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UAVSAR Observations of InSAR Polarimetric Phase Diversity: Implications for NISAR Ionospheric Phase Estimation

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Abstract

The NASA-ISRO Synthetic Aperture Radar (NISAR) is a repeat-pass radar mission that will acquire fully polarimetric SAR data in an innovative acquisition mode known as quasi-quad pol (QQP). It consists of simultaneously operating a HH/HV and a VH/VV dual-pol modes in the lowest and upper parts of the transmitted frequency spectrum. Compared to more traditional acquisition modes, the ionospheric phase estimation algorithms for QQP repeat-pass data will likely exploit the difference of two sub-band SAR interferograms acquired not only at distinct center frequencies but also at different polarizations (e.g., HH/VV), making the ionospheric phase estimation vulnerable to possible bias caused by polarimetric interferometric scattering phase components. Using UAVSAR airborne data, we show that temporal variations of the interferometric scattering phase may introduce spurious polarimetric-dependent phase terms which may bias QQP ionospheric phase estimates. The magnitude of this bias depends on the type of observed land cover. For bare soil and forested areas, we detect HH-VV interferometric phase discrepancies up to 30° over 12 days, corresponding to a 10 cm bias at L-band. Over comparable time intervals, changes in vegetation vitality introduce HHI-VV interferometric phase inconsistencies beyond 90° for vertically oriented agricultural fields. We simulate the QQP ionospheric phase screen over the San Andreas Fault, USA, a region characterized by a mixture of vegetated and bare soil surfaces. Based on the results from the UAVSAR data analysis, we recommend using the same polarization on the main and side-bands of the NISAR operational science modes (e.g., single-pol or dual-pol) to avoid potential biases in the ionospheric phase estimates.

1. Introduction

The National Aeronautics and Space Administration (NASA) and Indian Space Research Organization (ISRO) Synthetic Aperture Radar (NISAR) is a dual-frequency (L- and S-bands) repeat-pass radar mission that will acquire near-global SAR data with a revisit time of 12 days (Rosen et al., 2015). The primary objective of the NISAR mission is to disentangle the complexity of several geophysical processes deforming the Earth’s surface ranging from natural hazards (e.g., earthquakes, ice sheet collapse, volcano eruptions) to ecosystem disturbances, offering an unprecedented spatial and temporal coverage (Donnellan et al., 2008). Compared to other existing operational missions (e.g., Sentinel-1 A/B), the long-wavelength (~24 cm) of the L-band radar, built by NASA, will improve our understanding of several deformation processes occurring in moderate to heavily vegetated areas and usually undetectable with shorter wavelength SAR systems (Rosen et al., 2015). The L-band radar is equipped with a set of operational modes (e.g., single-, dual-, quad-pol) accommodating the capability of obtaining SAR observations at different polarimetric channels (Rosen et al., 2015). At a given frequency band (e.g., L-band), the radar instrument allows acquiring SAR data over a total range bandwidth of ~80 MHz. By selecting smaller parts of the available range spectrum (i.e., 20 or 40 MHz on the upper part and 5 or 20 on the lower part), it is possible to obtain two SAR images with slightly different center frequencies which can be used to estimate the differential ionospheric phase delay typically affecting repeat-pass SAR measurements (Fattahi et al., 2017; Gomba et al., 2015). Differently from more traditional SAR systems (e.g., ALOS/PALSAR) for which the full scattering matrix is measured by alternately transmitting horizontal (H) and vertical (V) polarized waveforms while simultaneously receiving H and V backscattered signals (Woodhouse, 2005), NISAR is capable of adopting a variant of the traditional quad-pol mode known as quasi-quad pol (QQP) (Rosen et al., 2015). The QQP mode consists of transmitting, at the same time, two dual-pol modes (i.e., HH/HV and VH/VV), respectively in the lower and upper parts of the allowable transmitted frequency.
spectrum providing two sub-band SAR images at different polarizations and with slightly different center frequencies (Rosen et al., 2015). Being disjoint in frequency, the interference caused by these two dual-pol modes is negligible (Rosen et al., 2015). Repeat-pass interferometric SAR (InSAR) measurements are typically affected by changes in the microwave propagation through the Earth’s ionosphere. This differential ionospheric signal introduces, among other effects, an additional spurious interferometric phase term which, if not properly accounted for, can drastically downgrade the accuracy of InSAR surface deformation measurements (Fattahi et al., 2017). To mitigate the effect of the ionospheric phase delay, a commonly-used approach is to take advantage of the dispersive nature of the ionosphere medium (Ishimaru et al., 1999). This is commonly achieved with a technique called range split-spectrum wherein the range frequency spectrum of the radar signal is divided into two smaller sub-bands to form two SAR images at a lower resolution and with different center frequencies (Brcic et al., 2010; Rosen et al., 2010). Sub-band images from two temporally-separated SAR acquisitions are then coherently combined to form two sub-band interferograms; their difference allows to estimate the dispersive (i.e., the ionospheric phase) and nondispersive components of the interferometric phase (Fattahi et al., 2017). Unlike the traditional range split-spectrum technique (Gomba et al., 2015), the two sub-band interferograms for QQP InSAR observations will be obtained not only at different center frequencies but also at distinct polarizations, e.g., a HH or HV interferogram at one frequency and VV or VH interferogram at the other frequency. This implies that any temporal change in the polarimetric scattering properties of the observed scene may introduce unwanted polarimetric-dependent terms in the interferometric phase (Brancato & Hajnsek, 2018a; Zwieback & Hajnsek, 2016). These spurious phase terms can then potentially bias QQP ionospheric phase estimates. To understand the impact of NISAR QQP acquisition mode on ionospheric phase estimation, we use airborne SAR data collected with the NASA-Jet Propulsion Laboratory (JPL)’s UAVSAR radar system and document observations of L-band interferometric phase discrepancies between HH and VV interferograms (i.e., InSAR polarimetric phase diversity) for various land cover types. We analyze and quantify the impact of these spurious polarimetric-dependent terms on QQP ionospheric phase estimates and provide insights on their implications for geodetic products derived from QQP data. At present, UAVSAR is the only L-band SAR system capable of providing fully polarimetric SAR data over a wide variety of land cover types, with image geometries similar to NISAR (i.e., small spatial baselines), and with the convenient observation frequency characteristic of airborne SAR systems (Hensley et al., 2008). Using the values of HH-VV InSAR phase discrepancies observed in the UAVSAR data, we simulate the ionospheric phase screen for QQP repeat-pass measurements over the San Andreas Valley, California, USA. This area offers an excellent test case to evaluate the accuracy of QQP ionospheric phase estimates since this region is characterized by a mixture of bare soil patches (e.g., desert) embedded in an agricultural landscape with a variety of cultivations. We conclude that unless downgrading the spatial resolution of the QQP ionospheric phase estimates, the observed InSAR polarization diversity can introduce biases around 30 cm with consequent degradations of the accuracy of geodetic products obtained with NISAR QQP repeat-pass data.

2. Theoretical Considerations

2.1. Repeat-Pass SAR Interferometry (InSAR)

A more general formulation of SAR interferometry requires to introduce the 3-D scattering vector \( \mathbf{k} \), i.e., a vectorization of the scattering matrix expressed in e.g., a lexicographic polarization basis (Cloude, 2010), where \( a \) represents a single-look complex (SLC) SAR image. Repeat-pass SAR interferometry (InSAR) coherently combines two temporally-separated scattering vectors \( \mathbf{k}_a \) and \( \mathbf{k}_b \) obtained with slightly different viewing geometries (Bamler & Hartl, 1998) to form a normalized complex observable known as interferometric coherence (Rosen et al., 2000)

\[
\gamma_{a,b}(\omega) = |\gamma_{a,b}(\omega)| e^{j\phi_{a,b}(\omega)} = \frac{\omega \langle \mathbf{k}_a \cdot \mathbf{k}_b^* \rangle \omega}{\sqrt{\omega \langle \mathbf{k}_a \cdot \mathbf{k}_a^* \rangle \omega \omega \langle \mathbf{k}_b \cdot \mathbf{k}_b^* \rangle \omega}}
\]

(1)

where \( j \) is the imaginary unit, \(|\gamma_{a,b}(\omega)|\) is the coherence magnitude encoding the similarity between the SAR images \( a \) and \( b \), \( \phi_{a,b}(\omega) \) represents the SAR interferogram while \( \langle \cdot \rangle \) is the external cross-product operator
The interferometric phase $\Phi_{f_0,HH}$ at frequency $f_0$ and polarization e.g., HH can be modeled as the superposition of several phase terms

$$\Phi_{f_0,HH} = \Phi_{f_0,HH}^{\text{iono}} + \Phi_{f_0,HH}^{\text{prop}} + \Phi_{f_0,HH}^{\text{displ}} + \Phi_{f_0,HH}^{\text{scatt}} + \Phi_{f_0,HH}^{\text{noise}}$$

where we omitted the dependency on the acquisition indices $a$ and $b$ for the sake of notation simplicity. In Equation 2, $\Phi_{f_0,HH}^{\text{iono}}$ is the phase associated to changes in the microwave propagation within the Earth’s ionosphere (Fattahi et al., 2017; Gomba et al., 2015), $\Phi_{f_0,HH}^{\text{prop}}$ is the phase due to the differential tropospheric path delay (Jolivet et al., 2011), $\Phi_{f_0,HH}^{\text{displ}}$, is the phase caused by target movements along the radar line of sight direction (Rosen et al., 2010), and $\Phi_{f_0,HH}^{\text{noise}}$ is the term including all unlisted interferometric noise contributions (e.g., mis-registration). Instead $\Phi_{f_0,HH}^{\text{scatt}}$ models the phase due to changes in the electromagnetic scattering behavior in between pairs of SAR acquisitions (Rosen et al., 2000) and it is commonly considered negligible for a wide variety of interferometric applications (e.g., generation of surface topography maps) (Bamler & Hartl, 1998). This phase term can be further decomposed as the sum of a phase contribution $\Phi_{f_0,HH}^{\text{nondisp}}$ caused by temporal changes in soil water content and a term $\Phi_{f_0,HH}^{\text{veg}}$ attributable to changes in vegetation wet biomass (Brancato & Hajnsek, 2018b). Equation 2 can be more generally factorized as the combination of a dispersive (i.e., frequency-dependent) and nondispersive phase components (Fattahi et al., 2017; Gomba et al., 2015)

$$\Phi_{f_0,HH} = \Phi_{f_0,HH}^{\text{nondisp}} + \Phi_{f_0,HH}^{\text{iono}} = \frac{4\pi f_0}{c} \Delta r^{\text{nondisp}} - \frac{4\pi K}{c f_0} \Delta \text{TEC}$$

where $K = 40.31 \text{ m}^3/\text{s}^2$ is a constant, $c$ is the speed of light in vacuum, while $\Delta \text{TEC}$ is the variation of the total electron content (TEC) in the ionosphere medium (Ishimaru et al., 1999). $\Delta r^{\text{nondisp}}$ models range changes from the radar to the observed scatterer and it includes the tropospheric delay, ground displacement, and phase noise (Rosen et al., 2010). Under the assumption that in the frequency spectrum of interest the scattering phase $\Phi_{f_0,HH}^{\text{scatt}}$ exhibits a nondispersive behavior (Sibley, 1973; Varslot et al., 2010), also changes in soil and vegetation water content will contribute to $\Delta r^{\text{nondisp}}$, leaving the ionospheric phase as the only dispersive term in Equation 3. If it exists another InSAR interferogram at a frequency $f_1$, the ionospheric phase $\Phi_{f_0,HH}^{\text{iono}}$ can be estimated by exploiting the dispersive nature of the ionosphere medium (Brcic et al., 2010; Ishimaru et al., 1999; Rosen et al., 2010)

$$\Phi_{f_0,HH}^{\text{iono}} = \frac{f_0 f_1}{f_1 - f_0} \left( \frac{f_0}{f_1} \Phi_{f_0,HH} - \Phi_{f_1,HH} \right)$$

For NISAR QQP repeat-pass observations, the additional sideband at frequency $f_1$ (5 MHz bandwidth) is acquired at a different polarization than the main band (20 or 40 MHz bandwidth depending on the mode of operation) leading to a different equation for estimating the ionospheric phase (Rosen et al., 2015).
In the following, we will focus on cases wherein the main and the sideband are acquired at the co-polarized channels HH and VV, as operational use of the cross-polarized sub-band interferograms is severely affected by temporal decorrelation (Lavalle et al., 2011) and by radio frequency interference (Meyer et al., 2013). These sources of disturbance contribute to increase the overall noise level of the cross-polarized InSAR interferograms and further complicate the unwrapping of the estimated ionospheric phase (Fattahi et al., 2017). The InSAR phase terms due to ground displacement and tropospheric delay are expected to be identical at the co-polarized channels and their contribution cancels out when estimating Equation 5 (Hensley et al., 2011). Conversely, interferometric phase changes due to soil moisture (Hensley et al., 2011) and agricultural vegetation biomass might exhibit a polarimetric dependency at L-band (Brancato & Hajnsek, 2018a; Zwieback & Hajnsek, 2016). Therefore, it is essential to understand the nature, the spatiotemporal pattern as well as the magnitude of HH-VV polarimetric InSAR phase inconsistencies over different land cover types to better understand their impact on ionosphere phase estimation for QQP NISAR data.

3. UAVSAR Data

To investigate the presence of InSAR polarimetric phase diversity, we partition the Earth's surface into three different land cover types i.e., bare soil, vegetated agricultural surfaces, and forested areas. For each of the identified land covers, we analyze fully polarimetric InSAR observations acquired in the frame of several UAVSAR airborne campaigns. Existing UAVSAR data covering unlisted parts of the Earth's surface (e.g., permafrost regions, temperate glaciers) do not provide a sufficiently dense time series to study the HH-VV InSAR phase discrepancies over time intervals characteristic of the NISAR mission (i.e., 12–36 days). Therefore, they will be excluded from our analyses.

3.1. Bare Soil: CanEx-SM10

The Canadian Experiment for Soil Moisture in 2010 (CanEx-SM10) is an airborne and ground measurements campaign primarily designed to support the calibration and validation activities of the European Space Agency (ESA)'s Soil Moisture and Ocean Salinity mission (Magagi et al., 2012). Among the collected remote sensing data, there are six quad-pol UAVSAR flights acquired over Kenaston, Saskatchewan, Canada (51° 30′ N, 106° 18′ W) between 2–15 June 2010 with irregular time intervals (one to three days) and a nominal spatial baseline of 0 m (Hensley et al., 2011). The surveyed area is characterized by rainfed agricultural fields, grassland, and pasture over a rather gentle terrain topography (Magagi et al., 2012) (Figure 1). Prior to the UAVSAR campaign, the predominance of wet soil conditions led to an increased amount of standing water occupying 1.5% of the surveyed surface with an irregular spatial pattern (Magagi et al., 2012). The test site benefits from existing soil moisture sensor networks mainly operated by Environment Canada (Magagi et al., 2012). Each sensor collects hourly soil moisture measurements at several depths, of which we consider those within the topsoil layer (0–5 cm). For the 59 surveyed sites, the overall variation of the soil moisture measurements is about 15% volume percent. However, for individual fields, the temporal variations are within 5%-6% volume percent (Figure S1). Visual inspections of field tillage, vegetation cover, and crop type are available for most of the fields (Table S1). For most of the surveyed fields, the vegetation cover varies throughout the campaign reaching a density less than 30% and a maximum crop height of 30 cm (see Table S1) (Magagi et al., 2012).

3.2. Agricultural and Forest Areas: SMAPVEX12 and AM-PM Campaigns

The Soil Moisture Active and Passive (SMAP) Validation Experiment in 2012 (SMAPVEX12) is a remote sensing and in situ measurement campaign designed to support the prelaunch calibration and validation of SMAP soil moisture products (McNairn et al., 2014). The twelve UAVSAR flights collected in one month
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Cover an area within the Red River Watershed, Manitoba, Canada (49° 40′ N, 97° 59′ W) with irregular temporal baselines (1–5 days) and a zero-baseline geometry (McNairn et al., 2014). Annual crops occupy most of the surveyed surface and include cereals (32.2% of the area), canola (13.2%), corn (7%), and soybeans (6.7%) (Figure 2). Hourly topsoil soil moisture data and weekly vegetation parameter measurements (e.g., wet biomass, crop height) were collected for a total of 45 fields, (canola: 7, corn: 8, soybeans: 17, wheat:13) (Figures S2, S3, and Table S2) (McNairn et al., 2014). The overall soil moisture variation was about 25% volume percent with a dynamic range (difference of minimum and maximum measured soil moisture) of 13% for the majority of the agricultural fields and 35% for the forest area (Figure S2) located in the upper part of the test site (Figure 2). Crop phenology and wet biomass accumulation change throughout the SMAPVEX12 campaign (Figure S3) with different rates depending on the planted crop type (Wiseman et al., 2014). Corn development was primarily limited to the increase of leaf coverage and stem elongation while tasseling and flowering occurred toward the final week of the campaign (McNairn et al., 2014; Wiseman et al., 2014). Spring wheat exhibits a steady increase of wet biomass until the mid-campaign with the ripening stage beginning at the end of the UAVSAR acquisition period. Most of the canola fields accumulate wet biomass until flowering and ripening (mid of campaign) to slowly decrease their total water content to the end of the campaign (Wiseman et al., 2014). Soybeans fields were seeded by mid-May with seeding patterns spatially varying among the fields. These differences led to significantly different wet biomass accumulations (Wiseman et al., 2014). No in situ observations are available for any of the barley fields within the test site (McNairn et al., 2014; Wiseman et al., 2014). The AM-PM is a UAVSAR campaign flown in 2019 with the primary objective to guide the development of NISAR ecosystem science algorithms as well as the generation of data products after NISAR launch in 2022 (Chapman & Kasischke, 2018; Kraatz et al., 2019). The data set consists of six full-pol UAVSAR flights acquired over Stuttgart, Arkansas, USA (92° 50’ N, 34° 50’ W) with irregular temporal baselines (12–49 days) spanning June to October 2019 (Kraatz et al., 2019). The test site is characterized by several rainfed and irrigated agricultural fields (Figure 3) which include...
cotton, peanut, pasture, soybeans, corn, and rice as the main crop types (Kraatz et al., 2019). The area also includes an extensive forest patch mainly located in the southwest of the site (Figure 3). In situ measurements for this test site are not publicly available at the time of preparation of this manuscript.

4. UAVSAR Interferometric Processing

We employ standard co-registered stacks of UAVSAR SLCs multilooked by $2 \times 8$ looks in range and azimuth, respectively (Hensley et al., 2008). For a comprehensive description of the UAVSAR SLC processing chain, we address the reader to (Fore et al., 2015; Hensley et al., 2009). We interferometrically process each UAVSAR data stack with the UAVSAR stack processor developed at JPL and embedded in the InSAR Scientific Computing Environment (ISCE2) open-source software (Rosen et al., 2012). For each polarization channel, we form a set of SAR interferograms by coherently combining all possible pairs of acquisitions available within each campaign. This procedure results in a total of 28 interferograms for CanEx-SM10, 91 interferograms for SMAPVEX12, and 15 interferograms for AM-PM. We multilook each interferogram
by $6 \times 15$ pixels corresponding to a window size on the ground of $5.7 \times 9$ m in slant range and azimuth. We form the difference of a HH and VV interferogram sharing the same reference and secondary SLC images (Brancato & Hajnsek, 2018a) and the same center frequency since we assume that the dispersive contribution due to temporal changes in the scattering phase (see Equation 2) is negligible within the frequency bandwidth of interest i.e., 20 or 40 MHz centered at 1.23 GHz (Sibley, 1973). The difference of co-polarized SAR interferograms, indicated as $\varphi_{cp}$ or InSAR polarimetric phase diversity hereafter, has the advantage of eliminating interferometric phase contributions common to the HH and VV polarimetric channels e.g., residual baseline errors, atmospheric phase delays, DEM inaccuracies, and any sort of deformation signal (e.g., soil expansion) (Brancato & Hajnsek, 2018a; Hensley et al., 2011). Therefore, any residual phase variation in $\varphi_{cp}$ is the result of either change in soil and/or vegetation water content (Brancato & Hajnsek, 2018a; Hensley et al., 2011) or potentially due to the temporal instability of the UAVSAR HH-VV polarimetric phase calibration i.e., the phase difference of HH and VV SLC images at the same acquisition date (Fore et al., 2015). For each of the analyzed data stacks, we find that the temporal changes in the UAVSAR HH-VV polarimetric phase calibration are lower than $10^\circ$ (see Supporting Information). Therefore, we conclude that potential polarimetric miscalibration signals do not significantly affect the InSAR polarimetric phase diversity $\varphi_{cp}$ observed in the analyzed UAVSAR campaigns (Fore et al., 2015).
Table 1
Summary of the Observed HH-VV InSAR Phase Discrepancies (φ_{cp}) for an Incident Angle of 40° and a Temporal Baseline Δt

| Test site     | Land cover      | Δt (days) | φ_{cp} (deg) |
|---------------|-----------------|-----------|--------------|
| CanEx-SM10    | Bare soil       | 12        | 15           |
| SMAPVEX-12    | Wheat           | 12        | 65           |
| SMAPVEX-12    | Barley          | 12        | −70          |
| SMAPVEX-12    | Corn            | 12        | 105          |
| SMAPVEX-12    | Canola          | 12        | −50          |
| SMAPVEX-12    | Soybean         | 12        | 5            |
| SMAPVEX-12    | Forest          | 12        | 11           |
| AM/PM         | Forest          | 9         | 13           |

5. Results

5.1. CanEx-SM10

The availability of a time series of UAVSAR images allows to track the HH-VV InSAR phase variations throughout the CanEx-SM10 campaign, as shown for the subset of HH-VV interferograms in Figures 1a–1c. These interferometric products are formed by co-registering each secondary SLC acquisition to the same reference image acquired at the Day of Year (DoY) 154 (June 2, 2010) to form interferograms with a temporal baseline of 3 (Figure 1a), 7 (Figure 1b), and 12 (Figure 1c) days, respectively. For each HH-VV interferogram, we remove pixels with either a HH or VV coherence magnitude lower than 0.5 (Hensley et al., 2011). This procedure not only improves the overall standard deviation of our interferometric products (Bamler & Hartl, 1998) but also allows to exclude pixels associated with pools of standing water formed due to the occurrence of above normal rainfalls throughout the UAVSAR campaign (Magagi et al., 2012).

The observed InSAR polarimetric diversity φ_{cp} exhibits a spatial pattern which varies according to the temporal baseline of the formed interferograms (Hensley et al., 2011). Over a time interval of 3 days (Figure 1a), the observed φ_{cp} exhibits a gentle and homogeneous spatial variation across the scene with magnitudes bounded within 5° (Figure 1d), occasionally reaching 15° for some of the fields located in the southeast of the test site (lower part of Figure 1a). These fields are mainly located at incident angles between 50° and 60°. As the temporal baseline increases to 7 days (Figure 1b), the spatial pattern of the observed φ_{cp} mainly varies on a field-basis scale and exhibits HH-VV phase magnitudes exceeding 10° for most of the surveyed fields (Figure 1d) (Hensley et al., 2011). The occurrence of a rain event on DoY 159 (Magagi et al., 2012) leads to the HH-VV InSAR spatial patterns observed in Figure 1c wherein the majority of the fields exhibits HH-VV phase discrepancies with magnitudes exceeding 15° with occasional deviations as large as 30° for fields located at shallower incident angles. These temporal changes are also captured in the HH-VV InSAR phase profiles in Figure 1d taken along a transect in the across-track direction for a range of incident angles between 30° and 40°. Considering the average along the transect, the magnitude of the observed φ_{cp} increases from 0 to approximately 16° in a time interval of 12 days (Table 1). However, as shown in Figure 1e, the magnitude of the InSAR polarimetric diversity is a function of the incident angle i.e., the shallower the incident angle the greater the observed HH-VV phase discrepancies, reaching almost 30° for incident angles over 60° (Hensley et al., 2011). Since the phase values in Figure 1e are averaged on a field-basis and, thus, composed of hundreds of looks, their measurement precision is far better than a couple of degrees (Hensley et al., 2011).

5.2. SMAPVEX-12 and AM-PM

Figure 2 shows a subset of the SMAPVEX12 HH-VV interferograms formed by referencing each secondary SLC image to the UAVSAR acquisition collected on DoY 169 (June 17, 2012). The obtained interferograms have a temporal baseline of 2 (Figure 2b), 12 (Figure 2c), and 30 days (Figure 2d), respectively. Similarly, Figure 3 shows a subset of the AM-PM HH-VV interferograms sharing the same reference acquisition collected on DoY 200 (July 18, 2019) and with temporal baselines of 9 (Figure 3a) and 27 days (Figure 3b). For both test sites, the spatiotemporal patterns, as well as the magnitude of the observed φ_{cp}, markedly depend on the type of vegetation cover present in the area, e.g., agricultural fields or forest patches (Kraatz et al., 2019; McNairn et al., 2014). Over the agricultural fields of the SMAPVEX12 test site (lower part of Figure 2 panels), φ_{cp} varies on a field-basis scale but is rather homogenous within a single field. This consideration excludes canola fields (light green patches in Figure 2a) which exhibit some degrees of heterogeneity within the field boundaries, as shown in the insets of Figures 2b and 2d. The magnitude of the observed φ_{cp} varies depending on the type of crop planted within each field (Brancato & Hajnsek, 2018a; Zwieback & Hajnsek, 2016). Wheat (gray fields in Figure 2a), barley (dark yellow), canola (light green), and corn (light yellow) fields, exhibit HH-VV InSAR phase discrepancies going from few tens of degrees over short temporal baselines (i.e., 3–5 days) to hundreds of degrees for the longest temporal baselines overflown in this campaign (i.e., 30 days), as shown in Figure 4. For wheat and barley fields, the observed HH-VV
phase discrepancies are associated with standard deviations of a couple of degrees (Figures 4a and 4b), symptomatic of high coherence magnitudes irrespective of temporal baseline and polarization (Figure S4). Conversely, the HH-VV phase standard deviations of canola and cornfields exceed 20° for time intervals longer than 15 days, indicating an increase in temporal decorrelation (Brancato & Hajnsek, 2018a; Lavalle et al., 2011). Irrespective of the crop type, the observed HH-VV InSAR phase discrepancies exceed 90° with standard deviations generally lower than 10° over time intervals characteristics of NISAR revisit period i.e., 12 days (Rosen et al., 2015). As observed in (Brancato & Hajnsek, 2018a), the magnitude of these inconsistencies also tends to be higher for shallower incident angles. Other remaining crop types (e.g., soybeans) exhibit HH-VV phase inconsistencies amounting to a couple of degrees throughout the campaign (Figure 4f).

Similar considerations can be extended for the AM-PM site despite we are unable to relate the magnitude of $\phi_{cp}$ to physical crop dynamics due to the unavailability of a land classification map. For the AM-PM, the HH-VV phase variations exceed 45° for most of the fields with some local deviations as large as 90° for shallower incident angles and long temporal baselines (27 days). Forest areas for both the SMAPVEX12 and AM-PM campaigns exhibit a rather homogeneous spatiotemporal pattern compared to agricultural patches. The magnitude of the observed $\phi_{cp}$ ranges from a couple of degrees over short temporal baselines (2–5 days) to tens of degrees for longer time intervals (Figure 4d, insets of Figures 3a and 3b), occasionally reaching 60° in certain spatial locations (Figure 2f).

### 6. Discussion

In our UAVSAR analysis, we recognize two main sources of HH-VV InSAR phase variations i.e., soil moisture and wet biomass changes (Brancato & Hajnsek, 2018a; Hensley et al., 2011). In the following, we analyze these sources separately and quantify their impact on NISAR QQP ionospheric phase estimates. We also discuss other potential sources of HH-VV phase inconsistencies.
6.1. Soil Moisture

To analytically deal with the complexity posed by the natural world, most soil moisture retrieval algorithms assume that the soil moisture contained in the topsoil layer (0–5 cm from the soil surface) is uniformly distributed with depth (Fung et al., 1992; Oh, 2004). This simplification is tantamount to surmise that the inhomogeneities embedded in the topsoil layer are much smaller than the wavelength of the transmitted radar signal. Therefore, their contribution to the overall scattering process can be considered negligible (Fung et al., 1992). It is trivial to experimentally verify that the soil moisture profiles contained within the topsoil of natural surfaces are very rarely uniform (Collingwood et al., 2018), due to the presence of a significant fraction of millimeter-scale air voids, as well as other kinds of heterogeneities (e.g., pebbles) (Rabus et al., 2010). As observed in a numerical electromagnetic model of an inhomogeneous soil (Rabus et al., 2010), the combination of a vertical soil moisture gradient and air-filled voids can generate an HH-VV InSAR phase exceeding 30° at C-band (5 cm wavelength) when the soil moisture varies from 3% to 30% volume percent in the uppermost 2 cm of soil. Phase changes of this magnitude can be easily detected by many commonly-used InSAR spaceborne techniques (Rabus et al., 2010) and represent a noise source for many geophysical estimates (e.g., surface deformation) and applications (De Zan et al., 2013). The large HH-VV InSAR phase difference (i.e., 15°–30° at L-band) observed in the CanEx-SM10 campaign, mostly characterized by bare agricultural fields, might be the result of the interaction of electromagnetic waves with a vertically stratified soil volume containing a soil moisture gradient (Hensley et al., 2011). This conjecture is a plausible physical explanation which may lead to HH-VV InSAR phase magnitudes above the noise level and it can also explain the observed dependency on the incident angle. However, it is not supported by any of the existing soil moisture retrieval models (Hensley et al., 2011). Interferometric models for heterogeneous soil volumes either neglect the polarimetric dependency of the InSAR phase (De Zan et al., 2013) or do not quantify it explicitly (Zwieback et al., 2015). Conversely, comparisons of the CanEx-SM10 HH-VV InSAR phase discrepancies with those predicted by interferometric parameterization of simple surface scattering models, the Small Perturbation Model (Beckman & Spizzichino, 1963) and the Oh model (Oh, 2004), show that the observed HH-VV phase variance is much larger than the model measurement precision (Hensley et al., 2011). This pronounced discrepancy indicates that there are some aspects of the electromagnetic scattering physics not contained in these models, e.g., vertical distribution of soil water content (Hensley et al., 2011). The overall soil moisture level for the CanEx-SM10 campaign varied about 15% volume percent with temporal variations for each field on the order of 5%–6% volume percent (Hensley et al., 2011) (Figure S1). Therefore, to fully verify that observed HH-VV phase discrepancies are governed by the presence of a topsoil soil moisture gradient, it is critical to have interferometric measurements with very dry soil conditions to be contrasted with observations over very wet soils (Hensley et al., 2011). As observed in (Rabus et al., 2010), another physical explanation of large HH-VV InSAR phase differences at C-band might be caused by the occurrence of multiple scattering within the soil layer. To our knowledge, this effect has not been yet observed at L-band.

6.2. Vegetation Biomass

For zero-baseline SAR data and a static scene (i.e., no temporal changes in the dielectric or geometric properties of the scatterers), the difference of the interferometric phase at different polarizations is expected to be zero (Lavalle et al., 2011; Zwieback & Hajnsek, 2016). By contrast, changes in vegetation water content may lead to polarimetric InSAR discrepancies (Brancato & Hajnsek, 2018a; Zwieback & Hajnsek, 2016). A possible origin of the InSAR phase diversity observed over agricultural areas has been attributed to birefringence i.e., the propagation velocity of the transmitted electromagnetic wave exhibits a dependency on polarization (Orfanidis, 2003). Observations of birefringence are very scarce despite its existence has often been surmised to impact microwave propagation through vegetation canopies and to influence standard polarimetric SAR observables (e.g., the HH-VV polarimetric phase difference) (Ulaby et al., 1987, 1990). The presence of birefringence was first inferred for a cornfield at C-band while radar observations at L-band were inconclusive (Ulaby et al., 1987). Dielectric changes in a homogeneous birefringent medium (i.e., the refractive index depends on polarization) have been observed to critically undermine the uniqueness of surface deformation estimates i.e., over agricultural areas there are as many deformation estimates as possible origin of the InSAR phase diversity observed over agricultural areas has been attributed to birefringence. The propagation explains the bulk of the polarimetric InSAR inconsistencies observed over the agricultural areas.
of the SMAPVEX12 and AM-PM campaigns. A closer look at the fields wherein these discrepancies occur shows that the vegetation constituents (e.g., leaves, stems) therein exhibit a preferential vertical orientation (Figure S5). For vertically oriented vegetated fields (e.g., wheat, barley), the propagating electromagnetic waves are expected to interact more in VV than in HH polarization, unless the horizontal extent or thickness of the scatterers is larger than the wavelength of the transmitted signal (Orfanidis, 2003). In a first-order scattering model, these inconsistencies have been observed to arise either from propagation or scattering effects (Zwieback & Hajnsek, 2016). The former may occur when the vegetation properties change throughout the interferometric time series due to, e.g., vegetation growth (Brancato & Hajnsek, 2018a; Zwieback & Hajnsek, 2016). The latter, instead, might arise due to changes in the scatterers’ properties (e.g., dielectric constant) (Zwieback & Hajnsek, 2016). The magnitude of the polarimetric InSAR discrepancies observed in wheat and barley fields is related to changes in vegetation wet biomass (Figure S6) (Brancato & Hajnsek, 2018a) rather than soil moisture (Figure S7). This consideration can be likewise applied for canola and cornfields, with the exception that over temporal baselines longer than 15 days, the HH-VV InSAR diversity is dominated by the imprecision of the interferometric measurements (due to e.g., temporal decorrelation) rather than by polarimetric differences (Brancato & Hajnsek, 2018a). The pronounced interferometric decorrelation observed over these fields (Figure S4) is consistent with the predominance of volume scattering, typically observed during the vegetative phase of these crops (McNairn et al., 2014; Zwieback & Hajnsek, 2016). Apart from the dependency on the crop type, the HH-VV discrepancies are related to the incident angle (Brancato & Hajnsek, 2018a). They tend to be smaller in magnitude in near range and to increase with the incident angle (Figure S7) (Brancato & Hajnsek, 2018a; Zwieback & Hajnsek, 2016). For all those fields not exhibiting a preferential orientation (e.g., soybeans, pasture), the magnitude of the HH-VV phase discrepancies might be mainly governed by changes in soil moisture rather than vegetation dynamics (Hensley et al., 2011). A similar consideration might apply for forested areas wherein the magnitude of the HH-VV InSAR phase inconsistencies observed in the SMAPVEX12 and AM-PM campaign are more consistent with those observed over bare fields than over vegetated areas (Table 1). There is no consensus on the presence of birefringent microwave propagation through forested areas. A pine canopy observed at 1.6 GHz exhibits no significant anisotropic effects (Ulaby et al., 1990). However, depending on the structure, it cannot be excluded that other forest types might exhibit a significant polarimetric-dependent propagation at L-band (Antropov et al., 2017).

6.3. Other Sources of InSAR Polarimetric Diversity

Our classification of the Earth surface does not satisfactorily represent the variety of land cover types characterizing the terrestrial globe. To our knowledge, at present, there has been no substantial evidence of the presence of polarimetric InSAR phase diversity over land cover types other than bare soil and vegetated agricultural areas. This conclusion primarily originates from the lack of suitable SAR data sets tailored to analyze, with sufficient detail, the spatiotemporal variation of this effect. Existing SAR data sets either are not fully polarimetric, or not sufficiently dense in time, or have been acquired over land cover types for which the HH-VV phase inconsistencies have already been characterized (Brancato & Hajnsek, 2018a). Therefore, due to the lack of information, we cannot exclude that other land cover types might show evidence of HH-VV InSAR phase inconsistencies. Arctic permafrost regions offer a scattering scenario electromagnetically similar to that of the bare soil areas presented in this study. The topsoil layer of permafrost rich soils is characterized by seasonal variations of soil moisture and surface deformation controlled by ground temperatures, summer air temperatures, and summer precipitations (Bartsch et al., 2019). It is not unrealistic to assume that seasonal permafrost variations may lead to a vertical distribution of soil moisture within the topsoil layer (Collingwood et al., 2018). Consequently, this might originate HH-VV InSAR phase discrepancies of tens of degrees as for the case of bare soil areas. To the best of our knowledge, permafrost regions have been barely observed at L-band and their polarimetric scattering properties are still largely unexplored (Bartsch et al., 2019). Nonzero L-band HH-VV polarimetric phase differences have also been observed over several polythermal glaciers in Iceland and Svalbard (Minchew et al., 2015; Parrella et al., 2015). The origin of this polarimetric diversity has been mainly attributed to the presence of an oriented volume of scatterers composed of ice lenses and pipes embedded in the glacier snowpack (Parrella et al., 2015). However, temporal changes in the snow layer and their implications on SAR interferometry at different polarizations still need to be fully investigated.
We simulate the ionospheric phase for NISAR QQP repeat-pass data using Equation 5 and the values of HH-VV InSAR phase discrepancies observed in the analyzed UAVSAR campaigns. Compared to Equation 5, we assume the sub-band interferograms $\phi_{HH}$ and $\phi_{VV}$ to be at the same center frequency $f_0$. This assumption arises from considering the dispersive scattering due to soil and vegetation electromagnetic interactions to be negligible within the frequency bandwidth of interest (Sibley, 1973; Varslot et al., 2010). To perform our simulations, we select an area of 250 × 250 km (roughly the size of a NISAR frame) within the San Andreas Valley, California, USA (Figure 5). This region is characterized by a wide variety of land cover types (e.g., bare soil, vegetated agricultural areas) but also by an active and rather complex surface deformation pattern (Henstock et al., 1997). We simulate the impact of changes in the topsoil soil moisture level by generating a phase ramp with a slope of 10° across the scene, consistently to the HH-VV phase magnitudes observed in the CanEx-SM10 data at mid-range (30°–45° of incident angle). To reproduce the HH-VV phase inconsistencies due to changes in vegetation biomass, we use the land cover classification map (Figure S8) provided by the National Agricultural Statistics Service (NASS, CropScape project) for the year 2018 (Boryan et al., 2011). For those crop types for which we have knowledge of the presence of the HH-VV InSAR phase inconsistencies (Table 1), we uniformly assign, within each field boundary, the worst (i.e., the biggest in magnitude) HH-VV phase values observed in the SMAPVEX12 and AM-PM campaigns over a time interval of 12 days. This procedure allows to generate the synthetic interferograms in Figures 5a–5d, respectively at

**Figure 5.** Simulated ionospheric phase for NISAR L-band QQP repeat-pass data at 30 and 90 m posting. (a) Simulated HH-VV InSAR interferograms at 90 m posting based on the HH-VV InSAR phase discrepancies observed in the analyzed UAVSAR campaigns and the land cover classification map from the NASS CropScape project (Boryan et al., 2011). (b) Unfiltered QQP ionospheric phase estimate at 90 m posting obtained by upscaling the interferogram in (a) by the frequency factor in Equation 5. (c) Ionospheric phase estimate at 90 m posting filtered with a 2-D Gaussian weighted filter with a kernel size corresponding to 5 km on the ground. (d), (e), and (f) are the same as (a), (b), and (c) but with a posting of 30 m.

### 6.4. QQP Ionospheric Phase Simulation

We simulate the ionospheric phase for NISAR QQP repeat-pass data using Equation 5 and the values of HH-VV InSAR phase discrepancies observed in the analyzed UAVSAR campaigns. Compared to Equation 5, we assume the sub-band interferograms $\phi_{HH}$ and $\phi_{VV}$ to be at the same center frequency $f_0$. This assumption arises from considering the dispersive scattering due to soil and vegetation electromagnetic interactions to be negligible within the frequency bandwidth of interest (Sibley, 1973; Varslot et al., 2010). To perform our simulations, we select an area of 250 × 250 km (roughly the size of a NISAR frame) within the San Andreas Valley, California, USA (Figure 5). This region is characterized by a wide variety of land cover types (e.g., bare soil, vegetated agricultural areas) but also by an active and rather complex surface deformation pattern (Henstock et al., 1997). We simulate the impact of changes in the topsoil soil moisture level by generating a phase ramp with a slope of 10° across the scene, consistently to the HH-VV phase magnitudes observed in the CanEx-SM10 data at mid-range (30°–45° of incident angle). To reproduce the HH-VV phase inconsistencies due to changes in vegetation biomass, we use the land cover classification map (Figure S8) provided by the National Agricultural Statistics Service (NASS, CropScape project) for the year 2018 (Boryan et al., 2011). For those crop types for which we have knowledge of the presence of the HH-VV InSAR phase inconsistencies (Table 1), we uniformly assign, within each field boundary, the worst (i.e., the biggest in magnitude) HH-VV phase values observed in the SMAPVEX12 and AM-PM campaigns over a time interval of 12 days. This procedure allows to generate the synthetic interferograms in Figures 5a–5d, respectively at

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and 30 m spacing depending on the posting of the original land cover map. The unfiltered ionospheric phase is obtained by computing Equation 5 and shown in Figures 5b–5d. Every signal contained in the original simulated interferogram is amplified approximately 10 times when upscaled by the frequency factor in Equation 5 (Gomba et al., 2015). Given that the ionosphere has a rather smooth spatial variation, its estimates are very often spatially correlated (Gomba et al., 2015). Therefore, to improve their overall accuracy, it is a good practice to filter the obtained ionospheric phase estimates, i.e., removing potential high-frequency components (Fattahi et al., 2017; Gomba et al., 2015). We use a 2-D Gaussian weighted filter with a kernel size of 5 km on the ground, to obtain the filtered QQP ionospheric phase estimates shown in Figures 5c–5f. Irrespective of the posting, the simulated ionospheric phase delay varies across the 250 km scene from less than one (11.8 cm) to more than one phase cycle depending if the observed region is located within a bare soil or agricultural area. Additionally, high-resolution interferometric products (e.g., 30 m posting) are more severely affected than products with a coarser resolution (e.g., 90 m posting) as observed in the filtered ionospheric estimates of Figures 5c–5f. The primary requirement for NISAR Solid Earth interferometric products is to measure the two-components surface displacement vector with an accuracy better than 2 mm/year over the 70% of the NISAR coverage and over spatial scales between 0.1 and 50 km (Simons et al., 2017). As shown in Figure 6a for 20 MHz NISAR data, ionospheric phase estimates with an uncertainty lower than 1 mm can be comfortably obtained with spatial resolutions better than 6 km and coherence magnitudes higher than 0.2 when using a traditional split-spectrum technique i.e., the main and side-bands are acquired at the same polarization. Conversely, Figure 6b shows the ionosphere phase uncertainty for the simulated QQP data over the San Andreas test site filtered with a Gaussian kernel having a spatial length on the ground of 5 (b) and 20 (c) km. Negative (positive) values of the ionosphere phase uncertainty color-coded in blue (yellow) corresponds to a virtual surface movement away from (closer to) the radar sensor.
the size of the filtering kernel are smoothed out and not recovered (Gomba et al., 2015) at the expenses of introducing a bias due to an excessive amount of smoothing (Gomba et al., 2015).

### 6.4.1. Impact of Range Bandwidth on Ionosphere Phase Estimation

The L- and S-band NISAR radars are capable of operating in a QQP mode using a main range bandwidth of 20 or 40 MHz. Both modes offer an additional sideband of 5 MHz allocated for the estimation of the differential ionospheric phase delay (Rosen et al., 2015). A way to circumvent the polarimetric InSAR phase diversity affecting QQP repeat-pass data is to apply the split-spectrum technique to the main band i.e., to compute the two sub-band interferograms by dividing the main range bandwidth into smaller sub-bands and declining to use the additional 5 MHz bandwidth for ionospheric phase estimation. The main advantage of this solution is to obtain two sub-band interferograms with the same polarization. Figure 7 provides an overview of the ionospheric phase uncertainties achievable with a traditional use of the split-spectrum technique (main- and side-bands at the same polarization) and by splitting the main band of the QQP data. For the 20 MHz NISAR data, the ionosphere phase uncertainty obtained by splitting the main range bandwidth into smaller sub-bands (orange solid line in Figure 7) is approximately 5.1 times larger than the ionosphere uncertainty achievable with the use of a 20 MHz dual-pol mode plus an additional sideband of 5 MHz (red solid line). Instead, the ionosphere phase uncertainty obtained from the application of the split-spectrum to the QQP 40 + 5 MHz data (brown line) is approximately 1.8 larger than that achievable from dual-pol 20 + 5 MHz data. Overall, the standard deviation of the ionospheric phase obtained by splitting the main band of QQP 40 + 5 MHz data (blue line) is 3 times lower than that estimated by splitting the main band of 20 + 5 MHz data (orange line).

### 6.4.2. Alternative Acquisition Modes

Among its polarimetric modes, NISAR is also equipped with the capability of transmitting circularly polarized electromagnetic waves and receiving radar echoes in a horizontal/vertical polarization basis (Rosen et al., 2015). This acquisition mode, commonly known as compact-pol (Souyris et al., 2005), might offer a valid alternative to the use of QQP. The successful applicability of compact-pol has been documented for a wide variety of geophysical and biophysical applications (Cloude et al., 2012; Neumann & Saatchi, 2013; Souyris et al., 2005; Truong-Loi et al., 2009). It has been observed that under the assumption of azimuthal symmetry, it is possible to produce a synthesized cross-pol return from compact-pol data for a wide variety of land cover types (Souyris et al., 2005). However, over urban areas, forest, and wet snow areas, compact-pol exhibits lower performance than a dual-pol mode i.e., the reconstructed HV signal from compact-pol data overestimates that from dual-pol (Neumann & Saatchi, 2013; Souyris et al., 2005). Further analyses are needed to recommend an operational use of the compact-pol mode for NISAR. Particularly, more work is needed to understand how the use of compact-pol might affect the different NISAR science applications and if the use of compact-pol would allow to reliably estimate the polarimetric scattering mechanisms (e.g., polarimetric alpha angle) and the degree of randomness of the scattering process (e.g., polarimetric entropy) (Cloude et al., 2012; Souyris et al., 2005).

### 7. Conclusions

In a QQP mode, the NISAR repeat-pass L-band data will include a 5 MHz sideband acquired at a different polarization than the main band (20 or 40 MHz). This additional sideband is mainly allocated for estimating the differential ionospheric phase delay affecting interferometric QQP NISAR data. Using several UAVSAR airborne data sets, we show that if the main- and side-bands are acquired at the co-polar channels (HH and VV), temporal variations of the interferometric scattering phase over agricultural and bare soil fields may introduce spurious polarimetric-dependent phase terms which may bias the estimation of the ionospheric...
phase for QQP data. At L-band, we observe that, over bare soils, the phase diversity is mainly governed by soil moisture changes and likely caused by a vertically stratified soil volume containing a soil moisture gradient. Over agricultural areas, the HH-VV phase inconsistencies are dominated by birefringence and they are mainly pronounced over fields containing vertically oriented crops (e.g., barley, wheat, corn). Irrespective of its presumed origin, the observed HH-VV InSAR phase diversity can induce a bias up to 30 cm on the QQP ionospheric phase estimates. Splitting the main bandwidth of NISAR SLC products would allow circumventing the presence of the polarimetric InSAR bias at the cost of noise amplification, which might significantly affect small range bandwidth products (e.g., 20 MHz). The presence and the magnitude of the HH-VV phase inconsistencies have not been systematically investigated over land cover types other than bare and vegetated agricultural fields. Their characterization over large spatial scales, different time intervals, and various land cover types remains still an important open question. At present, the QQP mode is among the available NISAR acquisition capabilities but its operational use has yet to be decided and it will be restricted to a limited set of targets. If NISAR will adopt an operational QQP mode, we recommend using a larger range bandwidth for the main band (i.e., 40 instead of 20 MHz) to reduce by approximately 3 times the ionospheric phase uncertainty caused by applying the split-spectrum to the main range bandwidth. Additionally, we recommend limiting the use of the QQP mode to highly coherent mid-latitudes regions where ionospheric irregularities are generally absent and thus the ionospheric phase is dominated by long spatial-wavelength components. This would allow smoothing the estimated ionospheric phase with larger filter sizes. In general, NISAR has available single (HH or VV), dual-pol (HH/HV or VV/VH), quad-pol and compact-pol (RH/RV) capabilities on both L- and S-bands. Compact pol might be a valid alternative to the use of QQP. However, to unambiguously recommend compact pol as an operational mode for NISAR, it is required to perform a more in-depth analysis of its impacts on the various polarimetric and interferometric NISAR applications. At this stage, with the available information, results from this study recommend the use of the same polarization on the main and side-bands of the NISAR operational science modes (e.g., single-pol or dual-pol) to avoid potential biases in the ionospheric phase estimates.

Data Availability Statement

All the SAR interferograms used to produce the results described in this study are available at https://data.nasa.gov/Earth-Science/SAR-Interferograms-for-NISAR-Quasi-quad-pol-mode-s/pibz-q4ma. The raw data is available in the link: https://doi.org/10.6084/m9.figshare.12816488.v5

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