Geodetic Imaging of Volcanic Deformation with Time Series Radar Interferometry

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UNIVERSITY OF MIAMI

GEODE蒂C IMAGING OF VOLCANIC DEFORMATION
WITH TIME SERIES RADAR INTERFEROMETRY

By
Zhang Yunjun

A DISSERTATION

Submitted to the Faculty
of the University of Miami
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the requirements for the degree of
Doctor of Philosophy

GEODETIC IMAGING OF VOLCANIC DEFORMATION
WITH TIME SERIES RADAR INTERFEROMETRY

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Volcanic hazards threaten millions of people in their vicinity worldwide. To mitigate the volcanic risk, we need to know which volcanoes are actively deforming and how much have they deformed. Ideally, ascending magma leads to surface uplift through elastic response, which can be precisely measured using the technique of interferometric synthetic aperture radar (InSAR) and inferred through geophysical inverse model, such as the point pressure source. In practice, the (de)pressurization process could have complex geometry in space and change non-linearly in time, posing challenging for the deformation mapping and risk assessment afterwards.

Here, I first develop algorithms to correct for phase unwrapping error in InSAR stack processing and merge them with other state-of-art algorithms to form a generic routine workflow, implement as the Miami INsar Time-series software in PYthon (MintPy). Then I demonstrate the power of this software by applying to the Kyushu Island in SW Japan using all available L-band SAR data from 1992 to 2019 and detect five out of eight actively deforming volcanoes in addition to subsidence due to anthropogenic activities. Next, I combine the radar imaging with geodetic modeling to study the shallow hydrothermal and magmatic systems in Kirishima volcanic complex during the recent unrest since 2008, covering the 2008-2010, 2011, 2017 and 2018 eruption at Shinmoedake and the 2018 eruption in Iwo-yama.
Acknowledgement

Many people have helped me during my Ph.D., and I would like to thank them for their guidance and supports. First, I thank my advisor, Falk Amelung, who supported and guided me relentlessly throughout my Ph.D. with patience, encouragement and fun. I am also grateful to my committee members, Shimon Wdowinski, Guoqing Lin and Timothy Dixon, for their advices and supports. I would like to thank Yosuke Aoki for his helps to use the ALOS-1/2 and GSI DEHM and GPS products for volcanic studies in Japan, Xiaohua Xu who helped me with the L1-norm regularized least squares approximation, Mehdi Nikkhoo for his helps to better understand the geophysical modeling. I would like to own my special thanks to my friend and colleague, Heresh Fattahi, who has been always very constructive during our discussions and extremely supportive.

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<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>DS</td>
<td>Distributed scatterer.</td>
</tr>
<tr>
<td>FIM</td>
<td>Fisher information matrix.</td>
</tr>
<tr>
<td>GAM</td>
<td>Global atmospheric model.</td>
</tr>
<tr>
<td>GIAnT</td>
<td>Generic InSAR Analysis Toolbox.</td>
</tr>
<tr>
<td>G-SBAS</td>
<td>Small baseline subset in GIAnT.</td>
</tr>
<tr>
<td>G-NSBAS</td>
<td>New small baseline subset in GIAnT.</td>
</tr>
<tr>
<td>G-TimeFun</td>
<td>Multiscale InSAR Time-Series in GIAnT.</td>
</tr>
<tr>
<td>LASSO</td>
<td>Least absolute shrinkage and selection operator</td>
</tr>
<tr>
<td>LOS</td>
<td>Line of sight.</td>
</tr>
<tr>
<td>MAD</td>
<td>Median absolute deviation.</td>
</tr>
<tr>
<td>MST</td>
<td>Minimum spanning tree.</td>
</tr>
<tr>
<td>PDF</td>
<td>Probability density function.</td>
</tr>
<tr>
<td>PS</td>
<td>Persistent scatterer.</td>
</tr>
<tr>
<td>RMS</td>
<td>Root mean square.</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square error.</td>
</tr>
<tr>
<td>SBAS</td>
<td>Small baseline subset.</td>
</tr>
<tr>
<td>SLC</td>
<td>Single look complex.</td>
</tr>
<tr>
<td>SNAPHU</td>
<td>Statistical-cost, Network-flow Algorithm for Phase Unwrapping.</td>
</tr>
<tr>
<td>WLS</td>
<td>Weighted least squares.</td>
</tr>
</tbody>
</table>
## List of Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$</td>
<td>Design matrix for network inversion in size of $M \times (N - 1)$.</td>
</tr>
<tr>
<td>$C$</td>
<td>Design matrix for the closure phase of interferogram triplets.</td>
</tr>
<tr>
<td>$H$</td>
<td>All-one column matrix in size of $M \times 1$.</td>
</tr>
<tr>
<td>$L$</td>
<td>Number of looks in range and azimuth directions in total.</td>
</tr>
<tr>
<td>$M$</td>
<td>Number of interferograms.</td>
</tr>
<tr>
<td>$N$</td>
<td>Number of SAR acquisitions.</td>
</tr>
<tr>
<td>$T$</td>
<td>Number of interferogram triplets.</td>
</tr>
<tr>
<td>$U$</td>
<td>Matrix of the phase-unwrapping integer ambiguity in size of $M \times 1$.</td>
</tr>
<tr>
<td>$W$</td>
<td>Weight matrix for network inversion in size of $M \times M$.</td>
</tr>
<tr>
<td>$C_{ijk}^{\text{int}}$</td>
<td>Closure phase of the interferograms triplet formed from acquisitions at $t_i$, $t_j$, and $t_k$.</td>
</tr>
<tr>
<td>$C_{ijk}$</td>
<td>Integer ambiguity of $C_{ijk}^{\text{int}}$.</td>
</tr>
<tr>
<td>$T_{\text{int}}$</td>
<td>Number of triplets with non-zero $C_{ijk}^{\text{int}}$ among all triplets.</td>
</tr>
<tr>
<td>$\Delta\phi^j$</td>
<td>Interferometric phase of the $j_{th}$ unwrapped interferogram.</td>
</tr>
<tr>
<td>$\Delta\phi^j_\epsilon$</td>
<td>Interferometric phase residual of the $j_{th}$ unwrapped interferogram.</td>
</tr>
<tr>
<td>$\Delta\phi$</td>
<td>Vector of the interferometric phase of all interferograms.</td>
</tr>
<tr>
<td>$\Delta\phi_\epsilon$</td>
<td>Vector of the interferometric phase residual of all interferograms.</td>
</tr>
<tr>
<td>$\phi^i$</td>
<td>Raw phase between the $i_{th}$ and the $I_{st}$ acquisition.</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Vector of raw phase of all acquisitions (raw phase time-series).</td>
</tr>
</tbody>
</table>
\( \hat{\phi} \) The estimated vector of raw phase time-series.

\( \phi_{\text{dis}} \) Phase due to the displacement between the \( i_{th} \) and the \( 1_{st} \) acquisition.

\( \hat{\phi}_{\text{tropo}} \) Estimated tropospheric delay between the \( i_{th} \) and the \( 1_{st} \) acquisition.

\( \hat{\phi}_{\text{geom}} \) Estimated geometrical range difference between the \( i_{th} \) and the \( 1_{st} \) acquisition caused by the non-zero spatial baseline.

\( \phi_{\text{resid}} \) Residual phase remained between the \( i_{th} \) and the \( 1_{st} \) acquisition.

\( \phi_{\text{resid}} \) Vector of the residual phase of all acquisitions (residual phase time-series)

\( \hat{\phi}_{\text{resid}}(p) \) Estimated vector of the residual phase time-series on pixel \( p \).

\( \delta L_p \) Integrated absolute single path tropospheric delay between the \( i_{th} \) and the \( 1_{st} \) acquisition on pixel \( p \) in meters.

\( \hat{\phi}_{\text{trop}}(p) \) Estimated phase of the relative double path tropospheric delay between the \( i_{th} \) and the \( 1_{st} \) acquisition on pixel \( p \) with respect to pixel \( \text{ref} \).

\( \sigma_{\Delta \phi j}^2 \) Variance of the interferometric phase of the \( j_{th} \) interferogram.

\( \gamma^j \) Spatial coherence of \( j_{th} \) interferogram.

\( \gamma_{\text{temp}} \) Temporal coherence.

\( \lambda \) Radar wavelength in meters.

\( z_{\varepsilon} \) Topographic residual in meters.
Chapter 1. Introduction

Volcanic hazards threaten millions of people in their vicinity worldwide. Understanding the plumbing system for the magmatic and hydrothermal fluid migration underneath the volcano and how it evolves is fundamental to any attempt to assess the volcanic risks and to forecast their future behavior. Despite of the lack of direct observations of the processes controlling the fluid migration underground, many of these processes deform the ground surface with variable spatial and temporal characteristics. Precise measurements of ground surface deformation are the key observations to shed light on these hidden processes.

Japanese volcanoes, especially the ones in Kyushu Island, SW Japan, represent natural laboratories for the volcanic studies because of their frequent activities, abundant observations and potentially catastrophic risk to affect millions of people’s lives (Tatsumi & Suzuki, 2014). Here I improve the time series analysis technique of interferometric synthetic aperture radar (InSAR) and apply it at regional scale with high temporal and spatial resolutions to the volcanoes in Kyushu Island to better understand the volcanic plumbing system and their associated volcanic hazards.

In this chapter I will provide an overview of the volcanic subsidence, which is widespread in Kyushu volcanoes, the rationale and challenge of InSAR time series analysis and the background of study area. Finally, I present the aims and objectives along with a roadmap of this thesis.
1.1 Volcanic Subsidence

Among over 200 volcanoes known to be deforming, around 20 volcanoes are having long-term subsidence (Caricchi et al., 2014; Biggs et al., 2014). The long-term volcanic subsidence provides insights into the inter-eruptive processes, which is the longest process among the volcano eruptive cycle (Parker et al., 2016). There are several causes of subsidence at volcanoes: i) magma movement at depth; ii) magma cooling and crystallization; iii) hydrothermal fluid migration; iv) loading of the volcano edifice or dense intrusion and v) crustal thinning due to tectonic extension.

Five types of mechanisms are distinguishable through their different timescales and spatial geometries of deformation on the surface measured through GPS and InSAR, except for the magmatic or hydrothermal fluid migration where either gravity or petrological observation is required to quantitively assess each cause.

1.1.1 Magma Movement

Magma removal from a subsurface chamber, often due to the emptying of a magma reservoir, is usually modeled as a pressure source with volume contraction, such as the 1914 eruption of Sakurajima volcano (Mogi, 1958). Based on the migration direction, there are three types of potential causes.

The first potential cause is the deflation of a magma chamber following the eruption (upward or outward transport), such as the 1991 eruption of Hekla volcano in Iceland (Sigmundsson et al., 1992), the 1960 collapse of Kilauea volcano in Hawaii (Delaney and McTigue, 1994; Johnson et al., 2000) and the 1970 eruption of Okmok volcano in Alaska (Lu et al., 2000). The second potential cause is the lateral transport of magma in the
subsurface away from the source area, such as the 1999 dike intrusion in Kilauea volcano, Hawaii (Cervelli et al., 2002). Both the first and second causes lead to transient deformation.

The third potential cause is magma drainage from a shallow chamber to a deeper reservoir, such as the long-term deflation observed at Askja volcano in Iceland with microgravity measurements (Fig. 1.1; de Zeeuw-van Dalfsen et al., 2005). The magma drainage could be facilitated by the extensional tectonic forces.

![Figure 1.1. Magma drainage at Askja volcano, Iceland from leveling and microgravity measurements (de Zeeuw-van Dalfsen et al., 2005). Left: locations of gravity stations in Askja caldera modified after Rymer and Tryggvason (1993). Dots represent the stations (numbered 1 to 13) which are divided into three groups (dashed ellipses): the northern, southeastern and center. The levelling line is indicated by the thin solid line going through stations 4, 5 and 6. Right: microgravity data from 1988 to 2003. Symbols represent average yearly gravity changes in µGal with respect to station 83001 and referred to 1988. Solid lines show the data trend, dashed lines show expected microgravity calculated using the observed deformation and measured FAG. If the data trend is higher than the expected microgravity, as for the southeastern stations, this implies a net microgravity increase. If the data trend (solid lines) is less than expected (dashed lines), as for the center stations, there is a net microgravity decrease. Vertical bars show average error on the data.](image-url)
1.1.2 Magma Cooling and Crystallization

Volume loss due to the cooling of a magma body involves the following three processes (Caricchi et al., 2014): i) thermal contraction of a cooling mass. This is more likely in a volatile-undersaturated magma body. The associated subsidence rate varies, depending on the density ratio of the crystallization phases and the residual melt. ii) crystallization of liquid melt. This process partitions volatiles into the remaining melt until saturation, forms bubbles and removes bubbles if the system became permeable. This process results in inflating signal not related with magma injection at the first few years, then turns into deflating signal eventually when gases are expelled from the system. iii) re-melting of the host rock. All three processes are functions of temperature and depend on the initial state of the host and injected magma, which can be determined from petrological observations. The melt-crystal-volatile fraction can be calculated following the phase equilibria using the thermodynamic software MELTS (Ghiorso and Sack, 1995).

Caricchi et al., 2014

![Diagram](image-url)
Figure 1.2. Magma cooling, crystallization and re-melting at Okmok volcano, Alaska (Caricchi et al., 2014). Left panel: Topography and location of Okmok volcano on the top and the temporal evolution of volume change inverted from geodetic observations (Biggs et al., 2010). Central panel: relative volumetric fraction of crystal, melt and volatile as a function of temperature considering different water content in the system from top to bottom. Right panel: volume of crystal, melt and gas as a function of time. Both central and right panels are calculated using MELT software.

Poland et al. (2006) considered the second process using a finite element thermoelastic model for Medicine Lake Volcano and conclude that it cannot fully explain the present deformation. Caricchi et al. (2014) considered all three processes for the inter-ruptive deflating signal on Okmok during 2002-2005 and suggest the cause of deformation as the injection of a water-saturated basalt, followed by a minor crystallization and degassing (Fig. 1.2). Fournier (1989) attributed the episodic subsidence of Yellowstone caldera to crystallization of rhyolitic magma and the associated release of aqueous magmatic fluids.

1.1.3 Hydrothermal Fluid Migration

Hydrothermal processes can be responsible for both uplift and subsidence signals on volcanoes. The hydrothermal unrest and associated ground deformation are controlled by the thermal-poro-elastic response of the subsurface (Fournier and Chardot, 2012). Although simple, inverting geodetic observations using point or finite source can still yield useful information about these processes, especially the depth (Fournier and Chardot, 2012). For uplift at least, deformation is first controlled by poro-elastic response, which can be determined by well fitted pressure source; then by thermal expansion.

Subsidence occurs when there is a breach of the self-sealed zone trapping the fluids (Hamling et al., 2015). This can be: i) continuous degassing of a crystallizing magma body and the accumulation of evolved fluids become sufficiently enough to rupture by
tensile failure; ii) upward injection of a new pulse of magma from depths; iii) a sector collapse of a portion of the overlaying volcanic edifice; iv) rupture caused by earthquake swarms.

Dzurisin et al. (1999) approximated the alternating cycles of subsidence and uplift over annual to decadal timescales in Yellowstone as deflating horizontal dislocations at shallow depths. Similar interpretation is also made in the Coso hot springs in eastern California (Wicks et al., 2001) and in Campi Flegrei caldera in Italy (Lundgren et al., 2001; Todesco et al., 2014). Pritchard et al. (2013) interpreted the additional subsidence in volcanic areas after the 2010 Maule earthquake as the sudden release of hydrothermal fluids due to the increased permeability of hydrothermal system caused by coseismic extension (Hosono et al., 2019). All these literatures interpret the observed subsidence signal as hydrothermal by excluding the other possible causes, but no direct evidence or modeling calculating has been shown.

Battaglia et al. (2006) inverted the pressure source with density at Campi Flegrei caldera for the 1980-84 inflation and the 1990-95 deflation using leveling, trilateration and gravity measurements, excluded the intrusion of magma and indicated the migration of fluids to and from the hydrothermal system as the cause of ground deformation (Fig. 1.3).
1.1.4 Surface Loading

Lava flows, volcanic edifice, dome growth, the filling of a lava pond or subvolcanic intrusion will compress the elastic crust that supports the load. Surface loading is a significant deformation mechanism at large basaltic shields volcanoes (Williams and Zuber, 1995), especially the ones in oceanic islands, such as Hawaii (Walcott, 1970; Moore, 1970), Samoa (Dickinson, 2007) and extraterrestrial volcanoes and seamounts (Lambeck and Nakiboglu, 1980).

The geometry of flexural subsidence of lithosphere under a surface load requires i) differential subsidence at different radical distances from the load and ii) annular (ring-shaped) flexural uplift surrounding the cone of depression, though this uplift signal sometimes may be too small to be measurable. The Hekla volcano in Iceland is a precious example for the ring-shaped flexural uplift (Fig. 1.4; Ofeigsson et al., 2011).

**Figure 1.3.** Inverting the subsidence at Campi Flegrei, Italy using leveling, trilateration and gravity measurements (Battaglia et al., 2006).

**Figure 3.** A possible scenario for unrest at Campi Flegrei.
1.1.5 Crustal Extension

Tectonic extension and shear could enhance and facilitate any existing subsidence mechanisms, such as at Medicine Lake Volcano (Dzurisin et al., 2002). Tectonic extension has not been identified as the primary driving force in any volcano yet, because to be accounted as the primary factor, the subsidence should be ongoing for thousands of years and the relative short-term subsidence in most volcanoes would require a recent change in the regional tectonics to be explained by crustal thinning (Poland et al., 2006). Similarly, as Askja caldera in Iceland, the divergent plate boundary is playing an important role in the contracting of magma chamber together with the cooling effect (de Zeeuz-van Dalsfen et al., 2012; 2013)
1.2 InSAR Time Series Analysis

InSAR time-series has proven to be a powerful geodetic technique to extract the temporal evolution of ground surface deformation over a wide area (tens to hundreds of km). The accuracy and precision of the retrieved displacement is limited by i) the decorrelation among repeated SAR signals, ii) atmospheric delays and iii) phase unwrapping error from data processing.

To mitigate the decorrelation effect, especially for early SAR satellites with the relative long revisit time, non-regular acquisitions and large orbit separation (baseline) between repeated acquisitions, two groups of time series techniques have been developed: persistent scatterer (PS) methods, which focus on the phase-stable point scatterers with applications limited on cities and man-made infrastructures (Ferretti et al., 2001; Hooper et al., 2004), and distributed scatterer (DS) methods, which relaxed the strict limit on the phase stability and included areas that are affected by decorrelation through the exploitation of the redundant network of interferograms (Berardino et al., 2002; Schmidt and Bürgmann, 2003; López-Quiroz et al., 2009; Lauknes et al., 2011; Hetland et al., 2012; Perissin and Wang, 2012; Samiei-Esfahany et al., 2016). DS methods can be further divided into two categories: the small baseline approach, which limits the analysis to networks of interferograms with small temporal and spatial baselines, and the full network approach, which uses all possible interferograms with a full exploitation of the network redundancy (Guarnieri and Tebaldini, 2008; Ferretti et al., 2011; Fornaro et al., 2015; Ansari et al., 2017; 2018).

To separate the tropospheric delays from displacement, three groups of methods have been developed: i) the spatial-temporal filtering of the phase time-series by taking
account their different frequency characteristics in time and space domain and assuming a temporal deformation model (Ferretti et al., 2001; Berardino et al., 2002); ii) external datasets such as GPS wet delay, MERIS, MODIS or global atmospheric models (GAMs) (Onn and Zebker, 2006; Li et al., 2005, 2009; Jolivet et al., 2011; 2014; Yu et al., 2017; 2018); and iii) empirical correction of the stratified tropospheric delay based on their relationship with topography (Doin et al., 2009; Lin et al., 2010; Bekaert et al., 2015).

To evaluate the phase unwrapping and to correct unwrapping errors, several attempts have been pursued. Yang et al. (2013) used a region growing algorithm to detect and correct unwrapping errors. López-Quiroz et al. (2009) used the residual of interferometric phase from the network inversion to guide an iterative unwrapping procedure. Biggs et al. (2007) visually identify and correct the unwrapping error based on the closure phase of interferograms triplet. Hussain et al. (2016) used the closure phase to adjust the coast in the iterative 3D phase unwrapping.

Despite the major progress in the first two aspects of limitations for InSAR, only a few of the developed algorithms are freely available and open sourced to the science community (Rosen et al., 2012; Fattahi et al., 2016; Jolivet et al., 2011; 2014; Hooper et al., 2004; 2008; Bekaert et al., 2015a; 2015b; Agram et al., 2013; Yu et al., 2018; Doin et al., 2011). An updated version of time series analysis with state-of-the-art algorithms is desired.

1.3 Kyushu Island

Japan is part of the “Ring of Fire”, the belt of earthquakes and volcanic activities that lies around the active margins of the Pacific Ocean. Tectonics of the Japanese islands is
controlled by the interaction of four plates: Pacific, Philippine Sea, Eurasian and North American. Kyushu is the third largest island in Japan, located in the southwest with an area of ~36,000 km².

1.3.1 Tectonic Setting

The tectonics of Kyushu is dominated by the subduction of Philippine Sea Plate (PSP) underneath the Amurian Plate at Nankai trough and Ryukyu trench with a slight oblique (right-lateral sense) angle (Fig. 1.5). The subducting PSP can be spatially split by Kyushu-Palau Ridge into two parts with significantly different ages: the young (27–15 Ma; Okino et al., 1999) Shikoku Basin lithosphere subducting at the Nankai trough and the older Cretaceous oceanic lithosphere (Deschamps and Lallemand, 2002) subducting beneath southeast Kyushu and the Okinawa arc. On the central Kyushu, rifting within the Beppu-Shimabara graben occurs adjacent to the northern boundary of the Okinawa trough (Kamata and Kodama, 1994). On the southern Kyushu, active extension occurs in the Kagoshima graben (Kodama et al., 1995) at a rate of 7-9 mm/yr (Wallace et al., 2009).
1.3.2 Active Volcanism

Volcanism in Kyushu is driven by the tectonic subduction with a clear volcanic front and sporadic back-arc volcanism, except for Unzen volcano, which appears to be influenced by both arc and back-arc processes (Chapman et al, 2009). The location of volcanism in Kyushu appears to be strongly correlated with the local and regional tectonics (Kamata and Kodama, 1999; Nakajima and Hasegawa, 2007): all active volcanoes in Kyushu are located within two grabens: Beppu-Shimabara graben in the center and Kagoshima graben in the south. Note that the Japanese Meteorological Agency (JMA) defines active volcanoes in Japan as “Volcanoes which has erupted within the last 10,000 years or volcanoes with vigorous fumarolic activity”.

Figure 1.5. Tectonic and volcanic setting of Kyushu Island. Inset shows the location of SW Japan. Regional tectonics is dominated by the Median Tectonic Line in Honshu and Shikoku and Oita-Kumamoto Tectonic Line in central Kyushu.
The central volcanic region is physically dominated by Aso caldera. Four caldera forming eruptions of Aso volcano occurred at 0.3 Ma, 0.14 Ma, 012 Ma and 0.09 Ma. Currently Aso is in the post-caldera phase with two active centers: Kometsuka basaltic scoria cone and Kishima-dake. However, several stratocones and cinder cones in the middle of the caldera have erupted as recently as 2005 (Chapman et al., 2009).

In the northeast, Kuju volcano, formed at 0.15 Ma, covers an area of 20 km EW and 15 km NE. Eruptive activities at Kuju has migrated eastward during the last 5000 years with active center located in Kuro-dake lava dome (Siebert et al., 2011). In the west, Unzen volcano lies on the Shimabara peninsula, shows repeated lava dome formation, which led to several devastating pyroclastic flows. The 1792 collapse of the lava dome triggered a mega tsunami, which killed over 14,000 people in Japan, making it the worst volcanic-related disaster. The most recent 1991 eruption generated a pyroclastic flow that killed 43 people including 3 volcanologists.

The southern volcanic region includes two major volcanic centers, together with several volcanoes. The northmost one is Kirishima volcano on the southern rim of Kakuto caldera. Kirishima volcano comprises more than 25 stratovolcanoes and pyroclastic cones (Nakada et al., 2013). These volcanic centers form an elliptical zone with an area of 30 km by 20 km trending NW to SE, with younger volcanisms towards the southeast. Iwo-yama, Shinmoe-dake and Ohachi are the most active volcanic centers. Moving southward comes to the massive Aira caldera, which is the home of Sakurajima volcano. The caldera forming eruption of Aira occurred at 0.025 Ma. Sakurajima is the post caldera volcano, which formed at 0.022 Ma. Sakurajima contains two stratovolcanoes, Kita-dake, Naka-dake and Minami-dake. The noticeable recent eruption
is the 1914 eruption. Further to the south lies the Kagoshima graben, Ata caldera formed at 0.11 Ma. Ata caldera is a 25 km by 12 km submarine caldera. The southmost volcanism includes Ikeda-ko and Kaimon-dake volcano, in the west of Ata caldera. Kaimon-dake is a perfectly formed cone with eruptions as recently as 885 (Chapman, 2009).

Offshore to the south, Kikai caldera is located ~40 km away in the Ryukyu arc. The VEI=7 Kikai caldera forming eruption occurred at 6.3 ka, is the largest eruption in the Holocene in Japan (Newhall and Self, 1982).

1.4 Objectives and Roadmap

Until now, deformation observations on Kyushu volcanoes have been primarily from continuous GNSS networks, tiltmeters and differential InSAR observations. The lack of continuous InSAR displacement time-series led to missing of deformation signals especially in areas without ground instruments and to poorly constrained solution for the temporal evolution of volcanic systems. To achieve a better assessment of the volcanic risks in Kyushu using InSAR observations, I have defined the following objectives:

- Develop phase unwrapping error correction methods for InSAR.
- Develop a near-automatic approach for InSAR time series analysis
- Generate displacement time-series maps of Kyushu volcanoes from InSAR

In chapter 2, I evaluate the characteristics of phase unwrapping error in interferograms stack in space and time domain and develop two methods to correct unwrapping errors accordingly. I also review the mathematical formulation of weighted network inversion and for the post-inversion phase corrections for time series analysis of
small baseline InSAR stacks. Together with the manuscript, I release the Miami INsar Time series software in PYthon (MintPy), which is available on GitHub: https://github.com/insarlab/MintPy.git. This chapter completes the 1st and 2nd objectives.

In chapter 3, I conduct the time series InSAR survey to the Kyushu Island using all available L-band SAR data from 1992-2019.

In chapter 4, I combine the InSAR time-series with geodetic modeling and petrological, geoelectric and seismic observations to study the shallow hydrothermal and magmatic processes in Kirishima volcanic complex covering the 2008-2010, 2011, 2017 and 2018 eruptions at Shinmoe-dake and 2018 eruption at Iwo-yama. Chapter 3 and 4 completes the 3rd objective.

In chapter 5, I present the conclusion of this dissertation and the direction of future research.
Chapter 2. Small Baseline InSAR Time Series Analysis: Unwrapping Error Correction and Noise Reduction

2.1 Summary

We present a review of small baseline interferometric synthetic aperture radar (InSAR) time series analysis with a new processing workflow and software implemented in Python, named MintPy (https://github.com/insarlab/MintPy). The time series analysis is formulated as a weighted least squares inversion. The inversion is unbiased for a fully connected network of interferograms without multiple subsets, such as provided by modern SAR satellites with small orbital tube and short revisit time. In the routine workflow, we first invert the interferogram stack for the raw phase time-series, then correct for the deterministic phase components: the tropospheric delay (using global atmospheric models or the delay-elevation ratio), the topographic residual and/or phase ramp, to obtain the noise-reduced displacement time-series. Next, we estimate the average velocity excluding noisy SAR acquisitions, which are identified using an outlier detection method based on the root mean square of the residual phase. The routine workflow includes three new methods to correct or exclude phase-unwrapping errors for two-dimensional algorithms: (i) the bridging method connecting reliable regions with minimum spanning tree bridges (particularly suitable for islands), (ii) the phase closure method exploiting the conservativeness of the integer ambiguity of interferogram triplets (well suited for highly redundant networks), and (iii) coherence-based network modification to identify and exclude interferograms with remaining coherent phase-unwrapping errors.
We apply the routine workflow to the Galápagos volcanoes using Sentinel-1 and ALOS-1 data, assess the qualities of the essential steps in the workflow and compare the results with independent GPS measurements. We discuss the advantages and limitations of temporal coherence as a reliability measure, evaluate the impact of network redundancy on the precision and reliability of the InSAR measurements and its practical implication for interferometric pairs selection. A comparison with another open-source time series analysis software demonstrates the superior performance of the approach implemented in MintPy in challenging scenarios.

2.2 Overview

Time series Interferometric Synthetic Aperture Radar (InSAR) is a powerful geodetic technique to extract the temporal evolution of surface deformation from a set of repeated SAR images. Accuracy and precision of the retrieved surface displacement history are limited by the decorrelation of the SAR signal, the atmospheric delay and the phase-unwrapping error. Decorrelation is mainly caused by changes of the surface backscatter characteristics over time and by the non-ideal acquisition strategy of SAR satellites (Hanssen, 2001; Zebker and Villasenor, 1992). To overcome the limitations associated with early SAR satellites, including the relative long revisit time with non-regular acquisitions and the large orbit separation (baseline) between repeat acquisitions, two groups of InSAR time series techniques have been developed: persistent scatterer (PS) methods, which focus on the phase-stable point scatterers with applications limited to cities and man-made infrastructures (Ferretti et al., 2001; Hooper et al., 2004), and distributed scatterer (DS) methods, which relaxed the strict limit on the phase stability
and included areas that are affected by decorrelation through the exploitation of the redundant network of interferograms. The DS methods are the focus of this paper.

Depending on the network of interferograms, DS methods can be divided into two categories. The first category uses the network of interferograms with small temporal and spatial baselines, known as small baseline subsets (SBAS) (Berardino et al., 2002; Schmidt and Bürgmann, 2003). These methods solve a system of linear observation equations using least squares estimation or $L^1$-norm minimization (Lauknes et al., 2011). In cases of a non-fully connected network, singular value decomposition or a regularization constraint (López-Quiroz et al., 2009) is applied to find physically sound solutions. These methods require phase-unwrapped interferograms. In cases of low interferometric coherence, an integer least squares estimator can be applied to the wrapped interferograms, but this estimator is computationally expensive (Samiei-Esfahany et al., 2016).

The second category uses the network consisting of all possible interferograms with full exploitation of the network redundancy (Ferretti et al., 2011; Fornaro et al., 2015; Guarnieri and Tebaldini, 2008). The solution is provided by the maximum likelihood estimator with performance close to the Cramér-Rao bound, the highest achievable precision (Guarnieri and Tebaldini, 2007), or by eigenvalue decomposition of the covariance matrix, which has been shown to be suboptimal for phase estimation (Ansari et al., 2018; Samiei-Esfahany et al., 2016). These methods swap the processing order and apply the network inversion as pre-processing steps for the estimation of optimal phases before phase unwrapping.
Despite the evident strengths of the full network approaches, especially the capability of phase estimation on low coherent areas, they remain computationally inefficient relative to the small baseline network approaches. Herein, we emphasize on the algorithmic efficiency; accordingly, we implemented a weighted least squares (WLS) estimator based on SBAS method with linear optimization. This process is known as phase linking or phase triangulation (Ansari et al., 2018; Ferretti et al., 2011) and referred hereafter as network inversion. The precision of network inversion depends on the temporal behavior of decorrelation: the small baseline network approaches provide higher precision when it is fast decorrelation, while the full network approaches provide higher precision when there is weak but long-term coherence (Ansari et al., 2017; Samiei-Esfahany et al., 2016).

To separate the tropospheric delay from displacement, both PS and DS methods traditionally rely on the spatio-temporal filtering of the phase time-series by taking into account their different frequency characteristics in time and space domain and assuming a temporal deformation model (Berardino et al., 2002; Ferretti et al., 2001), which can be unrealistic in complex natural environments such as volcanic deformation. Recent developments use global atmospheric models (GAMs), MERIS, MODIS or GPS wet delay (Jolivet et al., 2011; 2014; Li et al., 2009; Onn and Zebker, 2006; Yu et al., 2018), or empirical correlation between stratified tropospheric delay and topography (Bekaert et al., 2015; Doin et al., 2009; Lin et al., 2010) to correct interferograms before network inversion. Since the contribution of tropospheric delay is a deterministic component in InSAR phase observation, it is in principle preserved in the estimated phase time-series and therefore can be mitigated in the time-series domain after network inversion. Similar
swaps of the processing sequence have been applied to phase unwrapping (Guarnieri and Tebaldini, 2008) and topographic residual correction (Fattahi and Amelung, 2013).

A disconnected network of interferograms with multiple interferogram subsets biases the time-series estimation, especially when there is no overlap in temporal or spatial baseline among interferogram subsets (Lanari et al., 2004; López-Quiroz et al., 2009). For modern SAR satellites with improved orbital control and short revisit time such as Sentinel-1, the interferograms network can be easily fully connected, simplifying the network inversion into an unbiased WLS estimation of an overdetermined system. This robust inversion allows separating phase corrections from network inversion (Pepe et al., 2011).

Here we present a new processing chain for InSAR time series analysis with phase corrections in the time-series domain, in contrast to the traditional interferogram domain. We refer the time-series domain as a series of phases indexed in time order with respect to a common reference acquisition, in contrast to the interferogram domain where the phases are indexed in acquisition pairs order. The basic idea is to split the time series analysis into two steps (Pepe et al., 2011): i) invert network of interferograms for raw phase time-series and ii) separate tropospheric delay, topographic residual, timing error and orbital error from raw phase time-series to derive the displacement time-series. We also present two new methods to correct phase-unwrapping errors in interferograms unwrapped by two-dimensional phase unwrapping algorithms.

This paper is organized as follows. We first elaborate the theoretical basis of the weighted least squares estimator and evaluate the weight functions using simulated data (section 2.3). The phase-unwrapping error correction methods are presented in section 2.4.
We then describe the processing chain (section 2.5) and apply it to data on the Galápagos volcanoes (section 2.6), followed by a discussion of results (section 2.7) and conclusions (section 2.8).

2.3 Review of Weighted Least Squares Estimator

2.3.1 Theoretical Basis

We consider $N$ SAR images of the same area acquired with similar imaging geometry at times $(t_1,\ldots,t_N)$, which are used to generate $M$ interferograms coregistered to a common SAR acquisition, corrected for earth curvature and topography and spatially phase-unwrapped, referred to in the following as a stack of unwrapped interferograms. Building on Berardino et al. (2002), we model the network inversion problem as a system of $M$ linear observation equations with the raw phase time-series $\phi = [\phi^2,\ldots,\phi^N]^T$ as the vector of the $N-1$ unknown parameters with reference acquisition at $t_1$. $\phi$ corresponds to the observed physical path difference or range change from the SAR antenna to a ground target between each acquisition and the reference one, inclusive of all systematic components including ground deformation, atmospheric propagation delay and geometrical interferometric phase residuals such as those caused by inaccuracy in Digital Elevation Models (DEM). For each pixel, the functional model is described as:

$$\Delta \phi = A\phi + \Delta \phi_\epsilon$$  \hspace{1cm} (2.1)

where $\Delta \phi = [\Delta \phi^1,\ldots,\Delta \phi^N]^T$ is the interferometric phase vector with $\Delta \phi^j$ as the phase of the $j_{th}$ interferogram, $A$ is an $M \times (N-1)$ design matrix indicating the
acquisition pairs used for interferograms generation. It consists of -1, 0 and 1 for each row with -1 for reference acquisition, 1 for secondary acquisition and 0 for the rest. An example to generate \( A \) is provided in the Supplementary Information section A2.1. \( \Delta \phi_e = [\Delta \phi_e^1, \ldots, \Delta \phi_e^M]^T \) is the vector of interferometric phase residual that does not fulfill the zero phase closure of interferogram triplets. It includes the decorrelation noise, phase contribution due to the change of dielectric properties of ground scatterers such as soil moisture (De Zan et al., 2014; Morrison et al., 2011), processing inconsistency such as filtering, multilooking, coregistration and interpolation errors (Agram and Simons, 2015; Hanssen, 2001), and/or phase-unwrapping errors.

A fully connected network of interferograms corresponds to a full rank design matrix \( A \). Then the estimation of \( \phi \) can be treated as an unbiased weighted least squares inversion of an overdetermined system. The solution of equation (2.1) can be obtained by minimizing the \( L^2 \)-norm of the residual phase vector \( \Delta \phi_e \) as:

\[
\hat{\phi} = \arg\min ||W^{1/2}(\Delta \phi - A\phi)||_2 = (A^TWA)^{-1}A^TWA\Delta \phi
\]  

(2.2)

where \( \hat{\phi} \) is the estimated raw phase time-series and \( W \) is an \( M \times M \) diagonal weight matrix, discussed in detail below. The misfit between the estimated and true raw phase time-series is given as: \( \hat{\phi}_e = \phi - \hat{\phi} \). It’s propagated from \( \Delta \phi_e \) through the network of interferograms.

An alternative objective function to solve equation (2.1) is minimizing the \( L^2 \)-norm of the residual of phase velocity of adjacent acquisitions (equation (16) in Berardino et al. (2002)). Optimizations with both objective functions give nearly identical solutions for a
fully connected network. For a non-fully connected network, only the minimum-norm phase velocity gives a physically sound solution (this is used by default in the software, although both objective functions are supported).

For each pixel the quality of the inverted raw phase time-series can be assessed using the temporal coherence $\gamma_{\text{temp}}$ (Pepe and Lanari, 2006):

$$\gamma_{\text{temp}} = \frac{1}{M} |H^T \exp[j(\Delta\phi - A\hat{\phi})]|$$

(2.3)

where $j$ is the imaginary unit, $H$ is an $M \times 1$ all-ones column vector. A threshold for temporal coherence (0.7 by default) is used to select pixels with reliable network inversion. These pixels are referred to in the following as the reliable pixels. Some limitations of this reliability measure are discussed in section 2.7.4. For simplicity, in what follows we add $\hat{\phi}^1 = 0$ and refer to the vector $\hat{\phi} = [\hat{\phi}^1, \ldots, \hat{\phi}^N]^T$ hereafter as the inverted raw phase time-series.

Since contributions of tropospheric delays, topographic residuals and/or phase ramps are deterministic components in InSAR phase observations, they are preserved and therefore can be mitigated in the time-series domain to obtain the displacement time-series:

$$\phi^{i}_{\text{dis}} = \hat{\phi}^{i} - \hat{\phi}^{i}_{\text{tropo}} - \hat{\phi}^{i}_{\text{geom}} - \phi^{i}_{\text{resid}}$$

(2.4)

where $i \in [1, \ldots N]$, $\hat{\phi}^{i}_{\text{tropo}}$ represents the estimated phase contribution due to the difference in propagation delay through the troposphere between $t_i$ and $t_1$; $\hat{\phi}^{i}_{\text{geom}}$
represents the estimated geometrical range difference from radar to target caused by the non-zero spatial baseline between two orbits at $t_i$ and $t_1$, including the topographic phase residual due to DEM error, phase ramp due to orbital error, and possible phase ramp in range direction due to timing error of SAR satellite; $\phi_{\text{resid}}^i$ represents the residual phase, including the residual tropospheric delay, uncorrected ionospheric delay, unmodeled non-tectonic ocean tidal loads (DiCaprio and Simons, 2008), the remaining decorrelation noise and/or phase-unwrapping errors inherited from $\Delta \phi_e$.

The phase introduced by orbital errors can be modeled as a linear or quadratic ramp. It can be estimated and removed using GPS (Tong et al., 2013), making InSAR measurement dependent on GPS. Considering its stochastic behavior and insignificant contribution to the uncertainty of velocity estimation compared with the atmospheric delay for most SAR satellites with precise orbits (Fattahi and Amelung, 2014), we do not correct orbital errors.

### 2.3.2 Implicit Assumptions

The presented approach has two implicit simplifications. First, we assume that the residual term $\Delta \phi_e$ in the phase triangulation functional model in equation (2.1) is zero or strictly controlled to be negligible during the least squares estimation. The assumption might not be true due to the non-conservativeness of phases in triplets of multilooked interferograms caused by the changes in the scattering mechanisms. This non-conservativeness has been attributed to soil moisture variations between SAR acquisitions (De Zan et al., 2014), which is especially significant for L-band (De Zan and Gomba, 2018) and discussed in section 2.4.2 and 2.6.3.2.
Second, we ignored the spatial correlation of decorrelation noise between pixels. This assumption is only satisfied when the SAR system resolution equals the pixel spacing. It is not the case in urban areas with strong reflecting structures, or in filtered interferograms with reduced resolution due to the cropped bandwidth (Agram and Simons, 2015).

2.3.3 Choice of Weight Function

Four different interferogram weighting strategies are implemented in the software. The first strategy is uniform or no weighting, as used in the classic SBAS approach (Berardino et al., 2002). In this case, the weight matrix $W$ is equal to the identity matrix and the WLS inversion simplifies into an ordinary least squares inversion. The other strategies are three different forms of coherence weighting, giving observations with high coherence (low variance) more weight than observations with low coherence (high variance).

In the second strategy, interferograms are directly weighted by their spatial coherence at each pixel (Perissin and Wang, 2012; Pepe et al., 2015). The weight matrix takes the form:

\[
Y = \begin{bmatrix} C \end{bmatrix} Q \begin{bmatrix} S \\
\end{bmatrix}
\]

(2.5)

where $C$ is the spatial coherence of the $j$th interferogram.

In a third strategy, interferograms are weighted by the inverse of the phase variance (Tough et al., 1995). The matrix takes the form:

\[
W = diag\{\gamma^1, \ldots, \gamma^M\}
\]
\[ W = \text{diag}\{1/\sigma^2_{\Delta\phi_1}, \ldots, 1/\sigma^2_{\Delta\phi_M}\} \] (2.6)

where \( \sigma^2_{\Delta\phi_j} \) is the phase variance of the \( j \)-th interferogram calculated through the integration of the phase probability distribution function (PDF). For distributed scatterers, the phase PDF is given by equation (A.15) in the Supplementary Information section A3.2 (Tough et al., 1995) and used in the software. For persistent scatterers, the Cramér-Rao bound of variance is given directly by equation (25) from Rodriguez and Martin (1992). The difference of phase PDFs between distributed scatterers and persistent scatterers tends to vanish when a large number of looks is applied (see supp. Fig. A.1a). In practice, a lookup table is generated to facilitate the conversion from spatial coherence to phase variance (see supp. Fig. A.1b).

The fourth strategy for interferogram weighting is the nonparametric Fisher information matrix (FIM), which accounts for the information loss due to noise and decorrelation, defined as (Samiei-Esfahany et al., 2016; Seymour and Cumming, 1994):

\[ W = \text{diag}\left\{ \frac{2L_y^2}{1-\gamma^2}, \ldots, \frac{2L_y^B}{1-\gamma^2} \right\} \] (2.7)

where \( L \) is the number of independent looks used for the estimation of spatial coherence \( \gamma \). Note that FIM is identical to the inverse-variance matrix for persistent scatterers.
2.3.4 Performance Assessment of Weight Functions Using Data Simulations

We evaluate the performance of the different weight functions using simulated data to address the question of the optimum choice of weighting for phase estimation (Cao et al., 2015). Note that the maximum achievable precision is bounded by phase decorrelation, indicating the inverse of phase variance is the optimum choice theoretically (Guarnieri and Tebaldini, 2007).

2.3.4.1 Simulation Setting

We generate the stack of interferograms for a sequential interferogram network with 10 connections for each image. We use the temporal and perpendicular spatial baselines from the Sentinel-1 dataset of section 2.6. First, we specify an arbitrary temporal deformation model and generate the corresponding interferometric phases (Fig. 2.1a). Then we simulate the spatial coherence of each interferogram using a decorrelation model with exponential decay for temporal decorrelation (Fig. 2.1b) (Hanssen, 2001; Parizzi et al., 2009; Rocca, 2007; Zebker and Villasenor, 1992). Next, we simulate the corresponding decorrelation phase noise for a given number of looks \( L \) by generating a random number with the PDF of the interferometric phase of a distributed scatterer with the given spatial coherence and number of looks and add it to the noise-free phases (Fig. 2.1c, for \( 3 \times 1 \) looks). The construction of the spatial coherence from the decorrelation model and the simulation of the decorrelation noise are described in detail in the Supplementary Information section A3. Finally, we estimate the variance of the simulated interferometric phase \( \sigma^2_{\Delta\phi} \) using windows of \( 5 \times 5 \) pixels and transform it to
equivalent spatial coherence using \( \gamma^l = 1/\sqrt{1 + 2 \cdot L \cdot \sigma^2_{\Delta \phi^l}} \) (Fig. 2.1d) (Agram and Simons, 2015). This coherence is used to calculate the weight for the inversion.

### 2.3.4.2 Performance Assessment

To quantify the performance of the time-series estimator for the four different weight functions, we evaluate the difference between the inverted phase \( \hat{\phi}^l \) and the specified, true phase \( \phi^l \) using a root mean square error (RMSE) given as \( \text{RMSE}_{\text{sim}} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{\phi}^l - \phi^l)^2 / (N - 1)} \), where \( N \) is the number of acquisitions (\( N = 98 \)).

Fig. 2.1e shows the mean RMSE for 10,000 realizations for the four different weighting approaches as a function of the number of looks. To highlight differences, we also show the difference in mean RMSE with respect to inverse-variance weighting (Fig. 2.1f). The three weighted approaches outperform uniform weighting with coherence weighting performing poorer than inverse-variance weighting (as shown by a positive difference in RMSE). Compared to inverse-variance weighting, FIM weighting gives similar performance for more than 15 looks and mixed performance for fewer looks. Similar mixed and unstable performance of FIM weighting for small numbers of looks has also been observed at other simulated scenarios with both higher and lower coherences (see supp. Fig. A.2). This is different from a previous study which supports the superiority of FIM over inverse-variance but considered only 25 looks (Fig. 8 of Samiei-Esfahany et al., 2016). Thus, we use the inverse of phase variance as the default weight function in the software, although all four weighting strategies are supported.
Figure 2.1. Simulations for weight functions performance assessment. Upper panel: a simulated network of interferograms. (a-b) simulated (true) unwrapped phase and spatial coherence; (c) noise-containing unwrapped phase with $L = 3 \times 1$, (d) estimated coherence from the variance of (c). Phase data are wrapped into $[-\pi, \pi]$ for display. (e) Mean RMSE of 10,000 realizations of inverted phase time-series as a function of $L$ as the performance indicator for the four weight functions. (f) Same as (e) but the difference in mean RMSE with respect to inverse-variance weighting.

2.4 Unwrapping Error Correction

The inverted raw phase time-series can be potentially biased by wrong integer numbers of cycles ($2\pi$ rad) added to the interferometric phase during the two-dimensional phase unwrapping, to which we refer simply as unwrapping errors. Here we describe two methods to automatically correct unwrapping errors using constraints from the space and time domain, respectively.

2.4.1 Bridging of Reliable Regions

In the space domain, unwrapping errors introduce phase offsets among groups of pixels that are believed to be free of relative local unwrapping errors. Such a group of
pixels are referred to as a reliable region (see Chen and Zebker (2002) for a quantitative definition). These regions usually have moderate to high spatial coherence and are separated from each other due to decorrelation or high deformation phase gradients.

We assume that the phase differences between neighboring reliable regions are less than a one-half cycle (π rad) in magnitude. Then the task of unwrapping error correction is to determine the integer-cycle phase offsets to be added to each reliable region in order to align phase values among the regions. We present a bridging scheme to automatically connect reliable regions using tree searching algorithms. This is similar to region assembly in the secondary network in phase unwrapping (Carballo and Fieguth, 2002; Chen and Zebker, 2002), but in the tertiary level. To fulfill the assumption of smooth phase gradients between neighboring reliable regions, one could remove contributions from the troposphere, DEM error, deformation model, ramps before phase unwrapping and add them back in after correction. This method is particularly well suited for correcting unwrapping errors between regions separated by narrow decorrelated features such as rivers, narrow water bodies or steep topography.

2.4.1.1 Algorithm

The bridging scheme can be described as a three-step procedure for each interferogram. The first step is to identify reliable regions using the connected component information from the phase unwrapping algorithm such as SNAPHU (Chen and Zebker, 2001). Regions smaller than a preselected size are discarded. For each region, pixels on the boundaries are discarded using the erosion in morphological image processing with a preselected shape and size. The second step is to construct directed bridges to connect all
reliable regions using the minimum spanning tree (MST) algorithm minimizing the total bridge length. We use the breadth-first algorithm to determine the order and direction (Cormen et al., 2009), starting from the largest reliable region. The third step is to estimate for each bridge the integer-cycle phase offset between the two regions. For that, we first estimate the phase difference as the difference in median values of pixels within windows of preselected size centered on the two bridge endpoints. The integer-cycle phase offset is the integer numbers of cycles to bring down the phase difference into \([-\pi, \pi)\). The algorithm has the option to estimate a linear or quadratic phase ramp based on the largest reliable region, which is removed from the entire interferogram before the offset estimation and added back after the correction (switched off by default).

2.4.1.2 Simulated Data

We demonstrate the bridging method using a simulated interferogram of western Kyushu, Japan (Fig. 2.2), a region with multiple islands, considering decorrelation noise, ground displacement, tropospheric turbulence and phase ramps. We specify spatial coherence of 0.6 and 0.001 for pixels on land and water respectively and simulate the corresponding decorrelation noise (see section 2.3.4.1). The simulation for the other phase contributions is shown in supp. Fig. A.3. We wrap the simulated phase (Fig. 2.2a), unwrap using the SNAPHU algorithm, and apply the bridging method. Fig. 2.2b-c show the phase residual \(\Delta \phi^i_e\) after phase unwrapping (unwrapping error) without and with unwrapping error correction, respectively. The reduction in unwrapping errors (from \(-2\pi\) rad in orange shadings for the islands on the west in Fig. 2.2b to 0 rad in green shadings in Fig. 2.2c) demonstrates that the method works.
Figure 2.2. Simulation of unwrapping error correction using the bridging method. (a) Simulated wrapped phase, (b and c) phase residual (unwrapping error) without and with unwrapping error correction, respectively. (d) Reliable regions and bridges (white solid lines) generated based on connected components from SNAPHU. White shadings in (b and c): areas not considered by the connected components. Black squares represent the reference point.

2.4.2 Phase Closure of Interferograms Triplets

In the time domain, unwrapping errors could break the consistency of triplets of interferometric phases (Biggs et al., 2007). The closure phase is the cyclic product of the unwrapped interferometric phases:

\[
C^{ijk} = \Delta \phi^{ij} + \Delta \phi^{jk} - \Delta \phi^{ik}
\]  

(2.8)

where \(\Delta \phi^{ij}, \Delta \phi^{jk}\) and \(\Delta \phi^{ik}\) are three unwrapped interferometric phases generated from the SAR acquisitions at \(t_i, t_j\) and \(t_k\). The integer ambiguity of the closure phase is given as:

\[
C_{int}^{ijk} = (C^{ijk} - \text{wrap}(C^{ijk})) / (2\pi)
\]  

(2.9)
where wrap is an operator to wrap the input number into \([-\pi, \pi]\). A triplet without unwrapping errors has \(C^{ijk}_{\text{int}} \equiv 0\). The number of triplets with non-zero \(C^{ijk}_{\text{int}}\) among all triplets is given as: 
\[
T_{\text{int}} = \sum_{i=1}^{T} (C^{ijk}_{\text{int}} \neq 0),
\]
where \(T\) is the number of triplets \((T_{\text{int}} \leq T)\). 

\(T_{\text{int}}\) can be used to detect unwrapping errors.

Fig. 2.3 shows the characteristics of unwrapping errors in the closure phase from the Sentinel-1 dataset (stack of multilooked unwrapped interferograms) of section 2.6. The non-zero \(C^{ijk}\) in Fig. 2.3a-b are caused by the interferometric phase residuals (see equation (2.1)), whereas the non-zero \(C^{ijk}_{\text{int}}\) in Fig. 2.3c are caused by unwrapping errors.

Fig. 2.3d-e show the distribution of \(T_{\text{int}}\). On Isabela island, pixels in non-vegetated area have \(T_{\text{int}} = 0\) (dark blue in Fig. 2.3d) and are free of unwrapping errors; while pixels in vegetated area, such as the light-blue to green area on Sierra Negra’s south flank in Fig. 2.3d, have wide-distributed \(T_{\text{int}}\) values, indicating random unwrapping errors, which are difficult to correct. On Fernandina and Santiago island, most pixels share the common \(T_{\text{int}}\) of 229 and 576 out of 940 triplets, respectively, indicating coherent unwrapping errors and can be corrected.

Several attempts have been pursued to evaluate the phase unwrapping and correct the unwrapping errors using the close phase information. Hussain et al. (2016) use the close phase to adjust the cost in the three-dimensional phase unwrapping procedure iteratively. Biggs et al. (2007) visually identify and correct the unwrapping errors by manually adding the integer-cycle phase offsets to badly unwrapped regions of pixels. Built on this idea, we develop an algorithm to automatically detect and correct the unwrapping errors in the network of interferograms.
2.4.2.1 Algorithm

For a redundant network of interferograms, the temporal consistency of the integer ambiguities of unwrapped interferometric phases can be expressed for each pixel as:

$$CU + (C\Delta\varphi - \text{wrap}(C\Delta\varphi)) / (2\pi) = 0$$  \hspace{1cm} (2.10)
where $C$ is a $T \times M$ design matrix of all possible interferogram triplets, $U$ is an $M \times 1$ vector of integer numbers for cycles required to meet the consistency of the interferometric phases. An example of $C$ is provided in the Supplementary Information section A2.2. Note that equation (2.10) can be ill-posed and does not always has a unique solution, especially when $T < M$. Thus, regularization is required to obtain an optimal solution. We assume that the solution is more likely to be small than large, and more likely to be sparse than dense. Accordingly, we apply the $L^1$-norm regularized least squares optimization (Andersen et al., 2011; Xu and Sandwell, 2019), which is also known as least absolute shrinkage and selection operator (LASSO), to obtain the solution as:

$$\hat{U} = \arg \min \|CU + (C\Delta \phi - \text{wrap}(C\Delta \phi)) / (2\pi)\|_2 + \alpha \|U\|_1$$  (2.11)

where $\alpha = 0.01$ is a nonnegative parameter for the trade-off between the $L^1$ and $L^2$-norm term, with value chosen based on simulations with various values of $\alpha$ (see supp. Fig. A.4). The corrected unwrapped interferometric phase is given as: $\Delta \phi_c = \Delta \phi + 2\pi \cdot \text{round} (\hat{U})$, where $\text{round}$ is an operator to round the input number to the nearest integer.

### 2.4.2.2 Simulated Data

We demonstrate the phase closure method using a simulated interferogram stack for one pixel (Fig. 2.4). We first simulate the decorrelation noise and ground deformation (see section 2.3.4.1) for an interferogram network with 5 sequential connections using the
temporal and perpendicular spatial baselines from the Sentinel-1 dataset of section 2.6. Then we randomly select 20% of the interferograms to add unwrapping errors with randomly selected cycles (maximum of 2) of magnitude and randomly selected sign. Next, we apply the phase closure method and compare the unwrapping errors before and after the correction, as shown in orange and blue bars in Fig. 2.4a, respectively. The method decreases the number of interferograms affected by unwrapping errors from 20% to 2% and reduces the magnitude of the remaining unwrapping errors (Fig. 2.4a). We note that the method could potentially introduce new unwrapping errors to the unwrapped interferograms (blue bars in Fig. 2.4a where there is no orange bar).

We evaluate the performance of the phase closure method by comparing the input and output percentages of interferograms with unwrapping errors (before and after correction), considering different input percentages and redundancies of the interferogram network. Fig. 2.4b shows for 100 realizations the mean output percentage after correction versus the input percentage for networks with 3, 5 and 10 sequential interferograms. For 5 connections (orange dots in Fig. 2.4b), the method fully corrects unwrapping errors if there are less than 20% of interferograms affected; then the improvement slows down with the increasing input percentage until it reaches a turning point of 35%, beyond which the improvement is marginal. The maximum input percentages with full correction for 3, 5 and 10 connections are at 5, 20 and 35%, respectively, indicating better performance for more redundant networks. Fig. 2.4c shows the performances for 5 connections network with maximum of 2, 5 and 10 cycles of unwrapping errors. The similarity before 30% shows that the method is robust for various magnitudes of unwrapping errors. Thus, we conclude that the phase closure method is
suitable for highly redundant networks of interferograms with not too many unwrapping errors.

**Figure 2.4.** Simulations of unwrapping error correction using the phase closure method. (a) Unwrapping errors in interferograms before (orange bars, account for 20%) and after correction (blue bars, account for 2%). A network of interferograms with 5 sequential connections is used. A maximum of 2 cycles of unwrapping errors are added randomly. (b) Mean output percentage of 100 realizations of interferograms with unwrapping errors versus the input percentage, with a fixed maximum of 2 cycles of unwrapping errors and color coded by network redundancy. (c) Same as (b) but with a fixed network of 5 connections and color coded by maximum unwrapping error magnitudes.

### 2.5 Workflow of InSAR Time Series Analysis

We have implemented a generic routine processing workflow for InSAR time series analysis from a stack of unwrapped interferograms to displacement time-series (Fig. 2.5). The workflow consists of two main blocks: (i) correcting unwrapping errors and inversion for the raw phase time-series (blue ovals in Fig. 2.5), and (ii) correcting for phase contributions from different sources to obtain the displacement time-series (green ovals in Fig. 2.5). It includes some optional steps, which are switched off by default
(marked by dashed boundaries in Fig. 2.5), here we present the workflow in its most complete form. Configuration parameters for each step are initiated with default values in a customizable text file (link on GitHub).

**Figure 2.5.** Routine workflow of InSAR time series analysis. Blue ovals: steps in the interferogram domain including unwrapping error correction and network inversion; green ovals: steps in the time-series domain including phase corrections for the tropospheric delay, phase ramps, and topographic residuals. White rectangles: input data. Green rectangles: output data. Optional steps/data are marked by dashed boundaries.

**2.5.1 Starting Point: Stack of Unwrapped Interferograms**

As described above, the starting point is a stack of phase-unwrapped interferograms coregistered to a common SAR acquisition, corrected for earth curvature and topography. We currently support interferogram stacks produced by ISCE, GAMMA and ROI_PAC software (Rosen et al., 2004; Rosen et al, 2012; Werner et al., 2000).
2.5.2 Network Modification

In order to exclude outliers affected by coherent pixels with unwrapping errors, the software provides network modification to exclude affected interferograms if the spatially averaged coherence for an area of interest falls below a predefined threshold value (switched off by default). This is similar to Chaussard et al. (2015) excluding interferograms with a low percentage of high coherent pixels. An extra constraint could be applied to keep those interferograms if they are part of the MST network providing the maximum spatially averaged coherence (Perissin and Wang, 2012) to ensure a fully connected network (switched on by default). The approach is referred to as coherence-based network modification. This is based on the empirical observation that reliable regions with unwrapping errors are usually surrounded by decorrelated areas. The default area of interest is all pixels on land, a customized area of interest including the decorrelated areas around the reliable regions is usually more effective. The software also supports other approaches for network modification, such as thresholds of the temporal and spatial baselines, maximum number of connections for each acquisition, and exclusion of specific acquisitions, interferograms.

2.5.3 Reference Selection in Space

The reference pixel is selected randomly among the pixels with high average spatial coherence (≥ 0.85 by default) or can be specified using prior knowledge of the study area. The reference pixel should be (i) located in a coherent area; (ii) not affected by strong atmospheric turbulence such as ionospheric streaks and (iii) close to and with similar elevation as the area of interest to minimize the impact of the spatially correlated
atmospheric delay. For example, Chaussard et al. (2013) studied volcano deformation using reference points on inactive, neighboring volcanoes.

2.5.4 Unwrapping Error Correction

Three methods are available to possibly detect and correct unwrapping errors in the stack of interferograms. The first method is bridging as described in section 2.4.1. This method is well suited for unwrapping errors occurred among islands or on areas separated by steep topography. The second method is based on the phase closure as described in section 2.4.2. It’s well suited for unwrapping errors in a highly redundant network of interferograms. Both methods are operated in the region level, thus are efficient. The third approach is to apply both methods, bridging followed by phase closure, as they exploit aspects of unwrapping errors in space and time domain, respectively. The default is no unwrapping error correction.

2.5.5 Network Inversion

The raw phase time-series is solved by minimizing the interferometric phase residual $\Delta \phi_e$. Then, the temporal coherence is computed based on equation (2.3) and used to generate a temporal coherence mask for pixels with reliable time-series estimation with a predefined threshold (0.7 by default). Pixels in shallow and water bodies are masked out if shallow mask and water body mask are available.

2.5.5.1 Phase Masking

In order to exclude outliers affected by decorrelation, the software provides masking options (switched off by default) based on the spatial coherence (default threshold of 0.4)
or using the connected component information from phase unwrapping. Note that masking based on spatial coherence is equivalent to weighting with a step function.

After masking, the pixels may have different numbers of interferograms. We use not only the pixels that are coherent in all interferograms (Agram and Simons, 2015), but relax the pixel selection criterion and also use pixels with fewer interferograms as long as a predefined minimum number of interferograms is available for each SAR acquisition (1 by default). Note that with this pixel selection strategy after masking, the network inversion result is not sensitive to the few very low coherent interferograms in a redundant network, giving robust and consistent spatial coverage.

2.5.6 Tropospheric Delay Correction

Two different approaches for tropospheric delay correction are available. In the first approach, the tropospheric delay is estimated using Global Atmospheric Models (GAMs). The estimated relative double path tropospheric delay at \( t_i \) between a given pixel \( p \) and a reference pixel is given in radians as:

\[
\hat{\phi}_{tropo}(p) = (\delta L_p^i - \delta L_p^1) \frac{4\pi}{\lambda} - (\delta L_{ref}^i - \delta L_{ref}^1) \frac{4\pi}{\lambda} \tag{2.12}
\]

where \( i \in [1, \ldots N] \), \( \delta L_x^i \) is the integrated absolute single path tropospheric delay at \( t_i \) on pixels \( x \) in meters in satellite line-of-sight (LOS) direction (\( \delta L_p^1 \) for \( t_1 \)) and \( \lambda \) is the radar wavelength in meters. The supported datasets include ERA-5 and ERA-Interim from European Center for Medium-Range Weather Forecast, NARR (North American
Regional Reanalysis) from NOAA and MERRA (Modern-Era Retrospective Analysis) from NASA (applied by default, using PyAPS software from Jolivet et al. (2011; 2014)).

The second approach is based on the empirical linear relationship between the InSAR phase delay and elevation (Doin et al., 2009) which in areas with strong topographic variations sometimes outperforms corrections using GAMs. On the other hand, the empirical approach cannot distinguish between the stratified tropospheric delay and the ground deformation correlated with topography such as at volcanoes.

### 2.5.7 Phase Deramping

Phase ramps are caused by residual tropospheric and ionospheric delays and to a lesser extent, by orbital errors. For long spatial wavelength deformation signals such as interseismic deformation, ramps should not be removed. Instead, physical and statistical approaches should be applied to correct the ionospheric delay (Fattahi et al., 2017; Gomba et al., 2016; Liang et al., 2018) and/or assess the measurement uncertainties (Fattahi and Amelung, 2014; 2015; Fattahi et al., 2017). For short spatial wavelength deformation signals such as volcanic deformation, landslides, and urban subsidence it is recommended to estimate and then to remove linear or quadratic ramps from the displacement time-series at each acquisition on the reliable pixels (default is no ramp removal).

### 2.5.8 Topographic Residual Correction

The systematic topographic phase residual caused by a DEM error is estimated based on the proportionality with the perpendicular baseline time-series (Fattahi and Amelung, 2013). The original method assumes a cubic temporal deformation model, which is not
able to capture high-frequency displacement components, such as offsets caused by earthquakes or volcanic eruptions. The software provides options to account for permanent displacement jumps using step functions (Hetland et al., 2012) and to generalize polynomial functions with a user-defined polynomial order $N_{\text{poly}}$. The DEM error $z_e$ for each pixel is then given by:

$$
\hat{\phi}^i - \hat{\phi}_{\text{tropo}}^i = \left( \frac{B_{\perp}^i}{r \sin(\theta)} z_e + \sum_{k=0}^{N_{\text{poly}}} \frac{c_k (t_i - t_1)^k}{k!} + \sum_{t \in I} s_t H(t_i - t_i) \right) \frac{-4\pi}{\lambda} + \phi_{\text{resid}}^i
$$

where $i \in [1, \ldots N]$, $B_{\perp}^i$ is the perpendicular baseline between $t_i$ and $t_1$, $r$ is the slant range between the target and the radar antenna, $\theta$ is the incidence angle, $H(t_i - t_i)$ is a Heaviside step function centered at $t_i$, $I$ is a set of indices describing offsets at specific prior selected times. $z_e$, $c_k$ and/or $s_t$ are the unknown parameters, which can be estimated by minimizing the $L^2$-norm of residual phase time-series $\phi_{\text{resid}} = [\phi_{\text{resid}}^1, \ldots, \phi_{\text{resid}}^N]^T$.

An example design matrix and the numerical solution of least squares estimation are provided in the Supplementary Information section 2.3.3. The necessity of the step function(s) in the presence of deformation jump(s) is demonstrated in supp. Fig. A.5 (default is no step function with $N_{\text{poly}} = 2$).

As we are interested in the estimation of $z^2$, the assumed deformation model does not need to be a comprehensive representation of the deformation processes. Note, however, that equation (2.13) offers the possibility to parameterize the geophysical
processes using more complex models, e.g. using the regularization functions from Hetland et al. (2012).

### 2.5.9 Residual Phase for Noise Evaluation

The estimate of residual phase $\hat{\phi}_{\text{resid}}$, a by-product of equation (2.13), is the phase component that can neither be corrected nor be modeled as ground deformation, thus, is used to characterize the noise level of the InSAR time-series. For each SAR acquisition, we compute the root mean square (RMS) of the residual phase as:

$$ RMS^i = \sqrt{\frac{1}{N_\Omega} \sum_{p \in \Omega} (\hat{\phi}_{\text{resid}}^i(p) \cdot \frac{\lambda}{-4\pi})^2} \quad (2.14) $$

where $i = [1, \ldots, N]$, $\hat{\phi}_{\text{resid}}^i(p)$ represent the residual phase at $t_i$ for pixel $p$, $\Omega$ is the set of reliable pixels selected based on temporal coherence during the network inversion with the total number of $N_\Omega$. Due to the inadequate knowledge of the long spatial wavelength phase components in $\hat{\phi}_{\text{resid}}$, we focused on the noise evaluation of the short spatial wavelength phase components only, including residual tropospheric turbulence, uncorrected ionospheric turbulence, and remaining decorrelation noise. Therefore, we remove a quadratic ramp from the residual phase of each acquisition before calculating the RMS (Lohman and Simons, 2005; Sudhaus and Jónsson, 2009).

#### 2.5.9.1 Identifying Noisy SAR Acquisitions

Assuming the residual tropospheric delay in $\hat{\phi}_{\text{resid}}$ is stochastic and Gaussian distributed in time (Fattahi and Amelung, 2015), we can treat the noisy SAR acquisitions
contaminated by severe atmospheric turbulence as outliers. Following Rousseeuw and Hubert (2011), we calculate the median absolute deviation (MAD) value and mark a SAR acquisition as noisy if its RMS value is larger than the predefined cutoff (3 MADs by default giving 99.7% confidence). Note that we assume a zero-mean value for the distribution considering the positive nature of RMS. The automatically identified noisy acquisitions will be excluded in the topographic residual estimation (during re-run) and velocity estimation.

2.5.9.2 Selecting the Optimal Reference Date

The SAR acquisition with the smallest RMS value can be interpreted as the date with minimum atmospheric turbulence and is used as the reference date. We note that changing the reference date is equivalent to adding a constant to the displacement time-series, which does not change the velocity, or any other information derived from the displacement time-series.

2.5.10 Average Velocity Estimation

For applications with interest on the deformation rate, the velocity $v$ is estimated as the slope of the best fitting line to the displacement time-series, given as $\phi_{dis}^i \cdot \lambda / (-4\pi) = v \cdot t_i + c, i = 1, \ldots, N$, where $c$ is an unknown offset constant. Noisy SAR acquisitions are excluded by default during the estimation. The standard deviation of the estimated velocity is given by equation (10) from Fattahi and Amelung (2015).
2.6 Application to Galápagos Volcanoes, Ecuador

We apply the routine workflow outlined in the previous section to the western Galápagos Islands, Ecuador, located around 1000 km west of Ecuador mainland (Fig. 2.6 inset). We consider interferogram stacks from the Sentinel-1 and ALOS-1 satellite. For Sentinel-1 (we consider the December 2014 to June 2018 period) we use the stack Sentinel processor (Fattahi et al, 2016) within ISCE (Rosen et al, 2012) for processing the stack of interferograms; we pair each SAR image with its five nearest neighbors back in time (sequential network); we multilook each interferogram by 15 and 5 looks in range and azimuth direction respectively, filter using a Goldstein filter with a strength of 0.2 (configuration file). For ALOS-1 we use ROI_PAC (Rosen et al., 2004) for processing the stack of interferograms; we select interferometric pairs with small temporal (1800 days) and spatial baselines (1800 m) and with over 15% of Centroid doppler frequency overlap in azimuth direction; we multilook each interferogram by 8 and 16 looks in range and azimuth direction respectively, filter using a Goldstein filter with a strength of 0.5 and an adaptive smoothing with a width of 4 pixels (configuration file). We remove the topographic phase component using SRTM DEM (SRTMGL1, ~30m, 1 arc second with void-filled; Farr et al., 2007). The interferograms are phase-unwrapped using the minimum cost flow method (Chen and Zebker, 2001). In the routine workflow for the Sentinel-1 dataset we correct unwrapping errors using the bridging and phase closure method. In the routine workflow for the ALOS-1 dataset we exclude interferograms using coherence-based network modification with a customized area of interest (blue rectangle in Fig. 2.10b) and correct unwrapping errors using the bridging method. We remove linear phase ramps from both datasets.
The Islands host seven active volcanoes characterized by large summit calderas with several km radii and by distinguished nonlinear deformation behavior. The surface coverage ranges from bare lava flows to dense vegetation. We discuss observations of Sierra Negra, Cerro Azul, Alcedo, Wolf and Fernandina volcanoes. Sierra Negra erupted in 26 June 2018, Wolf volcano in May 2015 and Fernandina volcano in September 2017 and June 2018.

Products of the routine workflow include the mean LOS velocity (Fig. 2.6) and the displacement time-series (Fig. 2.7, shown for Fernandina island only). The center of Sierra Negra caldera uplifted at a mean rate of 60 cm/yr (Fig. 2.6) but the uplift rate varied with time (Fig. 2.8). The deformation at Cerro Azul volcano was caused by a sill intrusion in March 2017 (Bagnardi and Hooper, 2018).

Figure 2.6. Mean LOS velocity at Isabela, Fernandina, and Santiago (main image), the westernmost islands in the Galápagos archipelago (inset). The velocity is estimated from
98 Sentinel-1 descending track 128 SAR acquisitions from December 2014 to 19 June 2018 and wrapped into [-3, 7] cm/yr for display so that one color-cycle represents 10 cm/yr displacement velocity. Black square represents the reference point. Black triangle indicates the location of the pixel covered by the lava flow of the 2015 Wolf eruption used in Fig. 2.15b and c. Dark blue in Santiago island indicates biased velocity estimation caused by remaining unwrapping errors. The southeast part of the caldera of Volcán Alcedo has been subsiding at a rate of -3.1 cm/yr. The center of Fernandina caldera uplifted by 14 cm before the September 2017 eruption, subsided during the eruption and uplifted by 35 cm until the June 2018 eruption (Fig. 2.7).

**Figure 2.7.** Displacement time-series on Fernandina volcano with Sentinel-1 data. Dashed lines: eruption events on September 2017 and June 2018. Orange star:
automatically selected reference date. The reference point is on Isabela island (black square in Fig. 2.6). Data are wrapped into \([-10, 10)\) cm for display.

### 2.6.1 Comparison with GPS

To validate the InSAR measurements we use the continuous GPS measurements at stations in the Sierra Negra caldera (circles in Fig. 2.8a; Blewitt et al., 2018). All three GPS components in east, north and vertical directions are used to project displacements into InSAR LOS direction. Both InSAR and GPS time-series are referenced to station GV01 in space and a common reference date in time. The InSAR data for each GPS point is obtained by linear interpolation (InSAR pixel size is \(64 \times 70 \text{ m}^2\)). The InSAR and GPS total displacements for the period of interest (Fig. 2.8a) and the displacement time-series (Fig. 2.8b) agree very well, except for GV10 discussed below. To quantify the agreement, we assume the GPS time-series as truth and compute the coefficient of determination \(R^2\) between InSAR time-series and GPS time-series and the RMSE given as:

\[
RMSE_{\text{InSAR}} = \sqrt{\frac{\sum_{i=1}^{N_{\text{comm}}} (d_{\text{InSAR}}^i - d_{\text{GPS}}^i)^2}{(N_{\text{comm}} - 1)}} \quad (2.15)
\]

where \(d_{\text{InSAR}}^i = \phi_{\text{dis}} \cdot \frac{\lambda}{\lambda A} \) and \(d_{\text{GPS}}^i\) are the InSAR and GPS time-series in LOS direction, respectively, at the \(i_{th}\) common date. \(N_{\text{comm}}\) is the total number of common dates.

The temporal coherence at the GPS stations varies from 0.96 to 1.0 (Fig. 2.8b) indicating reliable InSAR measurements at these locations (except GV10). The \(R^2\) at the GPS stations are 1.0 and the RMSE varies from 0.5 to 1.8 cm (Fig. 2.8b), confirming the good agreement of the two measurements. The exception is station GV10 (\(R^2\) of 0.72 and
RMSE of 3.9 cm), which is eliminated during posterior quality assessment due to low temporal coherence of 0.64 (below the threshold of 0.7). This station is located in a more densely vegetated area outside the caldera on the rim where decorrelation due to vegetation affects the interferometric coherence (see supp. Fig. A.6).

Figure 2.8. Comparing InSAR with GPS. (a) Total displacements in LOS direction for Sierra Negra caldera from InSAR and GPS during 13 December 2014 - 19 June 2018. Circles: GPS stations colored by displacement. Positive displacements indicate motion towards the satellite. (b) Displacement time-series from InSAR and GPS relative to GV01
Blue GPS error bars: three sigma uncertainties (in LOS direction propagated from the uncertainties in east, north and up direction). 12 April 2015 is selected as the common reference because this SAR acquisition is characterized by small residual phase RMS. Gray circles: unreliable InSAR time-series with temporal coherence less than 0.7 (masked out by default).

2.6.2 Assessment of Unwrapping Error Correction

The islands of Fernandina and Santiago exhibit unwrapping errors relative to Isabela island due to the water separation. The unwrapping errors are represented by the low temporal coherence of about 0.49 and 0.07 for Fernandina and Santiago with Sentinel-1 dataset, respectively (pixel A and B in Fig. 2.9a). Since there is no indication of localized submarine deformation between Isabela and Fernandina or between Isabela and Santiago during the time period of Sentinel-1 dataset, we believe the phase differences among the three islands fulfill the bridging assumption (less than π rad in magnitude). Thus, we applied the bridging method followed by the phase closure method to correct the potential unwrapping errors in the interferogram stack (Fig. 2.9). The bridging method leads to increased temporal coherence of 0.96 and 0.55 at these two points, respectively (Fig. 2.9b). The phase closure method leads to further increased temporal coherence of 1.00 and 1.00, respectively (Fig. 2.9c).

We note that for Santiago, however, the phase closure method did not fully correct the large amount of unwrapping errors, resulting in a biased average velocity estimation of -0.5 cm/yr (Fig. 2.6). This is due to the assumption of sparse unwrapping errors in the phase closure method, which is not the case for the Sentinel-1 dataset in Santiago: 576 out of 940 interferogram triplets have non-zero integer ambiguity (Fig. 2.3e). Conversely temporal coherence after the phase closure correction can be partly biased.
2.6.3 Assessment of Network Inversion

2.6.3.1 Temporal Coherence

The quality of the network inversion can be evaluated posteriorly using the temporal coherence. In Fig. 2.10, we compare for the ALOS-1 dataset the temporal coherence obtained by inverting a network of small baseline interferograms using uniform weighting (classic SBAS; Fig. 2.10a-c) with that obtained by inverting the network after coherence-based network modification (an option of the routine workflow) using inverse-variance weighting (Fig. 2.10d-f). The first approach assumes an oversimplified linear relationship between the spatial coherence of each interferogram and its spatial and temporal baseline (Hooper et al., 2007; Zebker and Villasenor, 1992); while the second approach uses the observed spatial coherence on the manually specified area of interest (blue rectangle in Fig. 2.10b and e). This approach more reliably identifies the coherent interferograms, especially when the simple decorrelation model does not apply, e.g. vegetated areas, long temporal baseline interferograms on Sierra Negra caldera with low
coherence due to high deformation phase gradient (Baran et al., 2005). The improvement in temporal coherence using the second approach leads to additional reliable pixels (Fig. 2.10c and f).

![Figure 2.10. Impact of network modification on temporal coherence for ALOS-1 dataset. (a) Network configuration, (b) temporal coherence and (c) reliable pixels with temporal coherence > 0.7 from inversion of small baseline network with uniform weighting. (d-e): same as (a-c) but from inversion of a network obtained by coherence-based network modification with inverse-variance weighting. Lines in (a) and (d) represent interferograms colored by the average spatial coherence within the Sierra Negra caldera (blue rectangle in (b, d)). Black squares in (b, e) indicate the reference point.

2.6.3.2 Inverted Raw Phase

The temporal filtering performed by the inversion of a redundant network of interferograms is illustrated by comparing an observed interferogram with the interferogram reconstructed from the inverted raw phase time-series (referred to by some authors as linked phase). Fig. 2.11 shows an ALOS-1 interferogram with 3.5 years temporal baseline. The observed and the reconstructed interferograms (Fig. 2.11a-b) are
very similar except at the south and east of the caldera, where the observed interferogram is incoherent but not the reconstructed interferogram as shown by the high-frequency noise in the interferogram difference (Fig. 2.11c). This area is forested and characterized by a low spatial coherence (Fig. 2.11d-e). This example, although with an extreme temporal baseline, demonstrates how the network inversion filters out the temporal decorrelation noise (Ansari, 2017; Guarnieri and Tebaldini, 2008; Pepe et al., 2015).

There is a difference in the north of the decorrelated area (yellow colors marked by white rectangle in Fig. 2.11c). These areas are lightly vegetated (Fig. 2.11e), the discrepancy in phase is likely caused by the soil or tree moisture considering its sensitivity to L-band SAR data (De Zan and Gomba, 2018) and land cover (Fig. 2.11e).

![Image](image-url)

**Figure 2.11.** Spatial inspection of the inverted raw phase. (a) Observed interferometric phase and (b) reconstructed phase from the inverted raw phase time-series; (c) difference between (a) and (b); (d) observed spatial coherence; (e) optical image from Google Earth. The ALOS-1 interferogram has temporal baseline of 3.5 years (2 Mar 2007 - 10 Sep 2010) and perpendicular baseline of 219 m. In (a) part of the caldera is masked out during phase unwrapping because of low coherence. White rectangles in (c and e): areas likely affected by soil or tree moisture. The phase is wrapped into $[-\pi, \pi]$ for display.
2.6.4 Noisy SAR Acquisitions

Noisy acquisitions with severe atmospheric delays or decorrelation noise could potentially bias the estimation of topographic residuals, the average velocity or coefficients of any temporal deformation model. In the routine workflow, they are automatically identified and excluded in the estimations.

Fig. 2.12 shows the impact of noisy acquisitions on the average velocity estimation for the L-band ALOS-1 dataset. Several acquisitions are severely contaminated by ionospheric streaks and identified by high residual phase RMS value (gray bars in Fig. 2.12a). Comparing the estimated average velocities from displacement time-series with noisy acquisitions (Fig. 2.12b) and without noisy acquisitions (Fig. 2.12c) reveals that excluding the noisy acquisitions significantly reduces the estimation bias. The residual phase time-series $\hat{\phi}_{\text{resid}}$ estimated from equation (2.13) is shown in supp. Fig. A.7.

![Figure 2.12. Impact of noisy acquisitions on velocity estimation. (a) RMS of the residual phase estimates $\hat{\phi}_{\text{resid}}$ for each acquisition in the ALOS-1 dataset calculated using equation (2.14). Dashed line: threshold (three times MAD of the RMS time-series by default). Gray bars: noisy acquisitions with RMS larger than the threshold. (b and c): estimated average LOS velocities from displacement time-series with and without noisy acquisitions, respectively. Velocities are wrapped into [-5, 5] cm/yr for display.](image-url)
2.7 Discussion

2.7.1 Phase Corrections in the Time-series Domain

In the presented approach the phase corrections are applied in the time-series domain in contrast to other approaches where they are applied in the interferogram domain (Agram et al., 2013; Berardino et al., 2002). Both types of approaches give identical results, but the time-series domain approach has two advantages: first, it is computationally more efficient because it uses $N-1$ unwrapped phases, in contrast to the much larger number of interferograms for the interferogram domain approach (up to $N \times (N-1)/2$ for all possible interferograms); second, the impact of the corrections is readily evaluated in both the spatial and temporal domains.

Fig. 2.13 upper panel (a) shows how the displacement at one acquisition is obtained by subtracting the estimations of the tropospheric delay, of the phase ramp and of the topographic residual from the raw phase. The time-series for a pixel along the southern coast of Isabela demonstrates the power of the corrections (Fig. 2.13b). The area experienced a sill intrusion in March 2017 (dashed line in Fig. 2.13b; Bagnardi and Hooper, 2018). The permanent ground displacement of 5 cm in LOS direction is difficult to discern in the raw phase time-series but becomes visible after applying the three corrections. Note that this pixel is far away from the intrusion in the first stage and only affected by the intrusion in the second stage, thus showing only one jump in the displacement time-series. For Sentinel-1 the topographic residuals are small (less than 4 cm in this dataset) due to the small orbital tube but this is different for other sensors (Fattahi and Amelung, 2013).
Figure 2.13. Illustration of phase corrections in the time-series domain: (a) at one acquisition (12 May 2016; the reference date is 27 September 2015); (b) at one pixel (southern flank of Cerro Azul, marked as a triangle in the upper panel; \(W 91.1917^\circ, S 1.0352^\circ\)). Displacements are obtained by subtracting the estimated tropospheric delay, phase ramp and topographic residual from the raw phase (equation (2.4)). Black square in (a) indicates the reference point. Data are wrapped into \([-\pi, \pi]\) for display. All range change histories in (b) start at zero but are shifted for display. The permanent displacement due to a sill intrusion in March 2017 (marked as dashed line) is visible after phase corrections.

2.7.2 Order of Phase Corrections

In our proposed workflow the tropospheric delay correction using external independent GAMs should be applied first. The order of the other phase corrections is interchangeable because they exploit different aspects of the InSAR data. Empirical tropospheric delay correction based on delay-elevation ratio removes signals correlated with the topography. Phase deramping removes signals correlated with the spatial coordinates (linearly or quadratically). Topographic residual correction removes signals
correlated in time with the perpendicular baseline. We recommend applying phase deramping before topographic residual correction so that the estimated step functions do not have to be deramped again.

### 2.7.3 Interferogram Network Redundancy

We consider stacks of Sentinel-1 interferograms from section 2.6 with different numbers of sequential connections for each acquisition to assess the impact of network redundancy on the estimation of (i) the displacement time-series and (ii) the temporal coherence (the reliability measure). We compute the RMSE of the InSAR time-series at the GPS stations within Sierra Negra caldera, assuming that the GPS measurements are the truth (see section 2.6.1; Fig. 2.14) and examine the temporal coherence for these pixels. We also count the number of reliable pixels (spatial coverage; temporal coherence $\geq 0.7$).

The average RMSE (bars in Fig. 2.14; GV10 excluded) decreases (improves) with the increasing number of sequential connections rapidly until 5 connections then slowly until the reduction becomes negligible. The temporal coherence (orange triangles in Fig. 2.14) stays at high values (above 0.9) for all stations, except for GV10, for which it decreases to 0.65 at 4 connections and to 0.24 at 20 connections. The low temporal coherence indicates that this is not a reliable pixel. It also has a relatively large RMSE (Fig. 2.8b in section 2.6.1). This example shows that increasing network redundancy leads to improved identification of reliable pixels. For this specific dataset, a network of interferograms with 5 connections gives a good balance among precision, reliability and spatial coverage (green dots in Fig. 2.14).
We note that in this case decorrelation noise is the dominant error source. Unwrapping errors remaining after unwrapping error correction were excluded by removal of affected interferograms using coherence-based network modification (see supp. Fig. A.8). Still remaining unwrap errors were suppressed by the weighting. Thus, more observations always help to reduce the stochastic decorrelation noise, resulting in a more accurate estimation of the displacement measurement (lower RMSE) and of the reliability measure (temporal coherence).

![Figure 2.14](image.png)

**Figure 2.14.** Average RMSE of InSAR time-series (black bars), temporal coherence (orange triangles) at GPS stations and number of reliable pixels (green dots) as functions of the number of sequential connections. Dotted orange line: temporal coherent threshold of 0.7.

As a practical implication, more interferograms are always preferred if the computing capacity allows (Ansari et al., 2017). Since we cannot get the estimated spatial coherence before the interferogram generation (due to the imperfect coherence model), generating a more redundant network provides room to exclude low coherent interferograms especially those containing reliable regions with unwrapping errors and still keep the network redundancy (temporal coherence would always be one and meaningless if the system of network inversion is not overdetermined, shown as orange
triangles in Fig. 2.14 at 1 connection). In addition, a more redundant network could potentially lead to a better unwrapping error correction based on phase closure. Thus, we recommend using relatively relaxed interferogram selection thresholds (more connections in sequential networks, larger temporal and perpendicular baselines in small baseline networks) to generate more potentially coherent interferograms.

2.7.4 Temporal Coherence as the Reliability Measure

We discuss the advantages and limitations of using the temporal coherence as the reliability measure. An advantage is that the temporal coherence is a more robust reliability measure for the inverted raw phase time-series compared to the average spatial coherence, because the temporal coherence indicates not only the overall decorrelation noise, but also the overall level of non-closing interferogram triplets. Non-closing triplets may be caused by the interferometric phase residual (equation (2.1)), including decorrelation noise, possible phase-unwrapping errors and interferometric phase contributions due to changes in the scatterers. An example of the latter is the interferometric phase caused by changes in the dielectric properties of subsurface scatterers in the result of soil moisture changes (De Zan et al., 2014; Morrison et al., 2011). Fig. 2.15a shows how the temporal coherence is affected by unwrapping errors. In the absence of unwrapping errors (pixels on Isabela island) the temporal and average spatial coherence are correlated but not when unwrapping errors are present (pixels on Fernandina and Santiago islands). The improvement in temporal coherence by phase-unwrapping error correction is illustrated in Fig. 2.9.

However, a limitation is that the temporal coherence cannot capture temporal variations of the reliability of the phase time-series. Fig. 2.15b and c show the
displacement time-series and coherence matrix of a pixel that was covered by a lava flow during the 2015 Wolf eruption (marked as a black triangle in Fig. 2.6). The surface change brings down the spatial coherence to 0.3 during May-July 2015 (red grids in Fig. 2.15c), resulting in coherent, connected interferogram networks only before and after the lava flow emplacement. This, however, has negligible impact on the temporal coherence. With a temporal coherence of 0.94 the pixel is considered reliable although valid displacement measurements were possible only before and after the flow emplacement (after flow emplacement the pixel shows surface subsidence due to lava cooling). A three-dimensional reliability measure such as the covariance matrix of decorrelation noise (Agram and Simons, 2015) is more meaningful in this case of partially coherent scatterers, but this is beyond the scope of this manuscript.

**Figure 2.15.** Advantage and limitation of temporal coherence as reliability measure. (a) Temporal coherence versus average spatial coherence for land pixels of the Sentinel-1 dataset without unwrapping error correction. Dashed line: default temporal coherence threshold of 0.7. Three point clouds represent pixels on Isabela, Fernandina and Santiago islands. (b and c) Displacement time-series and the diagonal section of coherence matrix of a pixel on the lava flow of the 2015 Wolf eruption located at [W91.2838°, N0.0232°] (black triangle in Fig. 2.6). Reference pixel is located ~600 m to the west [W91.2891°, N0.0243°]. The coherence matrix is rotated 45° anticlockwise and shows the five diagonals below and above the main diagonal. Dashed lines: period of lava flow emplacement.
2.7.5 Comparing MintPy with GIAnT

We compare the performance of the MintPy routine workflow with the classic SBAS approach (Berardino et al., 2002), the New Small Baseline Subset (NSBAS) approach (Doin et al., 2011; López-Quiroz et al., 2009) and the Multiscale InSAR Time-Series approach (Hetland et al., 2012), as implemented in the Generic InSAR Analysis Toolbox (GIAnT) (Agram et al., 2013) and referred to as G-SBAS, G-NSBAS, and G-TimeFun, respectively. We use the Galápagos Sentinel-1 dataset and a spatial coherence threshold of 0.25 (as commonly done with GIAnT, Agram and Simons, 2015) for all approaches including MintPy. Tropospheric delays are corrected from the ERA-Interim model using the PyAPS software (Jolivet et al., 2011).

In the following we discuss the differences between the four approaches (summarized in table 2.1). We demonstrate the impact on the displacement time-series using three pixels (Fig. 2.16i): a high coherent pixel (pixel A), a low coherent pixel (pixel B) and a high coherent pixel with unwrapping errors and complex displacement (pixel C). The coherence matrices of the three pixels are shown in Fig. 2.16j. For the high coherent pixel A, all approaches give nearly identical results (Fig. 2.16i).

2.7.5.1 Initial Pixel Selection

MintPy selects pixels which have for every SAR acquisition a minimum number of coherent interferograms (1 by default); G-SBAS and G-TimeFun select pixels that are coherent in all interferograms; while G-NSBAS selects pixels with a predefined total minimum number of coherent interferograms (we use a minimum of 300 out of 475). This leads to differences in the spatial measurement coverage between the four
approaches (Fig. 2.16e-h). Compared with G-SBAS and G-TimeFun, MintPy has better coverage within the calderas of Alcedo and Fernandina and along Alcedo’s flank. G-NSBAS has the best spatial coverage among all approaches. The spatial coverages are shown by the distribution of the number of interferograms for pixels selected by the four approaches (Fig. 2.16a-d).

**2.7.5.2 Weighted Network Inversion**

MintPy uses weighting (the inverse-variance by default) during the network inversion while the other three approaches in GIAnT do not. The impact on the estimated displacement time-series is not negligible when there is significant quality variation among the observations. One example is the displacement time-series of the low coherent pixel B in Fig. 2.16i. This is confirmed by the nearly identical result between G-NSBAS and MintPy without weighting (see supp. Fig. A.9a). Note that the asymmetric red grids along the horizontal black grids in Fig. 2.16j indicate the masked out interferogram due to spatial coherence thresholding, thus, only MintPy and G-NSBAS give estimation results.

**2.7.5.3 Unwrapping Error Correction**

MintPy supports bridging and phase closure methods to correct unwrapping errors in the interferograms, which GIAnT does not. Unwrap errors introduce bias in the estimated phase ramps and displacement time-series. One example is the difference of the displacement time-series on pixel C in Fig. 2.16i between MintPy and G-(N)SBAS. This is confirmed by the nearly identical result between G-(N)SBAS and MintPy without unwrapping error correction (see supp. Fig. A.9b). The bias introduced by unwrapping
errors is also evident in the velocity field at the west side of Fernandina volcano (Fig. 2.16e-h).

2.7.5.4 No Deformation Model

MintPy and G-SBAS do not assume temporal deformation model in network inversion. G-NSBAS and G-TimeFun require temporal deformation models: G-NSBAS uses the model only when the network is not fully connected in order to link multiple subsets of interferograms; while G-TimeFun requires over-complete, potentially redundant models, which can be added manually by user (Agram et al., 2013; Hetland et al., 2012). Thus, with the default configuration in this case, G-TimeFun did not resolve the displacement jump due to the September 2017 Fernandina eruption (pixel C in Fig. 2.16i).

2.7.5.5 Reliable Pixel Selection

In contrast to approaches in GIAnT, MintPy assesses the quality of the inverted phase time-series using temporal coherence and masks out unreliable pixels (gray area in Fig. 2.16a). We note that a higher temporal coherence threshold (0.8 instead of the default 0.7) is used because the spatial coherence thresholding reduces the number of interferograms for unreliable pixels, bringing up the temporal coherence value.

Table 2.1. Summary of the differences of time-series analysis approaches in MintPy and GIAnT. All approaches use small baseline network of unwrapped interferograms and linear optimization time-series estimator.

<table>
<thead>
<tr>
<th>Aspect</th>
<th>MintPy</th>
<th>G-SBAS</th>
<th>G-NSBAS</th>
<th>G-TimeFun</th>
</tr>
</thead>
<tbody>
<tr>
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<td>a minimum number of coherent</td>
<td>coherent in all interferogram</td>
<td>a total minimum</td>
<td>coherent in all interferograms</td>
</tr>
<tr>
<td></td>
<td>interferograms for every acquisition</td>
<td>s</td>
<td>number of coherent interferograms</td>
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<td>-------------------------------------</td>
<td>---</td>
<td>----------------------------------</td>
<td></td>
</tr>
<tr>
<td>weighted inversion</td>
<td>yes</td>
<td>no</td>
<td>no</td>
<td></td>
</tr>
<tr>
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<td>bridging / phase closure</td>
<td>no</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>posterior quality assessment</td>
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<td>no</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>prior deformation model</td>
<td>no</td>
<td>no</td>
<td>yes</td>
<td></td>
</tr>
<tr>
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<td>time-series domain</td>
<td>interferogram domain</td>
<td>interferogram domain</td>
<td>interferogram domain</td>
</tr>
</tbody>
</table>

**Figure 2.16.** Comparison of MintPy with GIAnT approaches for the Sentinel-1 dataset for the Galápagos. (a-d): Distribution of the number of interferograms for pixels used.
(number of pixels for each interferogram bin) by the four time-series approaches on the entire Isabela and Fernandina islands in log scale. Gray area in (a): unreliable pixels (pixels processed but discarded because of low temporal coherence). (e-h): LOS velocity estimated from the displacement time-series produced by the four time-series approaches on Fernandina and Alcedo volcano. Velocities are wrapped into [-2, 2] cm/yr for display. Black squares: reference point. (i): Displacement time-series for pixels marked in (e-h). (j): Coherence matrix for pixels in (i) (rotated to make the matrix diagonal line horizontal; only showed the main diagonal and the five diagonals below and above; only showed the data from 7 May 2017 - 19 June 2018). The lower and upper half: interferograms before and after phase masking, respectively. The asymmetric red grids between the upper and lower half for pixel B indicate masked out interferograms with spatial coherence < 0.25.

2.8 Conclusion

We have reviewed the mathematical formulation for the weighted network inversion and for the post-inversion phase corrections for time series analysis of small baseline InSAR stacks. In contrast to some persistent scatterer methods, the presented approach does not require prior deformation models or temporal filtering and is therefore well suited to extract nonlinear displacements. Reliable pixels are identified using the temporal coherence. Noisy acquisitions with severe atmospheric turbulence are identified using an outlier detection method based on the median absolute deviation of the residual phase RMS and are excluded during the estimations of topographic residual and average velocity.

Our workflow includes two methods to correct for, and one method to exclude remaining phase-unwrapping errors. The first unwrapping error correction method is bridging. This method uses MST bridges to connect the reliable regions of each interferogram, assuming that the phase differences between neighboring regions are less than π rad in magnitude. This method is particularly well-suited for islands and/or areas with steep topography. The second method is the phase closure method. This method
exploits the conservativeness of the integer ambiguities of interferogram triplets. A sparse solution for the phase-unwrapping integer ambiguity is obtained using the $L^1$-norm regularized least squares approximation. Coherent phase-unwrapping errors can be identified using the distribution of the number of triplets with non-zero integer ambiguity of the closure phase. Best results are obtained by combining these two methods.

The method to exclude remaining coherent phase-unwrapping errors is coherence-based network modification. In this approach affected interferograms are identified and excluded using a threshold of average spatial coherence calculated over a customized area of interest that includes the low coherent areas surrounding the areas with coherent phase-unwrapping errors.

We have applied the routine workflow to ALOS-1 and Sentinel-1 data acquired over the Galápagos volcanoes. The InSAR results show very good agreement with independent GPS measurements. A comparison with the algorithms implemented in the GIAnT software shows similar performance in the high coherent areas but superior performance in the low coherent areas and the high coherent areas with phase-unwrapping errors or complex displacement because of unwrapping error correction, weighted network inversion, initial and reliable pixel selection using temporal coherence.

We investigated how some configurations of the routine workflow affect the precision and accuracy of the InSAR measurement using real and/or simulated data. The conclusions are:

1. Inverse-variance weighting gives the most robust and one of the best performances for network inversion among four different weighting functions: uniform, coherence, inverse-variance and Fisher information matrix.
2. For interferogram networks with 3, 5 and 10 sequential connections, the phase closure method fully corrects for phase-unwrapping errors if less than 5, 20 and 35% of the interferograms are affected by phase-unwrapping errors, respectively (with maximum errors of 2 cycles). This shows that the phase closure method performs better for more redundant networks.

3. Increasing the network redundancy improves the network inversion and the estimation of temporal coherence (as long as phase-unwrapping errors have been corrected or excluded), resulting in more accurate estimation of the displacement time-series and identification of reliable pixels. Thus, we recommend using more connections in sequential networks, and to use larger temporal and perpendicular baselines in small baseline networks.

4. The order of the InSAR-data-dependent phase corrections (the empirical tropospheric delay correction based on the delay-elevation ratio, topographic residual correction and phase deramping) is interchangeable and has negligible impact on the noise-reduced displacement time-series.

5. Temporal coherence is a more robust reliability measure than average spatial coherence because it accounts for phase-unwrapping errors. However, it does not capture temporal variations of the reliability of the phase time-series, limiting its usefulness for partially coherent scatterers.

2.9 Computer Code Availability

The presented workflow is implemented as the Miami INsar Time-series software in PYthon (MintPy), with open-source code, documentation, tutorials in Jupyter Notebook.
and test data freely available on GitHub (https://github.com/insarlab/MintPy) under GNU Generic Public License version 3. Figures in this manuscript are plotted using Jupyter Notebook and available on GitHub (https://github.com/geodesymiami/Yunjun_et_al-2019-MintPy). Time-series products from the routine workflow in this manuscript are available at https://zenodo.org/record/3464191 and displayed at https://insarmaps.miami.edu.

2.10 Acknowledgments

The Sentinel-1 and ALOS-1 data were provided by ESA and JAXA, respectively, and obtained from Alaska Satellite Facility (ASF) via the Seamless SAR Archive (SSARA), a service provided by the UNAVCO facility. The ownership of ALOS-1 data belongs to JAXA and the Ministry of Economy, Trade and Industry. GPS data was provided by the University of Nevada, Reno. We thank Yunmeng Cao and Sara Mirzaee for discussions, Xiaohua Xu for pointing us to the sparse solution of the integer ambiguity of the closure phase. We thank undergraduate students Joshua Zahner, David Grossman and Alfredo Terrero for code contributions. The software is based on the initial code by Noel Gourmelen and Scott Baker. This work was supported by NASA Headquarters under the Earth and Space Science Fellowship program (Grant No. NNX15AN13H), the NISAR Science Team (Grant No. NNX16AK52G) and National Science Foundation’s Geophysics program (Grant No. EAR1345129). Part of the research was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration.
3.1 Summary

We use interferometric synthetic aperture radar (InSAR) time series analysis of L-band SAR data spanning the years from 1992 to 2019 to resolve the volcanic and anthropogenic deformation in Kyushu, southwest Japan. Our survey reveals regional deformation in 2 volcanoes (Kirishima and Aira caldera), localized deformation in 5 volcanoes (Kuju, Aso, Unzen, Kirishima and Sakurajima). The volcanic deformation is attributed to the magmatic movement (Aira, Sakurajima, Kirishima), hydrothermal fluid migration (Kirishima), magma cooling and crystallization (Unzen, Aso) and subsidence of the lava flow deposit (Sakurajima). One more sentence on the interpretation of volcanic deformation.

Subsidence is detected near Hatchobaru and Yamagawa geothermal power plant caused by water pumping. Land subsidence is detected in the reclaimed land in Isahaya Bay and in the natural gas field near Miyazaki. Two more sentences on the statistical behavior from mass data analysis.

3.2 Background

Kyushu volcanoes have the potential of catastrophic risk to millions of people’s lives (Tatsumi and Suzuki, 2014). Deformation observations of volcanoes have been primarily from continuous GNSS network, GNSS campaign, tiltmeter and differential InSAR.
However, comprehensive mapping using InSAR time-series technique has not been applied to Kyushu volcanoes yet. The lack of continuous displacement measurement could lead to missed detections of deformation signals, especially in areas without dense ground instruments and to poorly constrained solution for complex temporal evolution of volcanic systems.

There are typically 28 scenes of ALOS-1 SAR images per frame for both ascending and descending passes covering the entire southwest Japan, compared to typically 22 scenes of images with only ascending pass available for the other places of the world. Thus, time series analysis in Kyushu is expected to have higher redundancy of observations.

### 3.3 Tectonic and Volcanic Setting

Kyushu is seated in the Amurian Plate where the Philippine Sea Plate is subducted underneath at Ryukyu Trench and Nankai Trough to the northwest at a rate of $\sim 7 \text{ cm/yr}$ (Wallace et al., 2009). Active volcanism in Kyushu is driven by the tectonic subduction with a clear volcanic front and sporadic back-arc rifting (Chapman et al., 2009). All active volcanoes in Kyushu are located within two grabens: Beppu-Shimabara graben in the center and Kagoshima graben in the south.
**Figure 3.1.** Tectonic and volcanic setting of Kyushu Island. Red solid line indicates the volcanic front. Red dashed lines mark the caldera boundaries. Black solid line for fault; black dashed line for the active graben. Inset on the top left shows the location of Kyushu Island. Insets on the right show the SAR data used in this study.

### 3.4 Data and Method

#### 3.4.1 InSAR Time Series Analysis

To survey 40,000 km² over Kyushu volcanic area, we use ~6 years (1992 to 1998) of JERS descending acquisitions, ~5 years (2006 to 2011) of ALOS-1 ascending and
descending acquisitions and ~5 years (2014-2019) of ALOS-2 ascending and descending acquisitions (Fig. 3.1b-f). Over 900 SAR images are processed to produce ?? interferograms. All SAR images are operated at L-band, which enables ground deformation mapping at highly vegetated area [Sandwell et al., 2008], providing consistent measurement without spatial and temporal gaps.

3.4.2 Modeling of Volcanic Pressure Sources

Since all signals we found have both ascending and descending observations available, some of them with two adjacent tracks of ascending and descending data, 2.5 or 3-dimensional displacement decomposition is possible. This allows us to joint invert observations from multiple viewing geometries to robustly invert the pressure source parameters. CDM model may work for most cases.

3.5 Results

First, we present the results for Kyushu Island in the form of average quais-vertical velocity map (Fig. 3.2) obtained from ascending and descending ALOS-1 data. This map allows the identification of areas with volcanic and anthropogenic deformation. Second, we present for each identified deformation signal the map of cumulative quasi-vertical displacement and LOS displacement time-series, which represent either ground motion, atmospheric delays. Positive LOS displacements represent motion toward the satellite (uplift).

We detect five volcanoes with significant deformation: Kuju, Aso, Unzen, Kirishima and Aira caldera. No clear deformation is observed at Yufu-Tsurumi and Yonemaru Sumiyoshi. Ambiguous LOS range change is observed at Kaimon in Ata caldera.
We detect three geothermal fields with subsidence: Hatchobaru geothermal power plant near Kuju volcano, Yamagawa geothermal power plant near Ata caldera and Yunotani Nagano hot spring within Aso caldera. Subsidence are also observed in two urban areas: the reclaimed land in Isahaya Bay and the natural gas field in the coastal area of Miyazaki.

Figure 3.2. Summary of localized deformation in Kyushu Island.
3.5.1 Deforming Volcanoes

We detect five out of eight volcanoes in Kyushu are actively deforming (Fig. 3.3).

Figure 3.3. Deforming volcanoes in Kyushu.
3.5.1.1 Kuju

Mt. Hoshisho in Kuju has been subsiding in a linear rate of 2-3 cm/year. The localized deformation pattern suggests a shallow pressure source.

Figure 3.4. Subsidence in Mt. Hoshisho, Kuju.
3.5.1.2 Aso

We observed obvious subsidence in Nada-dake, Aso only since the early 2011 of ~5 cm. The deflation might be caused by the hydrothermal reservoir at depths of 1-1.5 km beneath the crater (Kenashima et al., 1996).

Aso had Strombolian explosions from November 2014 to February 2015 (Zobin and Sudo, 2017). Liquefaction-induced horizontal displacement are observed in the Aso Valley during the 2016 Kumamoto earthquake, along with the tectonic crustal deformation by the earthquake (Fujiwara et al., 2017).

3.5.1.3 Unzen

Unzen volcano is located ~70 km behind the volcanic front of the southwest Japan arc. Volcanism might be due to the upwelling of mantle in the back-arc. Unzen had a dome-forming eruption in 1990-1995. Preceded by a small phreatic eruption in November 1990 after about 200 years of dormancy, the 1990-1995 eruption at Unzen volcano began with phreatomagmatic eruptions in February 1991 and developed into a
dacite dome eruption eruption in May 1991 that lasted for four years (Nakada et al., 1999). The inflation during the phreatic and phreatomagmatic stage and deflation after growth of the lava dome are observed from campaign GPS measurements, which has been modeled as a point source about 6 km west of the active crater at a depth of 11 km. Magma intrusion in Unzen occurred in December 1989 at the latest (Nishi et al., 1989). Subsidence around the lava dome after the pyroclastic flow ceased has been detected from InSAR using JERA-1 data (Takeuchi et al., 2001). More from Lamb et al., 2015.

Fugen-dake has been subsiding at a linear rate of 4.4 cm/year from 1992 to 1998 and decayed to a rate of -2 cm/year from 2006 to 2011.

![Figure 3.6. Deformation at Unzen volcano.](image)

**3.5.1.4 Kirishima**

Kirishima had its first magmatic eruption in January 2011 after about 300 years of dormancy. We observed 5-7 km of pre-eruptive inflation and co-eruptive deflation on the western flank of the volcanic complex from ALOS-1 ascending track 424. Localized deflation around the crater of Shinmoe-dake is also observed between the 2008 and 2010
phreatic eruptions (Yunjun et al., 2019, submitted). The observed magmatic inflation and deflation can be modeled as a sill at a depth of 10 km.

Figure 3.7. Deformation at Kirishima volcano group.

3.5.1.5 Aira caldera

We observed diverse deformation patterns around Aira caldera. The caldera rim has been inflating at a rate of ~1 cm/year around the coast of Kagoshima Bay. Sakurajima, the resurgent dome, has variable deformation patterns. The northern flank has been inflating since September 2009 until at least May 2011. The Showa crater, the youngest volcanic center of Sakurajima had a dike intrusion event in 15 August 2015 (Morishita et al., 2016) and might have additional dike intrusion events between November 2009 and January 2010 (Fig. 3.10b). Kita-dake has been subsiding at a linear rate of 1.3 cm/year. The Kurokami lava flow on the eastern flank of the volcano is subsiding at a rate of 0.6 cm/year due to the lava cooling effect.
3.5.2 Subsidence at Geothermal Fields

We detect subsidence in the two largest geothermal power plants in Kyushu Island: the Hatchobaru geothermal power plant near Aso and Yamagawa geothermal power plant (Fushime geothermal field) near Ata caldera. No obvious subsidence is observed in the other geothermal power plants.
3.5.2.1 Hatchobaru Geothermal Power Plant

The Hatchobaru geothermal power plant is located on the west of Kuju volcano and within the Beppu-Shimabara graben. The Hatchobaru No. 1 and 2 unit and the Ohtake geothermal power station 2 km north has generated 122.5 MW of peak power. The geothermal reservoir is located at depths of 500-1500 below the surface in high permeable zones along faults. Pressure decrease in the reservoir has been observed by gravity during 1990-1992, by GPS during 1998-99 and by InSAR during 2007-2010 (Saito et al., 2006; Ishitsuka et al., 2016).

Here we confirm the subsidence with ALOS-1 datasets from different viewing geometry to show the three-dimensional ground deformation at the geothermal field.

Figure 3.10. Deformation at Hatchobaru geothermal power plant from ALOS-1.
3.5.2.2 Yamagawa (Fushime) Geothermal Power Plant

The Yamagawa geothermal power plant is located in the Fushime geothermal field and has generated 30 MW of peak power (Okada et al., 2000). The power plant has been subsiding at a rate of 1 cm/year during 2006-2011.

Figure 3.11. Subsidence at Yamagawa geothermal power plant.

3.5.2.3 Yunotani Nagano Hot Spring

The hot spring (onsen) of Yunotani has been subsiding in a near-linear rate of -1.5 cm/year during 2007-2011.

Figure 3.12. Subsidence near Yunotani Nagano hot spring near Aso.
3.5.3 Land Subsidence at Urban Areas

3.5.3.1 Isahaya Bay Land Reclamation

Isahaya Bay has been cut off water from the Ariake Sea by a 7 km seawall since 1997. The Isahaya tidal flat was drained. Initiated in 1986 and completed in 2008, the construction of this seawall by the government has caused conflicts for twenty years between the fishermen, seaweed collectors and conservationists against farmers for the reclaimed land for agriculture (Ota, 2018). We observed near-linear subsidence rate of 2 cm/year from 1992-1998 and of 0.8 cm/year from 2007-2011 in the reclaimed tidal land.

Figure 3.13. Subsidence of the reclaimed land in Isahaya Bay.
3.5.3.2 Miyazaki Natural Gas Field

The observed 1-2 cm/year of subsidence in the coastal area of Miyazaki Plain is likely due to the continued subsidence caused by water pumping from the exploration of the natural gas field, back in 1989 (Esaki et al., 1991).

![Figure 3.14](image)

**Figure 3.14.** Subsidence in the natural gas field in the coastal area of Shimotonda, Miyazaki.

3.5.4 Ambiguous Signals

Ambiguous LOS decrease has been observed in Kaimon from both ascending and descending orbit of ALOS-1 data (Fig. 3.11). The LOS decrease could be caused by shadowing on the back-slope of the mountain in the line-of-sight direction of the satellite, or due to east-west ground displacement, which, however, cannot be distinguished from the stratified tropospheric delay due to its correlation with topography.

3.6 Conclusion

We have observed edifice-wide deformation in two volcanoes: Kirishima and Aira caldera and localized deformation in five volcanoes: Kuju, Aso, Unzen, Kirishima and Sakurajima. Several types of causes have been identified for volcanic deformation,
including the magma movement beneath Aira caldera, Sakurajima and Kirishima; hydrothermal fluid migration beneath Kirishima; magma cooling and crystallization at Unzen and subsidence of the lava flow deposit in Sakurajima.

We also detected subsidence in the Hatchobaru and Yamagawa geothermal power plant and subsidence in the reclaimed land in Isahaya Bay and in the natural gas field in Miyazaki coast area.

### 3.7 Data and Code Availability

All final displacement time-series and velocity are available on Zenodo in HDF-EOS5 and Google Earth KMZ format and displayed at https://insarmaps.miami.edu. Figures in the paper is plotted using GMT and Matplotlib in Jupyter Notebook, available on GitHub: https://github.com/geodesymiami/Yunjun_et_al-2020-Kyushu

### 3.8 Acknowledgments

The ALOS-1 and ALOS-2 data are provided by the Japanese Space Agency (JAXA) and the Japanese Ministry of Economy, Trade and Industry (METI) and made available by the PALSAR Interferometry Consortium to Study our Evolving Land surface (PIXEL) under a cooperative research contract with the Earthquake Research Institute, University of Tokyo. We thank JAXA for providing JERS data; GSI for providing DEM data. This work was supported by NASA Headquarters under the Earth and Space Science Fellowship program (Grant No. NNX15AN13H), the NISAR Science Team (Grant No. NNX16AK52G) and National Science Foundation’s Geophysics program (Grant No. EAR1345129).
Chapter 4. Shallow Hydrothermal and Magmatic Pressurization at Kirishima Volcanic Complex, Japan Constrained by InSAR

4.1 Summary

Phreatic eruptions are caused by the pressurization of the subsurface hydrothermal system at shallow levels. Compared with typical magmatic eruptions, phreatic eruptions are relatively small but can be very hazardous. However, due to the small and localized signal, geophysical monitoring is difficult. Here we show deformation measurements in the Kirishima volcanic complex from ALOS-1/2 interferometric synthetic aperture radar (InSAR) time-series during 2007-2019. Shinmoe-dake deflated 6 cm prior to its last phreatic eruption in July 2010, inflated 5 cm prior to its October 2017 magmatic eruption and deflated again after its March-June 2018 magmatic eruption. The deflation and inflation can be modeled as an ellipsoid at depths of 700-800 m a.s.l. with volume changes of -140 ± 40 and 80 ± 50 × 10^3 m^3, respectively. Iwo-yama inflated 20 cm within the crater during the whole time period and expanded the inflation to the southern and western vent of 7 cm since December 2017. The inflation can be modeled as a sphere on top of an ellipsoid at depths of 1180 m and 950 m a.s.l. with a volume change of 80 ± 40 × 10^3 m^3, which can be interpreted as fluid accumulation within a hydrothermal reservoir and volume increase due to the liquid-gas transition. The ongoing expanded inflation indicates continuous fluid accumulation beneath Iwo-yama, posing a potential threat of a future eruption.
4.2 Background

Ground deformation at volcanoes reflect pressure changes within the subsurface volcanic systems which can be caused by magma movement at depth (Sigmundsson et al., 1992; Amelung et al., 2000), magma cooling and crystallization (Caricchi et al., 2014), fluid migration from a hydrothermal reservoir (Battaglia et al., 2006; Fournier and Chardot, 2012), surface loading (Ofeigsson et al., 2011) and crustal extension (Dzurisin et al., 2002). Magmatic eruptions at Shinmoedake, Kirishima, occurred in 2011, 2017 and 2018 after about 300 years dormancy, with a series of precursory phreatic eruptions in 2008 and 2010 (Geshi et al., 2010; Nakada et al., 2013). Although the pre-, co- and post-eruptive deformation of the 2011 magmatic eruption has been studied using tiltmeter, GPS and interferometric synthetic aperture radar (InSAR) observations (Ueda et al., 2013; Nakao et al., 2013; Miyagi et al., 2013; 2014).

Phreatic eruptions are generally thought to be related to the heat transfer from magma to groundwater and the subsequent eruption of steam and country rock, usually without fresh magma (Germanovich and Lowell, 1995). Phreatic eruptions can be highly dangerous when they occurred close to densely populated areas, as evidenced by the 1979 Dieng eruption in Indonesia with 149 casualties (Le Guern et al., 1982) and the 2014 Ontake eruption in Japan with 58 casualties (Yamaoka et al., 2015). Unlike magmatic and phreatomagmatic eruptions, phreatic eruptions usually have localized deformation signal with relatively small magnitude, making geophysical monitoring challenging and relevant studies scarce.
In this study we report InSAR observations of deformation on the Kirishima volcanic complex from 2007 to 2011 and from 2014 to 2019. We estimate the location, geometry and volume change of the pressure sources. Combined with observations from seismicity, resistivity and petrology, we update the picture of the plumbing system of the central Kirishima volcanoes.

4.3 Geological Setting

The Kirishima volcanic complex (Japanese for foggy mountain) in southern Kyushu lies in the northernmost portion of the Kagoshima graben. Volcanism is due to the subduction of the Philippine Sea Plate beneath the Amurian Plate (Wallace et al., 2009). The complex consists of more than 25 craters, cones and lava domes produced by the southward migration of eruption centers in the last 330 ka (Fig. 4.1; Nakada et al., 2013). These volcanic centers form an elliptical 30 by 20 km northwest trending zone with younger volcanism generally in the southeast (Chapman et al., 2009). The most active eruptive centers are Shinmoe-dake, Iwo-yama, and Ohachi (altitudes of 1,313 m, 1,421 m and 1,408 m, respectively). Hydrothermal systems are widely distributed in shallow levels throughout Kirishima (Aizawa et al., 2014; Kagiyama et al., 1996; Uchida and Sasaki, 2006).

The 2011 Shinmoe-dake eruption was the first magmatic eruption in the complex after about 300 years. Previous eruptions at Shinmoe-dake in 1822, 1959 and 1991 were phreatic and not followed by magmatic eruptions (Imura and Kobayashi, 1991; Tsutsui et al., 2005). Iwo-yama, the youngest volcanic center, was formed in the 16th-17th century
and had a phreatic eruption in 1768 (Tajima et al., 2014). Ohachi had a series of eruptions between 1880 and 1923 (GVP, 2013).

Figure 4.1. Geological setting of Kirishima volcanic complex. Inset: location of Kirishima in red. Dashed thick black circle: horizontal location of deep magmatic pressure source from Nakao et al. (2013). Blue solid lines: cross section of Fig. 4.5. Empty squares: GPS sites.

4.4 The 2008–2019 Activity

The recent unrest of Shinmoe-dake started with a substantial increase in seismicity three days before the first phreatic eruption on 22 August 2008 when a lake was present in the crater (Geshi et al., 2010) and additional phreatic eruptions from March to July 2010 (dashed blue line/box in Fig. 4.2a). The 2011 eruption started with a phreatomagmatic eruption on 19 January 2011 and three sub-Plinian eruptions on 26-27
January, followed by stages of lava extrusion, Vulcanian and phreatomagmatic eruptions until September 2011 (Geshi et al., 2010; Nakada et al., 2013). Shinmoe-dake had new magmatic eruptions on 11-17 October 2017 and 1 March to 27 June 2018 (dashed orange line/box in Fig. 4.2a; GVP, 2013).

In December 2009, more than 1 year after the first phreatic eruption, GPS and InSAR data showed inflation over the western flank of the volcanic complex that was attributed to an inflating pressure source ~5 km northwest of Shinmoe-dake at ~10 km depth (dashed black circle in Fig. 4.1; Nakao et al., 2013; Miyagi et al., 2013). The source deflated during the climactic phase of the 2011 Shinmoe-dake eruption and re-inflated until November 2011 (Nakao et al., 2013; Ueda et al., 2013).

About an hour and a half prior to the first sub-Plinian eruption tiltmeter and broadband seismometer recorded localized inflation near the crater suggesting a shallow pressure source (Takeo et al., 2013). In the following two weeks this source underwent a sequence of inflation-deflation cycles during the sub-Plinian, lava accumulation and Vulcanian stages. The deformation signals, synchronized with volcanic tremor or long-period events, were attributed to the pressurization of a shallow conduit beneath the crater (Nakamichi et al., 2013; Takeo et al., 2013). Localized deflation and inflation patterns were also observed from November 2011 to May 2013 and prior to the 2017 magmatic eruption (Miyagi et al., 2014; Morishita and Kobayashi, 2018).

The recent unrest of Iwo-yama started with an increase in seismicity in December 2013, followed by tremors in August 2014, thermal anomalies and weak fumarolic activity since December 2015, small phreatic eruptions on 19-27 April 2018 with new vents appearing on the southern and western side of the crater. Fumarolic activity and
mud ejection continued from the southern and western vent as of September 2019 (JMA, 2019).

Figure 4.2. 2008-2019 geophysical observations for Kirishima volcanic complex. (a) Monthly number of earthquakes (GVP, 2013; Nakada et al., 2013). (b) Baseline change between GEONET GPS stations 950486 and 960714 (marked as black empty squares in Fig. 4.1). (c-e) Quasi-vertical displacement for time periods with distinct signal at Shinmoe-dake: (c) between the 2008-2010 phreatic eruptions, (d) before and (e) after the October 2017 magmatic eruption. (f) Line-of-sight (LOS) displacement time-series for Shinmoe-dake and Iwo-yama in direction from ALOS-1/2 descending orbit (positive displacement indicates motion toward the satellite). Data are wrapped into [-5, 5] cm for display. Black squares: reference point. Blue dotted and orange dashed lines/boxes: phreatic and magmatic eruption time period of Shinmoe-dake, respectively. Blue solid box: phreatic eruption time period of Iwo-yama. Black dots in (c-e): locations of points shown in (f). Black square in (c-e): reference point. Contour lines in (c-e) every 100 m. Empty triangles in (f): noisy acquisitions excluded from the average velocity estimation.
4.5 Data and Analysis Approach

We use 2006-2011 ALOS-1 (ascending track 424 and descending track 73) and 2014-2019 ALOS-2 (ascending track 131 and descending track 23) L-Band stripmap imagery and consider small temporal and spatial baseline interferograms (less than 1800 days and 1800 m for ALOS-1 and less than 400 days and 200 m for ALOS-2; see Table B.1 and Fig. B.1 in the supporting information). To form the interferograms, we resample the ALOS-1 SAR images which are acquired in fine beam dual polarization (FBD) mode with 14 MHz bandwidth to 28 MHz, the bandwidth of fine beam single polarization (FBS) mode. For the ALOS-1 and ALOS-2 interferograms we take 8 by 10 and 4 by 10 looks in range and azimuth directions, respectively; filter using a Goldstein filter with a strength of 0.5, remove the topographic phase using the Digital Ellipsoidal Height Model released by Geospatial Information Authority of Japan (DEHM, 0.4 arc second, ~10 m), and phase-unwrap the interferograms using the minimum cost flow method (Chen and Zebker, 2001). Ionospheric delays are not corrected for.

We use the stripmap stack processor (Fattahi et al., 2017) of the ISCE software (Rosen et al., 2012) for interferogram processing and the Miami InSAR time-series software in Python (MintPy) for time series analysis (Yunjun et al., 2019). We exclude low-coherence interferograms using coherence-based network modification with a custom area of interest around Shinmoe-dake (black empty squares in supp. Fig. B.2) for the average coherence calculation and thresholds of 0.7 for ALOS-1 descending track 73 and 0.8 for the others. We correct for the stratified tropospheric delay (Jolivet et al., 2011) using the ERA-5 global atmospheric reanalysis model (Copernicus Climate Change Service, 2017), for topographic residuals (Fattahi and Amelung, 2013) and for long
spatial-wavelength phase components by removing linear phase ramps from all acquisitions. We use a temporal coherence threshold of 0.8 to eliminate unreliable pixels. Noisy acquisitions with residual phase root mean squares larger than the predefined cutoff (1 and 2 median absolute deviation for ALOS-1 and ALOS-2 dataset, respectively) are excluded during the estimation of topographic residual and average velocity (empty triangles in Fig. 4.2f; supp. Fig. B.7).

To obtain optimal measurement for time periods of interest (Fig. 4.2c-e), we apply two extra steps in addition to the routine MintPy workflow. First, to maximize the number of valid pixels we exclude interferograms with acquisitions after the 2011 and 2017 eruptions, which are decorrelated by local processes inside the crater and/or by the newly deposited ash nearby. Second, to mitigate residual atmospheric turbulence we estimate the average LOS velocities for the time periods of interest and convert them to cumulative displacements instead of using the differential displacement between two acquisitions (see Fig. B.9 in the supporting information for a comparison between the two approaches).

4.6 Results

We obtain the quasi-vertical displacements from ascending and descending data (Wright et al., 2004) during 2006-2019 to examine the deformation at the Kirishima volcanic complex and find five distinct spatial patterns, three at Shinmoe-dake and two at Iwo-yama during three different time periods (Fig. 4.2c-e). Shinmoe-dake deflated ~6 cm between the 2008-2010 phreatic eruptions (blue colors in Fig. 4.2c), inflated ~5 cm prior to the 2017 magmatic eruption (yellow-red colors in Fig. 4.2d) and has been deflating
since the end of the 2018 magmatic eruption (Fig. 4.2e). Iwo-yama does not show any signal before 2011 (Fig. 4.2c) but has been inflating since at least 2015. The deformation is localized and concentrated on the crater area (Fig. 4.2d) during 2015-2017, then expanded to a larger area in December 2017 (Fig. 4.2e), four months prior to the 19 April 2018 phreatic eruption (marked by dark blue solid line in Fig. 4.1d) when new vents appeared on the southern and western sides of the crater.

The line-of-sight (LOS) displacement time-series show temporal details (Fig. 4.2f). At Shinmoe-dake, the eastern crater rim (point A, Fig. 4.2f-bottom left) shows no deformation prior to the 2008 phreatic eruption (marked by blue dashed line) and ~6 cm of linear LOS increase between the 2008-2010 phreatic eruptions; the western crater rim (point B, Fig. 4.2f-bottom right) shows ~4 cm of LOS decrease prior to the 2017 magmatic eruption (marked by orange dashed line in Fig. 4.2f) and a net ~4 cm of near-linear LOS increase after the 2018 magmatic eruption. At Iwo-yama, the crater (point D, Fig. 4.2f-top) shows ~20 cm of near-linear LOS decrease during 2014-2019 while the southern vent (point C, Fig. 4.2f-central) shows no displacements before December 2017 and ~7 cm of LOS decrease afterwards.

Note that the relatively strong localized inflation on the western summit flank of Shinmoe-dake prior to the 2017 eruption (Fig. 4.2d) is likely related to a potentially partially solidified fissure from which the previous 2008-2010 eruptions occurred (Geshi et al., 2010). We don’t interpret the measurements at Shinmoe-dake between the 2017 eruption and the end of the 2018 eruption (blue colors in Fig. 4.2e) because they are affected by signals from the erupted ash.
4.7 Modeling

We use geophysical inverse models to constrain the sources of deformation at Shinmoe-dake during 2008-2010 and 2015-2017 and at Iwo-yama during 2015-2017 and 2017-2019. We assume an isotropic elastic half-space and use the finite compound dislocation model (CDM; Nikkhoo et al., 2016), composed of three mutually orthogonal rectangular dislocations with uniform opening and full rotational degrees of freedom (Nikkhoo et al., 2016), which represents a generic ellipsoid eliminating the need to specify the source geometry such as sphere or ellipsoid. For Shinmoe-dake during 2015-2017 we use the finite spherical source model (McTigue, 1987) because the shape and orientation of the CDM can’t be resolved due to the lack of near field observations (we eliminated data points in the crater affected by local processes). Although hydrothermal processes deform the ground in a thermo-poro-elastic fashion, simple elastic models are well suited to infer the source geometric features for deformation lasts over 5-300 years depending on the dimension (Fournier and Chardot, 2012; Lu et al., 2002). We use a Poisson’s ratio of 0.25.

We account for the elevation effect of the topography using the varying-source depth method (Williams and Wadge, 1998). To ensure that inverted pressure sources are below the free surface we assign low-elevation data points (located in the far field) height values of 1100 m for the Shinmoe-dake and of 1300 m for the Iwo-yama. We can neglect the elastic effect of the topography as all data points are in the summit areas where topographic relief is less than 10°. We convert height values of the GSI DEHM from the ellipsoid to the geoid.
We jointly invert the ascending and descending InSAR LOS displacement measurements using a Bayesian approach as implemented in the GBIS software (Bagnardi and Hooper, 2018). We subsampled the data using a gradient-based adaptive quadtree method (Jónsson et al., 2002; see also Decriem et al., 2010) in the near field and use uniform sampling in the far-field (where the signal-to-noise ratio is low, see supp. Fig. B.10 for the subsampled data). We account for the data uncertainties using unbounded exponential one-dimensional functions with a nugget approximated from data semivariograms (Lohman and Simons, 2005). We use uniform prior PDFs bounded by geologically realistic values. The inversion algorithm samples posterior probability density functions (PDFs) of source model parameters through a Markov chain Monte Carlo method with 1,000,000 iterations. The optimal (maximum a posteriori probability) parameter value and 95% confidence intervals are shown in Table 4.1 and the joint PDFs of the estimated parameters for all models are shown in the supporting information Fig. B.11-14. All model parameters converged well except the radius and dimensionless overpressure of the finite sphere for Shinmoe-dake during 2015-2017 (marked by #). There are trade-offs between some parameters but does not affect the depth and derived volume change.

For Shinmoe-dake, the optimal CDM for the 2008-2010 deflation is a slightly inclined prolate ellipsoid (Fig. 4.3a-e) under the northeastern crater section with centroid at ~640 ± 50 m below the summit (780 m a.s.l., marked as orange stars in Fig. 4.3c-d). For the 2015-2017 inflation the optimal finite sphere is located under the crater center at a depth of ~720 ± 250 m below the summit (700 m a.s.l., marked as blue starts in Fig.
4.3h-i). The estimated changes of the cavity volume for the two time periods are $-140 \pm 40 \times 10^3 \text{m}^3$ and $80 \pm 50 \times 10^3 \text{m}^3$, respectively.

For Iwo-yama, the optimal CDM for the 2015-2017 inflation has equidimensional $\sim 60$ m semi-axes, corresponding to a sphere at a depth of $\sim 130 \pm 10$ m below the summit (1180 m a.s.l.) with an estimated cavity volume increase of $15 \pm 2 \times 10^3 \text{m}^3$. The optimal model for 2017-2019 inflation are two CDMs on top of each other: one finite sphere with fixed geometry and location and free opening bounded by the 95% confidence intervals from the previous time period assuming constant opening rate and one ellipsoid located at a depth of $\sim 360 \pm 80$ m below the summit (950 m a.s.l.) with elongated dimension along the east-west direction. The estimated cavity volume increase is $80 \pm 40 \times 10^3 \text{m}^3$.

**4.8 Discussion**

The InSAR time series have shown for Shinmoe-dake 6 cm of deflation between the 2008-2010 phreatic eruptions and 4 cm of inflation prior to the 2017 magmatic eruption and at Iwo-yama a total of 20 cm of inflation during 2015-2019. We now will address the whether the sources were of hydrothermal or magmatic origin, which has implications for volcanic hazards.

**4.8.1 Depth and Geometry of the Sources**

These deformation patterns can be explained by the pressurization or depressurization of ellipsoidal bodies at shallow depths within the volcanic edifice centered at 130 m below the surface for Iwo-yama to 720 m for Shinmoe-dake. These depths are well constrained (uncertainties of 10 m and 250 m, respectively) as we accounted for the volcano’s topography, but are based on the assumption of elastic
homogeneity. If mechanically weak layers are present the sources are deeper than estimated using the homogeneous models (Manconi et al., 2008).
Figure 4.3. Inversion results of deformation at Shinmoe-dake and Iwo-yama. (a-b) Observed LOS displacement at Shinmoe-dake between 2008-2010 phreatic eruptions from ascending and descending orbit, respectively. (c-d) Predicted displacement for (a-b) from the CDM respectively. Data are wrapped into [-5, 5] cm for display. (e) Profile of observed (empty circles) and predicted (solid lines) displacement (orange for ascending, blue for descending) and the topography (gray filled areas) along the dashed line in (a-d). (f-j) Same as (a-e) but for the displacement in Shinmoe-dake prior to the 2017 magmatic eruption with predicted displacement from finite spherical source. (k-o) and (p-t) Same as (a-e) but for the displacement at Iwo-yama (k-o) during 2015-2017 with one CDM and (p-t) during 2017-2019 with two CDMs, respectively. Black solid circles in (a-d and f-i): Shinmoe-dake crater rim. Orange triangles in (c): main vent of the 2008-2010 phreatic eruptions (Geshi et al., 2010). Orange and blue stars in (c-d) and (h-i): horizontal location of the pressure source centroid. Red solid lines in (o and t): Iwo-yama crater.
Table 4.1. Optimal parameters of compound dislocation or finite sphere source models for two periods at Shinmoe-dake and Iwo-yama as given by the maximum a posteriori probability solution with 95% confidence intervals.

<table>
<thead>
<tr>
<th>Period/model</th>
<th>Shinmoe-dake</th>
<th>Iwo-yama</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Longitude [°]</td>
<td>Latitude [°]</td>
</tr>
<tr>
<td>2008-2010a</td>
<td>130.8844</td>
<td>31.9125</td>
</tr>
<tr>
<td>2015-2017b</td>
<td>130.8826</td>
<td>31.9111</td>
</tr>
<tr>
<td>2015-2017c</td>
<td>130.8532</td>
<td>31.9470</td>
</tr>
<tr>
<td>2017-2019c</td>
<td>130.8530</td>
<td>31.9463</td>
</tr>
</tbody>
</table>

Note: The 95% confidence intervals of longitude and latitude less than 100 m (~0.001°) are not shown. Depth of the model centroid is with respect to mean sea level with positive upward. ωi and αi, i = X,Y,Z are the rotation angle (positive for clockwise) and length of the semi-axis along i axes, respectively. u: uniform opening of the CDM. ΔV is the cavity volume change in 10^3 m^3 with: \(ΔV = 4 \cdot (a_xa_y + a_ya_z + a_xa_z) \cdot u\) for CDM (Nikhoo et al., 2016) and \(ΔV = ΔP/μ \cdot πr^3\) for finite sphere (McTigue, 1987). a compound dislocation model, Nikhoo et al. (2016), b finite-sphere model (McTigue, 1987), c two compound dislocations one of which is fixed using 2015-2017 parameters. # not-converged parameters. *fixed parameters.
At Shinmoe-dake the excellent quality of the 2008-2010 data inside the caldera allows to constrain the geometry of the depressurizing body. We found a near-vertical prolate spheroid with long and short axes of 280 and 180 m, respectively. As for 2015-2017 there is no data inside the caldera, we have hypothesized that the same source was active but with opposite sign. A possible explanation for the prolate source shape is that the material in a previous magmatic conduit can get pressurized.


The 2008-2010 deflation between two phreatic eruptions was almost certainly of hydrothermal origin. Petrological analysis showed that 30-65 vol% of the 2008 erupted material was hydrothermally altered (Suzuki et al., 2013), consistent with magnetotelluric surveys that detected widespread low-resistivity zones at shallow levels, suggesting the presence of water-saturated porous layers (Aizawa et al., 2014; Kagiyama et al., 1996; Uchida and Sasaki, 2006). Most of the deflation occurred prior to the first sign of renewed magmatic activity at Kirishima, which was the onset of inflation of the deep source in December 2009.

A possible mechanism for deflation is the release of hydrothermal fluids by steam emission through cracks which were opened by the 2008 phreatic eruption. The lack of InSAR-detected inflation prior to this and the 2010 phreatic eruption suggests that the pressurization of the hydrothermal system occurred over days to weeks prior to the eruptions and that it was missed by the InSAR sampling (SAR acquisitions were taken X and Y days prior to the two eruptions, respectively). Rapid pressurization of the
hydrothermal system is consistent with the observed increase in the seismicity three days before the 2008 phreatic eruption (Fig. 4.1a; Geshi et al., 2010).

The spatial pattern of inflation prior to the 2017 magmatic eruption was very similar to the 2008-2010 pattern. The depths of the pressure sources at 600-700 m below the summit for these two periods (Fig. 4.4a) is the same as those for the Vulcanian stage of the 2011 magmatic eruption (Takeo et al., 2013) and for the November 2011 to May 2013 magma extrusion period (Miyagi et al., 2014), suggesting a persistent source that was moved a few hundred meters west by processes during the 2011 eruption.

**Figure 4.4.** Marginal posterior density distribution of the depths of pressure sources. (a) Depths of pressure sources beneath Shinmoe-dake for deflation between the 2008-2010 phreatic eruptions, inflation-deflation cycles (error bar) during the Vulcanian stage in February 2011 (Takeo et al., 2013), deflation (empty bar) during the 2011-2013 lava extrusion stage (Miyagi et al., 2014) and inflation before the 2017 magmatic eruption. (b) Depths of pressure sources beneath Iwo-yama for inflation before and after December 2017, respectively. Horizontal line in (b): depth of the fixed CDM from the solution before December 2017. Blue and orange: hydrothermal and magmatic source, respectively.
4.8.3 Cause of Uplift at Iwo-yama

Tsukamoto et al. (2018) observed a low-resistivity layer beneath Iwo-yama at depths between 200 to 800 m below the summit, which they interpreted as a smectite-dominant, low-permeability clay-rich layer with a 200 °C isotherm (inferred from the stability range of smectite) at the bottom. This together with the increased seismicity and fumarolic activity, steam emission, and ejection of hot water and mud at Iwo-yama since 2014 strongly suggests that the observed inflation is a hydrothermal effect, e.g. the accumulation of hydrothermal fluids.

Phase of fluids can be determined based on pressure and temperature conditions using the phase diagram. Considering the steaming and water ejection activity, we assume an open hydrothermal system beneath Iwo-yama with hydrostatic conditions. In this condition, water at 200 °C starts to change from liquid to gas at depths of 150 to 400 m considering pure water or water with 1% mass fraction of CO₂ (Pritchett, 1981). This depth range suggests that shallow pressure source (at ~130 m depth) is created by vaporization of the ascending water (Tsukamoto et al., 2018) and the deeper pressure source (at ~360 m depth) could be the result of increased supply of fluids or phase transition at greater depth because of volatile contents.

4.8.4 Comparing Hydrothermal Systems between Shinmoe-dake and Iwo-yama

The hydrothermal system beneath Shinmoe-dake is different from the one beneath Iwo-yama in three aspects. First, the average volume change rate of the associate phreatic eruptions in Shinmoe-dake (~50 × 10^3 m/year) is higher than the one in Iwo-yama (~20 ×
10 m³/year). Second, the system at Shinmoe-dake lies at greater depth than the one in Iwo-yama (Fig. 4.4). The depth difference might explain the stronger explosivity of phreatic eruptions in terms of earthquake number at Shinmoe-dake compared to Iwo-yama (Fig. 4.2a) because the shallow hydrothermal seal should fail more easily under less overpressure (Stix and de Moor, 2018). Third, the steaming activity in Shinmoe-dake during 2008-2010 is less stable and consistent than the steaming activity in Iwo-yama (Fig. 4.2b), suggesting a more static magmatic input beneath Iwo-yama, e.g. magma cooling and crystallizing rather than magma ascending and decompressing (Stix and de Moor, 2018), implying a declining level of activities.

4.8.5 Conceptual Model of the Plumbing System

Our interpretation of the plumbing system in the central section of Kirishima volcanic complex is summarized in Fig. 4.5. In the shallow level (~800 m a.s.l.) beneath Shinmoe-dake crater, the heat-driven depressurization source was evacuating gas and steam from the nearby hydrothermal system between phreatic eruptions in the August 2008 and July 2010. In the middle of this deflation process, the deep (~10 km a.s.l.) magmatic source beneath Ebino-dake started accumulating fresh magma in December 2009 until the January 2011 Shinmoe-dake eruption (Nakao et al., 2013; Suzuki et al., 2013). The 2011 eruption turned the previous shallow hydrothermal depressurization source into a magma storage unit, causing nearfield inflation/deflation cycles during the climactic phase from 26 January to 10 February 2011 (Takeo et al., 2013) and deflation during the lava extrusion from November 2011 to May 2013 (Miyagi et al., 2014). This shallow source (~800 m a.s.l.) has been accumulating magma since at least January 2015.
and fed the October 2017 and March-June 2018 magmatic eruptions in Shinmoe-dake. Since then, Shinmoe-dake has been subsidencing, indicating weakened volcanic activity.

About 5 km northwest, the shallow (1,180 m a.s.l.) hydrothermal pressure source beneath Iwo-yama has been boiling since at least January 2015. The increased volume due to the liquid-gas transition caused inflation around the crater. About two months after the 2017 magmatic eruption in Shinmoe-dake, increase fluid supply started to accumulate at a slightly greater depth (950 m a.s.l.) or mixing of CO2/SO2 in the pure water brought the liquid-gas transition downward beneath Iwo-yama, causing a precursory inflation in a larger spatial scale four months before the April 2018 phreatic eruption. Instant deflation is observed right after the eruption, then inflation continued. The ongoing expanded inflation indicates continuous fluid accumulation beneath Iwo-yama, posing a potential threat of a future eruption.

Figure 4.5. Schematic cross section of the plumbing system in the central Kirishima. Topography is exaggerated in the vertical direction. Spheres and ellipsoids represent the estimated pressure source with blue for hydrothermal and orange for magmatic. Size is...
based on the dimension of the Shinmoe-dake 2008-2010 deflation solution but scaled to
the estimated volume change with a fixed opening of 0.2 m except for the 2011 eruption,
whose size is scaled with a fixed opening of 2 m.

4.9 Conclusions

We documented five different localized deformation patterns in the Kirishima
volcanic complex during three selected episodes using InSAR time-series observations
from 2006 to 2019: three at Shinmoe-dake and two at Iwo-yama. Small magnitude of
displacement field in the presence of residual atmospheric turbulence and strong
decorrelation noise is derived by excluding interferograms after large eruptions and by
converting the average velocity for the time period of interest into cumulative
displacement.

At Shinmoe-dake, the 6 cm of deflation between the 2008-2010 phreatic eruptions
and the 5 cm of inflation prior to the 2017 magmatic eruption can be explained by a
volume decrease of $140 \pm 40 \times 10^3 \text{m}^3$ from a prolate ellipsoid and by a volume increase of
$80 \pm 50 \times 10^3 \text{m}^3$ from a sphere, respectively, at depths of 780 and 700 m a.s.l., respectively.
The similarity in spatial patterns and depths suggest that the two processes are caused by
the same source, which turned from a hydrothermal reservoir into a magmatic storage
unit during the 2011 magmatic eruption.

At Iwo-yama, the inflation before October 2017 and inflation expansion after
December 2017 can be explained by the pressurization of a small sphere on top of an
ellipsoid elongated in the west-east direction at depths of 1,180 and 950 m a.s.l. (130 and
360 m below the summit), respectively. Combing with resistivity studies, we interpreted
the shallow source as a volume increase due to liquid-gas transition during the
hydrothermal fluid ascending and the deeper source as the result of increased supply of
fluids or phase transition at greater depth because of volatile contents. The ongoing expanded inflation indicates continuous fluid accumulation beneath Iwo-yama, posing a potential threat of a future eruption.

4.10 Data and Code Availability

The InSAR displacement products in this manuscript are available at Zenodo (Link) and displayed in https://insarmaps.miami.edu. Figures are prepared using GMT and Jupyter Notebook, with scripts available on GitHub (https://github.com/geodesymiami/Yunjun_et_al-2019-Kirishima).

4.11 Acknowledgment

The ALOS-1 and ALOS-2 data are provided by the Japanese Space Agency (JAXA) and the Japanese Ministry of Economy, Trade and Industry (METI) and made available by the PALSAR Interferometry Consortium to Study our Evolving Land surface (PIXEL) under a cooperative research contract with the Earthquake Research Institute, University of Tokyo. We thank Jun Oikawa for providing the hypocenter data; François Beauducel for providing the CDM code; We thank the Geospatial Information Authority of Japan for providing the GEONET GPS data and DEM, JMA for providing seismic data. We thank Jamie Farquharson, Heresh Fattahi, Mehdi Nikkhoo and Bhuvan Varugu for discussions. This work was supported by NASA Headquarters under the Earth and Space Science Fellowship program (Grant No. NNX15AN13H), the NISAR Science Team (Grant No. NNX16AK52G) and National Science Foundation’s Geophysics program (Grant No. EAR1345129).
Chapter 5. Conclusions

In this dissertation I developed new algorithms to correct for the phase unwrapping error in stack of interferograms and implemented a generic routine workflow for InSAR time series analysis. I applied the developed method to the ALOS-1 and Sentinel-1 data acquired over Galápagos volcanoes in Ecuador and all available L-band SAR data over Kyushu Island in SW Japan. I combined with geophysical inversion models and other datasets to assess the volcanic risk. The main conclusions of this dissertation are discussed in more details below.

5.1 Unwrapping Error Correction

Phase-unwrapping errors introduces phase offset among different reliable regions in space and breaks the temporal consistency of interferogram triplets in time by introducing a non-zero integer ambiguity. The number of triplets with non-zero integer ambiguity can be used to detect the phase-unwrapping error. Based on these characteristics, two methods are developed.

In space domain, the bridging method uses MST bridges to connect the reliable regions of each interferogram, assuming that the phase difference between neighboring regions are less than $\pi$ rad in magnitude. This method is particularly well-suited for islands and/or areas with steep topography.

In time domain, the phase closure method exploits the conservativeness of the integer ambiguity of interferograms triplets using the sparse solution from the L1-norm
regularized least squares approximation. It’s well suited for redundant network of interferogram when there are not too many phase-unwrapping errors.

To exclude the remaining coherent phase-unwrapping errors, we developed the coherence-based network modification to identify and exclude interferograms using a threshold of average spatial coherence calculated over a customized area of interest. With proper setup, this method could significantly improve the spatial coverage of InSAR time-series measurement.

5.2 Small Baseline InSAR Time Series Analysis

I have reviewed the mathematical formulation for the weighted network inversion and for the post-inversion phase corrections for time series analysis of small baseline InSAR stacks. In contrast to some persistent scatterer methods, this approach does not require temporal deformation models or temporal filtering and is therefore well suited to extract nonlinear displacements. Noisy acquisitions with severe atmospheric turbulence are identified using an outlier detection method based on the median absolute deviation of the residual phase RMS and are excluded during the estimation of topographic residual and average velocity.

Inverse-variance weighting gives the most robust and one of the best performances for network inversion among four different weighting functions: uniform, coherence, inverse-variance and Fisher information matrix.

Increasing the network redundancy improves the network inversion and the estimation of temporal coherence (as long as phase-unwrapping errors have been corrected or excluded), resulting in more accurate estimation of the displacement time-
series and identification of reliable pixels. Thus, we recommend using more connections in sequential networks, and to use larger temporal and perpendicular baselines in small baseline networks.

5.3 Deforming Volcanoes in Kyushu Island

Time series InSAR survey from 1992 to 2019 detects five out of eight active volcanoes in Kyushu Island are deforming with edifice-wide deformation pattern in Kirishima and Aira caldera and with localized deformation pattern in Kuju, Aso, Unzen, Kirishima and Sakurajima. Several types of causes have been identified for volcanic deformation, including the magma movement beneath Aira caldera, Sakurajima and Kirishima; hydrothermal fluid migration beneath Kirishima; magma cooling and crystallization at Unzen and subsidence of the lava flow deposit in Sakurajima.

5.4 Shallow Hydrothermal and Magmatic Pressurization at Kirishima Volcanic Complex

InSAR time-series data from 2006-2019 provide new insights into the shallow volcanic system of the Kirishima volcanic complex, in addition to the well-established deep source. The data show that the summit of Shinmoe-dake deflated 6 cm during 2008-2010 and inflated 4 cm during 2015-2017 while the summit of Iwo-yama inflated a total of 20 cm during 2015-2019. The surface displacement can be explained by the pressurization or depressurization of ellipsoidal bodies at shallow depths within the volcanic edifice centered at 640 and 720 m beneath the summit of Shinmoe-dake and at 130 and 360 m beneath the surface of Iwo-yama.
The replacement of previous hydrothermal system by magmatic body at Shinmoe-dake highlights the potential threat of phreatic eruptions. The detailed mapping of ground deformation demonstrates the power of high-resolution observation from InSAR for volcanic risk assessment.
References


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Zhao, W., 2017, Small Deformation Detected from InSAR Time-Series and Their Applications in Geophysics, Dissertation thesis, 153 pp, University of Miami, Miami, FL.

Appendices

A1. Supplemental Figures and Tables for Chapter 2

This section provides figures A.1 to A.11 and table A.1 to A.2. Fig. A.1 shows the standard deviation of the interferometric phase as a function of the spatial coherence and number of looks. Fig. A.2 demonstrates the performance of four weighting functions in different temporal decorrelation settings using the mean RMSE of 10,000 realizations of the inverted phase time-series as a function of the number of looks. Fig. A.3 demonstrates the simulation of the unwrapped interferogram for unwrapping error correction with the bridging method, considering the ground deformation, tropospheric turbulence, phase ramps and decorrelation noise. Fig. A.4 shows the output percentage of interferograms with unwrapping errors as a function of the LASSO parameter to find its suitable value range. Fig. A.5 demonstrates the necessity of adding the step function during the topographic residual correction in the presence of displacement jump using both simulated and read data. Fig. A.6 shows the coherence matrix of Sentinel-1 dataset for GPS stations within Sierra Negra. Fig. A.7 shows the estimated residual phase time-series. Fig. A.8 shows the coherence-based network modification for the Sentinel-1 data used in the discussion of the network redundancy in section 2.7.3. Fig. A.9 compares the displacement time-series from the approaches in GIAnT and MintPy with and without unwrapping error correction and weighted network inversion. Fig. A.10 shows the average velocities estimated from displacement time-series with different tropospheric delay corrections using customized recipe with individual MintPy scripts. Fig. A.11 demonstrates the spatial filtering tool in MintPy.
Fig. A.12 demonstrates the interferometric pair selection tool in MintPy. The SAR data information used in the paper is summarized in Table A.1. All stand-alone scripts included in the software is listed in Table A.2.

Figure A.1. Phase standard deviation versus spatial coherence for PS and DS. Related to equation (2.6). (a) Standard deviation of interferometric phase as function of coherence for DS (solid lines) and PS (dashed lines) with 1, 4 and 20 looks. The black dashed line marks the effective boundary for PS ($0.9 < |\gamma| \leq 1$). (b) Lookup table to convert spatial coherence to phase standard deviation for number of looks in [1, 80].
Figure A.2. Performance indicator for four weighting functions based on (left panel) the mean RMSE of 10,000 realizations of inverted phase time-series as a function of the number of looks. Related to Fig. 2.1. Right panel: same as left panel but shown in differential RMSE with respect to inverse-variance weighting. From top to bottom for different temporal decorrelation settings.
Figure A.3. Simulate interferogram for unwrapping error correction with the bridging method. Related to Fig. 2.2. We consider an area of 300 by 300 pixels with spatial resolution of 62 m in both directions, illustrated by radar echoes in a Sentinel-1-like geometry in descending orbit (with an incidence angle of 34 deg and heading angle of -168 deg). (a) Deformation phase caused by a Mogi source (x = 120 row, y = 120 col, z = 2 km under the surface with a volume change of $10^6$ m$^3$), (b) tropospheric turbulence modeled as an isotropic two-dimensional surface with a power law behavior (the multiplier of spectrum amplitude $p0=1e-3$, assuming a flat area without stratified tropospheric delay; Hanssen, 2001), (c) phase ramp modeled as a linear surface, and (d) simulated decorrelation noise (see section A3). The water body mask is rescaled from the real DEM in western Kyushu, Japan. We specify the spatial coherence of 0.6 and 0.001 for pixels on land and water respectively with the number of looks of 15 by 5.
**Figure A.4.** Optimal LASSO parameter $\alpha$. Related to equation (2.11) and Fig. 2.4. Mean output percentage of 100 realization of interferograms with unwrapping errors after correction as a function of the nonnegative $\alpha$ value for different input percentage of interferograms with unwrapping errors. The network of interferograms is the same as Fig. 2.4a. The simulation result shows that any number of $\alpha$ in $[10^{-4}, 10^0]$ works. We choose $10^{-2}$ as default value.
Figure A.5. Illustration of the step function in topographic residual correction in presence of displacement jumps. Related to equation (2.13) in section 2.5.6. (a and b) Perpendicular baseline history (from the Sentinel-1 data of section 2.6) and an arbitrary displacement time-series using simulated data (with a permanent displacement jump at 1 March 2016 with a magnitude of 20 cm, shown as the dashed black line in (b), in addition to the topographic residual contribution from a DEM error of 50 m). Blue empty circles and orange triangles represent displacement time-series after topographic residual correction assuming quadratic model without and with a step function, respectively. (c and d) Same as (a and b) but (i) using ALOS-1 data for one pixel on Cerro Azul located at [W91.270°, S0.928°] and (ii) the black dashed line for the displacement time-series without topographic residual correction. In both simulated and real data, the disagreement between the low-frequency quadratic model and the high-frequency displacement jump leads to biased estimation of the topographic residual (Du et al., 2007) and adding a step function could effectively eliminate this estimation bias. This estimation bias is amplified in the first ALOS-1 acquisition by its large perpendicular baseline (the difference between black dashed line and the blue empty circles in (d)).
Figure A.6. Coherence matrix of Sentinel-1 dataset for GPS stations within Sierra Negra. Both X and Y axis indicate number of SAR acquisitions. Station GV10 is located in a densely vegetated area outside the caldera on the rim, resulting in fast decorrelation with low spatial coherence on interferograms with more than 2 lags.
Figure A.7. The estimated residual phase time-series $\hat{\phi}_{\text{resid}}$ of ALOS-1 dataset. Related to equation (2.13-14) and Fig. 2.13. A quadratic phase ramp has been estimated and removed from each acquisition. This is used in equation (2.14) to calculate the residual phase RMS value. Phases on 2 September 2007, 10 March 2010 and 25 April 2010 are severely contaminated by ionospheric streaks and are automatically identified as outliers. Phase on 2- January 2009 is contaminated by ionosphere also but is not identified as outlier due to its relatively small magnitude.
Figure A.8. Coherence-based network modification for Sentinel-1 data used in section 2.7.3 in Sierra Negra. Related to Fig. 2.14. (a) Coherence matrix of the customized area of interest along the trap door fault within Sierra Negra caldera (marked by the white rectangle in (b)). The upper triangle shows the interferogram kept after the network modification; while the lower triangle shows all the generated interferograms. A network of interferograms with 30 sequential connections (2475 in total) are generated from 98 SAR acquisitions. A maximum of 20 connections are shown in Fig. 2.14 only. (b) Temporal coherence of the network inversion from the interferogram stack with a maximum of 20 connections.
Figure A.9. Impact of (a) weighted network inversion and (b) unwrapping error correction on the displacement time-series. Related to Fig. 2.16. The comparison within (a) shows that the difference on pixel B (Alcedo’s flank) between MintPy and G-NSBAS is caused by the weighting during the network inversion. The comparison within (b) shows that the difference on pixel C (Fernandina’s crater) between MintPy and G-(N)SBAS is caused by the unwrapping error correction.
Figure A.10. Deformation velocity maps on Alcedo volcano from Sentinel-1 (a) without tropospheric correction, with tropospheric correction using (b) ERA-Interim, (c) MERRA-2 and (d) the empirical phase-elevation ratio method. Related to section 2.8.1. The results are generated with individual MintPy scripts from displacement time-series (link on GitHub).
Figure A.11. Illustration of the spatial filtering. Related to section 2.8.2. The LOS velocity from ALOS-1 ascending track 495 acquired over Sinabung volcano, Indonesia during January 2007 to January 2011 is used. (a) Original velocity in LOS direction, (b and c) velocities after lowpass and highpass Gaussian filtering with the standard deviation of 3.0. (a) is the sum of (b) and (c). The lowpass filtering eliminated the very short spatial wavelength features, thus, highlighted the relatively long spatial wavelength deformation features, such as the volcanic deformation along the Sinabung’s southeast flank and an undocumented patchy, rapid subsidence area (up to -5.6 cm/year) is found ~6 km to the southwest of the volcano. The spatial pattern of the subsidence signal correlates well with the agricultural land use, suggesting that subsidence is caused by groundwater extraction (Chaussard et al., 2013). Reference point is a pixel at [E98.4999°, N3.1069°] outside of this figure. (d) Google Earth image for the marked rectangle area. (e) LOS displacement time-series for pixel marked by red circle in (a) at [E98.3466°, N3.1163°].
Figure A.12. Illustration of interferometric pairs selection. Related to section 2.8.3. The temporal and perpendicular baselines are from Sentinel-1 dataset of section 2.6. For each method, network configuration on the left and the corresponding coherence matrix on the right. The spatial coherence calculation is described in supp. section A3.1 with decorrelation rate of 200 days and long-term coherence of 0.2. The small baseline method selects interferograms with temporal and perpendicular baseline within the predefined thresholds (120 days and 200 m; Berardino et al., 2002). The sequential method selects for each acquisition with a predefined number (5) of its nearest neighbors back in time (Reeves and Zhao, 1999). The hierarchical method specifies a predefined list of temporal and perpendicular baselines as [6 days, 300 m; 12 days, 200 m; 48 days, 100 m; 96 days, 50 m], each pair of temporal and perpendicular thresholds selects interferograms the same as small baseline method (Zhao, 2017). The Delaunay triangulation method generates triangulations in the temporal and perpendicular baseline domain and selects interferograms within the predefined maximum temporal and perpendicular baseline (120 days and 200 m; Pepe and Lanari, 2006). The minimum spanning tree method calculates a spatial coherence value based on its simple relationship with the temporal and perpendicular baseline and selects $N-1$ interferograms that maximizes the total coherence (Perissin and Wang, 2012). The star-like method selects network of $N-1$ interferograms with single common reference acquisition (usually in the center of the time period; Ferretti et al., 2001).
Table A.1. SAR dataset information with parameters used in InSAR stack processing

<table>
<thead>
<tr>
<th>Satellite</th>
<th>ALOS-1</th>
<th>Sentinel-1A/B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orbit direction</td>
<td>Ascending</td>
<td>Descending</td>
</tr>
<tr>
<td>Track number</td>
<td>133</td>
<td>128 (swath 1 &amp; 2)</td>
</tr>
<tr>
<td>Network selection criteria (# of Interferograms)</td>
<td>$B_{\text{temp}} \leq 1800$ days $B_\perp \leq 1800$ m (228)</td>
<td>Sequential with 5 connections (475)</td>
</tr>
<tr>
<td># of looks in range / azimuth direction</td>
<td>$8 \times 16$</td>
<td>$15 \times 5$</td>
</tr>
<tr>
<td>Ground pixel size in range / azimuth direction (m)</td>
<td>$60 \times 51$</td>
<td>$62 \times 70$</td>
</tr>
<tr>
<td>InSAR Processor</td>
<td>ROI_PAC</td>
<td>ISCE</td>
</tr>
<tr>
<td>Phase Unwrapping</td>
<td>SNAPHU</td>
<td>SNAPHU</td>
</tr>
</tbody>
</table>
Table A.2. Stand-alone scripts in MintPy

<table>
<thead>
<tr>
<th>Script Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>add.py</td>
<td>Generate the sum of multiple input files</td>
</tr>
<tr>
<td>asc_desc2horz_vert.py</td>
<td>Project ascending and descending displacement in LOS direction to horizontal and vertical direction</td>
</tr>
<tr>
<td>dem_error.py</td>
<td>DEM error (topographic residual) correction</td>
</tr>
<tr>
<td>diff.py</td>
<td>Generate the difference of two input files</td>
</tr>
<tr>
<td>generate_mask.py</td>
<td>Generate mask file from input file</td>
</tr>
<tr>
<td>geocode.py</td>
<td>Resample radar-coded files into geo coordinates, or vice versa.</td>
</tr>
<tr>
<td>ifgram_inversion.py</td>
<td>Invert network of interferograms into time-series.</td>
</tr>
<tr>
<td>image_reconstruction.py</td>
<td>Reconstruct network of interferograms from time-series</td>
</tr>
<tr>
<td>image_math.py</td>
<td>Basic mathematic operation of input file(s)</td>
</tr>
<tr>
<td>info.py</td>
<td>Display metadata / structure of input file</td>
</tr>
<tr>
<td>load_data.py</td>
<td>Load a stack of interferograms into HDF5 files</td>
</tr>
<tr>
<td>load_hdf5.py</td>
<td>Load the binary file(s) into an HDF5 file</td>
</tr>
<tr>
<td>local_oscillator_drift.py</td>
<td>Correct local oscillator drift for Envisat data</td>
</tr>
<tr>
<td>mask.py</td>
<td>Mask input data file with input mask file by setting values on the unselected pixels into Nan or zero.</td>
</tr>
<tr>
<td>match.py</td>
<td>Merge two or more geocoded files which share common area into one file.</td>
</tr>
<tr>
<td>File Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>modify_network.py</td>
<td>Modify the network setting of an ifgramStack HDF5 file.</td>
</tr>
<tr>
<td>multilook.py</td>
<td>Multilook input file.</td>
</tr>
<tr>
<td>plot_coherence_matrix.py</td>
<td>Plot the coherence matrix of one pixel, interactively.</td>
</tr>
<tr>
<td>plot_network.py</td>
<td>Plot the network configuration of an ifgramStack HDF5 file.</td>
</tr>
<tr>
<td>prep_gamma.py</td>
<td>Prepare metadata file for GAMMA files.</td>
</tr>
<tr>
<td>prep_giant.py</td>
<td>Prepare metadata file for GIAnT files.</td>
</tr>
<tr>
<td>prep_isce.py</td>
<td>Prepare metadata file for ISCE files.</td>
</tr>
<tr>
<td>prep_roipac.py</td>
<td>Prepare metadata file for ROI_PAC files.</td>
</tr>
<tr>
<td>reference_date.py</td>
<td>Change the reference date of a time-series HDF5 file.</td>
</tr>
<tr>
<td>reference_point.py</td>
<td>Change the reference pixel of an input file.</td>
</tr>
<tr>
<td>remove_ramp.h5</td>
<td>Remove phase ramps for input file.</td>
</tr>
<tr>
<td>save_gmt.py</td>
<td>Save input file in GMT *.grd file format.</td>
</tr>
<tr>
<td>save_hdfeos5.py</td>
<td>Save input time-series into HDF-EOS5 format.</td>
</tr>
<tr>
<td>save_kmz.py</td>
<td>Save input file into Google Earth raster image.</td>
</tr>
<tr>
<td>save_kmz_timeseries.h5</td>
<td>Save input file into Google Earth points, interactively.</td>
</tr>
<tr>
<td>save_roipac.py</td>
<td>Save input file into ROI_PAC style binary file format.</td>
</tr>
<tr>
<td>File Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>select_network.py</td>
<td>Select interferometric pairs from input baseline configurations</td>
</tr>
<tr>
<td>smallbaselineApp.py</td>
<td>Routine time series analysis for small baseline InSAR stack.</td>
</tr>
<tr>
<td>spatial_average.py</td>
<td>Calculate average in space domain.</td>
</tr>
<tr>
<td>spatial_filter.py</td>
<td>Spatial filtering of input file.</td>
</tr>
<tr>
<td>subset.py</td>
<td>Generate a subset of (crop) input file.</td>
</tr>
<tr>
<td>temporal_average.py</td>
<td>Calculate average in time domain.</td>
</tr>
<tr>
<td>temporal_derivative.py</td>
<td>Calculate the temporal derivative of displacement time-series.</td>
</tr>
<tr>
<td>temporal_filter.py</td>
<td>Smooth time-series in time domain with a moving Gaussian window.</td>
</tr>
<tr>
<td>timeseries2velocity.py</td>
<td>Invert time-series for the average velocity.</td>
</tr>
<tr>
<td>timeseries_rms.py</td>
<td>Calculate the root mean square for each acquisition of the input time-series file.</td>
</tr>
<tr>
<td>transect.py</td>
<td>Generate/plot an transect/profile along a line of the input file.</td>
</tr>
<tr>
<td>tropo_phase_elevation.py</td>
<td>Correct stratified tropospheretic delay based on the empirical phase/elevation ratio method.</td>
</tr>
<tr>
<td>tropo_pyaps.py</td>
<td>Correct tropospheric delay estimated from global atmospheric model (GAM) using PyAPS software (Jolivet et al., 2011; 2014).</td>
</tr>
<tr>
<td>File Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------</td>
<td>-------------</td>
</tr>
<tr>
<td>tsview.py</td>
<td>Interactive time-series viewer.</td>
</tr>
<tr>
<td>unwrap_error_bridging.py</td>
<td>Correct phase-unwrapping errors with bridging method.</td>
</tr>
<tr>
<td>unwrap_error_phase_closure.py</td>
<td>Correct phase-unwrapping errors with the phase closure method.</td>
</tr>
<tr>
<td>view.py</td>
<td>2D matrix viewer.</td>
</tr>
</tbody>
</table>
A2. Design Matrices for InSAR Time Series Analysis

This section shows examples to generate the design matrices used in the software. A demo set of $N = 8$ SAR images acquired at $[t_1, ..., t_8]$ is used as the example. A stack of $M = 18$ interferograms is selected using the sequential method with 3 connections. An earthquake or volcanic eruption event occurred between $t_6$ and $t_7$ (red dashed line), which caused a permanent ground displacement offset.

![Network configuration of the demo dataset. Red dashed line marks the time of a displacement offset due to an earthquake or volcanic eruption.](image)

**Figure A.13.** Network configuration of the demo dataset. Red dashed line marks the time of a displacement offset due to an earthquake or volcanic eruption.

A2.1 Network Inversion

To generate the design matrix $A$ for network inversion used in equation (2.1) in section 2.3.1, we first generate a $M \times N$ matrix. For each row, it consists -1, 0 and 1 with -1 for the reference acquisition, 1 for the secondary acquisition and 0 for the rest. Due to the relative nature of InSAR measurement, the phase on the reference date (the first date by default) cannot be resolved, thus, we can only solve $[\phi^2, ..., \phi^N]$ instead of $[\phi^1, ..., \phi^N]$ and the corresponding column (the first column by default) is eliminated in the design matrix $A$, which results in size of $M \times (N - 1)$.
\[ A = \begin{bmatrix}
-1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
-1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
-1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & -1 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & -1 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & -1 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & -1 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & -1 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & -1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & -1 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & -1 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & -1 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & -1 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & -1 & 1
\end{bmatrix} \] (A.1)

### A2.2 Phase Closure of Interferograms Triplets

Design matrix \( C \) describe the combination of interferograms to form the triplets used in equation (2.10) in section 2.4.2 for the phase closure unwrapping error correction. An example of \( C \) is shown below based on the demo network with number of triplets \( T = 16 \).

\[ C = \begin{bmatrix}
1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & -1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix} \] (A.2)
A2.3 Topographic Residual Correction

Design matrix $G$ is used in equation (2.13) for topographic residual correction in section 2.5.6. It is in size of $N \times (1 + N_{poly} + N_{step})$, where $N_{poly}$ is the user-defined polynomial order $N_{poly}$ (2 by default), $N_{step}$ is the number of Heaviside step functions (0 by default) describing offsets at specific prior selected times. An example of $G$ is shown below based on the demo network.

$$
G = \begin{bmatrix}
\frac{4\pi B_1^1}{\lambda \sin(\theta)} & 1 & (t_1 - t_1) & \frac{(t_1-t_1)^2}{2} & 0 \\
\frac{4\pi B_2^1}{\lambda \sin(\theta)} & 1 & (t_2 - t_1) & \frac{(t_2-t_1)^2}{2} & 0 \\
\frac{4\pi B_3^1}{\lambda \sin(\theta)} & 1 & (t_3 - t_1) & \frac{(t_3-t_1)^2}{2} & 0 \\
\frac{4\pi B_4^1}{\lambda \sin(\theta)} & 1 & (t_4 - t_1) & \frac{(t_4-t_1)^2}{2} & 0 \\
\frac{4\pi B_5^1}{\lambda \sin(\theta)} & 1 & (t_5 - t_1) & \frac{(t_5-t_1)^2}{2} & 0 \\
\frac{4\pi B_6^1}{\lambda \sin(\theta)} & 1 & (t_6 - t_1) & \frac{(t_6-t_1)^2}{2} & 0 \\
\frac{4\pi B_7^1}{\lambda \sin(\theta)} & 1 & (t_7 - t_1) & \frac{(t_7-t_1)^2}{2} & 1 \\
\frac{4\pi B_8^1}{\lambda \sin(\theta)} & 1 & (t_8 - t_1) & \frac{(t_8-t_1)^2}{2} & 1
\end{bmatrix}
$$

\hspace{1cm} (A.3)

Then equation (2.13) can be formed as a linear system with $N$ equations as below:

$$
\hat{\Phi} - \hat{\Phi}_{tropo} = GX + \phi_{resid}
$$

\hspace{1cm} (A.4)

where $X = [z_e, c_0, c_1, c_2, s_7]^T$ is the vector of unknown parameters, $\hat{\Phi}$, $\hat{\Phi}_{tropo}$ and $\phi_{resid}$ are the $N \times 1$ inverted raw phase time-series, estimated tropospheric delay time-series and residual phase time-series, respectively. We apply the least squares estimation to obtain the solution as:

$$
\hat{X} = (G^T G)^{-1} G^T (\hat{\Phi} - \hat{\Phi}_{tropo})
$$

\hspace{1cm} (A.5)

$$
\phi_{resid} = \hat{\Phi} - \hat{\Phi}_{tropo} - G\hat{X}
$$

\hspace{1cm} (A.6)
The estimated residual phase $\hat{\phi}_{\text{resid}}$ is used to characterize the noise of phase time-series using equation (2.14) in section 2.5.7. The noise-reduced displacement time-series is given as:

$$\phi_{\text{dis}}^i = \hat{\phi}^i - \hat{\phi}_{\text{tropo}}^i - \frac{-4\pi}{\lambda} \frac{b_1}{r \sin(\theta)} \hat{z}_e$$ (A.7)

where $i = 1, \ldots, N$ and $\hat{z}_e$ is the estimated DEM error in $\mathcal{X}$.

**A2.4 Average Velocity Estimation**

For each pixel, the average velocity is estimated as $d^i = vt_i + c$, where $d^i = -\frac{\lambda}{4\pi} \phi_{\text{dis}}^i$ is the displacement at $t_i$ in meters, $v$ is the unknown velocity and $c$ is the unknown offset. The solution can be obtained using least squares approximation. An example of the design matrix $E$ is shown below based on the demo network.

$$E = \begin{bmatrix}
t_1 - t_1 & 1 \\
t_2 - t_1 & 1 \\
t_3 - t_1 & 1 \\
t_4 - t_1 & 1 \\
t_5 - t_1 & 1 \\
t_6 - t_1 & 1 \\
t_7 - t_1 & 1 \\
t_8 - t_1 & 1 \\
\end{bmatrix}$$ (A.8)

For linear displacement, the uncertainty of the estimated velocity $\sigma_v$ is given by equation (10) in Fattahi and Amelung (2015) as:

$$\sigma_v = \sqrt{\frac{\sum_{i=1}^{N}(\phi_{\text{dis}}^i - \hat{\phi}_{\text{dis}}^i)^2}{(N-2) \sum_{i=1}^{N}(t_i - \bar{t})^2}}$$ (A.9)

where $\hat{\phi}_{\text{dis}}^i$ is the predicted linear displacement at $i_{th}$ acquisition $\bar{t}$ is the mean value of time in years.
A3. Decorrelation Noise Simulation

A3.1 Coherence Model

We simulate the coherence for a stack of interferograms on one pixel using a decorrelation model with exponential decay for temporal decorrelation. The spatial coherence $\gamma_j$ of the $j_{th}$ interferogram can be expressed as (Zebker and Villasenor, 1992; Hanssen, 2001; Parizzi et al., 2009):

$$\gamma = \gamma_{geom} \cdot \gamma_{DC} \cdot \gamma_{temporal}$$ (A.10)

where $\gamma_{geom}$ represents the geometric decorrelation, $\gamma_{DC}$ represents the Doppler centroid decorrelation, $\gamma_{temporal}$ represents the temporal decorrelation, given by the equations below. Note that the thermal decorrelation $\gamma_{thermal}$ is served as the instantaneous decorrelation in temporal decorrelation $\gamma_{temporal}$ (Parizzi et al., 2009).

$$\gamma_{geom} = \begin{cases} 1 - \frac{|B_\perp|}{B_{\perp}^{crit}}, & |B_\perp| \leq B_{\perp}^{crit} \\ 0, & |B_\perp| > B_{\perp}^{crit} \end{cases}$$ (A.11)

$$\gamma_{DC} = \begin{cases} 1 - \frac{|\Delta f_{DC}|}{B_{az}}, & |\Delta f_{DC}| \leq B_{az} \\ 0, & |\Delta f_{DC}| > B_{az} \end{cases}$$ (A.12)

$$\gamma_{temporal}(t) = (\gamma_{thermal} - \gamma_\infty) e^{-t/\tau} + \gamma_\infty$$ (A.13)

$$\gamma_{thermal} = \frac{1}{1 - SNR^{-1}}$$ (A.14)

The critical perpendicular baseline $B_{\perp}^{crit} = \lambda \frac{B_{rg}}{c} R \cdot tan(\theta)$ is the baseline causing a spectral shift equal to the radar bandwidth $B_{rg}$ in range direction (Zebker and Villasenor, 1992; Hanssen, 2001), where $\lambda$ is the radar wavelength, $c$ is the speed of light, $R$ is the distance between radar antenna and ground target and $\theta$ is the incidence angle, $SNR$ is the thermal signal-to-noise ratio of radar receiver. $\tau$ is the time constant which depends on
radar wavelength $\lambda$, it’s the time for coherence to drop down to $1/e$, i.e. 0.36, from its initial value (Parizzi et al., 2009; Rocca, 2007). $\gamma_\infty$ is the long-term coherence, or minimum attainable coherence value, which converged over time, usually with high value in urban area and low value in vegetated area. Note that this model does not consider the seasonal behavior of temporal decorrelation, volume decorrelation, and processing-induced decorrelation. For a given set of SAR acquisitions, the geometric and Doppler centroid decorrelation is almost constant among all pixels. All parameters are deployed with typical parameters of Sentinel-1 SAR sensor.

Figure A.14. Simulated coherence as a function of temporal baseline, color coded by different $\tau$ and $\gamma_\infty$ setting used in Fig. A.2.

### A3.2 Simulate Decorrelation Noise from Coherence

For distributed scatterers (DS) in natural, vegetated terrain the interferometric phase exhibits highly unpredictable speckle characteristics. Its phase can be appropriately modeled by a random process, complex, stationary, circular Gaussian process in the case of SAR image. Applying the central limit theorem, the probability density function $pdf(\Delta \phi)$ of interferometric phase is obtained using equation (66) from Tough et al., 1995; equation (4.2.23) from Hanssen, 2001):
\[
pdf(\Delta \phi) = \frac{(1-|\gamma|^2)^L}{2\pi} \left\{ \frac{\Gamma(2L-1)}{[\Gamma(L)]^2 2^{2L-1}} \times \left[ \frac{-(2L-1)\beta}{(1-\beta^2)^{L+1/2}} \left( \frac{\pi}{2} + \arcsin\beta \right) \right] + \frac{1}{(1-\beta^2)L} + D \right\} \\
D = \frac{1}{2(L-1)} \sum_{r=0}^{L-2} \frac{\Gamma(L - \frac{1}{2})}{\Gamma(L - 1)} \frac{\Gamma(L - 1 - r)}{\Gamma(L - 1)} \frac{1 + (2r + 1)\beta^2}{(1-\beta^2)^{r+2}}
\]

where \( \beta = |\gamma|\cos(\Delta \phi - \Delta \phi_0) \), expected interferometric phase \( \Delta \phi_0 = E\{\Delta \phi\} \), gamma function \( \Gamma(L) = \int_0^\infty t^{L-1}e^{-t}dt \), for \( L \in \mathbb{R} \) and \( D \) a finite summation term. Note that \( D \) vanishes for single-look datasets \( L=1 \).

The 100000 realizations/samples of decorrelation noise of each interferogram (used in section 2.3.3) is simulated by generating a distribution given by equation (A.15) with corresponding coherence \( \gamma \) and number of looks \( L \). One example with \( \gamma = 0.1 \) and \( L = 3 \times 9 \) is shown below.

![Figure A.15](image-url)
Figure A.16. Time-series configuration for simulation. (a) Perpendicular baseline history from the 98 Sentinel-1 images of section 2.6. (b) Specified time-dependent displacement used in section 2.3.3 and 2.4.2.2.
B1. Supplemental Figures and Tables for Chapter 4

Table B.1. SAR dataset information with parameters used in InSAR stack processing

<table>
<thead>
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<th>Satellite</th>
<th>Pass (A / D)</th>
<th>Track</th>
<th>Frame</th>
<th>Start Date</th>
<th>End Date</th>
<th># of images</th>
<th># of interferograms</th>
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<tr>
<td>ALOS-1</td>
<td>A</td>
<td>424</td>
<td>620-630</td>
<td>2006-06-24</td>
<td>2011-04-07</td>
<td>29</td>
<td>225</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>73</td>
<td>2970-2980</td>
<td>2007-01-07</td>
<td>2011-04-20</td>
<td>21</td>
<td>115</td>
</tr>
<tr>
<td>ALOS-2</td>
<td>A</td>
<td>131</td>
<td>620</td>
<td>2014-09-30</td>
<td>2019-07-02</td>
<td>36</td>
<td>204</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>23</td>
<td>2970</td>
<td>2015-02-09</td>
<td>2019-08-19</td>
<td>49</td>
<td>341</td>
</tr>
</tbody>
</table>
Figure B.1. The network configuration of interferograms stacks. For ALOS-1, all interferometric pairs with temporal baseline less than 1800 days and spatial perpendicular baseline less than 1800 m are selected. For ALOS-2 with smaller orbital tubes, all interferometric pairs with temporal baseline less than 400 days and spatial perpendicular baseline less than 200 m are selected. Line colors represent the average spatial coherence of the interferogram calculated over all pixels on land. Dashed lines represent the interferograms excluded during the time-series analysis due to low coherence.
Figure B.2. Temporal coherence of all four datasets from the routine MintPy workflow. Black squares: the custom area of interest used for the coherence-based network modification.
Figure B.3. LOS (line-of-sight) displacement time-series of Kirishima from ALOS-1 ascending track 424. Data are wrapped into [-5, 5] cm for display. Data coverage is the same as Fig. 4.2. Black squares represent the reference point.
Figure B.4. Same as Fig. B.2 but for ALOS-1 descending track 73.
Figure B.5. Same as Fig. B.2 but for ALOS-2 ascending track 131 with data wrapped into [-8, 8) cm for display.
Figure B.6. Same as Fig. B.2 but for ALOS-2 descending track 23 with data wrapped into [-8, 8) cm for display.
Figure B.7. Residual phase root mean squares (RMS) time-series with noisy acquisitions. The orange bar indicates the acquisition with minimum residual phase RMS and the optimal reference date for each dataset. The gray bars indicate acquisitions with residual phase RMS larger than the predefined threshold (dashed black lines), thus, considered as noisy and excluded during the average velocity estimation.
Figure B.8. Pre- and co-eruptive deformation of the 2011 Shinmoe-dake eruption in LOS direction from ALOS-1 ascending track 424 orbit.
Figure B.9. Comparison between two approaches to estimate LOS displacements. Left panel (used in the paper): displacements obtained from the average velocity for the time periods of interest, estimated from displacement time-series estimated after additional modification of the network of interferograms by removing acquisitions acquired after the 2011 and 2017 magmatic eruptions. Right panel: differential displacements between two acquisitions from displacement time-series estimated from the network of interferograms including post-eruptive interferograms.
Figure B.10. Subsampled LOS displacement data from ALOS-1/2 ascending and descending orbit.
Figure B.11. Marginal posterior probability distributions for the estimated parameters of the compound dislocation models (CDM) for the deflation between the 2008-2010 phreatic eruptions in Shinmoe-dake. Related to Fig. 4.3a-e. Fixed parameters are not shown. Blask bars in the diagonal: posterior probability distribution for each parameter. Red lines: maximum a posteriori probability (optimal) solution.
Figure B.12. Same as Fig. B.11 but for the finite spherical source for the pre-eruptive inflation of the 2017 magmatic eruption in Shinmoe-dake. Related to Fig. 4.3f-j. $G$ is the shear modulus.
Figure B.13. Same as Fig. B.11 but for the CDM for the inflation before October 2017 in Iwo-yama. Related to Fig. 4.3k-o.
Figure B.14. Same as Fig. B.11 but for the two CDMs (one with fixed geometry and one free) for the expanded inflation after 2017 in Iwo-yama. Related to Fig. 4.3p-t.