

Evaluating ALOS-2 L-Band InSAR Observations of Tectonic Motion in the Western United States

C. Liang^{1*}, X. Li¹, Y. Wang¹, Z. Liu², M. Simons³, E. J. Fielding², Y.-K. Liu³, and S.-H. Yun^{4,5,6}

¹Institute of Remote Sensing and Geographic Information System, School of Earth and Space Sciences, Peking University, Beijing 100871 China.

²Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109 USA.

³Seismological Laboratory, Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA 91125 USA.

⁴Earth Observatory of Singapore, Nanyang Technological University, Singapore 639798.

⁵Asian School of the Environment, Nanyang Technological University, Singapore 639798.

⁶School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798.

Corresponding author: Cunren Liang (cunren.liang@pku.edu.cn)

Key Points:

- Tectonic motion is measured across the western United States, including the Cascadia subduction zone, using ALOS-2 L-band InSAR data.
- Evaluation of the results suggests the potential of L-band InSAR time series for independently measuring global tectonic motions.

Abstract

Focusing on ALOS-2 observations over the western United States, we evaluate the ability of L-band satellite InSAR to measure regional-scale tectonic motions. We develop a suite of new techniques to enable efficient, robust and precise processing of ALOS-2 ScanSAR data and remove confounding contributions to the InSAR observations. We consider data spanning the years 2015 to 2023 and validate the derived motions against GNSS data. The InSAR results extend to the highly challenging Cascadia subduction zone. Residual ramps relative to GNSS are generally along the range direction and less than 2 mm/yr across the 350 km wide swath. Even a single pair with a long temporal baseline can reveal secular tectonic motions of a few mm/yr. The primary challenges are decorrelation induced by seasonal snow cover and inaccuracies in ionospheric phase estimation in the presence of spatial TEC irregularities. These results show that L-band InSAR time series can independently measure regional tectonic motions at the mm/yr level without GNSS constraint even in conventionally challenging regions, suggesting the potential for global coverage.

Plain Language Summary

Tectonic activities induce motions of the Earth's surface, often ranging from mm/yr to cm/yr. These motions are a key quantity for understanding the underlying tectonic processes and can be measured by different geodetic techniques. Among them, Synthetic Aperture Radar (SAR) Interferometry (InSAR) is unique in offering high spatial resolution and wide-area coverage at low cost. However, InSAR measurements can be degraded or even corrupted by undesired signals, errors, and noise, which limits its ability to provide global coverage and makes it reliant on external constraints such as the Global Navigation Satellite System (GNSS). The rapid expansion of L-band SAR satellites creates an opportunity to overcome these challenges. We developed new techniques to optimally process L-band InSAR data acquired in wide swath mode by the ALOS-2 satellite. The results over the western United States show that InSAR measurements can be obtained in regions that were previously considered challenging for InSAR, such as the Cascadia subduction zone. Furthermore, the results show that L-band InSAR can independently measure regional tectonic motions at the mm/yr level without GNSS constraint. While there are still minor issues, the results generally suggest the potential of L-band InSAR for measuring global tectonic motions without relying on external constraints.

1 Introduction

Measuring global tectonic motion using Interferometric Synthetic Aperture Radar (InSAR) time series alone, without external constraints to determine relative motion or motion velocity between spatially separated measurements, has been a long-standing goal of the geodesy community. Recently, InSAR processing over large spatial extents has become increasingly pervasive, including in regions such as the Tibetan Plateau in China ([Chen et al., 2024](#); [Elliott et al., 2026](#); [Lemrabet et al., 2023](#); [Ou et al., 2022](#); [Shen et al., 2024](#); [Wang C et al., 2021](#); [Wright et al., 2026](#); [Zinke et al., 2024](#)), the San Andreas Fault in the United States ([Jolivet et al., 2015](#); [Tong et al., 2013](#); [Xu et al., 2021](#)), and the North and East Anatolian Faults in Türkiye ([Elliott et al., 2026](#); [Weiss et al., 2020](#)). However, two major challenges remain:

60 achieving InSAR measurements independent of the Global Navigation Satellite System (GNSS)
61 and achieving robust global coverage.

62 Regarding measurement independence, it remains challenging to measure long-
63 wavelength tectonic motions without external constraints due to the presence of long-
64 wavelength systematic and processing errors, and confounding signals not of interest to solid
65 Earth sciences. These long-wavelength errors and signals, sometimes referred to as “ramps”,
66 arise from a variety of sources. Previous studies have primarily focused on addressing a subset
67 of them (DiCaprio & Simons, 2008; Jolivet et al., 2014; Liang et al., 2019; Stephenson et al.,
68 2022; Xu & Sandwell, 2020; Yu et al., 2018). To mitigate their impacts, most InSAR tectonic
69 motion measurements rely on constraints from external measurements, predominantly from
70 GNSS, to resolve long-wavelength tectonic motions (e.g. Elliott et al., 2026; Wright et al., 2026;
71 Xu et al., 2021). In other instances, residual long-wavelength errors and signals are empirically
72 removed through polynomial fitting or baseline re-estimation (e.g. Biggs et al., 2007; Maubant
73 et al., 2020; Wu et al., 2026). This approach entails the risk of also attenuating the desired long-
74 wavelength tectonic signal itself. Although recent progress has demonstrated the potential for
75 achieving measurement independence (Liu et al., 2025; Stephenson et al., 2022), the results
76 have not yet been fully validated against GNSS measurements.

77 Global coverage is hampered by low-coherence regions, for instance, along the southern
78 margin of the Tibetan Plateau and the Cascadia subduction zone to the north of California,
79 where decorrelation noise, along with the resulting phase unwrapping errors, restricts the
80 applicability of InSAR, especially at higher-frequency bands (e.g. X- and C-bands). Although
81 permanent scatterer techniques can help overcome this issue (Ferretti et al., 2001), the density
82 of permanent scatterers is typically insufficient in non-urban areas, restricting their applicability
83 to large-scale tectonic problems. Low coherence also poses a challenge when using the range
84 split-spectrum method (Brcic et al., 2010; Gomba et al., 2016; Rosen et al., 2010) to estimate
85 ionospheric phase, which is often the most significant source of undesired long-wavelength
86 signals.

87 In this work, we evaluate the potential of L-band SAR satellites in overcoming these
88 challenges using data acquired by the ALOS-2 satellite in ScanSAR mode. We conduct
89 experiments in the western United States, which serves as an ideal region to test InSAR
90 techniques because it encompasses a diverse range of land covers, topography, and climate
91 conditions. In particular, the Cascadia subduction zone is rich in volcanic and tectonic activities
92 (e.g., Li et al., 2018; McCaffrey et al., 2007; Michel et al., 2019; Schmalzle et al., 2014; Wang K
93 et al., 2003) but has long challenged the application of InSAR techniques. In what follows, we:

94 1) Develop a suite of new InSAR processing techniques and an InSAR stack
95 processor for efficient, robust, and precise processing of ScanSAR data acquired by the ALOS-2
96 satellite.

97 2) Quantify and remove contributions from confounding signals. In addition to the
98 well-documented signals from the ionosphere, troposphere, solid Earth tide, and ocean tide
99 loading, we incorporate an expanded suite of tidal and loading signals.

3) Show the potential to achieve measurement independence. Long-wavelength tectonic motions spanning hundreds to thousands of kilometers are independently measured via InSAR time series. Validation against GNSS data shows that long-wavelength residuals are generally along the range direction and less than 2 mm/yr across the 350 km wide swath.

4) Show the potential to achieve near global coverage. For the first time, tectonic motions in the challenging Cascadia subduction zone, including both short- and long-wavelength components, are fully and independently measured using InSAR time series.

2 Unique role of L-band SAR satellites in independently measuring global tectonic motion with InSAR time series

Within the microwave spectrum used for active remote sensing, the L-band currently represents the most viable candidate for measuring global tectonic motion using InSAR time series, independently of GNSS observations. This capability is also supported by the recent surge in L-band SAR missions, as shown in Figure 1. Significant challenges arise when higher- and lower-frequency bands are used.

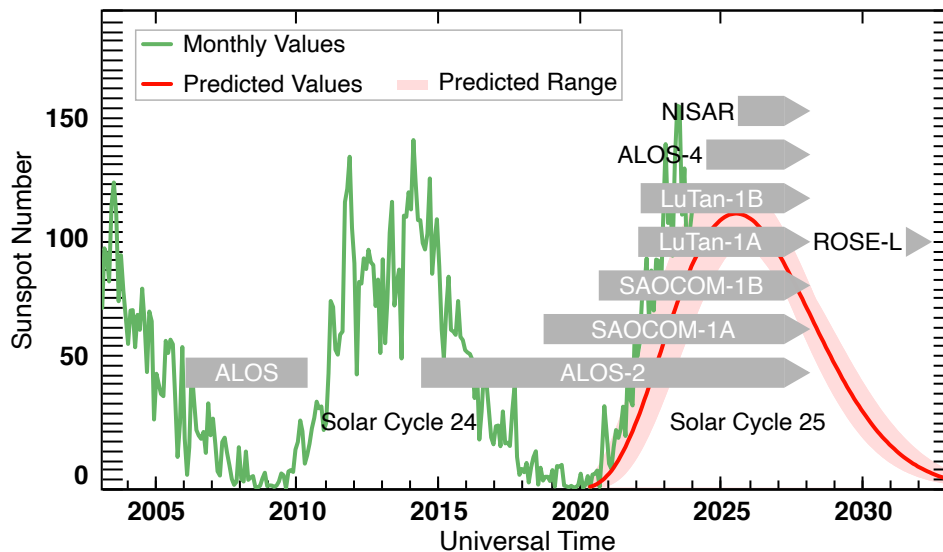


Figure 1. Operational lifetimes of L-band SAR satellites relative to solar cycles, indicated by sunspot numbers from the Space Weather Prediction Center of the United States National Oceanic and Atmospheric Administration.

2.1 Challenges in the higher-frequency bands of the microwave spectrum

The InSAR phase measurement comprises not only desired signals, but also various other components. The left half of Figure 2 lists the known contributors to the InSAR phase measurement. In the right half of Figure 2, we regroup them into four categories:

- 1) Signals of interest for geophysical interpretation.
- 2) Contributions that can be removed with robust models (Appendix A).
- 3) Systematic and processing errors that are negligible or can be carefully accounted for (Section 3.4).

4) Noise induced by temporal decorrelation, phase unwrapping errors caused by decorrelation noise and high intrinsic interferometric fringe rates, and phase advances accrued in the ionosphere.

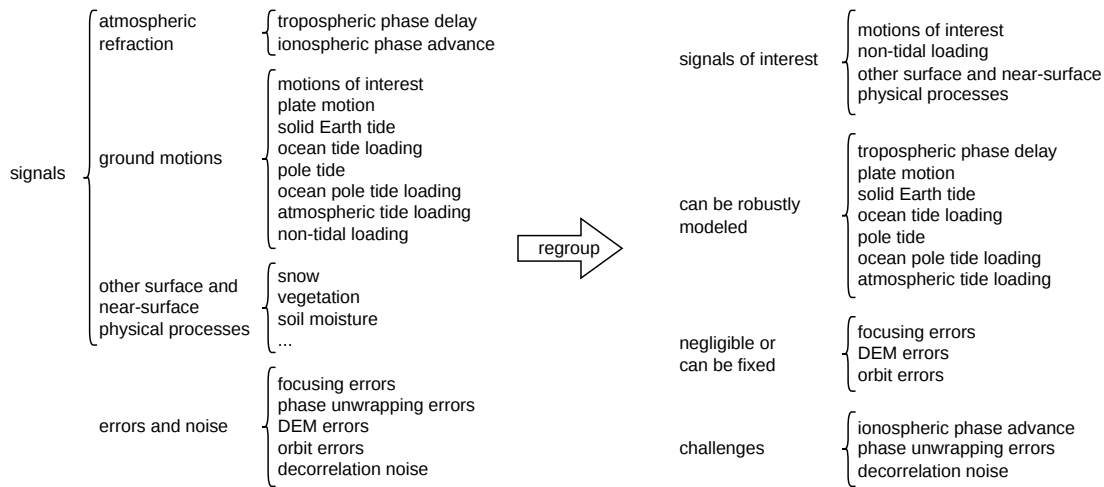


Figure 2. Known InSAR phase components.

To precisely and accurately retrieve the signals in Category 1), the challenges primarily stem from Category 4) and generally intensify with increasing radar frequency. At C- and X-bands, the strong decorrelation noise and high probability of phase unwrapping errors have hindered InSAR from achieving robust global coverage. Furthermore, they significantly restrict the applicability of the range split-spectrum method (Brcic et al., 2010; Gomba et al., 2016; Rosen et al., 2010) for estimating the ionospheric phase, which is critical for achieving InSAR measurement independence.

The low-frequency L-band SAR can potentially mitigate these challenges. First, the relatively high temporal coherence of L-band observations is well documented (Rosen et al., 1996; Zebker & Villasenor, 1992). Moreover, the inherently lower fringe rate of L-band interferograms results in a lower noise level in multilooked interferograms and allows a much larger multilook window with a lower risk of aliasing, potentially making many interferograms in low-coherence areas usable. Note that a large multilook window, corresponding to a spatial resolution of several hundred meters, remains acceptable for most solid Earth science applications. Collectively, these factors facilitate substantially more robust phase unwrapping for L-band interferograms. This lower noise level and reduced susceptibility to phase unwrapping errors enable the range split-spectrum method to be effective in nearly all regions, following the technical improvements discussed in Section 3.

2.2 Challenges in the lower-frequency bands of the microwave spectrum

According to Section 2.1, P-band, which lies at lower frequencies than L-band, should in principle be even more advantageous. However, its performance is significantly constrained by radio spectrum allocation and assignment issues as well as radio frequency interference (RFI). Table 1 summarizes the spectrum allocations for the Earth Exploration-Satellite Service (EESS)

(active) by the Radiocommunication Sector of the International Telecommunications Union (ITU-R) as of 2024 (ITU, 2024).

The available bandwidth at P-band is only 6 MHz, corresponding to a slant range resolution of 24.98 m. This narrow bandwidth restricts the number of looks available for multilooking to suppress decorrelation noise and significantly degrades the performance of the range split-spectrum method. Moreover, an allocated band is typically shared among multiple services, and a spectrum allocation does not necessarily mean a spectrum assignment, which is the actual permission to radiate at a specific transmit power in a given band over a particular region of the Earth (Spencer & Ulaby, 2016). As indicated in Table 1, P-band is allocated to EESS (active) only on a secondary basis, implying lower priority relative to other services. Consequently, the P-band BIOMASS mission has been denied permission to operate within the Line-of-Sight (LOS) field of view of space object tracking radars in North America and Europe, essentially precluding global coverage at P-band. Furthermore, the narrow bandwidth is also predicted to be subject to heavy Radio Frequency Interference (RFI), a phenomenon increasingly found in SAR observations, with its occurrence probability inversely correlated with frequency (Wang Y et al., 2025). In contrast, these issues are either absent or less pronounced at L-band.

Table 1. Radio spectrum allocations for the Earth Exploration-Satellite Service (EESS) (active) under the International Telecommunication Union (ITU) as of 2024, incorporating the latest decisions from the World Radiocommunication Conference 2023 (WRC-23) held in Dubai, United Arab Emirates.

Band Designation	mm	W	Ka	K	Ku	X	C	S	L	P
Frequency [MHz]	130000-134000	94000-94100	35500-36000	24050-24250	13250-13750 17200-17300	8550-8650 9200-10000	5250-5570	3100-3300	1215-1300	432-438
Bandwidth [MHz]	4000	100	500	200	500 100	100 800	320	200	85	6
Allocation Status	Primary	Primary	Primary	Secondary	Primary	Secondary (9800-9900) Primary (other bands)	Primary	Secondary	Primary	Secondary

3 New techniques for InSAR stack processing of ALOS-2 ScanSAR data

The ALOS-2 ScanSAR archive represents a great opportunity for evaluating the feasibility of independently measuring global tectonic motion with L-band satellite InSAR time series. However, efficient, robust, and precise processing of ALOS-2 ScanSAR data remains challenging for several reasons:

1) The data volume is large. The default ScanSAR mode, officially designated as the WBD mode, consists of five subswaths and two polarizations. The file size of a single full-aperture WBD product is 57 G. Moreover, owing to the high coherence of L-band data,

significantly more InSAR pairs, including those with very long temporal baselines as discussed in [Section 4](#), can be formed to suppress noise and closure phase in stack processing ([Ansari et al., 2021](#); [Zheng et al., 2022](#)).

2) The characteristics of the full-aperture product necessitate the development of new techniques, particularly those that enable robust, operational processing.

3) Certain parameters in the products lack the precision required for high-quality processing. These parameters must be known with high precision to achieve InSAR measurement independence.

4) Operational and precise ionospheric phase estimation via the range split-spectrum method presents significant challenges due to the following factors:

4.1) The narrow range bandwidth (Nominal: 14 MHz, true: 11.9 MHz, WBS and WBD modes) and low resolution result in a high noise level in the initial ionospheric phase estimates, necessitating a sophisticated smoothing filter.

4.2) Uncertainties in product parameters hinder the seamless mosaicking of sub-band interferograms from different subswaths and frames with sufficient precision. Imprecise mosaicking introduces long-wavelength errors into the ionospheric phase estimates.

4.3) In low-coherence areas, it remains challenging to obtain ionospheric phase estimates with sufficient precision. The first two issues in [4.1](#)) and [4.2](#)) further exacerbate this challenge. Low-coherence areas are pervasive in tectonically active regions and thus critical for achieving global coverage.

Recognizing that previously developed techniques ([Fattahi et al., 2017](#); [Liang & Fielding, 2017a, 2017b](#)) cannot fully meet the stringent requirements for InSAR measurement independence and for processing data over low-coherence regions, we introduce a suite of newly developed techniques. The workflow, as illustrated in [Figure 3](#), comprises three sub-workflows: single-date processing, InSAR processing, and ionospheric phase estimation. The latter two sub-workflows are largely independent, each utilizing a dedicated set of parameters optimized for its specific purpose. In the following subsections, we elaborate on the key processing steps in the grey boxes in each sub-workflow.

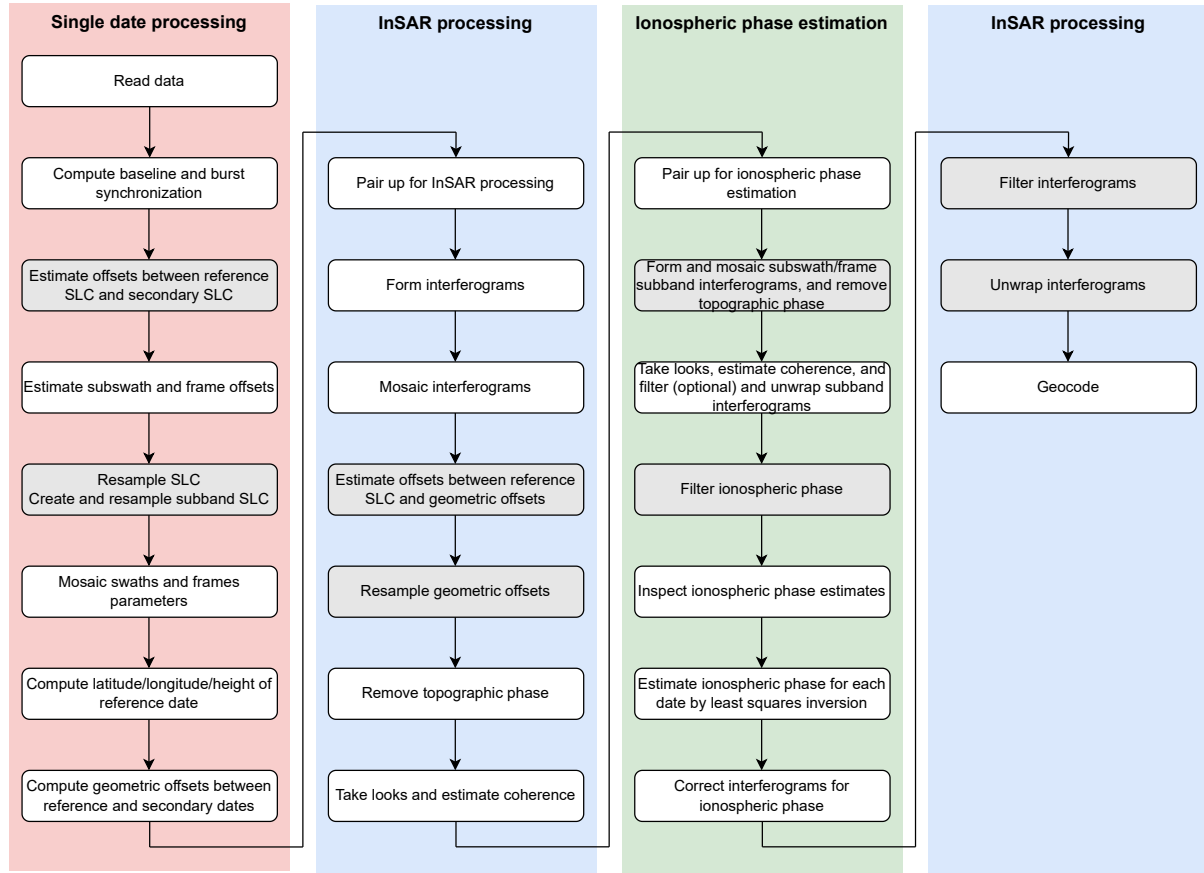


Figure 3. Workflow for InSAR stack processing of ALOS-2 ScanSAR data. The workflow comprises three sub-workflows for single-date processing, InSAR processing, and ionospheric phase estimation. The grey boxes indicate the key processing steps.

3.1 Single-date processing

In single-date processing, the coregistration between reference and secondary SLCs, which involves offset estimation and resampling, requires special attention. These steps are critical to the efficiency and robustness of the workflow.

Regarding the offsets, those derived from imaging geometry are inadequate, as both range and azimuth offsets induced by the ionosphere can be substantial at L-band. Instead, we employ incoherent cross correlation to estimate the offsets. However, conventional cross-correlation techniques are prone to producing outliers in the azimuth offsets due to narrow spikes in the full-aperture images (Holzner & Bamler, 2002), as illustrated in Figure 4 (a). To address this issue, we first perform azimuth lowpass filtering on the image chips used for cross correlation to remove the spikes. An accurate yet coarse offset is estimated using these filtered image chips. This preliminary estimate serves as an initial guess for the cross correlation of the unfiltered image chips, effectively steering the algorithm away from the outliers. This strategy substantially reduces the occurrence of outliers, as demonstrated in Figure 4 (b). To further enhance robustness, we employ a significantly larger azimuth image chip size of 4096 samples, which almost completely eliminates the outliers as shown in Figure 4 (c). A robust offset

estimation technique is pivotal for operational stack processing, as reprocessing due to outliers is highly time consuming. We find the aforementioned techniques to be highly effective, thereby facilitating the automated, operational processing of the vast ALOS-2 ScanSAR archive.

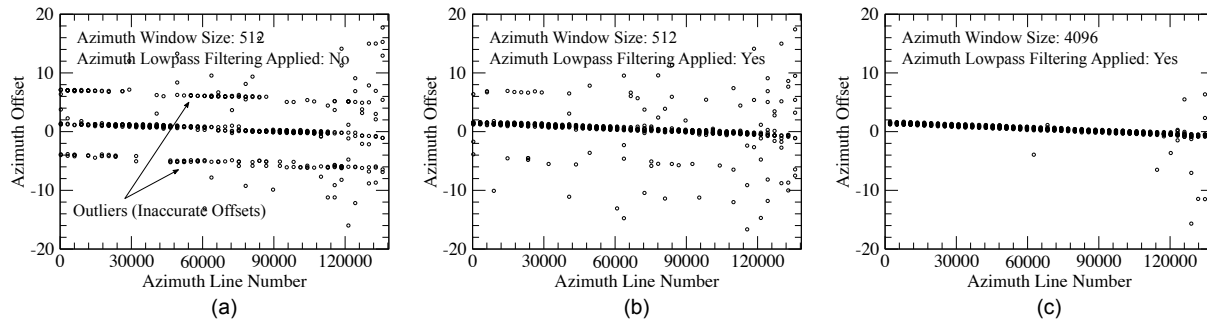


Figure 4. Improvements in azimuth incoherent cross correlation for full-aperture ScanSAR images. Data: subswath 1, pair 190921-150228, frame 2950, track D164.

For SLC resampling, we incorporate three critical offset components to efficiently manage the large data volume:

- 1) The offset from the two-stage estimation approach described above.
- 2) Offsets associated with the starting range, the azimuth starting time, and the range and azimuth sample sizes of each subswath and frame.
- 3) Offsets associated with the number of range and azimuth looks applied in forming the interferograms.

The latter two components are introduced to facilitate the efficient mosaicking of multilooked interferograms from different subswaths and frames. Typically, the interferogram is formed at the subswath level and subsequently multilooked before being mosaicked. However, because the azimuth sample size varies across subswaths, and the offsets between adjacent subswaths and frames are not integer multiples of the sample spacings, direct mosaicking without resampling is unfeasible. Incorporating the latter two components in SLC resampling eliminates the need for resampling during interferogram mosaicking. This approach is crucial for stack processing, given the massive data volume and the large number of interferograms to be formed.

During SLC resampling, a reference subswath and frame can be selected to align other subswaths and frames based on the latter two components. The reference subswath and frame can be chosen from the reference date. Since the azimuth bandwidth only varies slightly across different subswaths, minor adjustments in the sampling interval do not induce substantial aliasing. Sub-band SLCs used in ionospheric phase estimation can likewise be resampled in the same manner at this stage.

Other important steps that differ from basic InSAR processing include high-precision estimation of burst synchronization, as well as subswath and frame offsets. For these tasks, we employ the methods developed in (Liang & Fielding, 2017b).

3.2 InSAR processing

For the InSAR processing sub-workflow, we focus on improving topographic phase removal and phase unwrapping.

Removing topographic phase from the interferogram requires coregistration between the reference image and the geometric range offset used for topographic phase removal. While the geometric range offset is typically defined in a coordinate system determined purely by the SAR imaging geometry, the reference image is subject to sample shifts arising from several sources. The primary driver is atmospheric delay, with other contributors including systematic and processing errors. For example, the stop-and-go approximation assumed during focusing, as discussed later in [Section 3.4](#), induces an azimuth sample shift that varies with range. We estimate the resulting offset between the reference image and the geometric range offset by performing a cross correlation between the reference image and a SAR image simulated using a DEM and the reference imaging geometry. Subsequently, the range geometric offset is resampled using the estimated offset prior to being used to remove the topographic phase.

Robust phase unwrapping is crucial in low-coherence areas. To improve phase unwrapping reliability, we designed a spatially adaptive Gaussian filter by leveraging the low fringe rate of L-band interferograms, which is approximately four times lower than that of C-band interferograms. Specifically, a sample with a coherence lower than a predefined threshold is replaced by a weighted average of neighboring samples within a Gaussian window. The weight is determined by the Gaussian window coefficient and the theoretical phase standard deviation, which depends on coherence and the number of looks. The theoretical phase standard deviation of the filtered sample can then be derived. Conversely, by specifying the desired phase standard deviation, the corresponding window size can be determined. If this value is held constant, the window size varies across the interferogram, resulting in a spatially adaptive filter.

The adaptive Gaussian filter substantially improves the performance of phase unwrapping in low-coherence regions. The filtered and unwrapped interferogram serves as a reference, based on which integer multiples of 2π are added to the original interferogram to obtain the final unwrapped interferogram. Consequently, the final unwrapped interferogram remains unfiltered, but its phase unwrapping is guided by the filtered interferogram.

3.3 Ionospheric phase estimation

While the theory underlying the range split-spectrum method for InSAR ionospheric phase estimation is straightforward ([Brcic et al., 2010](#); [Gomba et al., 2016](#); [Rosen et al., 2010](#)), the true challenge lies in achieving operational, high-precision estimation that meets the stringent requirements for measurement independence.

We first address the challenge of high-precision mosaicking of subswath sub-band interferograms. Typically, the range center frequency of the sub-band SLCs should be shifted to zero, which can be achieved by multiplying the bandpass-filtered SLC by a linear phase term proportional to the center frequency. A common origin must be used for the linear phase across all subswaths; otherwise, the phases of the subswath sub-band SLCs become

inconsistent, introducing significant relative phase errors between subswaths in the estimated ionospheric phase. This requires high-precision starting ranges of the subswaths, but they are provided only as integers in meters in the products, which is far from sufficient for this purpose. In [Liang and Fielding \(2017a\)](#), the phase difference between adjacent subswaths is estimated using their overlap area. However, the precision of the estimated phase difference depends on the coherence of the overlap area; therefore, the method is not sufficiently robust for operational use.

Here we propose a new technique to address this problem. If we set the origin of the linear phase to the first sample of each subswath and analyze a large number of resulting phase differences between adjacent subswath sub-band interferograms, we find that these phase differences consistently converge to a small number of constants. We leverage the highly coherent signals in Neom, Saudi Arabia and the surrounding regions to precisely estimate these constants. We use a stack of 29 acquisitions covering this region (frame 3050, track D77) and form a total of 81 InSAR pairs by connecting each date with its three subsequent dates. Each pair comprises five subswaths and two sub-bands. In total, we obtain 648 highly coherent overlap areas between adjacent subswaths. Using samples within these areas, the constants are estimated as follows:

$$\pm[0.0, 0.47540, 0.95099, 1.42616, 2.17966, 2.67669, 3.13081] \quad (1)$$

An additional constant was identified when processing other stacks

$$\pm[0.75459] \quad (2)$$

To use these constants in mosaicking subswath sub-band interferograms, we estimate the phase difference using the overlap area in two adjacent subswaths, compare the estimate against these constants, and select the one yielding the minimum residual. This technique significantly enhances inter-subswath phase consistency, particularly in low-coherence areas. It is crucial for achieving measurement independence when quantifying long-wavelength motions. See [Figure 5](#) for an example.

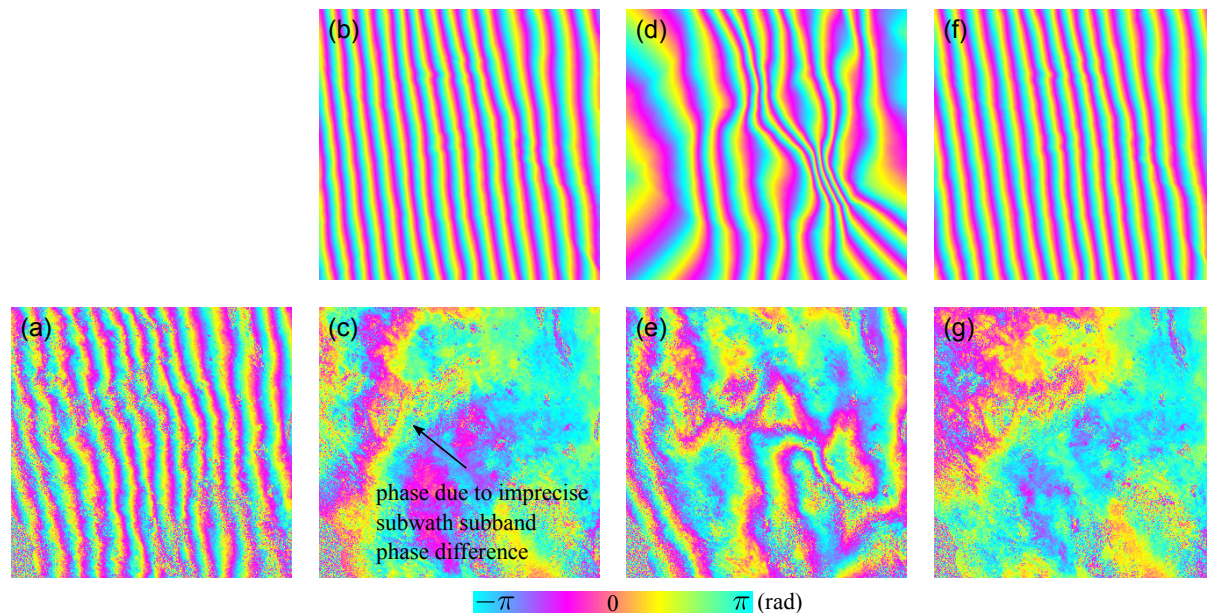


Figure 5. Improvements in ionospheric phase estimation for an ALOS-2 ScanSAR pair covering Northern California (pair 150408-190904, frame 2800, track D169). First row: Estimated ionospheric phase. Second row: Corrected interferograms. (a) Original interferogram. (b) and (c) Constant phase differences not used in estimating the phase difference between subswath sub-band interferograms. The clear phase difference between subswaths 4 and 5 in (c), which is smoothed during filtering, results from the imprecise phase difference used. (d) and (e) Polynomial fitting not performed before Gaussian filtering. (f) and (g) Constant phase differences used and polynomial fitting performed. An adaptive window size is employed in the filtering. The standard deviation of the filtered ionospheric phase is set to 0.2 rad. Tropospheric phase is removed from all interferograms using ERA-5 data.

In extremely low-coherence areas, the initial estimate of the subswath phase difference exhibits poor precision and may erroneously converge to an incorrect constant. In such cases, strong filtering of the sub-band interferograms in the overlap area is required before estimating the phase difference. However, this approach is time consuming and still carries a risk of selecting an erroneous constant. To further address this issue, we can first form sequential pairs using only neighboring dates. These sequential pairs minimize temporal decorrelation, thereby maximizing the probability of identifying the correct constant. Once the phase differences between neighboring dates are determined, the phase differences between other dates, which are also among the constants in (1) and (2), can be easily derived. This method proves to be highly effective for processing pairs in low-coherence areas.

After subswath sub-band interferograms are mosaicked, we proceed to mosaic the resulting frame sub-band interferograms. Estimating the phase difference between adjacent frame sub-band interferograms is significantly easier: The raw data from different frames within the overlap area are essentially identical, but are focused separately within each frame. Theoretically, the correlation between the two interferograms in the overlap area should be unity, enabling a high-precision estimate of the phase difference. The excellent consistency observed between adjacent subswaths and frames in Figures. 6-18 demonstrate the superior performance of these mosaicking techniques.

Next, we address the challenge of achieving high-precision ionospheric phase estimation in the presence of strong noise, particularly in low-coherence areas. Overcoming this challenge relies on robustly filtering the initial ionospheric phase estimate. A simple Gaussian filter, as used in previous works (Gomba et al., 2016), tends to introduce various artifacts. Here we propose a new filter. Given a Gaussian window size, the precision of the spatially filtered result depends on the sample coherence within the window. To obtain a result with spatially uniform precision, we employ an adaptive window size. By fixing the output precision to a constant value, the window size at each sample, which varies across the image, can be dynamically determined. This spatially varying window size inevitably leads to a spatially varying accuracy, or bias, in the output. A larger window size generally tends to introduce a greater bias. We address this bias below.

The Gaussian filter is essentially a lowpass filter, with a passband centered at zero. The frequency components of the ionospheric phase, however, do not necessarily fall within this passband. Consequently, using this filter risks attenuating the frequency components outside of

the passband along with the high frequency noise, thereby introducing the aforementioned bias. To mitigate this risk, we fit a two-dimensional polynomial to the phase within the Gaussian window to capture its dominant frequency components. The phase standard deviation is used to compute the weight used in the least-squares inversion of the polynomial coefficients. We find that a first- or second- order polynomial is sufficient in most cases. A 2D phase surface is then computed from the polynomial and subtracted from the original phase within the window, followed by the adaptive Gaussian filtering. Subsequently, the computed 2D phase surface is added back to the filtering result. This approach significantly reduces the bias, as well as its spatial variations. It also improves the overall performance at image margins, where the convolution is incomplete. [Figure 5](#) shows an example of these improvements. Although these techniques are designed for the highly challenging case of ALOS-2 ScanSAR data, they can enhance results from other missions as well.

Quick-look images are then generated for inspecting the ionospheric phase estimates. Poor results, e.g., those exhibiting dense abnormal fringes due to phase unwrapping errors, are discarded, and the remaining ones are used in a least-squares inversion to solve for the single-date ionospheric phase estimates. These single-date estimates are subsequently used to correct interferograms.

Remaining issues in ionospheric phase estimation include:

- 1) The area with sufficient coherence is too small to support precise estimation through spatial filtering.
- 2) The interferogram covers isolated areas, e.g., islands, leading to relative phase unwrapping errors between different areas and consequently large estimation errors. If an isolated area is sufficiently large to allow effective filtering, estimation can be performed separately for the area.
- 3) Spatially rapid variations in the TEC, such as those induced by the sporadic E layers and scintillations, cannot be effectively captured by the method. Moreover, they can even lead to phase differences exceeding $\pm\pi$ between neighboring samples as illustrated in [Figure 6](#), resulting in phase unwrapping errors. These phase unwrapping errors may lead to significant estimation errors.
- 4) Destructive decorrelation and occasional abrupt phase discontinuities, caused by seasonal snow and its melting process, result in severe noise and unwrapping-induced errors in the estimates. [Figure 7](#) presents such an example in the Cascadia subduction zone. In contrast, firn does not appear to constitute a significant problem. [Figure 8](#) presents an example from the Himalayas, which contains both firn and seasonal snow. The firn layer does not induce destructive decorrelation, and does not complicate the estimation. Notably, the dense vegetation in South Asia, which has long been considered a major source of strong decorrelation, induces only moderate decorrelation compared to seasonal snow cover. The InSAR pair also exhibits a large ionospheric phase, as the data were acquired around solar maximum (See [Figure 1](#)) in the north crest region of the Equatorial Ionization Anomaly (EIA), which is driven by the fountain effect.

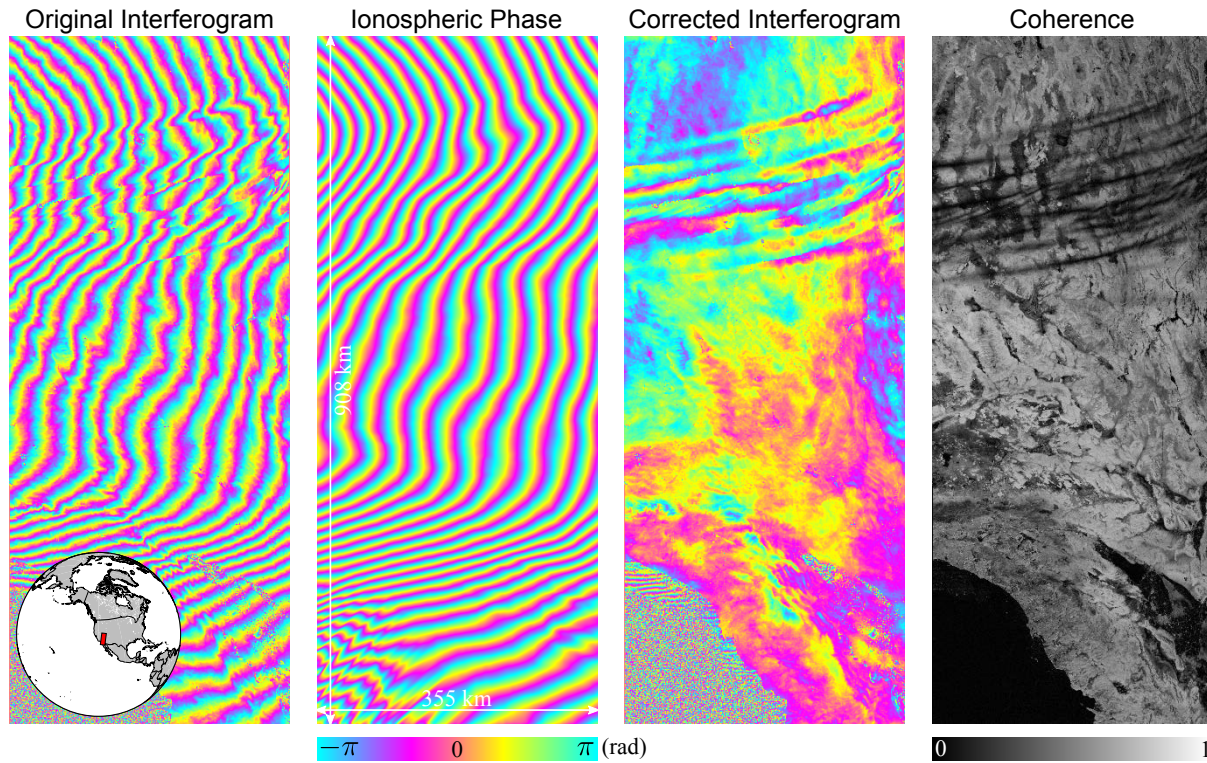


Figure 6. Spatially rapid variations in ionospheric TEC. Data are from the pair 150514-161013, track D165. In this case, manual correction of phase unwrapping errors caused by these spatially rapid variations is required to obtain a more accurate ionospheric phase estimate.

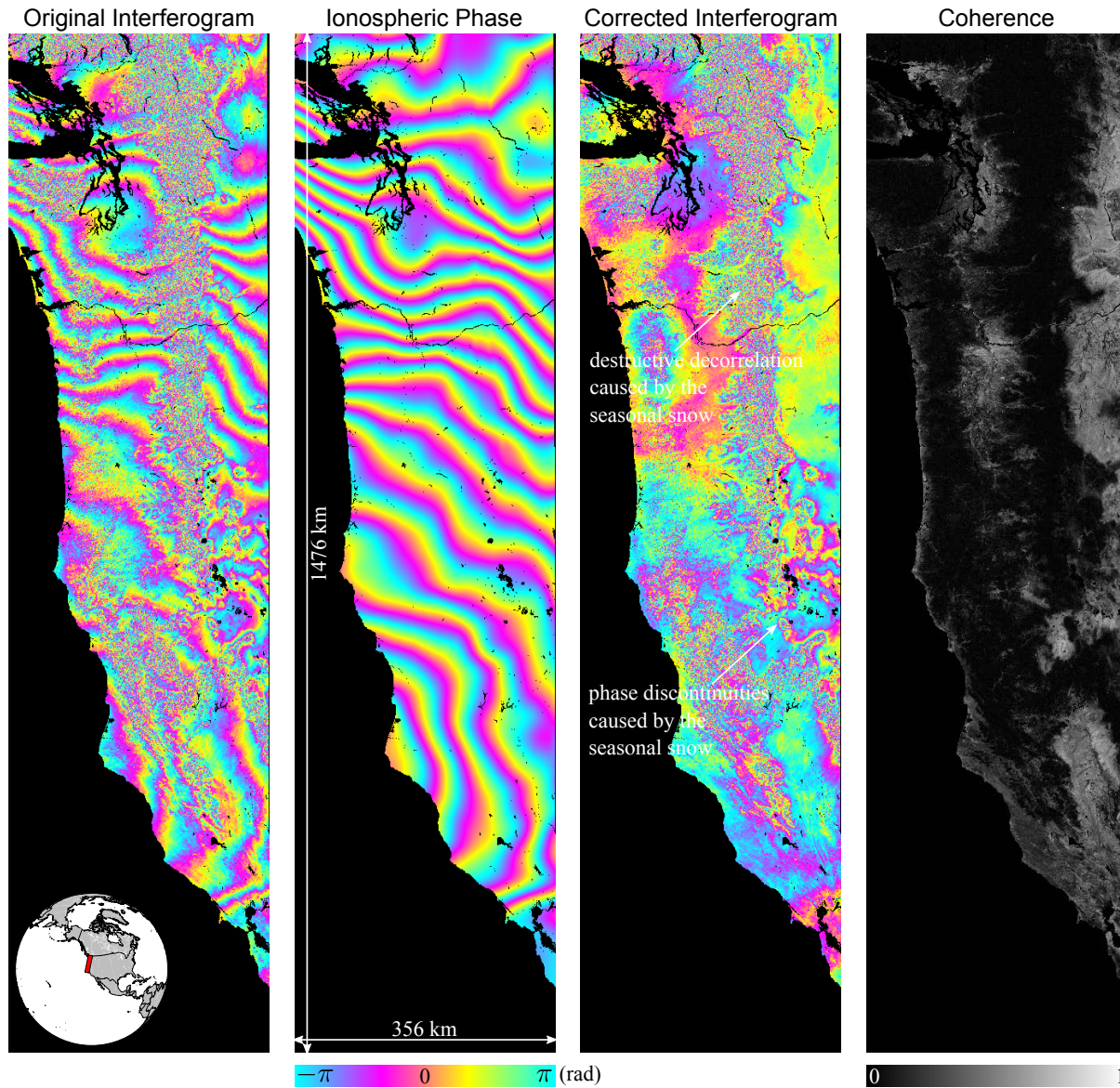


Figure 7. Effects of seasonal snow in a 2.3-month ALOS-2 ScanSAR pair covering the Cascadia subduction zone (pair 211018-211227, frames 2650, 2700, 2750, 2800 and 2850, track D170). Destructive decorrelation and phase discontinuities are caused by seasonal snow cover. In this case, manual correction of phase unwrapping errors is required to improve the ionospheric phase estimate.

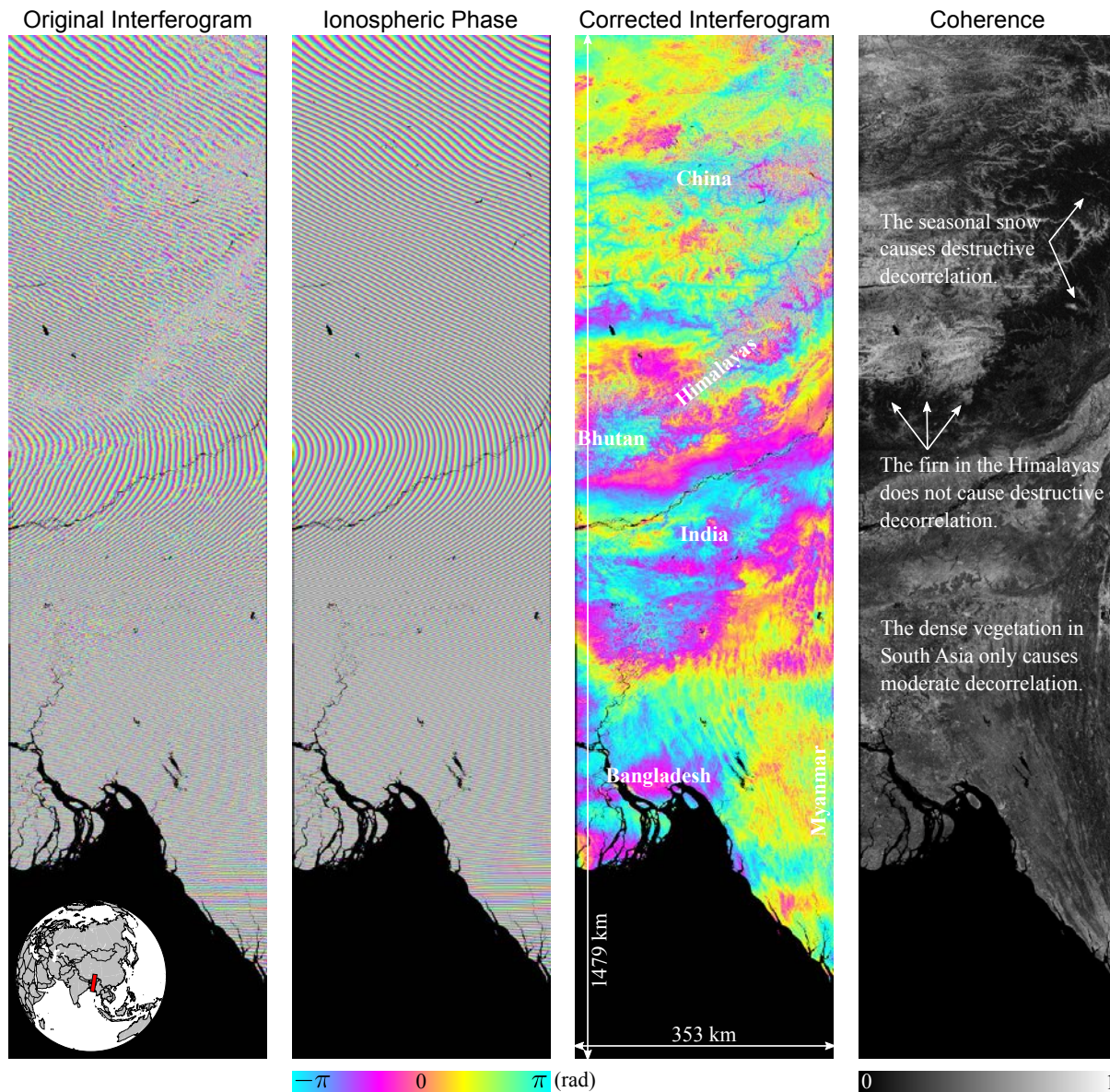


Figure 8. Effects of seasonal snow, firn and vegetation in a 2.8-month ALOS-2 ScanSAR pair (pair 231225-240318, frames 3000, 3050, 3100, 3150 and 3200, track D44). Destructive decorrelation is caused by seasonal snow cover. Automatic ionospheric phase estimation fails to produce reliable results in snow-covered regions, requiring adjustment of the filtering parameters to achieve good performance. The firn in the Himalayas does not cause destructive decorrelation, and does not pose a challenge to the estimation. Dense vegetation in South Asia leads only to moderate decorrelation. The ionospheric phase is exceptionally large, as the data were acquired around solar maximum in the north crest region of the Equatorial Ionization Anomaly (EIA), driven by the fountain effect.

3.4 Other signals and errors

Achieving InSAR measurement independence requires the rigorous mitigation of undesired signals. A comprehensive discussion of these signals, along with their quantitative computation and removal, is provided in [Appendix A](#).

Achieving measurement independence also requires reducing systematic and processing errors, which lead to long-wavelength errors in the interferograms, to sufficiently low levels. These errors can originate from orbit data and SAR focusing. The 3D orbit precision of ALOS-2 is 5 cm ([Akiyama et al., 2016](#)). According to its Basic Observation Scenario (BOS), the acquisition frequency for measuring global crustal motion with ScanSAR mode ranges from 4 to 9 times per year ([JAXA, 2025](#)). Given that ALOS-2 has been in space for more than a decade, the long-wavelength errors in the estimated mean velocity arising from orbit errors are comparable to those of Envisat. For the Envisat beam IS2, the range and azimuth long-wavelength errors caused by orbit errors in the mean velocity were estimated at 0.48 and 0.88 mm/yr/100 km, assuming orbit standard deviations of 4 (horizontal) and 2 (vertical) cm, and an 8-year operation period with 6 acquisitions per year ([Fattahi & Amelung, 2014](#)).

Regarding SAR focusing, the following effects are typically neglected in commonly used algorithms:

- 1) The intrapulse motion of the radar (commonly approximated by the "stop-and-go" assumption) that induces an azimuth sample shift that varies with range ([Gisinger et al., 2021](#)).
- 2) The range Doppler frequency shift that results in a range shift as a function of the Doppler centroid frequency ([Gisinger et al., 2021](#)).
- 3) The topography-dependent variation in the azimuth Frequency Modulation (FM) rate that induces both an azimuth shift and a phase error.

These errors are generally small and remain nearly unchanged across acquisitions, given the tight control of the ALOS-2 orbit and attitude. Hence, they largely cancel out when forming the interferogram. The relative sample shift effect is further minimized through cross-correlation matching between the reference and secondary SLCs in the processing workflow. The absolute sample shift effect is minimized by the matching between the reference SLC and the range geometric offset used for topographic phase removal in the processing workflow.

4 Evaluation of ALOS-2 data in the western United States

The western United States encompasses two major plate boundaries and broadly distributed continental motion extending as far east as the Rocky Mountains. To the north, the Juan de Fuca, Gorda, and Explorer oceanic plates subduct beneath the continental North American plate, forming the Cascadia subduction zone and the Cascade Volcanic Arc. To the south, the Pacific Plate moves northward relative to the North American Plate, forming the San Andreas Fault system and its various strands. The region is also subject to substantial ground subsidence caused by anthropogenic activities, such as groundwater pumping in the Central Valley, California, and oil pumping in California, among other activities.

Consequently, the region exhibits both short- and long-wavelength motions. Moreover, the region's proximity to the ocean provides an opportunity to evaluate the effects of ocean tide loading. The diverse land covers, topography, and climate conditions lead to varying degrees of decorrelation. The large number of GNSS stations in this region facilitates the validation of InSAR results.

Previous InSAR studies have been mostly limited to California and/or relied on constraints from GNSS to resolve long-wavelength tectonic motions (Tong et al., 2013; Xu et al., 2021). By leveraging the newly developed techniques and data, we are able to cover a much larger area without requiring GNSS data to constrain long-wavelength motions.

4.1 Data processing

The ALOS-2 satellite has systematically acquired data in the western United States using its ScanSAR mode (WBD mode, with a 350 km swath width). We use the data acquired from February 2015 to June 2023, as burst synchronization was not controlled prior to February 8, 2015 (see Table 2 for details). The total north-south extent of the data is approximately 2200 km. While we aim to cover the largest possible area, not all frames were acquired on each date for most tracks. For these tracks, we processed two stacks: One stack comprises more frames but fewer acquisitions, whereas the other consists of fewer frames but more acquisitions. Figure 9 shows the superior coherence of L-band ALOS-2 data compared to C-band Sentinel-1 data in the challenging Cascadia subduction zone.

Table 2. ALOS-2 ScanSAR (WBD mode) data for the western United States used in this study.

Track	D164		D165	D166		D167		D168		D169	D170
Frames	2950	2900	2850	2900	2800	2850	2750	2850	2700	2800	2650
		2950	2900	2950	2850	2900	2800	2900	2750	2850	2700
			2950		2900	2950	2850		2800		2750
					2950		2900		2850		2800
							2950		2900		2850
Number of Dates	76	23	35	47	26	60	37	72	35	111	70
Number of Dates Used	76	23	34	44	21	58	35	60	32	91	44

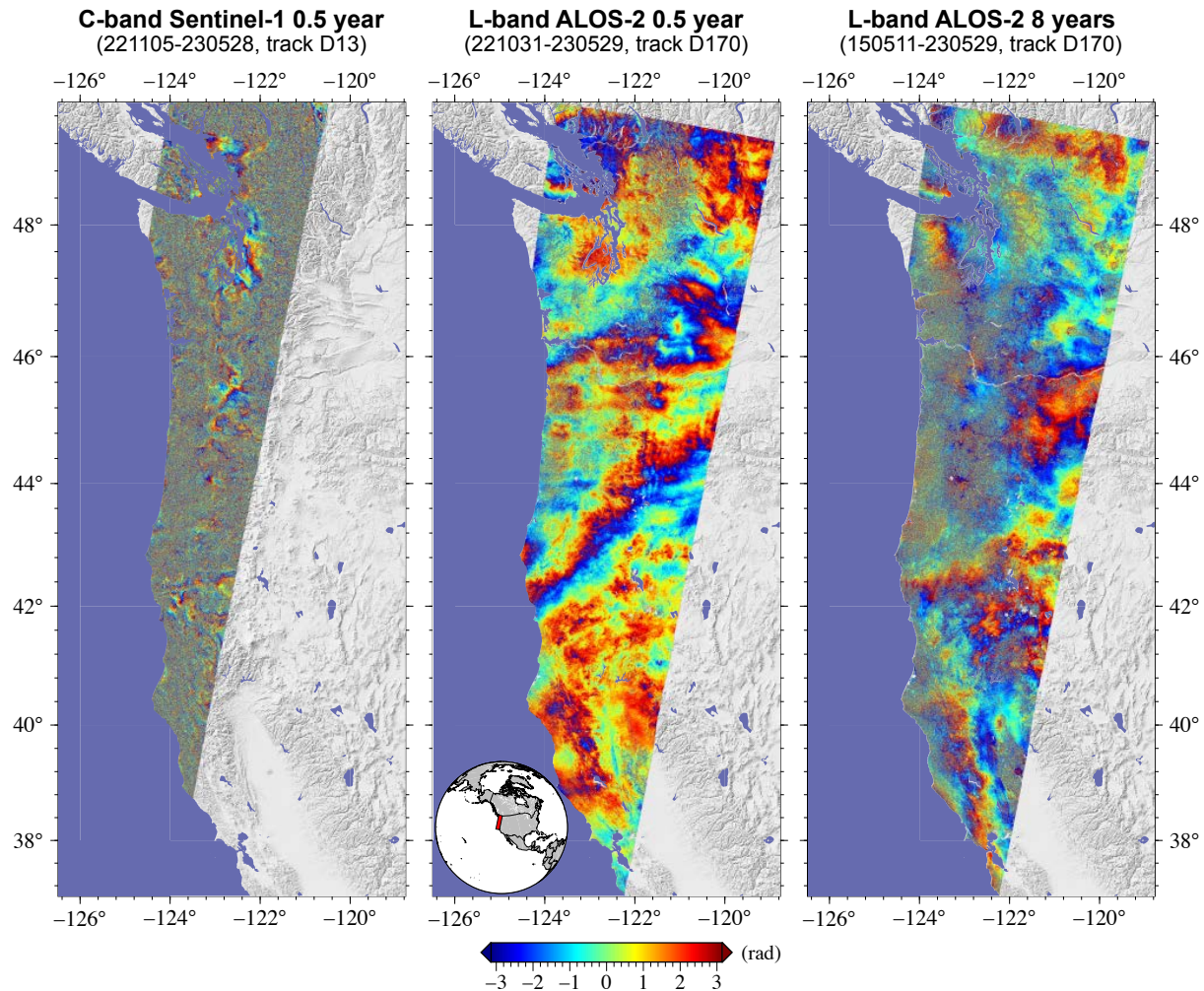


Figure 9. Comparison of interferograms of different wavelengths in the Cascadia subduction zone in the northwestern United States, which is characterized by forests, mountains and even firn. Left: Half-year C-band Sentinel-1 interferogram. Middle: Half-year L-band ALOS-2 interferogram. Right: 8-year L-band ALOS-2 interferogram. The sample size of the interferograms is 172 m $\times$ 292 m (slant range $\times$ azimuth on the ground). The number of looks for the Sentinel-1 interferogram is approximately three times that for the ALOS-2 interferograms. Ionospheric phase has been removed from ALOS-2 interferograms.

We used the techniques and software described in Section 3 to process the data. The topographic phase was removed using the 30 m Shuttle Radar Topography Mission (SRTM) DEM (Farr et al., 2007). For each stack, a reference date was selected from the middle of the respective time span. Winter dates were excluded from the reference date selection to avoid the adverse effects of seasonal snow. Taking advantage of the high coherence of the data, all possible pairs were formed for both InSAR processing and ionospheric phase estimation. For the ionospheric phase estimation stacks of tracks D169 and D170, where coherence is lower, each date was connected to up to half the total number of dates that follow it. As mentioned earlier, a major limitation arises from seasonal snow cover and its melting process.

Consequently, dates significantly affected by snow were identified and excluded from the respective stacks.

We used 10×56 (range $\times$ azimuth) looks for the InSAR processing of tracks D164-168, corresponding to a slant range sample size of 85.83 m, and an azimuth sample size on the ground of 145.87 m. The corresponding ground range sample size at the swath center is 132.59 m. For tracks D169 and D170, which exhibit lower coherence, the number of looks in both range and azimuth was doubled. Note that the true number of looks in azimuth should be divided by at least five, as the full synthetic aperture is shared among five subswaths. For ionospheric phase estimation, a much larger number of looks of 80×448 (range $\times$ azimuth) was used for all tracks.

For this region, we needed to further address three issues. First, the coastal islands are not sufficiently large to support effective spatial filtering in ionospheric phase estimation; therefore, these islands were masked in the processing. Second, secular fault motions over long time spans can generate large phase signals. Conventionally, such slow secular fault motions can be effectively measured only through InSAR time series; however, some of these signals become clearly visible in interferograms with very long temporal baselines, as shown in [Figure 10](#). In some cases, they even lead to phase variations exceeding $\pm\pi$ between neighboring samples, presenting challenges for phase unwrapping. To address this issue, a time-span threshold was set, and fault traces were masked in interferograms exceeding this threshold. Third, ground motions caused by earthquakes also lead to abrupt phase variations between neighboring samples. Several earthquakes occurred in the region during the data acquisition period. The affected areas were therefore masked in the relevant interferograms.

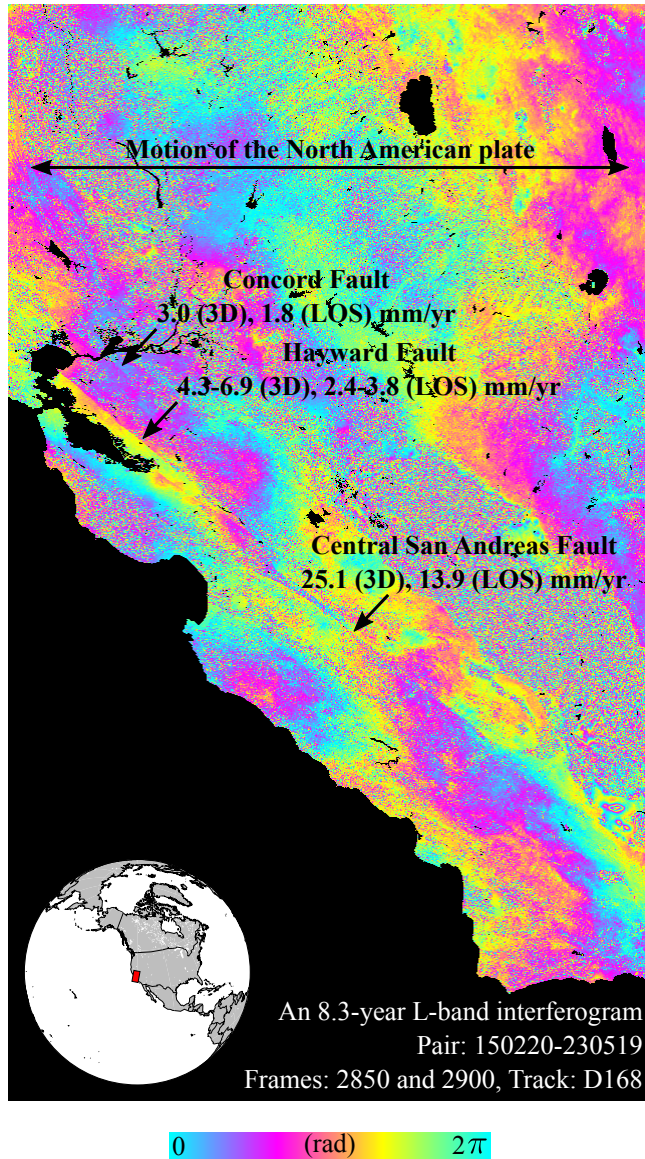


Figure 10. An 8.3-year L-band interferogram with ionospheric phase and tropospheric phase removed. The interferogram covers an area with moderate coherence. The long temporal baseline results in a high signal to noise ratio for measuring certain motions. The 3D and LOS velocities of the Concord Fault, Hayward Fault and Central San Andreas Fault are labeled near the faults. Small secular fault motions, conventionally measured with InSAR time series, are now visible in this long-temporal-baseline interferogram. The phase variation due to motion across the Central San Andreas Fault even exceeds 2π , resulting in phase unwrapping errors. The motion of the North American plate, projected into the LOS direction, manifests as a range ramp in the interferogram. The interferogram dimension is $356 \text{ km} \times 637 \text{ km}$.

The performance of different time series analysis techniques can vary substantially. To isolate the performance gains attributable solely to L-band observations and the processing techniques introduced in Section 3, we adopted the simplest possible time series approach: a basic least-squares inversion of the unwrapped interferograms, deliberately excluding any

544 additional gains from sophisticated time series analysis techniques. Typically, a weight derived
545 from the number of looks and coherence is applied in the least-squares estimation. This weight
546 tends to suppress the contribution of long-temporal-baseline pairs due to their stronger
547 temporal decorrelation. However, this weight does not necessarily improve the velocity
548 estimate, as the velocity estimate also depends on the time span. Moreover, long-temporal-
549 baseline pairs are less susceptible to the impacts of the non-zero closure phase (Ansari et al.,
550 2021). In fact, we found that a better estimate could be obtained without applying the weight.
551 Therefore, our least-squares inversion omitted the weight.

552 We also performed a simple least-squares inversion on ionospheric phase estimates to
553 solve for single-date estimates. To obtain a more refined result, the following procedure was
554 implemented. First, an initial least-squares inversion was performed on the results that were
555 not spatially filtered, yielding estimates for individual dates that were then differenced to form
556 updated results. These results were subsequently spatially filtered and used as input to a
557 second least-squares inversion to obtain the final estimates for individual dates.

558 We applied the techniques described in Appendix A to remove various undesired signals
559 from the motion time series. A mean velocity was then estimated by fitting a first-order
560 polynomial to the motion time series. The results, along with the contributions from undesired
561 signals, are presented in Figures 11-15 for tracks with even track numbers and more frames.
562 These stacks comprise more frames, but have fewer acquisitions, featuring broader spatial
563 coverage. Here we prioritized broader spatial coverage, because we are particularly interested
564 in evaluating the performance of independently measuring long-wavelength and small-
565 magnitude motions, which remains a primary challenge in InSAR for solid Earth science
566 applications. Since the contributions from ocean tide loading and pole tide are relatively small,
567 they are combined in Figure 14 and Figure 15. The contributions from ocean pole tide loading
568 and atmospheric tide loading are even smaller, and are not presented here to avoid repeating
569 similar results.

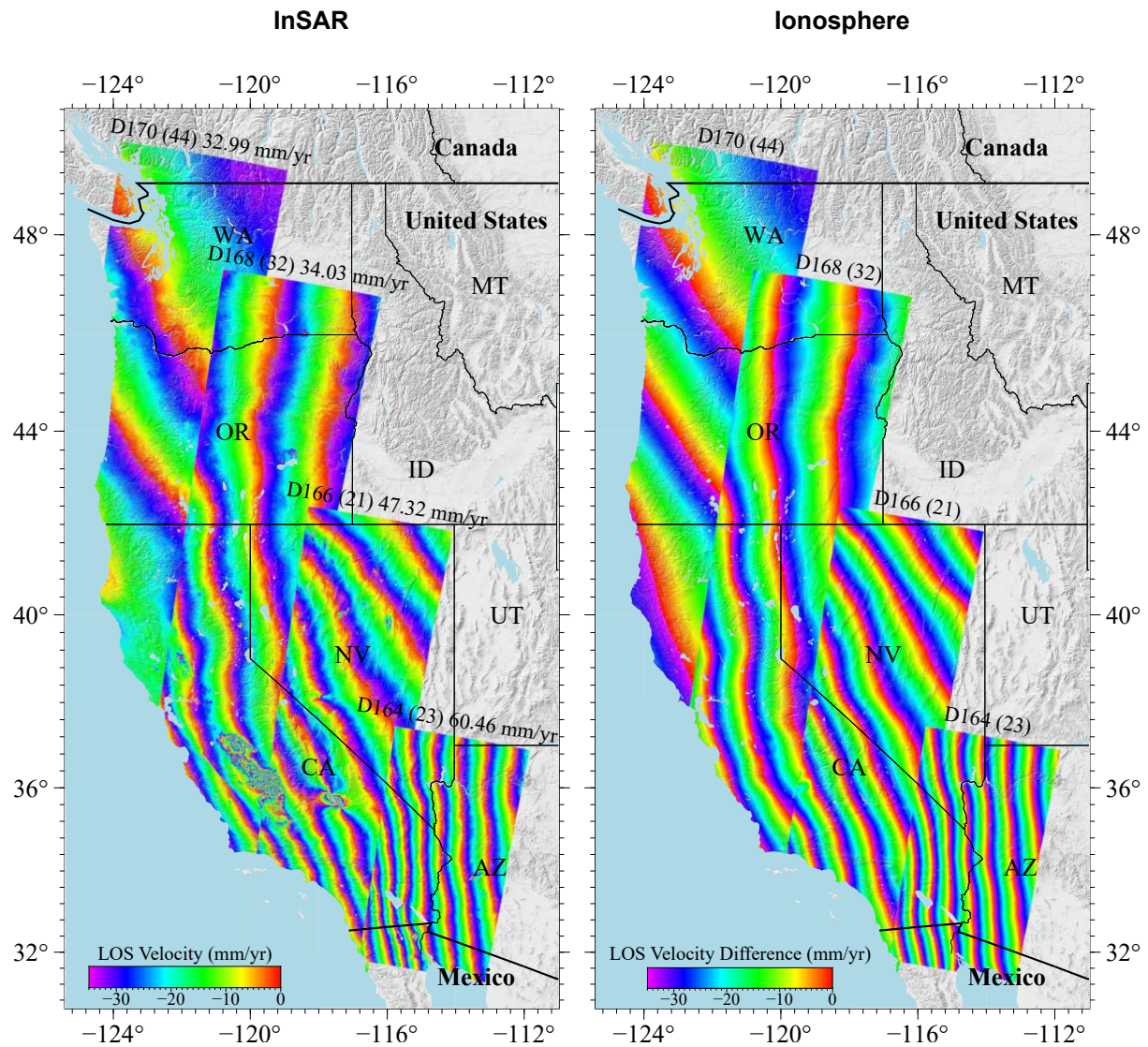


Figure 11. InSAR LOS velocities for tracks with even track numbers. These stacks comprise more frames, but fewer acquisitions, featuring broader spatial coverage. Left: Original InSAR velocities. The track numbers, number of dates, and RMS between InSAR and GNSS velocities are labeled on top of each track. Right: Velocity errors due to the ionosphere.

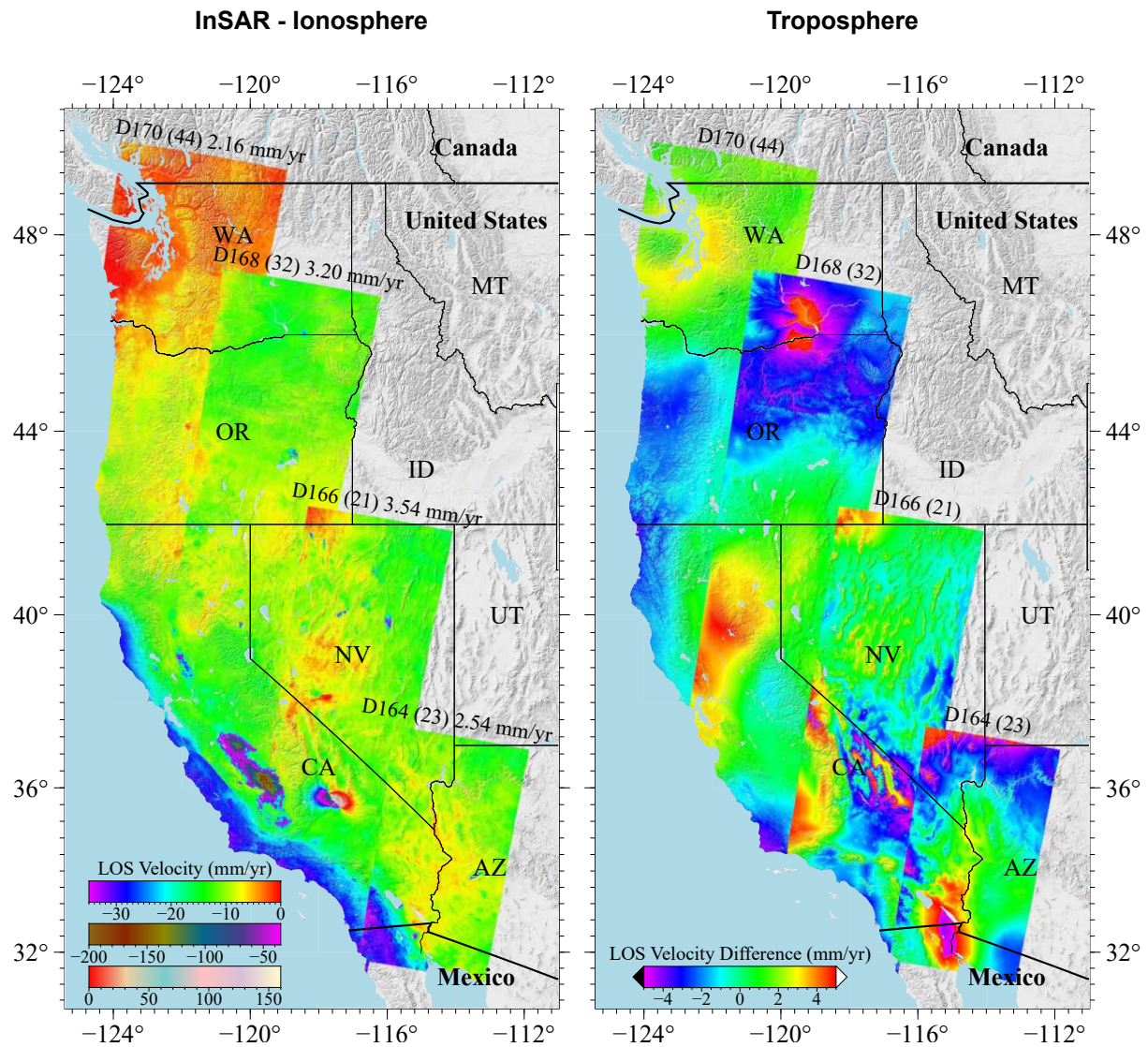


Figure 12. InSAR LOS velocities for tracks with even track numbers. These stacks comprise more frames, but fewer acquisitions, featuring broader spatial coverage. Left: InSAR velocities after removing contributions from ionosphere. The track numbers, number of dates, and RMS between InSAR and GNSS velocities are labeled on top of each track. Right: Velocity errors due to the troposphere.

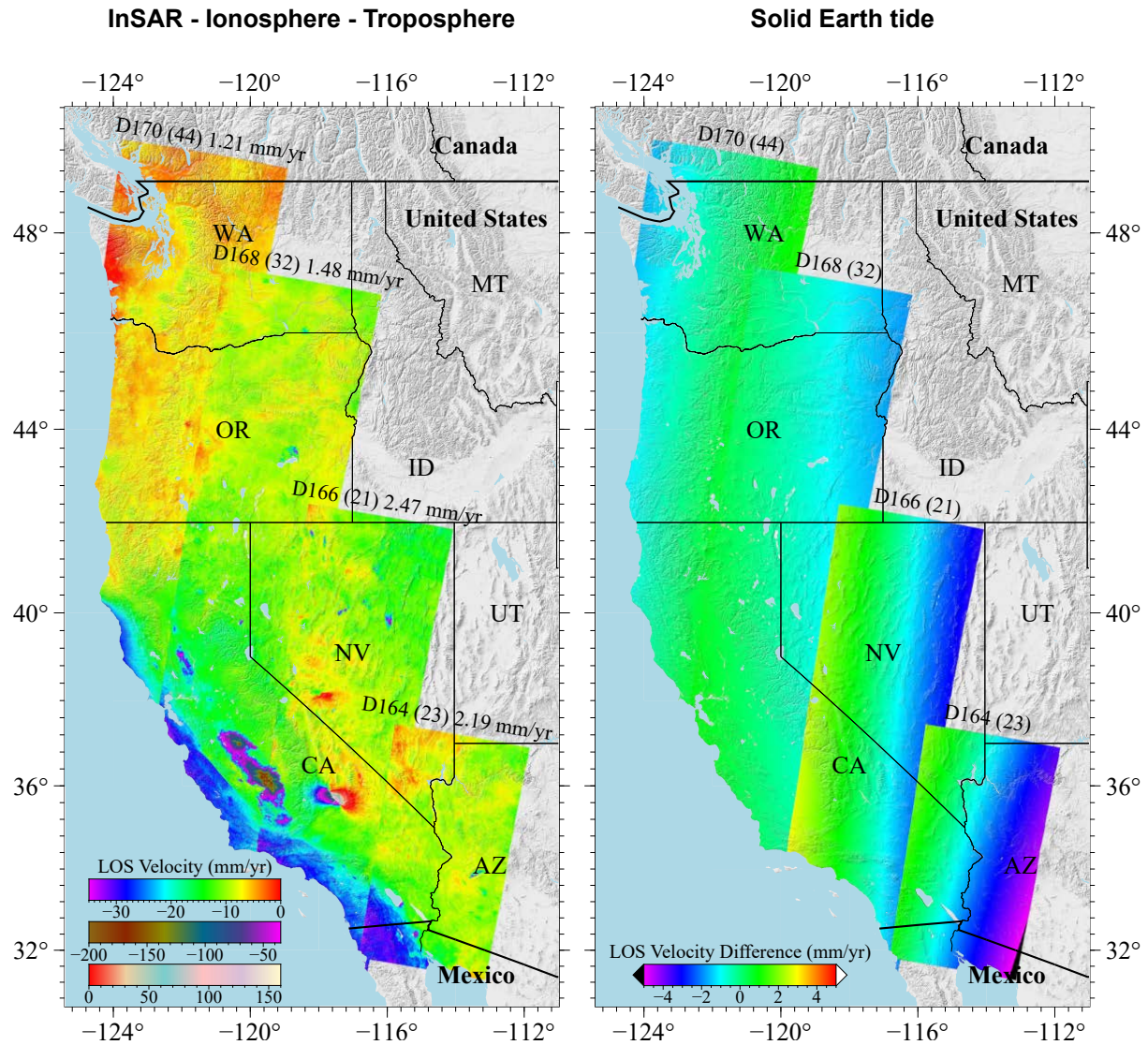


Figure 13. InSAR LOS velocities for tracks with even track numbers. These stacks comprise more frames, but fewer acquisitions, featuring broader spatial coverage. Left: InSAR velocities after removing contributions from the ionosphere and troposphere. The track numbers, number of dates, and RMS between InSAR and GNSS velocities are labeled on top of each track. Right: Velocity errors due to solid Earth tide.

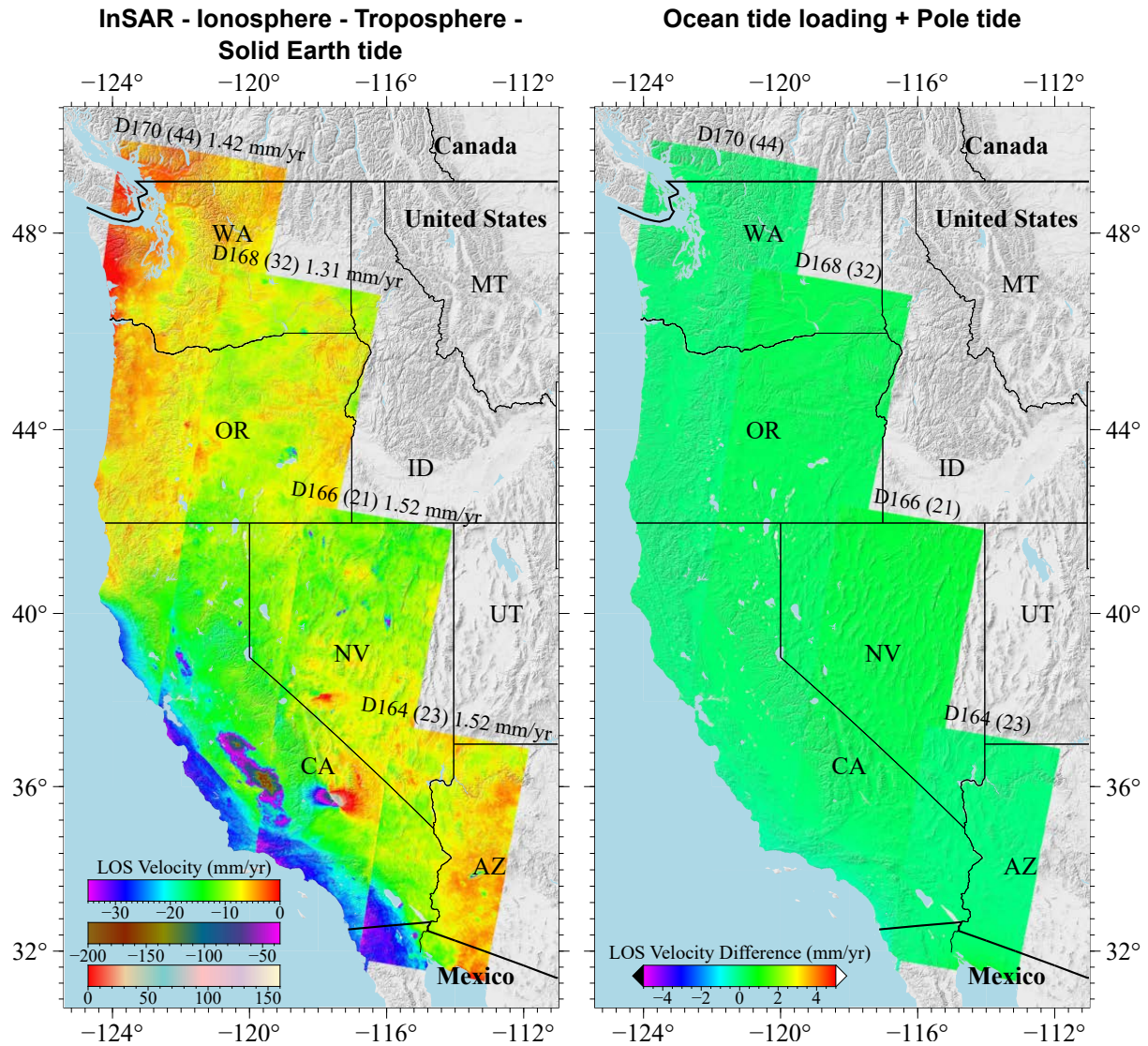


Figure 14. InSAR LOS velocities for tracks with even track numbers. These stacks comprise more frames, but fewer acquisitions, featuring broader spatial coverage. Left: InSAR velocities after removing contributions from the ionosphere, troposphere, and solid Earth tide. The track numbers, number of dates, and RMS between InSAR and GNSS velocities are labeled on top of each track. Right: Velocity errors due to ocean tide loading and pole tide.

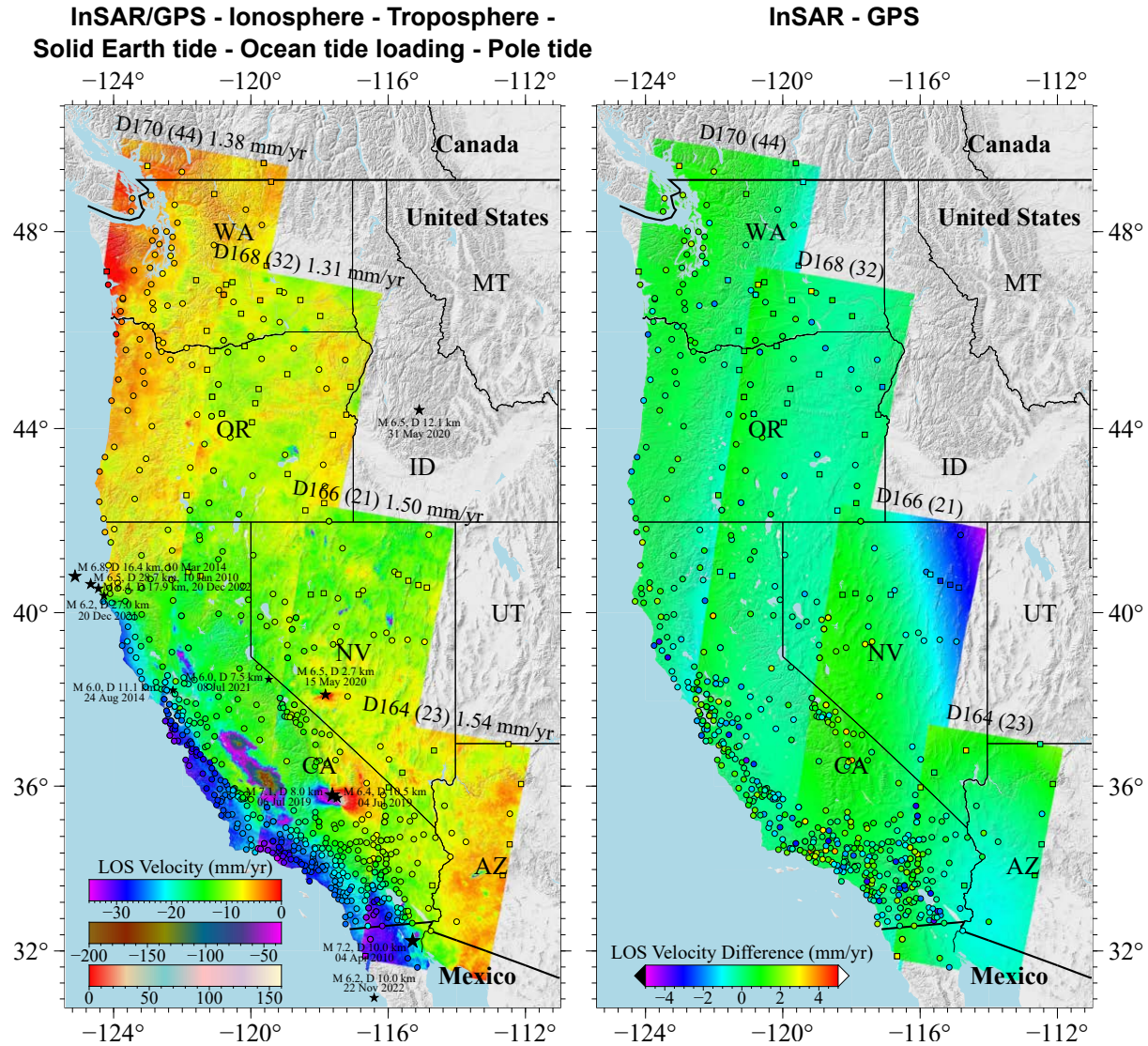


Figure 15. InSAR LOS velocities for tracks with even track numbers. These stacks comprise more frames, but fewer acquisitions, featuring broader spatial coverage. Left: InSAR and GNSS velocities after removing contributions from the ionosphere, troposphere, solid Earth tide, ocean tide loading, and pole tide. The track numbers, number of dates, and RMS between InSAR and GNSS velocities are labeled on top of each track. Circles and squares denote high- and lower-quality GNSS stations, respectively. Colors in the circles and squares represent the 3D GNSS velocities projected into LOS directions. Right: InSAR and GNSS velocity differences (InSAR-GNSS). Colors in the circles and squares represent the velocity differences at GNSS stations, while background colors represent differences computed by fitting a 2nd-order polynomial to the velocity differences.

4.2 Validation with GNSS measurements

To validate the InSAR measurements against GNSS observations, both datasets should be in the same reference frame and contain the same signals. This requirement is crucial for evaluating the capability of achieving measurement independence.

We used the GNSS time series from the NASA MEaSUREs project ([Bock et al., 2021](#)) for validation. We first consider establishing a common reference frame. InSAR measurements are tied to the orbit data from positioning instruments onboard SAR satellites, which are now primarily GNSS receivers. They naturally inherit the International Terrestrial Reference Frame (ITRF) commonly adopted by GNSS ([Liu et al., 2025](#); [Stephenson et al., 2022](#)). Therefore, they are in the same reference frame as GNSS measurements, provided that the same ITRF version is used to process the data from GNSS receivers both on the ground and onboard the SAR satellite. The MEaSUREs products were processed in the terrestrial reference frame ITRF2014. Although the ITRF version used for ALOS-2 orbit data is not explicitly stated, the differences between different versions are negligible for our purpose, as demonstrated later.

The second problem is that both measurements should contain the same signals. Among the undesired signals described in Appendix A, contributions from the troposphere, ionosphere, solid Earth tide, ocean tide loading, and pole tide have been removed from the MEaSUREs products. Tidal and loading motions are computed following the IERS conventions (2010) ([Petit & Luzum, 2010](#)). In the SOPAC solution for processing the GNSS data, the motion induced by ocean tide loading is computed using the FES04 model with center of mass correction ([Agnew, 2012](#)). We also removed these undesired signals from InSAR measurements. As shown in [Figure 2](#), InSAR is also sensitive to signals associated with surface and near-surface physical processes other than motions. Currently, we are unable to remove these signals.

We are highly selective in using the GNSS measurements for the comparison, as they also contain various noise and artifacts that could significantly affect the validation. The large number of stations in the western United States provides an opportunity for us to select only high-quality stations. Specifically, the following categories of stations are excluded:

- 1) Low-quality stations with large errors;
- 2) Moderate-quality stations located in the vicinity of high-quality stations;
- 3) Stations lacking sufficient data over the time span of SAR acquisitions;
- 4) Stations situated in areas with spatially rapidly varying motions.

These strict criteria result in a station network that is not sufficiently dense in some areas. In these areas, we relaxed the criteria and included additional usable stations that, while lacking a full data record, exhibit stable secular motions.

The InSAR time series are inherently relative both temporally and spatially. Temporally, we used the first date in each stack as the reference date for the time series. Spatially, we chose a reference area for each stack. Consequently, the InSAR velocity can be expressed as

$$\begin{aligned}
v_{\text{InSAR}}(x, y, z) &= \frac{\mathbf{D}(x, y, z, t) \cdot \mathbf{LOS}(x, y, z)}{dt} - \frac{\mathbf{D}(x_0, y_0, z_0, t) \cdot \mathbf{LOS}(x_0, y_0, z_0)}{dt} \\
&= \frac{\mathbf{d}(x, y, z, t)}{dt} - \frac{\mathbf{d}(x_0, y_0, z_0, t)}{dt} \\
&= v(x, y, z) - v(x_0, y_0, z_0)
\end{aligned} \tag{3}$$

where t is the time, (x, y, z) is the position, the subscript 0 denotes the reference time or position, $\mathbf{D}(x, y, z, t)$ is the 3D motion time series with respect to the reference time t_0 , $\mathbf{LOS}(x, y, z)$ is the unit vector in the SAR LOS direction, $\mathbf{d}(x, y, z, t)$ is the LOS motion time series with respect to the reference time t_0 , and $v(x, y, z)$ is the mean LOS motion velocity. Therefore, the measured InSAR LOS velocity $v_{\text{InSAR}}(x, y, z)$ contains an unresolved constant $v(x_0, y_0, z_0)$, which represents the mean velocity of the reference position. For each stack, this constant was estimated as the mean difference between the InSAR and GNSS LOS velocities, and was subsequently removed from $v_{\text{InSAR}}(x, y, z)$. At each GNSS station, the mean InSAR velocity within a 3×3 window centered on the station was used for comparison.

The comparison results for tracks with even track numbers and more frames are presented in [Figure 15](#). A second-order polynomial was also fitted to the differences for each stack, as shown in the right panel of [Figure 15](#). Results for the remaining tracks are provided in [Figures 16-18](#). Most of these InSAR results exhibit no discernable ramps. As shown in [Figure 15](#), long-wavelength and small-magnitude motions are measured with high precision even in the challenging Cascadia subduction zone, which is generally infeasible with conventional techniques and data. As an additional quality metric, the root-mean-square (RMS) values are remarkably small, ranging from 1.15 to 1.61 mm/yr.

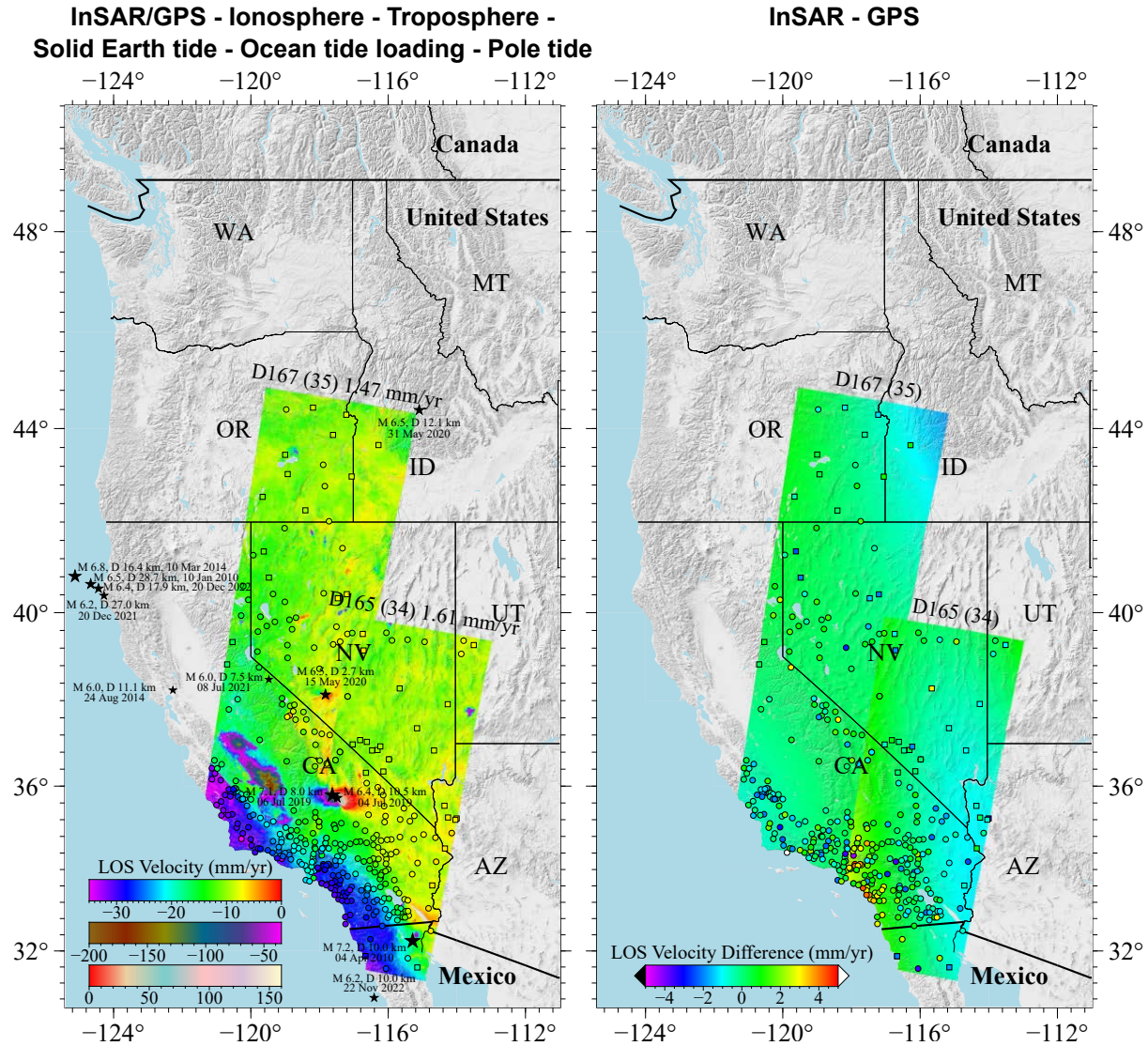


Figure 16. InSAR LOS velocities for tracks with odd track numbers. These stacks comprise more frames, but fewer acquisitions, featuring broader spatial coverage. Left: InSAR and GNSS velocities after removing contributions from the ionosphere, troposphere, solid Earth tide, ocean tide loading, and pole tide. The track numbers, number of dates, and RMS between InSAR and GNSS velocities are labeled on top of each track. Circles and squares denote high- and lower-quality GNSS stations. Colors in the circles and squares represent the 3D GNSS velocities projected into LOS directions. Right: InSAR and GNSS velocity differences (InSAR-GNSS). Colors in the circles and squares represent the velocity differences at GNSS stations, while background colors represent differences computed by fitting a 2nd-order polynomial to the velocity differences.

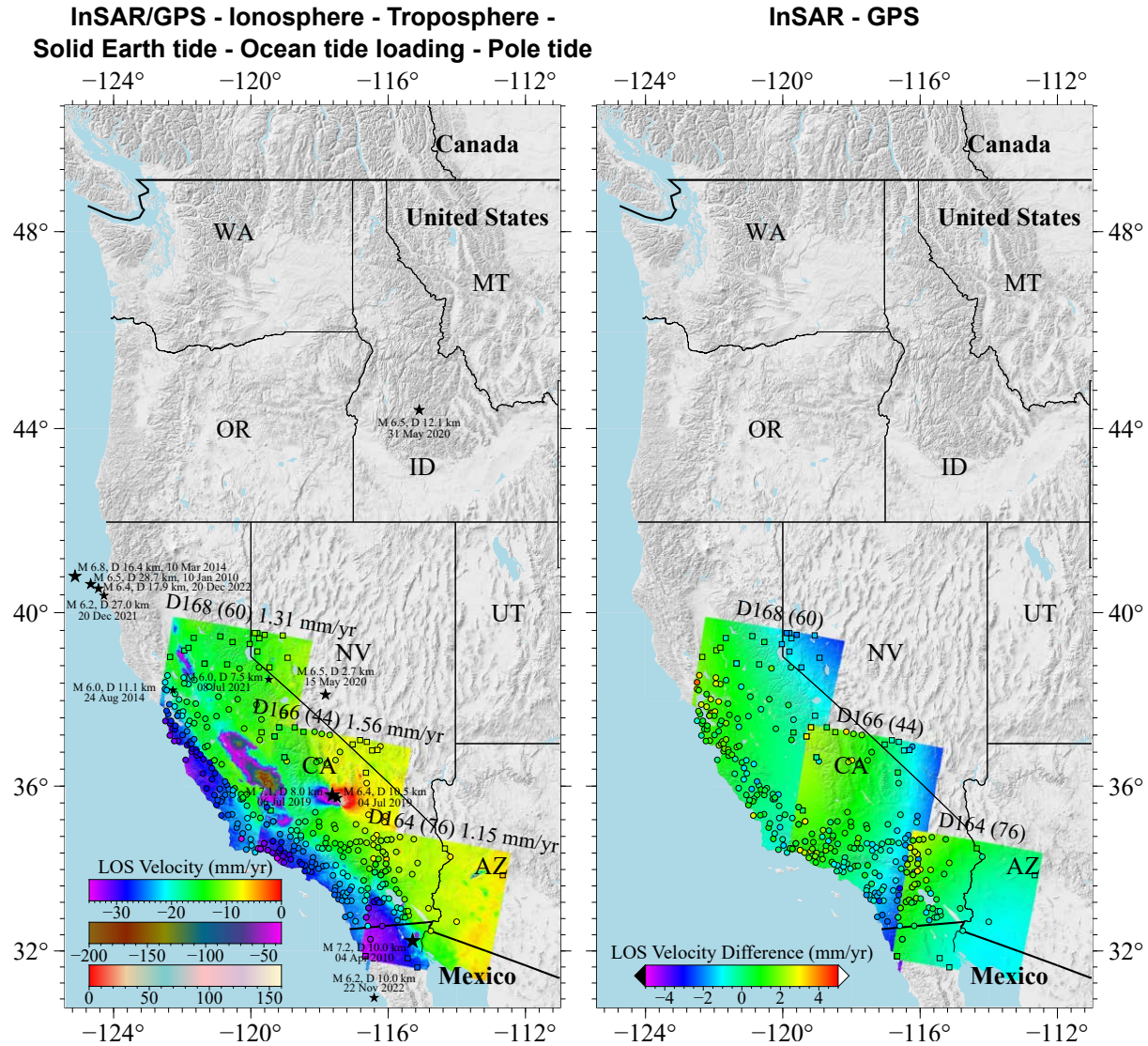


Figure 17. InSAR LOS velocities for tracks with even track numbers. These stacks comprise fewer frames, but more acquisitions. Left: InSAR and GNSS velocities after removing contributions from the ionosphere, troposphere, solid Earth tide, ocean tide loading, and pole tide. The track numbers, number of dates, and RMS between InSAR and GNSS velocities are labeled on top of each track. Circles and squares denote high- and lower-quality GNSS stations. Colors in the circles and squares represent the 3D GNSS velocities projected into InSAR LOS directions. Right: InSAR and GNSS velocity differences (InSAR-GNSS). Colors in the circles and squares represent the velocity differences at GNSS stations, while background colors represent the differences computed by fitting a 2nd-order polynomial to the velocity differences.

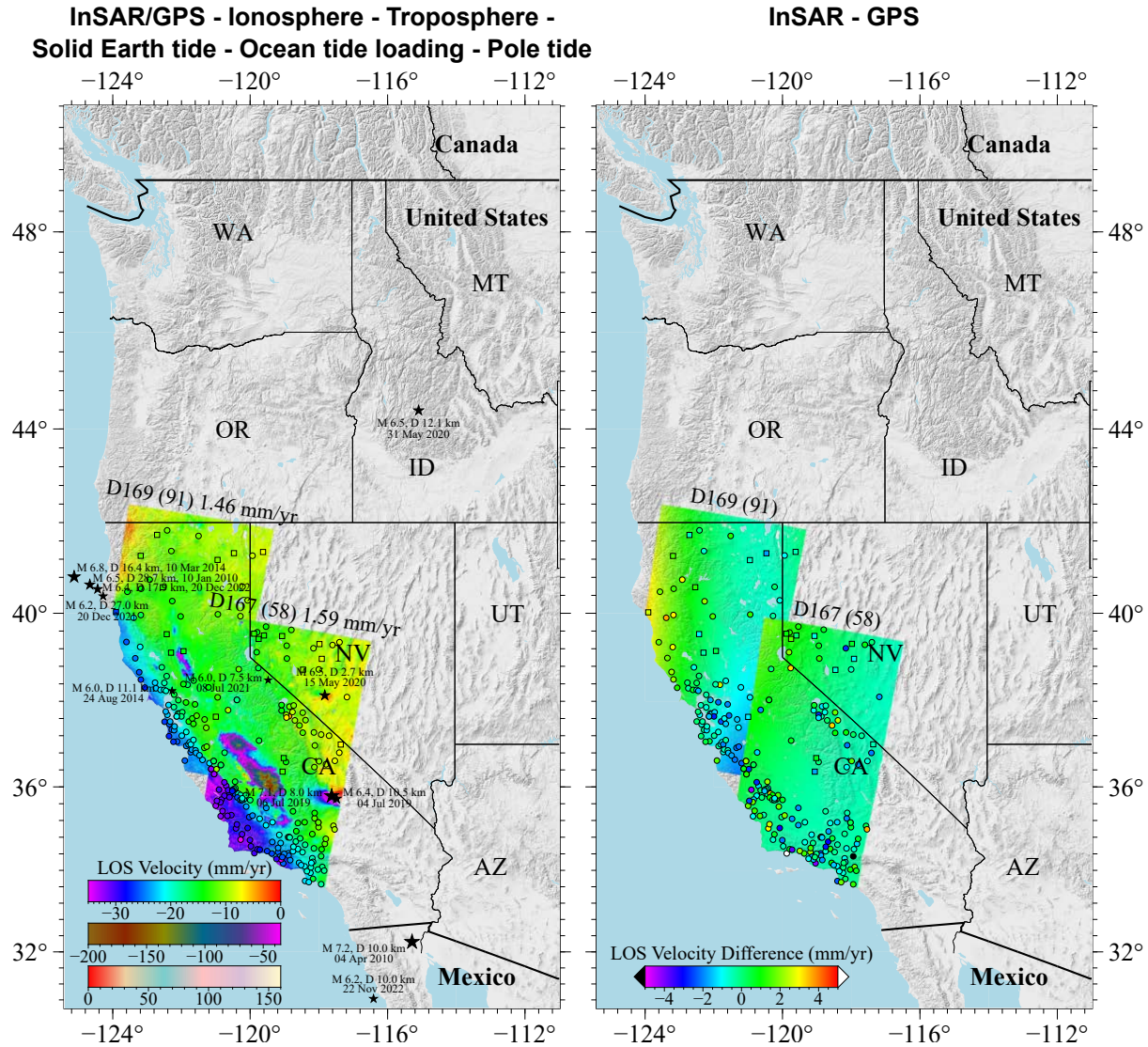


Figure 18. InSAR LOS velocities for tracks with odd track numbers. These stacks comprise fewer frames, but more acquisitions. Left: InSAR and GNSS velocities after removing contributions from the ionosphere, troposphere, solid Earth tide, ocean tide loading, and pole tide. The track numbers, number of dates, and RMS between InSAR and GNSS velocities are labeled on top of each track. Circles and squares denote high- and lower-quality GNSS stations. Colors in the circles and squares represent the 3D GNSS velocities projected into InSAR LOS directions. Right: InSAR and GNSS velocity differences (InSAR-GNSS). Colors in the circles and squares represent the velocity differences at GNSS stations, while background colors represent the differences computed by fitting a 2nd-order polynomial to the velocity differences.

There are two issues in the results that deserve further investigation. The first concerns local differences, such as the one in the top right corner of track D166 in the right panel of Figure 15. A major error source in the results is the residual tropospheric signal arising from the limited spatiotemporal resolution of the ERA5 data. In this stack, there are only 21 acquisitions; therefore, these residuals might have contributed to the observed differences. A similar issue is

observed in the top right corner of track D168 in the right panel of [Figure 17](#). Here, the difference is closely related to topography and landcover, indicating that it might be caused by topographically correlated residual tropospheric signals.

We also find relatively small range ramps in some of the stacks. These range ramps are mostly less than 2 mm/yr over the 350 km swath and consistently increase from near range to far range, suggesting they are unlikely to be caused by orbit errors and might instead be systematic. To explore potential causes, we investigate the effects of different ITRF versions. The GNSS measurements are referenced to ITRF2014. While the ITRF version used for ALOS-2 orbit data remains unknown, we can compute the LOS velocity difference between different ITRF versions. [Figure 19](#) shows the North American plate motions computed using the plate motion models in ITRF2008 ([Altamimi et al., 2012](#)) and ITRF2014 ([Altamimi et al., 2017](#)) for track D170. Plate motion is a major source of the observed long-wavelength motions. However, as illustrated, the LOS velocity difference is actually very small; therefore, ITRF version difference is unlikely to account for the observed ramps. Among all the factors affecting measurement independence described in [Section 3](#), the only one that remains unclear to us is SAR focusing. Unfortunately, the technical details of ALOS-2 products required for further investigation of the small range ramps are not publicly available.

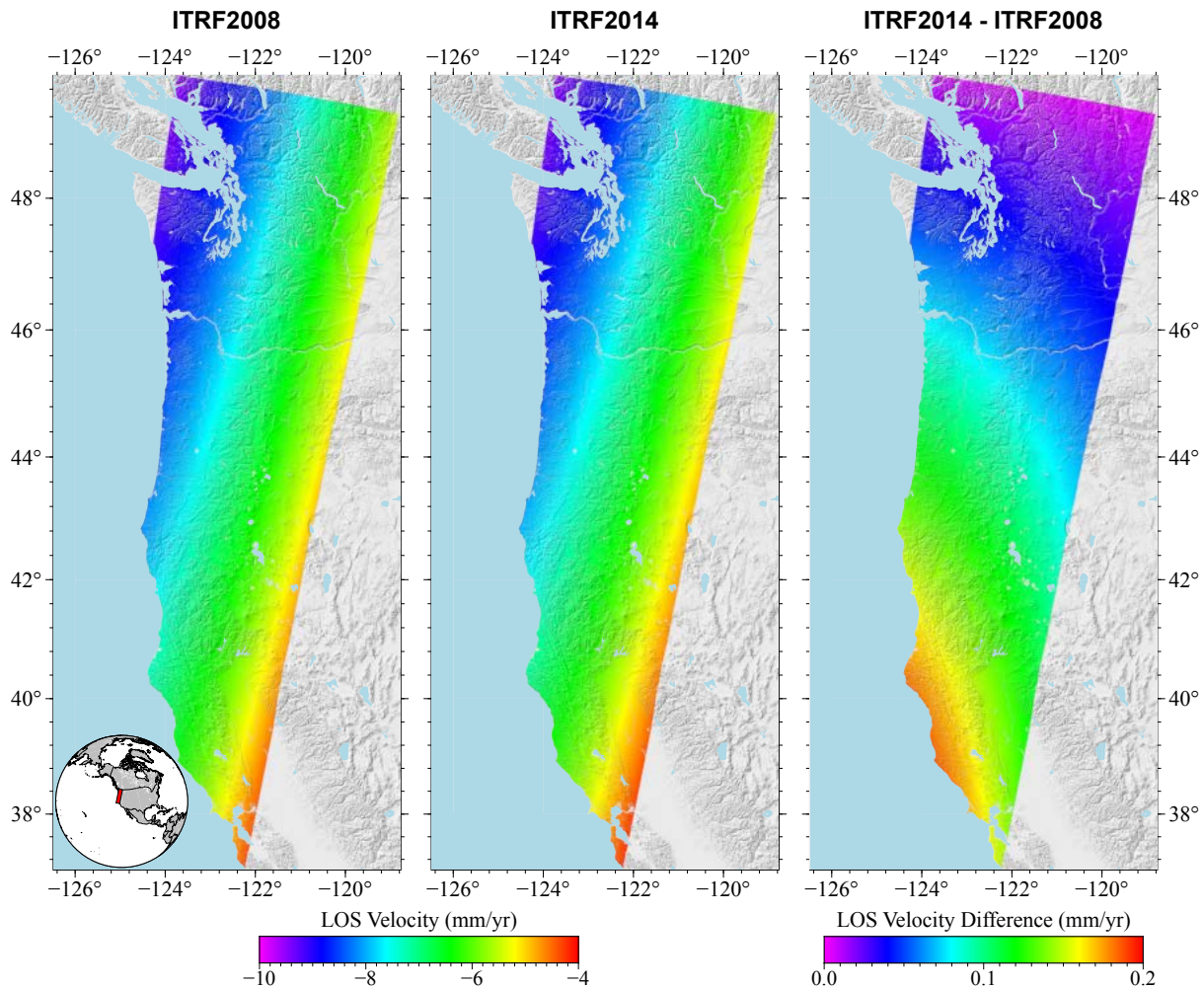


Figure 19. North American plate motions computed using plate motion models in ITRF2008 and ITRF2014 for track D170. The motions are projected into LOS directions.

4.3 Analysis of selected areas

Section 4.2 primarily focuses on the performance of independently measuring long-wavelength motions. This section presents several examples of measured short-wavelength motions. In particular, we examine the performance in low-coherence areas.

The Superstition Hills Fault in Southern California crept steadily for 13 years before a spontaneous Slow Slip Event (SSE) began May 16, 2023 (UTC) (Vavra et al., 2024). The final acquisition of the one-frame stack of track D164 was on May 13, 2023 (UTC), immediately preceding the SSE; therefore, the entire stack was acquired before the SSE. During this period, the averaged surface creep rate was 3.2 mm/yr (Vavra et al., 2024), corresponding to 1.9 mm/yr when projected into the LOS direction. InSAR measurements show a nearly identical creep rate, as illustrated in Figure 20.

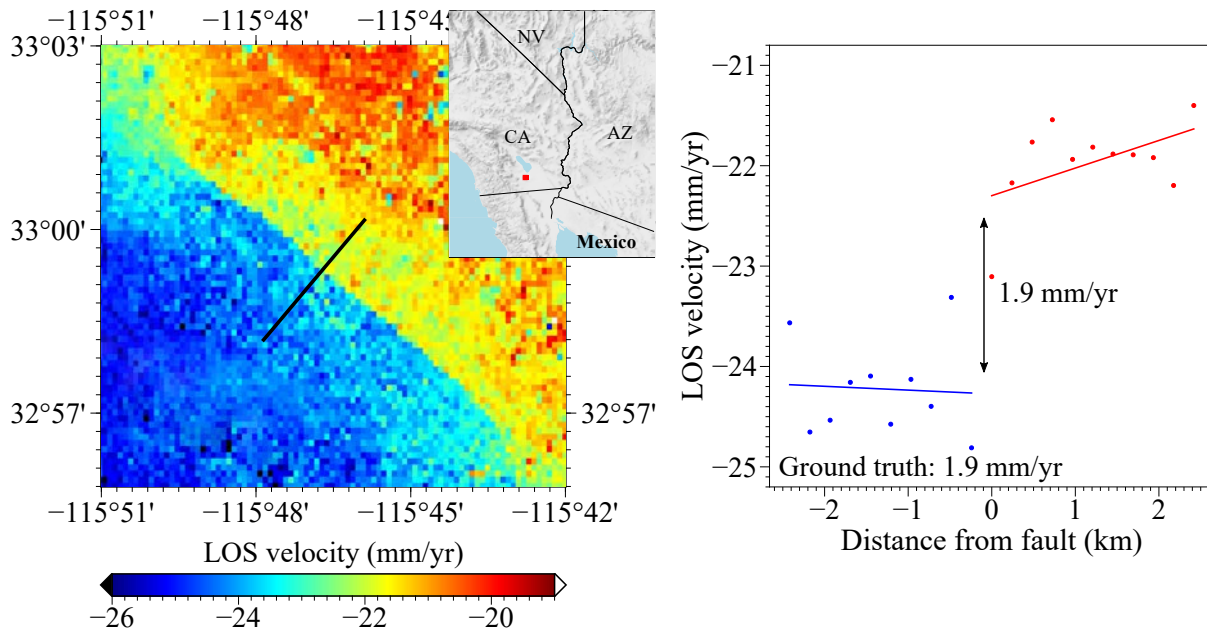


Figure 20. LOS motion velocities of the Superstition Hills Fault in Southern California. Left: LOS velocity map. Right: Velocity profile perpendicular to the fault. Data are from track D164.

The secular surface creep rates of several faults in the northern San Andreas fault system have been comprehensively measured using alignment array and GNSS techniques (Lienkaemper et al., 2014). Using these measurements as a reference, we examined the surface creep rates of three faults. The InSAR measurements were derived from the two-frame stack of track D168 and are shown in Figure 21.

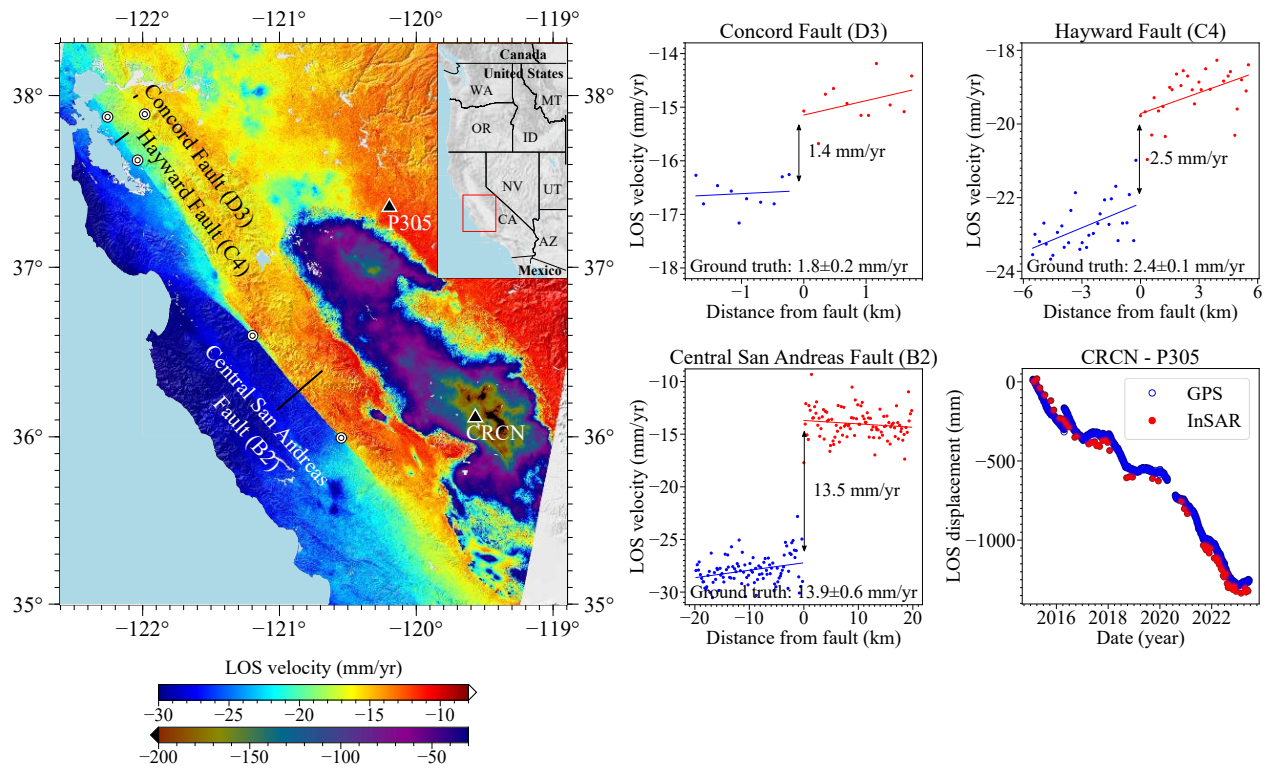


Figure 21. LOS motions of the Concord Fault (section D3), Hayward Fault (section C4), and Central San Andreas Fault (section B2), as well as subsidence in the Central Valley, California. Fault sections D3, C4 and B2 are defined in (Lienkaemper et al., 2014), and are marked in the left panel. Section D3 also includes the southern Green Valley Fault to the north of the Concord Fault, which is not fully covered in the figure. Profiles perpendicular to the faults are shown in the right panels. Motions at GNSS station CRCN relative to those at station P305 are shown in the lower right panel. Data are from track D168.

Along the rapidly creeping Central San Andreas Fault (Fault section B2 in Lienkaemper et al. (2014)), the surface creep rate exhibits little variation. The mean surface creep rate along the 93 km B2 section is 25.1 ± 1.0 mm/yr, which corresponds to 13.9 ± 0.6 mm/yr when projected into the LOS direction. The Hayward fault was segmented into three sections by Lienkaemper et al. (2014): the more slowly creeping central section (C4), and the two faster creeping northern (C5), and southern (C3) sections. The mean surface creep rate of the 32-km C4 section is 4.3 ± 0.2 mm/yr, equivalent to 2.4 ± 0.1 mm/yr in the LOS direction. The Concord fault and the southern Green Valley fault were combined into a single section (D3). The mean surface creep rate of the 74-km D3 section is 3.0 ± 0.3 mm/yr, equivalent to 1.8 ± 0.2 mm/yr in the LOS direction. InSAR results show good agreement with all of these reference values. Several studies have measured the surface creep rates in this region using InSAR data (Jolivet et al., 2015; Shirzaei & Bürgmann, 2013; Tong et al., 2013; Xu et al., 2021). Among them, Shirzaei and Bürgmann (2013) achieved comparable precision for the Hayward fault using InSAR data acquired by ERS-1/2 and Envisat satellites also on descending tracks, but with many more acquisitions (102 acquisitions over 18 years) and a more advanced time series technique.

The Central Valley in California has long experienced rapid subsidence due to groundwater pumping. The subsidence in this region has been continuously monitored by InSAR over the years (Farr et al., 2017; Govorcin et al., 2025; Liu et al., 2019; Ojha et al., 2018; Xu et al., 2021). The new result from this work generally agrees with previous results in both magnitude and spatial pattern. Here, we compared the motion time series derived from InSAR and GNSS. Using GNSS station P305 as a reference, we subtracted its measurements from those of station CRCN, and projected the resulting relative motions into the LOS direction. As shown in the lower right panel of Figure 21, the two independent measurements exhibit a high degree of consistency in capturing the temporal evolution of the subsidence.

Since the crustal uplift at the Three Sisters volcanic center of the central Oregon Cascade Range was discovered (Wicks et al., 2002), several studies have attempted to measure the resulting surface deformation using InSAR (Dzurisin et al., 2006, 2009; Lisowski et al., 2021; Riddick & Schmidt, 2011). However, the dense vegetation and snow posed a significant challenge to these studies, which primarily relied on C-band data. With L-band ALOS-2 data, their effects are substantially reduced. The ongoing uplift measured from track D170 is presented in Figure 22. A continuous GNSS station, HUSB, was installed by the U.S. Geological Survey (USGS) in the deforming area in May 2001 (Lisowski et al., 2021). A second station, named PMAR, was installed outside the deforming area in early 2002. Using PMAR as a reference, we compared the InSAR and GNSS motion time series at HUSB. The results in Figure 22 demonstrate excellent agreement between the two independent measurements.

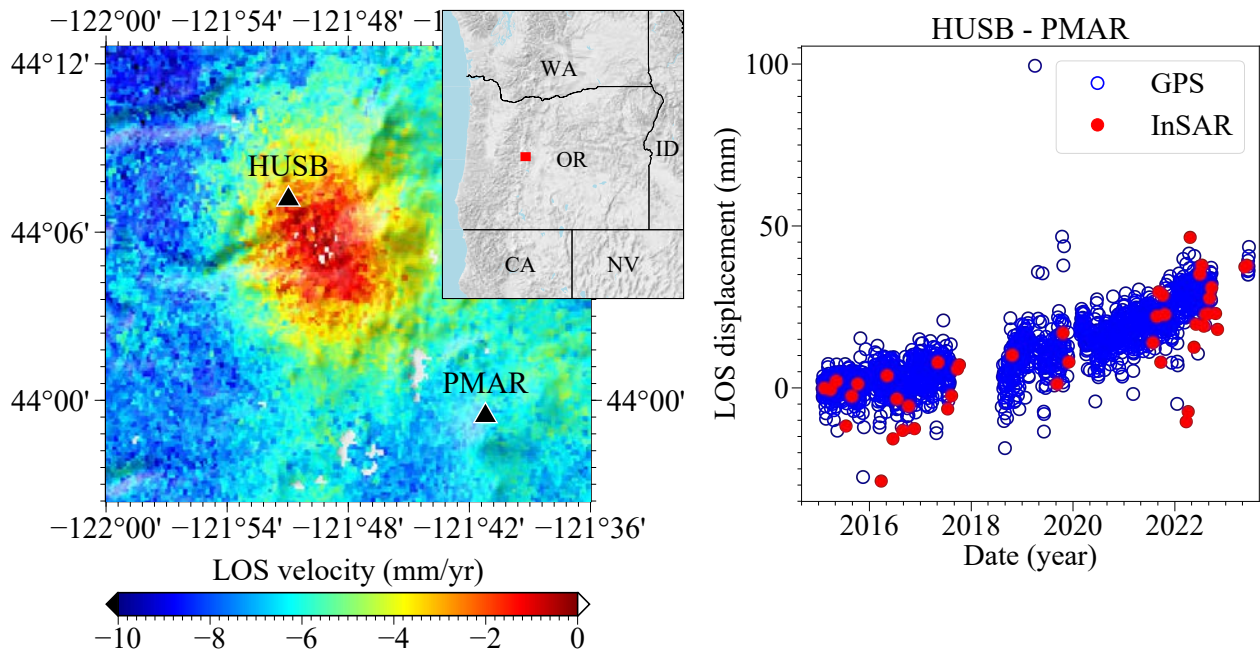


Figure 22. LOS motions of the Three Sisters volcanic center in the central Oregon Cascade Range. The motion time series at GNSS station HUSB relative to station PMAR, measured by InSAR and GNSS, are compared in the right panel. Data are from track D170.

The Cascadia subduction zone is recognized as being capable of generating magnitude 9 (M9) megathrust earthquakes in the Pacific Northwest, with devastating tsunamigenic

potential. Improved imaging of interseismic strain accumulation resulting from interplate coupling can lead to better constraints on variations in interplate coupling along the subduction zone fault and the potential for future large earthquakes. To date, most interseismic plate coupling studies in Cascadia have relied primarily on onshore GNSS data (e.g., [Li et al., 2018](#); [McCaffrey et al., 2007, 2013](#); [Schmalzle et al., 2014](#)). While these GNSS-based estimates leverage horizontal velocities to provide robust first-order constraints on the coupling of the subduction fault, the relatively lower precision of vertical GNSS measurements and the limited spatial density of GNSS stations have hindered the ability to resolve fine-scale details of interseismic strain and coupling variation.

InSAR is inherently more sensitive to vertical motion and provides unparalleled spatial resolution for mapping interseismic motions arising from variations in plate coupling. However, the Cascadia subduction zone remains a challenging area for high-frequency SAR data and conventional InSAR techniques. [Zheng et al. \(2021\)](#) previously derived an InSAR result for this area, but with limited spatial coverage. Here, we extracted a broad profile of interseismic velocities from track D170 across a transition region from northern to central Cascadia and compared it with GNSS velocities. The results are shown in [Figure 23](#). The two datasets are in good agreement with each other, but InSAR reveals finer spatial details of the motion distribution. These results highlight the superior performance of L-band InSAR time series in conventionally challenging low-coherence areas, which is crucial for achieving global coverage.

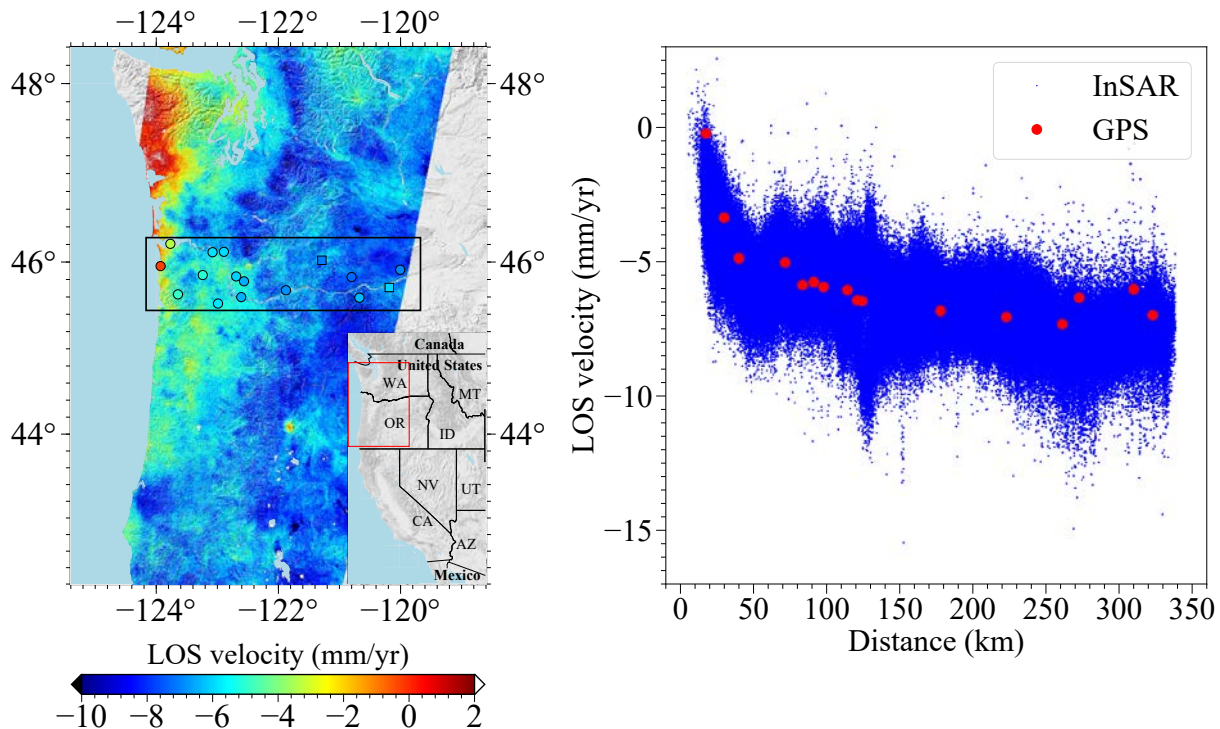


Figure 23. LOS motions in the Cascadia subduction zone. In the left panel, high- and lower-quality GNSS measurements are shown as circles and squares, with colors representing GNSS measurements projected into LOS directions. LOS motion velocities measured by GNSS and InSAR along the profile are compared in the right panel. Data are from track D170.

The northern part of the InSAR result, corresponding to the dark blue area in Figure 23, exhibits some anomalous motions. Inspection of the optical image reveals scattered areas with logging activities in the dark blue area, as shown in Figure 24. These signals likely result from logging activities. A similar phenomenon was reported by Bürgi & Lohman (2021). However, such signals are not observed in GNSS measurements, likely because GNSS stations are anchored to bedrocks and are thus unaffected by surface logging. This highlights that GNSS and InSAR do not measure exactly the same processes, underscoring the need for caution when comparing measurements from the two techniques.

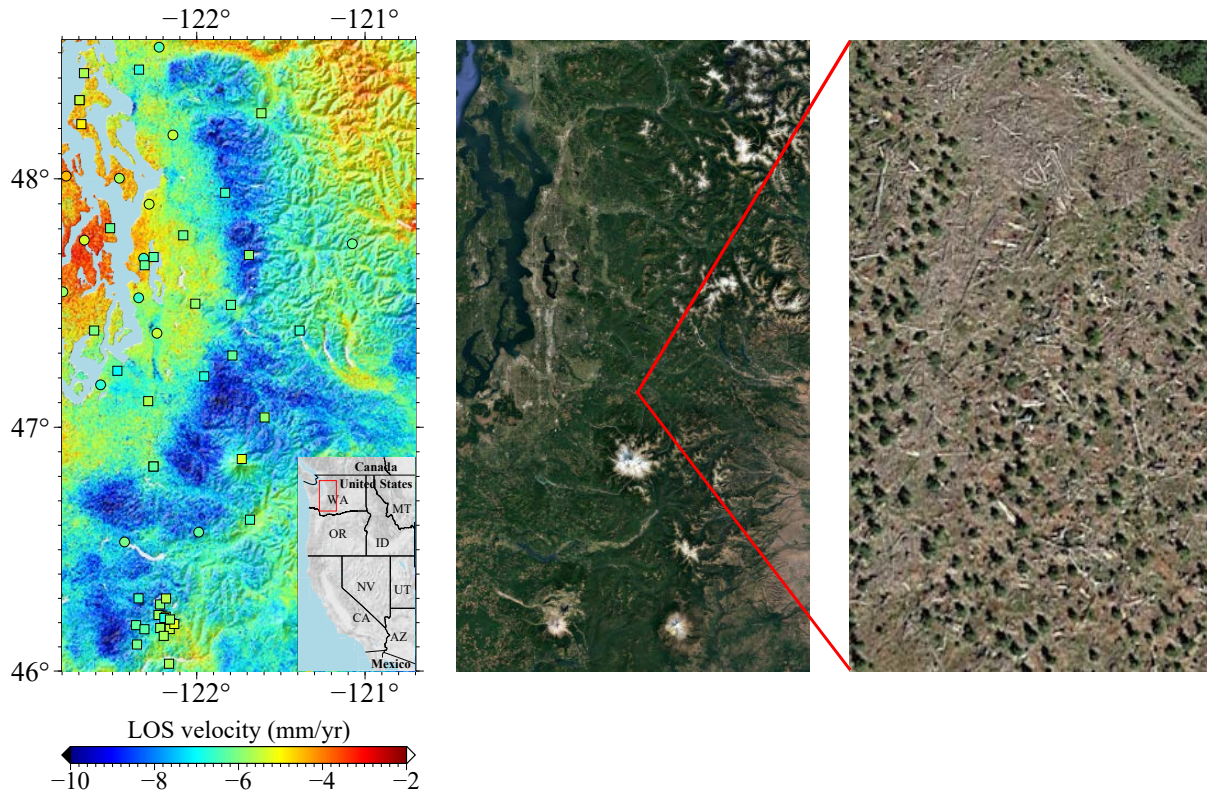


Figure 24. LOS motions in forested areas of Washington. Left: InSAR LOS motions. High- and lower-quality GNSS stations are shown as circles and squares, with colors representing their velocities projected into LOS directions. Middle: Optical image from Google Earth. Right: Zoom-in of the optical image, showing that the "moving" areas are primarily associated with logging activities. Data are from track D170.

5 Discussions

The large-scale processing of ALOS-2 data, together with the results, offers helpful implications for the future acquisition and processing of L-band data.

First, seasonal snow cover poses a major limitation. It causes not only destructive decorrelation, but also, at times, abrupt phase discontinuities. To optimize observation plans for InSAR motion measurement under a satellite mission with a limited duty cycle, we recommend shifting winter acquisitions to other seasons in snowy regions. This strategy differs from conventional practice for high-frequency SAR data, where winter acquisitions typically

exhibit higher coherence due to the reduction in vegetation. For InSAR processing, especially when designing an automated operational system, it may be necessary to screen out acquisitions affected by seasonal snow or mask snow-covered regions. A global evaluation of the decorrelation effects of seasonal snow cover could further help optimize such a system.

The second limitation arises from spatially rapid variations in ionospheric TEC, such as changes associated with sporadic E layers (Fujimoto et al., 2024) and scintillations (Meyer et al., 2016). These variations can lead to large coregistration errors and consequent coherence loss, high phase gradients that are difficult to remove, and sometimes even phase unwrapping errors. Another potential threat is RFI (Wang Y et al., 2025). In severe cases, an entire sub-band may be corrupted by RFI, rendering it no longer usable for ionospheric phase estimation.

As suggested by the case studies in Section 4, L-band satellite SAR has the potential for independently measuring global tectonic motions. This requires the removal of various undesired signals described in Appendix A, some of which are overlooked in current InSAR practices. We therefore recommend integrating modules for calculating various undesired signals into standard InSAR software packages, as has already been implemented in other geodetic techniques.

For tectonic motion measurements, undesired signals also include those associated with surface and near-surface physical processes involving changes in their electrical and geometric properties (Ulaby & Long, 2015). L-band microwaves penetrate deeper below the surface; therefore, near-surface physical processes may play a more important role in the InSAR phase. This requires further investigation of scattering mechanisms in the context of InSAR motion measurement, representing a promising avenue for future research. Some studies indicate that changes in soil moisture and vegetation can induce phase shifts of up to $\pi/2$ rad at L-band, corresponding to a motion of approximately 3 cm (Zwieback et al., 2015, 2017; Zwieback & Hajnsek, 2016).

We are now entering the golden age of L-band SAR satellites. New and upcoming missions, such as ALOS-4, NISAR, and, eventually, ROSE-L, feature enhancements in duty cycle, resolution, and the inclusion of a dedicated side band for ionospheric phase estimation. These advances will substantially improve the performance of both InSAR processing and ionospheric phase estimation. Moreover, more open data policies, such as those for NISAR, will facilitate tracing the sources of any residual long-wavelength errors.

6 Conclusions

Measuring global tectonic motion solely through InSAR has been challenging. Currently, L-band SAR satellites represent the only viable candidate for overcoming this challenge. Evaluation through large-scale InSAR time series processing of ALOS-2 ScanSAR data acquired from 2015 to 2023 over the western United States shows that:

- 1) Residual long-wavelength errors and signals are mostly less than 2 mm/yr along range over the 350 km swath, or are even indiscernible in the InSAR-GNSS differences. This suggests the potential of L-band InSAR time series in achieving measurement independence.

2) Both short- and long-wavelength motions are precisely measured without the need for external constraints in the challenging Cascadia subduction zone. In many areas, even a single interferogram with a long temporal baseline can reveal secular fault motions of a few mm/yr, which is conventionally only possible with time series analysis. This suggests the potential of L-band InSAR time series in achieving global coverage.

3) Among the various signals not of interest to solid Earth sciences, troposphere, ionosphere, and solid Earth tides have significant impacts on the measured motions. The effects of ocean tide loading and pole tide are relatively small, while those of ocean pole tide loading and atmospheric tide loading are negligible.

4) The major limitations are decorrelation induced by seasonal snow cover and inaccuracies in ionospheric phase estimation in the presence of spatially rapid variations in TEC. Vegetation, long thought to be a major source of decorrelation, has a much smaller impact on coherence at L-band compared to seasonal snow cover.

To the best of our knowledge, this constitutes the largest-scale L-band InSAR processing endeavor to date, yielding promising results. With new missions that feature enhanced capabilities, measuring tectonic motion globally solely through InSAR is likely becoming viable.

Appendix A. Undesired signals, and their routine computation and removal

'Systematic' signals from the atmosphere and tidal forces should be removed from InSAR measurements to isolate the desired signals. Tropospheric phase delays and ionospheric phase advances can be estimated using their respective refractive indices (Brcic et al., 2010; Gomba et al., 2016; Jolivet et al., 2014; Rosen et al., 2010). Motions originating from body tides, including solid Earth tide and pole tide, can be derived by applying Love number theory to the tidal potentials (Love, 1909; Munk & Macdonald, 1960). Calculating the motions originating from load tides further requires convolution of a tidal model with the respective Green's functions (Agnew, 2015; Farrell, 1972). Previously, signals from the troposphere (Goldstein, 1995; Massonnet & Feigl, 1995; Rodriguez & Martin, 1992; Rosen et al., 1996; Tarayre & Massonnet, 1996; Zebker et al., 1997), the ionosphere (Goldstein, 1995; Massonnet & Feigl, 1995; Rodriguez & Martin, 1992; Rosen et al., 1996; Tarayre & Massonnet, 1996; Zebker et al., 1997), solid Earth tide (Eineder et al., 2010; Xu & Sandwell, 2020), and ocean tide loading (DiCaprio & Simons, 2008) have been examined in InSAR, but the remaining signals have not been addressed.

The PyAPS software (Jolivet et al., 2014) was employed to compute the tropospheric phase delay, using ERA5 products as input (Hersbach et al., 2020). Due to the limited spatiotemporal resolution of these climate reanalysis products, the results might be subject to substantial uncertainties. The range split-spectrum method for estimating ionospheric phase advance is explained in Section 3. Below we elaborate on the computation of signals arising from tidal forces.

A.1 Solid Earth tide

Tidal forces arising from the gravitational attraction of the Sun, Moon, and planets deform the Earth. The tidal forcing can be described to a very high precision thanks to the

extraordinarily high accuracy and precision of celestial mechanics (Agnew, 2015). Under these forces, the Earth's surface motion can be calculated for an elliptical, rotating, elastic, and oceanless Earth (Wahr, 1981). Better results can be obtained with improved Love and Shida numbers (Mathews et al., 1995). Considering further the resonance with ocean tide loading (Wahr & Sasao, 1981) and mantle anelasticity (Wahr & Bergen, 1986), surface motions from solid Earth tide can be determined up to a precision of 1 mm (Petit & Luzum, 2010). The motions induced by solid Earth tide often reach 20 cm and can exceed 30 cm (Milbert, 2025).

We computed the motions from solid Earth tide using the program solid (Milbert, 2025), which follows the IERS Conventions (2003) (McCarthy & Petit, 2004). The program computes the complete motions from solid Earth tide, including that from permanent tide, but the latter is actually not relevant as InSAR only measures temporally relative motion.

A.2 Ocean tide loading

The tidal forces from the celestial bodies also cause the redistribution of ocean water that loads the solid Earth. The resulting motions can be calculated through a sum of spherical harmonics or a convolution of the tide height with the respective Green's functions (Agnew, 2015; Farrell, 1972). The latter approach is adopted in all software packages, such as SPOTL (Agnew, 2012), GOTIC2 (Matsumoto et al., 2001), CONMODB, OLFG/OLMPP (Scherneck, 1991), CARGA (Bos & Baker, 2005) and LoadDef (Martens et al., 2019). The largest error in the computed motion often arises from the ocean tide models. The precision of the computed motion also depends on errors in the coastlines, Green's functions, and numerical implementations. Moreover, smaller errors arise from the common assumption of a spherically symmetric elastic Earth in these software packages (Martens & Simons, 2020). The variations among the results from different software packages are typically a few percent (Bos & Baker, 2005; Penna et al., 2008). The motions due to ocean tide loading can reach 100 mm (Petit & Luzum, 2010).

Earth's surface motions from load tides should be calculated using load Love numbers and Green's functions in a reference frame with an origin at the center of mass of the entire Earth system, including the atmosphere and oceans (CM), to be consistent with the International Terrestrial Reference Frame (ITRF) used by the positioning systems on SAR satellites (Blewitt, 2003; Dong et al., 2003).

We used the SPOTL software, along with the FES2004 ocean tide model (Lyard et al., 2006), to compute the motions induced by ocean tide loading.

A.3 Pole tide

The Earth's rotation undergoes variations as a result of internal dynamical processes and the external gravitational attraction of the celestial bodies. The dynamical processes involve almost every layer of the Earth, from the fluid core, the mantle and tectonic plates, to the oceans and atmosphere, and the global distribution of ice, snow and water (Gross, 2015). The induced rotation variations include precession and nutation (rotation axis motion in space relative to the directions of 'fixed' stars), variations in the angular speed of rotation, and polar motion (motion of the Earth's pole of rotation relative to the Earth) (Dehant & Mathews, 2015).

Polar motion is dominated by a forced annual wobble, a free 14-month Chandler wobble and a quasiperiodic Markowitz wobble varying on decadal timescales (Gross, 2015). Variations in the angular speed of rotation and polar motion perturb the centrifugal force and therefore further deform the Earth, a phenomenon known as the pole tide (Munk & Macdonald, 1960). The first-order perturbation in the centrifugal potential can be calculated by accounting only for polar motion as the contribution from variations in the angular speed of rotation is negligible (Wahr, 1985). The resulting Earth's surface motions can then be calculated using Love and Shida numbers (Munk & Macdonald, 1960). The maximum vertical and horizontal motions are about 25 mm and 7 mm, respectively (Petit & Luzum, 2010; Wahr, 1985).

We modified the pyTMD software (Sutterley et al., 2017) to compute the motions induced by the pole tide, following the IERS Conventions (2010) (Petit & Luzum, 2010).

A.4 Ocean pole tide loading

Variations in the centrifugal force due to variations in the Earth's rotation also redistribute ocean water that loads the solid Earth. This is known as ocean pole tide loading. The induced motions can be calculated by convolving an ocean pole tide model with the respective Green's functions (Farrell, 1972). The maximum motions are about 0.5 mm (East), 0.5 mm (North) and 1.8 (Up) mm, respectively (Petit & Luzum, 2010).

We modified the pyTMD software (Sutterley et al., 2017) to compute the motions induced by ocean pole tide loading. The motions are computed using a self-consistent equilibrium model of the ocean pole tide developed by Desai (2002), following the IERS Conventions (2010) (Petit & Luzum, 2010).

A.5. Atmospheric tide loading

Solar heating drives the variations in atmospheric surface pressure, giving rise to the atmospheric tide. Loading from the atmospheric tide deforms the solid Earth and peaks at the diurnal (S1) and semidiurnal (S2) frequencies. The induced motions can be calculated by convolving surface pressure variations with the respective Green's functions (Farrell, 1972; Petrov & Boy, 2004; van Dam & Wahr, 1987). The vertical and horizontal motions can reach 1.5 and 0.15 mm, respectively (Petit & Luzum, 2010).

Since current SAR satellites are mostly in sun-synchronous polar orbits, the motions induced by the S1 and S2 tides should cancel out in InSAR measurements. For completeness, we still compute the motions using the coefficients provided by van Dam & Ray (2010), which were computed by convolving the Green's functions with the S1 and S2 surface pressure tides extracted from ECMWF products by Ray & Ponte (2003).

A.6 Non-tidal loading

Typical non-tidal loadings include atmospheric loading, non-tidal ocean loading, hydrological loading, etc. These non-tidal loadings can induce Earth's surface motions that cannot be neglected. For example, atmospheric loadings, such as those from storms, can induce motions of up to 20 mm (vertical) and 3 mm (horizontal), respectively (Petrov & Boy, 2004; Rabbel & Zschau, 1985; van Dam & Wahr, 1987). Comparable motions from non-tidal ocean

loading are also observed in GNSS measurements (Williams & Penna, 2011). Local hydrological loading motions can reach 10~35 mm (Dill & Dobslaw, 2013). However, these motions are highly event-dependent, making their routine removal difficult. Instead, they can be treated as signals of interest for specific studies.

Following the above methods, all tidal and loading motions, except those from non-tidal loading, are computed. Subsequently, the results are projected into SAR LOS directions and removed from InSAR measurements. As an example, Figure A1 shows the motions induced by tidal and loading effects in an area imaged by ALOS-2 track D168 in the western United States. The temporal variations of the motions at the position marked by the black dot are shown in Figure A2. The time corresponding to the motions in Figure A1 is marked by the dashed line in Figure A2.

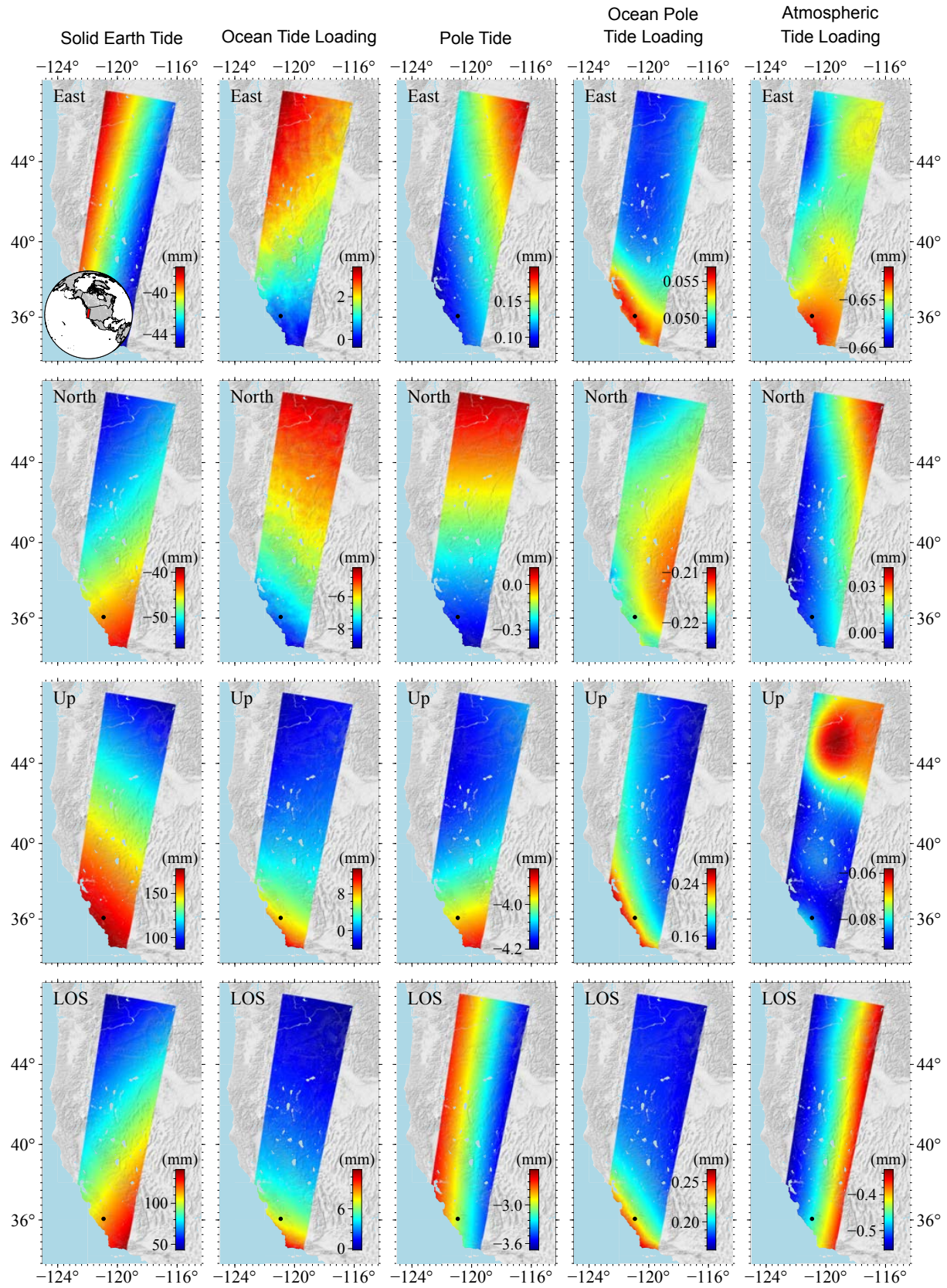


Figure A1. Spatial distribution of motions induced by tidal and loading effects. The motions are computed for ALOS-2 track D168 at 20:05:08 on May 15, 2015 (UTC), corresponding to the dashed line in Figure A2. The area covers approximately $356 \text{ km} \times 1407 \text{ km}$.

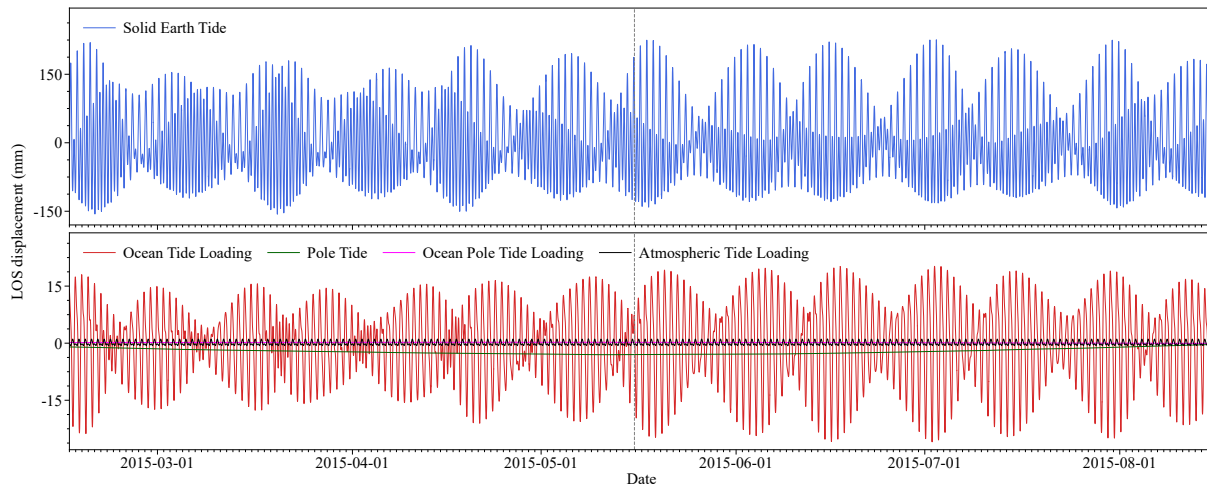


Figure A2. Temporal evolution of motions induced by tidal and loading effects. The motions are computed for the position marked by the black dot in Figure A1 and projected into the LOS direction.

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Open Research

The developed stack processor is released with the ISCE2 software and is available at:
<https://github.com/isce-framework/isce2/tree/main/contrib/stack/alosStack>. The processed InSAR time series are available at: <https://disk.pku.edu.cn/link/AABCFB38E347AD476E819F3DC317B97127> and <https://zenodo.org/records/14994596>.

Conflict of Interest Disclosure

The authors declare there are no conflicts of interest for this manuscript.

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