

Extracting Information on Wet Snow Avalanche Preconditions from Sentinel-1 Multi-Track Composites

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Abstract. Information about snowpack wetness at high temporal and spatial resolutions is important for timely identification of pre-disposing conditions for wet snow avalanche release. However, such information is often available only at specific instrumented locations. Spaceborne synthetic aperture radar (SAR) sensors can facilitate the acquisition of information over large areas and in remote and challenging terrain. In this work, we utilize Sentinel-1 (S1) SAR multi-track composites to monitor snow wetness evolution over four melting seasons for a study site of 400 km² around Davos in the eastern Swiss Alps. We evaluate the performance of our method using both in-situ measurements and modelled snowpack data. We compare snow wetness maps derived from dual-polarisation backscatter time series with wet avalanches records. We found statistically significant relationships between SAR backscatter decrease in both polarisations and increase in liquid water content expected in the snow pack. By calculating the percentage of detected wet snow to dry/no snow per elevation (wet snow ratio), the seasonal-elevation related melting can be tracked. Moreover, we show that a rise of dual-polarized wet snow ratio above 30% coincides with an increase in wet snow avalanche releases in corresponding elevation bands.

Our results suggest that wet snow products derived from S1 SAR data may assist in identifying regions featuring a potential increase of wet snow avalanche activity. However, the current temporal revisit of S1 does not allow us identifying potential precursors of wet avalanche occurrence, requiring sub-daily accuracy for operational monitoring.

1 Introduction

Wet snow avalanches can have a high destructive potential, however, they are still difficult to predict (Hendrick et al., 2023; Mitterer and Schweizer, 2013). This difficulty can be attributed to the limited availability of in-situ measurements of liquid water content, as well as the incomplete understanding of how liquid water influences the mechanical properties of the snow-pack. In this respect, knowledge of the spatio-temporal distribution of snowpack wetness is of major relevance for wet snow

20 avalanche hazard assessment, and in general for accurate run-off modelling (Wendleder et al., 2018; Nagler et al., 2018; Dietz
et al., 2012). Currently, avalanche warning is based on information from local observers, weather forecasts, in-situ weather
station measurements and spatial models (Hendrick et al., 2023). Temporally and spatially continual high-resolution monitor-
ing of wet snow on large spatial scales and in complex terrain could help to improve avalanche forecasting. Remotely sensed
data can help to overcome traditional challenges in poorly accessible terrains, helping to provide cost-effective methods to
25 efficiently monitor large and remote areas.

Spaceborne synthetic aperture radar (SAR) sensors, such as the ones onboard the ESA Copernicus Sentinel-1 (hereafter S1)
satellites, offer a promising approach to monitor snowpack evolution at regional scales. Specifically, changes in the backscat-
tered radar signal can be used to provide information on snow melt (Karbou et al., 2021; Marin et al., 2020; Truckenbrodt
et al., 2019; Nagler et al., 2016), but the interaction between snowpacks and microwave frequencies is complex and not yet
30 fully understood. The presence of liquid water in the snowpack attenuates the SAR backscattered amplitude (Marin et al.,
2020; Tsai et al., 2019; Linlor, 1980) due to alterations in the mixture of contributing scattering mechanisms (Murfit et al.,
2024). Singh and Varade (2025) suggest that wet snow is typically more cohesive than dry snow due to melting and refreezing
processes, thereby altering scattering mechanisms at play. The resulting signal loss is useful to detect wet snow in SAR images
by comparing signal backscatter amplitudes to a reference image without snow or with only dry snow (Nagler and Rott, 2000).
35 When the signal decreases below a pre-defined threshold compared to a known dry reference, wet snow is assumed to be
present, however the effect of different polarisations is still a matter of ongoing scientific discussion (Darychuk et al., 2025).
Marin et al. (2020) showed that, in comparison with ground data and with some temporal delay, indications of the moistening,
ripening and runoff phases can be found within the S1 data. By developing a representation style resolving the detected wet
snow maps in altitude-time and altitude-orientation diagrams, Karbou et al. (2021) was able to efficiently show the behaviour
40 of wet snow lines across large spatial scales aiming at avalanche prediction (also in Li et al. (2025)).

Publicly available products featuring wet snow coverage such as the service provided by European Environment Agency
(2023), currently have several drawbacks, i.e.: (i) they are limited to a resolution of 60x60 m; and (ii) they are prone to topo-
graphic distortions caused by variable SAR acquisition geometries. Regarding the latter, in mountainous terrain, the oblique,
right-looking viewing geometry of the S1 satellites leads to foreshortening, layover, shadowing and highly varying ground
45 resolution. Shadowing effects can be minimized by producing composites of radiometrically terrain-corrected (RTC) images
from ascending and descending orbits (Small et al., 2022). We combine the multi-track data following Small et al. (2022) by
taking local resolution available from each track into account. This approach of generating local resolution weighting (LRW)
composites makes use of multiple viewpoints on mountainous terrain to reduce missing data (shadow) from an individual orbit
(Small et al., 2022), employing the high ground resolution available when viewing backslopes. It further minimizes outlier-
50 effects and thereby reduces noise by applying weighted averaging in areas visible in multiple orbits. Furthermore, it allows
combination of information gathered from different orbits thereby potentially enabling higher temporal resolution than the
exact-repeat-orbit revisit interval.

In this study, we used LRW composites to mitigate the restrictions of traditional SAR images such as geometric effects. By
optimizing the S1 processing workflow, we improved spatial resolution compared to current altitude-melting diagrams such as

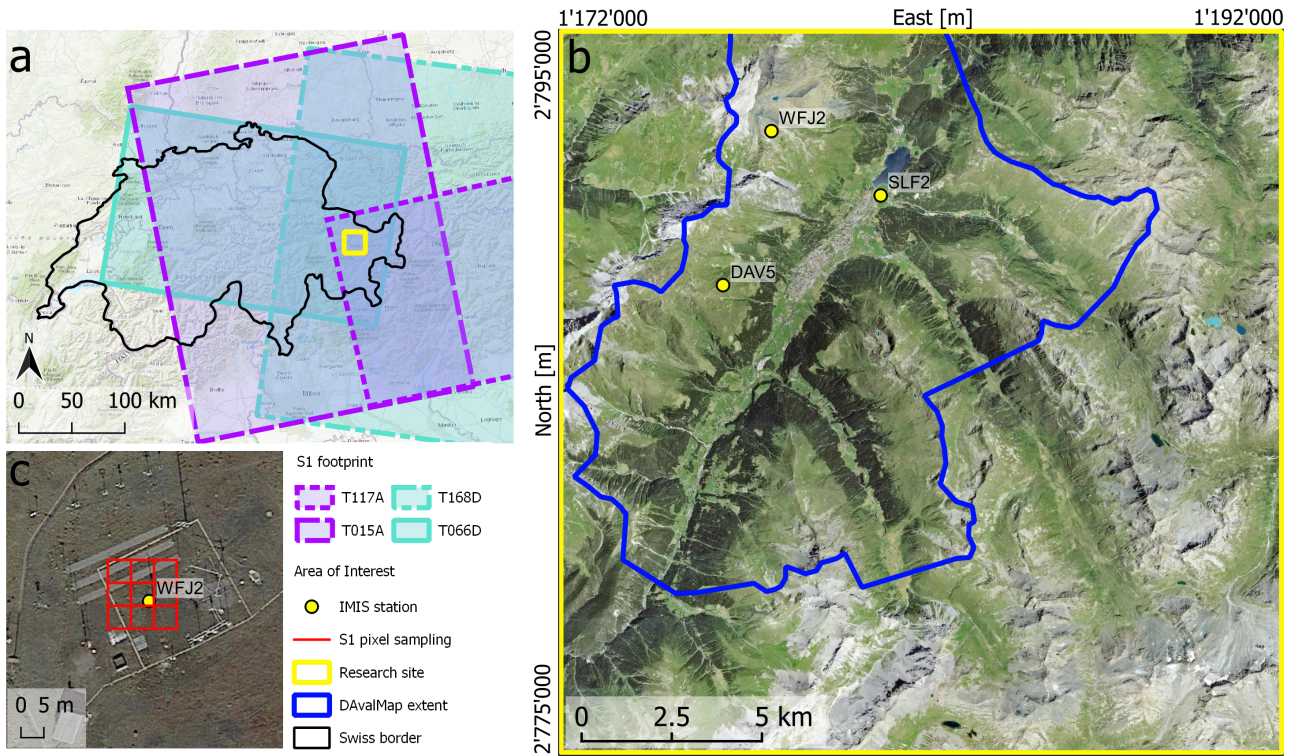


Figure 1. Overview of the area of research on three scales. (A) Outline of the Sentinel-1 footprints in relation to the research site of interest (Basemap © Esri). (b) Area of study (yellow outline, displayed in reference system CH1903+/LV95, with EPSG: 2056, Basemap © Esri), extent and location of the avalanche library (DAvalMap, blue outline (Northwards cut to research area extent)), and the IMIS stations used (yellow dots). (c) Indication of the 3x3 pixel window used to calculate the Sentinel-1 backscatter median around the corresponding IMIS station (Basemap © Google Maps).

55 Li et al. (2025); Karbou et al. (2021). We generated multi-track composites and oversampled the SAR data to match all data to
5x5 m ground sampling distance (GSD) over the study region. We applied the wet snow detection approach on a regional-scale
(400 km²) in the area of Davos, Switzerland, and compared it to a data set of observed wet snow avalanches. We evaluated
the reliability of our results by cross-correlating the time series with data recorded from three weather stations as well as from
the modelled snowpack information. This allowed us to perform validation assessment across the entire time series rather than
60 only during cloud free days, a limitation endemic to optical missions (as done by e.g. Li et al., 2025).

2 Data and methods

The study area is in the region of Davos, Switzerland (see Fig. 1), covering 400 km² and elevation ranges between 1542 and 3225 m a.s.l. (according to Federal Office of Topography and Swisstopo, 2022). The site is characterized by steep, mountainous terrain, with slope values ranging from 0° to 86° and a median of 28°, and the presence of seasonal snow cover. Mean values

65 of daily temperature in the area vary from min -27.4°C in winter (at WFJ) to max $+29.3^{\circ}\text{C}$ in summer (SLF), with an average daily temperature range of 9.03°C over the years 2019 to 2021. Approximately 15% of the study area is forested, with a median canopy height of ca. 10 m and dominated by coniferous species (Marty and Ginzler, 2025; Waser et al., 2025). The research area was selected due to its high alpine terrain as well as the availability of numerous reference data sets (station measurements and regular observations).

70 We used SAR data from the European Space Agency's S1 satellites. The mission provides C-band data with a central frequency of 5.405 GHz in the two polarisations VV and VH. S1 has an orbital repeat cycle over central Europe every six days (due to the S1B outage of December 2021, more recent projects have an extended time sampling of 12 days (European Space Agency, 2022)). Our analysis is based on the SAR images acquired on the relative orbits 066 and 168 (descending) as well as 015 and 177 (ascending; Fig. 1) in interferometric wide (IW) swath mode. Hereby, single-look-complex (SLC) data have a

75 pixel spacing of ~ 2.3 m in slant range and ~ 14.1 m in azimuth (Bourbigot et al., 2016). Depending on the location, S1 revisit times can go down to 36 h, when exploiting a combination of all available tracks and orbits. The S1 images over Davos were acquired at 05:34 (track 066), 05:27 (track 168) UTC on the descending tracks and at 17:15 (track 088) and 17:07 (track 117) UTC on the ascending tracks on consecutive days in this acquisition order (illustration in appendix Fig. A1). This lead to a time difference within the resulting composites of less than 84 h.

80 We applied radiometric terrain correction (γ_0 , following Small, 2011) to descending and ascending acquisitions and then combined the data into LRW composites. The latter products are calculated by considering a weighted function on at least two different flight tracks (here two descending, two ascending). Weighting is applied according to the local spatial resolution in the corresponding flight track (Small, 2012). We masked out areas that lie in radar shadow in all tracks, following the processing chain by Small et al. (2011) and Small et al. (2022). In cases where information was available in some track, i.e., lying in radar

85 shadow in others, only the available orbit was considered (as in Small et al., 2022). In total, we produced 424 LRW composites. To maximise consistency, composites missing one of the four tracks were discarded (see Tab. A1). We also calculated LRW using only tracks 066 and 015 to assess the effect of using two instead of four tracks (420 two-track LRW). To minimise noise and artifacts in the two-track LRWs, we calculated a temporal rolling median considering three samples for the time-series analysis, thereby executing a trade-off between a loss in detail and the influence of outliers.

90 Wet snow maps were generated by comparing an acquisition potentially featuring wet snow with a reference without snow or with dry snow (Nagler et al., 2016). Nagler et al. (2016) defined a threshold of 2 dB signal loss compared to a dry/no snow image for S1. In case of a stronger signal diminution, wet snow was assumed. No standard approach for the selection of a reference image is yet established, leaving space for potential differences in results (Li et al., 2025). Nagler et al. (2016) used a single image from summer, where the least amount of (melting) snow was assumed to be present in the scene. Rather than

95 relying on a single image, we calculated a median backscatter value per pixel over the entire available time series and used this value as a "dry" reference (indicated in black in Fig. 2). With this approach, we cope with the challenge of finding a suitable reference image, which becomes less accurate the longer the timespan between reference and acquisition becomes. Based on the median backscatter references, we calculated binary wet snow masks per polarisation, VV and VH, and then computed a

combined product. This product indicated wet snow occurrence only when wet snow was identified in both polarisations. We
100 selected this restrictive approach to optimize the balance between application effectiveness and interpretation complexity.

We additionally used data of elevation, forest and water bodies to assess their influences on the data and potentially mask
out areas where wet snow detection with S1 would be less reliable. A digital terrain model (DTM) provided by swisstopo with
ground sampling distance 5x5 m was considered to perform aspect dependency analysis in four aspect categories (N: 315–45°,
E: 45–135°, S: 135–225°, W: 225–315°) (Federal Office of Topography and Swisstopo, 2022). Information on the distribution
105 of water bodies was taken from the high resolution water and wetness (WAW) layer created by Copernicus (European Environ-
ment Agency, 2020). The data was provided at a 10x10 m grid scale, acquired between 2012 and 2018, and published in 2020.
The land classes were resampled to match the DTM pixel grid using nearest neighbour to ensure class consistency. The land
cover classes of permanent water, temporary water, permanently wet and temporarily wet were merged and used for masking.
Information on forest cover in the study area was sourced from the forest mask of the Swiss national forest inventory (Waser
110 et al., 2015). To assess the effect of spatial smoothing filters, a spatial median moving window filter with a kernel size of 3x3
was applied in the correspondingly marked wet snow ratio plots.

2.1 Reference data

Two different validation data sets were used. First, we analysed the sensitivity of SAR backscatter to snowpack characteristics
to identify the features influencing S1 backscatter on an RTC level by computing the correlation with respect to a variety of
115 both measured and modelled parameters. Second, we compared the wet snow maps from S1 to recorded wet snow avalanches.

2.1.1 Modelled Snowpack characteristics from SNOWPACK

The SNOWPACK snow cover model was developed to support an operational avalanche warning service based on the inter-
cantonal measurement and information system (IMIS) automatic weather station data (Lehning et al., 1999). SNOWPACK
simulates the detailed stratigraphy of the snowpack based on meteorological input data from automatic weather stations. Specif-
120 ically, the model uses local meteorological measurements, such as air temperature, snow depth or snow surface temperature,
to describe the snow microstructure, density, temperature and liquid water content of the layers in the snowpack. It models
snow as a three-phase porous medium made of ice, water and air with an arbitrary number of layers in the underlying soil and
in the snow (glacier ice when present is treated as snow layer with the physical properties of ice). It features a very detailed
description of snow properties including weak layer characterization (Stössel et al., 2010), phase changes, water transport in
125 snow with a simplified model (Hirashima et al., 2010) or with full Richards Equations (Wever et al., 2014) and water vapour
transport in snow (Jafari et al., 2022). SNOWPACK is used by several countries for their operational avalanche warning ser-
vices (Morin et al., 2020) but also in research. SNOWPACK is provided alongside its meteorological preprocessor MeteIO
(Bavay and Egger, 2013) and Graphical User Interface Inishell (Bavay et al., 2022) under an open source licence (LGPLv3).

In this study, we used the SNOWPACK version from December 2022 (git version: 98a23cd) in an operational setup. This
130 means that the simulations did not model soil, relying on a Dirichlet lower boundary condition (upper soil temperature). The
upper boundary condition (energy exchange between the snow or soil and the atmosphere) relied on either a measured snow

or soil surface temperature (Dirichlet when the surface temperature was less than -1 °C) or a parameterized incoming long wave radiation (Neumann) relying on an atmospheric cloudiness estimated from the measured short wave radiation (Carmona et al., 2014). These reanalyses additionally used a horizon computed from a 25 m resolution digital elevation model in order to distinguish shading by the terrain from cloudy sky, when parameterising the incoming long wave radiation. The SNOWPACK output includes both measured data at the nearest station as well as modelled parameters. The IMIS stations SLF2 (1563 m a.s.l.), at DAV5 (2315 m a.s.l.) and WFJ2 (2536 m a.s.l.) were within the boundaries of the research site (Fig. 1), the IMIS measurements were hence covering a variety of elevations within the region of interest in a flat field simulation. The timespan covered by available SNOWPACK data was September 2017 to August 2020. Due to a sensor failure, no SNOWPACK simulations could be performed at the SLF2 station for the 2018-19 season and hence the corresponding SNOWPACK data was not used in this analysis.

Our SNOWPACK runs provided outputs every 3 hours and we used the time closest to S1 acquisition on the corresponding day: namely 06:00 to match descending SAR image acquisitions and 18:00 to match the ascending acquisitions (UTC+1). We averaged the data from these SNOWPACK timestamps. The mean was calculated using the two SNOWPACK values closest to the ascending and descending acquisition times, ensuring consistency with S1 observations. SNOWPACK data was run to cover the time period between January 2018 and August 2021.

Finally, and in order to test the factors influencing the SAR backscatter time series, we performed a cross-correlation analysis between diverse variables in SNOWPACK at the corresponding station locations over time (see Fig. 6, appendices A6 and A7). We considered Pearsons correlation coefficient including RMSE values, as well as Spearmans rank coefficient. Pearson's was used to assess the potential strength and direction of linear relationships, while Spearman's captured monotonic trends between variables. To minimize correlation coefficient bias due to the effect of over-represented numerical values (e.g. zero is used by SNOWPACK when void), correlations were only calculated during the snow cover period (defined as snow height above zero within SNOWPACK). The significance level for both tests were set to p-values below 0.05.

After detection, wet snow was classified into elevation bands, and the relative occurrence was quantified using a modified plot design based on Karbou et al. (2021) showing elevation-dependent melting over time. Elevation bands were defined in 100 m increments, ranging from 1500 to 3000 m a.s.l., resulting in 15 elevation steps. Temporal classification followed the timing of ascending S1 acquisitions. Areas with slope angles below 28° were excluded to focus on potential avalanche release zones (Bühler et al., 2018). For each elevation band, we computed the wet snow ratio as:

$$R_{\text{wet}}(z) = \frac{N_{\text{wet}}(z)}{N_{\text{total}}(z)}, \quad (1)$$

where $R_{\text{wet}}(z)$ is the wet snow ratio at elevation band z , $N_{\text{wet}}(z)$ is the number of wet snow pixels, and $N_{\text{total}}(z)$ is the total number of non-void pixels in that elevation band.

2.1.2 Wet snow avalanche catalogue

As a further ground reference, we considered data from the Davos Avalanche Mapping Project (DAvalMap, detailed description in Hafner et al. (2021)). This data set was set up by the swiss avalanche warning service, designed to be an avalanche inventory

165 covering about 180 km². Systematic mapping was performed within the illustrated perimeter in Fig. 1 (Hafner et al., 2021) and is thus smaller than our study area. A part of DAvalMap in the North was excluded to match the research area, fitted to be within Swiss national boundaries for data consistency. Mappings outside the DAvalMap were only sporadic. Spontaneous avalanches considered small according to their type (50 m for slab avalanche and glide-snow avalanche, 100 m for loose snow avalanches in either dimension) were not recorded in the catalogue, thereby setting a minimum size of avalanches within the
170 data set. The data includes information on the release date, the snow condition (wet/dry snow avalanche) and the elevation zone at release.

For this study, we selected only the avalanches that were classified as wet snow avalanches situated within the research site (Fig. 1) inside the study's time range (January 2018 to August 2021). The recorded avalanches from DAvalMap were matched to wet snow ratio (see Equ. 1) plots according to the elevation of the release zone and the date of release (Karbou et al., 2021).
175 Temporal matching was performed by pooling the observed avalanches into one elevation-time bin by combining the avalanches occurring during the timerange one day before the LRW timespan to one day after (for illustration see appendix Fig. A1). This allowed coverage of a continuous time frame using a six day interval. This temporal matching also included avalanches after image acquisition. However, this is the most robust solution to approximate the wetness state of the snowpack and its corresponding proneness to wet snow avalanches, as it minimised temporal differences between avalanches and acquisitions.
180 In the season 2019–20, the size restriction of the recorded avalanches was handled less strictly, also including smaller loose snow avalanches which would have been excluded in the other years. The used data from DAvalMap contained 77, 723 and 261 wet snow avalanches for the seasons 2018–19, 2019–20 and 2020–21, respectively.

3 Results

3.1 Polarisation dependent S1 backscatter time series analysis

185 At WFJ2, the backscatter in both polarisations (VV & VH) fell clearly (> 3 dB) reaching beyond the set threshold for wet snow in late spring/early summer in each season, coinciding with snow melt at high alpine altitudes. Sporadic decreases of backscatter reaching below the threshold were also observed, where SNOWPACK data did not suggest the presence of snow wetness. However, for all such spurious events, the results diverged depending on the polarisation and they are accounted for when using the combined polarisation approach. So, while the combination of VV and VH polarisation (indicated by overlaid
190 shadings in Fig. 2) shortened the timespan of detected wet snow, it minimised the potentially false detection during off-season periods. When paired with a three-day rolling mean, the two-track composite (consisting of one ascending and one descending acquisition) produced a time series similar to that of the four-track composite, with the four-track LRW generally showing a more conservative behaviour (appendix A2).

Overall, similar results were observed at the DAV5 and SLF2 station locations (appendix A3 and A4). However, at SLF2 the
195 snowmelt in spring 2020 was not captured when combining both polarisations, as no distinct drop in co-polarized backscatter could be detected. At DAV5, the decrease in backscatter was less pronounced, and the time series exhibits reduced overall

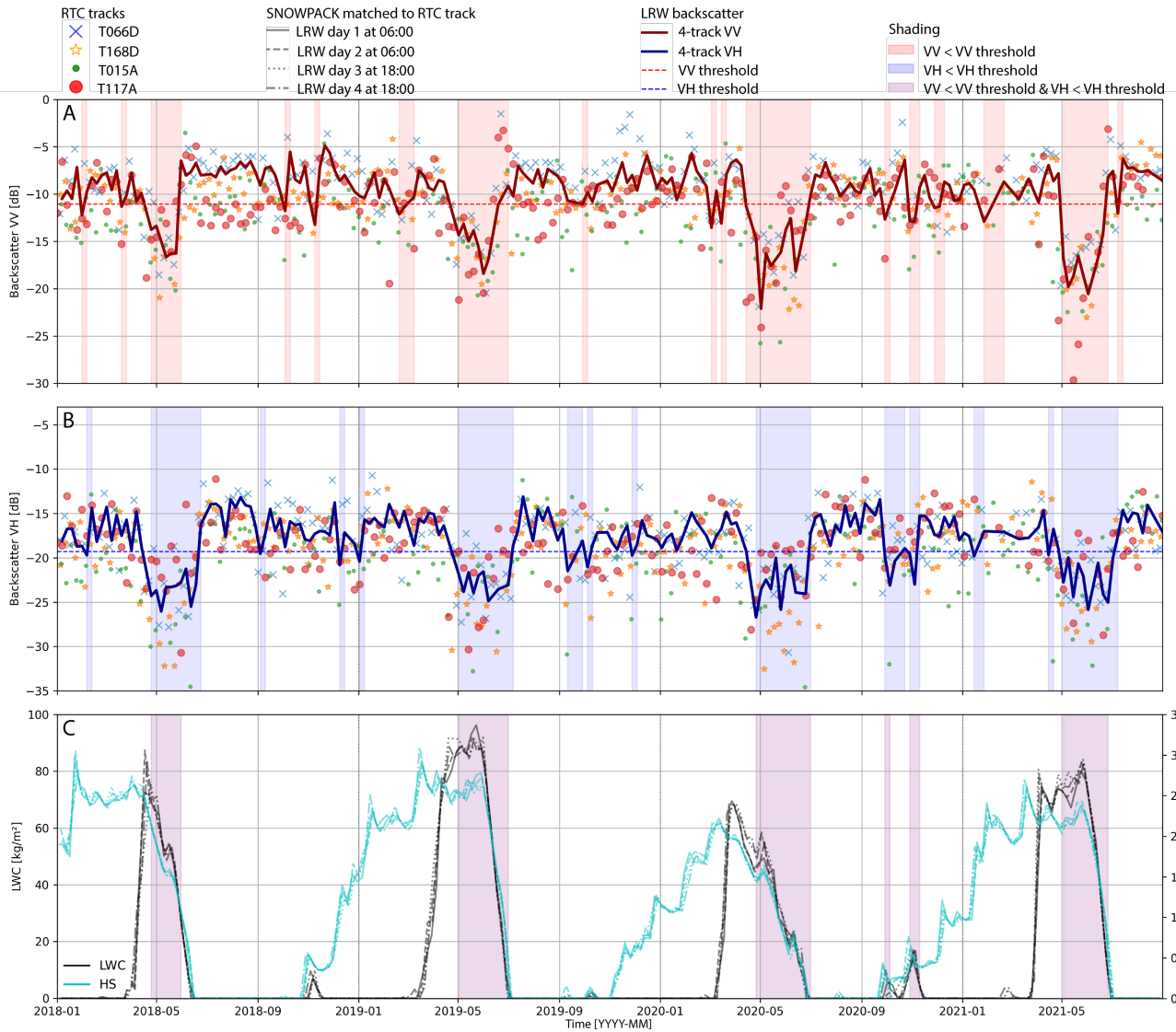


Figure 2. Time series of wet-snow evolution over 4 melting seasons from January 2018 until August 2021 at Weissfluhjoch (WFJ2). A) and B) show the time series extracted from the pixel within which the IMIS station is situated in co- (A) and cross-polarized (B) S1 data. The markers indicate the measured radar backscatter per RTC track, whereas the line indicates the corresponding LRW value. The horizontal line indicates the time series median and the shading background displays the times during which the backscatter falls lower than 2 dB below the calculated median in the corresponding polarisation. C) shows the time series of measured liquid water content (LWC) and measured snow height (HS) at the station as extracted from SNOWPACK data. In (C), the applied purple shading indicates when VV and VH both fall underneath their corresponding thresholds and corresponds to our wet snow combined polarisation product.

stability with more short-lived peaks (appendix Fig. A4). The median backscatter of the DAV5 station was observed to be several dB lower than the other stations (Tab. 1).

Table 1. Median of S1 backscatter per polarisations at the three different stations within the timeframe of 01.2018 to 08-2021.

Polarisation	SLF2	DAV5	WFJ2
VV	-10.05	-13.49	-9.07
VH	-17.92	-20.67	-17.30

Increasing Liquid Water Content (LWC) percentage coincided with a decrease in snow height (see Fig. 2c). In each melting season, an increase in LWC was found as well as sporadic peaks matching early snow melting events e.g. in November 2018. With a time shift of about a week, the backscatter signal diminished soon after the sudden increase in LWC and the decrease in snow height. This behaviour was found across all melting seasons (see Fig. 2).

Indication for negative correlation between S1 backscatter and SNOWPACK modelled LWC as well as measured runoff could be found at all stations, in most tracks. These correlations ranged, for LWC, between -0.12 (VV; SLF2) to -0.42 (VV; WFJ2) in Spearmans rank and -0.16 (RMSE: 13.93) to -0.30 (RMSE: 37.20) for Pearsons correlation, when averaged over the tracks per station per polarisation (Fig. 6, and appendices A6 and A7). At WFJ2 station, a negative correlation with the temperature variables was indicated, and a positive correlation with SNOWPACK’s potential albedo, however neither could be found in the other station locations.

3.2 Spatial distribution and elevation dependent melting

Time-elevation dependent melting seasonality was detected across the time series independent of polarisation and slope aspect (Fig. 3): In the seasons 2018–19 and 2020–21, the highest wet snow ratios were measured (mid March, classified into wet snow ratio of 70–80 %). The maximum ratios that were reached throughout the season 2019–20 amounted to 50–60 %. Increasing ratio values (above 30 %) were detected earlier in the season of 2020–21 between November to February at elevations ranging from 1500 to 2200 m a.s.l. In 2020–21 (see Fig. 3), the wet snow ratio rose again, achieving up to 70–80 % mid May.

The wet snow ratio mainly diverged between polarisation states in late summer and autumn periods, where the VV polarisation indicated maximum wet snow ratio (see equ. 1) values of up to 20 %, whereas the VH polarisation indicated a continuous time-elevation dependent increase in wet snow ratio with up to 40 % wet snow pixels per elevation class (appendix Fig. A8 and A9). VH indicated higher ratio values than VV polarized data at lower elevation classes (1500–1900 m a.s.l.). Based on this polarisation-dependent difference, only slight indications of late-autumn melt at higher elevations were visible; however, this period is of minor relevance due to the absence of avalanche-critical conditions and was therefore not the primary focus of this analysis.

Masking of land-cover classes such as forest and water bodies had little influence on the resulting time-elevation plots. Large water bodies such as lakes were mainly situated in the lowest classes and in flatlands, and were thereby already masked out by focusing on hillsides via the minimal slope threshold. On the other hand, the exclusion of forests resulted in measurable changes in elevation-based wet snow mapping (see appendix Fig. A5A to B) as they also occur in non-flat areas. Forests are

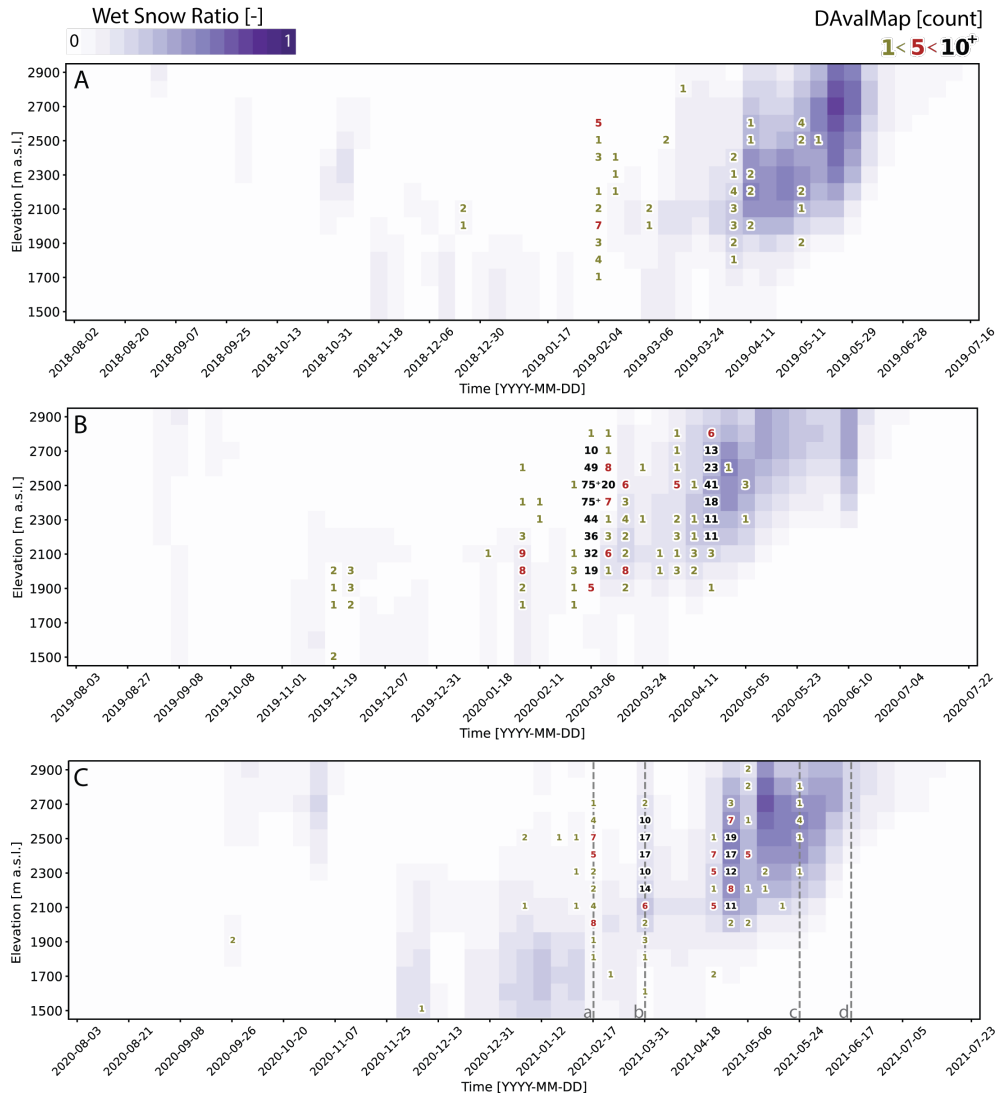


Figure 3. Time-elevation plots of wet snow ratio evolution for combined polarized product across three and a half melting seasons (A: 01.2018–07.2019, B: 08.2019–07.2020 and C: 08.2020–07.2021) featuring the area of Davos as indicated in Fig. 1, resolved at discrete 100 m elevation bands. The wet snow ratio is the percentage of pixel per elevation band that were detected as indicating wet snow using S1 data. Coloured numbers indicate the count of recorded wet snow avalanches per time step according to the DAvalMap data set at the corresponding elevation band (Hafner et al., 2021). No spatial smoothing or filtering was applied (these effects can be found in the appendix A5). Dashed lines and letters a–d in panel C correspond to the timeframes of the wet snow maps displayed in Fig. 5. Plot design was inspired by Karbou et al. (2021) and Karbou et al. (2022)

known to influence radar backscatter and cover a larger and more diverse landscape than water bodies. However, also their influence was mainly focused on a specific elevation range below 2000 m a.s.l. (see appendix Fig. A5A to B) Applying a

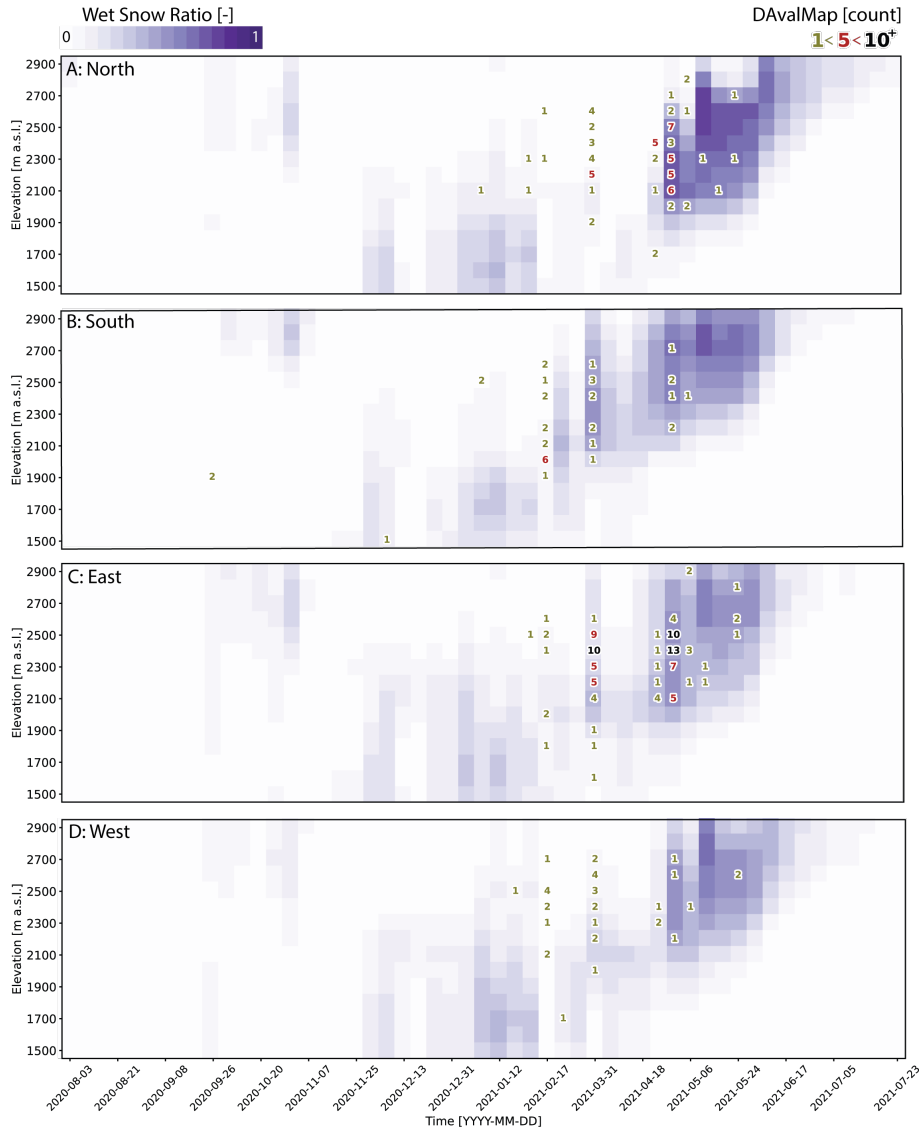


Figure 4. Time-elevation plots of wet snow ratio evolution for combined polarized product for the exemplary seasons of 2020–2021. Displayed are the time series resolved into the different slope aspects: A: North, B: South, C: East and D: West. The plot encompasses data featuring the area of Davos as indicated in Fig. 1, resolved at discrete 100 m elevation bands. The wet snow ratio is the percentage of pixel per elevation band that were detected as indicating wet snow using S1 data. Coloured numbers indicate the count of recorded wet snow avalanches per time step according to the DAvalMap data set at the corresponding elevation band (Hafner et al., 2021). Plot design was inspired by Karbou et al. (2021) and Karbou et al. (2022).

moving median filter smoothed the time-elevation plots (see appendix Fig. A5A to C). The noise reduction had less impact in high alpine areas, likely because the original signal was already relatively undisturbed. In contrast, at lower elevations, the

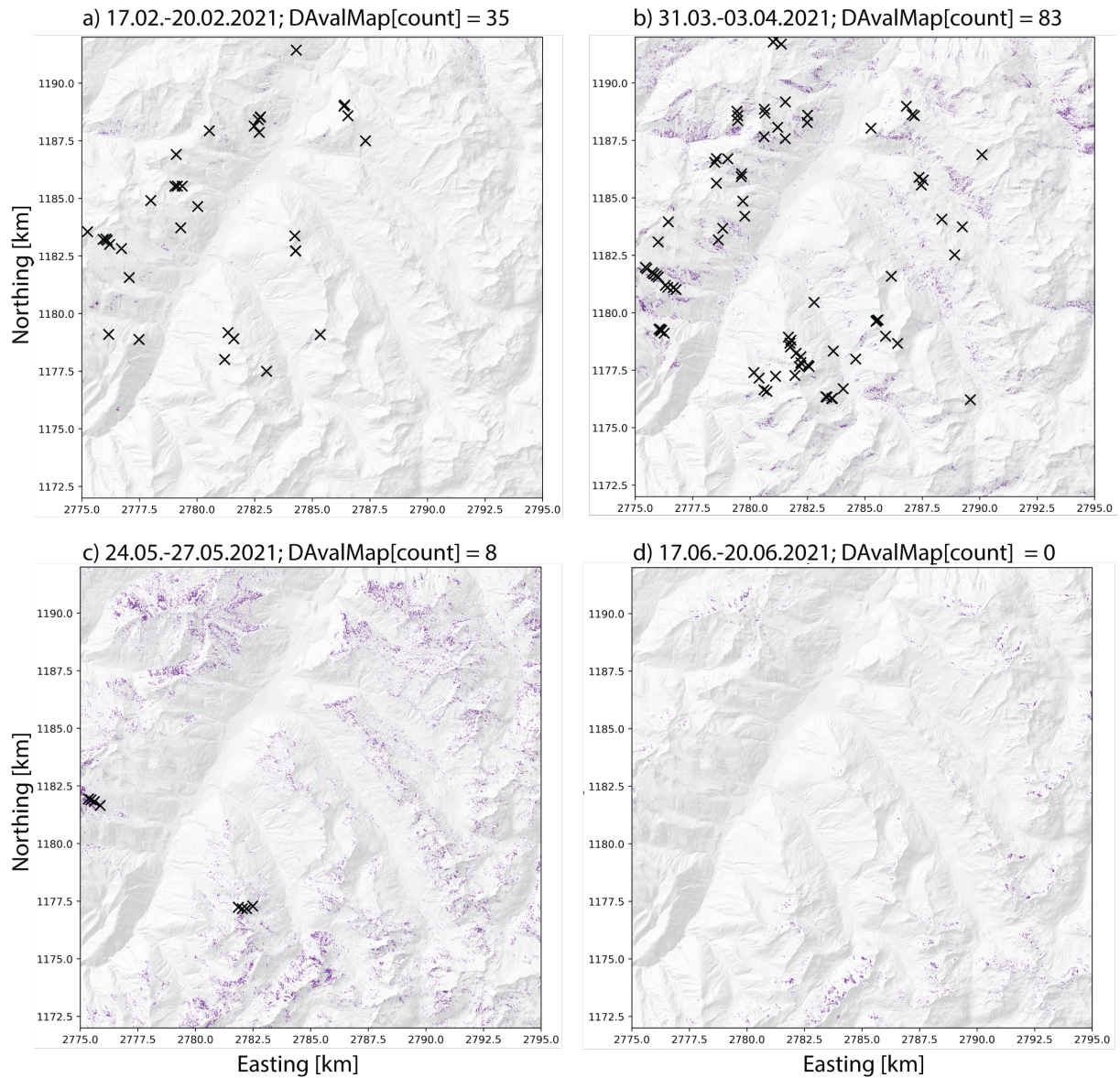


Figure 5. Spatial distribution of the detected wet snow pixel using the combined polarisation approach and the recorded avalanches in DAvalMap (Hafner et al., 2021) (black crosses) are displayed for four exemplary, different times (a–d) as indicated in Fig. 3. The acquisition days of the SAR images are indicated in the title per subplot on the left, while the DAvalMap indicates the number of recorded avalanches within the allocated timewindow (according to the temporal matching illustrated in the appendix A1). Background DEM by © Swisstopo

230 differences in classification between results with and without noise reduction can span two classes (from 0–10% to 30–40% wet snow ratio values), indicating a higher risk of also removing important signal components.

The time-elevation plots also clearly showed differences in aspects (see Fig. 4). South and East facing slopes showed an *earlier increase* in wet snow ratio to values above 40 % in the season than did West and especially North facing slopes (compare Fig. 4B and C to A and D). The highest ratios reaching 90–100 % wet snow ratio values were mainly located in
235 North facing slopes, where melting occurs later in the season and over a shorter time period. The same behaviour across time-elevation was found in VH polarized data, also across all seasons. The aspect-dependency was more relevant when a minimal slope steepness, e.g. 45° (high avalanche danger according to Bühler et al. (2018)) was defined.

Wet snow ratios did not show relevant changes before the first surge of wet snow avalanches recorded in DavalMap (see Fig. 3A, B and C). Instead, a second increase of avalanche occurrence observed in 2018–19 and 2020–21 ranging across various
240 elevation classes (Fig. 3B), coincided with wet snow ratio values of 25 to 30 % in altitudes from 2000–2200 m a.s.l. After this second event, a further increase in wet snow ratio characterizes the melting season (Fig. 3). Events of multiple avalanche occurrences that were recorded in DavalMap coincided with dual-polarized wet snow ratios above 30 % (Fig. 3).

4 Discussion

In this study, we analysed SAR-based wet snow maps by implementing a new processing chain and validating it with *in-situ*
245 measurements and modelled information. By relying on LRW composites, S1 data was exploited to combine backscatter from different tracks. Thus, the information on snow wetness in our study is provided ready-to-use and was considerably less noisy compared with methods used previously (European Environment Agency, 2023).

The available S1 based snow cover products SAR Wet Snow or Wet/Dry Snow by Copernicus offer a spatial grid sampling distance of 60x60 m (European Environment Agency, 2023) and hence may not suffice to adequately resolve the variability of
250 alpine topography (appendix Fig. 7). The discrepancy between the available products and our results is partly linked to the use of the more highly resolved SLCs rather than ground range detected (GRD) S1 European Environment Agency (2023); Karbou et al. (2021). Most especially, by using LRW composites, the influence of typical SAR geometry effects, such as shadowing and layover, was mitigated (see appendix Fig. 7). Having fewer areas that lack data and potentially improving the temporal resolution is important, for example for avalanche forecasting where accurate timing of capturing the start of the wetting of the
255 snowpack (Cluzet et al., 2024), a key factor to estimate the hazard of wet snow avalanche releases.

Validation of spatially continuous products providing information, where there was previously hardly any available, is challenging. Consequently, we relied on comparing data with *in-situ* measurements, where available, to minimise uncertainties related to the reference data. The SAR Wet Snow and Wet/Dry Snow layer were validated via a pixel-wise comparison to other remote sensing products such as snow cover maps from Landsat (European Environment Agency, 2023; Karbou et al., 2022).
260 Since the acquisition technique is still based on remote sensing approaches, the biases contained might also be similar, hence we believe our comparison to an independent product is less prone to bias. It further allows us to perform correlation assessments across the entire time series and not only under cloud-free conditions, a constant challenge when considering optical spaceborne imagery (Li et al., 2025; Cluzet et al., 2024). Also, we compared the results to snowpack characteristics instead of snow extent, thereby more reliably approximating what actually influences the signal. Nevertheless, an example comparison of

265 a wet snow mask from our multi-track LRW to the SAR Wet Snow layers and the best temporally matching false colour imagery from the same time range provided by Planet Labs Inc., showing a case of disappearance of snow during the time window of the LRW, can be found in appendix Fig. 7.

SAR backscatter is influenced by many factors, therefore to identify wet snow, a threshold needs to be set in comparison to a dry/no snow reference. This threshold is usually set between 2 and 3 dB signal loss relative to a reference image or annual median (this work) and is based on histogram analysis (e.g., Nagler et al., 2016). Adaptive and dynamic thresholds based on the underlying land cover class (Liu et al., 2022) or other additional datasets (James et al., 2024) have recently been suggested. However, we used the established and widely applied threshold of 2 dB for S1 data (Nagler et al., 2021, 2016, results indicated in Fig. 2). Although an adaptive backscatter analysis sounds promising, there were no widely available and regularly updated land cover products with suitable spatial resolution available in our case, and the most robust algorithm minimises requirements on the input data.

As previously mentioned, no standard approach for the generation of a reference image has been established. The Copernicus SAR Wet Snow layer is based on a reference image calculated as the median from a stack of summer acquisitions (assumed no snow; European Environment Agency, 2023). Other studies calculate the mean over dry or no snow images (e.g., Karbou et al., 2021; Li et al., 2025) or use a single reference image featuring either dry or no snow conditions (e.g., Mendes et al., 2022). Increasing temporal baselines between the image of interest and the reference image, results in greater errors due to changes over time. In the application of wet snow avalanche now- and forecasting, time efficiency and accuracy is of major importance. By choosing an "all season" median, we have wet snow contamination in the reference; however the results of our study indicate applicability of the method (see Fig. 2) and follow the process applied in Lievens et al. (2019). The advantage of reference image generation in that way is lower processing costs, reduced input requirements, a high automation level, and simplified update-ability.

Validation was performed using SNOWPACK data at three IMIS stations SLF2, DAV5, WFIJ2 (Fig. 6 and appendices A6 and A7). This allowed us to include both modelled and measured variables, thereby also allowing to check the validity of the gained results. The stations are all situated on mountain slopes but in rather flat areas. Hence, they are unlikely to accurately represent the conditions in highly variable topography limiting the possibility to validate LRW products in these areas. Additional limitations may come from the immediate surroundings of some of the stations having an impact on the radar backscatter. The mentioned signal instability at DAV5 is plausibly linked to interference from numerous nearby avalanche protection structures, which have stable backscatter properties and could thus bias the results. When seasonal transitions are less pronounced due to lower elevations, smaller melt events are often not captured. Which might explain that at SLF2 the snowmelt in spring 2020 is not captured when combining both polarisations, as no distinct drop in co-polarized backscatter could be detected. The SLF2 station's proximity to railway infrastructure suggests potential signal interference, with varying impact depending on the satellite track. Moreover, the increase in backscatter observed early in the year (appendix Fig. A4) coincided with the timing of the World Economic Forum, plausibly linked to temporary metal constructions for security around the nearby helicopter landing zone.

We tested the cross-correlation of values recorded on a single pixel in relation to diverse variables contained in SNOWPACK at IMIS station locations. However, single pixel analyses are prone to radar noise (e.g., speckle) and uncertainties, we therefore performed the same analysis on a 3x3 window (indicated in Fig. 1) and at three different locations. Across all tests, the liquid water content and the water runoff were among the strongest correlation values with the correlation assessment (Fig. 6 and appendices A6 and A7). This coincides with the ongoing understanding of the measured backscatter decrease being related to the amount of liquid water within a snowpack (e.g., Li et al., 2025; Lund et al., 2022; Nagler et al., 2021). Already with a LWC of 5 % in a snowpack, SAR penetration depth has been found to be minimized to one wavelength and hence SAR backscatter is already very low (Lund et al., 2022; Nagler et al., 2016).

The selection of polarisation modes from S1 data has varied between wet snow observation studies. While e.g. Gao and Ma (2024); Murfitt et al. (2024) used VV polarized data, James et al. (2024) used VH polarized and Darychuk et al. (2025); Li et al. (2025); Jans et al. (2025); Karbou et al. (2021) used a dual-polarized approach. In our results, the correlation values showed similar trends between the different polarisation modes (Fig. 6 and appendices A6 and A7). The strongest divergence between the wet snow ratio extracted from VV and VH polarisation was observed in late summer early autumn, whereby the VH polarisation indicated higher ratio values than VV. This might be related to a remaining influence of seasonal activity of vegetation (e.g. by occurrence of shrub forest), which is known to influence backscatter signal (Gao and Ma, 2024) or by the ripening which Marin et al. (2020) found to have a depolarizing effect on the signal. The time series showed similar results for both polarisation modes. The applied combination of both polarisations resulted in fewer misclassification, however, the approach also results in a loss of detail. In contrast to Karbou et al. (2021) we performed analysis on separate polarisation states before combining the wet snow masks, this mitigated the issue of using a thresholding approach developed by Nagler et al. (2016) on a dB scale on a ratio value as implemented by Karbou et al. (2021).

We observed a time lag between the decrease in snow height, the associated increase in LWC, and the detection of wet snow from S1 (see Fig. 2). Compared to the data from Marin et al. (2020) this indicates that we missed the moistening and ripening phase to measure the runoff. We believe this temporal gap might be attributed to the combination of four effects: i) the temporal gap between variables, as we made use of weighted S1 only every 6, or 12 days in case of a discharged composite (see appendix Table A1) ii) the potential filtering out of the onset of wetting in a snowpack as noise, iii) the limited sensitivity of the sensor up to a certain minimum water content threshold and iv) the dependence of the abundance of the LWC on the acquisition time of the images, as the snowpack's characteristics change over the course of the day (as also the data by Marin et al. (2020) suggest). If and how these factors contributed to the miss of the first avalanche surge should be investigated further in the future.

Our results showed an earlier start of the melting season at lower elevation zones with increasing melting later in the season in higher elevation zones (see Fig. 3). This agrees with the station data, where at the more highly situated stations winter lasts longer, with a more pronounced and later melting season. Lower elevations typically have a shorter and warmer winter season. This leads to a shorter period of signal attenuation during the melting phase than at stations with more snow coverage in higher elevation zones.

The DAvalMap library contains recorded avalanches within the area of the perimeter indicated in Fig. 1 (Hafner et al., 2021). Multiple aspects must be considered when interpreting the wet snow ratio per elevation to this data set: i) The monitored perimeter is smaller than the research site, so avalanches outside of the perimeter were not systematically monitored and mapped. This results in elevation bins above approx. 2800 m a.s.l. containing little to no recorded avalanche activity. ii) The avalanches used in the study were all wet snow avalanches, so the snowpack in the starting zone of the avalanches was assumed to be wet. Since this classification of snow wetness in the starting zone is challenging from a distance, some avalanches might have been incorrectly included. We assume that this influenced the miss of the first wet snow avalanche surge in our analysis, where the avalanches had wet snow deposits even though they started out as dry snow avalanches and we only considered start zone coordinates. Later when the snowpack is wet from the valley to the mountaintops, this potential classification error becomes negligible. iii) The information was based on *in-situ* observations dependent on good visibility, so the assigned release date might include uncertainties up to several days. Keeping in mind our S1 timeframe of six days, the influence of potentially incorrectly recorded release date would be minimal. However, no clear dependency of wet snow avalanches and measured rainfall was found, overcoming 0.2 at average daily rainfall of 17 kg/m² averaged across the stations, suggesting that rain-on-snow had a limited impact on avalanche release in this dataset (see appendix Fig. A10). And despite mentioned challenges, DAvalMap provides a unique opportunity to compare observed activity with snow wetting from S1 data.

The initial surge of wet snow avalanches did not coincide with a pronounced increase in the wet snow ratio across any of the investigated seasons (see Fig. 3). These events were both the most susceptible to misclassification as wet snow avalanches in the DAvalMap dataset and the most likely to occur during short-lived wetting phases that may go undetected due to the temporal resolution of S1 imagery. These limitations underscore the need for improved temporal coverage to enhance the timing accuracy of remotely sensed snowpack transitions.

We encourage future research to make use of not only multi-platform but also multi-frequency data such as a combination of X- and L-band with e.g. the upcoming NISAR mission (Oveisgharan et al., 2024). This would allow the capture of different stages of the melting due to differences in sensitivity to water presence with varying wavelengths, thereby enabling better estimates of the LWC and not only the presence of liquid water.

5 Conclusions

We used S1 SAR multi-track composites to derive snow wetness at different elevations and slope aspects around Davos. By exploiting LRW composites created from SLC products, we were able to more accurately resolve spatial variability of the snow wetness in alpine terrain than currently available products. We evaluated the performance of our approach by cross-correlating the data to in-situ measured and modelled snowpack variables as well as a wet snow avalanche inventory, finding relevant correlation between S1 backscatter and modelled liquid water content, as well as good agreement with the release of wet snow avalanches coinciding with the wetting of the snowpack at the corresponding elevations, aside from an exception of the very first surge of wet snow avalanches in spring. Our results indicated the potential of C-band SAR-based monitoring of wet snow avalanche preconditioning factors, provided the availability of data with higher spatiotemporal resolution than the current S1

orbit repeat interval offering. With the use of such multi-track composites, the robustness of time series increases substantially, as single missing acquisitions could be bridged and consistent monitoring maintained. This further highlights the potential of generating near-operational data products for wet snow detection in alpine terrain.

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Data availability. SAR data can be downloaded from the Copernicus Open Access Hub or from the Alaska Satellite Facility. SAR processing has been performed using the gamma software. The DAvalMap library and SNOWPACK data for WFJ station can be requested from SLF.

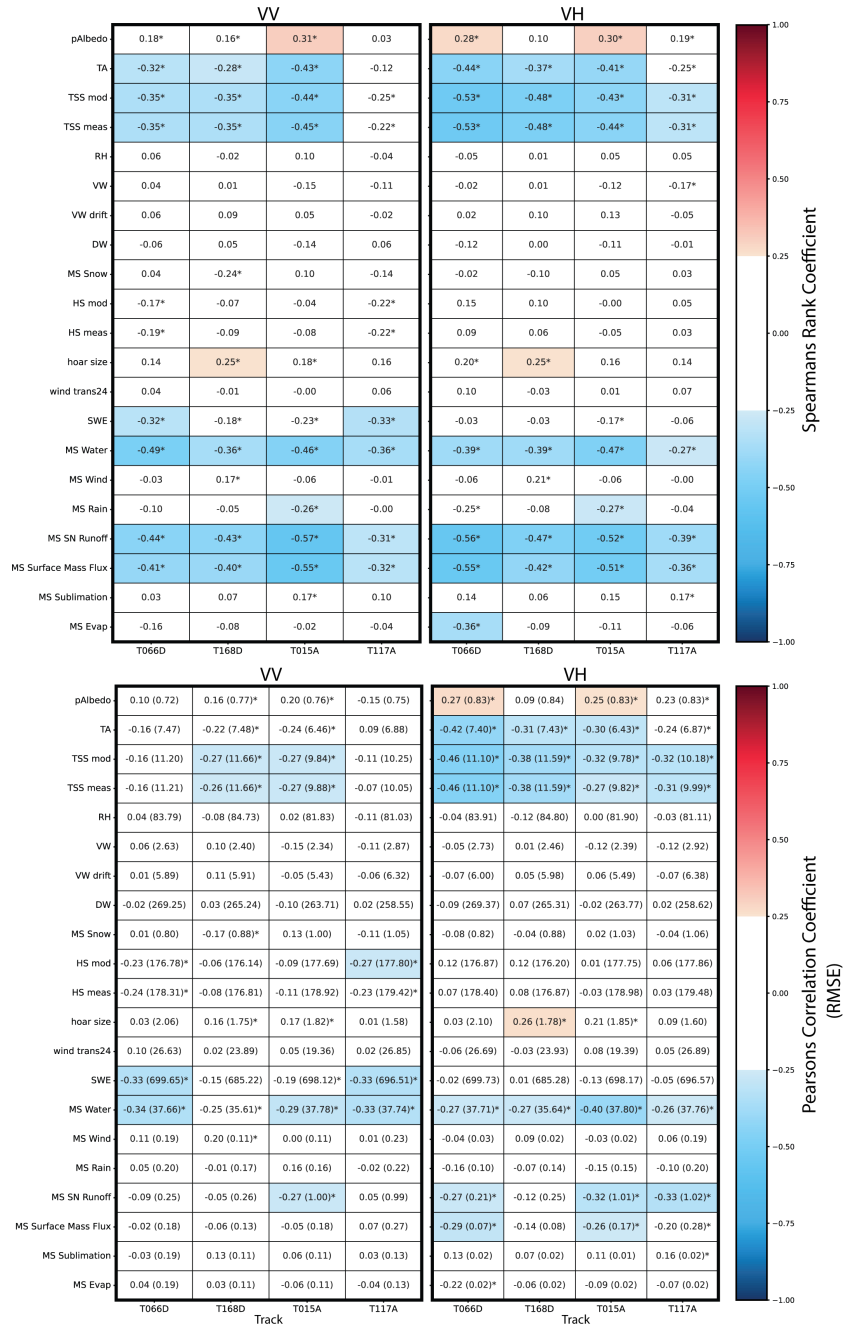


Figure 6. Correlation of analysed SNOWPACK variables compared to the median VV Sentinel-1 backscatter time series at the WFJ2 station per track (location see Fig. 1). The table includes the results per polarisation state for 3x3 window size. Included are the Spearman's (top) and Pearson's (bottom) correlation coefficient and the RMSE calculated between the Pearson's and the actual data. * indicate values that came with a p-value of below 0.05. Abbreviations can be found in Table A2 and the correlation of the other stations in appendices A6 and A7.

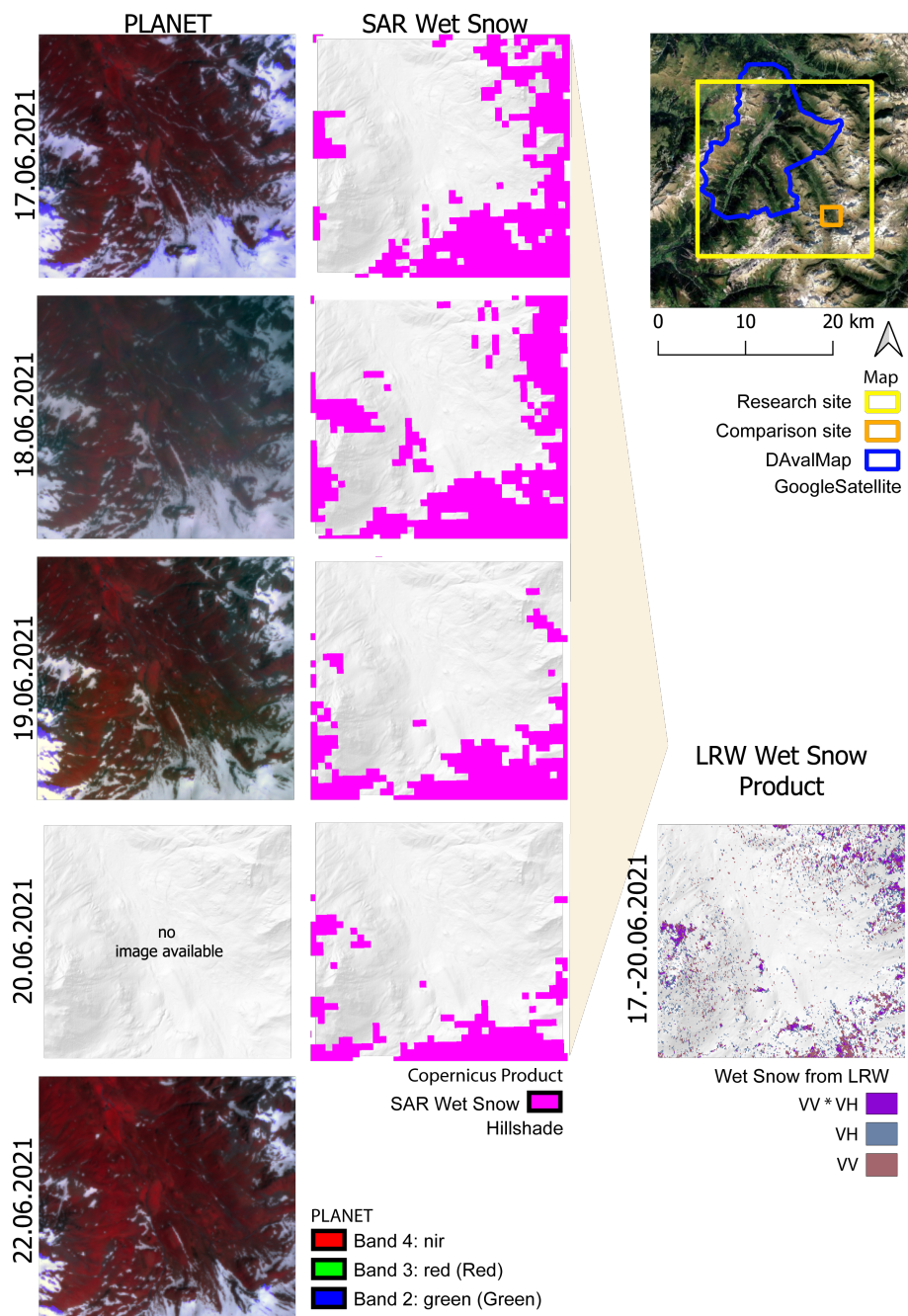


Figure 7. Visual comparison between false colour imagery from PlanetScope (© Planet Labs Inc.), the Copernicus SAR Wet Snow product and the LRW Wet Snow product created from our workflow. The inset map (background map by © Google Maps) shows the location of comparison. Location and time was chosen to optimize comparability during a period where snowmelt can be visually detected in the in the daily imagery from PlanetScope during the timeframe of an LRW.

Appendix A

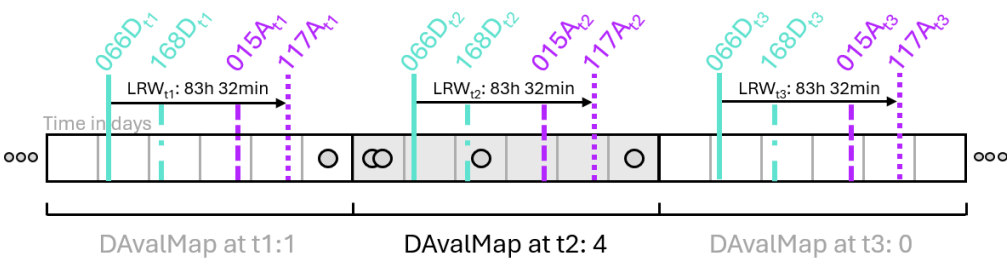


Figure A1. Exemplary illustration of performed temporal binning featuring the SAR acquisition times in descending and ascending tracks to corresponding local resolution composites (shading) in combination with the summed wet snow avalanches. Binning has been optimized to include all recorded wet snow avalanches (from DAvalMap catalogue, indicated in circles) while minimizing the temporal offset between an acquisition towards the avalanche to best match the wet snow condition.

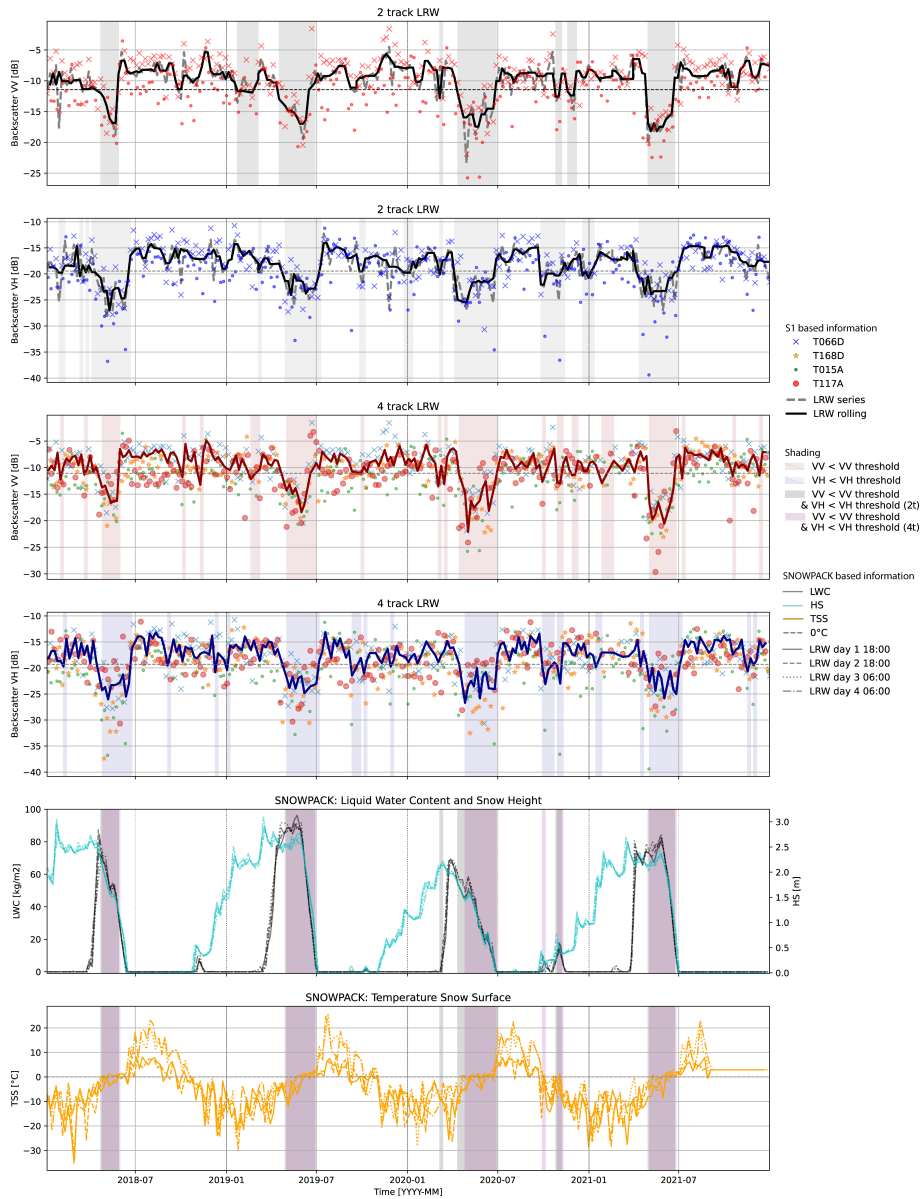


Figure A2. Time series of wet-snow evolution from January 2018 until August 2021 at Weissfluhjoch (WFJ2) for two-track rolling mean (a and b) and four-track LRW (c and d) in comparison to SNOWPACK data (e and f). The first two plots are the time series extracted from the 3x3 window within which the IMIS station is situated in co- and cross-polarized S1 data at two track LRWs and the middle ones from the 4-track LRW. The markers indicate the measured radar backscatter per RTC track, whereas the line indicates the LRW value. The horizontal lines indicate the time series median and the shading background displays the times during which the backscatter falls lower than 2 dB below the median in the corresponding polarisation. The lower panels shows the time series of measured liquid water content (LWC) and measured snow height (HS) and surface temperature (TSS) at the station as extracted from SNOWPACK data. The applied purple shading indicates when VV and VH correspond to our wet snow combined polarisation product. The different lines styles indicate the SNOWPACK data at the corresponding to the S1 matched acquisition.

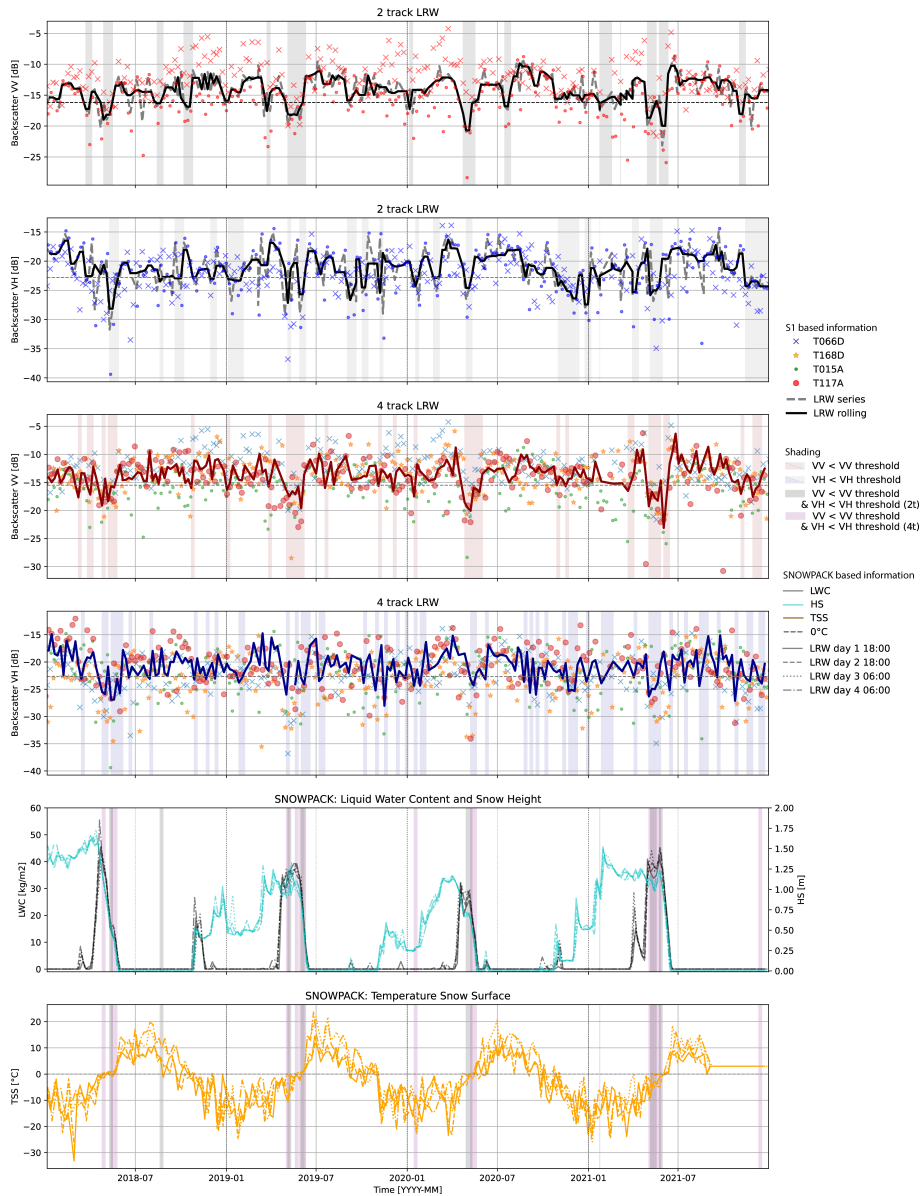


Figure A3. Time series of wet-snow evolution from January 2018 until August 2021 at the DAV5 station for two-track rolling mean (a and b) and four-track LRW (c and d) in comparison to SNOWPACK data (e and f). The first two plots are the time series extracted from the 3x3 window within which the IMIS station is situated in co- and cross-polarized Sentinel-1 data at two track LRWs and the middle ones from the 4-track LRW. The markers indicate the measured radar backscatter per RTC track, whereas the line indicates the LRW value. The horizontal lines indicate the time series median and the shading background displays the times during which the backscatter falls lower than 2 dB below the median in the corresponding polarisation. The lower panels shows the time series of measured liquid water content (LWC) and measured snow height (HS) and surface temperature (TSS) at the station as extracted from SNOWPACK data. The applied purple shading indicates when VV and VH correspond to our wet snow combined polarisation product. The different lines styles indicate the SNOWPACK data at the corresponding to the S1 matched acquisition.

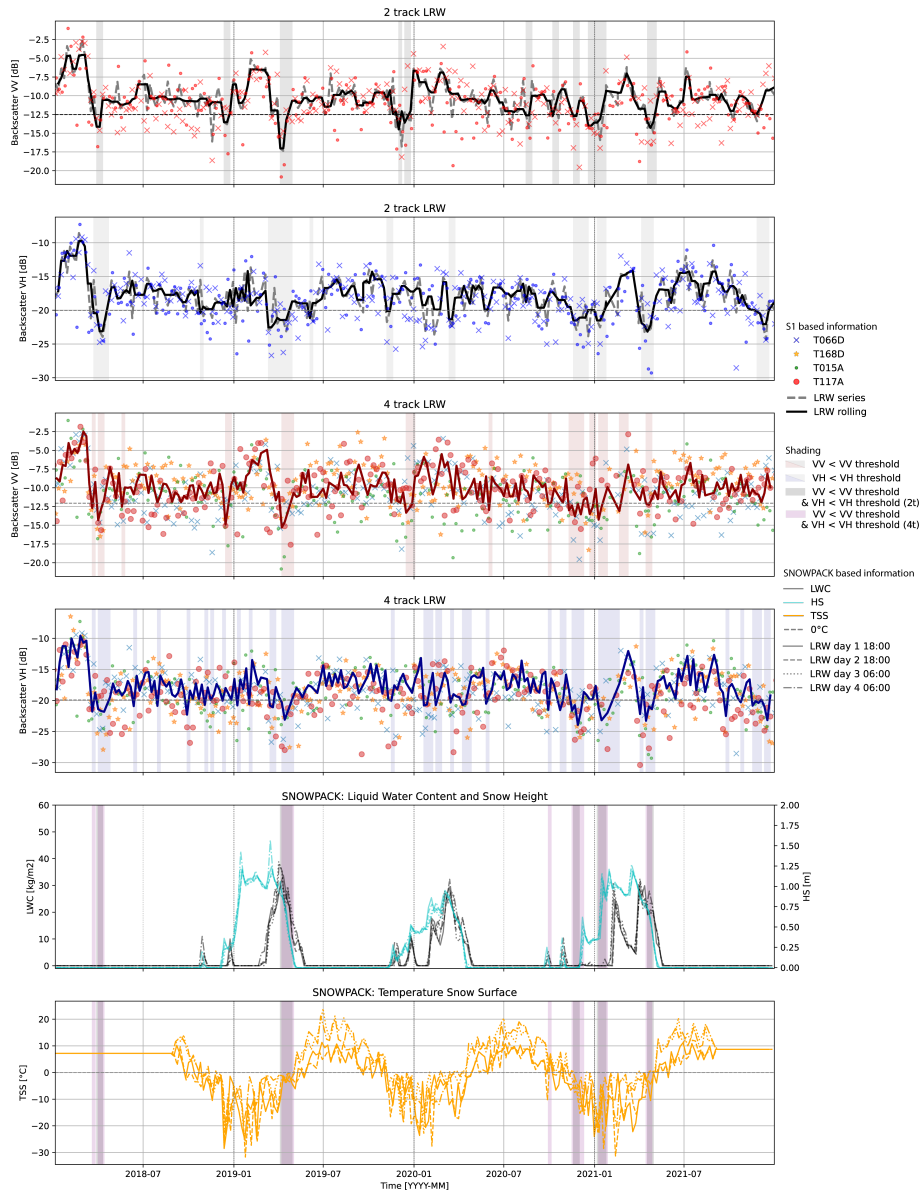


Figure A4. Time series of wet-snow evolution from January 2018 until August 2021 at the SLF2 station for two-track rolling mean (a and b) and four-track LRW (c and d) in comparison to SNOWPACK data (e and f). The first two plots are the time series extracted from the 3x3 window within which the IMIS station is situated in co- and cross-polarized Sentinel-1 data at two track LRWs and the middle ones from the 4-track LRW. The markers indicate the measured radar backscatter per RTC track, whereas the line indicates the LRW value. The horizontal lines indicate the time series median and the shading background displays the times during which the backscatter falls lower than 2 dB below the median in the corresponding polarisation. The lower panels shows the time series of measured liquid water content (LWC) and measured snow height (HS) and surface temperature (TSS) at the station as extracted from SNOWPACK data. The applied purple shading indicates when VV and VH correspond to our wet snow combined polarisation product. The different lines styles indicate the SNOWPACK data at the corresponding to the S1 matched acquisition.

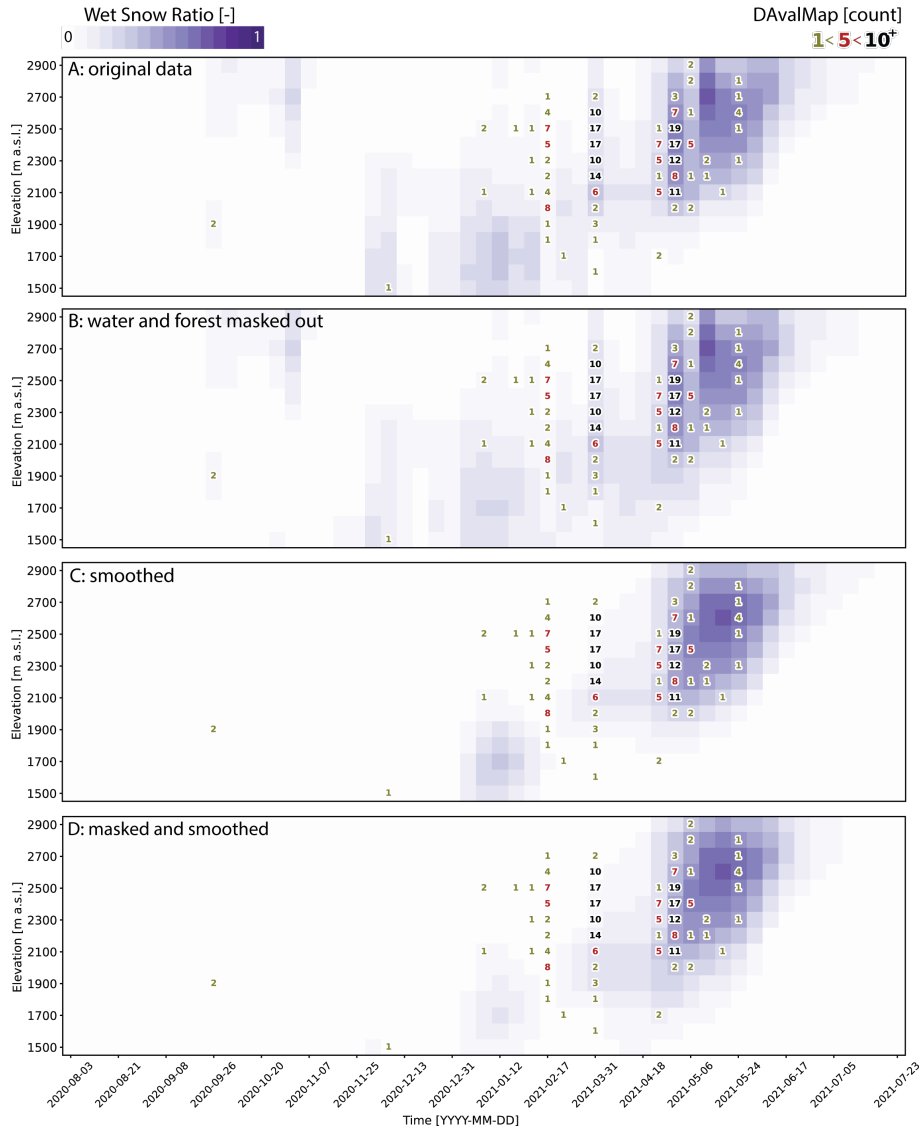


Figure A5. Time-elevation plots of wet snow evolution following Karbou et al. (2021) and Karbou et al. (2022) for VV polarisation for the exemplary seasons of 2020-2021. It shows the effect of filtering and masking: A) no filtering or masking applied, B: forest mask applied, C: spatial median filter with a window size of 3x3 applied, D: forest mask and spatial filtering combined. The plot encompasses data featuring the area of Davos as indicated in Fig. 1, resolved to 100 m spatial elevation classes. Coloured numbers indicate the count of recorded wet snow avalanches per time step according to the DAvalMap data set at the corresponding elevation band (Hafner et al., 2021).

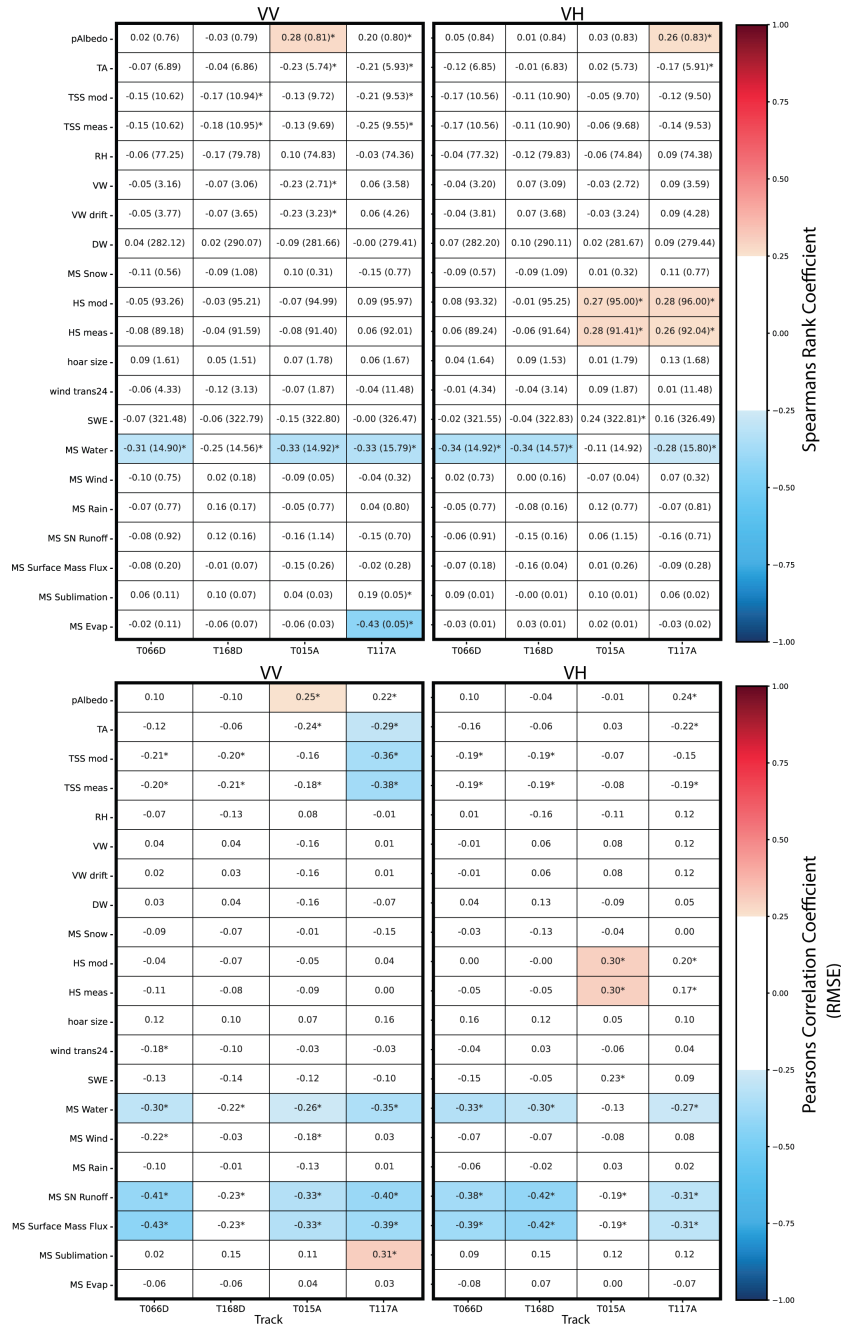


Figure A6. Correlation of analysed SNOWPACK variables compared to the median VV Sentinel-1 backscatter time series at the DAV5 station per track (location see Fig. 1). The table includes the results per polarisation state for 3x3 window size. Included are the Spearman's (top) and Pearson's (bottom) correlation coefficient and the RMSE calculated between the Pearson's and the actual data. * indicate values that came with a p-value of below 0.05. Abbreviations can be found in Table A2.

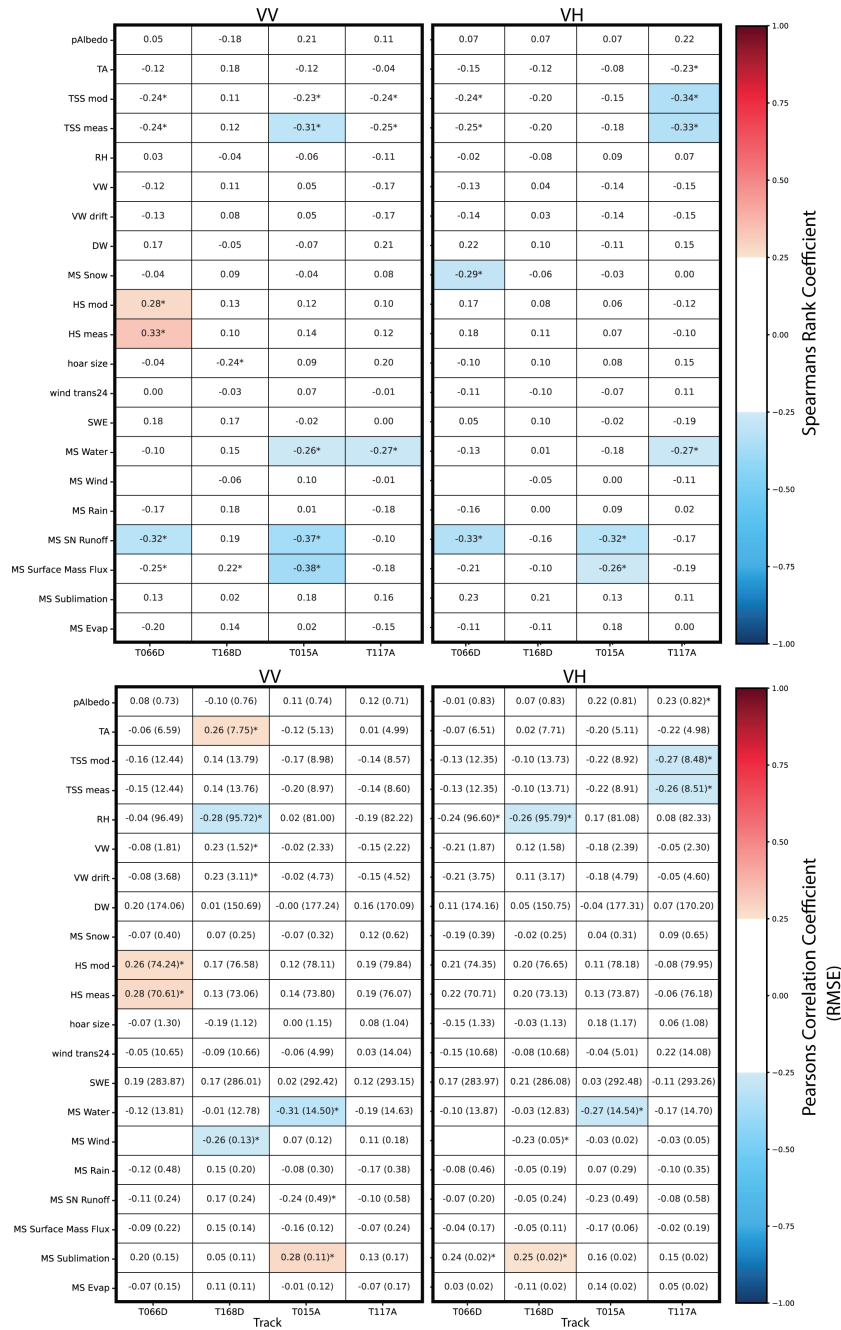


Figure A7. Correlation of analysed SNOWPACK variables compared to the median VV Sentinel-1 backscatter time series at the SLF2 station per track (location see Fig. 1). The table includes the results per polarisation state for 3x3 window size. Included are the Spearman's (top) and Pearson's (bottom) correlation coefficient and the RMSE calculated between the Pearson's and the actual data. * indicate values that came with a p-value of below 0.05. Abbreviations can be found in Table A2.

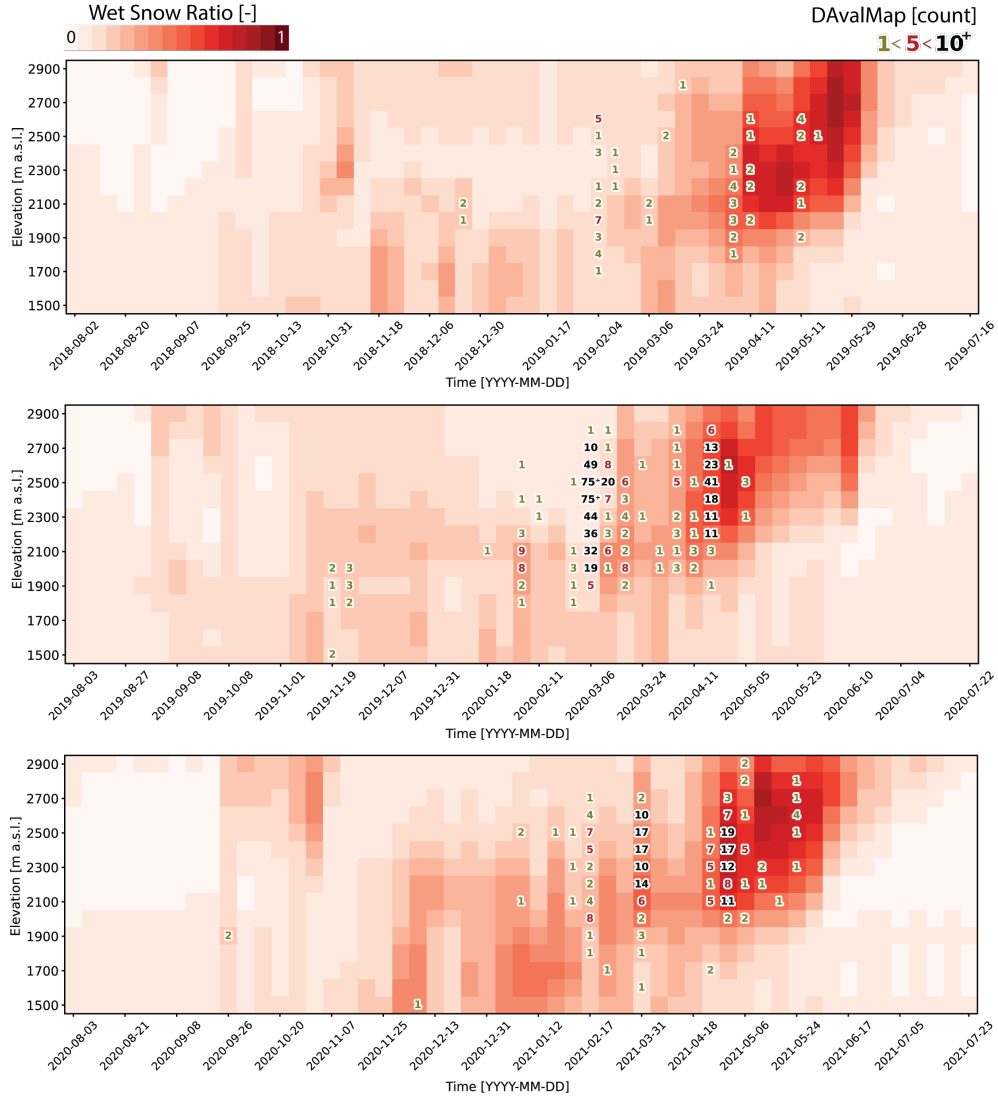


Figure A8. Time-elevation plots of wet snow ratio evolution for **VV**-polarized wet snow detection across three and a half seasons (A: 01.2018–07.2019, B: 08.2019–07.2020 and C: 08.2020–07.2021) featuring the area of Davos as indicated in Fig. 1, resolved at discrete 100 m elevation bands. The wet snow ratio is the percentage of pixel per elevation band that were detected as indicating wet snow using Sentinel-1 data. Coloured numbers indicate the count of recorded wet snow avalanches per time step according to the DAvalMap data set at the corresponding elevation band (Hafner et al., 2021). No spatial smoothing or filtering was applied. Plot design was inspired by Karbou et al. (2021) and Karbou et al. (2022).

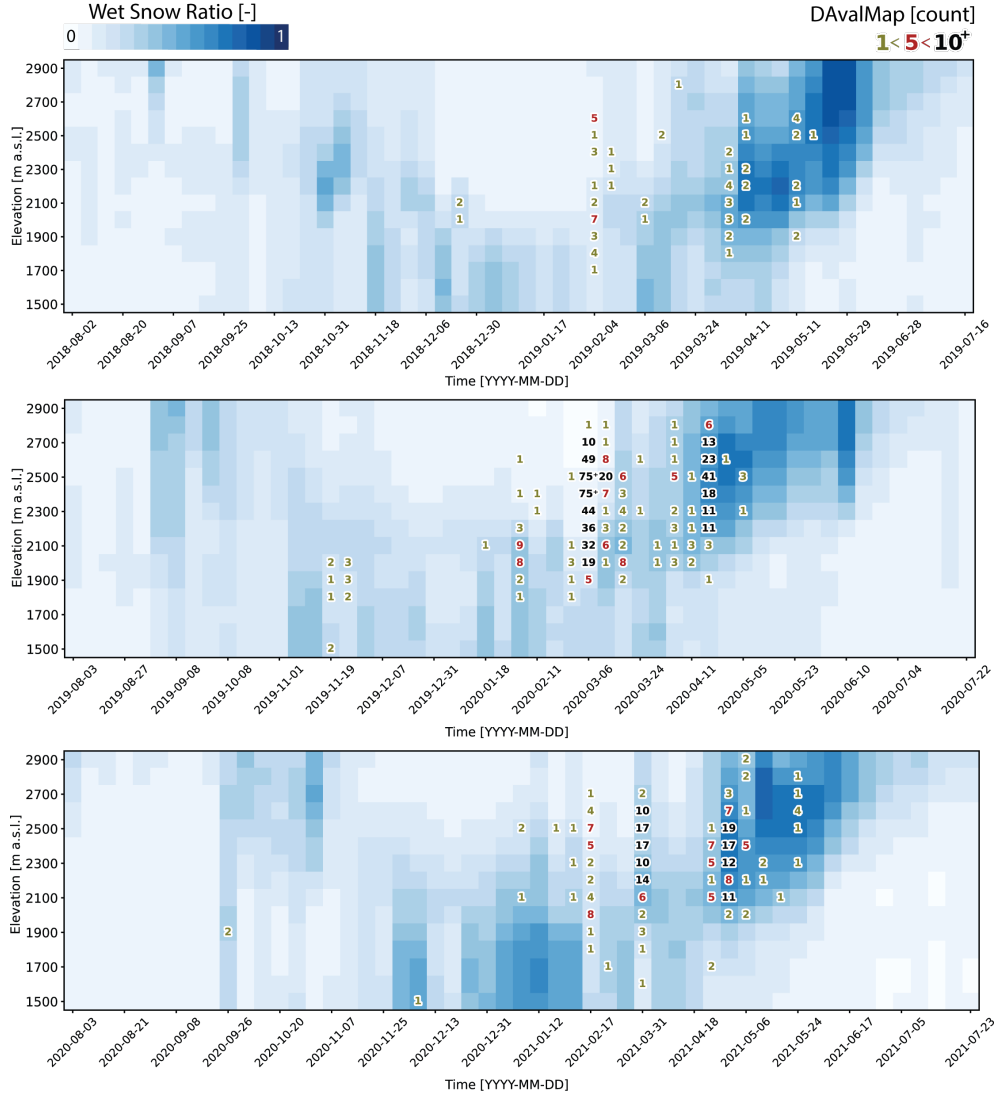


Figure A9. Time-elevation plots of wet snow ratio evolution for **VH**-polarized wet snow detection across three and a half seasons (A: 01.2018–07.2019, B: 08.2019–07.2020 and C: 08.2020–07.2021) featuring the area of Davos as indicated in Fig. 1, resolved at discrete 100 m elevation bands. The wet snow ratio is the percentage of pixel per elevation band that were detected as indicating wet snow using S1 data. Coloured numbers indicate the count of recorded wet snow avalanches per time step according to the DAvalMap data set at the corresponding elevation band (Hafner et al., 2021). No spatial smoothing or filtering was applied. Plot design was inspired by Karbou et al. (2021) and Karbou et al. (2022).

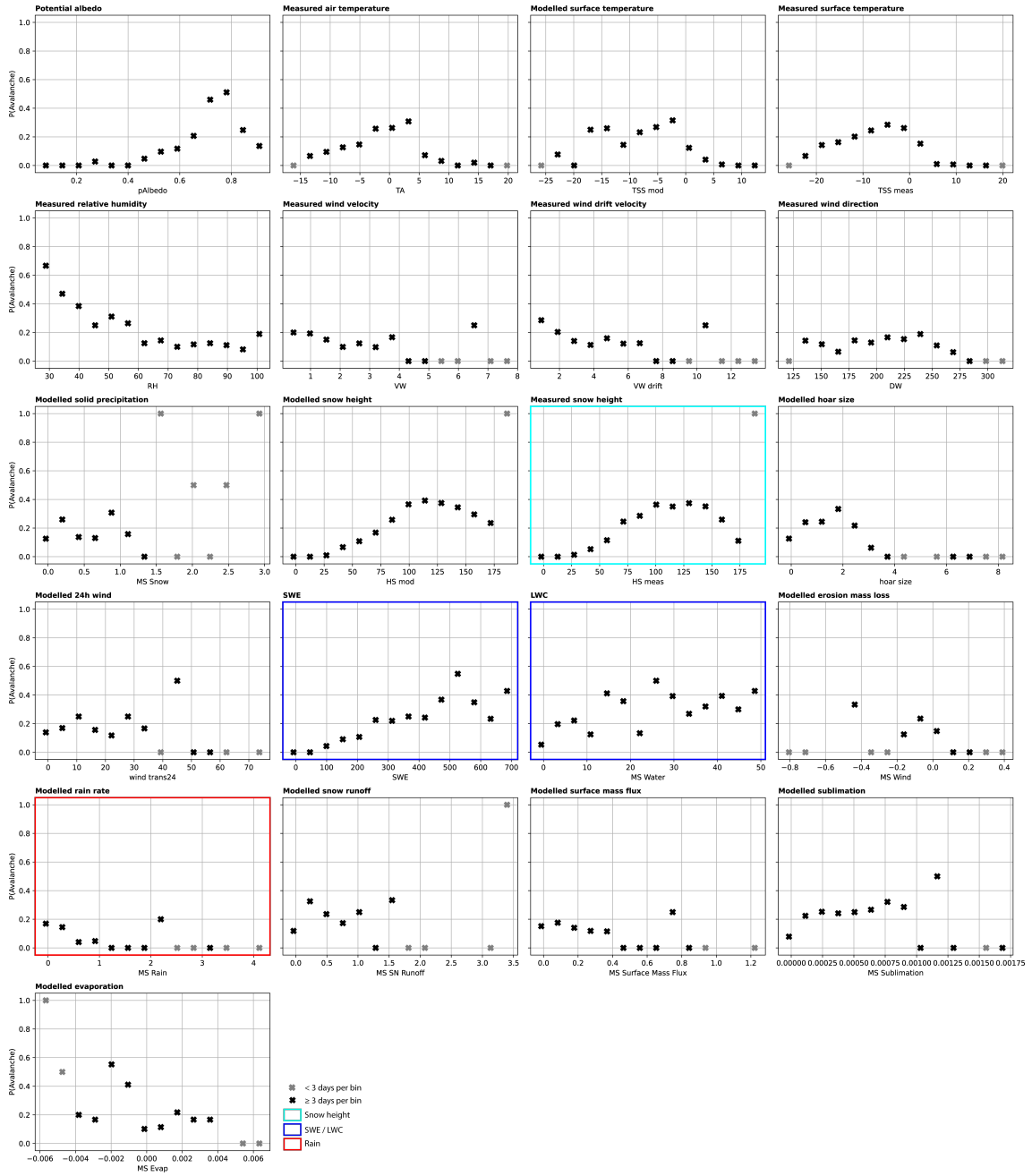


Figure A10. Probability of ≥ 1 avalanche report from the DAvalMap dataset as a function of SNOWPACK variables. Each subplot shows the conditional probability of at least one avalanche occurring on a day given a range of values for a specific variable (e.g., "On days with X mm of rain, what's the chance of ≥ 1 avalanche being reported?"). The variable measurement is the mean across the three stations WFJ2, DAV5, SLF2. To calculate probabilities, days were binned by the variable of interest, and the fraction of days with reported avalanches was computed within each bin as the mean of the binary avalanche indicator. This yields an empirical estimate of avalanche probability conditioned on variable ranges. In colours indicated are the variables used in plots and statements in the main text (see Fig. A2).

Table A1. List of dates [DD-MM-YYYY] of missing RTC acquisitions per track (T) with indication of orbit direction (A: ascending, D: descending) that resulted in discarded composites. Reason for missing data: *: missing in Copernicus Archive, °: data take change from SDH to SDV

T066D	T168D	T015A	T117A
28.02.2019*	18.04.2019*	18.04.2018*	21.12.2018*
14.09.2019*	11.06.2019°	29.06.2018*	23.09.2019*
18.01.2021°		12.02.2019*	02.02.2020*
30.01.2021°		25.04.2019*	26.02.2021*
05.02.2021°		24.06.2019*	08.06.2021*
11.02.2021°		23.08.2019*	19.08.2021*
01.03.2021°		22.10.2019*	25.08.2021*
13.03.2021°		21.12.2019*	
25.03.2021°		19.02.2020*	
16.08.2021*		19.04.2020*	
		18.06.2020*	
		16.10.2020*	
		13.02.2021*	

Table A2. Abbreviation table for the variables from SNOWPACK, which are also used in the following tables containing the cross-correlation variables.

Measured relative humidity	RH
Measured air temperature	TA
Measured surface temperature	TSS_meas
Modelled surface temperature	TSS_mod
Modelled hoar size	hoar_size
Measured snow height	HS_meas
Modelled snow height	HS_mod
Measured wind direction	DW
Measured wind velocity	VW
Measured wind drift velocity	VW_drift
Modelled 24h wind	wind_trans24
Modelled rain rate	MS_Rain
Modelled solid precipitation	MS_Snow
Modelled snow water equivalent (SWE)	SWE
Modelled total liquid water content (LWC)	MS_Water
Modelled sublimation	MS_Sublimation
Modelled evaporation	MS_Evap
Modelled erosion mass loss	MS_Wind
Modelled surface mass flux	MS_SM_Flux
Modelled snow runoff (virtual lysimeter)	MS_SN_Runoff
Potential albedo	pAlbedo

485 *Author contributions.* Conceptualization: AM, MJ; Data Curation: AM, GD, VB, MR; Formal Analysis, Investigation, Software, Visualization: GD, VB, MR; Methodology: GD, VB, AM, MR, MJ; Project Administration: AM, MJ; Validation: GD, VB, MR, EH; Writing – Original Draft Preparation: GD; Writing – Review & Editing: GD, VB, AM, MJ, MR, MB, EH, AvH; Revisions: GD, VB, AM, MJ, MR, MB, DS; Funding Acquisition: MJ, AvH; Supervision: AM

Competing interests. The contact author declares that none of the authors has competing interests.

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