

~~Monitoring snow wetness evolution~~ Extracting Information on Wet Snow Avalanche Preconditions ~~from satellite with Sentinel-1 multi-track composites~~ 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 ~~for specific~~, at specific instrumented locations. ~~Space-borne techniques such as~~ Spaceborne synthetic aperture radar (SAR) ~~allow us acquiring sensors can facilitate the acquisition of~~ information over large areas and in remote and challenging terrain. ~~Here, we show~~
5 ~~how~~ In this work, we utilize Sentinel-1 (S1) SAR multi-track composites ~~can be used~~ to monitor snow wetness evolution over ~~multiple~~ four melting seasons for a study site of 400 km² around Davos in the eastern Swiss Alps. We ~~validate~~ evaluate the performance of our method using both in-situ measurements and modelled snowpack data. ~~Moreover, we compared~~ We compare snow wetness maps ~~and derived from dual-polarisation backscatter~~ time series with wet avalanches records. We found ~~correlations~~ statistically significant relationships between SAR backscatter ~~and modelled decrease in both polarisations~~
10 ~~and increase in~~ liquid water content ~~between -0.25 and -0.59 for Spearman's rank coefficient and -0.25 and -0.64 for Pearson's correlation coefficient~~ expected in the snow pack. By calculating the percentage of detected wet snow to dry/no snow per elevation ~~, the season-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 ~~40~~ 30% coincides with an increase in wet snow ~~avalanches~~ avalanche releases in corresponding elevation bands.

15 Our results suggest that wet snow products derived from ~~Sentinel-1~~ S1 SAR data may assist in identifying regions featuring a potential increase of wet snow avalanche activity. However, ~~we could not find evidence of~~ the current temporal revisit of S1 does not allow us identifying potential precursors of wet avalanche ~~initiation with the accuracy required for operative monitoring applications~~ 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~~) ~~-(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 snowpack.~~ In this respect, knowledge of the spatio-temporal distribution of snowpack wetness is of major relevance for wet snow avalanche hazard assessment, and ~~more~~ 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, ~~and~~ in-situ weather station measurements and spatial models (Hendrick et al., 2023). Temporally and spatially ~~continuous~~ ~~continual~~ high-resolution monitoring of wet snow on large spatial scales and in complex terrain could ~~be of great~~ help to improve avalanche forecasting. Remotely sensed data can help to overcome traditional challenges in poorly accessible terrains, ~~thus providing helping to provide~~ cost-effective methods to efficiently monitor large and remote areas.
- ~~Space-borne~~ Spaceborne synthetic aperture radar (SAR) ~~sensors~~, such as ~~implemented on the the ones onboard the ESA Copernicus Sentinel-1 satellites, offers (hereafter S1) satellites, offer~~ a promising approach to monitor snowpack evolution at regional scales. Specifically, changes in the backscattered radar signal can be used to provide information on snow melt (~~Karbou et al., 2021; Truckenbrodt et al., 2019; Nagler et al., 2016~~) (~~Karbou et al., 2021; Marin et al., 2020; Truckenbrodt et al., 2019; Nagler et al., 2018~~), but the interaction between ~~the snowpack~~ snowpacks and microwave frequencies is complex and not yet fully understood (~~compare Lievens et al., 2019~~). ~~According to the current understanding, changes on SAR microwave signal can be measured only if the snowpack reaches several meters thickness (Dietz et al., 2012). Detailed sensitivity analyses between the interactions of SAR and snowpack characteristics is a focus of ongoing research (e.g., Lievens et al., 2019).~~ On the other end, ~~the~~ The presence of liquid water in the snowpack attenuates the SAR backscattered amplitude (~~Tsai et al., 2019~~). ~~This effect is (Marin et al., 2020; Tsai et al., 2019; Linlor, 1998)~~ due to alterations in the mixture of contributing scattering mechanisms (Murfitt 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). When the signal decreases below a pre-defined threshold compared to ~~the 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) ~~enabled to efficiently monitor was able to efficiently show~~ the behaviour of wet snow lines across large spatial ~~scale for avalanche prediction scales aiming at avalanche prediction (also in Li et al. (2025))~~.
- Publicly available products featuring wet snow coverage such as the ~~one~~ 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 ~~depend on multi-platform data fusion (optical and radar data) and therefore lack continuous, weather independent coverage; and (iii)~~

they are prone to ~~artifacts due to the SAR acquisition geometry~~ topographic distortions caused by variable SAR acquisition geometries. Regarding the latter, in mountainous terrain, the oblique, right-looking viewing geometry of the ~~Sentinel-1 S1~~ satellites leads to foreshortening, layover, shadowing and highly varying ground resolution. Shadowing effects can be minimized by producing composites of radiometrically terrain-corrected (RTC) images from ascending and descending orbits (Small et al., 2022). ~~By combining data in this way, mountainous terrain is viewed from two different angles, thus allowing for compensation of missing data (shadow) in an individual orbit (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 ~~the so-called~~ 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-effects and thereby reduces noise by ~~averaging~~ applying weighted averaging in areas visible in ~~both multiple~~ orbits. Furthermore, it allows ~~to combine~~ combination of information gathered from different ~~orbit~~ thereby permitting to increase temporal resolution to more than the orbit repeat 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 ~~Sentinel-1 S1~~ processing workflow, we improved ~~temporal and spatial resolutions~~ spatial resolution compared to current ~~products such as Karbou et al. (2021). We~~ altitude-melting diagrams such as 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 km^2) in the area of Davos, Switzerland, and compared it to a data set of observed wet snow avalanches. 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 validated the ~~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. ~~With this study, we aim at providing information on wet snow avalanche preconditioning~~ This allowed us to perform validation assessment across the entire time series rather than only during cloud free days, a limitation endemic to optical missions (Li et al., 2025).

2 Data and methods

The study area is in the region of Davos, Switzerland (see Fig. 1), covering 400 km^2 and elevation ranges between ~~1'542 and 3'225~~ 1542 and 3225 m a.s.l. (according to Federal Office of Topography and Swisstopo, 2022). The site is characterized by steep, mountainous terrain ~~and, with slope values ranging from 0 to 86 and a median of 28, and~~ the presence of seasonal snow cover. Mean values of daily temperature in ~~Davos (1'590 m a.s.l.) vary from -5° to 13°C (MeteoBlue).~~ 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).

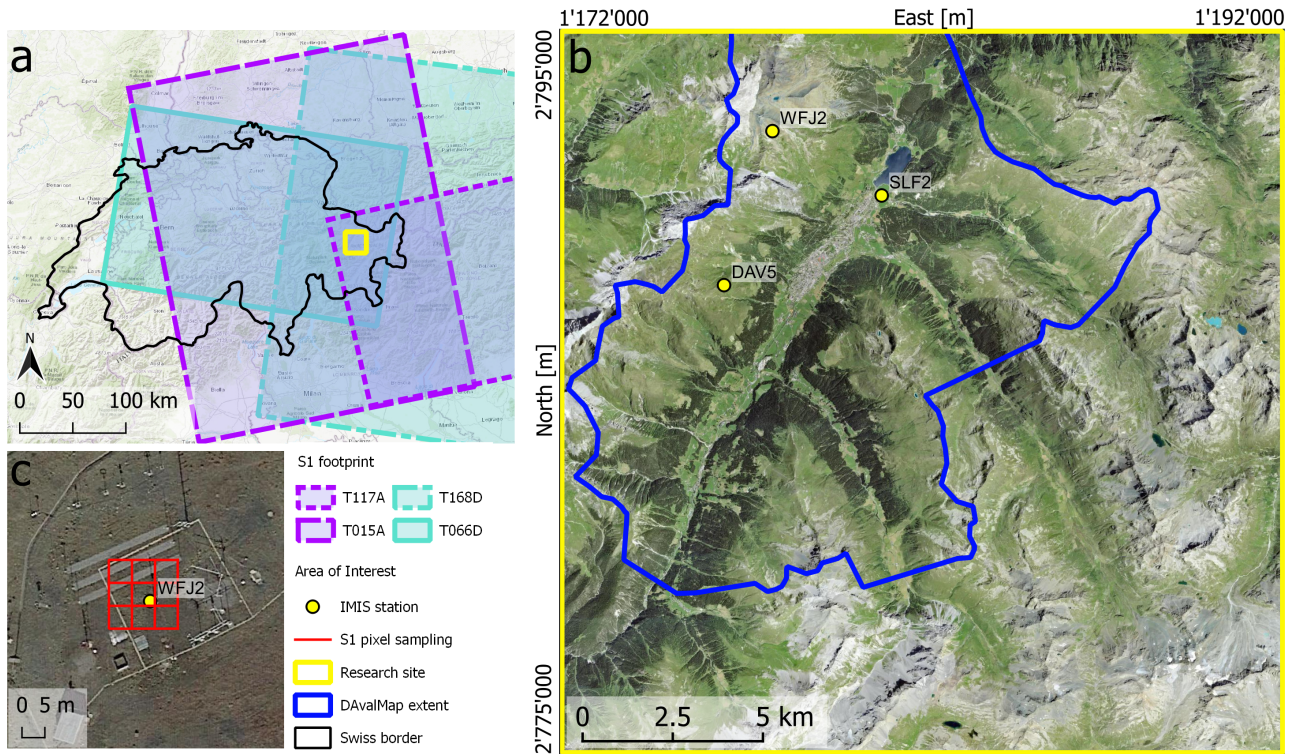


Figure 1. Overview of the area of research on three scales. (A) Outline of the Sentinel-1 footprints in relation ~~also~~ to the research site of interest ([Basemap](#) © Esri). (b) Area of study (yellow outline, displayed in reference system CH1903+/LV95, with EPSG: 2056, [Basemap](#) © Esri), extent 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).

We used SAR data from the European Space Agency's ~~Sentinel-1~~[S1](#) satellites. The mission provides C-band data with a central frequency of 5.405 GHz in the two ~~polarizations~~[polarisations](#) VV and VH. ~~Sentinel-1~~[S1](#) has an orbital repeat cycle over central Europe every six ~~to twelve days~~; ~~however, depending on the location, revisit times can go down to 36 h, when exploiting a combination of all available tracks and orbits~~[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 ~~66~~[066](#) and [168](#) (descending) ~~and 15~~[as well as 015 and 177](#) (ascending; Fig. 1) in interferometric wide (IW) swath mode, ~~where~~. ~~Hereby~~, single-look-complex (SLC) data ~~offer~~[have](#) a pixel spacing of ~ 2.3 m in slant range and ~ 14.1 m in azimuth (Bourbigot et al., 2016). ~~The Sentinel-1~~[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](#) ~~are~~[were](#) acquired at 05:34 ([track 066](#)), [05:27 \(track 168\)](#) UTC on the descending ~~track~~[tracks](#) and at 17:15 ~~UTC two days later~~[\(track 088\)](#) and 17:07 ([track 117](#)) UTC on the ascending ~~track~~[, leading tracks on consecutive days in this acquisition order](#) (illustration in appendix Fig. A1). This lead

to a time difference ~~between~~ within the resulting composites of less than 60 h (~~in other parts of Switzerland a lag of 36 h can be achieved~~). The revisit time in our data set is six days, but for current projects this would be reduced to 12 days due to the Sentinel-1B outage in December 2021 (European Space Agency, 2022). 84 h.

100 We applied radiometric terrain correction (~~gamma0, following Small et al., 2022~~) (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 ~~one ascending and one descending~~ 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 ~~both tracks, thereby slightly diverging from all tracks, following~~ the processing chain by Small et al. (2011) and Small et al. (2022). In cases where information ~~is available in only one~~ was available in some track, i.e., lying in radar shadow in ~~the other~~ others, only the available orbit was considered (~~as in Small, 2012; Small et al., 2022~~) (as in Small et al., 2022). In total, we produced ~~206 LRW composites, 58 for the period August 2018 to July 2019, 58 for August 2019 to July 2020, and 59 for August 2020 to July 2021. Eight composites were discarded because~~ 424 LRW composites. To maximise consistency, composites missing one of the ~~tracks was not available~~ four tracks were discarded (see Tab. A1). ~~To minimize~~ 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 ~~, thereby trading-off for the time-series analysis, thereby executing a trade-off~~ between a loss in detail and the influence of outliers.

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 ~~Sentinel-1 S1~~. In case of a stronger signal diminution, wet snow ~~is~~ was assumed. No standard approach for the selection of a reference image is yet established, leaving space for potential differences in results ~~As reference~~ (Li et al., 2025). Nagler et al. (2016) used a single image from summer, where the least amount of (melting) snow ~~is assumed~~ was assumed to be present in the scene. Rather than relying on a single image, we ~~calculate~~ calculated a median backscatter value per pixel over the entire available time series and ~~use~~ used this value as a "dry" reference (indicated in black in Fig. 2). With this approach, we ~~forego~~ cope with the challenge of finding a suitable reference image (~~see Karbou et al., 2021~~), 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 selected this restrictive approach to optimize the balance between application effectiveness and interpretation complexity.

125 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 ~~Sentinel-1 S1~~ would be less reliable. A ~~5x5-m~~ digital terrain model (DTM) provided by swisstopo ~~was used~~ (Federal Office of Topography and Swisstopo, 2022). ~~Aspect dependency analysis was performed by classifying the DTM into~~ with ground sampling distance 5x5 m was considered to perform aspect dependency analysis in four aspect categories (N: ~~315-45~~ 315-45, E: ~~45-135~~ 45-135, S: ~~135-225~~ 135-225, W: ~~225-315~~ 225-315) (Federal Office of Topography and Swisstopo, 2022). Information on the distribution of water bodies was taken from the high resolution water and wetness (WAW) layer created

by Copernicus (European Environment Agency, 2020). The data ~~is was~~ provided at a 10x10 m grid scale ~~and was~~, acquired between 2012 and 2018, and published in 2020. The land classes were resampled to match the ~~Sentinel-1 DTM~~ pixel grid using nearest neighbour to ~~assure the consistency of classes~~ 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 et al., 2015). ~~Spatial filtering was performed using~~ 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 ~~analyzed~~ analysed the sensitivity of SAR backscatter to snowpack characteristics to identify the features influencing ~~Sentinel-1 signal~~ S1 backscatter on an RTC level by computing the correlation with respect to a variety of both measured and modelled parameters. Second, we compared the wet snow maps from ~~Sentinel-1~~ S1 to recorded wet snow avalanches.

2.1.1 Modelled Snowpack characteristics from SNOWPACK

The SNOWPACK snow cover model ~~has been~~ was developed to support an operational avalanche warning service based on the intercantonal 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. Specifically, 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 snow with a simplified model (Hirashima et al., 2010) or with full Richards Equations (Wever et al., 2014) and water ~~vapor~~ vapour transport in snow (Jafari et al., 2022). SNOWPACK is used by several countries for their operational avalanche warning services (Morin et al., 2020) but also in research. SNOWPACK is provided alongside its meteorological preprocessor MeteoIO (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 means that the simulations did not model soil, relying on a Dirichlet lower boundary condition (upper soil temperature). ~~Moreover, the~~ The upper boundary condition (energy exchange between the snow or soil and the atmosphere) relied on either a measured snow ~~, a~~ or soil surface temperature (Dirichlet when the surface temperature ~~is was~~ less than -1 C) or a parameterized incoming long wave radiation (Neumann) ~~that evaluates the atmospheric cloudiness based on~~ 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 ~~parameterizing~~ 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.) ~~are were~~ within the boundaries of the research site (Fig. 1), the IMIS measurements ~~are hence covering different were hence covering a variety of~~ elevations within the region of interest in a flat field simulation. ~~Timespan The timespan~~ covered by available SNOWPACK data ~~is was~~ September 2017 to August 2020. Due to a sensor failure, ~~data from no SNOWPACK simulations could be performed at the~~ SLF2 ~~are not available for season station for the~~ 2018-19 season and hence the corresponding SNOWPACK data was not used in this analysis ~~due to lower reliability~~.

Our SNOWPACK runs provided outputs every 3 hours and we used the time closest to ~~Sentinel-1 S1~~ acquisition on the corresponding day: namely 06:00 to match descending SAR image ~~acquisition acquisitions~~ and 18:00 to match the ascending ~~acquisition acquisitions~~ (UTC+1). We averaged the data from these ~~two SNOWPACK timestamps, refraining from calculating a composite according to the applied weighting in the SAR images, as the IMIS stations are generally situated in flat terrain and so the weighting of the two orbits is similar~~ 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 ~~2020-2021~~.

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 ~~against~~ at the corresponding station ~~location locations~~ over time (see ~~appendices A3, A4 and A5~~ 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), ~~entries occurring more than 25% of the time were ignored in the correlation analysis. Significance 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, ~~we classified wet snow within different elevation classes, and calculated the ratio of pixels identified as wet snow in comparison to no/dry snow images following the plot design by Karbou et al. (2021). Elevation classes have been set to 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 and the range defined between increments, ranging from 1500 and to 3000 m a.s.l., resulting in 15 different elevation steps. Temporal classes were aligned according to the ascending Sentinel-1 classification followed the timing of ascending S1 acquisitions. Areas with a slope angle slope angles below 28 have been masked out were excluded to focus on avalanche release areas (Bühler et al., 2018). We calculated the ratio by dividing the amount 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 ~~by the total amount present pixels available at each~~, and $N_{\text{total}}(z)$ is the total number of non-void pixels in that elevation band.

2.1.2 Wet snow avalanche catalogue

200 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 ~~has-been-was~~ set up by the swiss avalanche warning service ~~and-is-~~ designed to be an avalanche inventory covering about 180 km². Systematic mapping ~~has-been-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 ~~has-been-was~~ excluded to match the research area, ~~which has-been-~~ fitted to be within ~~the-Swiss~~ national boundaries for data consistency. Mappings
205 outside the DAvalMap ~~are-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) ~~are-not-recorded-were not recorded in the catalogue~~, thereby setting a minimum size of avalanches within the data set. The data includes information on the release date, the snow ~~conditions-condition~~ (wet/dry snow avalanche) and the elevation zone at release.

For this study, we ~~select-selected~~ only the avalanches that ~~are-were~~ classified as wet snow avalanches ~~and-are~~ situated within
210 the research site (~~see-Fig. 1~~) ~~and-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). Temporal matching was performed by pooling the observed avalanches into one elevation-time bin by combining the avalanches occurring ~~up-to three days before ascending image acquisition, the ones occurring at the acquisition date itself and until to two days after the ascending image acquisition-during the timerange one day before the~~
215 ~~LRW timespan to one day after~~ (for illustration see appendix Fig. ~~A2A1~~). This allowed ~~to-cover coverage of~~ a continuous time frame ~~by-means-of-using~~ a six day interval. This temporal matching also ~~includes-included~~ avalanches after image acquisition. However, this is ~~a-the most~~ robust solution to approximate the wetness state of the snowpack and its corresponding proneness to wet snow avalanches ~~for-it-minimized, as it minimised~~ temporal differences between avalanches ~~to-and~~ acquisitions. In ~~season 2019-20-the season 2019-20,~~ the size restriction of the recorded avalanches was handled less ~~strict-strictly~~, also including
220 smaller loose snow avalanches which would have been excluded in the other years. The used data from DAvalMap ~~contains contained~~ 77, 723 and 261 wet snow avalanches for the seasons ~~2018-19, 2019-20 and 2020-21~~ ~~2018-19, 2019-20 and 2020-21,~~ respectively.

3 Results

3.1 ~~Polarization-Polarisation~~ dependent ~~Sentinel-1-S1~~ backscatter time series analysis

225 ~~The time series for both the VV and VH polarization over two and a half years at the IMIS station of WFJ2 are shown in Fig. 2a, with the corresponding median value indicated with dashed lines. Backscatter falling 2 dB below the median (see Fig. 2a) is categorized as presence of wet snow (indicated in shading in Fig. 2). Generally, the cross-polarized data shows a lower backscatter value (e.g. see Fig. 2a), its median at WFJ being 8.35 dB below the median of the co-polarized data (see Tab. 1). The median backscatter of the DAV5 station is found several dB lower than the other stations (see Tab. 1).~~

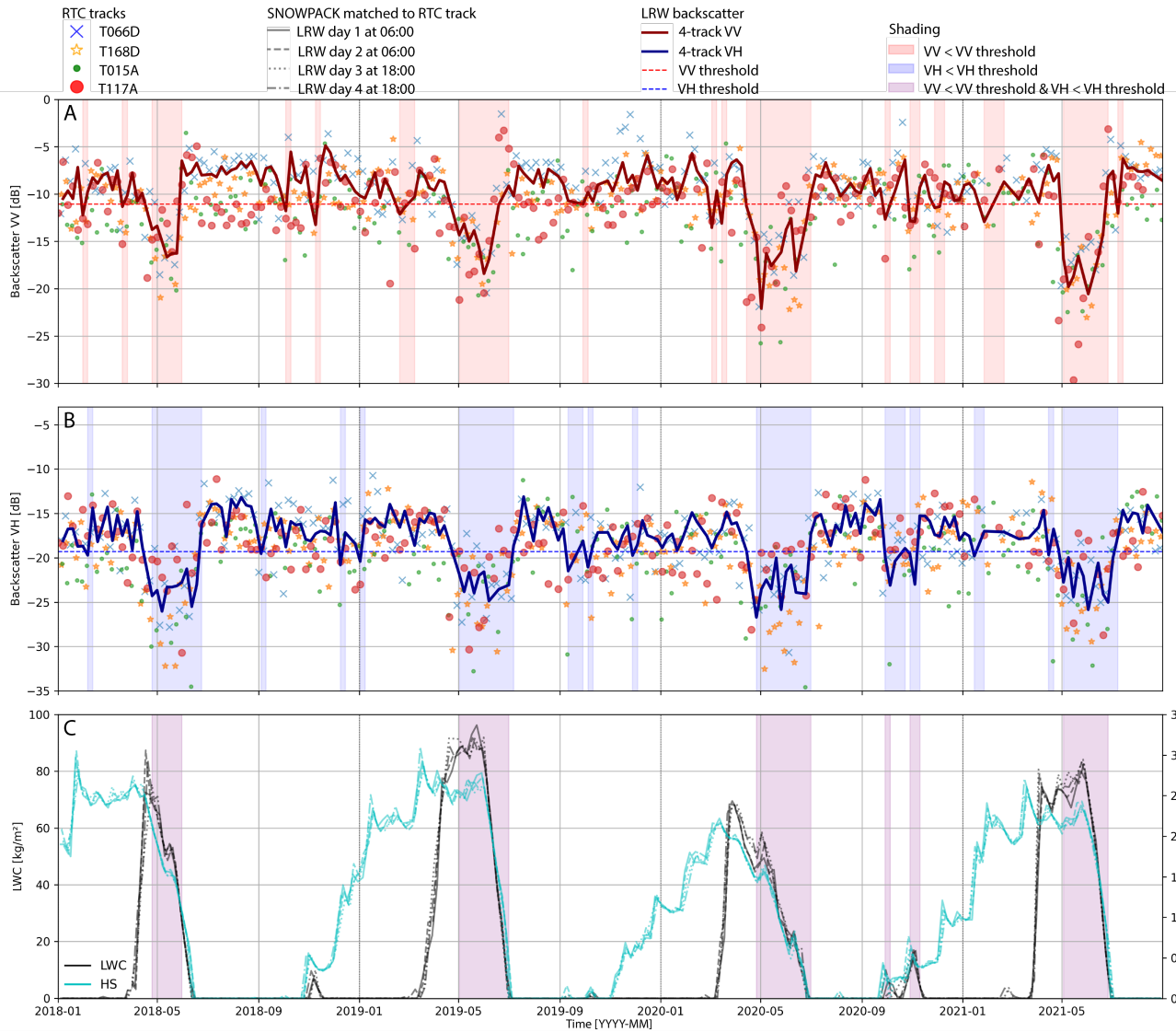


Figure 2. Time series of wet-snow evolution over 4 melting seasons from January 2018 until August 2020-2021 at Weissfluhjoch (WFJ2). The upper-panel (aA) shows and B) show the time series extracted from the pixel within which the IMIS station is situated in both co- (A) and cross-polarization states using a three sample rolling mean over cross-polarized (B) S1 data. The markers indicate the time-series 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 polarizationpolarisation. The lower-panel (bC) shows the time series of modelled-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.

Table 1. Median of ~~rolling-mean-of-Sentinel-1-S1~~ backscatter per ~~polarizations-polarisations~~ at the three different stations ~~within the timeframe of 01.2018 to 08.2021.~~

Polarization Polarisation	SLF2	DAV5	WFJ2
VV	-10.13 -10.05	-14.19 -13.49	-9.54 -9.07
VH	-17.71 -17.92	-20.25 -20.67	-17.88 -17.30

At ~~WFJ~~~~WFJ2~~, the backscatter in both ~~polarizations-polarisations~~ (VV & VH) fell clearly (> 3 dB) ~~below-reaching beyond~~ the set threshold for wet snow in late spring/early summer in each season, ~~thereby~~ coinciding with snow melt ~~in-at~~ high alpine altitudes. Sporadic ~~signal-losses~~~~decreases of backscatter~~ reaching below the threshold ~~can-be-found~~~~were also observed~~, where SNOWPACK data ~~does-not-suggest~~~~did not suggest the~~ presence of snow wetness,~~however only one of such events (February 2018) is detected in both polarizations. In other-~~. However, for all such spurious events, ~~such-as February 2019 or December 2019, results diverge the results diverged~~ depending on the ~~polarization-The~~~~polarisation~~ and they are accounted for when using the combined ~~polarisation~~ approach. So, while the combination of VV and VH ~~polarization-polarisation~~ (indicated by overlaid shadings in Fig. 2) ~~shortens~~~~shortened~~ the timespan of detected wet snow, ~~while-minimizing-the-it~~ ~~minimised the potentially false~~ detection during off-season periods. ~~While similar results were found in the station~~ 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 time series the 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 stability with more short-lived peaks (appendix Fig. A4). The median backscatter of the DAV5 station~~ ~~does not show a clear trend but rather extreme short lived peaks and hence unstable signal. This also results in lower backscatter median as shown in-~~ was observed to be several dB lower than the other stations (Tab. 1).

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

Indication for negative correlation between S1 backscatter and ~~SNOWPACKS-modelled-liquid-water-contents~~ ~~SNOWPACK modelled LWC as well as measured runoff~~ could be found ~~across-at~~ all stations, ~~polarizations-and kernel-sizes (see appendices A3, A4 and A5 in most tracks.~~ These correlations ranged ~~between -0.25 to -0.59 (spearmans rank)-and -0.25,~~ for LWC, between ~~-0.12 (VV; SLF2) to -0.42 (VV; WFJ2) in Spearmans rank and -0.16 (RMSE: 13.93) to -0.64 (Pearsons)-with an RMSE between 2.05 and 4.35 (see appendix A3-0.30 (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, ~~S1 indicated a negative correlation with the temperature variables was indicated, and~~ a positive correlation with SNOWPACK's potential albedo, however ~~this could not neither could~~ be found in the other ~~stations locations. station locations.~~

260 3.2 Spatial distribution and elevation dependent melting

Time-elevation dependent melting seasonality was detected across the time series independent of ~~polarization~~ polarisation and slope aspect (Fig. 33): ~~In season 2018-19 the~~ the seasons 2018–19 and 2020–21, the highest wet snow ratios were measured (~~VV polarization, mid March, classified into wet snow ratio of 80-90-70-80 %~~). ~~The maximum ratios that were reached throughout the season 2019-20 amounted to 50-60 %~~. Increasing ratio values (above ~~0.230 %~~) were detected earlier in the
265 season of ~~2019-20 between September to May in 2020-21 between November to February at~~ elevations ranging from ~~1800 to 2400-1500 to 2200 m a.s.l.~~ ~~The maximum ratios that were reached throughout this season amounted to 60-70 %~~. ~~In 2020-21 In 2020-21~~ (see Fig. 3)3), the wet snow ratio rose again, achieving up to ~~70-80 % between end of April to end of March. Wet 70-80 % mid May.~~

The wet snow ratio mainly diverged between ~~polarization~~ polarisation states in late summer and autumn periods, where ~~VV polarization indicates the VV polarisation indicated~~ maximum wet snow ratio (see equ. 1) values of up to ~~2-20 %~~, whereas ~~VH polarization indicates the VH polarisation indicated~~ a continuous time-elevation dependent increase in wet snow ratio with up to 40 % wet snow pixels per elevation class. ~~VH indicates (appendix Fig. A8 and A9). VH indicated~~ higher ratio values than VV polarized data ~~in at~~ lower elevation classes (~~1500-1900-1500-1900 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~~
275 ~~the absence of avalanche-critical conditions and was therefore not the primary focus of this analysis.~~

Masking of ~~landcover~~ land-cover classes such as forest and water bodies had little influence on the resulting time-elevation plots. Large water bodies such as lakes ~~are were~~ mainly situated in the lowest classes and in flatlands, ~~thereby already getting and were thereby already~~ masked out by focusing on hillsides via the minimal slope threshold (~~hence not extra shown in App. A5).~~. On the other ~~endhand~~, the exclusion of ~~forest results forests resulted~~ in measurable changes in elevation-based wet snow
280 mapping (see ~~App. A5: appendix Fig. A5A to B~~) as they also occur in non-flat areas. Forests are known to influence radar backscatter and cover a larger and more diverse landscape than water bodies. However, also their influence ~~is was~~ mainly focused on a specific elevation range below 2000 m a.s.l. (see ~~App. A5: appendix Fig. A5A to B~~) Applying a moving median filter ~~allows to smooth smoothed~~ the time-elevation plots (see ~~App. A5: appendix Fig. A5A to C~~). The ~~achieved noise reduction has noise reduction had~~ less impact in high alpine areas. ~~This is likely because less signal disturbance is present in the first~~
285 ~~ease. Elevation classes in lower elevation regions result in classification differences between,~~ likely because the original signal was already relatively undisturbed. In contrast, at lower elevations, the differences in classification between results with and without noise reduction ~~of can span~~ two classes (from ~~0-10 % to 30-40-0-10% to 30-40%~~ wet snow ratio values), ~~indicating a higher risk of also removing important signal components.~~

The time-elevation plots also clearly ~~shows showed~~ differences in aspects (see Fig. 44). South and East facing slopes showed
290 an ~~earlier increase earlier increase~~ in wet snow ratio to values above 40 % in the season than ~~did~~ West and especially North

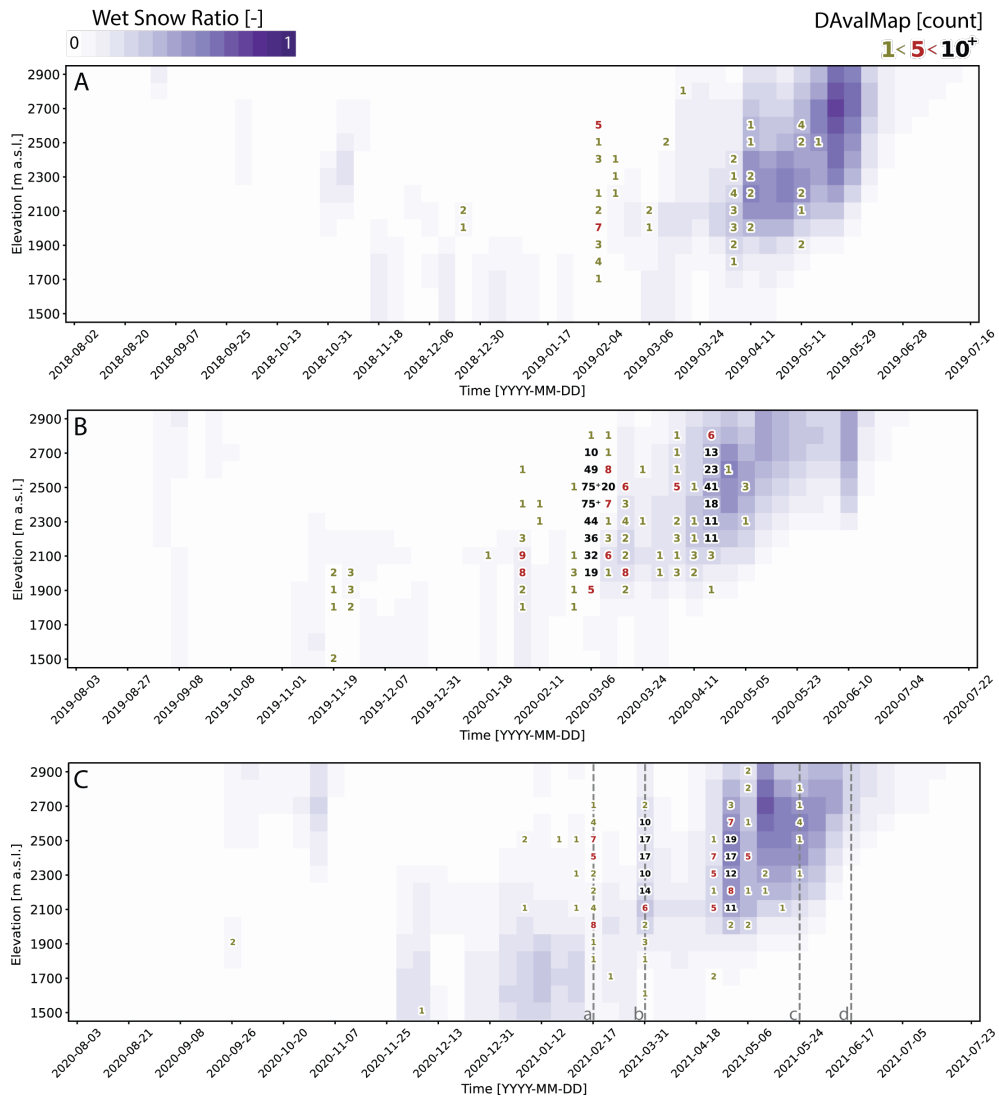


Figure 3. Time-elevation plots of wet snow ratio evolution for ~~VV and VH polarization combined polarized product~~ across three ~~and a~~ ~~halfmelting~~ seasons (~~2018-19A: 01.2018–07.2019~~, ~~2019-20 B: 08.2019–07.2020~~ and ~~2020-21C: 08.2020–07.2021~~) featuring the area of Davos as indicated in Fig. 1, resolved at ~~discrete~~ 100 m elevation bands. The wet snow ratio is the percentage of pixel per elevation band that ~~was were~~ detected as ~~indicating~~ wet snow using S1 data. ~~Circles Coloured numbers~~ indicate ~~a top-down view of a histogram featuring 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). ~~The hue of the circles corresponds to the avalanche count, black corresponds to 4~~ ~~No spatial smoothing~~ or ~~more avalanches~~. ~~Forest areas were masked out and a moving median filter filtering was applied to minimize (these effects can be found in the ffeet of noise appendix A5).~~ ~~Letters a-d~~ ~~Dashed lines and letters a–d in panel C~~ correspond to the timeframes of the wet snow maps displayed in Fig. ~~225~~. Plot design was inspired by Karbou et al. (2021) and Karbou et al. (2022)

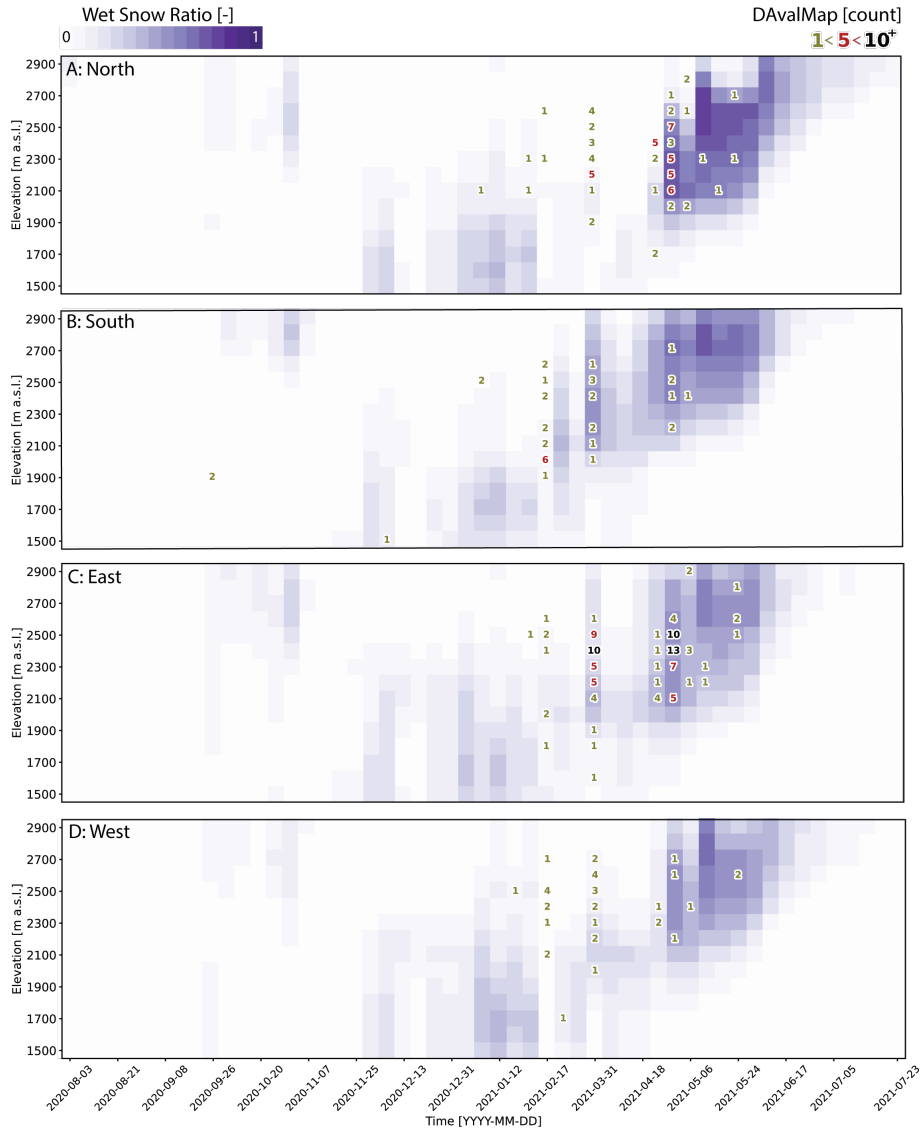


Figure 4. Time-elevation plots of wet snow ratio evolution for VV-polarization combined polarized product for the exemplary seasons of 2020-2021, 2020-2021. Displayed are the time series resolved into the different slope aspects: A: North, B: South, C: East and D: West. The plot encompasses data featuring 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 was/were detected as indicating wet snow using S1 data. Circles-Coloured numbers indicate a top-view of a histogram featuring 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). Letters a-d correspond to the timeframes of the wet snow maps displayed in Fig. 225. Plot design was inspired by Karbou et al. (2021) and Karbou et al. (2022).

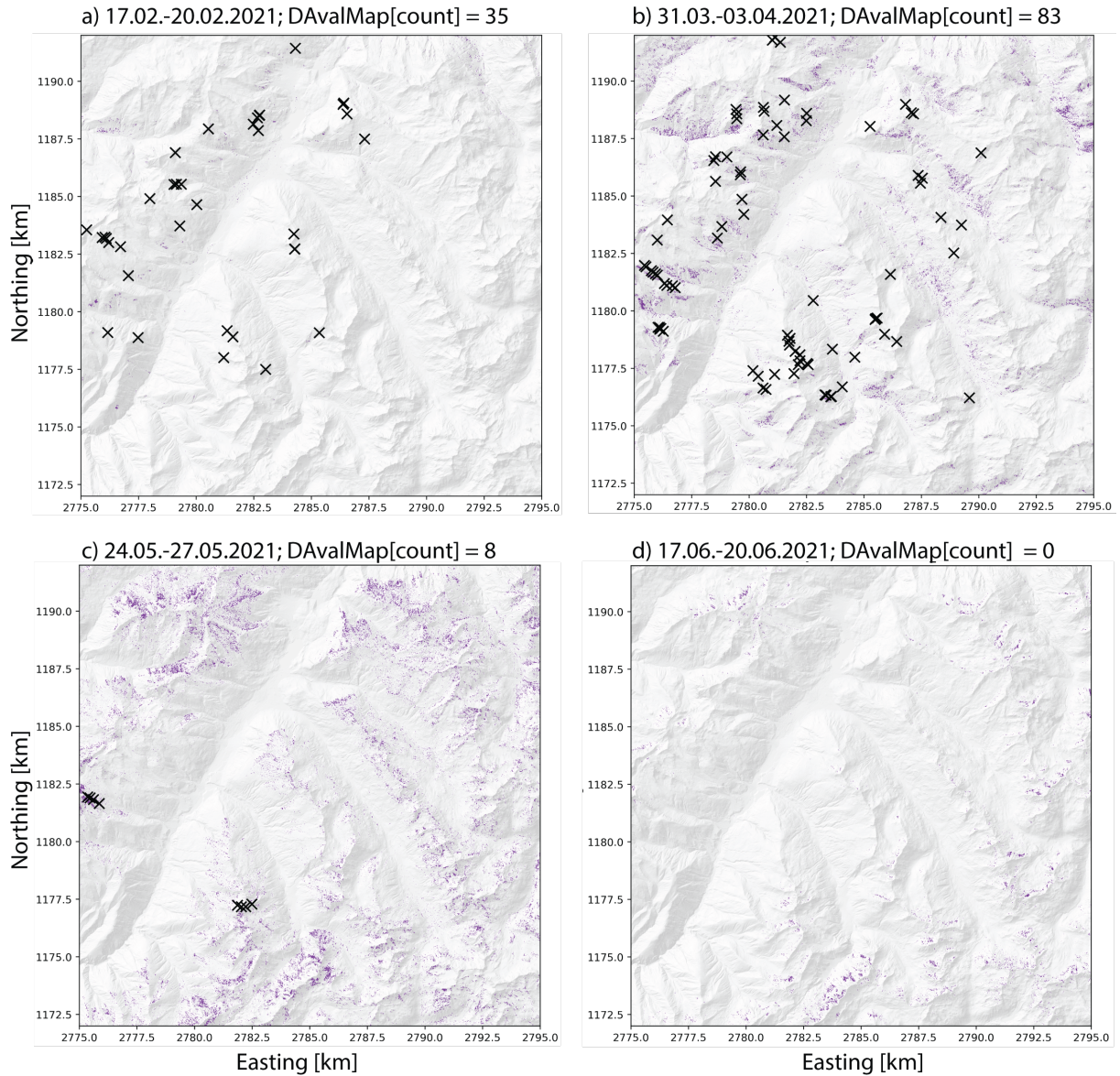


Figure 5. Spatial distribution of the detected wet snow ratio-pixel using the combined polarisation approach and the recorded avalanches in DAvalMap (Hafner et al., 2021) (black crosses) are displayed for four exemplary, different time-intervals-times (a-d) as indicated in Fig. 3 and Fig. 4. The acquisition times-days of the SAR images are indicated in the title per subplot on the left, while the DAvalMap indicates the time-frame-number of summarized wet snow-recorded avalanches within the allocated timewindow (according to the temporal matching illustrated in the appendix A1). Background DEM by © Swisstopo

facing slopes (compare Fig. 4.4B and C to A and D). ~~Highest ratios reaching 90–100~~ The highest ratios reaching 90–100 % wet snow ratio values ~~are were~~ mainly located in North facing slopes, where melting occurs later in the season and over a shorter time period. The same behaviour across time-elevation ~~can be was~~ found in VH polarized data ~~as well as~~, also across all seasons. The aspect-dependency ~~is more relevant if was more relevant when~~ a minimal slope steepness ~~to~~, e.g. 45 (high
295 avalanche danger according to Bühler et al. (2018)) ~~is was~~ defined.

Wet snow ratios ~~do did~~ not show relevant changes before the first surge of wet snow avalanches recorded in DavalMap (see ~~Figs. 3a, 4 and ??~~ Fig. 3A, B and C). Instead, a second increase of avalanche occurrence observed in ~~2018–19 and 2020–21~~ 2018–19 and 2020–21 ranging across various elevation classes (Fig. 3b), ~~is coinciding with a 3B~~, coincided with wet snow ratio values of ~~30 to 40~~ 25 to 30 % in altitudes from ~~2000–2200~~ 2000–2200 m a.s.l. After this second event, a further increase
300 in wet snow ratio characterizes the melting season (Fig. 33). Events of multiple avalanche occurrences that were recorded in DavalMap ~~coincide with~~ coincided with dual-polarized wet snow ratios above ~~40–30~~ % (Fig. 33).

4 Discussion

In this study, we ~~analyzed analysed~~ SAR-based wet snow maps by implementing a new processing chain and validating it with ~~in-situ in-situ~~ measurements and modelled information. By relying on LRW composites, ~~Sentinel-1 data has been S1 data~~
305 was exploited to combine ~~different orbits as well as different~~ backscatter from different tracks. Thus, the information on snow wetness in our study is provided with higher frequency ready-to-use and was considerably less noisy compared with methods used ~~at present previously~~ (European Environment Agency, 2023).

The available ~~Sentinel-1 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
310 the variability of alpine topography (appendix Fig. 7). ~~Additionally, as the Wet/Dry Snow layer fuses Sentinel-1 and -2, it is restricted to i) cloud-free Sentinel-2 acquisitions and to ii) dates where both Sentinel-1 and -2 were acquired. This results in a restricted temporal availability of the product (European Environment Agency, 2023).~~ The discrepancy between the available products and our results is partly linked to the use of the ~~higher resolved SLCs instead of the more highly resolved SLCs rather~~ than ground range detected ~~Sentinel-1 (GRD) S1~~ European Environment Agency (2023); Karbou et al. (2021). ~~Moreover Most~~
315 especially, by using LRW composites, the influence of typical SAR geometry effects, such as shadowing and layover, ~~could be minimized (see Fig. 5 was mitigated (see appendix Fig. 7)).~~ Having fewer areas ~~which that~~ lack data and ~~a better potentially improving the~~ temporal resolution is important, for example for avalanche forecasting where accurate timing of capturing the start of the wetting of the 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
320 challenging. Consequently, we relied on comparing data with ~~in-situ in-situ~~ measurements, where available, to ~~minimize uncertainties in minimise uncertainties related to~~ the reference data. The SAR Wet Snow and Wet/Dry Snow layer were validated ~~by 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). Since the acquisition technique is still based on remote sensing approaches, the bi-

ases contained might also be similar, hence we believe our comparison to an independent product ~~, though not covering the same~~
325 ~~area~~, 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 ~~compare~~ compared the results to snowpack characteristics instead of snow extent, thereby more reliably ~~approximate~~
~~what is actually influencing~~ approximating what actually influences the signal. Nevertheless, an example comparison of a wet
snow mask from our multi-track LRW to the SAR Wet Snow layers and the best temprally matching false colour imagery from
330 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.

~~The~~ SAR backscatter is influenced by many factors, therefore to identify wet snow, a threshold needs to be set in com-
parison 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
335 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 ~~have~~ used the established and widely applied threshold of 2 dB for ~~Sentinel-1 data~~
~~(Nagler et al., 2021, 2016, results indicated in Fig. 3).~~ Even though S1 data (Nagler et al., 2021, 2016, results indicated in Fig. 2)
. Although an adaptive backscatter analysis sounds promising, there ~~are~~ were no widely available and regularly updated land
cover products with suitable spatial resolution available ~~for our case and we try to minimize the~~ in our case, and the most robust
340 algorithm minimises requirements on the input data.

As previously mentioned, no standard approach for the generation of a reference image has been established. The Coper-
nicus 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)~~ (e.g., Karbou et al., 2021; Li et al., 2025) or use a single reference image featuring either dry or no
345 snow conditions (e.g., Mendes et al., 2022). Increasing temporal baselines between the image of interest and the reference
image, ~~also result in increase of 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~~ "all season" median,
we have wet snow contamination in the reference; however the results of our study indicate applicability of the method (see
Fig. 32) and follow the process applied in Lievens et al. (2019). The advantage of reference image generation in that way ~~are~~
350 ~~low is lower~~ processing costs, ~~low amount of input, reduced input requirements,~~ a high automation level, ~~data and easy and~~
simplified update-ability.

Validation ~~has been was~~ performed using SNOWPACK data at three IMIS stations SLF2, DAV5, WFJ2 (~~appendixes A3, A4~~
~~and A5~~ Fig. 6 and appendices A6 and A7). This ~~allows~~ 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.
355 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, ~~such as the infrastructures around the WFJ2.~~ 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 ~~have~~ 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 ~~have~~ 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 ~~was and the water runoff were~~ among the strongest correlation values (~~see appendixes A3, A4 and A5~~ with the correlation assessment (Fig. 6 and appendixes A6 and A7)). This coincides with the ongoing understanding of the measured ~~signal loss backscatter decrease~~ being related to the amount of liquid water within a snowpack (e.g., Lund et al., 2022; Nagler et al., 2021). ~~With increasing water presence, radar attenuation increases and measured signal decreases. (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 ~~is 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 ~~correlation values show~~ 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. (2024) used a dual-polarized approach. In our results, the correlation values showed similar trends between the different ~~polarization modes (see appendixes A3, A4 and A5)~~ polarisation modes (Fig. 6 and appendixes A6 and A7). The strongest divergence between the wet snow ratio extracted from VV and VH ~~polarization can be found~~ polarisation was observed in late summer early autumn, ~~when the VH polarization indicates 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 ~~non-masked occurrence of~~ shrubs 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 ~~shows showed~~ similar results for both ~~polarization modes. A polarisation modes. The applied~~ combination of both ~~polarization's as done by e.g. Karbou et al. (2021) could result~~ polarisations resulted in fewer misclassification, however, the approach ~~will also result also results~~ in a loss of detail. ~~A separate analysis of the polarization state also solves~~ 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 ~~done by (Karbou et al., 2021). Future research might examine the potential of a hotspot approach based on separate mapping of wet snow per polarization state for wet snow monitoring. 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 ~~Sentinel-1 S1~~ (see Fig. 3). 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 ~~gap may temporal gap might~~ be attributed to the combination of four ~~aspects effects~~: i) the temporal gap between variables, as we ~~make use of Sentinel-1 data acquired made use of weighted S1~~

only every ~~6 days,~~ or 12 days in case of a discharged composite (see appendix Table A1) ii) the potential filtering out of the
 395 onset of wetting in a snowpack as noise ~~due to temporal or spatial filters applied,~~ 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 ~~in~~
~~our case, descending images~~ the images, as the snowpack ~~might refreeze during a clear cold night's~~ characteristics change over
the course of the day (as also the data by Marin et al. (2020) suggest). If and how these factors ~~contribute~~ contributed to the
 miss of the first avalanche surge ~~needs to~~ should be investigated further in the future.

400 Our results ~~show~~ showed an earlier start of the melting season ~~in at~~ lower elevation zones with increasing melting later in
 the season in higher elevation zones (see Fig. 33). This agrees with the station data, where at the ~~higher more highly~~ situated
 stations winter lasts longer ~~and they have,~~ with a more pronounced and later melting season. Lower elevations typically have a
 shorter and warmer winter season. This ~~is leading~~ leads to a shorter period of signal attenuation during the melting phase than
~~in at~~ stations with more snow coverage in higher elevation zones.

405 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 moni-
 tored perimeter is smaller than the research site, so avalanches outside of the ~~parameter are~~ perimeter were not systematically
 monitored and mapped. This results in elevation bins above approx. 2800 m a.s.l. ~~to contain~~ 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
 410 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 ~~wrongly~~ 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 moun-
 taintops, this potential classification error becomes negligible. iii) The information ~~is based on in-situ~~ was based on in-situ
 415 observations dependent on good visibility, so the assigned release date ~~may~~ might include uncertainties up to several days.
~~However, with our Sentinel-1~~ Keeping in mind our S1 timeframe of six days ~~the influence will,~~ the influence of potentially
~~incorrectly recorded release date would~~ be minimal. ~~Despite those~~ 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
 420 challenges, DAvalMap provides a unique opportunity to compare observed activity with snow wetting from ~~Sentinel-1~~ S1 data.

The ~~first initial~~ surge of wet snow avalanches ~~could not be matched to a relevant~~ did not coincide with a pronounced increase
 in the wet snow ratio across ~~all any of the investigated~~ seasons (see Fig. 3). ~~This might be due to i) uncertainties in the DAvalMap~~
~~library such as dry/wet classification errors (see above); ii) the use of a median potentially biased by wet snow as reference~~
~~value; iii) an insufficient capability of temporally resolving the avalanche release dynamics based on the used SAR data.~~ 3).
 425 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 ~~to capture the capture~~ of different stages of the melting due to differences in sensitivity to water presence with varying wavelengths, thereby enabling ~~to better estimate~~ better estimates of the LWC and not only the presence of liquid water.

5 Conclusions

We used ~~Sentinel-1 S1~~ SAR multi-track composites to derive snow wetness at different elevations and slope aspects ~~in alpine~~ areas around Davos. By exploiting LRW composites created ~~on SLC data from SLC products~~, we were able to more accurately resolve spatial variability of the snow wetness in alpine terrain ~~. We validated than currently available products. We evaluated~~ the performance of our approach by cross-correlating the data to in-situ measured ~~, and~~ modelled snowpack variables ~~and as~~ well as a wet snow avalanche inventory, finding relevant correlation between ~~Sentinel-1 S1~~ backscatter and modelled liquid water content, as well as good agreement with the release of wet snow avalanches ~~coincided~~ coinciding with the wetting of ~~the snowpack at the~~ corresponding elevations, ~~with the aside from an~~ exception of the ~~first wet snow avalanche surge every~~ first surge of wet snow avalanches in spring. Our results ~~indicate potential of Sentinel-1 based~~ 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 ~~provided by the Sentinel-1 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.

~~Follow-up research in the area of Davos should make use of other available Sentinel-1 tracks, namely 117 and 168 to improve temporal resolution to the available revisit time instead of being restricted to the orbit repeat interval. This could help understand the underlying mechanisms better, even though the multi-orbit data is only available for selected regions. Despite this, our results suggests that the wet snow ratio per elevation bin calculated from SAR data may in the future help increase the accuracy of forecasting wet snow avalanches by nowcasting wet snow distribution also over large, challenging and remote areas.~~

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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
570 has been performed using the gamma software. The DAvalMap library and SNOWPACK data for WFJ station can be requested from SLF.

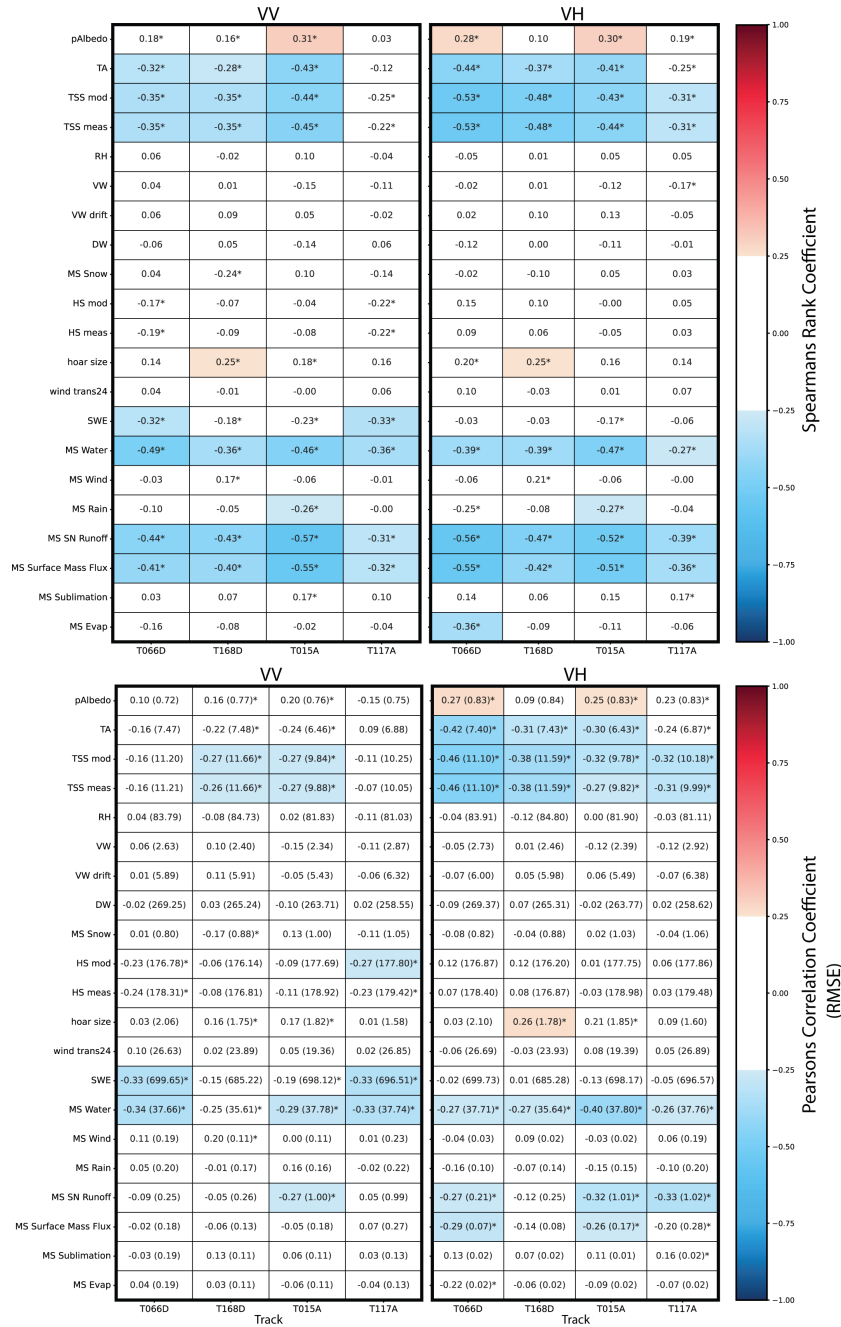


Figure 6. Correlation of analysed SNOWPACK variables compared to the median VV Sentinel-1 backscatter time series at the WFJ2 station per track (location see Fig. 1). The table includes the results per polarisation state for 3x3 window size. Included are the Spearman's (top) and Pearson's (bottom) correlation coefficient and the RMSE calculated between the Pearsons 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.

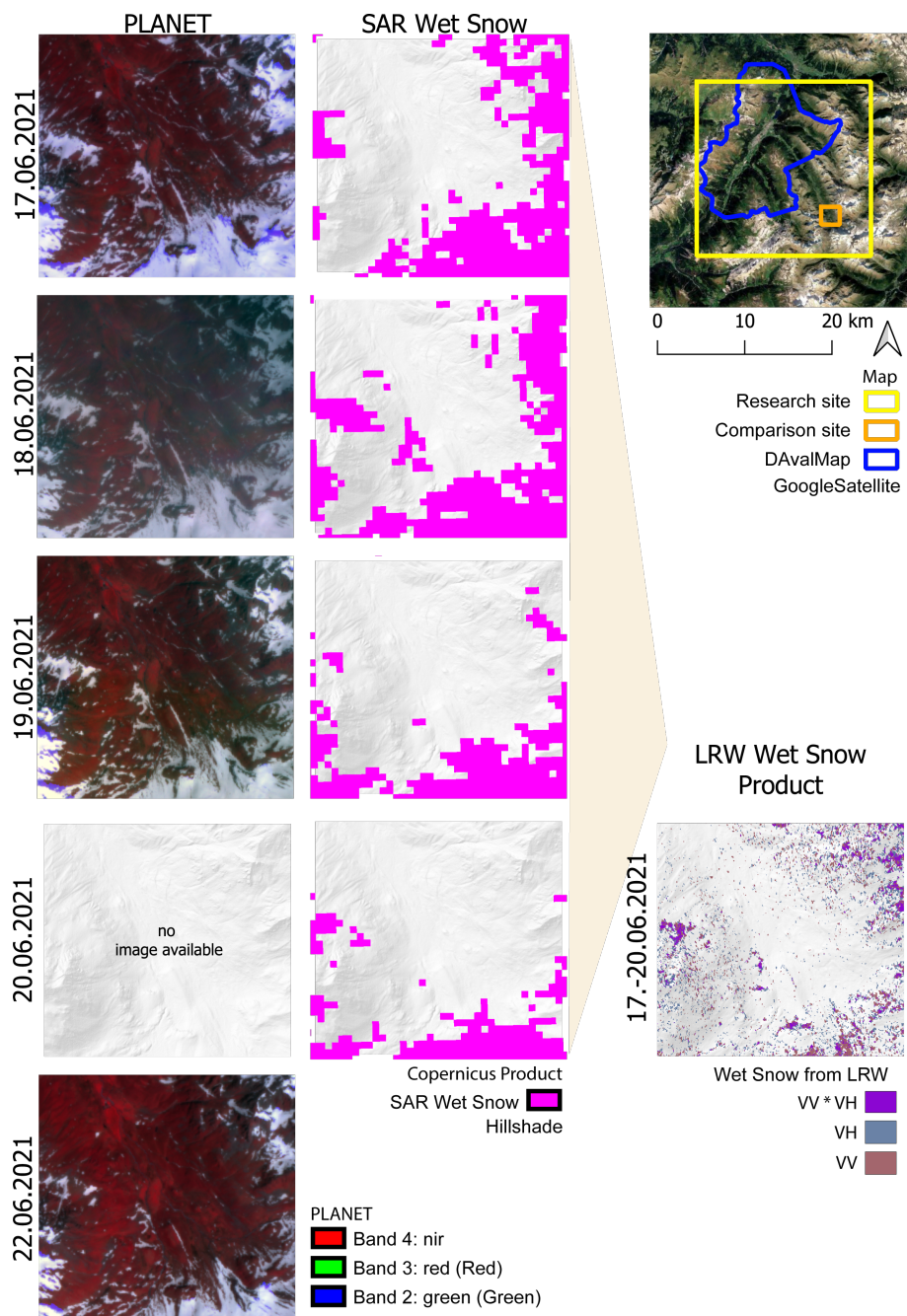


Figure 7. Visual comparison between false colour imagery from PlanetScope (© Planet Labs Inc.), the Copernicus SAR Wet Snow product and the LRW Wet Snow product created from our workflow. The inset map (background map by © Google Maps) shows the location of comparison. Location and time was chosen to 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

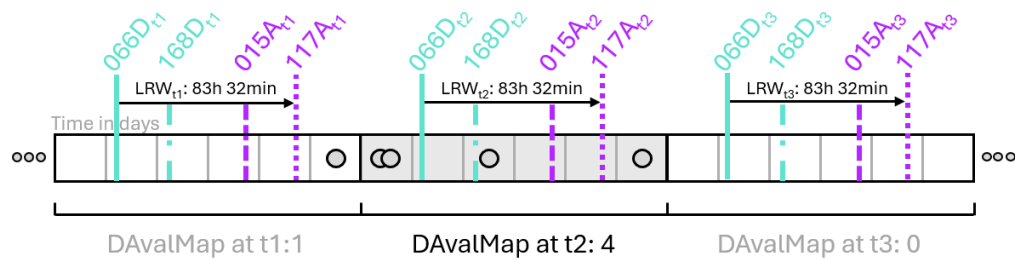


Figure A1. Exemplary illustration of performed temporal binning featuring the SAR acquisition times in descending and ascending tracks to corresponding local resolution composites (shading) in combination with the summed wet snow avalanches. Binning has been optimized to include all recorded wet snow 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.

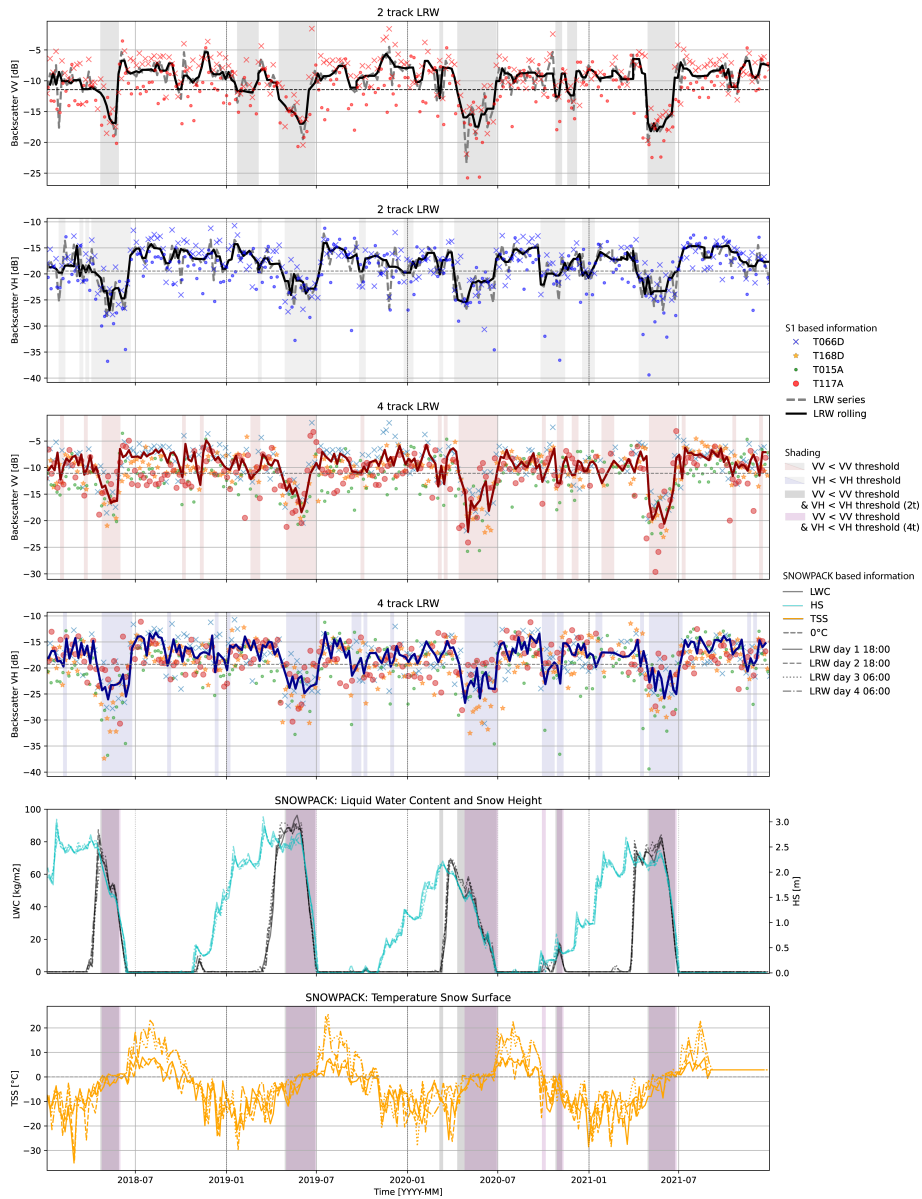


Figure A2. Time series of wet-snow evolution from January 2018 until August 2021 at Weissfluhjoch (WFJ2) for two-track rolling mean (a and b) and four-track LRW (c and d) in comparison to SNOWPACK data (e and f). The first two plots are the time series extracted from the 3x3 window within which the IMIS 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.

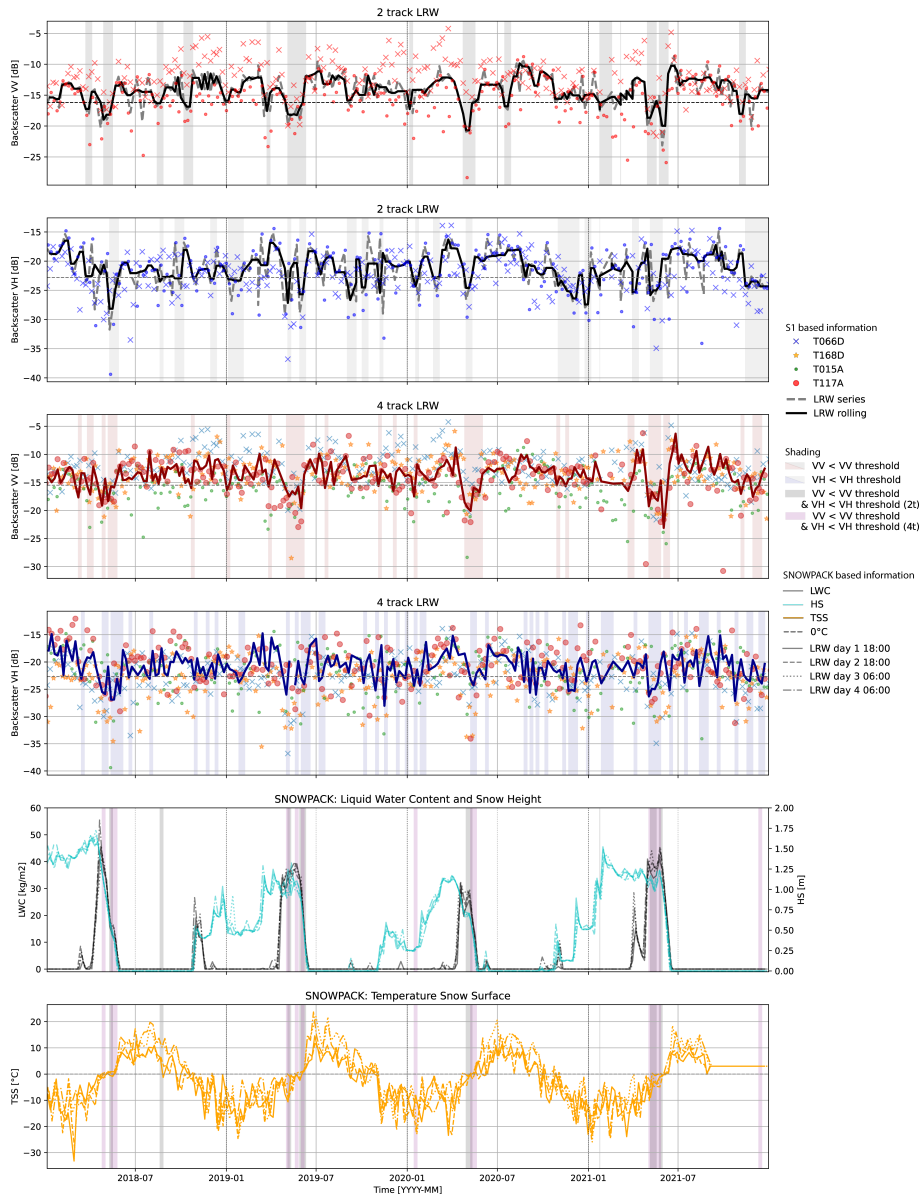


Figure A3. Time series of wet-snow evolution from January 2018 until August 2021 at the DAV5 station for two-track rolling mean (a and b) and four-track LRW (c and d) in comparison to SNOWPACK data (e and f). The first two plots are the time series extracted from the 3x3 window within which the IMIS 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.

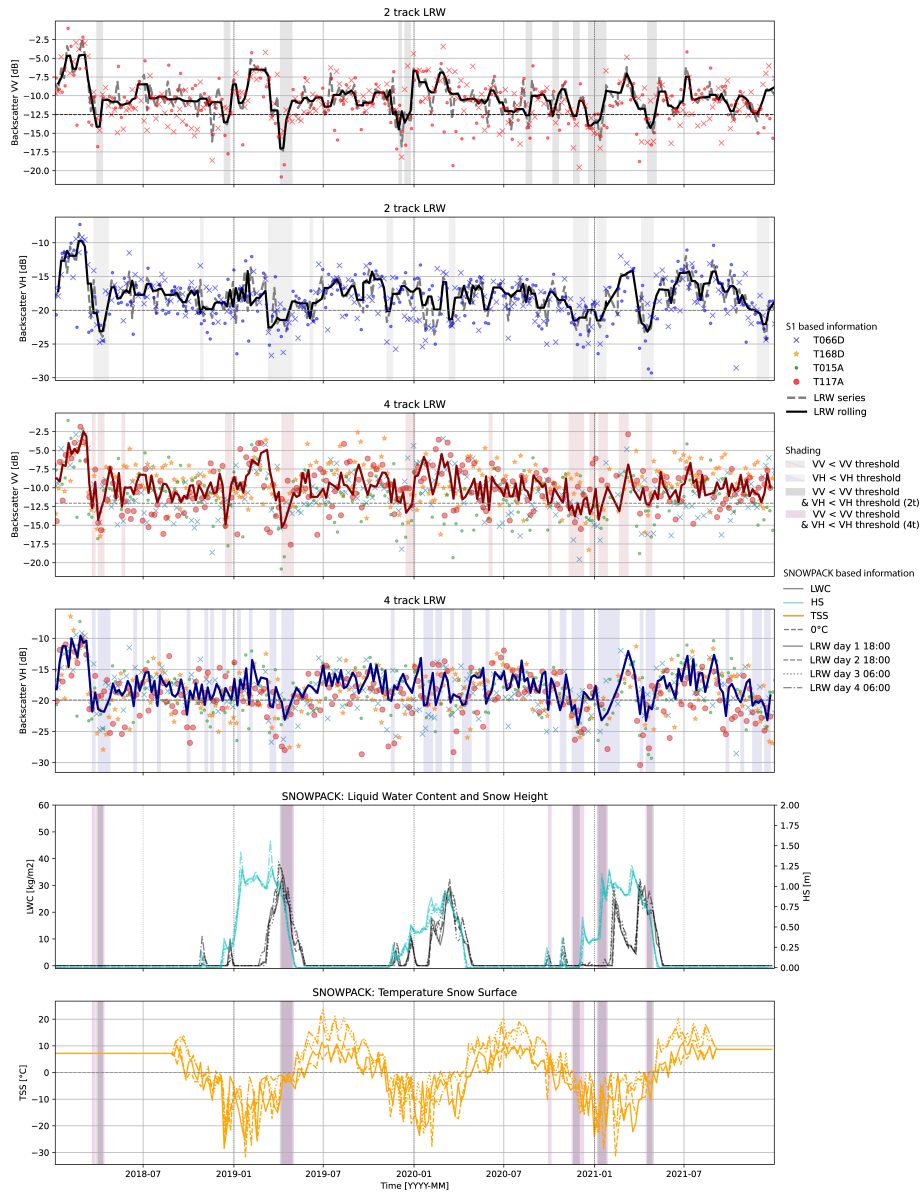


Figure A4. Time series of wet-snow evolution from January 2018 until August 2021 at the SLF2 station for two-track rolling mean (a and b) and four-track LRW (c and d) in comparison to SNOWPACK data (e and f). The first two plots are the time series extracted from the 3x3 window within which the IMIS 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.

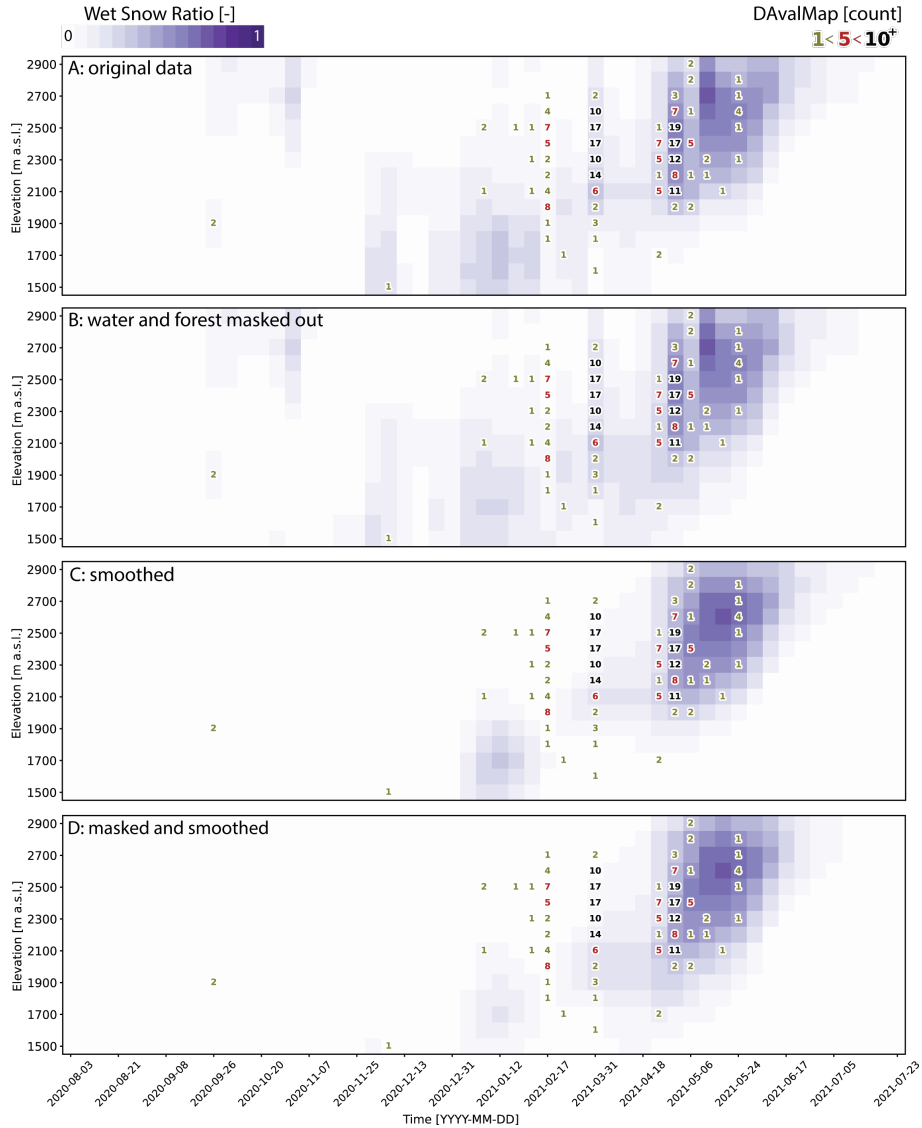


Figure A5. Time-elevation plots of wet snow evolution following Karbou et al. (2021) and Karbou et al. (2022) for VV **polarization** **polarisation** for the exemplary seasons of 2020-2021. It shows the effect of filtering and masking: A) no filtering or masking applied, B) forest mask applied, C) spatial median filter with a window size of 3x3 applied, D) forest mask and spatial filtering combined (same as in 3). The plot encompasses data featuring the area of Davos as indicated in Fig. 1, resolved to 100 m spatial elevation classes. **Circles Coloured numbers** indicate **a top view of a histogram featuring 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). **Letters a-d correspond to the timeframes of the wet snow maps displayed in Fig. 5.**

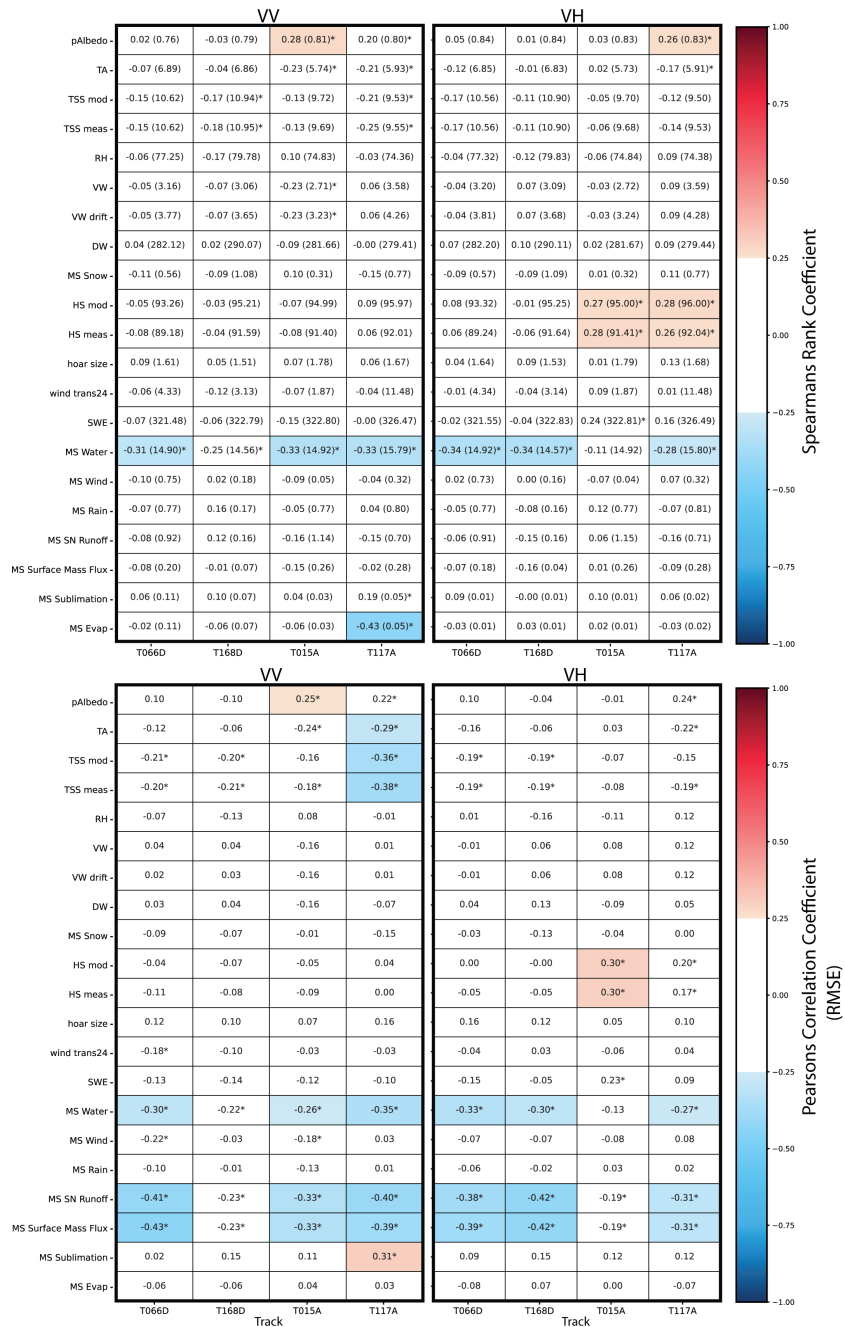


Figure A6. Exemplary illustration of performed temporal binning featuring analysed SNOWPACK variables compared to the SAR-acquisition times in descending (Dese) and ascending (Asc) median VV Sentinel-1 backscatter time series at the DAV5 station per track to corresponding local resolution composites (shading location see Fig. 1) in combination with. The table includes the summed wet snow avalanches results per polarisation state for 3x3 window size. Binning has been optimized to include all recorded wet snow avalanches. Included are the Spearmans (from DAvalMap catalogue, indicated in circle stop) while minimizing and Pearsons (bottom) correlation coefficient and the temporal offset RMSE calculated between an acquisition towards the avalanche to best match Pearsons and the wet snow condition actual data. * indicate values that came with a p-value below 0.05. Abbreviations can be found in Table A2.

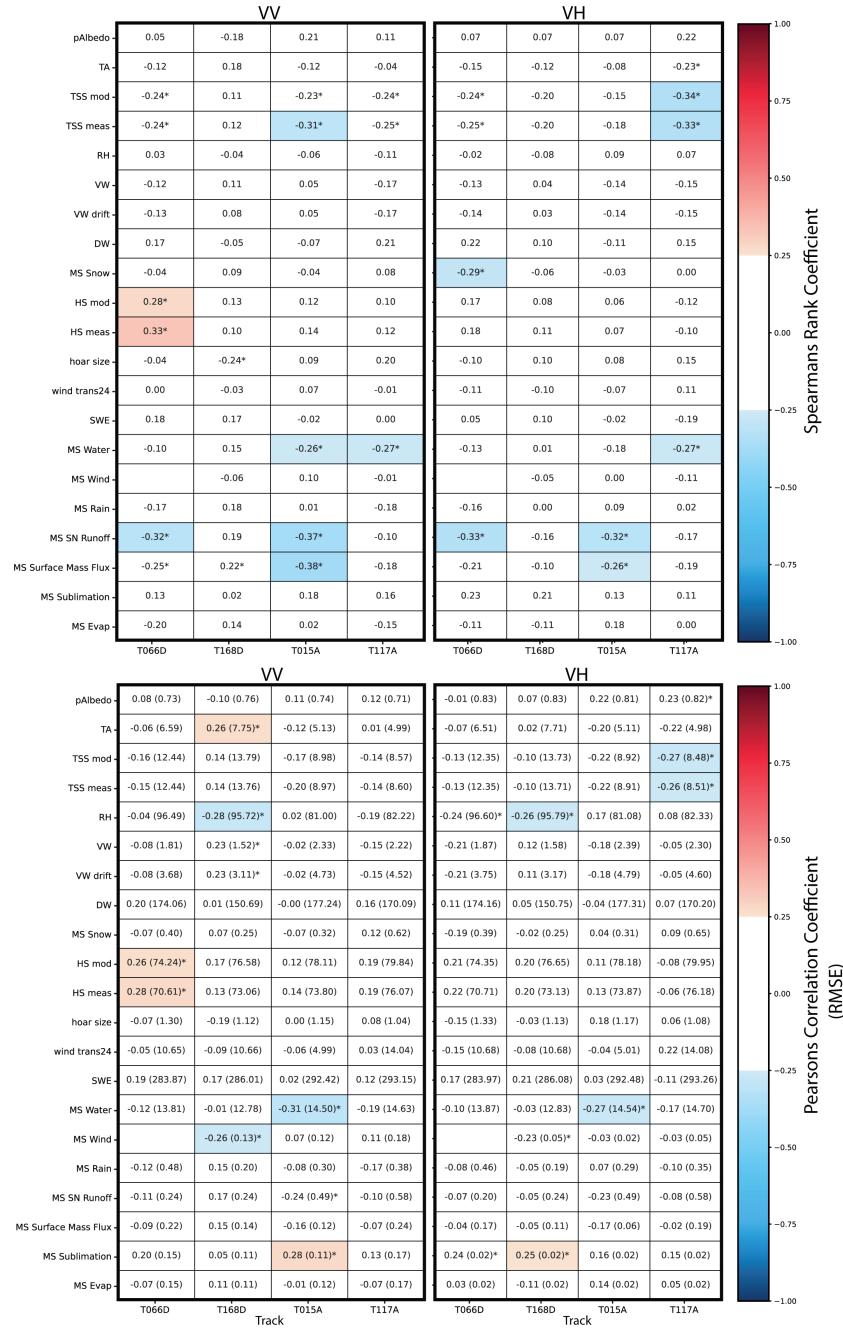


Figure A7. Correlation of analysed SNOWPACK variables compared to the median VV Sentinel-1 backscatter time series at the SLF2 station per track (location see Fig. 1). The table includes the results per polarisation state for 3x3 window size. Included are the Spearman's (top) and Pearson's (bottom) correlation 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.

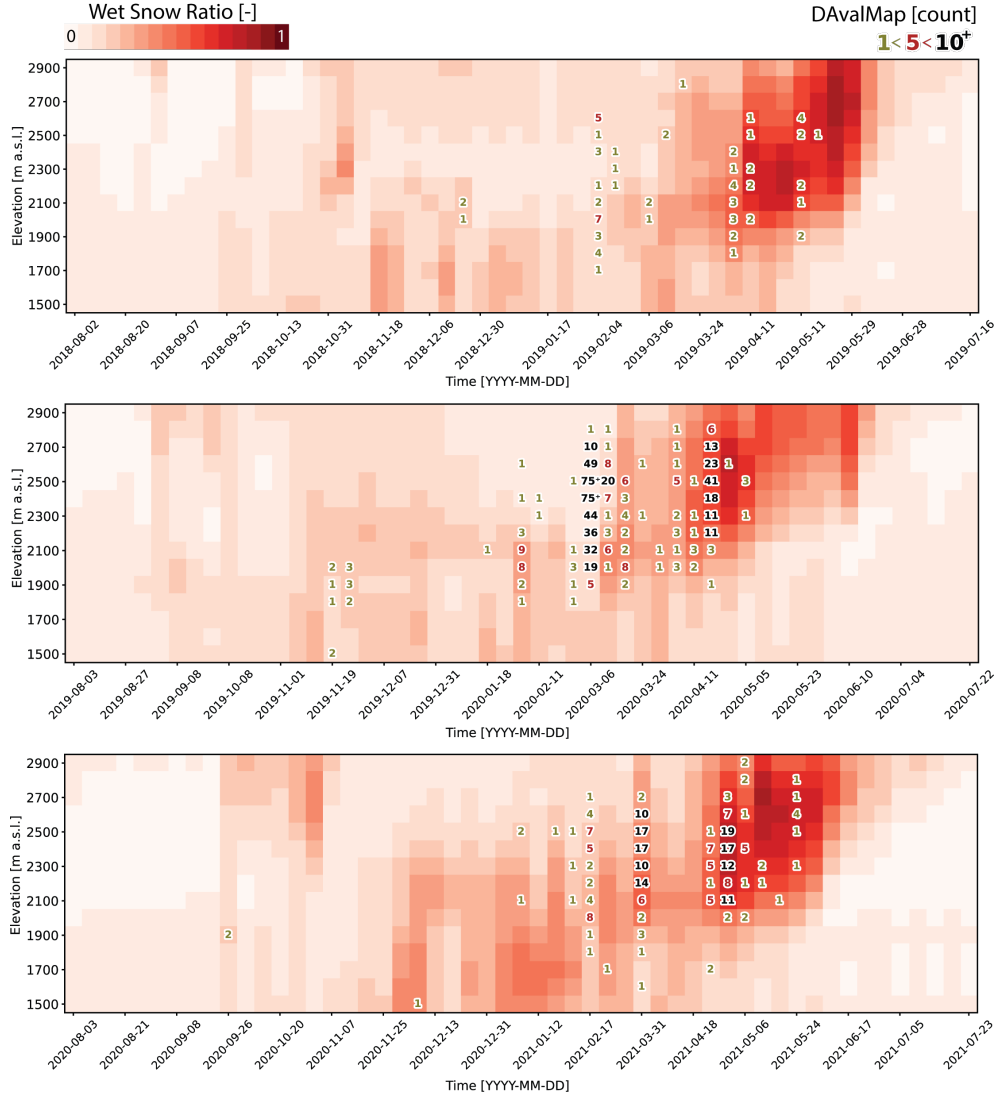


Figure A8. Time-elevation plots of wet snow ratio evolution for VV-polarized wet snow detection across three and a half seasons (A: 01.2018–07.2019, B: 08.2019–07.2020 and C: 08.2020–07.2021) featuring the area of Davos as indicated in Fig. 1, resolved at discrete 100 m elevation bands. The wet snow 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).

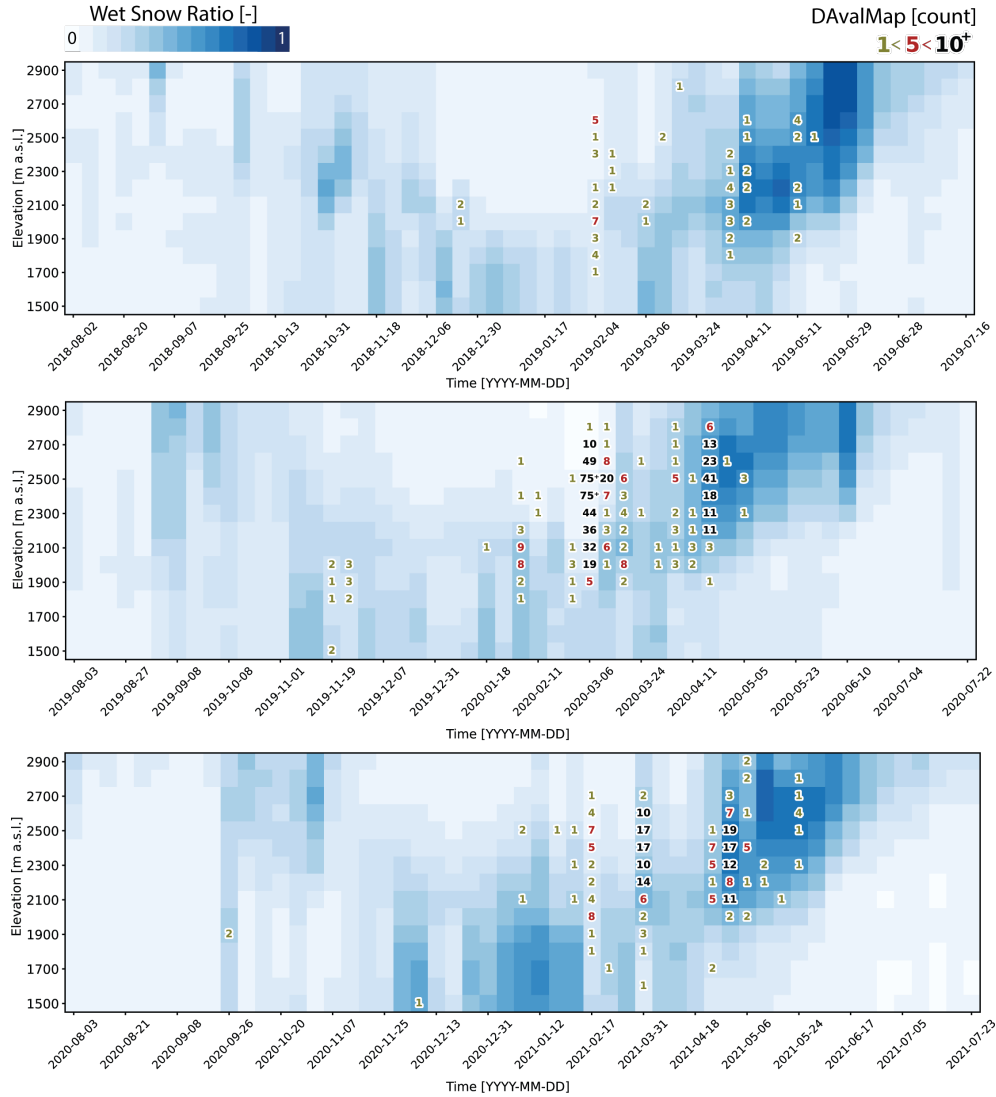


Figure A9. Time-elevation plots of wet snow ratio evolution for **VH**-polarized wet snow detection across three and a half seasons (A: 01.2018–07.2019, B: 08.2019–07.2020 and C: 08.2020–07.2021) featuring the area of Davos as indicated in Fig. 1, resolved at discrete 100 m elevation bands. The wet snow 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).

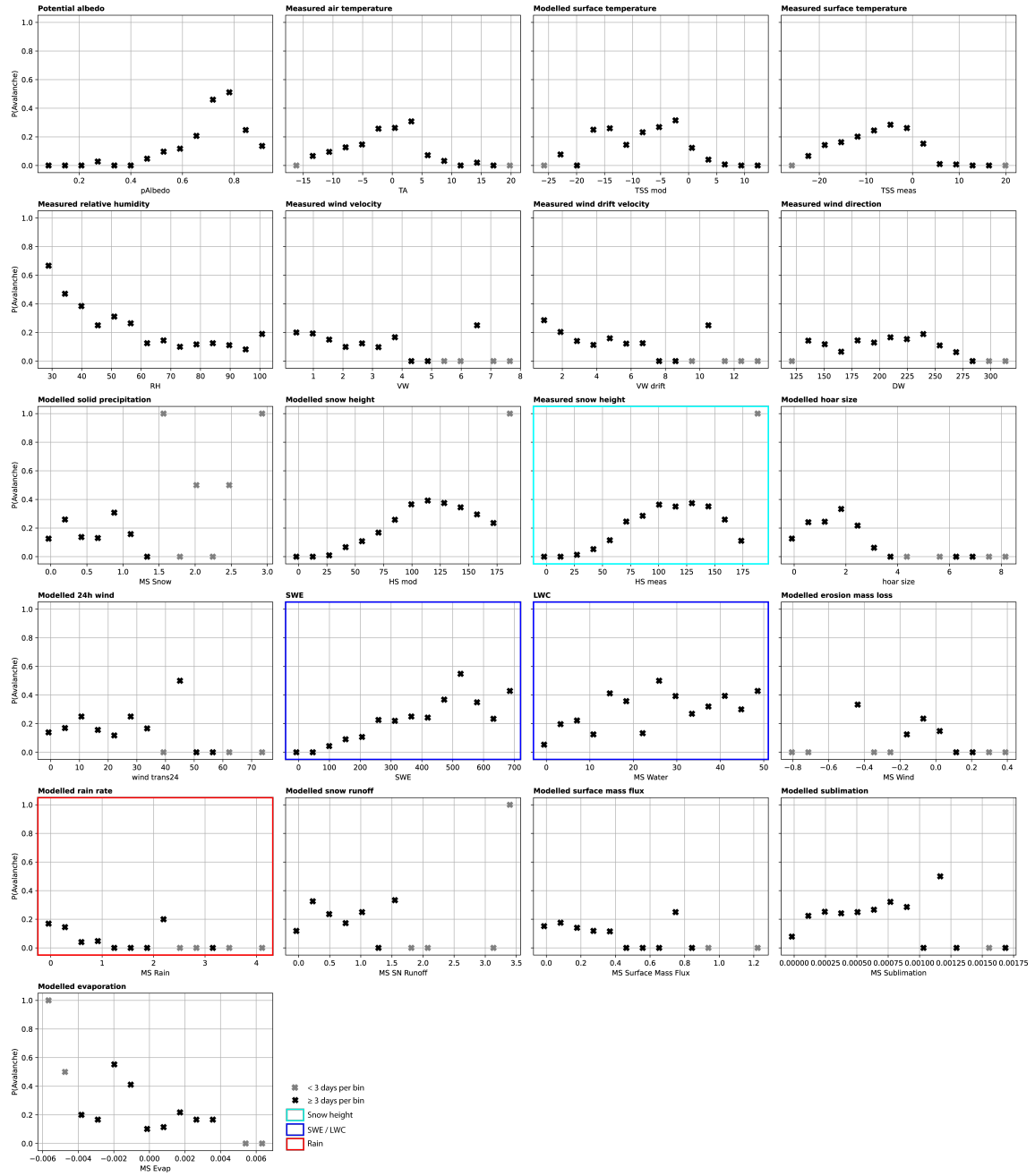


Figure A10. Probability of $\hat{\Omega}\tilde{N}$ avalanche report from the DAvalMap dataset as a function of SNOWPACK variables. Each subplot shows the conditional probability of at least one avalanche occurring on a day given a range of values for a specific variable (e.g., "On days with X mm of rain, what's the chance of $\hat{\Omega}\tilde{N}$ 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. ~~Dates~~ List of acquisition dates [DD-MM-YYYY] of ascending-orbit information ~~missing~~ RTC acquisitions per track (T) with indication of the 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

	<u>T066D</u>	<u>T168D</u>	<u>T015A</u>	<u>T117A</u>
	<u>28.02.2019*</u>	16.09 <u>18.04.2019*</u>	<u>18.04.2018*</u>	<u>21.12.2018*</u>
	20.04 <u>14.09.2019*</u>	<u>11.06.2019</u>	<u>29.06.2018*</u>	<u>23.09.2019*</u>
	<u>18.01.2021</u>	04.02	<u>12.02.2019*</u>	<u>02.02.2020*</u>
	<u>30.01.2021</u>		<u>25.04.2019*</u>	<u>26.02.2021*</u>
	07.02 <u>05.02.2021</u>	03.03	<u>24.06.2019*</u>	<u>08.06.2021*</u>
02.03	15.03 <u>11.02.2021</u>	27.03	<u>23.08.2019*</u>	<u>19.08.2021*</u>
	<u>01.03.2021</u>		<u>22.10.2019*</u>	<u>25.08.2021*</u>
	<u>13.03.2021</u>		<u>21.12.2019*</u>	~
	<u>25.03.2021</u>		<u>19.02.2020*</u>	~
	<u>16.08.2021*</u>		<u>19.04.2020*</u>	~
			<u>18.06.2020*</u>	~
			<u>16.10.2020*</u>	~
			<u>13.02.2021*</u>	~

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

Cross-correlation-analysis-table-of-the-analysed-SNOWPACK-variables-compared-to-the-median-VV-Sentinel-1-backscatter
time-series-at-the-WFJ2-station-(location-see-Fig.-1).-The-table-includes-the-results-per-polarization-state-for-3x3-window-size
(15x15-m)-and-1x1-pixel-size(5x5-m).-Included-are-the-Spearmans(Spearm.)-and-Pearsons(Pears.)-correlation-coefficient-and
575 the-RMSE-calculated-between-the-Pearsons-and-the-actuaall-data.*-indicate-values-that-came-with-a-p-value-of-below-0.05.-N-is
the-amount-of-available-data-per-variable-used-for-the-correlation.-Abbreviations-can-be-found-in-A2

N-3x3-VH-3x3-VV-1x1-VH-1x1-VV-Spearm.-Pears.-RMSE-Spearm.-Pears.-RMSE-Spearm.-Pears.-RMSE-Spearm.-Pears.-
RMSE-RH-149-0.1-0.05-3.38-0.09-0.05-3.2-0.1-0.07-3.73-0.06-0.05-3.56-TA-149-0.06-0.03-3.38-0.01-0.05-3.2-0.02-0.05
3.73-0.02-0.06-3.56-TSS_meas-149-0.12-0.07-3.38-0-0.01-3.21-0.07-0.04-3.73-0.02-0.03-3.57-TSS_mod-149-0.11-0.07-3.38
580 -0.02-0-3.21-0.06-0.04-3.73-0.04-0.03-3.57-hoar_size-41-0.24-0.22-2.96-0.17-0.06-2.75-0.25-0.21-3.33-0.16-0.04-3.38-HS_meas
102-0.05-0.07-3.48-0.24*-0.21*-3.54-0.01-0.03-3.92-0.26*-0.23*-3.94-HS_mod-102-0.1-0.13-3.45-0.21*-0.17-3.56-0.06-0.09
3.9-0.24*-0.2*-3.97-DW-149-0.01-0.04-3.38-0.11-0.13-3.18-0.01-0.05-3.73-0.12-0.14-3.53-VW-149-0.19*-0.13-3.35
-0.17*-0.15-3.17-0.17*-0.12-3.71-0.16-0.14-3.53-VW_drift-149-0.24*-0.13-3.36-0.13-0.1-3.19-0.21*-0.12-3.71-0.11
-0.09-3.55-wind_trans-24-70-0.07-0.05-2.94-0.21-0.24-3.25-0.1-0.08-3.28-0.16-0.23*-3.74-MS_Rain-33-0.03-0.12-3.6-0.04
585 0.07-4.1-0.03-0.12-3.81-0.02-0.07-4.49-MS_Snow-28-0.11-0.05-2.82-0.17-0.04-4.01-0.06-0.06-3.02-0.11-0.08-4.44-SWE-102
-0.07-0.05-3.48-0.38*-0.36*-3.37-0.1-0.08-3.9-0.39*-0.38*-3.75-MS_Water-52-0.3*-0.27*-3.42-0.45*-0.43*-3.46-0.3*-
-0.25-3.91-0.47*-0.42*-3.72-MS_Sublimation-36-0.02-0.05-3.01-0.06-0.01-2.95-0.01-0.02-3.31-0.12-0-3.62-MS_Evap-28
-0.32-0.35-2.92-0.09-0.12-4.01-0.35-0.38*-3.31-0-0.05-4.36-MS_Wind-7-0.04-0.01-2.34-0-0.17-2.58-0.18-0.02-2.42-0.07
0.18-2.9-MS_SM_Flux-45-0.27-0.17-3.59-0.12-0.02-4.13-0.25-0.17-4.06-0.07-0-4.4-MS_SN_Runoff-36-0.33*-0.37*-3.05
590 -0.31-0.25-3.81-0.29-0.34*-3.72-0.25-0.23-4.11-pAlbedo-103-0.48-0.31*-3.3-0.32*-0.09-3.58-0.46*-0.3*-3.72-0.29*-0.1-4.01

Cross-correlation-analysis-table-of-the-analysed-SNOWPACK-variables-compared-to-the-median-VV-Sentinel-1-backscatter
time-series-at-the-DAV5-station-(location-see-Fig.-1).-The-table-includes-the-results-per-polarization-state-for-3x3-window-size
(15x15-m)-and-1x1-pixel-size(5x5-m).-Included-are-the-Spearmans(Spearm.)-and-Pearsons(Pears.)-correlation-coefficient-and
595 the-RMSE-calculated-between-the-Pearsons-and-the-actuaall-data.*-indicate-values-that-came-with-a-p-value-of-below-0.05.-N-
is-the-amount-of-available-data-per-variable-used-for-the-correlation.-Abbreviations-can-be-found-in-A2.-N-VH-3x3-VV-3x3-
VH-1x1-VV-1x1-Spearm.-Pears.-RMSE-Spearm.-Pears.-RMSE-Spearm.-Pears.-RMSE-Spearm.-Pears.-RMSE-Spearm.-Pears.-RMSE-RH-149-0.16*-
-0.14-3.21-0.02-0.07-2.36-0.19*-0.15-3.85-0.02-0.06-2.78-TA-149-0.01-0.03-3.24-0.06-0.05-2.36-0.05-0.06-3.89-0.08-0.06
2.78-TSS_meas-149-0.03-0.01-3.25-0.08-0.08-2.35-0.01-0-3.9-0.07-0.07-2.78-TSS_mod-149-0.17-0.19-3.43-0.19-0.24*-
600 2.22-0.15-0.16-4.17-0.11-0.13-2.63-hoar_size-42-0.24-0.3-2.61-0.01-0-1.86-0.23-0.23-3.38-0.02-0.08-2.53-HS_meas-92
0.27*-0.23*-3.51-0.13-0.15-2.34-0.18-0.14-4.19-0.2-0.21*-2.57-HS_mod-92-0.28*-0.23*-3.5-0.07-0.11-2.36-0.18-0.13-4.19
-0.17-0.2*-2.58-DW-149-0.05-0.01-3.25-0.05-0.01-2.36-0-0.03-3.9-0.04-0.04-2.78-VW-149-0.03-0.02-3.25-0.18*-0.2*-2.32
0.04-0.02-3.9-0.2*-0.2-2.72-VW_drift-149-0.02-0.02-3.25-0.18*-0.2*-2.32-0.03-0.01-3.9-0.21*-0.2*-2.72-wind_trans-24-18
0.36-0.44-3.92-0.21-0.25-2.17-0.24-0.38-4.82-0.17-0.17-2.75-MS_Rain-34-0.17-0.1-2.82-0.28-0.01-2.7-0.04-0.08-3.49-0.31
605 0.04-3.41-MS_Snow-17-0.28-0.17-4.14-0.19-0.19-2.71-0.36-0.3-4.82-0.21-0.26-3.02-SWE-92-0.18-0.13-3.57-0.18-0.22*-
2.31-0.12-0.07-4.22-0.24*-0.27*-2.54-MS_Water-38-0.44*-0.41*-3.77-0.59*-0.64*-2.05-0.4*-0.38*-4.35-0.42*-0.52*

2.48 MS_Sublimation 27 -0.02 -0.11 2.91 0.03 0.1 1.64 -0.04 -0.09 3.75 0.11 0.1 2.23 MS_Evap 17 0.15 0.28 3.76 -0.36 -0.24
2.48 0.11 0.26 4.31 -0.31 -0.07 2.74 MS_Wind 7 -0.5 -0.18 4.37 0 0.22 2.61 -0.36 -0.19 4.94 0 0.34 3.09 MS_SM_Flux 43
0.02 -0.02 3.46 0.19 0.08 2.92 0.06 0.05 4.08 0.15 0.01 3.17 MS_SN_Runoff 24 0.17 0.23 3.75 -0.21 -0.06 2.69 0.27 0.31 4.26
610 -0.17 -0.06 2.85 pAlbedo 92 0.12 0.02 3.6 0.23* 0.15 2.34 0.02 -0.06 4.22 0.1 0.06 2.63

Cross-correlation analysis table of the analysed SNOWPACK variables compared to the median VV Sentinel-1 backscatter
time series at the SLF2 station (location see Fig. 1). The table includes the results per polarization state for 3x3 window size
(15x15 m) and 1x1 pixel size (5x5 m). Included are the Spearmans (Spearm.) and Pearsons (Pears.) correlation coefficient and
the RMSE calculated between the Pearsons and the actual data. * indicate values that came with a p-value of below 0.05. N
615 shows the amount of available data per variable used for the correlation. Abbreviations can be found in A2 N VH 3x3 VV 3x3
VH 1x1 VV 1x1 Spearm. Pears. RMSE Spearm. Pears. RMSE Spearm. Pears. RMSE Spearm. Pears. RMSE RH 111 -0.07 0
2.24 -0.03 -0.01 2.28 -0.04 0.01 2.53 0 0.01 2.57 TA 111 0.25* 0.23* 2.19 -0.13 -0.09 2.28 0.22* 0.22* 2.47 -0.13 -0.08 2.57
TSS_meas 111 0.26* 0.22* 2.19 -0.15 -0.11 2.27 0.23* 0.21* 2.48 -0.15 -0.1 2.56 TSS_mod 111 0.14 0.09 2.23 -0.1 -0.07
2.28 0.14 0.1 2.52 -0.1 -0.06 2.57 hoar_size 19 0.66* 0.5* 2.41 -0.16 -0.21 2.56 0.67* 0.5* 2.78 -0.16 -0.23 2.82 HS_meas 45
620 -0.08 -0.06 2.55 0.28 0.24 2.9 -0.14 -0.13 2.9 0.22 0.2 3.2 HS_mod 50 -0.13 -0.12 2.47 0.27 0.21 2.81 -0.18 -0.16 2.81 0.24
0.18 3.09 DW 111 0.01 0.02 2.24 0.05 0.07 2.28 0.02 0.05 2.53 0.06 0.08 2.57 VW 111 0.08 0.05 2.24 0.03 0.04 2.28 0.07 0.01 2.53 -0.01 0.02 2.57
wind_trans 24 20 0.04
-0.08 2.74 0.16 -0.03 3 0.07 -0.09 3.37 0.25 -0.03 3.53 MS_Rain 44 0.14 0.16 2.05 -0.02 0 2.11 0.14 0.14 2.42 -0.04 -0.02 2.26
MS_Snow 5 0.9* 0.87* 1.02 0.2 -0.36 1.98 0.9* 0.82 1.77 0.2 -0.11 2.86 SWE 30 -0.22 -0.24 2.42 0.16 0.08 2.86 -0.25 -0.25
625 2.75 0.14 0.05 3.14 MS_Water 38 -0.36* -0.4* 2.18 -0.26 -0.33* 2.77 -0.37* -0.36* 2.52 -0.25 -0.33* 2.98 MS_Sublimation
14 -0.15 -0.17 1.77 0.16 0.16 2.11 -0.07 -0.15 2.19 0.14 0.21 2.23 MS_Evap 18 0.22 0.16 2.34 -0.17 -0.14 2.79 0.22 0.18 2.56
-0.23 -0.13 2.98 MS_Wind 1 NaN NaN NaN NaN NaN NaN NaN NaN NaN NaN NaN MS_SM_Flux 44 0.22 0.1 2.13
0.18 0.13 1.94 0.23 0.08 2.34 0.14 0.11 2.29 MS_SN_Runoff 18 0.1 0.07 2.14 0.06 0.16 2.34 0.02 0.05 2.58 0.14 0.22 2.61
pAlbedo 54 0.14 0.07 2.51 0.23 0.1 2.79 0.13 0.03 2.84 0.28* 0.12 3.05

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