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REVIEW ARTICLE

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Interferometric Synthetic Aperture Radar (InSAR) for Monitoring Seasonal Snow

Key Points:

- InSAR snow water equivalent and snow depth retrievals have advanced substantially over the past 25 years
- NISAR offers an immediate opportunity to implement and evaluate basin-scale InSAR snowpack measurements
- Technique progression requires algorithmic maturation supported by robust validation data collection

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Abstract Interferometric Synthetic Aperture Radar (InSAR) offers a potential pathway for measuring seasonal snow water equivalent (SWE) and snow depth at spatial and temporal scales needed for basin-scale hydrology. First proposed for seasonal snow more than 25 years ago, InSAR uses repeat-pass radar phase differences to estimate changes in SWE or depth caused by microwave propagation through snow. This review synthesizes InSAR-based snow monitoring from early theoretical and satellite demonstrations through recent tower, airborne, and spaceborne studies. We summarize the retrieval physics, evaluate published validation results, compare performance across wavelengths and snow environments, and identify barriers to operational implementation. The literature shows that InSAR can provide high-resolution, spatially distributed information on snow accumulation and ablation, especially under dry-snow conditions when temporal coherence is maintained and snow phase can be separated from atmospheric, vegetation, soil-moisture, and other non-snow contributions. Longer wavelengths, particularly L-band, help maintain coherence, reduce phase-wrapping ambiguity, and support retrievals in some vegetated environments, making the NASA-ISRO Synthetic Aperture Radar (NISAR) mission a timely opportunity for basin-scale testing. Remaining challenges include correcting ionospheric and tropospheric delays; defining stable reference phases; identifying, correcting, or flagging coherence loss and phase-unwrapping errors; accounting for forest-canopy interactions; collecting spatially distributed validation data; and scaling site demonstrations to regional or global products. Operational use will require algorithmic maturation, robust validation, and integration with other remote sensing and modeling approaches. If these challenges are addressed, InSAR-capable satellites could become an important component of an integrated global snow observation suite.

Plain Language Summary Seasonal snow is a critical source of water for people, ecosystems, and agriculture, yet it remains difficult to measure. Ground stations cannot capture the large variability in mountain snow, and current satellite methods still struggle to measure snow water storage at scales needed for water management. Differential Interferometric Synthetic Aperture Radar (InSAR) offers a potential approach for mapping changes in snow mass from space. InSAR compares radar signals collected at different times and uses changes in signal phase to estimate changes in snow depth or snow water storage. For more than 25 years, InSAR snow methods have been tested using tower, airborne, and satellite observations. These studies show that InSAR can provide spatially detailed information on snow accumulation and melt, especially when snow is dry and the radar signal remains stable between observations. However, operational use still requires better treatment of atmospheric effects, reference phase, wet snow, forests, signal loss, phase unwrapping errors, and validation data. The NASA-ISRO Synthetic Aperture Radar (NISAR) mission

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provides a timely opportunity to test these methods over larger areas. With continued development, validation, and integration with other satellite and modeling approaches, InSAR could become an important part of future snow monitoring systems.

1. Introduction

The seasonal snowpack is a vital part of the hydrologic cycle, providing water resources for about one-sixth of the world's population—over one and a half billion people (Barnett et al., 2005; Mankin et al., 2015). Snow accumulates during the winter months and, as temperatures warm in the spring, melt initiates and contributes to discharge that supports agriculture and municipal water, groundwater recharge, hydropower, and ecological systems (Siirila-Woodburn et al., 2021). Snowpack accumulation and ablation are highly variable both temporally and spatially (Bales et al., 2006; Blöschl, 1999; Elder et al., 1991), which challenges the use of in situ monitoring stations for accurately estimating snow distributions at the watershed scale (Fleming et al., 2023). A vital parameter for hydrological forecasting is snow water equivalent (SWE), the vertically integrated amount of liquid water stored in the snowpack.

Snowpack variability is driven by many factors (e.g., climate, vegetation, and topography) that cause snow depth and SWE to exhibit length scales on the order of tens to hundreds of meters (Blöschl, 1999; Meehan et al., 2024; Trujillo et al., 2007). This variability makes satellite remote sensing appealing due to its large coverage, potentially high spatial resolution, and frequency of repeat acquisitions, which can more robustly capture spatial heterogeneity than in situ measurements. However, our ability to operationally measure SWE from satellites at spatiotemporal scales relevant to basin-scale water resource management remains elusive (Lettenmaier et al., 2015). Although snow mapping with passive optical and near-infrared multispectral satellites has been implemented for decades through various satellites and techniques (Bair et al., 2021; Bohn et al., 2025; Dozier, 1984; Dumont & Gascoin, 2016; Hall et al., 2002; Klein & Stroeve, 2002; Nolin et al., 1993; Painter et al., 2009; Rittger et al., 2021; Salomonson & Appel, 2004), these methods measure only the extent and surface properties of the snowpack (e.g., snow presence, grain size, and albedo) and cannot provide information about snow depth or SWE. This makes measuring SWE globally, especially in mid-latitude mountain ranges which provide melt vital for water resources (Immerzeel et al., 2020), the preeminent unsolved challenge facing snow hydrology (Dozier et al., 2016; Sturm et al., 2017). To address this challenge, the 2017–2027 Decadal Survey for Earth Science by the National Academies of Sciences, Engineering, and Medicine (NASEM) designated SWE and snow depth as one of the “Most Important” observational priorities and in the Targeted Observable category (NASEM, 2018), and emphasized the need to globally quantify rates of snow melt, accumulation, and sublimation at 100 m spatial resolution in mountain areas (Earth Science Objective H-1c).

Current state-of-the-art operational satellite remote sensing of SWE is produced using passive microwave radiometer measurements (Pulliainen et al., 2020). However, this technique is ill-posed to monitor seasonal snow for hydrological applications because it is limited by coarse resolution (~20–40 km), forests, and signal saturation in deep snow (~1 m depth; Foster et al., 2005; Vuyovich et al., 2014; Clifford, 2010; Larue et al., 2017). Airborne lidar provides high-resolution snow-surface elevation measurements and has been used to map snow depth and estimate SWE through integration with hyperspectral observations and physically based snowpack modeling (Painter et al., 2016). Lidar is especially valuable because it directly measures snow-surface elevation and can retrieve snow depth under both wet- and dry-snow conditions, avoiding several snow-state limitations that affect microwave radar and radiometer retrievals. However, airborne lidar acquisitions remain episodic and non-feasible for routine global implementation.

Current spaceborne lidar observations are limited by sparse ground-track sampling rather than dense, wall-to-wall coverage with frequent repeat observations (Fair et al., 2025). Efforts to derive snow depth from spaceborne lidars such as the Ice, Cloud, and land Elevation Satellite-2 (ICESat-2) are ongoing. This technique currently has larger uncertainties in mountain regions due to the large spatial variability in elevation, slope, and aspect (Besso et al., 2024; Deschamps-Berger et al., 2023; Enderlin et al., 2022) and alone would not provide the spatial and temporal coverage needed for operational snow mapping (Kwon et al., 2021). Future swath-mapping spaceborne lidar missions, including the Earth Dynamics Geodetic Explorer (EDGE), could reduce these spatial sampling limitations and strengthen the role of lidar in integrated snow observing systems if planned coverage and precision

are achieved (Garvin et al., 2026). To improve the spatiotemporal coverage of snow depth retrievals, experimental methods are being developed utilizing very-high-resolution satellite stereo imagery (e.g., Planet Labs, WorldView, and Pléiades) to generate snow depth maps (Deschamps-Berger et al., 2020; Hu et al., 2023; Marti et al., 2016). These approaches generally rely on differencing independently generated snow-on and snow-off elevation surfaces, analogous to other digital elevation model (DEM)-differencing methods that may use lidar, stereo optical imagery, or radar-derived elevation products. However, large-scale coverage of stereo imagery remains sparse globally, and snow depth errors are high in complex terrain and regions of dense forest cover.

Active radar remote sensing, commonly implemented as Synthetic Aperture Radar (SAR) from spaceborne and airborne platforms, has the potential to address various snow remote sensing deficiencies. The high spatial resolution (~10–100 m), frequent temporal revisit, daylight-independent operation, and radar's cloud-penetrating ability provide an opportunity to leverage these multifaceted data for seasonal snow monitoring. The majority of previous work on developing satellite missions for snowpack monitoring has focused on volume-scattering approaches using high-frequency (~8–20 GHz; Ku- and X-band) SAR (Tsang et al., 2022). At these higher frequencies, radar signals scatter on snow grains and layer interfaces. Therefore, the total amount of backscatter can be used in combination with knowledge of various snow microstructure properties to estimate SWE. Advances in technique have been driven by a variety of airborne and field campaigns: (a) NASA's Cold Land Processes Experiment (CLPX; Cline et al., 2009) in 2002–2003 and CLPX-II (Yueh et al., 2009) during 2007–2008; (b) ESA's Nordic Snow Radar Experiment (NoSREx; Lemmetyinen et al., 2016); and (c) NASA's SnowEx campaign (Durand et al., 2018) from 2017 to 2023. These efforts have produced two past and one current snow satellite mission concepts. The two past concepts include ESA's Cold Regions Hydrology High Resolution Observatory (CoReH₂O; Rott et al., 2010; ESA, 2012) and NASA's SnowGlobe (<https://snowglobe.illinois.edu/>), which were both dual Ku- and X-band concepts, with the Terrestrial Snow Mass Mission (TSMM; Derksen et al., 2021) currently under development by Environment and Climate Change Canada (ECCC) and the Canadian Space Agency (CSA). While a volume scattering approach would provide vital data for global snow measurements if launched, this method remains a prospective future solution.

Leveraging current on-orbit radar capabilities, an empirical Sentinel-1 C-band snow depth retrieval algorithm has been developed that uses the co-polarized and cross-polarized backscatter ratio (Lievens et al., 2019, 2022). Initial studies suggested promising results for measuring snow depths in deeper snowpacks (>1.5 m), but recent independent validation has shown the retrievals to have moderate to high uncertainty, with average error values ranging from 0.25 to 0.7 m (Broxton et al., 2024; Bulovic et al., 2025; Hoppinen, Palomaki, et al., 2024). Importantly, the physical mechanisms underlying the C-band radar backscatter in snowpacks are still being studied, whether through modeling (Jans et al., 2025; Zhu et al., 2023) or tower-based experiments (Brangers et al., 2024, 2025). These results suggest that volume scattering techniques offer potential for snow depth monitoring at C-band, but uncertainty in the retrievals especially for shallower snowpacks motivates the exploration of other radar-based techniques for more direct SWE estimation.

Radar-based snow measurement is not limited to backscatter-based approaches. Interferometric Synthetic Aperture Radar (InSAR) provides a complementary phase-based approach that uses phase differences between SAR acquisitions to measure topography or changes in surface position and propagation path (Rosen et al., 2000). InSAR methods can be broadly separated into single-pass and differential approaches. Single-pass InSAR uses nearly simultaneous SAR acquisitions from separated antennas or platforms and has been most prominently used for topographic mapping and global DEM generation, including the Shuttle Radar Topography Mission (SRTM; Farr et al., 2007) and TanDEM-X (Rizzoli et al., 2017; Wessel et al., 2018). In contrast, differential InSAR uses phase differences between SAR acquisitions collected at different times to measure changes in propagation path or surface position. Hereafter, unless otherwise specified, InSAR refers to differential InSAR.

The first InSAR seasonal snow retrieval algorithm was developed by Guneriusson et al. (2001), who formulated a relationship between InSAR phase change and change in snow depth and SWE on the ground between dry snow acquisitions. Since 2016, a marked increase in the number of publications and conference papers using InSAR and related radar phase approaches for snow has driven progress and helped mature the technique (Figure 1). The recent July 2025 launch of the NASA–Indian Space Research Organization (ISRO) Synthetic Aperture Radar (NISAR; Rosen et al., 2025) mission provides a unique and timely opportunity to leverage InSAR for snow remote sensing applications. NISAR has L-band (24 cm; 1.25 GHz) and S-band (9.4 cm; 3.19 GHz) radars, near-global coverage at L-band, a 12-day repeat orbit, and standardized globally available InSAR data products hosted

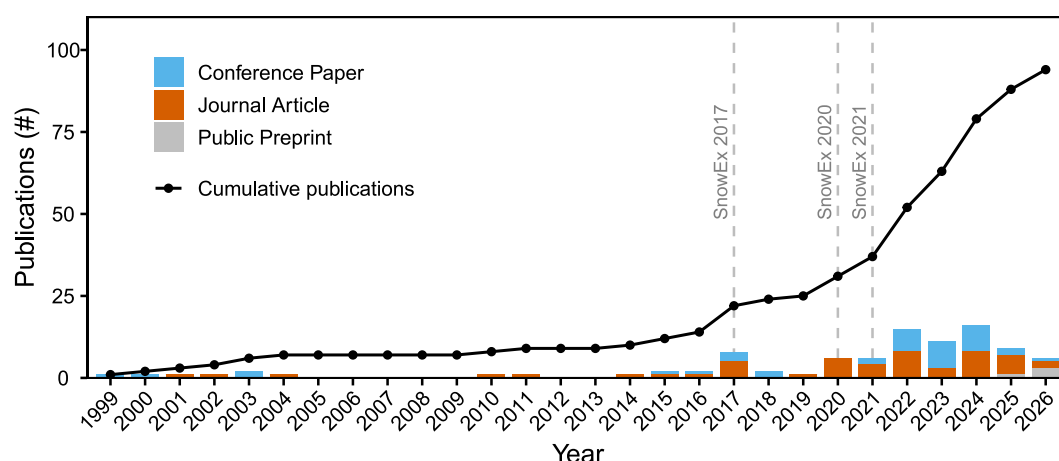


Figure 1. Annual publications on InSAR and related radar phase methods for SWE and snow-depth estimation. Stacked bars show conference papers (blue), journal articles (orange), and public preprints (gray). The black line shows the cumulative publication total through May 2026. Vertical gray dashed lines mark the SnowEx 2017, 2020, and 2021 Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) campaigns.

at the Alaska Satellite Facility Distributed Active Archive Center (DAAC). NISAR is tasked with observing near-surface glacial velocity, forest biomass, various natural hazards, and geomorphic/tectonic deformation; notably, terrestrial snow is not among the core mission science requirements. To evaluate NISAR's potential snow applications, the NASA SnowEx 2020–21 Time Series Experiment (Marshall et al., 2019, 2020) was designed to test SWE- and depth-change retrievals from L-band InSAR. Recent feasibility mapping across WUS mountain ecoregions suggests that L-band InSAR Δ SWE retrievals may be feasible over $\sim 65\%$ of the mountain ecoregion area and $\sim 73\%$ of SWE volume on 1 February, with feasibility declining as wet-snow conditions expand into spring (Kaur et al., 2026).

Multiple future InSAR satellite concepts are in various stages of development and may provide complementary information, building toward a global snowpack monitoring system. The European Space Agency (ESA) continues to support Earth observation with SAR satellites, with the recent launches of Sentinel-1C and Sentinel-1D in 2024 and 2025, and the Radar Observation System for Europe in L-band (ROSE-L) constellation near the end of the decade (Davidson et al., 2021). The continuation and expansion of satellites with InSAR capabilities strengthens the case for further maturation of snow-focused measurement techniques.

Despite marked progress, questions remain about the strengths and limitations of InSAR for measuring SWE and snow depth across a range of physiographic and snowpack conditions. This review synthesizes progress in InSAR-based SWE and snow-depth retrievals across wavelengths, platforms, and snow environments, while also contextualizing related radar phase approaches that may provide complementary information. We then identify key knowledge gaps and provide recommendations to advance the field. With this review, we aim to support the evaluation of NISAR and future InSAR-capable satellites as part of an integrated snow measurement strategy.

2. InSAR for Measuring Seasonal SWE and Snow Depth

Differential InSAR utilizes phase differences between two SAR acquisitions and was originally developed to map near-surface changes (Goldstein & Zebker, 1987). These phase differences, which represent changes in propagation time between repeat-pass acquisitions, have been used to calculate millimeter-scale deformation, soil moisture variations, ocean currents, atmospheric water vapor, near-surface glacial motion, and more (Rott, 2009).

The first application of InSAR to seasonal snow was theorized by Guneriusen et al. (2001), who demonstrated that the change in InSAR phase between repeat-pass acquisitions is related to the change in SWE on the ground under dry snow conditions (Figure 2). Dry snow generally has low attenuation at C-band and longer wavelengths (>5 cm) because both the conductance and magnetic permeability are negligible, and typical snow grain sizes are more than an order of magnitude smaller than C- and L-band. Thus, most of the backscatter originates from the snow–soil interface at frequencies below 10 GHz (Ulaby et al., 1984). The contrast in dielectric permittivities at

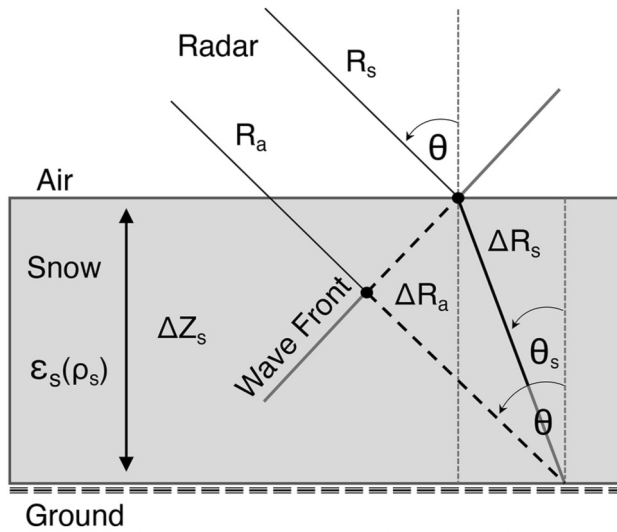


Figure 2. Schematic of the geometric principle for InSAR-based SWE estimation. Propagation through a snow-free atmosphere follows (R_a), while propagation through the snowpack to the reflecting wavefront follows R_s . The refraction angle (θ_s) and snow-modified wave speed are controlled by the snow permittivity (ϵ_s), expressed as a function of density (ρ_s). The resulting path-length difference, ($\Delta R_s - \Delta R_a$), produces the interferometric phase delay used to retrieve SWE changes. Reproduced from Figure 1 of Tarricone et al. (2023), published in *The Cryosphere*, licensed under CC BY 4.0. The original schematic was adapted from Leinss et al. (2015), after Guneriusen et al. (2001).

the air–snow interface causes a refraction of the radar propagation path and a decrease in speed as the signal propagates through the snowpack. In a dry snowpack, if snow accumulates or ablates between repeat-pass acquisitions, the change in the thickness of the snow medium on the second acquisition results in a change in the time of propagation, and therefore a change in phase (ϕ_{snow}). However, all other factors that impact the total phase variation (ϕ_{total}) must be taken into account before information on SWE change can be extracted. Collectively, these factors include:

$$\phi_{\text{total}} = \phi_{\text{snow}} + \phi_{\text{topo}} + \phi_{\text{flat}} + \phi_{\text{tropo}} + \phi_{\text{iono}} + \phi_{\text{other}} + \phi_{\text{error}} \quad (1)$$

where ϕ_{topo} is the DEM-dependent topographic phase contribution and ϕ_{flat} is the reference-surface, or flat-Earth, phase associated with the SAR imaging geometry, orbital baseline, and Earth curvature over the scene. Both terms are routinely modeled and removed during InSAR processing using precise orbit geometry, a reference ellipsoid, and a DEM. ϕ_{iono} is the phase contribution from the ionosphere due to varying electron densities. ϕ_{other} represents phase changes attributed to other physical or environmental factors including surface deformation, such as from permafrost (Zwieback & Meyer, 2021) or landslides (Bekaert et al., 2020), and changes in the dielectric permittivity, such as the freezing and melting of water/ice in vegetation (Schwank et al., 2021) or changes in soil moisture (De Zan et al., 2014). ϕ_{error} represents both random and systematic error. The majority of random error is caused by temporal decorrelation (Zebker et al., 1997), whereas systematic error stems from approximations in the radar instrument and processing chain, DEM uncertainty, imprecise satellite orbit calculations, residual processing ramps, and phase unwrapping errors (Jones et al., 2016).

For airborne InSAR applications, systematic errors primarily arise from uncertainties in the aircraft trajectory (Coscione et al., 2019). Processing workflows correct for aircraft motion using trajectory information from a Global Navigation Satellite System (GNSS) and an inertial navigation system (INS), typically combined during post-flight processing. However, residual centimeter-scale trajectory errors can remain. In some cases, this residual motion is not fully captured, producing residual phase errors that can bias estimates of ϕ_{snow} . For satellite-based applications, provided that the previously discussed positional errors have been mitigated as much as possible, isolating ϕ_{snow} , hereafter ϕ_s , from ϕ_{total} in InSAR data primarily depends on accurately correcting for the two largest remaining terms: (a) ϕ_{iono} , the phase contribution due to ionospheric advance, which is frequency-dependent and related to the total electron content (TEC) and the orientation of the geomagnetic field (Rosen et al., 2010), and (b) ϕ_{tropo} , the phase contribution resulting from temporal variations in atmospheric path delay (Hooper et al., 2012; Jolivet et al., 2014).

Assuming ϕ_s can be estimated, the resulting phase shifts are used to retrieve ΔSWE using the equation developed by Guneriusen et al. (2001), which incorporates both the change in path length due to refraction and the change in wave speed within the snowpack. Here, we define $\Delta z_s = z_{s,2} - z_{s,1}$, where $z_{s,1}$ and $z_{s,2}$ are the snow depths at the first and second acquisitions, respectively. Positive Δz_s therefore indicates snow accumulation between acquisitions. Following the common radar phase convention in which the returned phase is proportional to negative two-way path length, the negative sign in Equation 2 accounts for the radar phase response to the snow-induced propagation delay.

$$\Delta\phi_s = -\frac{4\pi}{\lambda} \Delta z_s \left(\cos \theta - \sqrt{\epsilon'_s - \sin^2 \theta} \right) \quad (2)$$

where $\Delta\phi_s$ is the snow-induced phase change between acquisitions, Δz_s is the change in snow depth, ϵ'_s is the real part of the bulk snowpack relative permittivity, λ is the radar wavelength, and θ is the incidence angle.

Snow relative permittivity is generally complex, $\epsilon_s = \epsilon'_s - i\epsilon''_s$, where $i = \sqrt{-1}$, and ϵ'_s and ϵ''_s are the real and dielectric-loss components, respectively (Bradford et al., 2009). For dry snow, dielectric losses are small ($\epsilon''_s \ll \epsilon'_s$), so Equation 2 can be evaluated using ϵ'_s alone under the low-loss approximation (Tiuri et al., 1984). This approximation may not be appropriate for appreciably wet snow. Spatially comprehensive measurements of ϵ'_s are rarely available from field observations and are difficult to obtain using remote sensing techniques; therefore, for dry snow, ϵ'_s is commonly parameterized as a function of bulk snow density ρ_s (Matzler, 1996):

$$\epsilon'_s \approx 1 + 1.6\rho_s + 1.8\rho_s^3 \quad (3)$$

Substituting Equation 3 into Equation 2 and solving for Δz_s gives:

$$\Delta z_s = -\frac{\Delta\phi_s \lambda}{4\pi} \left(\cos \theta - \sqrt{(1 + 1.6\rho_s + 1.8\rho_s^3) - \sin^2 \theta} \right)^{-1}. \quad (4)$$

If SWE is defined as water-equivalent depth (m), then $\Delta \text{SWE} = \Delta z_s (\rho_s / \rho_w)$, where ρ_w is the density of liquid water. Equivalently, $\Delta z_s = \Delta \text{SWE} (\rho_w / \rho_s)$, and substituting this relationship into Equation 2 and solving for ΔSWE yields:

$$\Delta \text{SWE} = -\Delta\phi_s \frac{\lambda \rho_s}{4\pi \rho_w \left(\cos \theta - \sqrt{\epsilon'_s - \sin^2 \theta} \right)} \quad (5)$$

which is the original formulation used by Guneriusson et al. (2001) and forms the mathematical basis for most InSAR–SWE studies. These formulations assume dry-snow conditions and represent the snowpack using an effective bulk density and permittivity over the repeat-pass interval. They therefore do not explicitly resolve temporal changes in density, stratigraphy, or liquid water distribution between acquisitions, except insofar as these changes are captured by the effective permittivity used in the phase-to-SWE conversion. Throughout this review, ΔSWE refers to the pairwise SWE change between two SAR acquisitions. In contrast, SWE refers to the total water-equivalent depth of the snowpack at a given time. When InSAR is used to estimate SWE, this generally requires integrating a time series of pairwise ΔSWE retrievals from an initial reference condition. Leinss et al. (2015) later showed that the density-dependent term $\left(\cos \theta - \sqrt{\epsilon'_s - \sin^2 \theta} \right)$ in Equation 2 is approximately linearly related to ρ_s by $-\frac{\alpha}{2}(1.59 + \theta^{5/2})$ for a broad range of incidence angles in dry snow conditions. With this approximation, Equation 5 can be written in the compact form:

$$\Delta \text{SWE} = \frac{\Delta\phi_s \lambda}{2\pi\alpha} (1.59 + \theta^{5/2})^{-1} \quad (6)$$

where α is a correction factor. The optimal correction factor α_{opt} in Equation 6 depends on θ and ρ_s , but remains within 0.95–1.05 for a wide range of incidence angles and snow densities.

Because liquid water has a very high relative permittivity (>80) and increases the effective electrical conductivity of the snowpack (Bradford et al., 2009), even small amounts of liquid water markedly increase both the real and imaginary parts of ϵ_s , reducing radar wave speed and penetration depth. Leinss et al. (2015) and Eppler et al. (2022) found that errors in ρ_s bias SWE-change estimates by $<5\%$ for dry snow over a wide range of θ (0° – 60°) and ρ_s (0 – 600 kg m^{-3}). However, in wet snow, Hoppinen, Oveisgharan et al. (2024) showed that small liquid water volume fractions in the upper meter of the snowpack (1% – 3% by volume) can cause retrieval overestimations of up to $\sim 10 \text{ cm}$ of SWE. Despite the additional error introduced by the snow permittivity approximation, Equation 6 is attractive for satellite-based applications at regional to global scales because it does not require snow density as an explicit input to derive SWE.

2.1. Alternative Phase-Based Radar Snow Measurement Techniques

While this review focuses on InSAR applications, several related radar approaches use propagation delay, phase, polarization, coherence, or amplitude to measure snow properties or to support validation. Time-of-flight radar

approaches, including ground-penetrating radar (GPR) and frequency-modulated continuous-wave (FMCW) radar, have been used for snowpack monitoring since the 1980s. Originally deployed from ground-based platforms (Gubler & Hiller, 1984; Marshall & Koh, 2008), these systems have more recently been extended to airborne (Kolpuke et al., 2024; Lewis et al., 2017; McGrath et al., 2018) and drone-based applications (Tan et al., 2021; Valence et al., 2022). When combined with estimates of snow density (ρ_s) and permittivity (ϵ_s), these measurements can provide non-destructive transects of snow depth and SWE that are useful for InSAR retrieval validation and calibration (Bonnell, McGrath, et al., 2024; Tarricone et al., 2023).

GNSS refractometry is a local, non-imaging approach that also exploits snow-induced propagation delay. In a typical configuration, a reference antenna remains above the snowpack while a second antenna near the ground receives GNSS signals after they propagate through the overlying snow; the resulting carrier-phase delay can be related to SWE. Initial studies demonstrated dry-snow SWE retrieval from GNSS carrier phases and evaluated buried-antenna observations over seasonal snowpacks (Henkel et al., 2018; Steiner et al., 2018). Later work combined phase delay and signal attenuation to retrieve SWE under both dry- and wet-snow conditions (Koch et al., 2019) and demonstrated automated near-real-time operation using fixed and mobile systems (Steiner et al., 2022). Although GNSS refractometry samples only a local footprint rather than providing imagery, SWE differences between SAR acquisition dates could supply independent point-scale Δ SWE observations for validating InSAR retrievals and constraining the additive reference-phase offset.

Other SAR and InSAR observables can also provide snow information beyond the repeat-pass phase delay used for Δ SWE retrieval. These include coherence, amplitude, and polarization. For example, Leinss et al. (2014) developed a snow-depth retrieval approach based on the co-polarized phase difference (CPD), which is induced by anisotropic characteristics of freshly fallen snow. Variants of this technique have since been tested across different platforms and study regions (Belinska, Fischer, & Hajnsek, 2024; Leinss et al., 2016; Patil et al., 2020, 2021). Another experimental approach is the dense-medium random-volume-over-ground (RVoG) method (Lei et al., 2023), which combines single-pass InSAR observations with physical scattering models to estimate snowpack properties. These approaches remain less broadly evaluated than repeat-pass InSAR Δ SWE retrievals, but after further refinement they may provide complementary information for snow monitoring.

2.1.1. P-Band SoOp SWE and Snow Depth Retrievals

Among these lower-maturity approaches, P-band (~ 1 m; 250–380 MHz) Signals of Opportunity (SoOp) passive radar is a potentially complementary long-wavelength technique for snow remote sensing (Yueh et al., 2021; Hale et al., 2025). We include it here because snow-focused P-band SoOp retrievals use snow-induced propagation delays that are physically related to the phase-delay mechanism used by InSAR, even though the measurement architecture is fundamentally different. SoOp uses existing satellite transmissions as illumination sources rather than carrying an onboard transmitter; therefore, SoOp is best understood as a bistatic radar architecture that can support phase-based retrievals, not as a traditional monostatic InSAR. A P-band SoOp snow concept has been developed as a potential pathway to spaceborne snow observations (Yueh et al., 2021). Its long wavelength and bistatic forward-scattering geometry may also provide sensitivity to wet-snow conditions, where the reflected signal can be dominated by the snow–air interface and therefore carry information about snow-depth change (Yueh, Xu, et al., 2017). Remote sensing of seasonal snow using P-band SoOp passive radar has received increasing attention since the mid-2010s (Garrison et al., 2024; Shah et al., 2017, 2018; Yueh et al., 2021, 2023, 2024).

The P-band SoOp snow concept exploits existing radio signals emitted by the Mobile User Objective System (MUOS) at frequencies of 250–270 MHz (~ 1 m wavelength) and 360–380 MHz (~ 80 cm wavelength). P-band SoOp bistatic radars use receivers to observe both the direct MUOS signal from the transmitter and the signal reflected by land surfaces. The direct and reflected signals are cross-correlated to estimate changes in the amplitude and phase of the reflected signal near the specular point relative to the direct reference signal. This technique therefore does not require decoding MUOS transmissions. Because the transmitter already exists, the radar receiver can require less power, lower mass, and lower cost than conventional active radar systems. The architecture also provides access to P-band frequencies that are difficult to use for conventional active radar transmission. These advantages also introduce additional requirements compared with conventional monostatic SAR, including accurate knowledge of transmitter position, receiver position and orientation, adequate signal strength, stable calibration, and careful correction of phase errors.

At P-band frequencies, volume scattering by snow grains is expected to be negligible for dry snowpacks and the reflected signal is primarily controlled by the soil surface (Yueh, Shah, Xu, Elder, Chae, Margulis, et al., 2017; Yueh et al., 2020, 2023). Soil moisture can influence the amplitude and phase of the reflected signal (De Zan et al., 2014). If soil moisture remains relatively stable through the snow accumulation season, the snowpack introduces an additional time delay, or phase shift, to the reflected signal. For dry snow conditions, the phase shift with respect to snow-free conditions can be related to ΔSWE , analogous to L- and C-band InSAR methods. For snowpacks with substantial near-surface wetness ($>5\%$), the reflected signal may instead be dominated by the snow–air interface, such that the phase delay is more directly related to changes in snow depth (Yueh, Xu, et al., 2017). This potential sensitivity to both dry-snow SWE change and wet-snow depth change is one reason P-band SoOp remains relevant to future integrated snow observing systems, but retrieval interpretation depends on snow wetness, soil moisture, vegetation, and bistatic geometry.

The SigNals of Opportunity: P-band Investigation mission (SNOOPI; Garrison et al., 2024) provides important context for a potential spaceborne P-band SoOp pathway, but it should not be interpreted as a validated demonstration of P-band snow retrieval from space. SNOOPI deployed a compact CubeSat receiver architecture for testing P-band SoOp observations from orbit. The mission was designed to validate P-band SoOp measurements relevant to root-zone soil moisture and SWE, but ended prematurely after six data captures because of a power anomaly, leaving limited data and uncertainty about whether science data products can be generated (Yin et al., 2025). Thus, SNOOPI supports a potential spaceborne implementation pathway for P-band SoOp, but does not currently provide a validated demonstration of P-band SWE retrieval from space.

The combination of SoOp with synthetic aperture processing has also been explored as a SoOpSAR technique (Yueh et al., 2021). Initial airborne work has examined P-band SoOpSAR measurement geometry, scattering behavior, and dry-snow penetration, but end-to-end airborne ΔSWE retrieval validation has not yet been robustly demonstrated. The primary hypothesized benefits of a bistatic P-band SoOpSAR snow mission concept include: (a) penetration through relatively dense forest canopies, (b) use of the strongly forward-scattered signal to improve signal-to-noise ratio for snow changes in wet-snow conditions, (c) maintenance of coherence over longer temporal periods, and (d) the relative simplicity of a radar system composed only of receivers. However, compared with traditional InSAR, SWE and snow-depth retrieval using P-band SoOp remains at a lower technique maturity level and will require substantial research, open validation data sets, and error-budget analysis before it can be confidently applied from satellite platforms.

3. InSAR SWE and Snow Depth Retrieval Progress

In this section, we review the published literature organized by acquisition platform, with Figure 1 showing yearly and cumulative InSAR snow monitoring publications since the technique's inception. Figure 3 maps the study locations scaled by number per site from Figure 1 overlaid on the Sturm and Liston (2021) snow classes. Although the method was first demonstrated from a satellite platform, we illustrate how the technique has been advanced from the ground up. We start with tower-based radars (Section 3.1), which were primarily tested in Finland. We then move onto airborne (Section 3.2), which includes both US and European campaigns. We end with spaceborne applications of the SWE retrieval technique (Section 3.3) from around the globe. Despite our organization, many of these studies were produced contemporaneously, highlighting the concerted and global effort to better understand InSAR-based snowpack monitoring.

3.1. Tower-Based Radars

The first tower-based interferometric snowpack study was conducted by Leinss et al. (2015) using the SnowScat real aperture radar near the town of Sodankylä, Finland, for the winter seasons of 2009–2013. SnowScat is a fully polarimetric real aperture radar with a frequency range of 9.2–17.8 GHz (Ku-to X-band; Werner et al., 2010) mounted on a 9-m high tower. The results of this study provided several key advancements in InSAR and phase-based snow monitoring, including a simplified phase-to-SWE relationship by showing that there is a nearly linear relationship between $\Delta\phi_s$ and ΔSWE for a given incidence angle as shown in Equation 6. This is a major advancement for future spaceborne InSAR applications as it minimizes the need for spatially distributed ρ_s information, which is difficult to measure or model accurately (Raleigh & Small, 2017).

Using 10.2 and 16.8 GHz and a 4 hr time-step to minimize coherence loss, Leinss et al. (2015) produced a novel integrated ΔSWE time series over four winter seasons and validated the results against measurements from an

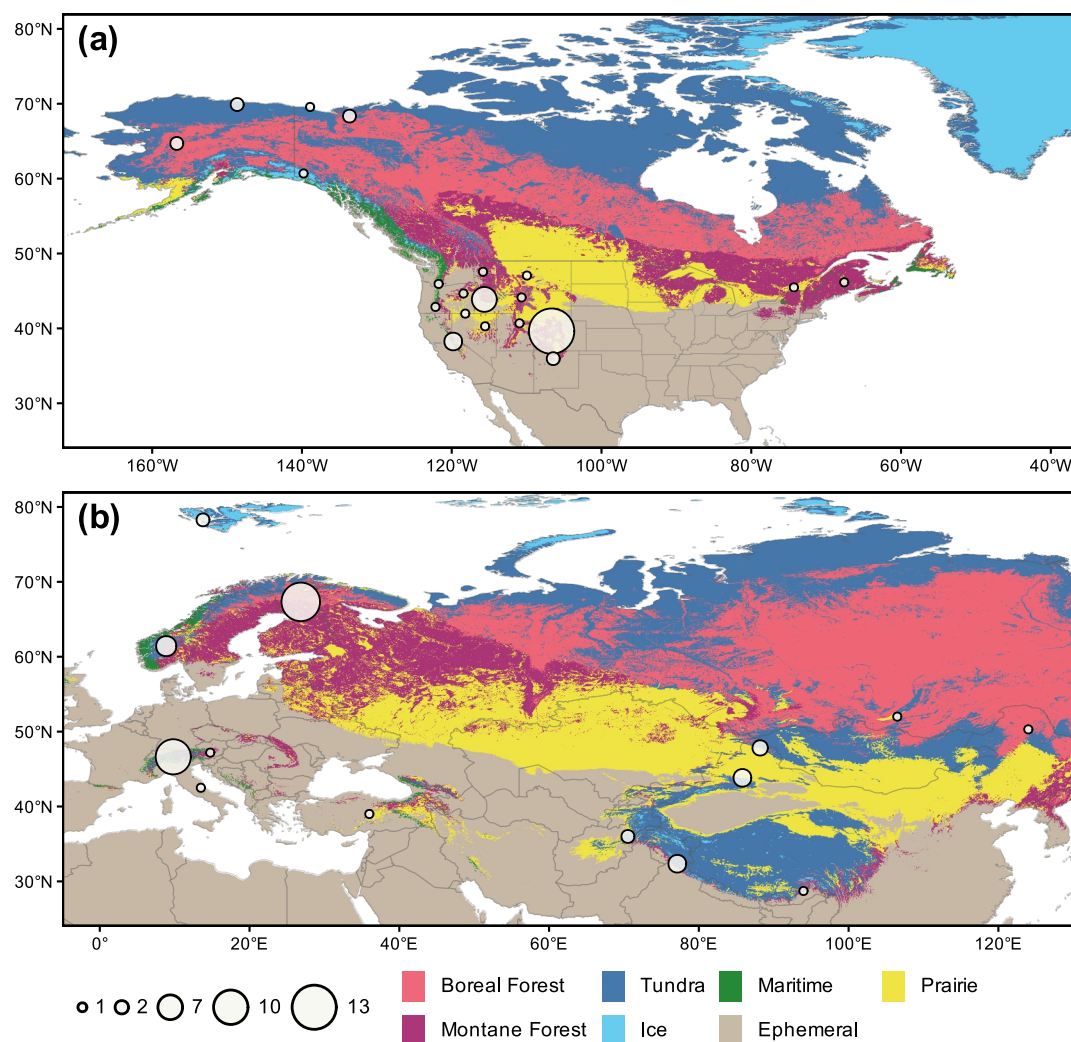


Figure 3. Geographic distribution of study locations for InSAR and related radar phase-based SWE and snow-depth estimation in (a) North America and (b) Eurasia. Circles show mapped empirical study locations, with nearby study locations clustered within 200 km for visualization. Circle size indicates the number of studies represented within each clustered location. Multi-site papers are represented by one mapped location per distinct study site before clustering. Review, mission-concept, instrument-concept, and modeling studies are excluded from the map. Background colors show seasonal snow classes from Sturm and Liston (2021). One South American study location is not shown.

experimental gamma radiation SWE instrument, an automated weather station, and snow pits repeated at weekly intervals. They found the SnowScat-derived total SWE data to have an accuracy of 0.5–1.5 cm depending on the given validation data set, and that 10.2 and 16.8 GHz agreed within 0.44 cm. These findings demonstrated for the first time, that in idealized conditions (i.e., cold, dry snow, no topographic or vegetation effects, short temporal baselines) there is a robust physical relationship between $\Delta\phi_s$ and ΔSWE over an entire winter season. The results from this groundbreaking study reignited global interest in InSAR SWE retrievals, as they suggested that the method could likely be scaled to a satellite-based InSAR platform.

The more recently developed Sodankylä Synthetic Aperture Radar (SodSAR; Jorge Ruiz et al., 2020) allowed for new studies to be conducted using InSAR-based SWE retrievals. SodSAR is a fully polarimetric tower-based radar mounted at 21 m above the ground that can operate between 1 and 10 GHz (L-, S-, C-, and X-band) and has representative frequencies of current (NISAR, Sentinel-1, and TerraSAR-X) and future (ROSE-L) satellite missions. A 5 m rail enables cross-range movement and SAR image formation. Utilizing SodSAR, Ruiz et al. (2022) investigated how meteorological factors impact InSAR temporal decorrelation at L-, S-, C-, and X-band frequencies using temporal baselines from 6 hr to 12 d. Above freezing temperatures, large snowpack

temperature gradients causing snow crystal growth, and intense wind and snow events were shown as the main drivers of temporal decorrelation. When compared to automated weather station total SWE data, they found that L-band had the lowest RMSE (0.34–2.61 cm, depending on the temporal baseline), with retrieval accuracy decreasing and coherence degrading as frequency increased. In addition, L-band also displayed the greatest coherence retention (~ 0.5 – 0.8). These results indicate that lower frequencies (L- and P-band) are preferred for satellite InSAR-based SWE measurements. Ruiz et al. (2022) further presents coherence conservation and SWE retrieval results over a boreal forest stand. L-band was shown to maintain reasonable coherence over vegetated areas and retrieve SWE, provided a short enough temporal baseline (< 6 days). Additional work from Lemmetyinen et al. (2022) using SodSAR radar backscatter data examined the radar attenuation impacts of air temperature and canopy intercepted snow. Canopy attenuation was found to decrease as air temperature drops below 0°C . They found lower frequencies have less attenuation, further supporting the use of L-band and showing it could potentially be used to measure SWE in forested environments from space.

3.2. Airborne

3.2.1. ESA Campaigns

European-based efforts have provided a range of different InSAR SWE implementations and technique advances. The first implementation of airborne InSAR for snow applications was conducted by Rott et al. (2003) in an ephemeral low-snow area near the German Aerospace Center (DLR) headquarters in Munich, Germany. They utilized the L-band Experimental SAR system (E-SAR) developed by DLR (Reigber & Scheiber, 2003) and conducted three flights; two snow-free acquisitions on 22 October 2002, and a third dry snow pass on 20 February 2003 that held sufficient coherence to estimate SWE. In situ snow measurements were not conducted coincident with the flights. However, the InSAR ΔSWE estimate of 43 mm falls within the range of snow depth measurements obtained from in situ snow depth observations of 12 and 20 cm when assuming a typical midwinter snow density (ρ_s) in the range of 250–300 kg/m^3 . This early study continued to add confidence in the physical basis of the retrievals and future satellite-based applications.

Nearly 20 years later in support of ESA's ROSE-L (Davidson et al., 2021) and the proposed geostationary C-band SAR Hydroterra+ mission (Hobbs et al., 2022), Nagler et al. (2022, 2024) continued their work by conducting a C- and L-band study during March 2021 in the Austrian Alps. Using DLR's dual-polarized (HH & VV) F-SAR instrument (Horn et al., 2017), they conducted a variety of repeat-pass flights in alpine environments during two snow accumulation events, with temporal baselines ranging from 0.2 hr to 17 d. Their preliminary results were especially promising for the L-band data. Between 9 and 19 March, a 10-day temporal baseline, the mean scene-wide coherence was 0.77 and the InSAR-based ΔSWE estimates had an RMSE of only 11.2 mm compared to in situ validation data. The C-band performed better for a smaller snowfall event between 4 and 8 March, but the data decorrelated after the higher intensity snowfall event during the 10–19 March InSAR pair. A subsequent preliminary analysis of the same Wörgetal F-SAR campaign found that, among the SAR observables tested, InSAR provided the most reproducible basis for event-scale ΔSWE retrievals. Changes in the VH/VV backscatter ratio and CPD were not consistently related to in situ snow depth changes or ΔSWE from the snowfall events, whereas L-band repeat-pass InSAR retrieved ΔSWE for both events with high coherence. C-band repeat-pass InSAR performed well for the smaller accumulation event but was limited by decorrelation and 2π phase ambiguity during the larger event (Rott et al., 2026).

In subsequent studies using the same F-SAR data set, Belinska, Fischer, and Hajnsek (2024) proposed augmenting InSAR-based ΔSWE with the CPD technique (Leinss et al., 2014) to detect and correct phase wraps, improving retrieval accuracy. They report wrap thresholds of ~ 15 mm (C-band) and ~ 61 mm (L-band) SWE at 34° incidence, with L-band maintaining higher coherence and yielding lower wavelength-normalized RMSE than C-band. The CPD-based correction depends on assumed fresh-snow density and anisotropy and can be impacted by metamorphism between acquisitions, so the authors applied quality masks (e.g., coherence > 0.25 , polarimetric coherence > 0.6 , $\theta > 20^{\circ}$, slope $< 25\%$). Broadly, this series of studies provided both early proof-of-concept and later foundational technique advancement.

3.2.2. NASA SnowEx UAVSAR Campaigns

To address knowledge gaps in snow remote sensing and prepare for a snow-focused satellite mission, the NASA Terrestrial Hydrology Program (THP) initiated the SnowEx campaign in 2016 (Durand et al., 2018). SnowEx was

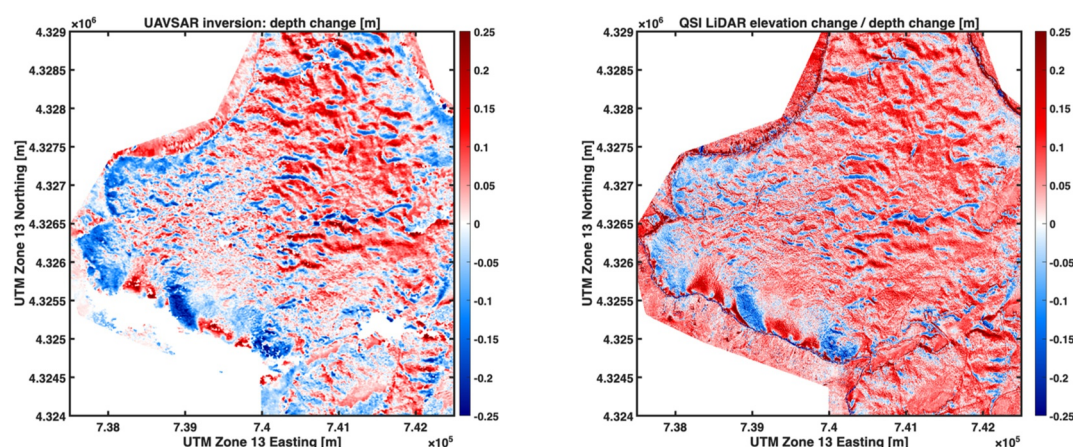


Figure 4. Comparison of UAVSAR L-band InSAR snow-depth change retrievals with coincident lidar-derived snow-depth change over Grand Mesa, Colorado. The left panel shows InSAR-derived snow-depth change, and the right panel shows lidar-derived snow-depth change over the same area. Grand Mesa provides a relatively favorable test site for InSAR snow retrieval because of its low relief, limited forest cover, and high-elevation dry-snow conditions. Replotted for this review from the underlying data and analysis reported in Marshall et al. (2021).

a multiyear effort to test experimental snow remote sensing technologies in a range of globally representative snow conditions. The goals of the campaign were to validate these remote sensing approaches against in situ data, modeling, and established remote sensing techniques like airborne lidar. To evaluate the potential of measuring seasonal snow with NISAR, SnowEx conducted multiple airborne Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR; Rosen et al., 2006; Hensley et al., 2008) time series campaigns (Marshall et al., 2019, 2020) across the WUS over three winter seasons (2017, 2020, and 2021). Like NISAR, UAVSAR has an L-band SAR with InSAR capabilities, allowing for airborne implementation of the SWE retrieval technique. The initial UAVSAR flights took place in SnowEx 2017 over Grand Mesa, CO (Deeb et al., 2017). These InSAR-based Δ SWE retrievals showed similar spatial patterns to lidar-based total snow depth, motivating a time series campaign in the winter seasons of 2020 and 2021 over 13 unique study sites across the WUS (Marshall et al., 2019). The goal was to test the InSAR-based SWE retrieval method in various snow conditions, land covers, and climate types. Each study site featured unique in situ and/or ground-based remote sensing observations collected coincident with the airborne retrievals for direct evaluation.

From the SnowEx UAVSAR campaigns, numerous studies have been published, with the results substantially advancing our understanding of the technique. The studies have demonstrated L-band InSAR's feasibility for mapping changes in SWE and snow depth, and quantifying uncertainties specific to different snow climates, in challenging topography, and in different land covers. When comparing InSAR-based changes in snow depth to coincident lidar snow depth change retrievals in flat terrain on Grand Mesa (Figure 4), a very-high correlation ($R^2 = 0.76$) and a low root-mean-square-error (RMSE) of ~ 1 cm SWE was found (Marshall et al., 2021). This indicated that InSAR can capture snow distribution patterns that agree with snow depth distribution from lidar, however Grand Mesa represents an idealized testing ground (e.g., flat, limited forest cover, and $\sim 3,000$ m elevation) and more work was needed to explore the physiographic complexity of most snow-dominated mountain watersheds in the WUS.

Building off these preliminary results over Grand Mesa, Tarricone et al. (2023) conducted a similar UAVSAR-based SWE retrieval validation analysis in the Jemez Mountains, NM, which contains more complex topography, warmer snowpack conditions, and a variety of different forest cover types. Once the interferograms were corrected for estimated atmospheric delay, the authors proposed a multi-sensor approach where they combined UAVSAR phase used in tandem with coincident Landsat fractional snow-covered area (fSCA; Selkowitz et al., 2017) data for robust snow cover delineation. They found that L-band InSAR can be used to track melting and refreezing snow using morning acquisitions during the spring melt onset; observed visually similar InSAR-based snow melt dynamics to those of fSCA melting patterns; and maintained good coherence and SWE change returns at a 14-d baseline. Additionally, Keskinen et al. (2022) developed the open-source `uavsar_pytools` package within the scope of this work, providing tools for systematically downloading, formatting, and analyzing UAVSAR data

products. This software has enabled broader adoption of UAVSAR data for snow studies. Altogether, the findings from Tarricone et al. (2023) further showed the utility of the technique in conditions thought to be highly unfavorable to radar remote sensing.

Using a UAVSAR InSAR pair with a 6-day baseline over a SnowEx site in the Montana prairie, Palomaki and Sproles (2023) showed that L-band InSAR was sensitive to the presence and spatial variability of shallow (~ 20 cm) prairie snow. UAV-based lidar validation data were collected over agricultural fields for this study. Although exposed agricultural vegetation beyond the top of the snowpack complicated lidar snow depth measurements, the L-band InSAR and lidar data sets showed similar spatial patterns. The largest differences between the InSAR and lidar snow data sets occurred where snow depth varied substantially within the approximately 6 m UAVSAR pixel footprint. Lastly, the lidar accuracy was on the order of snow depth changes during the study period, such that the shallow snow conditions challenged both techniques.

Hoppinen, Oveisgharan, et al. (2024) evaluated L-band UAVSAR Δ SWE and snow-depth retrievals over complex mountain terrain in central Idaho using SnowEx 2020 and 2021 observations. Their analysis used nine successfully unwrapped nearest-neighbor UAVSAR interferometric pairs from a larger 12-pair time series, with a mean temporal baseline of 8 d, over a $\sim 170 \times 16$ km flight box spanning the Boise foothills to the Sawtooth Mountains. Retrievals were compared with coincident SNOTEL and snow-pit observations, using retrieved values averaged within a 100 m box around each field location and snow pits within ± 2 d of the UAVSAR acquisitions. They reported strong agreement with in situ snow depth change ($R = 0.80$, RMSE = 0.10 m, $n = 64$) and moderate agreement with in situ SWE change ($R = 0.52$, RMSE = 0.039 m, $n = 57$). They also compared retrievals with 100 m SnowModel Δ SWE fields, finding $R = 0.60$ and RMSD = 0.023 m across successfully unwrapped pixels, with stronger agreement in pixels with no modeled melt and low tree cover ($R = 0.72$, RMSD = 0.013 m, $n = 6.5 \times 10^4$). Because SnowModel itself had non-negligible error relative to in situ observations, the model comparison is best interpreted as a spatial pattern assessment rather than independent truth. Their binned analyses showed reduced performance at lower elevations, higher tree cover and tree height, greater cumulative melt, and less favorable incidence-angle sensitivity, indicating that wet snow, vegetation, and retrieval geometry remain important controls on L-band InSAR snow retrieval accuracy.

In central and northern Colorado, Bonnell, McGrath et al. (2024) and Bonnell, Elder, et al. (2024) evaluated UAVSAR Δ SWE retrievals based on repeat surveys at small field sites (< 1.0 km²). In the Medicine Bow Mountains, Bonnell, McGrath et al. (2024) used a ground-penetrating radar (GPR) with a similar center-frequency to UAVSAR (1.0 GHz center-frequency) to collect SWE measurements along repeated > 1.5 km transects and repeat terrestrial lidar surveys at an open meadow and a severely burned site. Across the 10 InSAR pair time series, they found strong agreement for UAVSAR/GPR Δ SWE site-wide medians (median difference < 4 mm; Figure 5). They found high correlation and low RMSEs for both GPR ($R = 0.79$, RMSE = 22 mm; Figure 5) and terrestrial lidar ($R = 0.72$, RMSE = 19 mm), when compared to UAVSAR Δ SWE. Bonnell, Elder, et al. (2024) evaluated an eight pair UAVSAR time series with repeat snow pit and snow depth measurements at the Fraser Experimental Forest and found comparable accuracy metrics ($R = 0.55$ and RMSE = 18 mm). Their study primarily addressed the influence of forest cover fraction upon the UAVSAR Δ SWE time series. Based on in situ measurements, they demonstrated robust Δ SWE retrievals at forest cover fractions < 0.4 (RMSE = 14–17 mm), but increased uncertainty above forest cover fractions > 0.5 (RMSE > 33 mm). They supported these results through an expanded analysis that evaluated UAVSAR Δ SWE based on airborne lidar snow depths.

Collectively, these SnowEx UAVSAR studies demonstrated L-band InSAR's strong seasonal snow monitoring potential through the most robust validation to date and began to address the fundamental uncertainties in the technique. Building on these foundational validation studies, several recent efforts have begun addressing operational uncertainties and pathways for model integration. Alabi et al. (2025) tested multiple machine-learning models to estimate InSAR-based snow depth over Grand Mesa, CO, validating against in situ and airborne lidar measurements; XGBoost outperformed the other algorithms and achieved snow-depth RMSE of ~ 16 cm, approaching airborne-lidar accuracies (Tinkham et al., 2014). Tarricone et al. (2025) examined how optical snow-cover products influence volumetric InSAR SWE retrievals within a multisensor framework; aside from the U.S. Geological Survey Landsat fSCA product (Selkowitz et al., 2017), five other commonly used products yielded statistically similar results, and they recommended Normalized Difference Snow Index (Dozier, 1989) fSCA (Salomonson & Appel, 2004, 2006) from VIIRS for basin-scale InSAR-based SWE estimation with NISAR.

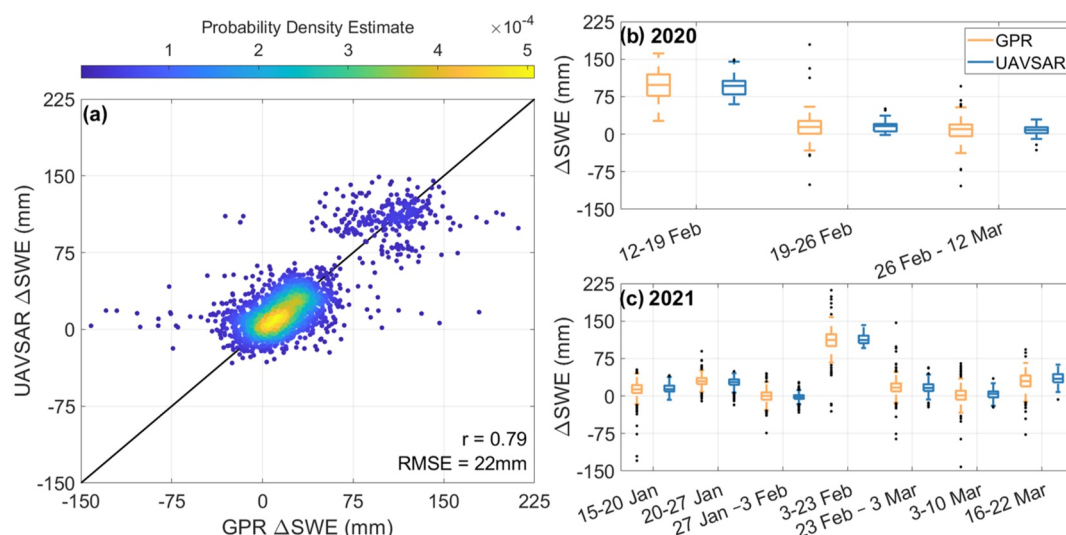


Figure 5. Evaluation of UAVSAR with GPR in northern Colorado. (a) UAVSAR Δ SWE compared with GPR Δ SWE, with points colored by point density. (b, c) Box-plot comparisons between UAVSAR and GPR for each survey date in 2020 and 2021, respectively. Absolute differences between UAVSAR and GPR median Δ SWE were 0–4 mm. Reproduced from Figure 7 of Bonnell, McGrath, et al. (2024), published in *The Cryosphere*, licensed under CC BY 4.0.

Finally, Shrestha and Barros (2025a) conducted an InSAR snow data-assimilation study, assimilating L-band InSAR snow-depth change—referenced with ASO lidar and modeled density—using the Multi-Physics Data Assimilation Platform (MPDAF v1.0; Shrestha & Barros, 2025b) coupled with the Multilayer Snow Hydrology Model (MSHM v3.0; Cao & Barros, 2020; Kang & Barros, 2012b, 2012a; Shrestha & Barros, 2025a) and the National Center for Atmospheric Research (NCAR) Data Assimilation Research Testbed (DART; Anderson et al., 2009; NCAR DART Team, 2021), yielding lower RMSE and improved spatial variability. Together, these studies outline viable routes to operationalize InSAR snow estimates via machine learning, multi-sensor fusion, and model-based assimilation.

3.3. Satellite

Satellite-based InSAR SWE and snow depth studies span a range of study locations, sensing platforms, and wavelengths. The technique was developed by Guneriusen et al. (2001) using ~ 24 -h baseline C-band data from the European Remote-Sensing Satellite (ERS-1) constellation. Future ERS-1-based studies continued to show positive yet preliminary results on the relationship between change in phase and dry snow. These include Rott et al. (2003) in Austria, which additionally provided the first demonstration from an airborne platform, as well as Li and Sturm (2002) which mapped wind-drifted snow (dunes/sastrugi) on Alaska's North Slope from InSAR fringes aligned with prevailing winds. Additionally, Engen et al. (2004) developed the delta- k method, which uses summer to winter shift in wavenumber (k) between SAR acquisitions to estimate SWE instead of interferometric phase. After a 7-year research lapse, Deeb et al. (2011) used 3-day C-band repeats over Alaska's North Slope to map relative SWE change, tying phase-gradients to wind redistribution, exposing single-layer model bias, and stating the need for L-band data and shorter temporal repeats. All of these studies demonstrated the potential of C-band InSAR to maintain coherence at short (~ 24 -h) baselines and produce physically reasonable Δ SWE estimates.

After the initial studies, there was a lull in technique progression due to the lack of open-access globally available InSAR data and validation data limited to a few point-based measurement stations. That said, a range of platforms and geographic locations with short temporal study periods were utilized to continue fueling interest in the technique (Li et al., 2017; Liu et al., 2017; Mahmoodzada et al., 2020, 2022; Torun & Ekercin, 2021; Varade et al., 2020; Yang & Li, 2021). While these partial season studies did not provide major advancements due to a limited amount of validation data, these studies continued to show InSAR's diverse utility in many geographic locations. However, two studies from this time period provided notable results: Conde et al. (2019) showed that robust explicit atmospheric phase correction for Sentinel-1 C-band data is needed to achieve high-accuracy

(~6 mm mean error) results when compared to limited in situ stations; and Y. Li et al. (2022) demonstrated that retrievals were possible in forested environments with canopy cover corrections.

Recent work has implemented multiple season InSAR time series, and both model- and airborne lidar-based spatially distributed snow validation data. Building upon the work of the partial season studies, a few studies have demonstrated the operational potential of InSAR for snowpack monitoring. Eppler et al. (2022) used RADARSAT-2 data near Inuvik, Northwest Territories, Canada, to develop the “SlopeVar” estimator, which allows Δ SWE estimation without phase unwrapping. Their 500-m InSAR-based estimates performed well when compared with in situ observations and SWE from ERA5, the fifth-generation European Centre for Medium-Range Weather Forecasts atmospheric reanalysis (Hersbach et al., 2020). Using the Japan Aerospace Exploration Agency's (JAXA) Advanced Land Observing Satellite-2 (ALOS-2) PALSAR-2 L-band radar, Ruiz et al. (2024) analyzed 2 years of InSAR retrievals data in northern Finland and evaluated the results based on tuned SnowModel (Liston & Elder, 2006) output and in situ snow data. They demonstrated good agreement between InSAR estimates and SnowModel estimates for temporal periods where temperatures were below freezing, but identified complexities of 14-day temporal baselines in dense boreal forest environments when temperatures were near the melting point.

Various recent studies have provided substantial methodological advancements to the InSAR monitoring technique, leveraging the utility of a variety of wavelengths and processing techniques. Belinska, Fischer, Parrella, and Hajnsek (2024) evaluated spaceborne X-, C-, and L-band InSAR for Δ SWE at Sodankylä, Finland, with the main focus on Sentinel-1 (C, 6 d) and ALOS-2 (L, 14 d) acquisitions from 2019. Critically, they demonstrate a novel multifrequency strategy: L-band Δ SWE, linearly interpolated in time, flags and corrects C-band unwrapping errors, yielding RMSE $\approx$ 10.1 mm without ground data. More recently, Belinska et al. (2026) extended this work by exploring D-Pol-InSAR coherence regions for SWE estimation, further showing how polarimetric and interferometric observables may help constrain snow-state-dependent retrieval behavior. These results motivate a coordinated multifrequency mission or observing strategy that pairs short-wavelength sensitivity with long-wavelength phase-wrapping margins for operational Δ SWE mapping. Building off these results Benedikter et al. (2024) introduce a simultaneous multiple-squint InSAR: two interferograms at different squints whose difference phase gives low-resolution, unbiased Δ SWE without unwrapping or reference points. The absolute phase (and thus Δ SWE) is recovered in moderate–high coherence by resolving the bulk 2π offset, with the phase ratio yielding an estimate ϵ_s and ρ_s . These results suggest the potential ESA Harmony Mission (López-Dekker et al., 2021) could provide robust snow measurement capabilities.

Lastly, a seminal study from Oveisgharan et al. (2023) provided the first demonstration of the operational potential of 6-day Sentinel-1 repeat passes in Idaho, USA, substantially advancing our understanding of season-long InSAR snow monitoring. They implemented a satellite-based time-series approach akin to Leinss et al. (2015). By integrating over each 6-day interferogram, they retrieved total SWE and snow depth, rather than only Δ SWE as in most prior studies. Validation used SNOTEL stations across Idaho and spatially distributed lidar snow depths from two mountain locations acquired by SnowEx (Figure 6). Relative to the InSAR-derived total SWE time series, the SNOTEL time series showed high correlation and low error (e.g., RMSE = 1–2 cm), and the SnowEx lidar maps exhibited similar spatial patterns with moderate correlation (e.g., R = 0.47–0.59). Collectively, the season-long time series and independent lidar validation demonstrate that InSAR can maintain coherence and provide spatially distributed SWE measurements over an entire winter season.

3.4. P-Band SoOp SWE and Snow Depth

A multiyear experimental campaign was conducted at the US Forest Service Fraser Experimental Forest, Colorado with two tower-based receivers to demonstrate the P-band SoOp technique. The subalpine study site (Figure 7a) has a cold and dry continental snow climate and surrounding montane forest. This campaign demonstrated the P-band SoOp radar measurement principle with the data confirming the feasibility for both total SWE (Figure 7b; RMSE = 1.15–1.6 cm) and snow depth (Figure 7c; RMSE = 7.8–8.9 cm) retrievals (Shah et al., 2017, 2018), as well as soil moisture (Yueh et al., 2020). The tower experiment demonstrated the technique with successful retrieval of SWE in dry snow condition and snow depth in wet snow condition over non-vegetated and minimally vegetated sites (Shah et al., 2018).

These results should be interpreted as an important proof-of-concept for P-band SoOp snow retrievals, rather than as a complete demonstration of operational readiness. The Fraser experiments demonstrate that tower-based

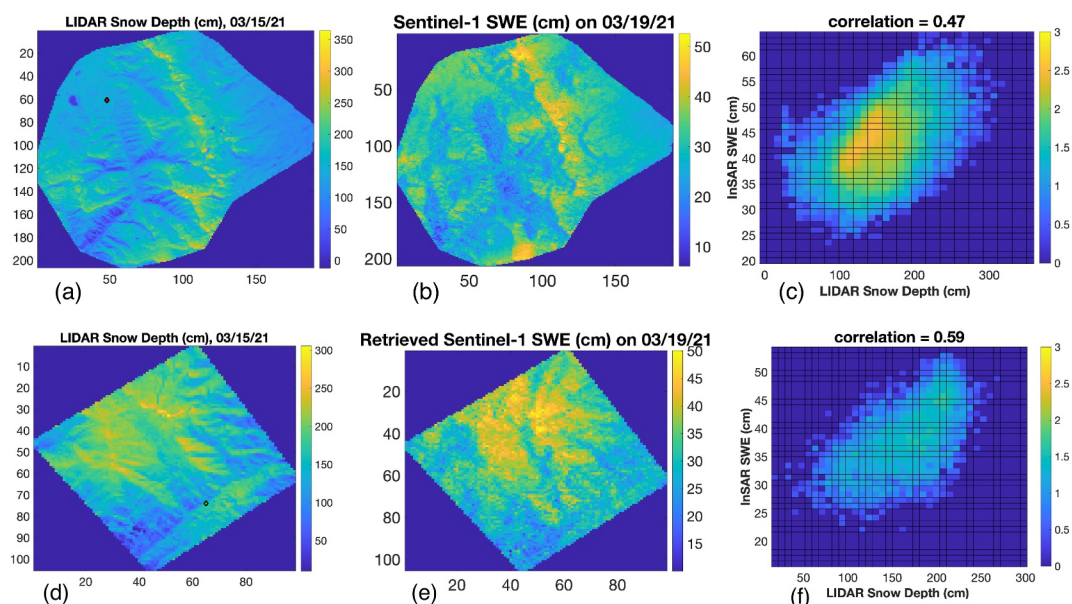


Figure 6. Snow depth and Sentinel-1 InSAR SWE over Banner Summit and Mores Creek, Idaho. Panels show (a–c) Banner Summit and (d–f) Mores Creek: (a, d) lidar snow depth from 15 March 2021, (b, e) Sentinel-1 InSAR total SWE accumulated from 1 December 2020 to 19 March 2021, and (c, f) density scatter plots comparing lidar snow depth with InSAR SWE. Adapted from Oveisgharan et al. (2024), published in *The Cryosphere*, licensed under CC BY 4.0.

P-band SoOp phase measurements are sensitive to snow properties, but the existing evaluations are limited in spatial extent, snow depth range, and vegetation complexity. Broader access to these data sets, or the collection of future openly available data sets, would help support independent assessment of retrieval robustness, algorithm intercomparison, and further methodological development. Some data sets discussed in this review, including P-band SoOp tower measurements from the Fraser Experimental Forest and airborne demonstration data, are not publicly archived to our knowledge as of submission. Given its long wavelength, P-band SoOp is a promising bistatic phase-based approach and complementary to volume-scattering methods, particularly because of its potential sensitivity in forested or wet-snow conditions. However, additional testing across deeper snowpacks,

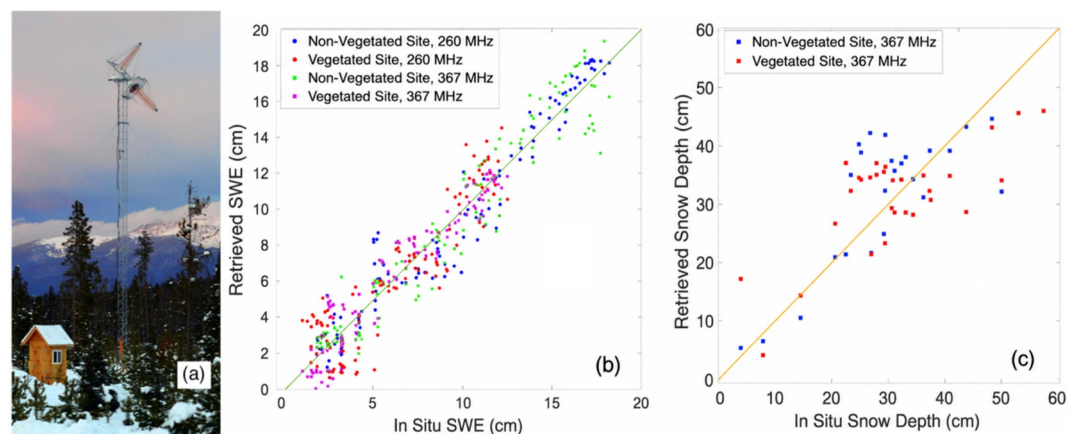


Figure 7. Tower-based P-band signals-of-opportunity (SoOp) snow retrievals at the Fraser Experimental Forest, Colorado. (a) P-band SoOp tower experiment and field setup. (b) Retrieved SWE versus in situ SWE for non-vegetated tower sites using 260 and 367 MHz observations. (c) Retrieved snow depth versus in situ snow depth for non-vegetated and vegetated tower sites using 367 MHz observations. Diagonal lines indicate 1:1 agreement between retrieved and in situ values. Photograph in panel (a) by R. Shah, used with permission. Panels (b, c) were prepared by R. Shah for this review from the underlying analyses reported in Shah et al. (2017, 2018).

more variable liquid water conditions, and more complex vegetation environments is needed to establish the conditions under which P-band SoOp provides the greatest value for seasonal snow monitoring.

Under the support of the NASA Earth Science Technology Office Instrument Incubator Program, a P-band SoOp radar instrument was developed by the Jet Propulsion Laboratory (JPL) and flown on the NASA Armstrong Flight Research Center (AFRC) Super King Air with multiple passes to demonstrate the P-band Signals of Opportunity Synthetic Aperture Radar (SoOpSAR) concept (Yueh et al., 2021) with three observation periods in August 2022, February and March 2023 over Grand Mesa, Colorado (Yueh et al., 2023). The airborne data confirmed the dominant surface scattering mechanism of P-band SoOp signals and the ability of P-band signals to penetrate dry snowpack (Yueh et al., 2023).

Recent theoretical modeling work (Jeong et al., 2023; Xu et al., 2024) has examined the impact of forest cover and terrain, respectively, on the reflection of P-band signals. Jeong et al. (2023) demonstrated that realistically dense forest canopies have high transmissivities ($\sim 70\%$ – 97%) for P-band signals and that the signal remains well correlated (>0.89) with relatively small phase variations ($<4^\circ$ phase uncertainty added by forest cover). Parametric models derived from their analysis could be applied as corrections for forest cover when retrieving snow-derived phase changes. Xu et al. (2024) demonstrated that in flat high alpine terrain (at Grand Mesa, CO) there is a high signal-to-noise ratio for P-band signals over a range of azimuth angles in the vicinity of the specular direction and that bistatic scattering coefficients in the forward direction are much larger than those in a radar backscattering configuration.

4. The State of InSAR SWE Measurements

As we have shown in this review, there has been substantial progress in InSAR and phase-based remote sensing of seasonal snow since the technique's inception nearly 25 years ago. However, this progress has not been linear (Figure 1), with only 12 studies conducted in the 14 years after the technique's inception (2001–2015). The lack of high-accuracy spatially distributed snow depth and SWE data sets hindered rigorous technique validation, constrained our ability to confidently quantify uncertainty, and ultimately slowed technique development during this period. Over the past 10 years (2016–2025), there has been a substantial increase in research activity. This increase was driven by the initiation of NASA's SnowEx campaign and ESA airborne efforts. SnowEx was especially important as it provided coordinated ground, tower, airborne, and satellite observations across multiple WUS basins. These data enabled the most robust validation of InSAR SWE and Δ SWE retrievals to date, laying the foundation for many of the advances highlighted below. We provide a summary of important advances and findings for InSAR snow monitoring reviewed in Section 3:

- Original inception: The original study from Guneriusen et al. (2001) derived an equation that physically explained the link between InSAR phase change and dry snow change on the ground.
- Tower validation: Tower-based Δ SWE radar observations can provide a winter-long time series of SWE with centimeter-scale accuracy, establishing a robust physical foundation for spaceborne InSAR applications (Leinss et al., 2015).
- Airborne validation: UAVSAR L-band InSAR can reproduce snow depth change measurements with accuracy comparable to airborne lidar under ideal conditions (i.e., dry snow, cold temperatures, low-relief, and minimal forest cover; Marshall et al., 2021).
- Strong temporal coherence: InSAR at C- and L-band can maintain temporal coherence over 7- to 14-day baselines in many dry snow environments (Bonnell, McGrath, et al., 2024; Hoppinen, Oveisgharan, et al., 2024; Ruiz et al., 2022; Tarricone et al., 2023).
- Spaceborne time series demonstration: Sentinel-1 C-band InSAR can generate total SWE values using an integrated Δ SWE time series with strong-to-moderate agreement to SNOTEL SWE and airborne lidar snow depths (Oveisgharan et al., 2024).
- Influence of forest cover: While tower-based studies identified lower Δ SWE retrieval accuracy over forest covered areas, particularly at higher frequencies (Ruiz et al., 2022), L-band UAVSAR studies demonstrated accurate Δ SWE retrievals for areas with low to moderate forest cover (0%–50%; Bonnell, Elder, et al., 2024; Hoppinen, Oveisgharan, et al., 2024).
- Multifrequency approaches: L-band can be paired with C- or X-band to correct phase wrapping, estimate ρ_s , and provide higher-accuracy Δ SWE estimates (Belinska, Fischer, & Hajnsek, 2024; Belinska, Fischer, Parrilla, & Hajnsek, 2024; Benedikter et al., 2024).

- Data assimilation utility: Assimilating InSAR snow and phase information can improve snowpack estimation ability (Alabi et al., 2025; Shrestha & Barros, 2025a).
- P-band SoOp maturity: P-band SoOp tower studies demonstrate sensitivity to snow properties, but the technique remains experimental for snow retrieval. Maturation requires open validation data sets, explicit error budgets, and testing across deeper snowpacks, variable wetness, and more complex vegetation before airborne or spaceborne retrievals can be evaluated confidently.

5. Current InSAR Snow Measurement Limitations

InSAR SWE and snow-depth retrievals have matured, but operational implementation remains limited by the need to isolate snow-driven phase from atmospheric delay, vegetation, soil-moisture change, wet-snow effects, terrain geometry, reference-phase error, and phase-unwrapping error. The following sections review these limitations and identify the algorithmic advances needed for basin-scale applications.

5.1. Atmospheric Impacts

All satellite InSAR applications must account for atmospheric phase delay, with the two main components being tropospheric (ϕ_{tropo}) and ionospheric (ϕ_{iono}) effects (Goldstein, 1995; Zebker et al., 1997). These atmospheric contributions are often among the largest sources of uncertainty in InSAR analyses (Bekaert et al., 2015). Tropospheric water vapor variability introduces largely frequency-independent path-delay errors, whereas ionospheric electron-density variability produces dispersive, or frequency-dependent, path-delay errors that are amplified at lower frequencies, such as L-band. Together, these effects can generate phase delays equivalent to apparent line-of-sight displacement errors on the order of a few centimeters (Parker et al., 2015), and up to ~10–20 cm in worst-case scenarios (Ding et al., 2008; Zebker et al., 1997). When interpreted as snow-related phase, these errors can translate into centimeter-scale or larger equivalent ΔSWE errors, depending on wavelength and incidence angle. In certain cases, these errors are comparable or larger than true snow-driven ΔSWE signals, particularly over 12-day satellite repeat intervals (Palomaki et al., 2026).

Snow applications impose correction requirements that differ from many geologic InSAR applications. Because snow evolves rapidly in space and time, each pairwise interferogram must be corrected well enough to support event-scale retrievals. One complicating relationship is that many snowfall events are orographically enhanced, while at the same time atmospheric delay can be directly related to elevation. Therefore, discriminating between the two phase signals will remain a challenge. Additionally, wet atmospheric delay components vary spatially over similar kilometer length scales to snow accumulation. These signal similarities between atmospheric delays and snow prevent the use of elevation or range distance based regression analyses since the two are likely covariates. These unique challenges make the development of a pairwise, operationally practical snow-focused tropospheric correction methodology critical for the implementation of InSAR-based snow monitoring for water resource management applications (Tarricone et al., 2025).

Although NISAR data products will have automated ionospheric and tropospheric corrections (Brancato et al., 2023), their performance in snow-covered mountain environments remains uncertain. Recent snow-focused works have employed unique atmospheric correction methods, including two UAVSAR-based studies (Hoppi-nen, Oveisgharan, et al., 2024; Tarricone et al., 2023). These UAVSAR studies are not directly transferable to NISAR-based analysis as UAVSAR and NISAR have vastly different sensing altitudes (~13.8 km vs. ~750 km, respectively) causing the need for different correction methodologies. However, they both displayed the importance of robust atmospheric correction.

For satellite-based work which could be directly applied to NISAR workflows, a variety of different correction methods have been used. For tropospheric delay, these include Conde et al. (2019), who used the Weather Research and Forecasting (WRF) model (Skamarock et al., 2005), the Python-based Atmospheric Phase Screen (PyAPS; Jolivet et al., 2011) integrated into the Miami InSAR Timeseries software in Python (MintPy; Yunjun et al., 2019) used in two recent studies (Oveisgharan et al., 2024; Zhou et al., 2025), and the Generic Atmospheric Correction Online Service for InSAR (GACOS; Yu, Li, Penna, & Crippa, 2018) by Bovenga et al. (2025). For ionospheric delay which is particularly important at L-band, Ruiz et al. (2024) implemented the split-spectrum method (Liang & Fielding, 2017). Most atmospheric correction methods were originally developed for other Earth observation communities (e.g., geology, glaciology) where InSAR analysis is more widely adopted

(Bekaert et al., 2015). These include continuing to adapt the previously implemented correction methods and looking toward other approaches such as persistent scatterer (Ferretti et al., 2001), GPS- or GNSS-derived tropospheric delay corrections that can reduce the bulk, particularly stratified, tropospheric signal (Yu, Li, & Penna, 2018), and recent machine learning methods like those developed for mountain glaciers Brencher et al. (2025). Developing and implementing pairwise, operationally practical correction methods for atmospheric and ionospheric phase delays, particularly for pairwise InSAR analyses, will be critical for enabling InSAR applications in snow hydrology and water resources management.

5.2. InSAR Reference Phase

InSAR phase-change data are relative measurements, so retrieving absolute Δ SWE requires estimating a reference phase from a stable coherent target, a known-change constraint, or an independently observed snow-change location. In conventional InSAR applications, stable coherent reference targets are often termed permanent or persistent scatterers. However, snow applications may lack suitable permanent scatterers and instead rely on snow-free ground, snow-pillow constraints, bare-soil locations, or other ancillary observations to define the reference phase. Selecting this reference for SWE applications in mountain environments is more complex due to amplified atmospheric impacts in mountain environments and the difficulty of identifying locations of dry, unchanging bare ground with sufficient radar signal coverage and quality. Past InSAR-based SWE studies have employed various methods for selecting the reference point. Tarricone et al. (2023) used in situ snow pit data to tie the InSAR phase data to a known change point, while other studies used the average phase/SWE change at snow pillow locations across larger study areas (Conde et al., 2019; Hoppinen, Oveisgharan, et al., 2024; Oveisgharan et al., 2024). Palomaki and Sproles (2023) used a point with bare soil (Δ SWE = 0) during both SAR acquisitions that had coincident soil moisture measurements. Another possible method would be to use optical data to delineate snow-free areas within the scene (e.g., snow free valley floors or windward alpine slopes) and use these to reference the phase (Tarricone et al., 2023). Perret et al. (2026) also demonstrated a controlled active-reflector approach for direct SWE retrieval from the Sentinel-1 InSAR phase response. Although this is not a basin-scale retrieval framework, it provides a useful reference experiment for evaluating the phase-to-SWE relationship under controlled scattering conditions. All of these methods have been subjectively selected without any systematic analysis of how InSAR reference-point selection impacts Δ SWE results. This uncertainty is especially important for time-series applications, where reference phase errors in individual interferograms can propagate into cumulative seasonal SWE estimates.

5.3. Forest Cover

Snow-covered forested environments span approximately 23% of global land area (Deschamps-Berger et al., 2025), and 42% of global snow cover occurs beneath forest canopies in mountain and boreal regions (Sturm & Liston, 2021). Accordingly, understanding how forest canopy impacts radar signal penetration and InSAR Δ SWE retrieval accuracy is essential for developing a sub-canopy SWE retrieval algorithm and enabling broader implementation of this technique. Signal penetration and temporal coherence will increase with wavelength, making P- and L-band the most optimal frequencies for potential forested snow retrievals (Jeong et al., 2023). At L-band, radar waves can penetrate through the leaves and smaller structural components of the forest canopy like branches, leaves, and needles, but are scattered off of tree trunks and large branches (Saatchi & McDonald, 1997). Canopy intercepted snow complicates the signal path and associated phase-delay relationship (Lemmetyinen et al., 2022), especially when any canopy snowmelt is occurring.

Although several studies have noted reduced accuracy in the forests or forest complications (Hoppinen, Oveisgharan, et al., 2024; Li et al., 2017), few studies have directly investigated this phenomenon from airborne or satellite-based InSAR. At L-band, Bonnell, Elder et al. (2024) found that at forest cover fractions <0.4, UAVSAR yielded high-quality Δ SWE measurements based on in situ measurements collected at three small montane forest field sites (3.1 km² total area; RMSE = 14–17 mm) and a broader region (62.5 km²) based on a normalized single lidar snow depth scan. Utilizing the L-band SAR on ALOS-2 PALSAR-2 L-band, Ruiz et al. (2024) retrieved spatially distributed Δ SWE data in the boreal forest region and found reduced accuracy at temperatures close to 0°C, suggesting temperature may play a significant role by increasing canopy relative permittivity. Continued work is needed across a variety of forest types, geographic regions, and snow classes to robustly identify how forest cover metrics (e.g., canopy density, height, and species) impact InSAR-based SWE retrievals. Once

identified, these relationships can be used to develop targeted corrections and further extend the utility of InSAR SWE monitoring.

5.4. Topography, Slope, & Incidence Angle

The steep relief and complex topography of mountainous regions increase the complexity of InSAR-based SWE retrievals. These areas pose a challenge to InSAR measurements because off-nadir SAR viewing geometry results in radar shadow and layover in steep terrain. Areas in radar shadow are completely occluded, resulting in low backscattered energy and decreased coherence in these regions. Even in areas illuminated by the radar, large incidence angles and DEM uncertainties are likely to cause errors in SWE retrievals. Conversely, near-nadir (0° – 20°) viewing geometries result in layover and reduced spatial resolution. NISAR will provide observations from ascending and descending viewing geometries, helping to mitigate areas with radar shadow.

Nevertheless, incidence angle will still impact interferometric coherence and phase. This behavior can be understood from the geometric relationship shown in Figure 2. Incidence angle (θ) controls both the refracted propagation path through the snowpack and the phase-to-SWE conversion in Equation 5. At larger θ , the radar path through the snowpack becomes more oblique, increasing the path length through the snow layer and changing the sensitivity of $\Delta\phi_s$ to a given vertical change in snow depth or SWE. However, in real terrain, the relationship between incidence angle and retrieval performance is not straightforward. Local terrain slope modifies the local incidence angle and resolution-cell geometry, while shadow, layover, foreshortening, and DEM uncertainty become more important in steep terrain. The phase-to-SWE relationship also assumes an effective bulk snow density and permittivity. A constant-density, single-layer snowpack will therefore produce a different phase response than a layered snowpack with vertical gradients in density, ice lenses, or liquid water, because the radar phase delay integrates propagation through layers with different permittivities along the refracted path.

Recent studies have provided preliminary investigations into the impact of incidence angle on SWE retrieval performance. Hoppinen, Oveisgharan, et al. (2024) compared UAVSAR Δ SWE estimates to modeled SWE and found that RMSD generally decreased with increasing incidence angle, which they attributed to greater phase sensitivity to SWE at steeper incidence angles. Consistent with this pattern, Bonnell, Elder et al. (2024) found that UAVSAR Δ SWE and normalized lidar snow depth distributions agreed best at incidence angles of 50° – 70° , with positive bias at incidence angles $<50^{\circ}$ and negative bias at incidence angles $>70^{\circ}$. Finally, the Δ SWE retrievals calculated from the Leinss et al. (2015) equation (Equation 6) yield greatly increased errors relative to the exact solution for incidence angles above 60° . Together, these studies illustrate that incidence angle influences SWE retrieval performance through competing effects of path-length sensitivity, terrain geometry, snowpack vertical structure, and retrieval approximation error. Systematic evaluation will be essential to optimize InSAR SWE retrievals for NISAR and future missions.

5.5. Wet Snow

The InSAR-based Δ SWE methodology was formulated assuming homogeneous, dry-snow conditions and that bulk snow density, ρ_s , is the primary variable used to estimate ϵ'_s through Equation 3. The addition of liquid water content (LWC) into the snowpack complicates this relationship as water has a relative permittivity of ~ 80 , compared to ~ 1 – 2 for dry snow (Bradford et al., 2009). High snowpack LWC may change the primary scattering centroid from the snow-ground interface to within the snowpack or near the air-snow interface (Leinss et al., 2014), causing signal decorrelation and coherence loss, rendering InSAR and other phase-based estimates of Δ SWE unreliable or even impossible. This relationship was leveraged by Nagler and Rott (2000); Nagler et al. (2016), who developed a decibel thresholding approach for mapping wet snow using C-band satellite data, with the exact threshold required for detection still poorly understood. However, this same relationship complicates the InSAR-based Δ SWE retrieval, as wet snow can increase permittivity and cause a phase delay similar to that of a SWE increase. If there is signal penetration, the addition of LWC will have a marked impact on radar velocity depending on the volumetric amount (Bonnell et al., 2021; Webb et al., 2021; Yueh, Xu, et al., 2017). Wet snow also attenuates the radar signal, causing large decreases in radar backscatter power (Bradford et al., 2009). Tarricone et al. (2023) showed that SWE loss can be measured with morning InSAR acquisitions when the snowpack is mainly frozen after cold overnight temperatures and LWC remains limited near the surface. This result extends the period of potential application but does not solve retrieval problems in late-season

snowpacks that lack diurnal refreezing. Additionally, many low-elevation snowpacks experience intermittent melt throughout the winter, rather than a simple seasonal progression from dry to wet snow, which further complicates retrieval interpretation. Bulk snowpack LWC alone is not sufficient to evaluate this problem because vertically averaged values do not capture the strong vertical LWC gradients that can drive InSAR decorrelation, including saturated layers near the air–snow interface above drier snow layers. Importantly, no study has explicitly evaluated how spatially and temporally varying snowpack LWC impacts InSAR Δ SWE retrieval performance.

To further extend the utility of radar phase methods into the melt season, future work should investigate retrievals when the snowpack is saturated and the air–snow interface becomes the dominant scattering surface. Under these conditions, repeat-pass phase-delay methods may no longer provide reliable Δ SWE, but single-pass InSAR DEM differencing may provide information on snow-surface height change, as demonstrated by TanDEM-X wet-snow depth experiments (Leinss et al., 2018). Related TanDEM-X work over glacier surfaces further shows that changes in penetration depth and scattering height can strongly affect InSAR-derived heights and velocity estimates (Leinss & Bernhard, 2021). Recent work on snow- and ice-dependent X-band penetration bias similarly shows that scattering-height changes must be explicitly considered when interpreting single-pass InSAR DEMs over snow and ice surfaces (Becker Campos et al., 2026). Defining the snowpack LWC, coherence, and backscatter conditions that reliably mark this transition is needed to determine when InSAR observations should be interpreted as Δ SWE, wet-snow extent, or snow-surface-height change.

5.6. Δ SWE Versus Cumulative Time Series Total SWE Errors

Approaches to addressing error in InSAR-derived SWE measurements may change depending on the application. For example, if the technique is used to measure the spatial distribution of snow across a basin after a single accumulation event, it is important to understand and address the errors in a single nearest-neighbor interferogram. On the other hand, tracking peak SWE using an InSAR approach involves integrating a timeseries of individual Δ SWE measurements over the accumulation season. In this case, the errors within any individual interferogram are less important than the cumulative effects over the season. Recent work from Palomaki et al. (2026) began to examine non-snow phase changes in more detail, and how these other factors ultimately introduce error into InSAR-derived SWE measurements. Some non-snow factors are frequency-dependent, including the electron density in the ionosphere which causes a phase advance that affects lower frequencies more strongly (Rosen et al., 2010). A NISAR-focused analysis found that changes in ionospheric composition within a given 12-day baseline introduce errors into SWE measurements equivalent to ~ 20 cm of SWE, much larger than the typical 12-day accumulation in this region (Palomaki et al., 2026).

Addressing ionospheric effects will be critical for deriving both Δ SWE and seasonal SWE measurements from NISAR data, although these effects may be less important if higher frequency data are used. Other non-snow factors including wet and dry tropospheric effects, soil and vegetation permittivity, and surface deformation are frequency-independent when the signal is converted to an equivalent Δ SWE measurement. Depending on environmental conditions, some of these individual error sources can partially offset each other. For example, at a number of SNOTEL stations across the WUS, changes in soil permittivity between SAR acquisitions introduce a consistently positive bias (overestimation) into InSAR-derived SWE measurements, with the magnitude and sign of the soil contribution depending on soil moisture, soil temperature, and frozen depth. In contrast, changes in tropospheric water vapor introduce a consistently negative bias (underestimation). When these errors are integrated over the accumulation season, the total error is relatively small on the order of a few centimeters of SWE. This example illustrates the importance of a careful approach to removing errors in InSAR-derived SWE measurements: if wet troposphere effects are removed from the phase, but the offsetting soil permittivity effects are not, this could actually result in a worse Δ SWE estimate. These initial error analyses were centered on point-based SNOTEL measurements within the context of nearest-neighbor NISAR interferograms. Future work in this area should consider more advanced InSAR data processing techniques like SBAS (S. Li et al., 2022) or phase-linking (Eppler & Rabus, 2022), expand the point-based analysis to larger basin or range scales, and consider temporal baselines relevant for other SAR satellites.

6. Recommendations for Continued Progress in InSAR SWE and Snow Depth Retrievals

This review has shown the substantial progress and current gaps in InSAR remote sensing of seasonal snow. The launch of NISAR provides an immediate opportunity to evaluate these methods using standardized, open-access, near-global L-band InSAR observations. NISAR was not designed as an operational snow mission, but its 12-day repeat cycle, ascending and descending viewing geometries, and systematic coverage make it an important pathfinder for determining where InSAR-based SWE and snow depth change retrievals can work, where they fail, and what validation and algorithm development are still needed. An example of NISAR's broad coverage of the WUS seasonal snow zone is shown in Figure 8. Over the past 25 years, the community has learned enough to define the next set of targeted validation and algorithmic maturation activities. In this section, we recommend the types of data, campaigns, software, and integration activities needed to make use of NISAR and future InSAR-capable missions for snow hydrology.

Technique advancement will be achieved by continued ground-based and airborne snow field campaigns, building on the success of SnowEx. Robust airborne campaigns (including lidar) should include contemporaneous in situ data from field teams on the ground and automated weather stations. Moreover, airborne campaigns are subject to uncertainty from the highly variable weather in mountain environments. This makes the continued and reliable collection of in situ data pivotal for NISAR validation. Field activities should include the collection of NISAR-coincident core snowpack and near-surface soil measurements, including snow depth, ρ_s , Δ SWE, LWC, underlying soil moisture, and soil temperature or frozen/thawed state. These efforts should also continue to leverage ground-based and UAV remote sensing platforms, such as GPR, terrestrial lidar, and drone-based lidar and photogrammetry. These measurements have a larger spatial scale than point-based weather stations and snowpits, as well as being more cost-effective and consistent than airborne lidar acquisitions. Measurements need to be repeated in the same locations, as demonstrated by the SnowEx campaigns. Lastly, to continue developing robust atmospheric corrections, UAV and airborne InSAR acquisitions could be deployed coincident with NISAR to help isolate tropospheric and ionospheric impacts of the NISAR retrievals.

Continuing to address and quantify the previously described uncertainties in InSAR-based SWE monitoring will require high-resolution, high-accuracy, spatially distributed SWE information. Currently, this is achieved by the combination of measuring snow depth from airborne lidar and estimating SWE through the combination of in situ data and snowpack modeling. The combination of assimilating 50 m lidar snow depths with 2–8 cm uncertainty (Currier et al., 2019; Raleigh & Small, 2017) into a physically-based snow model has been shown to provide precise SWE information (Hedrick et al., 2018; Margulis et al., 2019), with the majority of the SWE uncertainty coming from ρ_s modeled estimates (Raleigh & Small, 2017).

Published workflows have combined airborne lidar-derived snow depth with physically based snowpack models to produce basin-scale SWE estimates in WUS watersheds (Hedrick et al., 2018; Painter et al., 2016). Airborne Snow Observatories, Inc. (ASO) is one commercial provider that operationally combines airborne snow measurements with iSnobal (Marks et al., 1999), a spatially distributed, two-layer snow mass- and energy-balance model; modeled snow density is combined with lidar-derived snow depth to estimate SWE. Airborne lidar acquired by academic and governmental organizations or other private providers could similarly supply snow-depth observations for SWE estimation in additional watersheds. Targeted airborne lidar surveys coincident with NISAR overpasses across diverse snow climates are needed to advance and validate the technique.

While most of the ASO SWE data sets are derived for water resource management purposes, these and other airborne lidar data can serve as validation for experimental snow remote sensing techniques such as InSAR. To minimize temporal uncertainties, lidar flights should be as close to coincident with NISAR overpasses as possible. These SWE and snow depth data can then be directly compared to NISAR SWE estimates, as the 12-day repeat allows for the implementation of the time-series approach (Leinss et al., 2015; Oveisgharan et al., 2024). This contrasts with the SnowEx UAVSAR campaigns, which collected data for only a portion of the snow season, and therefore only allowed for Δ SWE comparisons.

Most of the InSAR snow studies have focused on mountain environments, dry snow, and water resource management applications (Alabi et al., 2025; Bonnell, McGrath, et al., 2024; Hoppinen, Oveisgharan, et al., 2024; Marshall et al., 2021; Nagler et al., 2022, 2024; Oveisgharan et al., 2023; Tarricone et al., 2025). The InSAR SWE technique has seen little validation in boreal forests (e.g., Ruiz et al., 2024), even though these forests comprise a

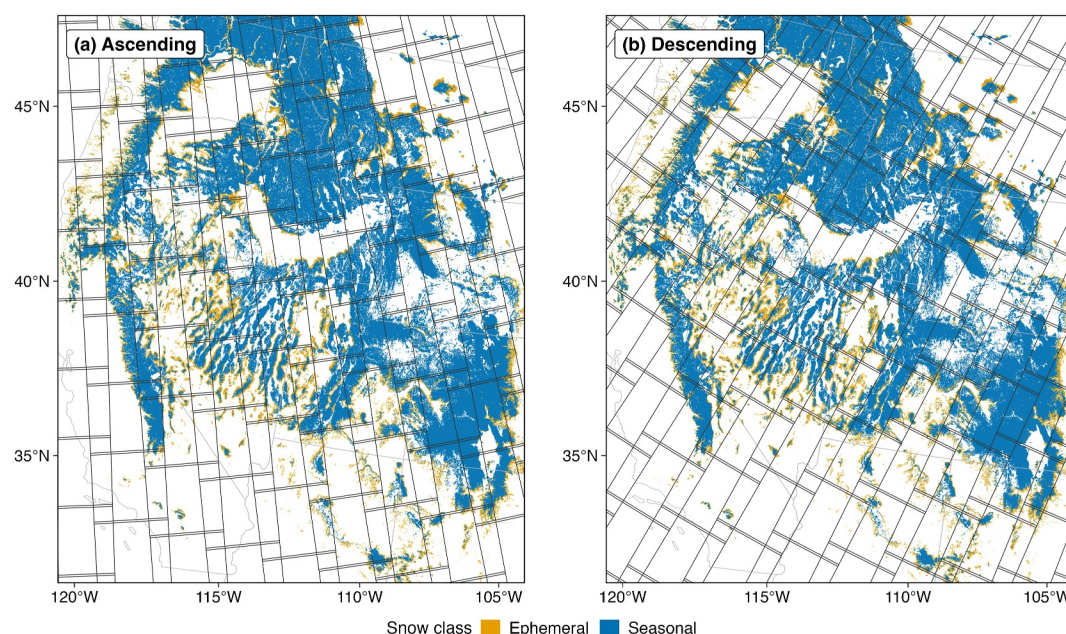


Figure 8. Western U.S. seasonal (blue) and ephemeral (orange) mountain snow zones from Wrzesien, Pavelsky, Durand, Dozier, and Lundquist (2019), with NISAR tracks and frames shown in dark gray for (a) ascending and (b) descending passes.

large fraction of the global seasonal snow-covered area (Sturm & Liston, 2021). Boreal forests provide unique challenges like consistently dense canopy and tussock-covered ground that creates air pockets and large variability in snow characteristics (Stuefer et al., 2025). Additionally, building on the encouraging wet-snow findings of Tarricone et al. (2023), a campaign should be designed to test the limitations of L-band InSAR during the snowmelt season. Lastly, while there was only the aforementioned single set of coincident lidar and UAVSAR pairs over Grand Mesa in 2020 (used by Marshall et al. [2021]) collected during the SnowEx campaigns, there are still numerous UAVSAR acquisitions with corresponding in situ data that present an opportunity to further evaluate the methodology in new locations.

Looking to the future, scientific infrastructure and resources will be needed to produce continental-to global-scale SWE products. While uncertainties in the retrievals remain to be fully understood, sustained funding will be required to produce scientific-quality data at large scales. Work should continue on developing open-source processing tools (Hoppinen, 2023; Keskinen et al., 2022) for NISAR-based snow analysis. The open-source nature of this code will enable broad community engagement and accelerate progress as more scientists are able to contribute.

InSAR has the potential to markedly advance snow remote sensing capabilities; that said, it will not work everywhere. Information on global snowpack will require the synergistic implementation of various remote sensing modalities (Durand et al., 2021), data assimilation into multiple modeling frameworks (Giroto et al., 2020; Ma et al., 2023; Margulis et al., 2026; Pflug et al., 2024), and in situ snow and atmospheric data from hydrologically important locations (Raleigh et al., 2025). While Shrestha and Barros (2025a) and Alabi et al. (2025) conducted small-scale studies on Grand Mesa, continued work on data assimilation and multisensor approaches in combination with InSAR is vital for producing spatiotemporally complete data sets.

6.1. P-Band SoOp Recommendations

P-band SoOp is substantially less mature than InSAR SWE retrieval. As such, it would benefit from experimentation across the range of snowpack, LWC, soil moisture, terrain, and vegetation environments. Such data sets should be made publicly available when possible to enable independent assessment, algorithm intercomparison, and development of data-assimilation or model-integration approaches. Previous tower-based studies (Shah et al., 2016, 2017, 2018; Yueh, Shah, Xu, Elder, & Chae, 2017) demonstrated the ability of P-band SoOp to

retrieve snow parameters under limited conditions (Figure 7), but these evaluations were conducted over relatively shallow snowpacks and sparse vegetation cover. As with repeat-pass InSAR, the sensitivity of P-band SoOp phase to non-snow geophysical factors, including slope, vegetation, soil moisture, soil freeze-thaw state, and snow wetness, requires more systematic evaluation.

A recent next step was the installation of tower-based measurements similar to those in (Shah et al., 2016) in the Sierra Nevada, California, a maritime snow climate. Such measurements would sample seasonal evolution from shallow to deep snowpacks, including intermittent transitions between dry and wet states. In situ measurements of snow depth, density, SWE, LWC, soil moisture, soil temperature, and frozen-depth conditions would allow direct tests of phase sensitivity to SWE and snow depth under both dry- and wet-snow conditions. Seasonal, approximately daily, time series would also help determine how dry-to-wet transitions affect retrieved phase, whether dry-dry pairs can provide stable SWE-change estimates, and whether wet-wet pairs can provide stable snow-depth or phase center change information. A key unresolved question is how vertical gradients in LWC, and the associated vertical structure of snowpack permittivity, affect the location and stability of the effective phase center during wet-snow retrievals (Yueh, Xu, et al., 2017; Yueh et al., 2020). If these studies demonstrate sufficient retrieval stability, airborne campaigns could provide a subsequent diagnostic step for evaluating P-band SoOp under more realistic terrain and vegetation conditions.

A more complete uncertainty budget is also required to evaluate the potential for spaceborne P-band SoOp snow retrievals. Instrument sensitivity and calibration stability, receiver trajectory or orbit knowledge, transmitter ephemeris knowledge, ground displacement, ionospheric delay, tropospheric delay, vegetation, soil moisture, and soil freeze-thaw state can each contribute to uncertainty in the phase delay associated with snow changes. Recent InSAR SWE error-budget analyses identify ionospheric delay as the primary explicitly frequency-dependent non-snow phase term because ionospheric phase advance is dispersive and becomes more important at lower radar frequencies (Palomaki et al., 2026). In that framework, tropospheric delay, vegetation effects, soil-moisture effects, and ground displacement can be treated as frequency independent when expressed as equivalent Δ SWE errors under the assumptions of the analysis. However, correction and evaluation of these terms still depend on ancillary data sets with different spatial resolutions, temporal sampling, and uncertainties, especially in complex mountain terrain. Quantifying each term will improve understanding of the limits within which snowpack phase changes can be detected and will help determine whether future retrieval requirements could be met.

7. Conclusions

Over the past 25 years, InSAR-based SWE and snow depth retrievals have substantially matured. Global and mountain snowpacks remain a critical uncertainty in our understanding of the hydrologic system, and InSAR is now poised to move from an experimental technique toward a useful component of operational hydrology. The coming decade will be an important test period for global snow monitoring, driven by new radar platforms, improved validation data sets, and advances in computation. The launch of NISAR provides a timely opportunity to implement and evaluate InSAR-based snow measurements from watershed to mountain range scales. Widespread use will require systematic validation with coincident, spatially distributed snowpack observations and error budgets that separate snow-driven phase from atmospheric, vegetation, soil, wet-snow, terrain, and processing contributions. While InSAR will not work in all locations, it could become an essential piece of a global snow monitoring strategy that integrates multiple remote sensing modalities, modeling, data assimilation, and in situ observations into a synergistic framework.

AI Tools Disclosure

The authors used OpenAI's ChatGPT to assist with language editing, organization, consistency checks, and code drafting/review support for selected preprocessing and visualization scripts. All scientific content, analyses, citations, figures, code, and final text were reviewed, revised, tested where applicable, and approved by the authors.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The data and code used to generate the original analyses shown in Figures 1, 3, and 8 are available from Zenodo at <https://doi.org/10.5281/zenodo.21776012> (Tarricone, 2026). Figure 3 uses the Global Seasonal-Snow Classification, Version 1 (Liston & Sturm, 2021), available from the NASA National Snow and Ice Data Center Distributed Active Archive Center at <https://doi.org/10.5067/99FTCYYYLAQ0>. Figure 8 additionally uses the Global Seasonal Mountain Snow Mask from MODIS MOD10A2 (Wrzesien, Pavelsky, Durand, Lundquist, & Dozier, 2019), available at <https://doi.org/10.5281/zenodo.2626737>.

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