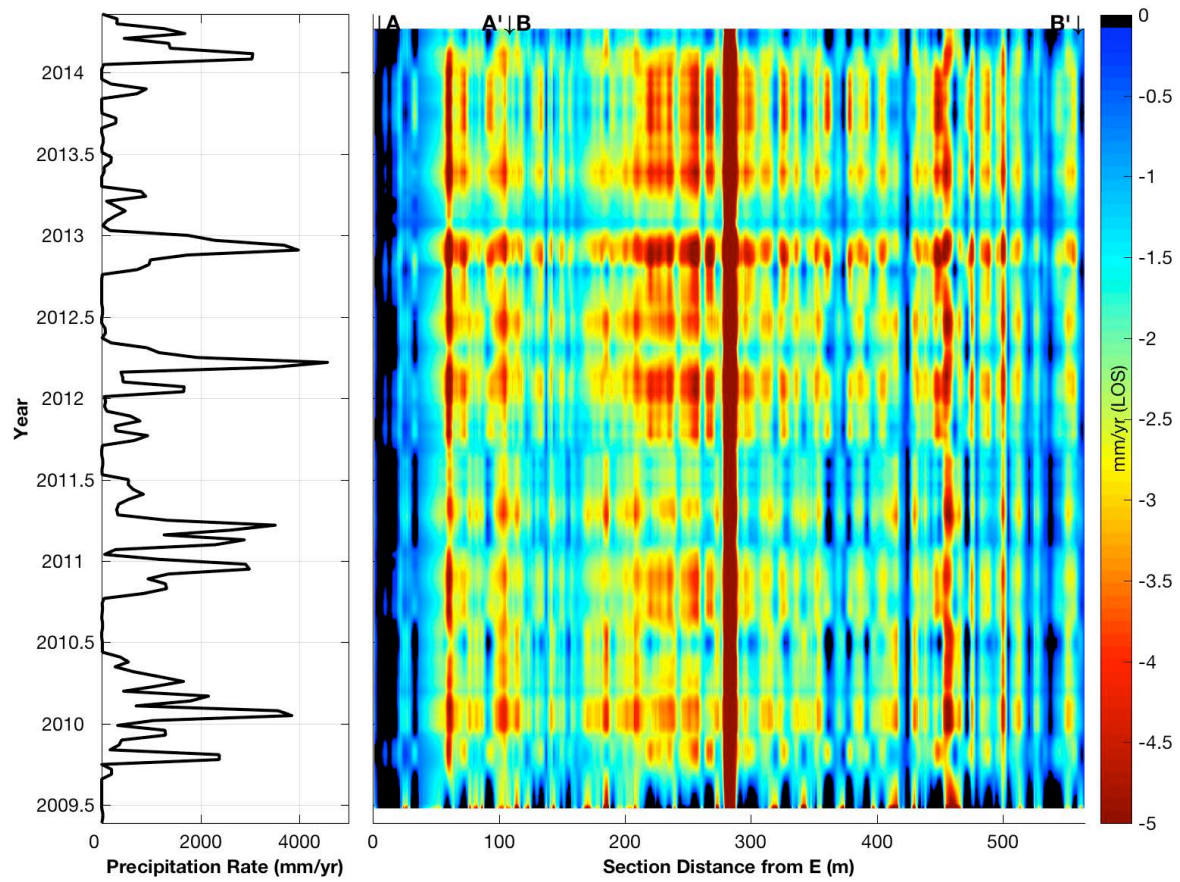


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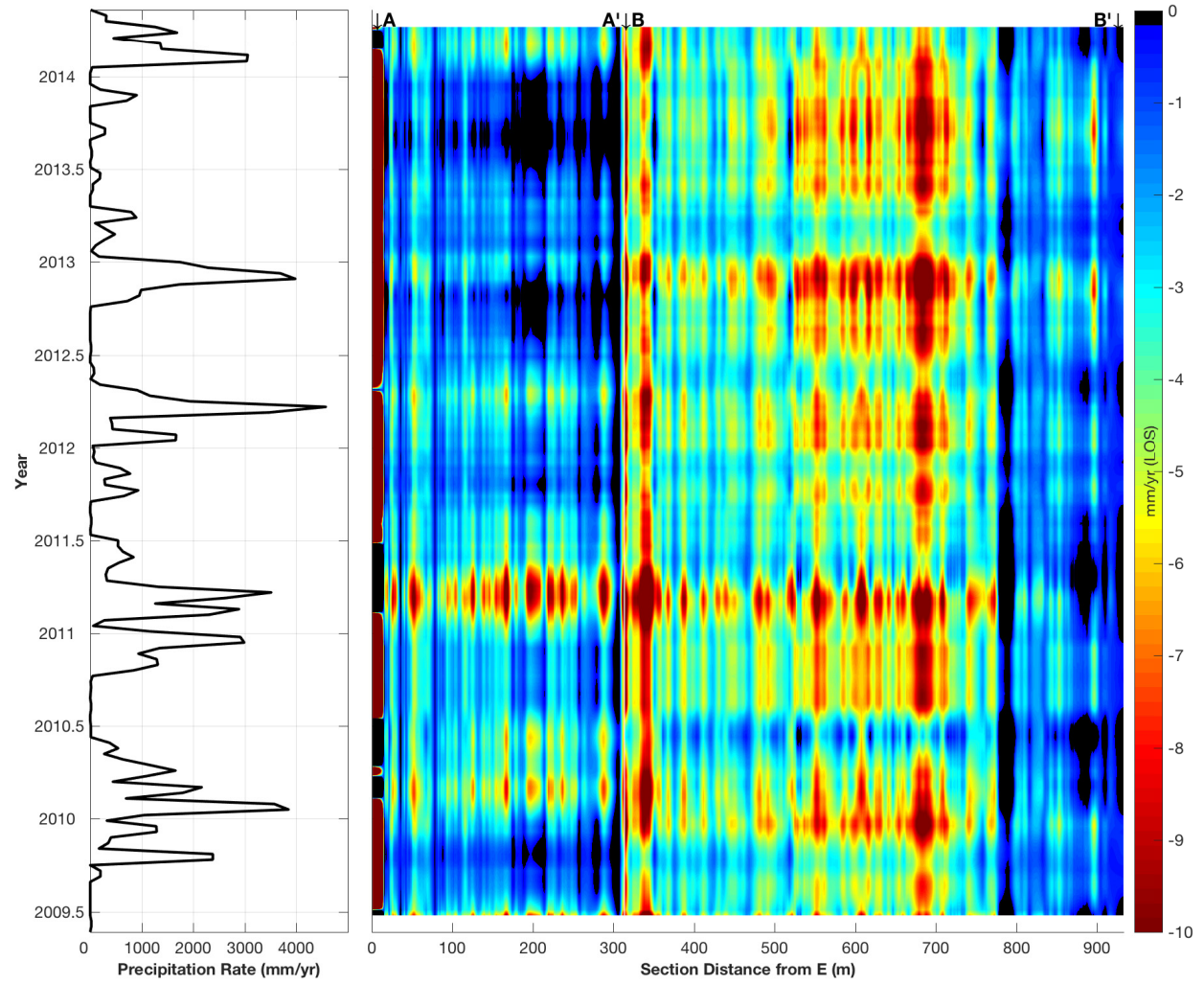


Velocity Cross-Section Figures

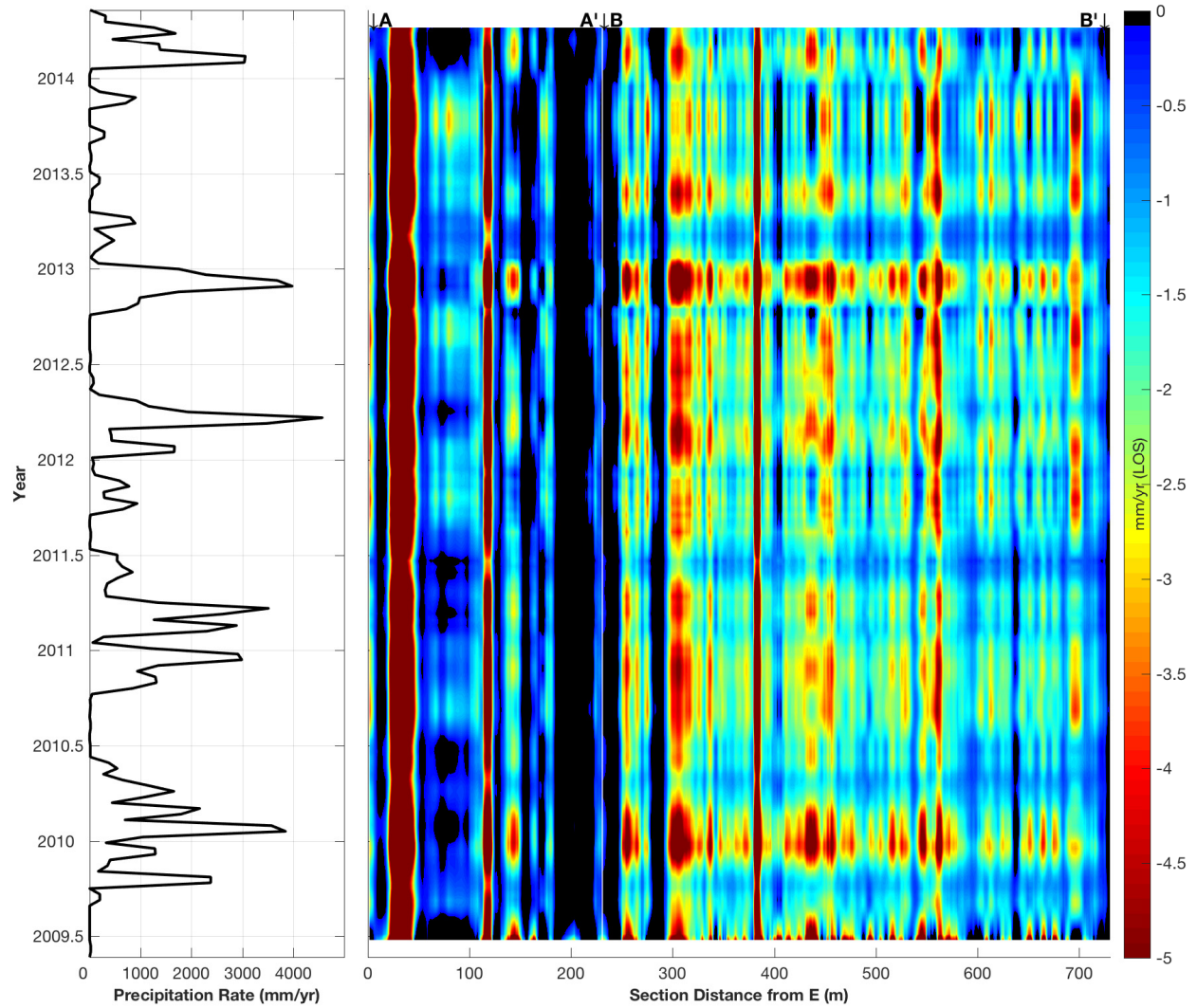
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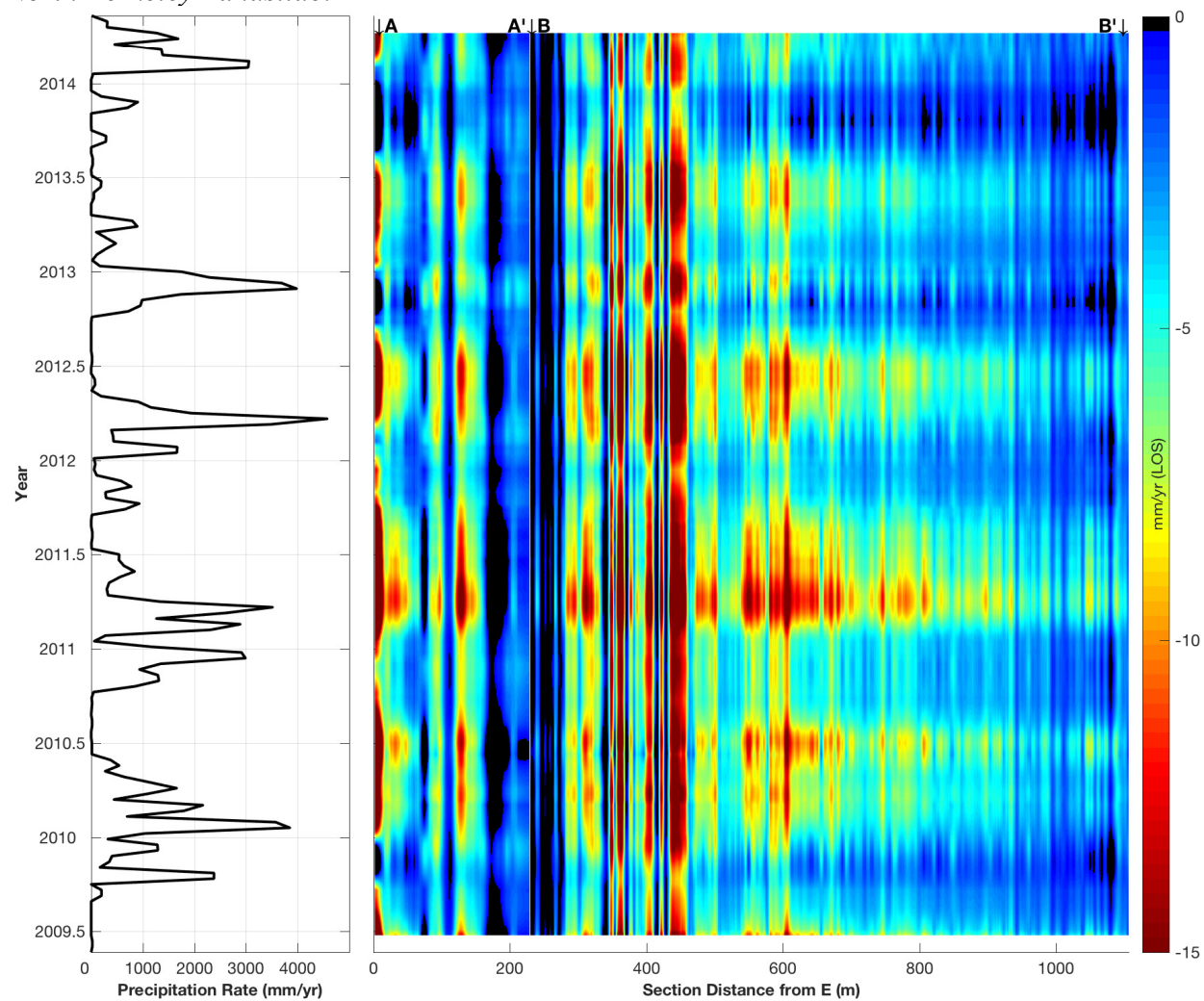


Thousand Oaks Landslide:



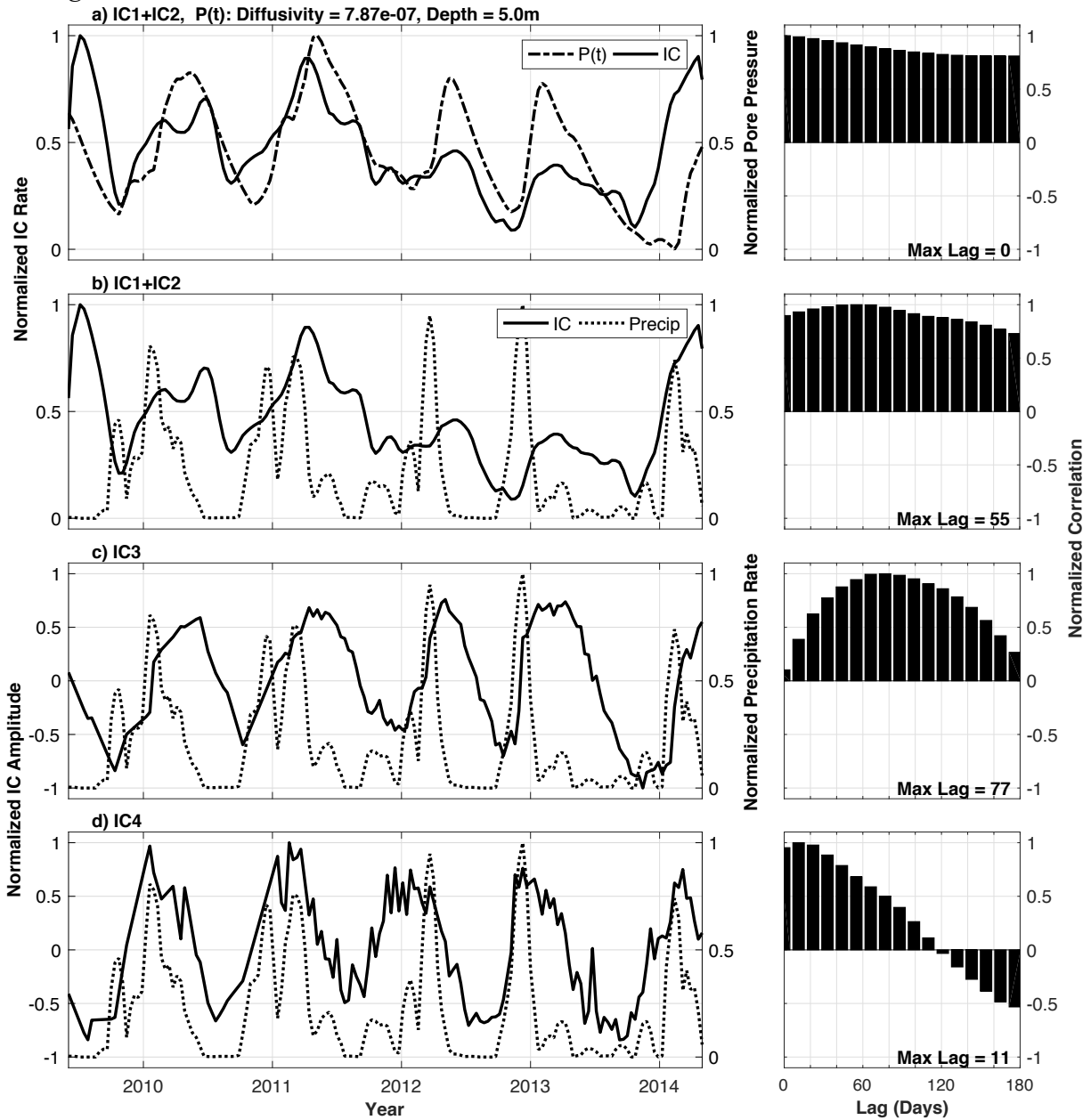
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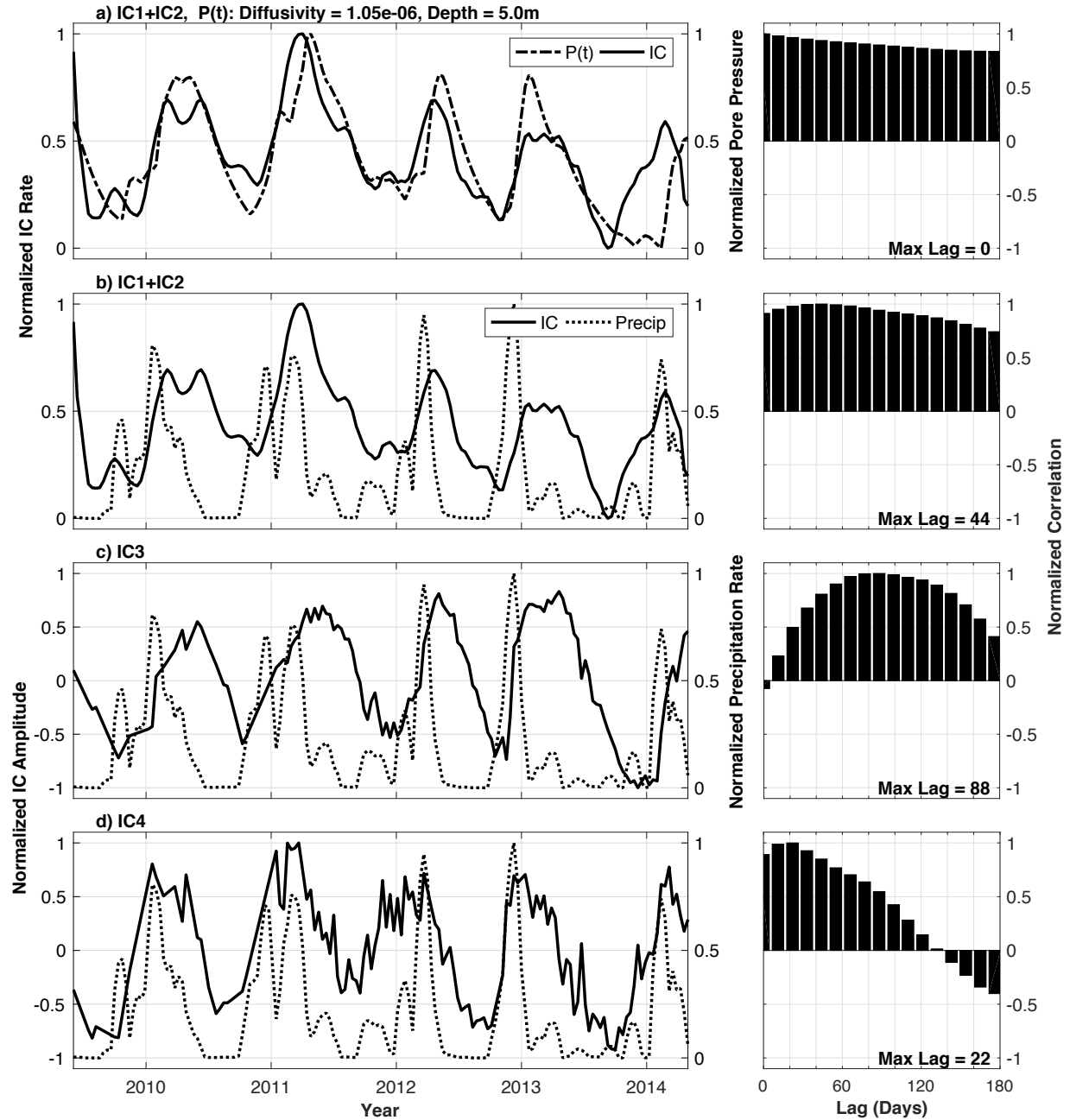
North Berkeley Landslide:

Cross Correlation Analysis Figures

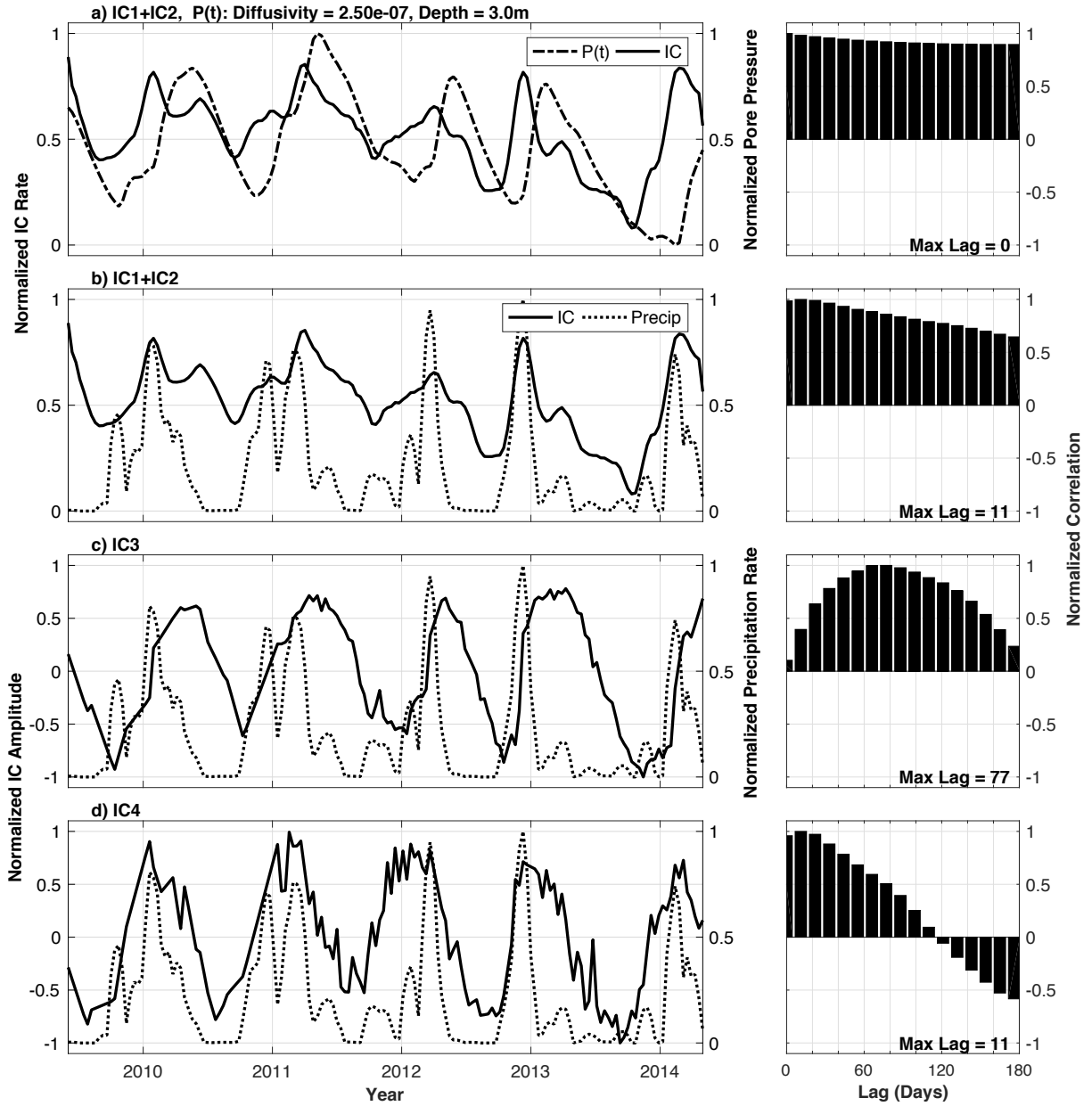
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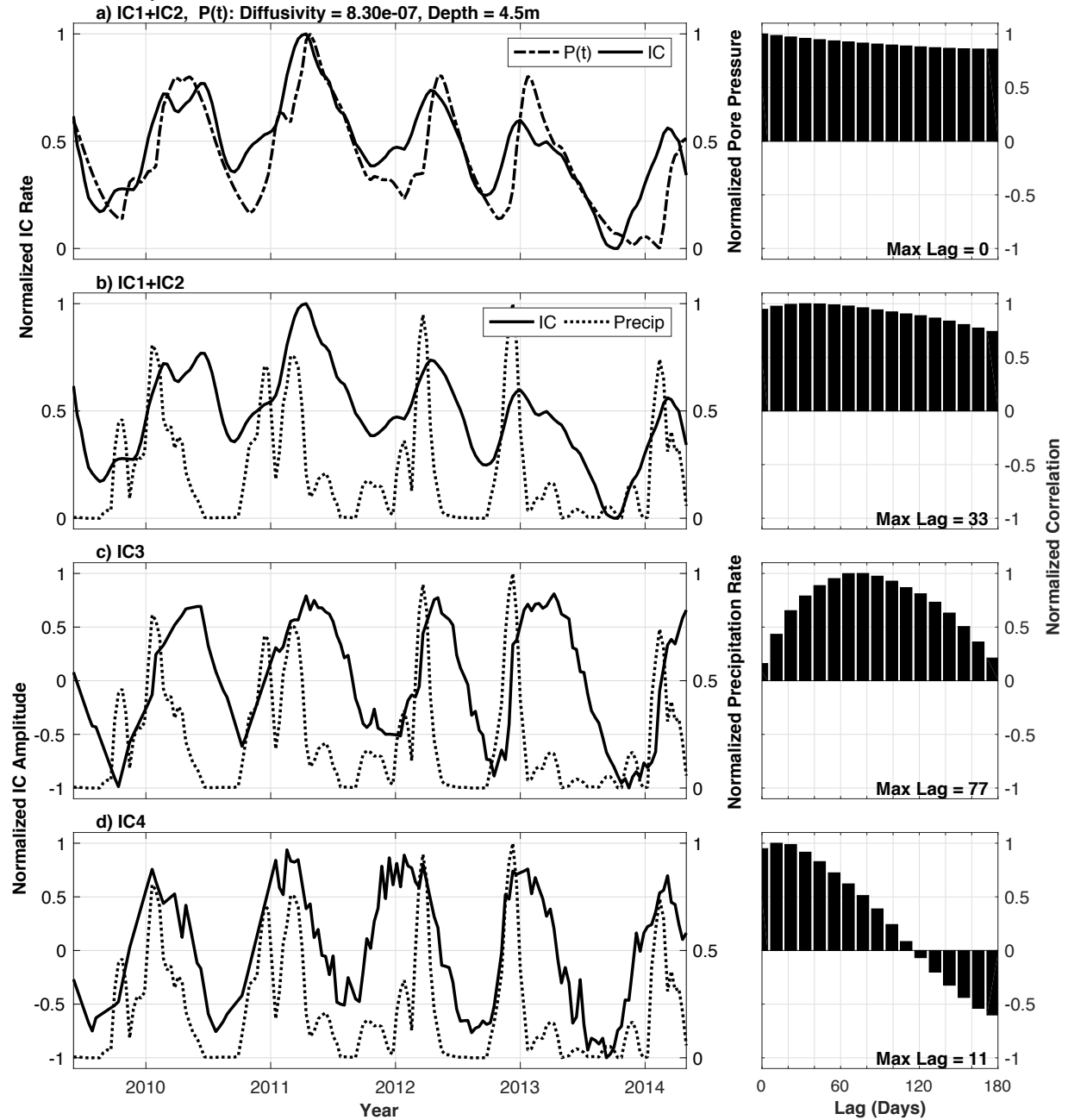
Thousand Oaks Landslide:



Marin Landslide:



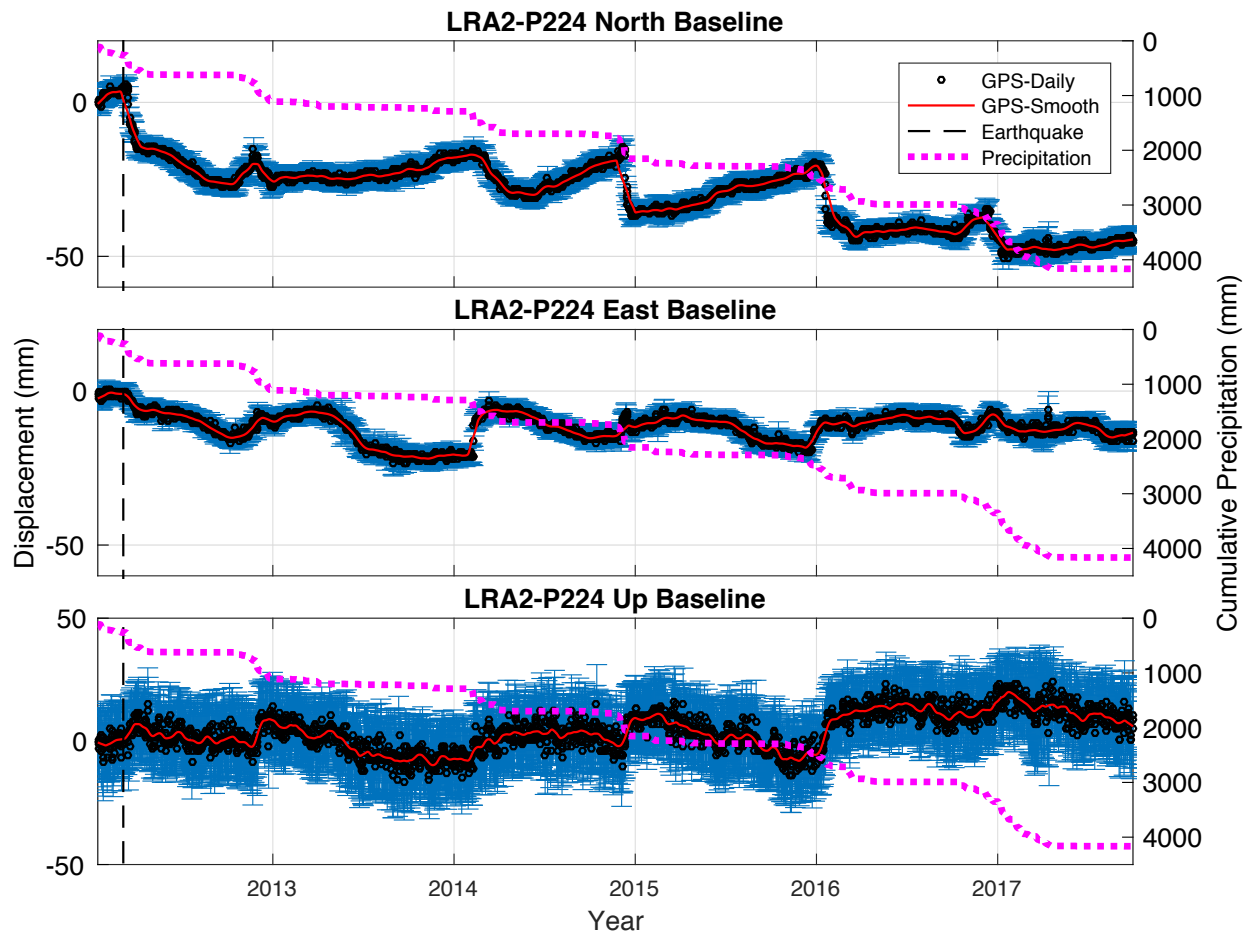
North Berkeley Landslide:



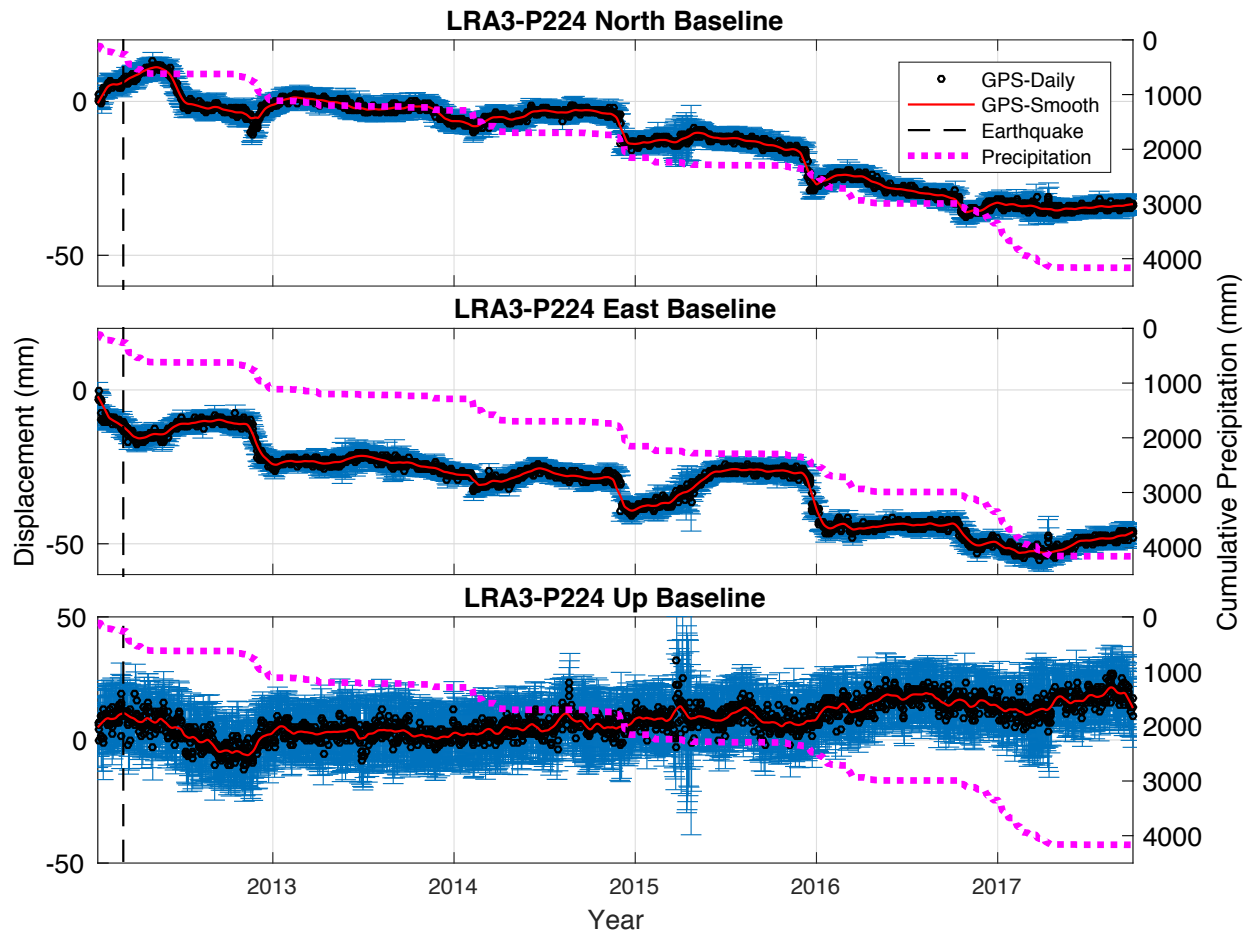
Appendix C – *GPS Analysis Supplemental Figures*

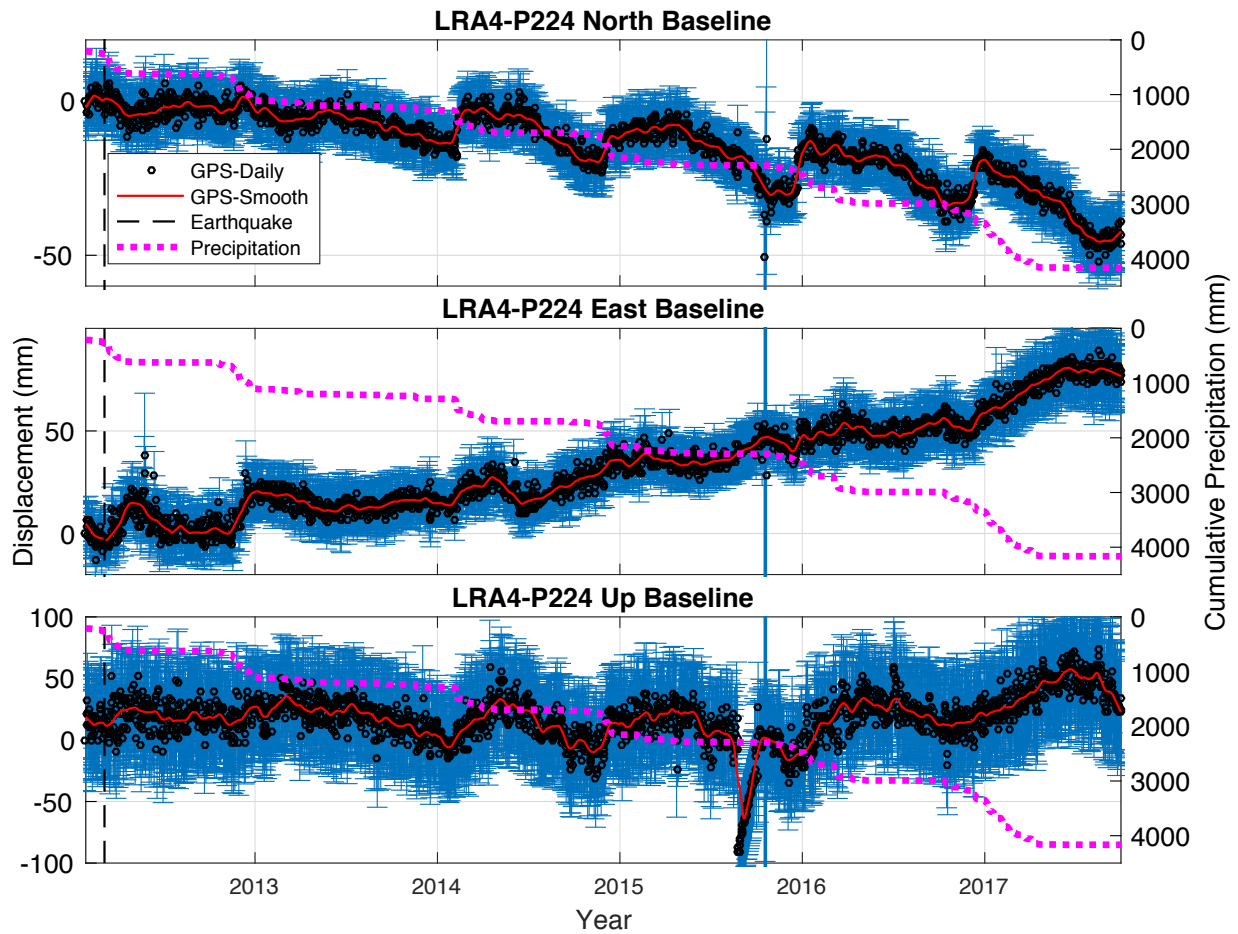
Baseline Time Series

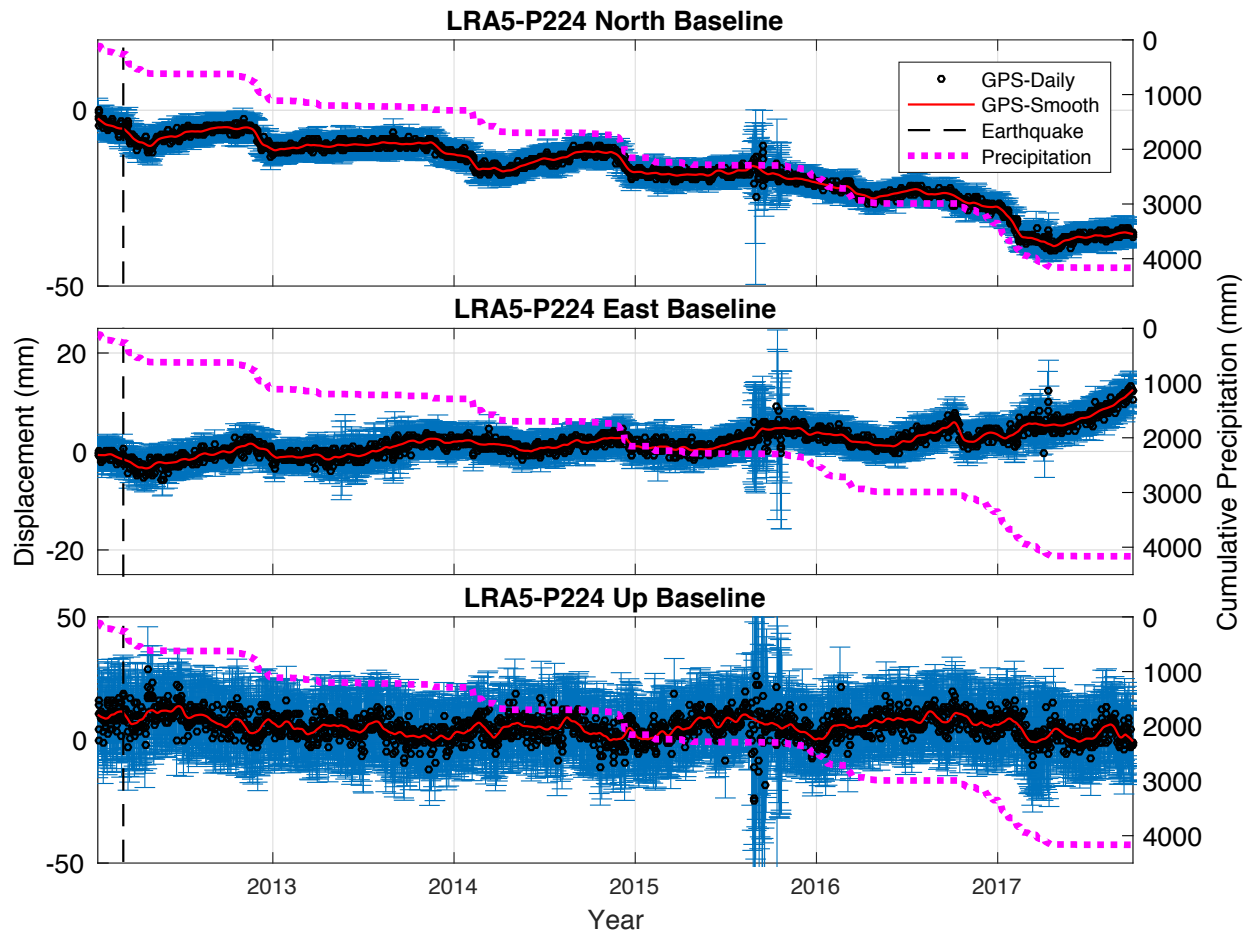
LRA2:

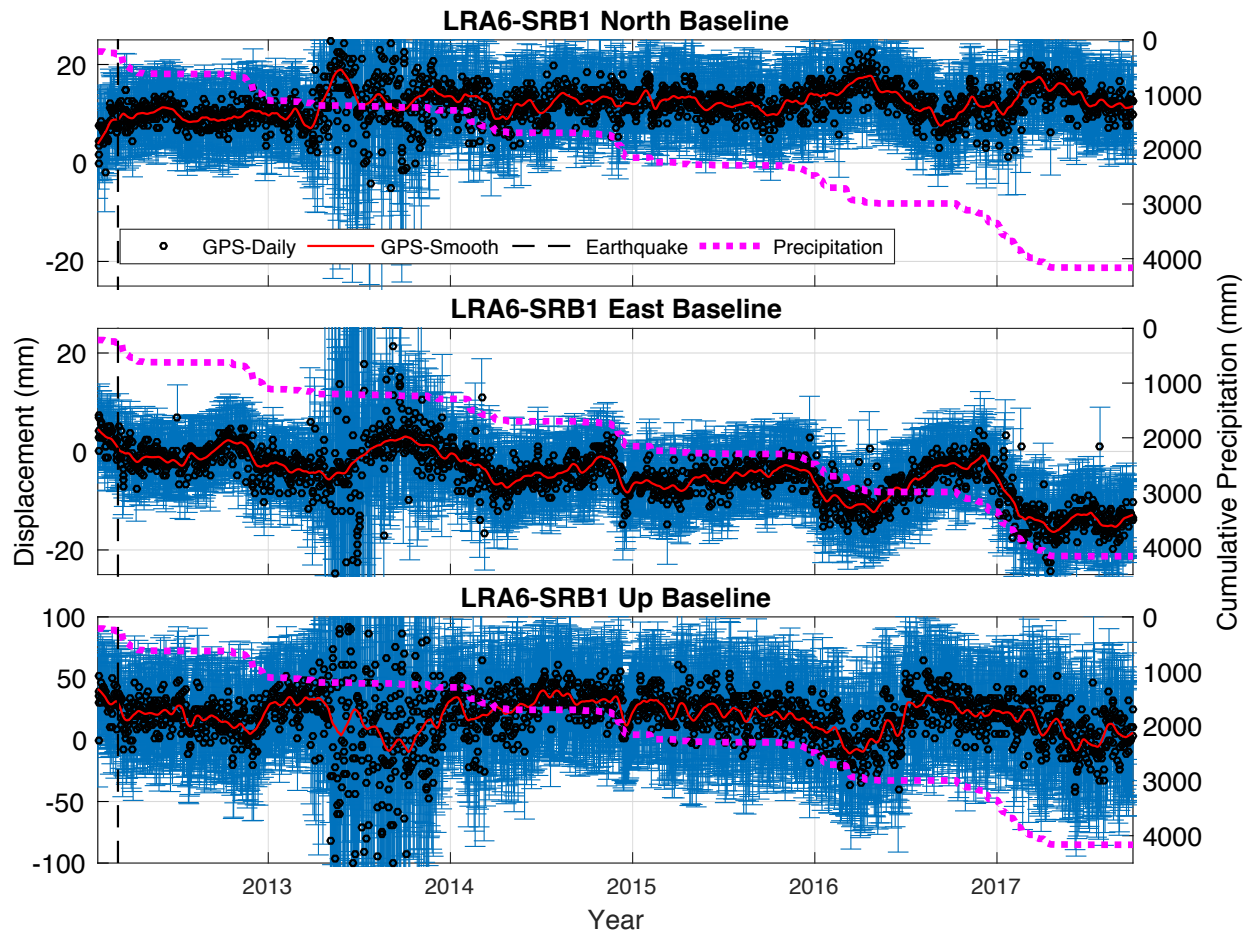


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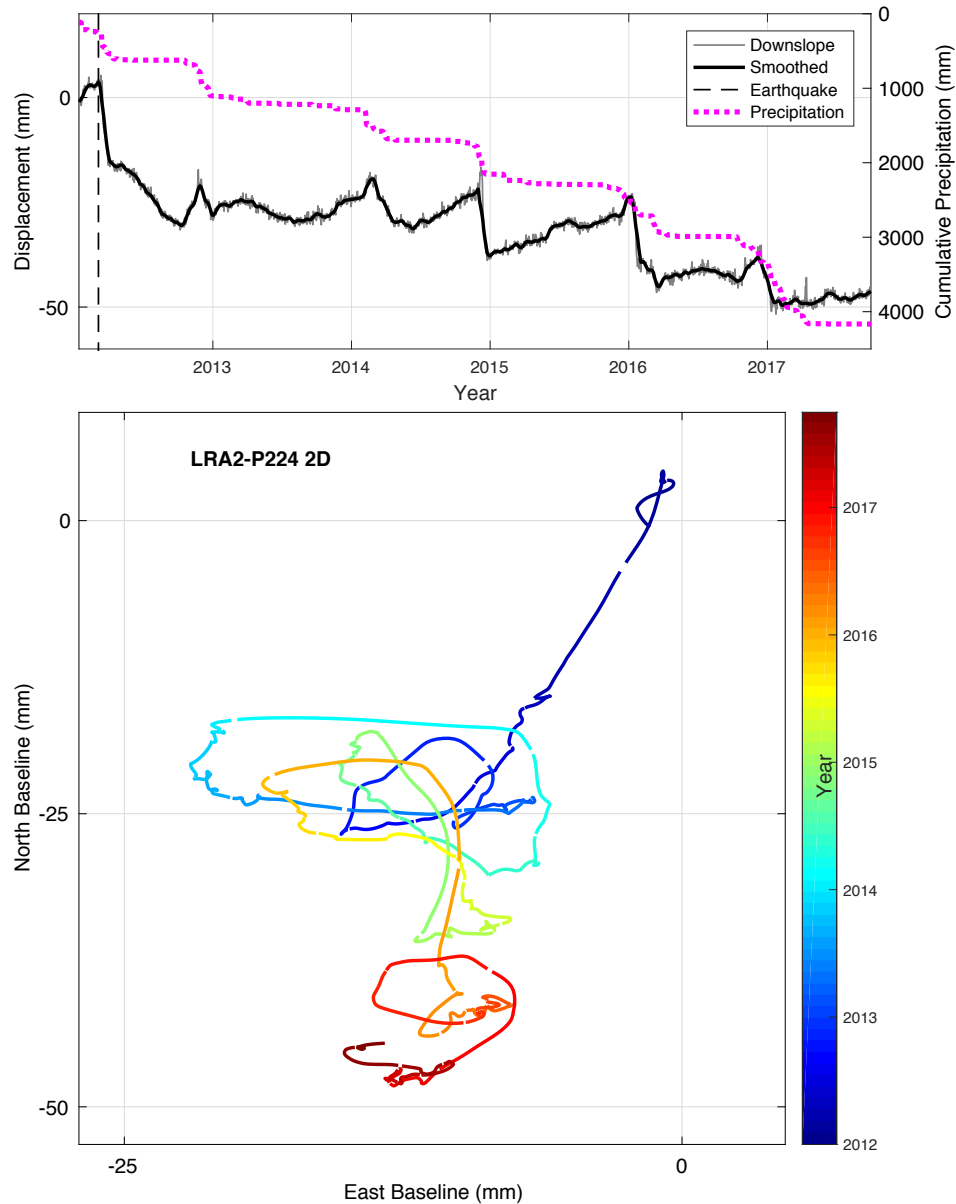
LRA4:

LRA5:

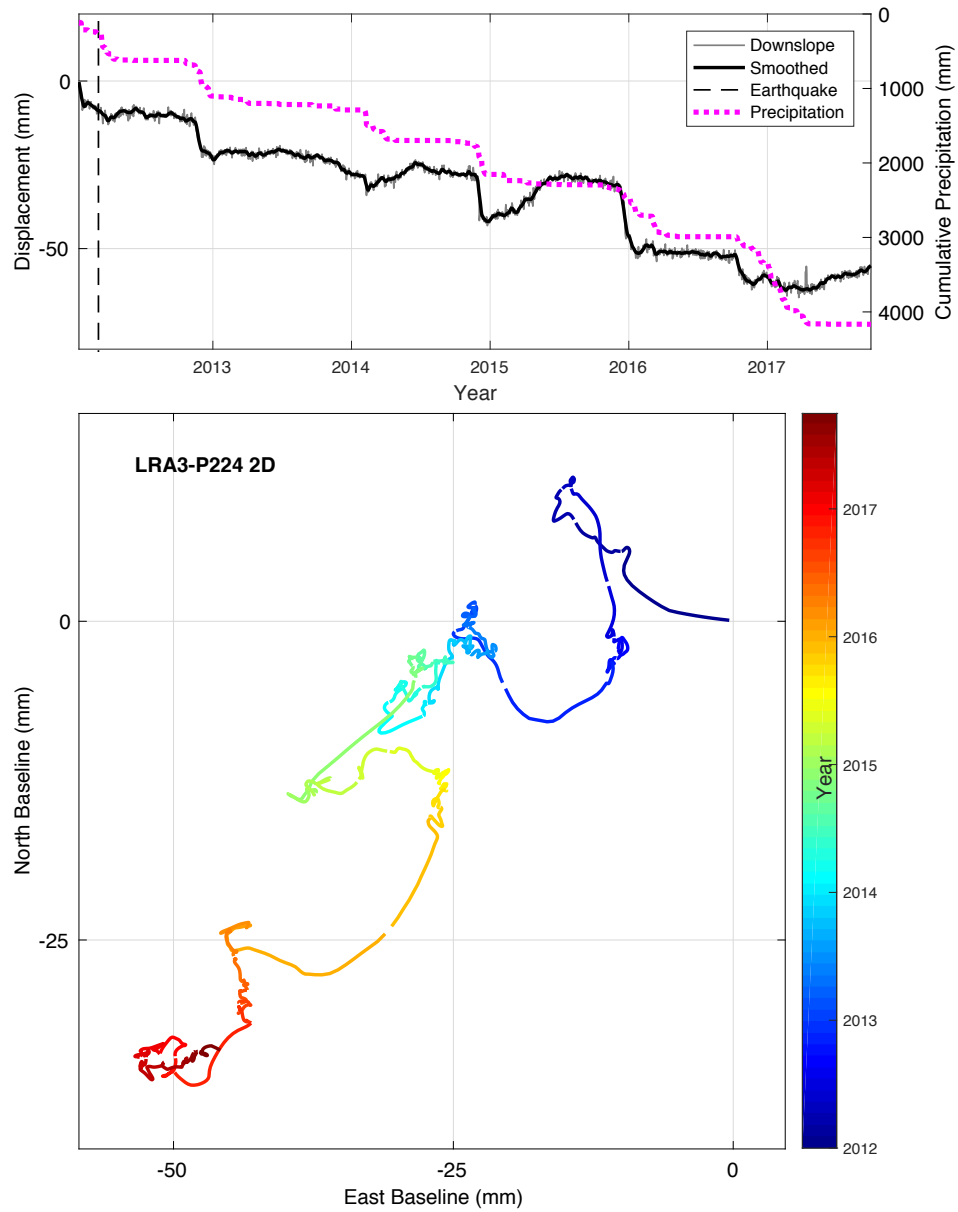
LRA6:

Downslope Projection and 2-D Displacement Time Series

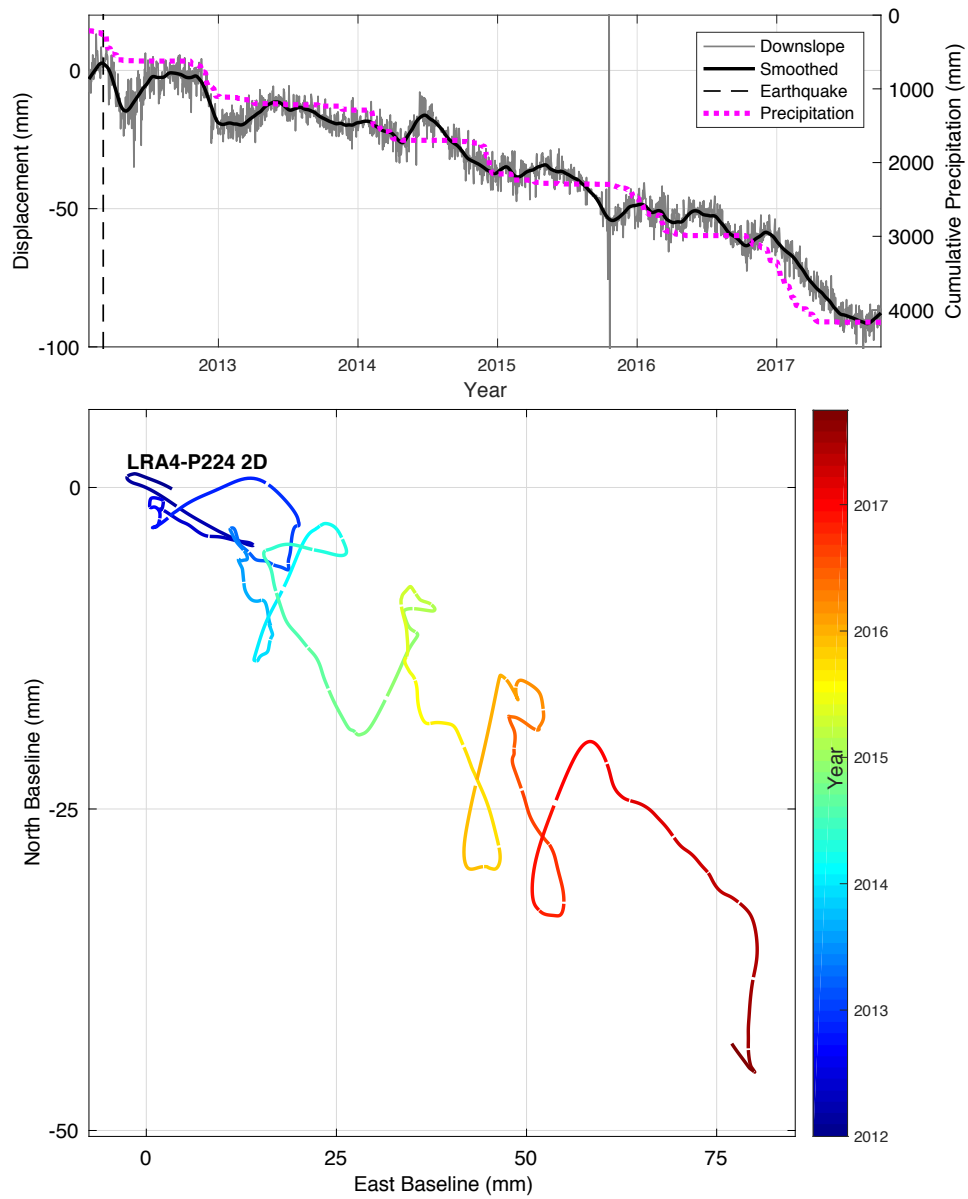
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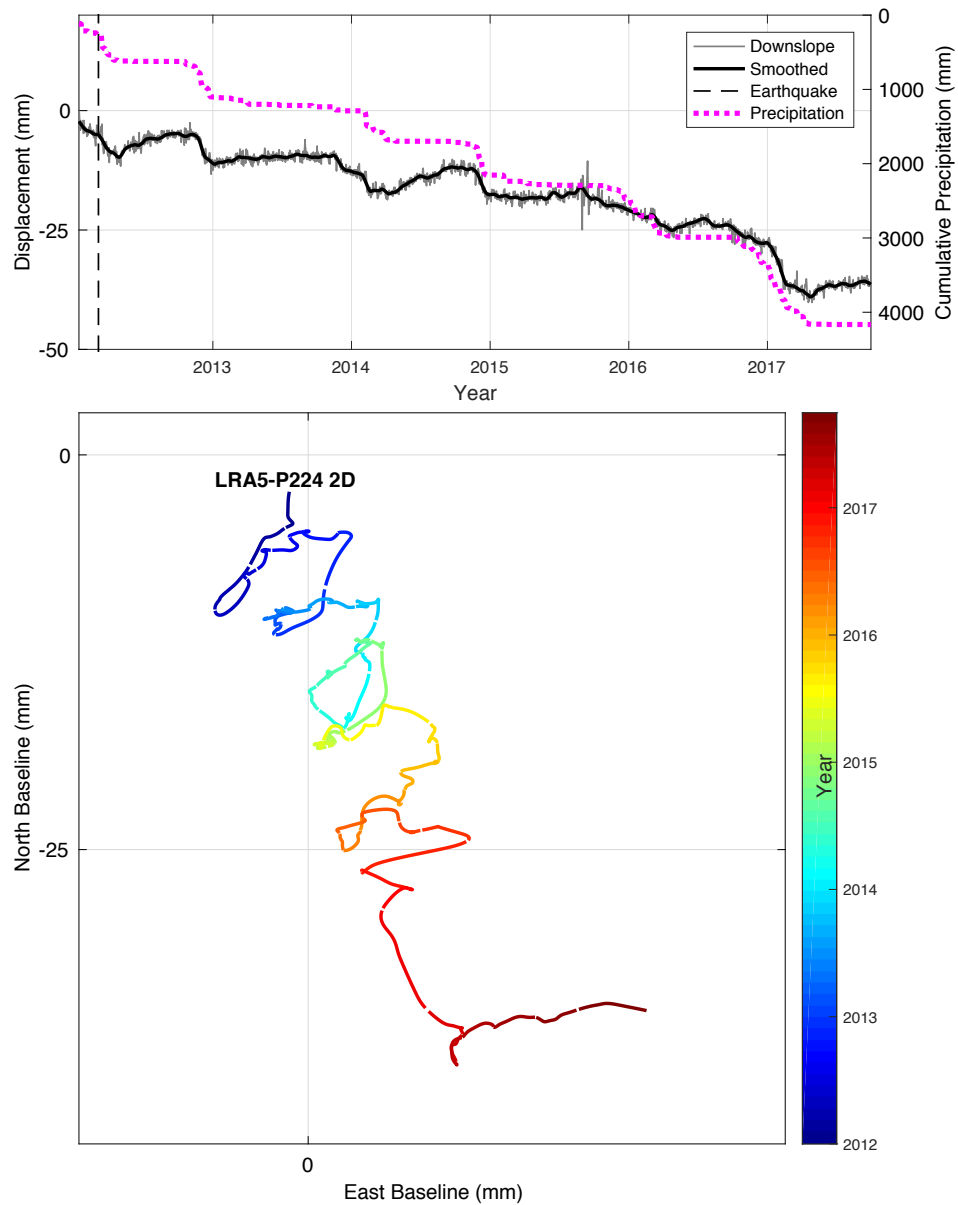
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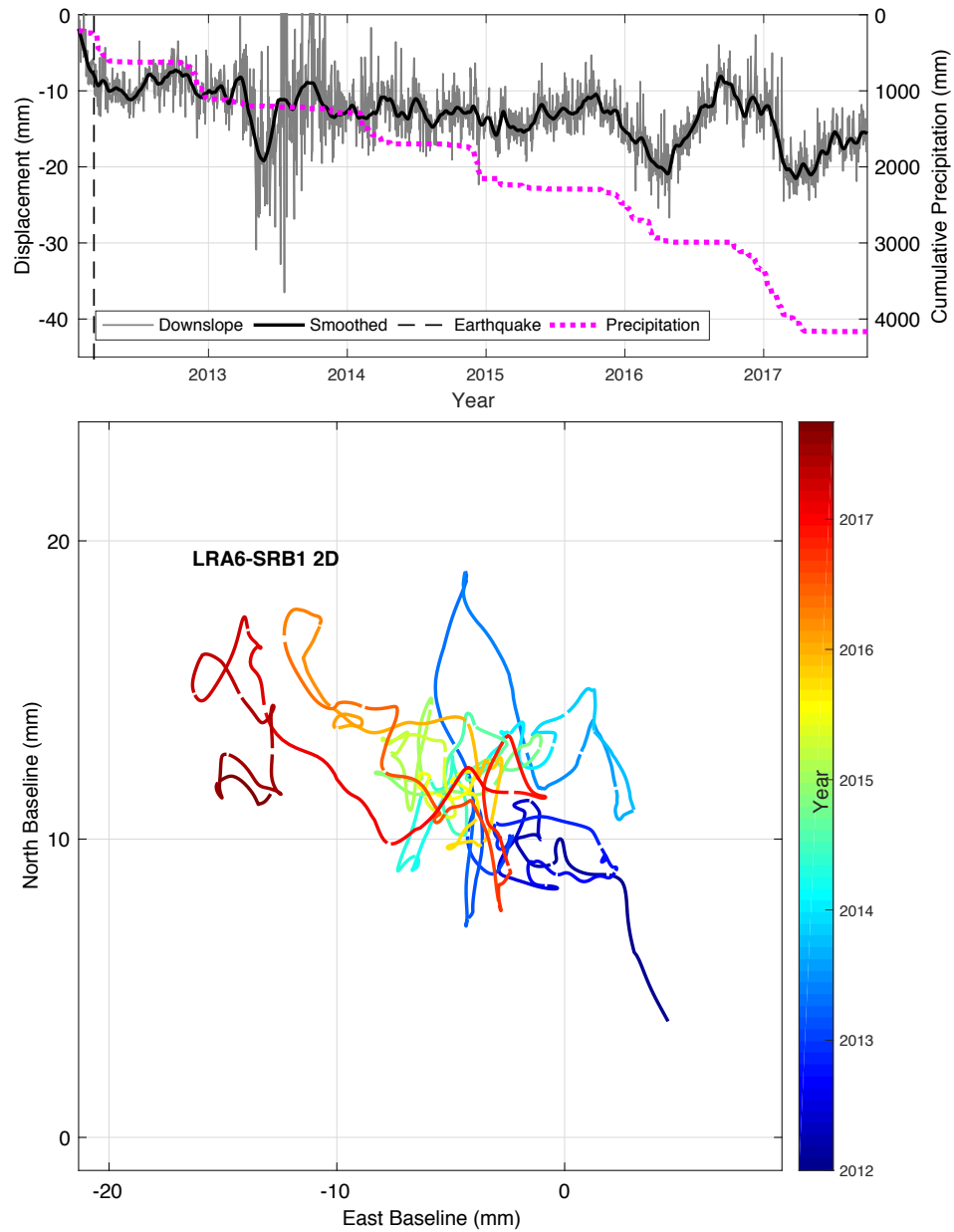
LRA4:



LRA5:

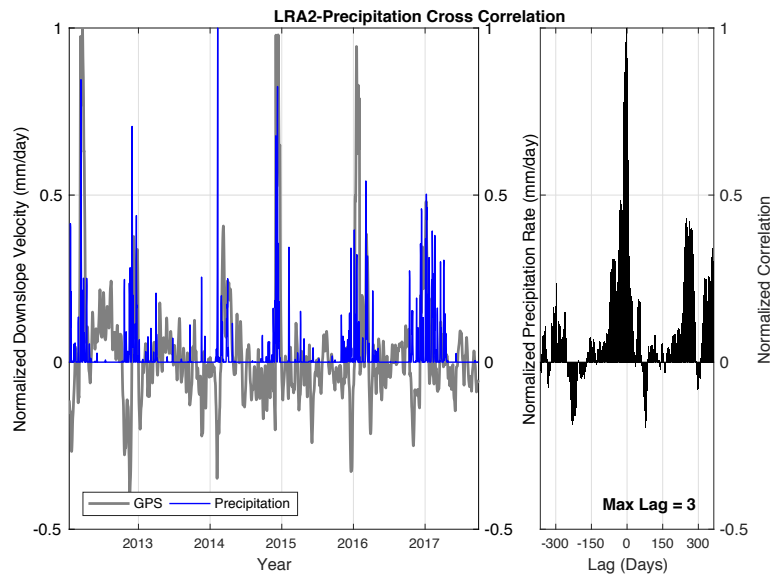


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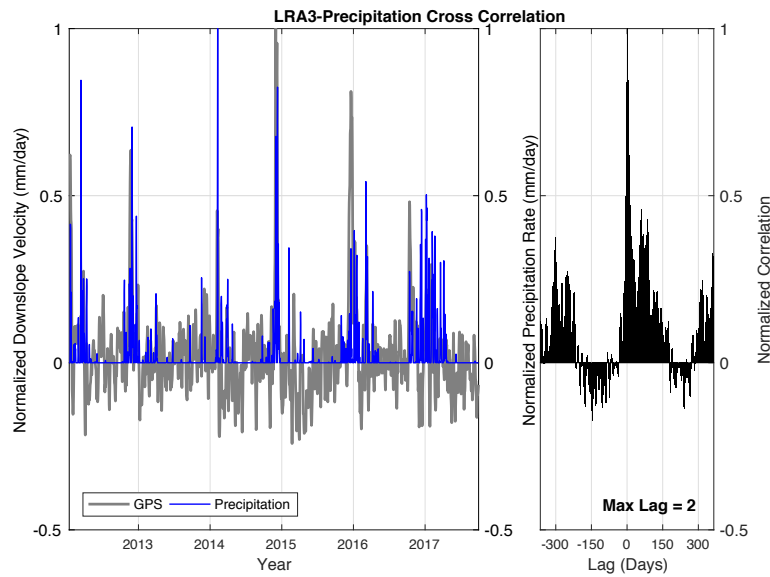


Cross Correlation Analysis Figures

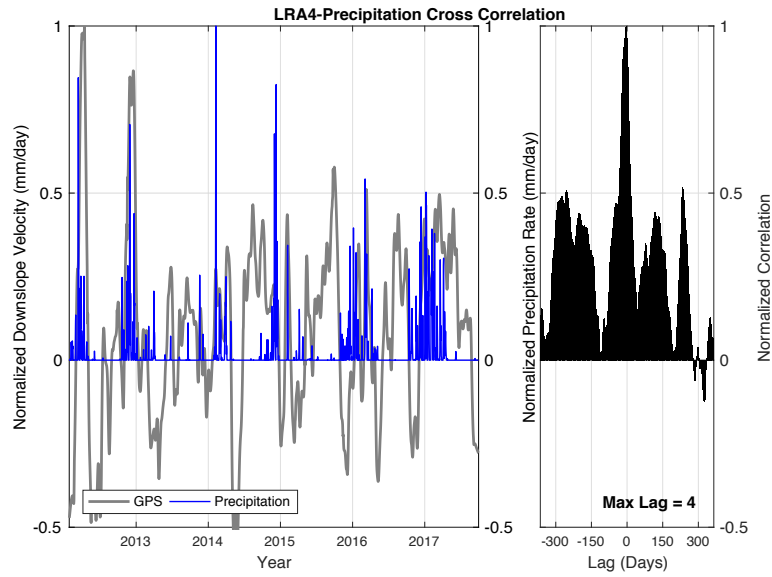
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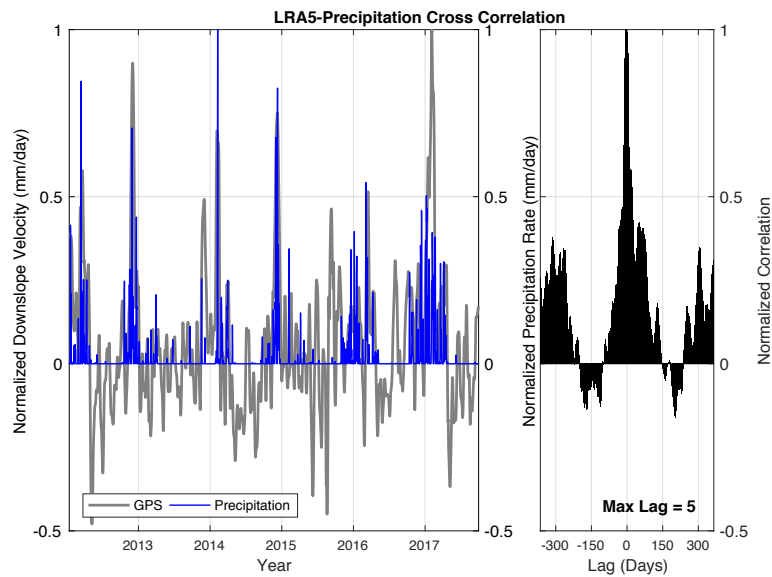
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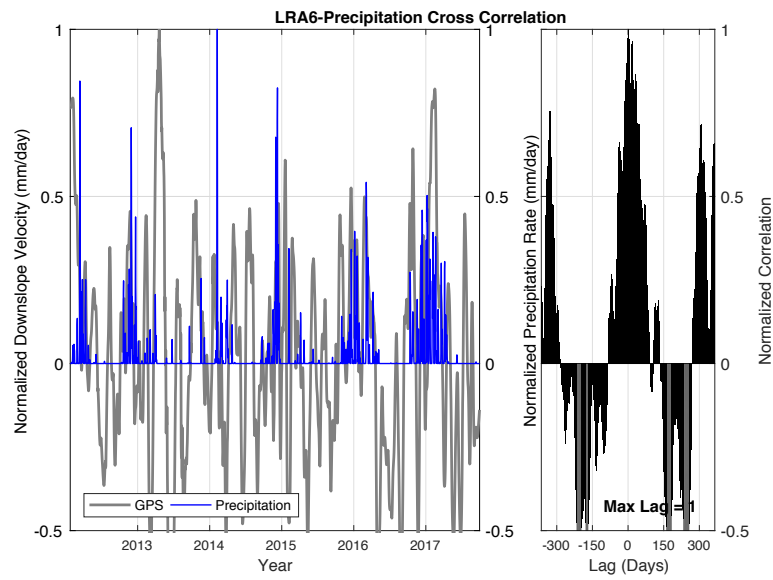
LRA4:



LRA5:

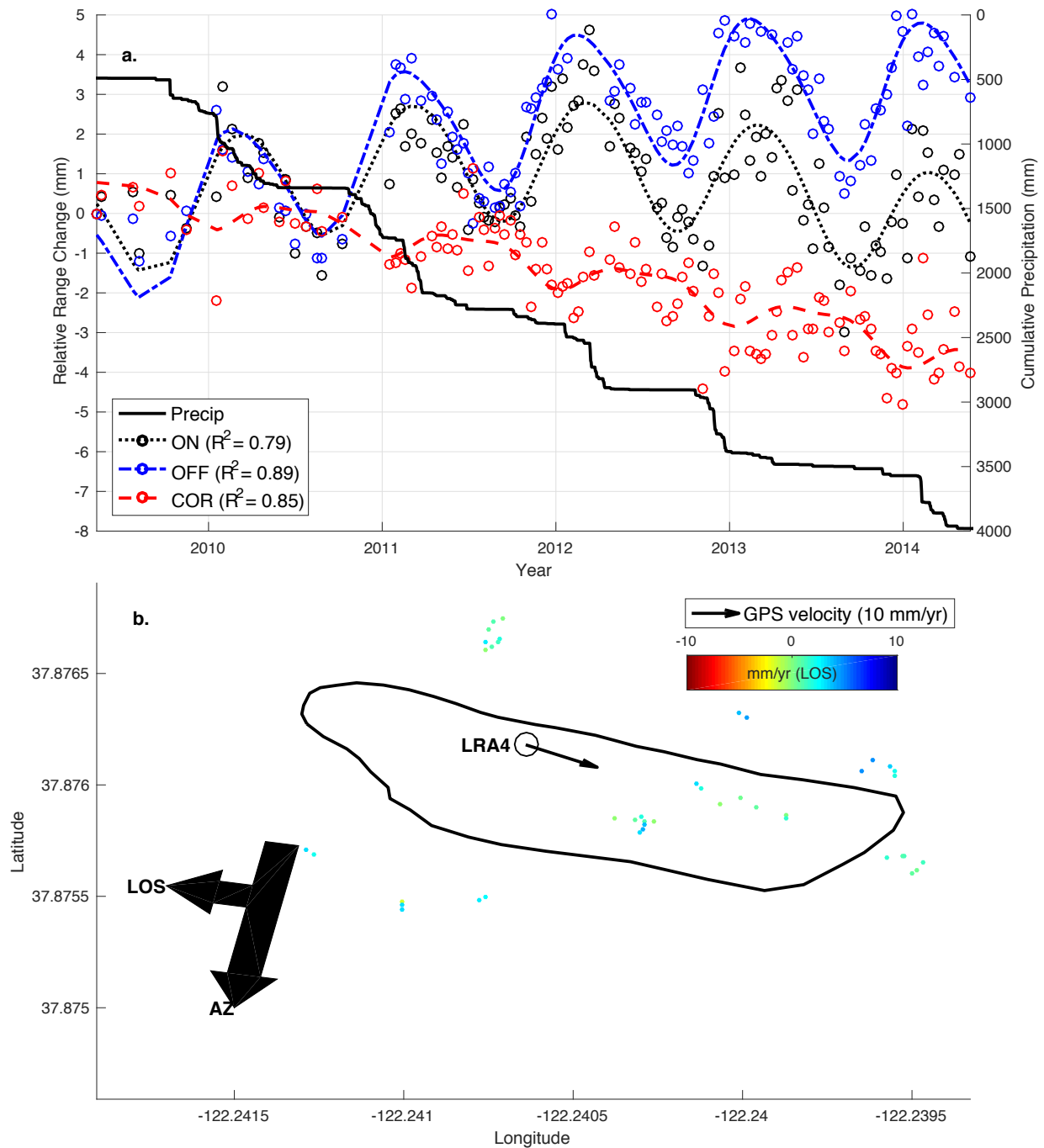


LRA6:



InSAR-cGPS Comparison Figure

Centennial Bridge Landslide-LRA4:



East Canyon Landslide-LRA5: