Investigation of Environmental Effects on Coherence Loss in SAR Interferometry for Snow Water Equivalent Retrieval

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Abstract—Interferometric synthetic aperture radar (InSAR) is a promising tool for the retrieval of snow water equivalent (SWE) from space. Due to refraction, the interferometric phase changes with snow depth and density, which is exploited by the InSAR method. While the method was first proposed two decades ago, qualitative research using experimental data analyzing factors affecting retrieval performance remains scarce. In this work, a tower-based 1–10-GHz, fully polarimetric SAR with InSAR capabilities was used to analyze the effect of meteorological events (air temperature, precipitation intensity, and wind) on the observed temporal decorrelation of interferometric image pairs at L-, S-, C-, and X-bands. These factors were found to be causes of decorrelation in snow, being the temperature the critical variable in the case of snowmelt events. Of the analyzed bands, the L-band presented the best coherence conservation properties. In addition, the phase change between pairs with sufficient coherence was applied to generate estimates of changes in SWE, studying the retrieval errors at different bands and over different temporal baselines. SWE accumulation was calculated from 6 h up to 12 days’ temporal baseline over a nonvegetated area. SWE accumulation profiles were successfully reconstructed for short temporal baselines and low frequencies, while an increase in the retrieval error was observed for high frequencies and long temporal baselines, indicating the limitations of higher frequencies for repeat-pass InSAR retrieval. The analysis was also reproduced over a forested area at the L-band with similar results as to the nonvegetated area.

Index Terms—Decorrelation, interferometric synthetic aperture radar (InSAR), SAR, snow water equivalent (SWE), snow, Sodankylä SAR (SodSAR), temporal coherence.

I. INTRODUCTION

The mass of seasonal snow cover, or snow water equivalent (SWE), remains a challenging parameter to measure from space. The use of passive microwave radiometry for SWE retrieval has been studied extensively [1], [2]. [3], [4], [5]. Supported by in situ observations of snow depth and SWE in data assimilation, microwave radiometry has been exploited to provide an understanding of the hemispheric-scale distribution and trend of snow mass over four decades [6], [7]. However, without the support of ancillary information, the accuracy of passive microwave estimates is still limited, impeding their use in, e.g., regional hydrological applications [8], [9].

An inherent problem of passive microwave radiometry is also the relatively coarse spatial resolution in the order of tens of kilometers. While initiatives to reprocess passive microwave radiometry datasets [10], [11], as well as improved sensors [12], will provide an improvement to spatial resolution, these will still fall short of the requirements of many applications. Observation of radar backscattering intensity has been proposed as a solution to address both the accuracy and limited spatial resolution of passive microwave observations [13]; however, despite progress in physically based SWE retrieval methods for radar [14], [15], challenges still remain in particular concerning the quantification of the role of snow microstructure in the radar response. Moreover, no satellite sensors using the required high frequencies have been launched to date. In an interesting development, the use of C-band copolarized and cross-polarized backscattering from operational Sentinel-1 satellites was recently proposed to observe snow depth over deep mountainous snowpacks [16]. However, the relatively low sensitivity for snow depths of less than 1 m limits the usability of the proposed method outside of mountainous areas [17]. Other methods, such as light detection and ranging (LiDAR) [18], provide accurate observations of snow depth but are limited by achievable area coverage and temporal resolution. Another recent novel approach based on the compensation of the snow-induced phase in the SAR focusing process has been proposed in [19], but this method is still at a conceptual level, and its applicability for space-borne sensors is still unclear.

SWE changes can be inferred by differencing DEMs generated by single-pass radar interferometry [20]. However, the high penetration of microwaves into snow makes it only viable in the presence of wet snow, which, in turn, presents a low backscatter, making the technique only suitable for low noise-equivalent sigma zero (NESZ) acquisitions. A Ka-band SAR system could potentially retrieve the snow height of even a dry snowpack [21]. However, the precise penetration of the Ka-band signal needs to be quantified.
Repeat-pass SAR interferometry has the potential to provide a viable tool for retrieving SWE accumulation at a high spatial resolution, reasonable spatiotemporal coverage, and with high accuracy. The theoretical relation between the interferometric phase and changes in SWE was introduced by Guneriussen et al. [22]. ERS-1/2 (C-band) tandem SAR imagery was used to generate interferograms and digital elevation models (DEMs) for later comparison with an external DEM. The results of the experiment proved that snowfall and changes in the snow properties induce phase changes, which can be exploited to estimate the accumulated SWE between interferometric pairs.

However, large increments of SWE can create ambiguities in its retrieval by inducing phase wrapping. To overcome this problem, the Delta-K technique for InSAR was proposed in [23] and [24]. However, because of the coregistration method used, the phase was not absolutely calibrated. The use of trihedral corner reflectors (CRs) in the area as reference phase points showed an improvement in accuracy in [25] using ENVISAT imagery.

Temporal decorrelation is one of the main sources of degradation in InSAR retrieval algorithms, usually resulting in misinterpretation of the data and presenting a limiting factor in the applicability of some techniques [26], [27], [28]. Temporal decorrelation is caused by changes in the target due to a mixture of sources, such as rain, wind, changes in the temperature, or changes in the structural or dielectric properties of the target. Due to the long temporal baselines in satellite imagery, the impact of the various sources of temporal decorrelation is often difficult to differentiate. In an experiment in Northern Finland, a ground-based instrument operated at X- to Ku-bands was applied to demonstrate interferometric SWE retrieval over a long and dense time series of measurements with a 4-h temporal baseline [29]. The exceptionally short temporal baseline is enabled to overcome temporal decorrelation.

Since high-frequency bands are more prone to suffer from phase wrapping problems (due to their shorter wavelength) and are generally more affected by temporal decorrelation [30], low-frequency bands emerge as an alternative to overcome these difficulties. Thanks to their long wavelength, L-band sensors, such as ALOS-2 (L-band) [31] or equivalent airborne sensors [32], offer a solution to avoid phase wrapping problems while also offering relatively good conservation of coherence over time [33].

Ground-based sensors provide a tool for validating techniques and algorithms since they typically can offer a finer temporal and spatial resolution, easier access to ancillary data, and relatively controlled measurement conditions. In addition, these systems do not have to deal with uncertainties related to the effect of the atmosphere on the interferometric phase [34]. Short temporal baselines are of special interest when analyzing the underlying mechanisms in temporal decorrelation. The ground-based BorealisCat [35], a polarimetric P-, L-, and C-band radar with tomographic capabilities has been used to assess the temporal coherence properties of a boreal forest stand under various conditions, such as different meteorological events or seasonal and daily variations [36].

Although significant effort has been made in the retrieval of SWE from InSAR [37], [38], there are important topics that need to be addressed, such as the effect of different meteorological events on the observed correlation, the effect of different temporal baselines, or the performance of different bands in the retrieval. This present work intends to investigate the effect of three environmental phenomena (air temperature, precipitation, and wind) on the observed coherence of a snow-covered surface and recover SWE accumulation profiles from a time series of SAR images.

In this work, we collected time series from two winter seasons using Sodankylä SAR (SodSAR), a ground-based 1–10-GHz SAR system with InSAR capabilities. Acquisitions were made with a temporal resolution of 12 and 6 h during the first winter and the second winter, respectively. The data were used to analyze the effect of air temperature, wind, and precipitation, registered with several in situ instruments, on the coherence over snow and to retrieve changes in SWE. Increases in air temperature leading to snow melt were found to cause a major drop in coherence. Moreover, large changes in temperature between interferometric pairs, even without snow melt, were found to be a source of decorrelation. In addition, wind and precipitation were also found to be causes of decorrelation, with the latter having a seemingly greater impact. SWE accumulation profiles were reconstructed for temporal baselines ranging from 6 h up to 12 days, with a root mean square error (RMSE) of as low as 3.36 and 19.99 mm, respectively, compared to SWE measured in situ.

Section II presents the data, the test site, and the ancillary data used in this study. The theoretical background of coherence conservation and SWE retrieval is presented in Section III. The coherence conservation analysis is presented in Section IV. Section V encompass the results of the SWE retrieval. Section VI closes this work with the conclusion.

A preceding conference paper of this work has appeared in [39].

II. Study Area and Dataset

A. Radar Setup

The study was conducted at the Finnish Meteorological Institute’s Arctic Space Centre (FMI-ARC) premises in Sodankylä, Northern Finland (67° 25′ N, 26° 36′ E). The research instrument was SodSAR, a fully polarimetric 1–10-GHz tower-based SAR [40]. SodSAR is based on a commercial VNA with an added RF front end. For the experiment, the instrument was mounted at a tower at a height of 19 m. The tower overlooked a sparse scots pine stand, including several clear-cut areas. Fig. 1 presents an optical image of SodSAR’s study area. SodSAR’s radar acquisitions were performed over the selected frequency bands every 2 cm along a 5-m displacement rail (for a total of 250 points per aperture); 501 frequency points were measured at each 1-GHz bandwidth for L (1–2 GHz)-, S (2.5–3.5 GHz)-, C (5–6 GHz)-, and X (9–10 GHz) bands. Both VV and VH polarizations were measured, but only VV-polarized images were analyzed in this study. The elevation angle was set to 40°, and the azimuthal
angle was set to 0° (which points the radar perpendicular to the rail movement).

Although SodSAR can complete a full sweep within 2 h [40], other sensitive instruments share the same infrastructure, limiting the operational time to a few hours a day. Measurements from two winter seasons are included in this study: 2019–2020 and 2020–2021. For the first winter, a total of 304 acquisitions were made between 11 October, 2019, and 20 April, 2020, at a temporal resolution of 12 h. For the second winter, a total of 453 acquisitions were between 12 December, 2020, and 30 April, 2021, at a temporal resolution of 6 h. For each season, some gaps in the acquisitions schedule are present due to malfunctions (mainly due to ice forming on the rail, which prevented the radar from moving along the aperture) and maintenance. The scene observed by SodSAR was divided into two areas (each with increasing slant range distance, as presented in Fig. 1). Area 1 was nonvegetated (biomass concentration of 0.63 kg/m² during 2019–2020, removed for 2020–2021), while Area 2 was sparsely covered by forest (biomass concentration of 10.30 kg/m²). None of the sections presented significant topographic features.

A trihedral CR with a side length of 90 cm was placed in a clear line of sight from the radar. The CR’s open face was covered with a protective plexiglass surface, which was cleaned regularly. Point 3 from Fig. 1 indicates the location of the CR during the 2019–2020 winter season. For the 2020–2021 winter season, it was reallocated to point 4 from Fig. 1.

B. Measurement Stability

SodSAR acquisitions suffer from uncertainties that can affect their quality. For example, high winds may shake the installation tower and distort the measured interferometric pairs. To ensure measurement stability, the mean slant range distance from the tower to a CR located in an open area with a clear sight view was calculated, as discussed in [40].

Fig. 2 presents the mean slant range distance measured from the tower for both seasons. Results indicate good stability throughout the whole season, with a standard deviation of below 0.05 m for 2019–2020 and 0.03 m for 2020–2021 in the measured slant range. The spikes that can be observed [e.g., 20 November, 2019, or 2 January, 2020 (see Fig. 2 (upper))] are linked to periods where above zero degrees temperatures were registered. This suggests the melting down of the snow over the plexiglass cover of the reference CR, masking its response. During the second season, the CR was cleaned regularly. The high variability of the measured slant range for April 2021 was caused by a mix between precipitation and large daily temperature variations.

C. Ancillary Data

Ancillary instruments used for this study include a snow scale located at a distance of fewer than 50 m from the observation tower (point 2 in Fig. 1) and an automatic weather station (AWS), located 500 m from the tower. The snow scale measures SWE by weighting the snow accumulating over the center panel with a temporal resolution of 1 min. The data extracted from the AWS were air temperature measured at 2 m above the ground, wind speed, wind gust, and the 10-min precipitation intensity average, measured from a weighing gauge. The AWS is calibrated annually and provides one measure of each of the abovementioned parameters every 10 min. Figs. 3(a) and 4(a) present the air temperature during the study periods. The recorded precipitation intensity during both seasons is depicted in Figs. 3(b) and 4(b). Finally, wind speed is presented in Figs. 3(c) and 4(c).

In addition, manual measurements of snow properties were measured weekly in the surroundings of the tower, recording bulk density and snow depth. Figs. 3(d) and 4(d) present the snow bulk density and the snow depth of the snowpack measured at the tower for both winter seasons. Analysis of the snow temperature profiles leads to the conclusion that dry snow conditions were predominant between 11 October, 2019, and 23 March, 2020, for the first season and
Fig. 3. Environmental conditions during the 2019–2020 winter season. (a) Air temperature (°C). (b) Precipitation intensity (mm/h). (c) Wind speed (m/s). (d) (Left) snow density (g/cm³) and (Right) snow depth (cm).

Fig. 4. Environmental conditions during the 2020–2021 winter season. (a) Air temperature (°C). (b) Precipitation intensity (mm/h). (c) Wind speed (m/s). (d) (Left) snow density (g/cm³) and (Right) snow depth (cm).

between 18 December, 2020, and 18 March, 2021, for the second season.

D. Data Preparation

SAR images were generated using the time-domain back-projection algorithm for SAR [41], with a pixel size of 0.075 m, for both range and azimuth. Each of the images was generated from −20 to 10 m in azimuth and from 3 to 50 m in the ground range. Each analyzed area encompassed a total of 100 × 130 pixels. All interferograms were generated with a coherence window of 10 pixels in both range and azimuth, as described in [40, Sec. V].

For the analysis of the coherence conservation, the whole dataset was employed. All possible interferometric pairs with temporal baselines up to seven days were generated. Then, the mean coherence within each area was computed.

For SWE retrieval, a series of interferograms for several temporal baselines were generated from the starting date up to the ending date of the dry snow periods, as described in Section II-C. In case it was not possible to generate an interferogram with the target temporal baseline (due to measurement breaks), the next SAR image in the time series was used.

III. METHODOLOGY

A. Coherence Conservation in Snow

Coherence is a critical parameter in InSAR applications that rely on the interpretation of phase, as it gives a quantitative measure of the amount of noise in the interferogram. The total observed coherence can be described as follows:

$$\gamma_{\text{InSAR}} = \gamma_{\text{thermal}} \cdot \gamma_{\text{geom}} \cdot \gamma_{\text{volume}} \cdot \gamma_{\text{temporal}} \cdot \gamma_{\text{others}}. \quad (1)$$

The thermal decorrelation ($\gamma_{\text{thermal}}$) is dependent on the signal-to-noise ratio (SNR). For the case of snow-covered surfaces and provided that the main reflection interface is between the ground and the snow (which is true for dry snow), the SNR is expected to be high, making the thermal decorrelation low. Wet snow presents a lower backscatter, and therefore, coherence is expected to be lower [20]. Moreover, in areas with lower SNR, this could be a source of significant decorrelation. Due to SodSAR’s setup (elevation angle and antenna beamwidth), high frequencies may be further affected by thermal decorrelation. The geometrical decorrelation ($\gamma_{\text{geom}}$) accounts for changes in the viewing geometry between the SAR images used to form the interferogram. SodSAR is a ground-based sensor with a zero-spatial baseline, which implies that the above-described term can be neglected. For sensors with nonzero spatial baseline, $\gamma_{\text{geom}}$ can be typically...
reduced using spectral filtering [42]. The volume decorrelation ($\gamma_{\text{volume}}$) is caused by the presence of multiple scatterers distributed at different heights within the resolution cell. The contribution for dry snow-covered surfaces can be considered negligible under 20 GHz since the radar wavelength used in this work is larger than the snow grain size [29]. However, vegetated areas present significant volume decorrelation.

The temporal decorrelation ($\gamma_{\text{temporal}}$) accounts for changes in the target properties. Due to the low thermal conductivity of snow, subnivean soil can be considered to be minimally affected by changes in air temperature, and it can be assumed to retain similar backscatter properties over the winter [43]. This suggests that the observed temporal decorrelation comes from changes in the snowpack properties.

The remaining term ($\gamma_{\text{others}}$) accounts for any other effect and is typically negligible. Satellite sensors may suffer from other sources of decorrelation due to the instability of the platform or orbit errors.

In areas where vegetation is present, the snow-covered ground contribution will be weaker. Furthermore, vegetation typically presents poor conservation of coherence, as it is heavily affected by wind [36]. Recent research indicates that, in winter, the transmissivity and backscatter from vegetation may strongly vary as a result of temperature changes [44], [45], [46].

Some atmospheric phenomena produce temporal decorrelation over snow-covered surfaces, as they produce changes in the snowpack properties. The main causes of decorrelation for snow are melting events induced by temperature, precipitation, and snow redistribution [32]. Changes in soil properties can also produce decorrelation. However, during the dry snow season, significant changes in soil were only observed during notable snow melt events, making it difficult to assess its effect. The temporal decorrelation can be divided as follows:

$$\gamma_{\text{temporal}} = \gamma_{\text{temperature}} \cdot \gamma_{\text{precipitation}} \cdot \gamma_{\text{redistribution}}$$

The term $\gamma_{\text{temperature}}$ stands for the decorrelation observed due to changes in the snow temperature. Temperatures higher than 0 °C will cause the upper layers of the snow to melt, increasing the amount of liquid water and, therefore, changing the reflection interface from the ground–snow to the snow–air. This is of special interest since the SWE retrieval technique relies on the fact that the main backscatter component comes from the ground–snow interface and wavelengths to be longer than the typical size of scattering (ice) particles so that volume scattering remains negligible. This holds for temperatures below zero and dry snow. Fig. 5 presents the basic principle of InSAR SWE retrieval. Snow has a permittivity of $\varepsilon$, which is dependent of its density $\rho$. Due to the permittivity of the snow, its presence increases the propagation path of the radar signal compared to the presence of air only. The distance from the radar to the common wavefront (QQ) is denoted by $R_a$ and $R_s$ for the scenarios without and with the presence of snow, respectively. The difference in distance from both Q and Q' to the ground point P is denoted as $\Delta R_a$ and $\Delta R_s$, and can be related to changes in SWE [29]. Changes in the snowpack will also induce changes in the interferometric phase $\Delta \Phi$. The relation between the interferometric phase $\Delta \Phi$ and $\Delta$SWE (changes in SWE) can be expressed as [29]

$$\Delta \Phi = 2\pi \cdot \frac{c}{2} \cdot (1.59 + \theta^2) \cdot \Delta \text{SWE}$$

where $\kappa$ is the wavenumber of the sensor’s central frequency, $\alpha$ is a factor, and $\theta$ is the incidence angle. The factor $\alpha$ is dependent on the incidence angle and the snow density. Equation (3) has been derived from a more general expression presented by Guneriussen et al. [22]. By selecting the optimal factor $\alpha$, (3) deviates from the general form only a small percentage for all snow densities and incidence angles $\theta < 50^\circ$.

Phase unwrapping was performed over the study area; then, for each pixel, $\Delta \text{SWE}$ was calculated using (3).
The mean value along with its associated standard deviation was computed for the study area in each interferogram, as a measure of ΔSWE and the spatial variability, respectively. Unrealistic results and outliers were masked out. This is mostly applied for the shorter temporal baselines and accounts for increments that are not observed in practice for our study area (e.g., 20 mm in 6 h).

In order to generate the SWE accumulation profiles, ΔSWE was summed up if the coherence of the section was higher than a threshold value. The threshold value for each temporal baseline and band was selected such that it minimizes the RMSE between the in situ SWE scale accumulation profile and the radar SWE accumulation profile. In order to assess the algorithm’s accuracy, the mean relative error (MRE) and the bias were also calculated.

For both winter seasons, SodSAR InSAR images were generated aiming for four temporal baselines. The selected temporal baselines were 12 h, one day, six days, and 12 days for 2019–2020 and 6 h, one day, six days, and 12 days for 2020–2021. Several measurement breaks occurred in both winters. In order to mitigate the degradation in the analysis of the temporal baselines, ΔSWE for interferograms whose temporal baseline exceeded seven times the analyzed one (e.g., seven days for the one day study case) was set to the change of SWE registered by the ground scale. The manual snow density measurements, described in Section II-C, could be used to set the factor from (3). However, in order to avoid overfitting, it was set to 1 for both seasons.

IV. COHERENCE CONSERVATION IN SNOW

A. Temporal Baseline

The mean coherence for each temporal baseline was calculated from the mean coherence of all interferograms with such a baseline. Fig. 6 presents the mean coherence over Area 1 for each temporal baseline for the two winter seasons. Coherence rapidly dropped for the X-band during both seasons. As frequency decreases, coherence presented better conservation properties. The second season exhibited superior coherence conservation compared to the previous one due to less precipitation.

B. Effect of Temperature

To analyze the effect of the temperature on the interferometric coherence, the mean air temperature between acquisitions is depicted against the mean coherence over Area 1. Using the air temperature between the acquisition times of each pair, possible wet ($T_{\text{air}} > 0$ °C) and dry ($T_{\text{air}} \leq 0$ °C) snow were classified. Figs. 7 and 8 present the mean observed coherence against the mean air temperature between the acquisition times, for both winters of 2019–2020 and 2020–2021, for 12 and 6 h of the temporal baseline, respectively. Red dots indicate acquisitions with possible snow melt ($T_{\text{Air}} > 0$ °C was observed between or during the acquisition of image pairs), while the difference in air temperature between the acquisition times is depicted in a color scale for dry snow. For all bands, low coherence was observed for interferometric pairs with mean air temperature close to 0 °C. However, they presented high coherence for air temperatures well below 0 °C. In Fig. 8, it can be seen that high coherence was also observed when the mean air temperature was higher than 0 °C.

Moreover, decorrelation was observed for large changes in the temperature gradient between acquisition times for dry snow, with seemingly greater effect for temperature drops (negative values in Figs. 7 and 8). A change in the temperature gradient is a driver for snow metamorphism [49], [50]; while changes in grain shape are unlikely to affect long wavelengths at the L-, S-, and C-bands, the loss of coherence also at
these bands implies other possible structural changes in the snow associated with the change in temperature gradients. An example is given in the Appendix. Fig. 23 presents an event of decorrelation between 25 February, 2020, and 27 February, 2020, caused by snow metamorphism. Fig. 23(a) depicts the snow temperature measured every 10 cm and the air temperature measured by the AWS. Fig. 23(b) and (c) presents the observed coherence for 12 h and one day temporal baselines during the event. Snow depth remained at 110 cm along the example, without changes in SWE. During the period encompassed in Fig. 23, no precipitation was observed and wind speed remained below 2 m/s. In addition, optical imagery of the study area did not present surface hoar that could explain the decorrelation.

C. Effect of Precipitation

The observed mean precipitation intensity (MPI) between the acquisition times was calculated for all interferograms. Then, the average MPI from all interferograms with precipitation was calculated to divide the scenarios into two different cases: low and high precipitation intensities. This value was approximately 0.15 mm/h for both seasons. In addition, in the best effort to isolate from other sources of decorrelation, interferograms with a mean air temperature higher than $-3 \, ^\circ\text{C}$ or mean wind speed (MWS) higher than 3 m/s were filtered out. The observed coherence of the interferograms over Area 1 for each precipitation range is plotted as a normalized fit histogram. Figs. 9 and 10 present the results for the 2019–2020 (with 12-h temporal baseline) and 2020–2021 (with 6-h temporal baseline) winter seasons, respectively. Acquisitions with low MPI presented overall higher coherence than those exposed to high MPI. In addition, the difference between both cases was accentuated when the temporal baseline was 12 h, with respect to the 6-h temporal baseline. Frequency-dependent behavior was observed, being greater decorrelation due to precipitation as frequency increased.

D. Effect of Wind

The MWS and the mean wind gust (MWG) between the acquisition times were calculated as a measure of the effect of the wind. In order to reduce other possible causes of decorrelation affecting the coherence, the interferometric pairs with mean air temperature higher than $-3 \, ^\circ\text{C}$ or MPI higher than 0.15 mm/h were discarded from the analysis. Then, the interferograms were divided by ranges (approximately corresponding to the Beaufort scale’s first three magnitudes) of MWS and MWG. Finally, the observed coherence over Area 1 for each range is plotted as a normalized fit histogram. Figs. 11 and 12 present the results for the wind speed for the four bands during the 2019–2020 (12-h temporal baseline) and 2020–2021 (6-h temporal baseline) winter seasons, respectively. Wind gust produced similar histograms as wind speed. An increasing decorrelation was observed as the MWS range increased. In addition, the difference between the three ranges was accentuated when the temporal baseline was 12 h with respect to the 6-h temporal baseline. Frequency-dependent behavior was observed, being greater decorrelation due to wind as frequency increased.
E. Discussion

Analysis of the temporal baseline between the interferometric pairs suggested that low-frequency bands were more resilient against temporal decorrelation than high-frequency bands. The latter suffered from a fast coherence drop even for the shortest temporal resolutions. The high-frequency bands suffered from a fast drop in coherence within the first day. In Fig. 6 (lower), a drop in coherence for the X-band close to 0.5 was observed already for 6 h of the temporal baseline. Moreover, differences in decorrelation were observed between seasons. The 2019–2020 season exhibits a faster temporal decorrelation due to greater precipitation compared to the 2020–2021 season.

Mean air temperatures approaching 0 °C induced a clear drop in coherence (see Figs. 7 and 8), corroborating the findings in [29]. The opposite behavior was observed for temperatures in the low end, where high values of coherence were observed. For low-frequencies bands, snow melt was the dominant source of decorrelation. However, for high-frequency bands, in addition to decorrelation due to temperature, the other sources presented a significant impact. The results from Fig. 8(a) were of special interest, as high coherence can be observed for interferograms with mean air temperatures well above 0 °C and with wet snow. Furthermore, decorrelation due to temperature changes between interferometric pairs was observed, suggesting that big temperature gradients in the snow can drive structural changes affecting the coherence.

Results from both seasons indicate an overall lower observed coherence for interferograms exposed to high precipitation intensity compared to low precipitation intensity. For the 6-h temporal baseline, as presented in Fig. 10, there was little difference in the observed coherence for the L-band and a small difference for the S-band. However, prolonged exposure to precipitation (among other sources of decorrelation) makes the difference between both scenarios more noticeable, as depicted in Fig. 9. Similar behavior was also observed for C- and X-bands, except that these two bands
already exhibited significant decorrelation for 6 h of temporal baseline.

Wind had an appreciable effect on coherence (see Fig. 12). For all bands and for both seasons, it can be observed that interferograms where low wind intensity was registered presented higher values of coherence compared to interferograms where moderate or high wind intensities. Frequency also seems to play an important role since low-frequency bands seem to be more resilient against wind-driven decorrelation as they presented high values of coherence even for high wind intensities. However, high-frequency bands (C- and X-bands) showed to be rather susceptible and presented the great difference between the low, medium, and high wind scenarios. This agrees with the observations in [29], where considerable decorrelation was observed for high wind gust at the Ku-band. Increased decorrelation was observed for the 12-h temporal baseline with respect to the 6-h temporal baseline. This could indicate that exposure to the wind had an accumulative effect on decorrelation. In addition, the effect of wind on coherence was found to be smaller than the effect of precipitation for the experiment.

As given in the Appendix, the same analysis performed in this section can be found but for Area 2. Note that, while, for vegetated areas, the worst temporal decorrelation behavior was expected, high-frequency bands showed overall higher coherence in the histograms for Area 2 than for Area 1. This is due to the polarization, antenna beam pattern, and elevation angle used, causing Area 2 to had higher SNR than Area 1, which was particularly noticeable for C- and X-bands. The effect of the temporal baseline was the same as for Area 1. While, for the low end of the mean air temperature, coherence behaved in the same way as in Area 1, for the high-temperature end, it did differently. This effect could be caused by temperature-dependent mechanisms of vegetation [44], [45] leading to an increase in volumetric decorrelation. As presented in Fig. 18, when the air temperature was higher than 0 °C, the observed coherence was low, in contrast with Fig. 8. The effect became more noticeable as frequency increased. The effect on precipitation and wind was similar in Area 2 as in Area 1. However, in the case of wind speed, decorrelation differences between the MWS ranges were smaller.

V. CALCULATION OF SWE ACCUMULATION PROFILES

A. 2019–2020 Season

Fig. 13 presents the results of the SWE retrieval for the four analyzed bands and for the 12 h, one day, six days, and 12 days’ temporal baselines. SWE was set to 0 mm for the first acquisition. The coherence threshold for each band and the temporal baseline are presented in Table I, along with the RMSE, MRE, and bias. This season exhibited an almost constant increase of SWE from precipitation, mostly until March. Long periods of time without significant changes in SWE were only present at the end of the season. SWE accumulation was reconstructed for the short temporal baselines of 12 h and one day for all bands. However, a less precise match between retrieved SWE and scale SWE was observed for the X-band. Only the L-band was able to retrieve SWE for the 12 days’ temporal baseline.

| Band | Temporal Baseline | Coherence Threshold | RMSE (mm) | MRE | Bias (mm) |
|------|-------------------|---------------------|-----------|-----|-----------|
| L    | 12 hours          | 0.60                | 8.77      | 0.08| 7.34      |
|      | 1 day             | 0.47                | 11.33     | 0.13| 9.41      |
|      | 6 days            | 0                   | 12.67     | 0.10| 9.79      |
|      | 12 days           | 0                   | 26.07     | 0.17| 21.28     |
| S    | 12 hours          | 0.47                | 10.29     | 0.13| 8.19      |
|      | 1 day             | 0.35                | 12.39     | 0.09| 9.98      |
|      | 6 days            | 0                   | 42.24     | 0.28| 37.42     |
|      | 12 days           | 0                  | 144.33    | 0.76| 125.02    |
| C    | 12 hours          | 0.40                | 12.16     | 0.16| 9.57      |
|      | 1 day             | 0.26                | 16.20     | 0.15| 14.51     |
|      | 6 days            | 0                   | 122.83    | 0.65| 105.64    |
|      | 12 days           | 0                   | 153.58    | 0.80| 133.50    |
| X    | 12 hours          | 0.24                | 14.12     | 0.15| 12.00     |
|      | 6 days            | 0.24                | 9.25      | 0.09| 7.15      |
|      | 1 day             | 0                   | 146.36    | 0.78| 127.58    |
|      | 12 days           | 0                   | 165.07    | 0.84| 142.19    |

![Fig. 13](image-url)
Fig. 14 presents the results of the SWE retrieval for the four analyzed bands and for the 6 h, one day, six days, and 12 days’ temporal baselines. SWE was set to 43.92 mm for the first acquisition, corresponding to the SWE value of the scale at the first acquisition time. The coherence threshold for each band and the temporal baseline are presented in Table II, along with the RMSE, MRE, and bias. SWE accumulation was reconstructed for the short temporal baselines of 6 h and one day for all bands. With respect to the previous season, an improved match between retrieved SWE and scale SWE was observed for high-frequency bands for the 6-h baseline. Both L- and S-bands were able to reconstruct the profile for six days’ temporal baseline. However, retrievals were unsuccessful for all bands using the 12 days’ temporal baseline.

C. Retrieval of SWE Over Forest

The same analysis was performed for Area 2, for both winter seasons but limited to just the L-band, as it is the only band with sufficient penetration over the canopy and with better temporal correlation properties. The analysis was performed with the same seasonal settings, as described in Sections V-A and V-B. Fig. 15 depicts the retrieval results for both seasons over Area 2 for the L-band and 12 h/6 h, one day, six days, and 12 days of the temporal baseline. Table III presents the coherence thresholds, RMSE, MRE, and the bias for both seasons and each temporal baseline. For the 2019–2020 winter season, similar results as Area 1 were observed, with the exception that SWE was underestimated using the 12 day temporal baseline. Moreover, for 2020–2021, the six days’ temporal baseline failed to reconstruct the SWE accumulation profile.

D. Discussion

For the first winter season, good estimates of SWE were retrieved using all four frequency bands at the end of the season for the 12 h and one day temporal baseline, with RMSE as small as 8.77 mm (see Fig. 13 and Table I). For the two shorter temporal baselines and the two lowest frequency bands, a good match between the radar-retrieved SWE and the scale SWE can be observed throughout the whole season. For the longer temporal baselines, the L-band was able to retrieve SWE within 12.67- and 26.07-mm RMSEs for six days and 12 days, respectively. However, the S-band showed a high RMSE of 42.24 mm for the six days’ temporal baseline due to underestimation of ΔSWE in a few interferograms. The high-frequency bands were only to retrieve SWE for the shorter temporal baselines, while they failed for the longer two. Both C- and X-bands presented high MRE and
bias for the six days’ temporal baseline caused by lost phase cycles due to an excessive SWE increment between the interferometric pairs. The optimal coherence thresholds for SWE accumulation decrease as both the frequency and temporal baseline increase. An increment of the temporal baseline also increased the spatial variability within Area 1. This was especially noticeable for the L-band and the S-band due to the big shifts in retrieved SWE that the small phase deviations cause. Furthermore, better results were observed for the one day compared to the 12-h temporal baseline for S- and C-bands, which could indicate diurnal cycles affecting the snowpack.

The second analyzed winter season presented relatively long periods without a big increment in SWE and with a smaller total accumulated SWE compared to the previous season (see Fig. 14 and Table II). All bands showed a good match between the radar-retrieved SWE and the scale SWE for the 6-h and one day temporal baselines. Some false detections were observed for S- and C-bands at the beginning of February when SWE only increased a few millimeters. For the six days’ temporal baseline, only the two lowest frequency bands were able to get a good approximation at the end of the season with an RMSE of 7.70 and 7.58 mm, respectively. The C-band was slightly underestimated at the end of the season for the six days’ temporal baseline with an RMSE of 17.31 mm. For the 12 days’ temporal baseline, only the L-band was able to obtain an acceptable approximation with an RMSE of 19.99 mm. While ΔSWE from many individual interferograms was successfully retrieved, few of them (corresponding to the big increments in late January and February) were underestimated. In a similar way to the previous season, coherence thresholds exhibited the same relation with frequency and temporal baseline. However, the coherence threshold value was shown to be higher for all temporal baselines for the low-frequency bands. For this season, spatial variability results were similar to the last season. For the low-frequency bands, bias and MRE were low for all temporal baselines but 12 days. The bias and MRE only showed high values for the six and 12 days’ temporal baselines of the high-frequency bands.

For both seasons, over Area 2, the two shorter temporal baselines were able to retrieve the SWE accumulation with slightly worse performance (see Fig. 15 and Table III). However, for six days’ temporal baseline, only the 2019–2020 season was able to retrieve the SWE accumulation profile, while the 2020–2021 season led to an increase in the RMSE, MRE, and bias. The 12 days’ temporal baseline underestimated SWE for both seasons. The coherence thresholds for all temporal baselines also exhibit a decrease with respect to the value of the nonvegetated area.

VI. Conclusion

This article presented an analysis of coherence conservation and SWE retrieval from InSAR images, collected using tower-based radar in Sodankylä, Northern Finland. In situ data from an AWS and an SWE scale, along with manual snow measurements, were used for coherence conservation analysis and SWE retrieval validation.

The effect of temporal baseline was discussed, indicating that high-frequency bands suffer from a fast decay in correlation. Among the meteorological events analyzed, the temperature seems to be the most critical since melting events produced by above-zero temperatures drastically lowered the observed coherence of the snow-covered surface. Big temperature gradients in the snow were also found to be sources of decorrelation. In addition, precipitation intensity and wind were shown to be causes of interferometric decorrelation in snow, corroborating previous studies [29], [32]. Results also indicate that there is a relation between the intensity of these events and the observed decorrelation. Furthermore, differences in the behavior of different bands were also observed. Low-frequency bands were shown to be more resilient against decorrelation effects, whereas high-frequency bands were more sensitive to the sources of decorrelation analyzed. These meteorological events presented a similar effect on the observed coherence over a forested area.

SWE retrieval based on analyzing the phase change between interferometric pairs was demonstrated at different bands and over different temporal baselines. For both seasons, SWE accumulation profiles were reconstructed for four different temporal baselines and the four bands measured by SodSAR over a nonvegetated area. The results indicate that both frequency and temporal baseline play a crucial role in the retrieval as precision was generally affected by them. The L-band analysis over the forested area indicated that SWE accumulation profiles can be reconstructed in the same way as for the nonvegetated area and with similar error performance in the retrieval, with exception of the longest temporal baselines.

The results from this work indicate that low-frequency bands, particularly the L-band, are the most suitable for satellite SWE retrievals, given that only L-band retrievals obtained the best results capturing the full SWE accumulation profile at temporal baselines corresponding to typical satellite repeat-pass times (six and 12 days) for Area 1. Moreover, the
Fig. 16. Mean observed coherence over Area 2 for an increasing temporal baseline. (Top) 2019–2020 winter season. (Bottom) 2020–2021 winter season.

Fig. 17. Mean observed coherence over Area 2 against mean air temperature between acquisition times of 6-h temporal baseline during 2020–2021 winter season for (a) L-band, (b) S-band, (c) C-band, and (d) X-band.

L-band was able to estimate SWE over temporal baselines for as long as six days and for both areas although only for one season. While SWE was retrieved successfully over the nonvegetated Area 1 using even a 12-day baseline, retrievals over the forested Area 2 resulted in an underestimation of SWE accumulation. Moreover, high-frequency bands showed high accuracy for short temporal baselines.

There are still open topics that need further analysis, such as the behavior of the above-described decorrelation mechanism for different surfaces, particularly in presence of topographic features. SodSAR’s current setup is limited to a small, flat area surrounded by forest, making it difficult to assess these aspects. Analysis considering these factors would be especially useful for the interpretation of satellite imagery. The physical explanation of the decorrelation caused by large temperature gradients is still unclear, and further research will be needed.

While coherence thresholding was used for short temporal baselines, it is cumbersome in practice, and other methods...
may be more suitable. One simple idea could be discarding acquisitions with wet snow from the time series, with the drawback of facing long temporal baselines and, therefore, increased temporal decorrelation.

APPENDIX

See Figs. 16–23.
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REFERENCES

[1] A. T. Chang, J. L. Foster, and D. K. Hall, “Nimbus-7 SMMR derived global snow cover parameters,” Ann. Glaciol., vol. 9, pp. 39–44, 1987, doi: 10.3189/026030587790002736.

[2] J. Foster, A. Chang, D. Hall, and A. Rango, “Derivation of snow water equivalent in boreal forests using microwave radiometry,” Arctic, vol. 44, no. 5, pp. 147–152, Jan. 1991. [Online]. Available: http://www.jstor.org/stable/40510992

[3] M. Hallikainen and D. P. Winebrenner, “The physical basis for sea ice remote sensing,” Washington DC Amer. Geophys. Union Geophys. Monograph, vol. 68, pp. 29–46, Jan. 1992.

[4] B. E. Goodison, R. D. Brown, and R. G. Crane, “Cryospheric systems,” in EOS Science Plan: The State of Science in the EOS Program, M. D. King, Ed. 1999, pp. 261–307.

[5] J. Pulliainen, “Retrieval of regional snow water equivalent from space-borne passive microwave observations,” Remote Sens. Environ., vol. 75, no. 1, pp. 76–85, Jan. 2001. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0034425700001577

[6] M. Takala et al., “Estimating Northern Hemisphere snow water equivalent for climate research through assimilation of space-borne radiometer data and ground-based measurements,” Remote Sens. Environ., vol. 115, pp. 3517–3529, Dec. 2011.

[7] J. Pulliainen et al., “Patterns and trends of Northern Hemisphere snow mass from 1980 to 2018,” Nature, vol. 581, no. 7808, pp. 294–298, May 2020, doi: 10.1038/s41586-020-2258-0.

[8] L. Tsang et al., “Review article: Global monitoring of snow water equivalent using high-frequency radar remote sensing,” Cryosphere, vol. 16, no. 9, pp. 3531–3573, 2022. [Online]. Available: https://cpc.copernicus.org/articles/16/3531/2022/

[9] J. King et al., “The influence of snow microstructure on dual-frequency radar measurements in a Tundra environment,” Remote Sens. Environ., vol. 215, pp. 242–254, Sep. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S003442571830258X

[10] H. Liens, I. Brangers, H.-P. Marshall, T. Jonas, M. Olesen, and G. De Lannoy, “Sentinel-1 snow depth retrieval at sub-kilometer resolution over the European Alps,” Cryosphere, vol. 16, no. 1, pp. 159–177, Jan. 2022. [Online]. Available: https://cpc.copernicus.org/articles/16/159/2022/

[11] P. Venäläinen, K. Luojus, J. Lemmetyinen, J. Pulliainen, J. Zebker, and G. De Lannoy, “Sentinel-1 snow depth retrieval at sub-kilometer resolution over the European Alps,” Cryosphere, vol. 16, no. 1, pp. 159–177, Jan. 2022. [Online]. Available: https://cpc.copernicus.org/articles/16/159/2022/

[12] T. H. Painter et al., “The airborne snow observatory: Fusion of scanning LiDAR, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo,” Remote Sens. Environ., vol. 184, pp. 139–152, Oct. 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0034425716302577

[13] J. Eppler and B. T. Rabus, “The effects of dry snow on the SAR impulse response and feasibility for single channel snow water equivalent estimation,” IEEE Trans. Geosci. Remote Sens., vol. 60, pp. 1–23, 2021.

[14] S. Leinss, O. Antropov, J. Vehviläinen, I. Hajnsek, and J. Praks, “Wet snow depth from TanDEM-X single-pass InSAR DEM differentiating,” in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), Jul. 2018, pp. 8500–8503.

[15] D. Moller, K. M. Andreadis, K. J. Bornmann, S. Hensley, and T. H. Painter, “Mapping snow depth from Ka-band interferometry: Proof of concept and comparison with scanning lidar retrievals,” IEEE Geosci. Remote Sens. Lett., vol. 14, no. 6, pp. 886–890, Jun. 2017.

[16] T. Gnerucciussen, A. K. Hogda, H. Johnsen, and I. Lauknes, “InSAR for estimation of changes in snow water equivalent of dry snow,” in Proc. IEEE Int. Geosci. Remote Sens. Symp. Taking Pulse Planet, Role Remote Sens. Manag. Environ. (IGARSS), vol. 2, Oct. 2000, pp. 463–466.

[17] G. Engen, T. Gnerucciussen, and O. Overeemin, “New approach for snow water equivalent (SWE) estimation using repeat pass interferometric SAR,” in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), Jul. 2003, pp. 857–859.

[18] G. Engen, T. Gnerucciussen, and Y. Overeemin, “Delta-K interferometric SAR technique for snow water equivalent (SWE) retrieval,” IEEE Geosci. Remote Sens. Lett., vol. 1, no. 2, pp. 57–61, Apr. 2004.

[19] G. Engen, T. Gnerucciussen, and Y. Overeemin, “Delta-K interferometric SAR technique for snow water equivalent (SWE) retrieval,” IEEE Geosci. Remote Sens. Lett., vol. 1, no. 2, pp. 57–61, Apr. 2004, doi: 10.1109/LGRS.2003.822880.

[20] H. A. Zebker and J. Villasenor, “Decorrelation in interferometric radar echoes,” IEEE Trans. Geosci. Remote Sens., vol. 30, no. 5, pp. 950–959, Sep. 1992.

[21] J. Jung, D.-J. Kim, M. Lavalle, and S.-H. Yun, “Coherent change detection using InSAR temporal decorrelation model: A case study for volcanic Ash detection,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 54, no. 10, pp. 5765–5775, Jul. 2016.

[22] S.-K. Lee, F. Kugler, K. P. Papathanassiou, and I. Hajnsek, “Quantification of temporal decorrelation effects at L-band for polarimetric SAR interferometry applications,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 6, no. 3, pp. 1351–1367, Jun. 2013.

[23] S. Leinss, A. Wiesmann, J. Lemmetyinen, and I. Hajnsek, “Snow water equivalent of dry snow measured by differential interferometry,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 8, no. 8, pp. 3773–3790, Aug. 2015.

[24] Y. Morishita and R. F. Hanssen, “Temporal decorrelation in L-, C-, and X-band satellite radar interferometry for pasture on drained peat soils,” IEEE Trans. Geosci. Remote Sens., vol. 53, no. 2, pp. 1096–1104, Feb. 2015.

[25] D. Dagarov et al., “Estimation of snow cover parameters by ALOS-2 PALSAR interferometry,” in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), Jul. 2018, pp. 5093–5096.

[26] H. Rott, T. Nagler, and R. Scheiber, “Snow mass retrieval by means of differential interferometry,” Proc. 3rd FRINGE Workshop, Eur. Space Agency, Earth Observ., 2003, pp. 1–6.

[27] A. Monteith and L. M. H. Ulander, “A tower-based radar study of snow water equivalent in boreal forests,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 11, no. 10, pp. 3564–3577, Oct. 2018.

[28] R. Goldstein, “Atmospheric limitations to repeat-track radar interferometry,” Geophys. Res. Lett., vol. 22, no. 18, pp. 2517–2520, 1995, doi: 10.1029/95GL02475.

[29] L. M. H. Ulander, A. Monteith, M. J. Soja, and L. E. B. Eriksson, “Multiport vector network analyzer radar for tomographic forest scattering measurements,” IEEE Trans. Geosci. Remote Sens. Lett., vol. 15, no. 12, pp. 1897–1901, Sep. 2018.

[30] A. Monteith and L. M. H. Ulander, “A tower-based radar study of temporal coherence of a boreal forest at P-, L-, and C-bands and linear cross polarization,” IEEE Trans. Geosci. Remote Sens., vol. 60, pp. 1–15, 2021.

[31] E. J. Deeb, R. R. Forster, and D. L. Kane, “Monitoring snowpack evolution using interferometric synthetic aperture radar on the North Slope of Alaska, USA,” Int. J. Remote Sens., vol. 32, no. 14, pp. 3985–4003, 2011, doi: 10.1080/01431161003801351.
[38] Y. Lei, P. Siqueira, and R. Treuhaft, “A dense medium electromagnetic scattering model for the InSAR correlation of snow,” Radio Sci., vol. 51, no. 5, pp. 461–480, May 2016, doi: 10.1002/2015RS005926.

[39] J. J. Ruiz et al., “Analysis of snow coherence conservation for SWE retrieval at L-, S-, C- and X-bands,” in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), Jul. 2021, pp. 860–863.

[40] J. Jorge Ruiz et al., “SoSAR: A tower-based 1–10 GHz SAR system for snow, soil and vegetation studies,” Sensors, vol. 20, no. 22, p. 6702, Nov. 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/22/6702

[41] M. I. Duer sch and D. G. Long, “Analysis of time-domain back-projection for stripmap SAR,” Int. J. Remote Sens., vol. 36, no. 8, pp. 2010–2036, 2015.

[42] F. Gatelli, A. M. Guamieri, F. Parizzi, P. Pasquali, C. Prati, and F. Rocca, “The wavenumber shift in SAR interferometry,” IEEE Trans. Geosci. Remote Sens., vol. 32, no. 4, pp. 855–865, Jul. 1994.

[43] Y. Zhang, S. Wang, A. G. Barr, and T. A. Black, “Impact of snow cover on soil temperature and its simulation in a boreal Aspen forest,” Cold Regions Sci. Technol., vol. 52, no. 3, pp. 355–370, May 2008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0165232X07001498

[44] M. Schwank et al., “Temperature effects on L-band vegetation optical depth of a boreal forest,” Remote Sens. Environ., vol. 263, Sep. 2021, Art. no. 112542. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0034425721002625

[45] Q. Li et al., “The influence of thermal properties and canopy-intercepted snow on passive microwave transmissivity of a scots pine,” IEEE Trans. Geosci. Remote Sens., vol. 57, no. 8, pp. 5424–5433, Mar. 2019.

[46] J. Lemmetyinen et al., “Attenuation of radar signal by a boreal forest canopy in winter,” IEEE Geosci. Remote Sens. Lett., vol. 19, pp. 1–5, 2022.

[47] A. Winstral, K. Elder, and R. E. Davis, “Spatial snow modeling of wind-redistributed snow using terrain-based parameters,” J. Hydrometeorol., vol. 3, no. 5, pp. 524–538, Oct. 2002.

[48] K. C. Leonard and T. Maksym, “The importance of wind-blow snow redistribution to snow accumulation on Bellinghausen sea ice,” Ann. Glaciol., vol. 52, no. 57, pp. 271–278, 2011.

[49] S. C. Colbeck, “An overview of seasonal snow metamorphism,” Rev. Geophys., vol. 20, no. 1, pp. 45–61, 1982, doi: 10.1029/RG020i001p000045.

[50] B. R. Pinzer and M. Schneebeli, “Snow metamorphism under alternating temperature gradients: Morphology and recrystallization in surface snow,” Geophys. Res. Lett., vol. 36, no. 23, pp. 1–4, 2009, doi: 10.1029/2009GL039618.

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