

~~Snow~~-Wet Snow Avalanche Preconditions from Sentinel-1 Multi-Track Composites

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Abstract.

1 Introduction

Avalanches are and will remain a major natural hazard in alpine regions, causing fatalities, infrastructure damage, and disruptions that underscore the need for reliable prediction tools. Wet snow avalanches ~~in particular have a~~, with their highly destructive potential, have been found to increase in frequency relative to dry snow avalanches (Eckert et al., 2024), yet they are difficult to predict (~~Hendrick et al., 2023; Mitterer and Schweizer, 2013~~)(Hendrick et al., 2023; Mitterer and Schweizer, 2013; Baggi and Schw). For one, this difficulty can be attributed to the limited availability of *in-situ* measurements of ~~the liquid water content in snow~~ ; snow conditions in the release areas (Reuter et al., 2025) 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 snow avalanche hazard assessment and more broadly 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 weather forecasts, local observers, automatic weather stations and spatially distributed environmental models (*e.g.*, gridded snowpack and meteorological models) (Hendrick et al., 2023). Temporally and spatially continuous high-resolution monitoring of snow wetting in complex and remote terrain could, therefore, help to improve the forecasting of wet snow avalanches ~~on~~ over large spatial scales. In this regard, remotely sensed data can help overcome traditional challenges related to terrain accessibility and data continuity over space and time, to provide cost-effective methods to efficiently monitor large and remote areas.

Synthetic aperture radar (SAR) from spaceborne sensors, such as the ones onboard the ~~ESA~~ European Space Agency's (ESA) Copernicus Sentinel-1 (hereafter S1), offers a promising approach to monitor the snowpack evolution at regional scales.

Even though the interaction between the snowpack and the microwave signal is complex and not yet fully understood, changes in the radar backscatter are well known to provide information on snow wetting (Karbou et al., 2021; Marin et al., 2020; Truckenbrodt et al., 2019; Nagler et al., 2016). The presence of liquid water in the snowpack attenuates the radar backscatter (Marin et al., 2020; Tsai et al., 2019; Linlor, 1980). This attenuation results from changes in the scattering mechanisms and the dielectric properties of the snowpack (Murfitt et al., 2024; Singh and Varade, 2025).

The resulting decrease in the backscatter amplitude can be leveraged to detect wet snow in SAR images by comparing it with a reference image without snow or with only dry snow (Nagler and Rott, 2000). When the signal decreases below the threshold of a known "dry" reference, wet snow is assumed to be present. The combination of co- and cross-polarisation has been found to be most effective for the detection of melt onset (Darychuk et al., 2025). In comparison with ground-based measurements and with some temporal delay, indications of the moistening, ripening and runoff phases can be found within the S1 data (Marin et al., 2020). The backscatter minimum has been connected to the isothermal state of the snowpack, when connecting the S1 data to pit-measured LWC (Detre et al., 2025). By developing a representation of detected wet snow based on elevation–time and elevation–aspect diagrams, wet snow lines (elevation where melting begins) can be derived across large spatial scales (Karbou et al. (2021), also in Li et al. (2025)).

Radar-derived wet snow maps – such as the SAR Wet Snow (SWS) product provided by the European Environment Agency (2023) – are nowadays publicly available, but (i) they are limited to a relatively low spatial resolution of 60 x 60 m; and (ii) in mountainous terrains they are prone to topographic distortions caused by the oblique, right-looking viewing geometry of S1 satellites. This leads to foreshortening, layover, shadowing and a highly variable ground resolution (Small et al., 2011). Topographic effects can be minimised by producing composites of radiometrically terrain-corrected (RTC) images from ascending and descending orbits (Small et al., 2022). To address these limitations, multi-track S1 acquisitions can be combined in a way that accounts for locally varying ground resolution. The approach of generating local resolution weighted (LRW) composites makes use of multiple viewpoints on mountainous terrain to improve local resolution and reduce missing data (shadow) from an individual orbit (Small et al., 2022)~~and employs the high-~~ This method exploits the enhanced ground resolution available on backslopes~~slopes oriented along the radar line of sight (backslopes).~~ This increases resolution arises from an increased number of resolution cells per standardised ground range interval, resulting in higher spatial sampling density and, consequently, greater radiometric stability (Small et al., 2022). This allows for minimisation of outlier-effects and thereby reduces noise by applying weighted averaging using the local resolution in areas visible in multiple orbits.

The aim of our work is to assess the suitability of S1 LRW composites vs the publicly available SWS products, for the detection of wet snow conditions and to understand whether this information can be leveraged for forecasting of wet snow avalanches. To achieve this, we first evaluated the sensitivity of radar backscatter to different snow characteristics in RTC images by correlating RTC data with measured and modelled snowpack data. We then generated multi-track LRW composites at a 5 x 5 m resolution and applied a wet snow detection approach on a regional-scale (400 km²) in the area of Davos, Switzerland. Finally, we compared the wet snow distribution to a dataset of observed wet and dry snow avalanches and evaluated whether a transition from dry to wet snow release conditions can be identified in the wet snow maps.

2 Study area

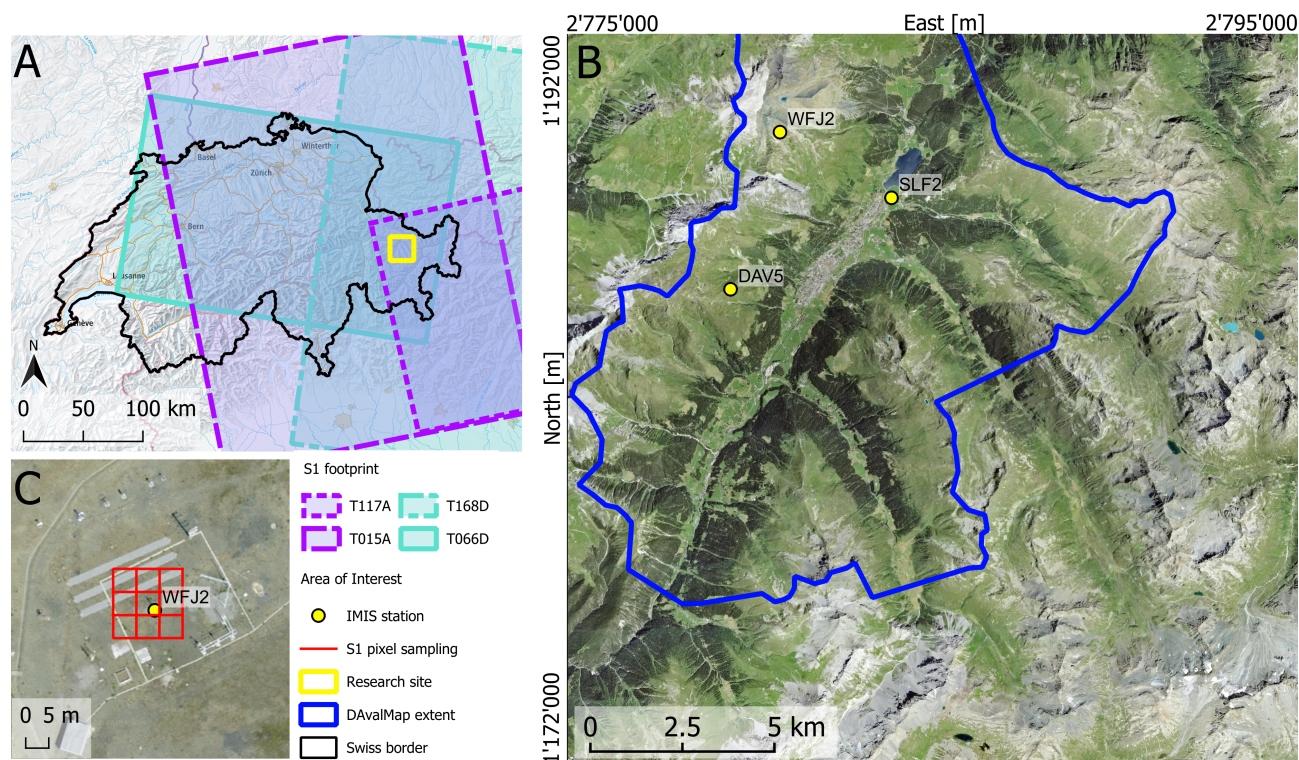


Figure 1. Overview of the area of study on three scales. (A) Outline of the Sentinel-1 footprints in relation to the study site of interest (Basemap © Esri, Swiss border © swissBOUNDARIES3D). (B) Area of study (displayed in reference system CH1903+/LV95, with EPSG: 2056, Basemap © Esri), extent and location of the avalanche library (DAvalMap, blue outline (Northwards cut to study area extent)), and the IMIS stations used (yellow dots). (C) Indication of the 3 x 3 pixel window used to calculate the Sentinel-1 backscatter median around the corresponding IMIS station (Basemap © Google Maps).

Davos's complex topography and dense monitoring network make this area an ideal study site for alpine wet snow dynamics (see Fig. 1). The region hosts national and regional monitoring efforts, resulting in a dense network of meteorological and snow monitoring stations and the availability of long-term observational data. This unique setting has enabled numerous local studies, such as multi-season field campaigns documenting avalanche release activity (Hafner et al., 2021).

The [here-assessed-study](#) area covers 400 km² between 1 542 and 3 225 m a.s.l. (according to Federal Office of Topography and Swisstopo, 2022). The site is characterized by steep, mountainous terrain and a pronounced winter season. Measured daily air temperature at the stations vary from min -27.4°C in winter (at WFJ2 station) to max +29.3°C in summer (SLF2 station). At WFJ2, mean daily air temperatures averaged -6.2 ± 5.1 °C in winter and -1.6 ± 5.0 °C in spring over the period 2018–2021 ([Intercantonal Measurement and Information System IMIS and WSL Institute for Snow and Avalanche Research SLF, 2023](#)).

3 Data

3.1 In-situ automated weather station data

65 We used data from three automatic weather stations which are part of the network of the intercantonal measurement and information system (IMIS): SLF2 (1 563 m a.s.l.), DAV5 (2 315 m a.s.l.) and WFJ2 (2 536 m a.s.l.), see Fig. 1. These stations provide automatic measurements every 30 minutes of: snow depth, air and surface temperature, wind speed and wind direction, relative humidity, reflected shortwave radiation, ground temperature, snow temperature at 25 cm, 50 cm and 100 cm above the ground, and precipitation (unheated rain gauge) for SLF2 and WFJ2 ([Intercantonal Measurement and Information System IMIS and WSL Institute](#)
70 . The variables indicated with "measured" in Tab. 1 are the ones we consider from the IMIS station ~~measurement~~measurements for this study.

3.2 Modelled data from SNOWPACK

To compare our data with relevant snowpack parameters, we used output data from the snow cover model SNOWPACK (Bavay, 2026b). This model was developed to support an operational avalanche warning service based on IMIS station data (Lehning
75 et al., 1999). SNOWPACK simulates the detailed stratigraphy of the snowpack based on meteorological input data. Specifically, the model uses local meteorological measurements, such as air temperature, snow depth or snow surface temperature, to predict the snow microstructure, density, temperature and liquid water content of the layers in the snowpack (parameters measured at IMIS stations mentioned above). The model produces a detailed description of snow properties including weak layer characterization (Stössel et al., 2010), phase changes, water transport in snow using a simplified model (Hirashima et al.,
80 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 services (Morin et al., 2020), but also in fundamental and applied research studies. 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). The whole dataset of reruns of the simulations performed for the operational avalanche warning service of Switzerland is available in Bavay (2026a).
85 In this study, we used the output data from the SNOWPACK version of December 2022 (git version: 98a23cd, (Bavay, 2026b)) in an operational setup. The SNOWPACK output includes both measured data at the station, providing its meteorological ~~foreings~~forcing, as well as modelled parameters and provides data every three hours from January 2018 to August 2021. Due to a sensor failure, no SNOWPACK simulations were available at the SLF2 station for the 2018–19 season. Tab. 1 shows all data provided by the model, including abbreviations and the information on which are measured at the three reference sites
90 and which ones are modelled.

3.3 Sentinel-1 data

We used SAR data from the European Space Agency's Sentinel-1 (S1) satellites between January 2018 and August 2021. The mission provides C-band data with a central frequency of 5.405 GHz in the two polarizations vertical-vertical (VV) and

Table 1. Abbreviation table for the variables from SNOWPACK, which were used in the following tables containing the correlation variables. The brackets indicate whether the variables were measured by IMIS and then forced into the model or modelled by SNOWPACK. **Speeded grouping highlights variables pertaining to: 1- temperatures (and RH is measured together with the temperature), 2- snow parameters (mostly measured), 3- mass balance parameters, 4- radiative forcings related parameters.**

Temperatures and Humidity	
relative humidity [measured]	RH
air temperature [measured]	TA
<u>snow</u> surface temperature [measured]	TSS_meas
<u>snow</u> surface temperature [modelled]	TSS_mod
Snow Parameters	
hoar size [modelled]	hoar_size
snow height [measured]	HS_meas
snow height [modelled]	HS_mod
wind direction [measured]	DW
wind velocity [measured]	VW
wind drift velocity [measured]	VW_drift
24h wind [modelled]	wind_trans24
Mass Balance Parameters	
rain rate [modelled]	MS_Rain
solid precipitation [modelled]	MS_Snow
snow water equivalent (SWE) [modelled]	SWE
total liquid water content [modelled]	MS_Water
sublimation [modelled]	MS_Sublimation
evaporation [modelled]	MS_Evap
erosion mass loss [modelled]	MS_Wind
surface mass flux [modelled]	MS_SM_Flux
snow runoff (virtual lysimeter) [modelled]	MS_SN_Runoff
Radiative Forcing Related Parameters	
Parametrised snow albedo [modelled]	pAlbedo

vertical-horizontal (VH). Over central Europe, S1 has long had an orbital repeat cycle of six days, though this is not always maintained due to the failure of S1B in December 2021 up to the launch of S1C (European Space Agency, 2022).

We processed SAR data from the descending orbits 066 and 168 as well as the ascending orbits 015 and 117 (Fig. 1) acquired in interferometric wide (IW) swath mode. The single-look-complex (SLC) data has a native pixel spacing of ~2.3 m in slant range and ~14.1 m in azimuth (Bourbigot et al., 2016). Over Davos, the images were acquired at 05:34 (track 066), 05:27

(track 168), 17:15 (track 15), and 17:07 (track 117) UTC over the course of four days (in consecutive order; see Appendix Fig. A1).

A digital terrain model (DTM) provided by swisstopo with a ground sampling distance 5x5 m was used in SAR data and 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).

Data from S1 is also the basis of the freely available Copernicus SAR Wet Snow (SWS) product. We downloaded the SWS products (version: 2025, Copernicus land monitoring service (2025)) for the period between 1 January 2018 to 31 July 2021 via the WEkEO platform ~~–This~~ (<https://wekeo.copernicus.eu/>, last accessed on 12.02.2026), the EU Copernicus reference service providing environmental data and virtual processing environments. The SWS dataset has a resolution of 60 x 60 m and is based on ground range detected (GRD) imagery, *i.e.* already focused SAR data, which was detected, multi-looked and projected onto an ellipsoidal model WGS84 (EUMETSAT and ECMWF and EEA and Mercator Ocean International, 2026). The data product offers classified information derived from S1 backscatter, specifically, wet snow (signal loss in comparison to stacked winter reference, class 110), dry snow, no snow or patchy snow (class 125). The product also includes pixel classes that are masked due to i) unsuitable radar geometry, ii) water, iii) forest, iv) urban area, v) non-mountain area and no data available. We treated classes i) to v) as voids. We then mosaiced same day products (different footprints) to cover the entire site and when the footprints were overlapping for valid pixels (meaning class wet snow 110 or dry/no snow 125), used the latest assigned class on that day.

3.4 DAvalMap: Snow avalanche catalogue

Our snow avalanche reference was the data from the Davos Avalanche Mapping Project (DAvalMap, detailed description in Hafner et al. (2021)). This inventory was created by the avalanche warning service SLF through systematic mapping of field observations within a perimeter covering roughly 180 km² (see Fig. 1; Hafner et al. (2021)). The dataset includes information on the release date, avalanche type (wet or dry snow avalanche) and the elevation zone at release. Small avalanches (50 m for slab and glide-snow avalanches, 100 m for loose snow avalanches) were generally not recorded in the catalogue, thereby setting a minimum size of avalanches within the data set.

We defined avalanche conditions to be dominated by wet or dry snow avalanches, when the majority was within the corresponding category (priority to wet avalanches, when equal). 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 number of avalanches by type and season used in this work is summarised in Table 2 and the used information as a subset of the database can be found in the supplementary material.

Table 2. Count of avalanches from DAvalMap sorted by type and ~~season~~year starting 1. August.

Type-per-season-count <u>Avalanche count per year</u>	2018–19	2019–20	2020–21
Wet snow avalanche-	77	723	261
Dry snow avalanche-	282	380	598
Unknown avalanche-	144	36	6

4 Methods

4.1 Sentinel-1 data processing

130 To create LRW composites from S1 data, we first performed a radiometric terrain correction (RTC) ~~(γ_0 , following Small, 2011)~~
~~; using the terrain-flattened γ_0 -convention, (Small, 2011))~~ on the S1 acquisitions and then combined the data into LRW composites. These composites were calculated by applying a weighted function to the RTC images based on the local incidence angle from at least two different flight tracks (in our site we had a maximum of two descending and two ascending tracks). Weighting was applied according to the local spatial resolution in the corresponding flight track (Small, 2012). We masked out
135 areas that lied 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 unavailable in some tracks, *i.e.* lying in radar shadow, only the available orbits were considered (as in Small et al., 2022). RTC values below -30 dB were classified as noise below the sensor sensitivity threshold and were therefore not considered in the LRW calculation (Torres et al., 2012).

Images ~~,where with~~ less than 75 % of the acquired scene ~~was valid, containing valid pixels~~ were discarded. This resulted
140 in 444 LRW composites ~~(, 186 entailing all tracks, 29 three-track composites, and 6 two-track composites per polarisation), as well as two dates where~~. ~~Two additional dates had~~ only one track ~~was available (these images remained on RTC level)~~ available therefore did not improve over RTC level. The maximum timespan covered by a composite was less than 84 h.

To generate wet snow maps we applied the common approach of comparing acquisition scenes to a no-snow or dry snow reference and identified a signal loss of 2 dB as an indication for the presence of wet snow (Nagler et al., 2016). No standard
145 approach for the selection of a reference image has yet been 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. The revised version of the SWS product (Copernicus land monitoring service, 2025) uses the mean of the winter months (December, January, February) as a dry snow reference. However, when working with large elevation ranges – as is the case in our study area – even images from December, January and February can contain wet snow and "contaminate"
150 the image. Conversely, a summer image is also likely to contain wet snow at high elevations and more likely to be affected by changes in seasonality across the imagery (*e.g.* vegetation related).

Therefore, rather than relying on a single image, or a purely calendar-based winter-month approach, we calculated a median backscatter value per pixel over the entire available time series (indicated in black in Fig. 2). With this approach, we ~~cope with~~

account for the challenge of finding a suitable reference image, which becomes less accurate the longer the time span between
155 the reference and acquisition becomes.

We then mapped wet snow on a pixel-by-pixel basis wherever the relative backscatter dropped below the 2 dB threshold at both polarisations. To increase robustness of the final product, we determined wet snow to be present only if it was identified in both polarisations.

4.2 ~~Timeseries~~ Time series analysis: S1 backscatter sensitivity to snow characteristics

160 ~~In order to test~~ To evaluate the factors influencing ~~the~~ SAR backscatter time series, we performed a correlation ~~analysis between~~
~~diverse parameters measured by the IMIS and modelled using SNOWPACK at the corresponding station locations~~ analyses
between various measured and modelled parameters over time (see Fig. 3, appendices A4 and A5). Since single pixel analyses
are prone to radar noise (*e.g.* speckle) and uncertainties, we tested the correlation of values recorded on a 3 x 3 pixel window
(indicated in Fig. 1.C) ~~in relation to diverse variables contained in SNOWPACK at three IMIS station locations (at IMIS stations~~
165 ~~Fig. 1.B)~~. We used the time closest to S1 acquisition on the corresponding day, where both IMIS and SNOWPACK data was
available: namely 06:00 to match descending SAR image acquisitions and 18:00 to match the ascending acquisitions (UTC+1).

~~We considered Pearson's correlation coefficient including~~ For the correlation analyses we calculated Pearson's correlation
coefficient and associated RMSE values, ~~as well as Spearman's~~ along with Spearman's rank coefficient. Pearson's was used
to assess the potential strength and direction of linear relationships, while Spearman's captured monotonic trends between
170 variables. To minimise the 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 was set to p-values below 0.05.

~~To quantify~~ We assessed the time difference between the onset of the main melting season and its detection ~~using in the~~ S1
LRW data to better quantify potential uncertainties introduced by the temporal binning inherent to using the multi-track LRW
175 data. We defined peak melt onset as the first date on which the 3-day median runoff exceeded the runoff threshold (set to 1
kg/m², from virtual lysimeter data in SNOWPACK). This date when the runoff exceeds the threshold, was then compared to
the current or first following composite time on which wet snow was detected in the LRW ~~timeseries~~.

4.3 ~~Retrieval of wet snow avalanche preconditions~~

~~After the successful detection of wet snow across the study site based on the composite timeseries,~~ time series. For example,
180 in spring 2018 the 3-day median runoff first exceeded the threshold on 25 May; this date lies within the concurrent multi-track
LRW composite (22–25 May 2018), in which wet snow was ~~classified into elevation bands, and already detected~~ (24 May
2018), corresponding to an offset of -1 day.

To quantitatively compare the S1 LRW wet snow product with the SWS dataset by taking all parts of the confusion matrix
into account, we calculated Matthews Correlation Coefficient (MCC) between the two binary products over all years (similarly
185 applied by e.g. Liu et al. (2025)). Further, evident false positive wet snow detections at WFJ2 were separately quantified by

calculating the frequency with which wet snow was detected, by either the multi-track LRW approach or the Copernicus SWS product, when the measured snow depth at the station was zero.

4.3 Retrieval of wet snow avalanche preconditions

After mapping wet snow across the study site, its relative occurrence ~~was quantified using a modified plot design based on Karbou et al. (2021) showing to dry/no snow was quantified by assessing~~ elevation-dependent melting over time ~~across elevation bands~~. Elevation bands were defined in 100 m increments ~~, ranging from 1 500 to 3 000 m a.s.l.~~ ~~Temporal classification was based on a six-day grid~~ Data was binned into six day increments, starting with the first LRW per season. ~~Areas with slope angles below 28° were excluded to focus on~~ To focus on areas that are potential avalanche release zones ~~we excluded areas with slopes below 28°~~ (Bühler et al., 2018). For homogeneity in the intercomparison with the coarser resolved SWS dataset, the latter has been oversampled using nearest neighbour ~~interpolation~~ onto the 5x5 m grid ~~to minimise data-loss~~.

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.

By comparing the wet snow detection from S1 with the event-based snow avalanche catalogue (DAvalMap), we retrieved information on the wet snow avalanche preconditions. After discarding duplicates ~~from the catalogue as well as and~~ data collected outside our study area ~~from the catalogue~~, the avalanches were matched to ~~the~~ wet snow ratio (see ~~EquEq. 1~~) plots according to the elevation of the release zone and the date of release ~~(Karbou et al., 2021)~~. Temporal matching to the LRW composites was performed to simulate an operational scenario, where avalanche occurrence is evaluated based on the most recent information on snowpack wetting. Avalanches were therefore assigned to the latest available LRW composite preceding their occurrence (illustrated in appendix Fig. A1).

To assess the potential for this wet snow ratio to ~~detect~~ ~~indicate~~ the transition from dry to wet snow avalanche dominated ~~releases~~ ~~conditions~~, we computed histograms and Gaussian distributions of recorded dry and wet snow avalanches in relation to the wet snow ratio. ~~This~~ To enable a performance comparison, this analysis was performed for both the LRW-based dataset presented here and the downloaded SWS product ~~to enable a performance comparison~~. We then related the dominant avalanche types to the wet snow ratio and determined the thresholds at which conditions transition from dry-dominated to wet-dominated and finally to wet snow avalanche ~~prevalence only~~. ~~This only~~. The wet snow avalanche only was defined as the ~~transitioning point~~ ~~threshold of wet snow ratio~~ above which wet snow ratio there were never more dry snow avalanches recorded than wet snow avalanches.

4.4 Comparison to SWS product

~~We performed the same wet snow ratio calculations as above on~~ Because the SWS product ~~. However, in contrast to the six day temporal grid used for the LRW approach above, we defined a daily grid to which we matched~~ ~~does not require temporal~~

increments as the LRW product, we were able to match the avalanches from the catalogue to near-daily increments. Avalanches that occurred when no data was provided were carried over to the next previously available date (see Appendix A1). We then extracted the thresholds from the distribution of wet snow ratios and the dominated avalanche type as before. This allowed us to compare and assess the feasibility between the two products for practice.

5 Results

5.1 Time series analysis

For each season, in general, the LRW backscatter signal fell below the threshold after the increase in runoff and the decrease in wet snow threshold slightly after runoff commenced and measured snow height began to decrease (Fig. 2). The time difference between detection using Wet snow detected by the S1 dual-polarisation approach and the increase preceded the rise of runoff above threshold was found to be within the 1 kg/m^2 by no more than one LRW acquisition interval (6 days of the LRW window) (Fig. 2: -1, +1.6, +5.1, +5.6 days delay for 2017/18, 2018/19, 2019/20, and 2020/21, respectively). The Every season, backscatter in both polarisations (VV & VH) fell 3 dB or more below the time-series median in late spring/early summer in each season, and coincided with the snow melt occurring, coincident with the onset of snow melt at high elevations (shaded in Fig. 2) and temperatures around the freezing-melting point (see Fig. 2.E). Sporadic decreases of backscatter, dropping below the threshold, were observed in both polarisations, during periods where SNOWPACK data (e.g. liquid water content or runoff) did not suggest the presence of snow wetness wet snow were observed in both polarisations in all years. However, for all such spurious events, the results diverged depending on the polarisation, occurring the drop only occurred in one polarisation but not in the other. The Overall, the combination of VV and VH polarisation (indicated by overlaid shadings in Fig. 2.D and E) shortened the time-span of detected wet snow and resulted in somewhat delayed detections (especially in season 2020/21), but minimised the potentially false detection detections during periods when snow melt should likely did not occur.

Statistical comparisons between the RTC level backscatter timeseries time series and the station measurements at all stations indicated revealed a negative correlation between S1 backscatter and SNOWPACK modelled liquid water content as well as measured runoff over the full timespan (Jan. (January 2018 to Aug. August 2021, Fig. 2). For runoff, the correlations ranged from -0.13 (VV; SLF2) to -0.49 (VH; WFI2) in Spearman's rank and from -0.28 to -0.26 for Pearson's correlation, when (averaged over the tracks per station per polarisation (Fig. 3, and appendices A4 and A5)). This and the slight correlation found with the liquid water content (0.15 in VH at SLF2 -0.49 in VV at WFI2 for Spearman's and -0.01 in VV at SLF2 to -0.4 at WFI2 for Pearson's) indicates the expected sensitivity of S1 to water within the snowpack (Nagler and Rott, 2000).

Among the SNOWPACK variables, Spearman rank correlations (restricted to snow-covered conditions, $HS > 0$) revealed a strong positive relationship between snow-runoff and liquid water content (0.74). Liquid water content showed a weak positive correlation with snow height (0.26), while no significant relationship was found between runoff and snow height (-0.03). This indicates that runoff is primarily controlled by the availability of liquid water within the snowpack rather than by snow depth itself. During melt periods, increases in runoff were particularly pronounced in the evening, with short-lived peaks associated

250 ~~with early melt events (e.g. November 2018)~~ While the stations at lower elevations showed a much lower signal stability (appendices A2 and A3), similar tendencies of correlations were found.

Comparing our detection of wet snow to the SWS product is not trivial due to the differences in spatial and temporal resolution and the lack of a spatially continuous reference data. However, the overall MCC value of 0.90 between SWS and LRW at WFJ2 station suggested a general agreement on the main melting phases ~~at all three stations~~ (Fig. 2.C for SWS and shadings in .D and .E for detected from LRW product, ~~with the same in appendices A2 and A3~~). While the SWS dataset often suggested wet snow at times when it could not be corroborated with SNOWPACK data, our approach based on LRWs often missed small melting phases. The stations at lower elevations showed a much lower signal stability and the usage of the dual-polarisation approach allowed us to minimise false positives (appendices A2 and A3), with yearly MCC values varying between 0.87 (2017/18 and 2019/20) and 0.94 (2018/19)).

260 Overall, the Copernicus SWS layer provides spatial coverage of 30–60% of the study area (median: 48.6%), whereas the multi-track LRW approach achieves 94–100% coverage (median: 99.9%). The reduced coverage of the SWS product is primarily attributable to masking strategies applied to minimise artifacts arising from radar geometry effects, from land cover types such as forest and water bodies (visual in appendix A10).

At the WFJ2 station, the Copernicus SWS product resulted in 17 false positive wet snow detections across the time series, 265 instances where wet snow was indicated in the absence of snow cover, whereas the dual-polarised multi-track LRW approach produced none.

5.2 Retrieval of wet snow avalanche ~~precondition~~preconditioning

Overall Across the whole study region, the wet snow ratio ~~decreased in elevation during the winter months and rose to higher elevations with the progression into summer~~ shows some distinct seasonal patterns that are consistent across years. At the beginning of the winter season, the elevation of areas with moderate wet snow ratios decreases, indicating the decrease of the snowline and a gradual transition to wide-spread dry snow. Once the melt season starts, there is both an overall rise of wet snow ratio as well as a rise in elevation of areas with high wet snow ratios (Fig. 4). Across the three analysed seasons, the ~~highest wet snow ratios occurred in~~ 2018–19 and 2020–21 ~~spring seasons reached higher wet snow ratios than 2019–2020~~, reaching 70–80 % in mid or late March, whereas 2019–20 ~~exhibited lower maximum values of~~ peaked at about 60 %. Both these two years saw ~~a warm phase~~ warm phases in February with wetting occurring quite early compared to other years. In 2020–21, elevated wet snow ratios (>30 %) appeared earlier in the season (November–February) between 1 500 and 2 200 m a.s.l., followed by a second peak of up to 70–80 % in mid-May.

Fig. 5.A ~~, .C, .E and .G~~ shows a histogram of avalanche types as a function of wet snow ratio. Fig. 5.B ~~, .D, .F and .H~~ then displays the wet snow ratio against the proportion ~~proportion~~ of wet snow avalanches among all avalanches. The transition between dry snow avalanche dominated conditions and wet ~~snow-dominated~~ snow-dominated conditions was found at a wet snow ratio of 0.17. The transition to exclusively wet snow avalanches occurred at a ratio of 0.35 when extracted from the LRW data (Fig. 5.~~IA-B~~).

When ~~resolving the data towards the four aspects~~ parsing the data by aspect ranges (Appendix A7), we found the highest sensitivity (lowest wet snow ratio threshold for transition to wet snow-dominated or only-wet snow) in south facing slopes (0.07 – 0.21), similar in east and west facing slopes (East: 0.23 – 0.39 and West: 0.20 – 0.37) and ~~the narrowest range in an immediate transition from dry dominated to wet snow avalanches only for~~ north facing slopes (at 0.13). ~~This indicated a slightly better performance.~~ The narrower transitioning phase in south and north facing slopes than in east and west facing slopes, indicates higher sensitivity in those aspect directions.

For the SWS product, the general transition between the avalanche release conditions was found to be less distinct (Fig. 5.HC-D). Although dry snow avalanches were more prevalent at lower wet snow ratios (below approximately 0.5), ~~no period~~ periods characterised exclusively by dry snow avalanche activity could not be distinguished. The transition to ~~conditions a~~ state dominated solely by wet snow avalanches occurred at a higher threshold, when compared to the multitrack LRW-based product, *i.e.* 0.81 (Fig. 5.HC-D).

6 Discussion

This study evaluates SAR-based wet snow conditions derived from LRW Sentinel-1 products ~~compared to local information~~. The use of LRW composites enables the integration of backscatter from different tracks and ~~allows us to make use of ready-to-use LRW datasets~~ optimise data coverage for avalanche-related purposes. The product allowed a clear separation between conditions where dry snow avalanches dominate, wet snow avalanches dominate, and only wet snow avalanches exist.

6.1 S1 sensitivity to snowpack characteristics

We compared the produced wet snow time series to ~~data gathered from automated weather stations and modelled using SNOWPACK at three IMIS stations (SLF2, DAV5, WFJ2; Fig. 3 and appendices A4 and A5)~~. However, this comes with its own challenges, as ~~*in-situ* data can primarily be used as an indicator for snow melt rather than as a full representative of the parameter measured (European Environmental Agency, 2026)~~. Adding modelled data, with all its inherent uncertainties, ~~allowed us~~ weather station data and modelled snow parameters extracted from SNOWPACK, using statistical analyses to assess the sensitivity of the radar ~~signal to additional snowpack characteristics~~ data to changes in the snowpack. In the following, we first discuss the findings and limitations related to measured variables from the weather stations, then evaluate the relationships obtained from modelled SNOWPACK variables, and finally combine both perspectives to interpret the radar signal response.

Among the measured variables, snow height (HS) in combination with snow surface temperatures (TSS) provided an indication of the seasonal evolution of the snowpack and the ~~timing of melt~~ conditions onset of melt. Periods with non-zero snow height together with temperatures around the freezing point can be interpreted as conditions favourable for snow wetting. However, the in-situ stations directly measure physical quantities such as snow depth and snow surface temperature, whereas the SAR-derived wet snow product infers the presence of liquid water indirectly from changes in backscatter intensity: the two approaches therefore do not measure the same quantity, which explains the rather low correlation statistics between S1 backscatter and measured variables at WFJ2. While single-point measurements cannot fully capture the spatial variability of

315 alpine terrain, the temporal agreement found between the observed snow depth, snow surface temperature, and the S1-detected wet snow periods nonetheless supports the feasibility of our approach.

However, the relationship between these variables and snow wetness remains indirect, explaining the rather low correlation statistics between S1 backscatter at WFJ2 and measured snow surface temperature. Furthermore, the representativeness of the station data is limited, as measurements are obtained at single points so the correlations calculated do not capture the
320 strong. While single-point measurements cannot fully capture the spatial variability of the alpine terrain, the temporal agreement found between the observed snow depth, snow surface temperature, and the S1-detected wet snow periods nonetheless supports the feasibility of our approach.

In contrast, additional to the measured parameters, certain parameters extracted from the SNOWPACK model SNOWPACK showed stronger relationships with the SAR backscatter signal. Across all tests, liquid water content (MS-Water) and snow
325 runoff (MS-SN-Runoff) exhibited the strongest correlations with the SAR derived snow wetness (Fig. 3 and appendices A4 and A5). This supports the assumption that decreases in SAR backscatter are linked to liquid water within the snowpack. Already at a liquid water content of 5 %, SAR penetration depth is reduced the water acts significantly as an absorbent and specular reflector to C-band frequencies, resulting in low backscatter values (Lund et al., 2022; Nagler et al., 2016).

Combining the two datasets, Combining the measured and modelled, at the station location allows data allowed us to define
330 the best possible initiation of the main melting season and to extract a most likely onset of the melting season at the station and to subsequently determine the time difference between the snowpacks' main melt initiation that and the wet snow detection. A time lag was observed. Interestingly, we observed a lag between the decrease in the snow height snow depth, the increase in modelled liquid water content, and the detection of wet snow from S1. However the LRWs. By contrast, the onset of runoff was matched within the timeframe of the LRWs without time lag (see Fig. 2). Compared to results by Marin et al. (2020), This
335 can be explained by the fact that runoff onset is itself delayed relative to the initial moistening and ripening phases, as the first meltwater is retained within the pore space of the snowpack before drainage occurs (Detre et al., 2025). The S1-derived wet snow signal therefore likely reflects a more advanced stage of the wetting process, by which time runoff onset is also imminent. Compared to Marin et al. (2020), who identified all three melt phases (i.e. moistening, ripening, and runoff) from multi-temporal SAR backscatter, this suggests that the moistening and ripening phase was not fully captured. The study by
340 Carletti et al. (2025) also found the our approach may not fully capture the early moistening phase. This is consistent with Carletti et al. (2025), who found liquid water content to be the highest impact at the start dominant control on S1 backscatter at the onset of the melting season and then being governed by surface. Temporal offsets of detected melting stages between SAR derived and SNOWPACK data is likely related to a combination of factors, including the acquisition interval of S1, the applied reference and the thresholding approach (Beltramone et al., 2022), limited sensitivity of the sensor below a certain water
345 content threshold, and diurnal variations in snowpack conditions, with surface roughness becoming increasingly influential thereafter. Nevertheless, the detection of runoff onset may still provide valuable information that can support the early warning of wet snow avalanches.

Local surroundings may influence the radar signal which was used for correlation, which helps to explain the timeseries instability and lower achieved correlation coefficients found at

350 In both the correlation analysis and the time series generation, data from the WFJ2 station outperformed the other two stations, but we believe that this is largely a consequence of local conditions and the effect of less pronounced snow conditions. The DAV5 station (Appendix Fig. A2) ~~is northwards-oriented and on three sides is on a north facing slope and is~~ surrounded by avalanche protection structures ~~likely affecting backscatter signal on three sides~~. These structures very likely affect the radar backscatter. At SLF2, the snowmelt in spring 2020 is not captured ~~when combining both~~ 355 ~~polarisations, as no distinct drop in co-polarised backscatter was detected at all~~. This station is situated at the lowest elevation of the three, so seasonal transitions are expected to be less pronounced and less intense melt events are more likely to be missed. The shallower snowpack and less pronounced winter conditions around SLF2 station is making this station-location most prone to the influence of surface roughness, which governs the S1 signal during patchy snow conditions (Carletti et al., 2025). Also at SLF2, proximity to infrastructure (>15 m) and temporary constructions may have caused signal interference~~(e.g. the increase in~~ 360 ~~. An example of this is likely the increased~~ backscatter observed early in the year ~~(Appendix Fig. A3) coincided with the timing of the coinciding with the~~ World Economic Forum, plausibly linked to temporary metal constructions for security around the nearby helicopter landing zone ~~)-(Appendix Fig. A3, especially in 2018)~~. The comparatively poor performance at the DAV5 and SLF2 stations highlights challenges faced by the product under specific local conditions. However, this is expected to have limited implications for the general applicability of the product to avalanche release assessment, as release zones are 365 typically situated at higher, more exposed elevations, where conditions more closely resemble those at WFJ2 station, at which the method performed well.

6.2 S1 based wet snow detection

The mapping of wet snow from S1 SAR data involves key methodological choices ~~that for which widely-used standards~~ do not yet ~~have standards within the community regarding threshold definition, reference image generation, and polarisation handling~~. 370 ~~Each of these influence the robustness and applicability of the resulting products.~~

~~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 exist. This is particularly true for generating the reference image, defining the wet snow threshold, 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~~ 375 ~~the handling of the different polarisations. Each of these can have an influence on the final product.~~

380 No standard approach for ~~the generation of generating~~ a reference image is established. The first version of the Copernicus SWS layer was based on a reference image calculated as the median from a stack of summer acquisitions (assumed no snow; European Environment Agency, 2023). Other studies as well as the current SWS dataset calculate the mean over dry or no snow images (e.g., Copernicus land monitoring service, 2025; 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
385 interest and the reference image, results in greater errors due to land use and land cover changes over time. In the application of
wet snow avalanche ~~now- and forecasting-forecasting and nowcasting~~, 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 a high ~~automation-level~~ level of automation, no arbitrary reference selection and a simplified
390 update-ability.

Once relative changes are computed, a threshold below which wet snow is present needs to be set. This threshold is usually
between 2 dB and 3 dB signal loss relative to a reference image or all-season 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
395 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.

The selection of polarisation modes from S1 data has varied between wet snow observation studies. While *e.g.* ~~Carletti et al. (2025); Gao and~~
Detre et al. (2025); Carletti et al. (2025); Gao and Ma (2024); Murfitt et al. (2024) used VV polarised data, James et al. (2024)
400 used VH polarised and Darychuk et al. (2025); Li et al. (2025); Jans et al. (2025); Karbou et al. (2021) used a dual-polarised
approach. In our results, the correlation values showed similar trends between the different polarisation modes (Fig. 3 and
appendices A4 and A5). In contrast to Karbou et al. (2021) we performed the 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). The strongest divergence between the wet snow ratio
405 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 occur-
rence 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~~
410 ~~of sensitivity~~ misclassifications and therefore higher robustness.

6.3 Benefit of using S1 multitrack LRW processing

~~High~~ Due to their complex topography, high mountain environments pose several well-known challenges for monitoring with
SAR data, ~~due to their complex topography, strong spatial variability, and geometric effects~~ and minimising these effects is
crucial for operational applications.

415 ~~Commonly~~ While the multi-track LRW approach and commonly available S1-based snow products such as the Copernicus
SWS or Wet/Dry Snow layers ~~offer a grid sampling of 60 m (European Environment Agency, 2023; Karbou et al., 2024), which
may not sufficiently resolve the variability of mountainous topography. (European Environment Agency, 2023) showed strong~~

overall seasonal agreement ($MCC = 0.9$), a direct quantitative comparison of both products against observed runoff carried too much uncertainty to be conclusive. The combined arbitrariness in defining melt season boundaries in the noisier SWS time series, the sensitivity of the chosen runoff thresholds, and the need to account for interruptions such as the runoff pause during the 2018/19 season, rendered such a comparison insufficiently stable. While the overall agreement is strong, the multi-track LRW approach addresses more subtle differences in spatial detail and coverage.

Instead of the commonly used GRD data, the usage of SLC data in combination with a high resolution DEM and LRW compositing allows for a higher spatial resolution ~~and so a more detailed spatial~~, resulting in more detailed representation of snow wetness patterns. Multi-track LRW ~~allow~~ allows the mitigation of typical SAR geometry effects such as layover and shadowing as well as the minimisation of noise in the dataset. By combining acquisitions from different viewing geometries, noise can be filtered and areas that would otherwise lack data can be partially recovered, increasing the spatial coverage of the resulting product. This is especially relevant in steep terrain, where single-track acquisitions often lead to systematic data gaps. This increased data availability also stabilises the derived wet snow ratios, as a larger number of valid pixels can be included in the calculations, reducing the influence of outliers. In addition to spatial improvements, the use of LRW composites enhances the temporal robustness of the time series. By integrating multiple acquisitions, the impact of missing individual scenes is reduced, allowing for more consistent monitoring of snow conditions over time. So while SWS offer a grid sampling of 60 m (European Environment Agency, 2023; Karbou et al., 2021), which may not sufficiently resolve the variability of mountainous topography, our S1 LRW approach offers more spatial detail.

These improvements are particularly relevant for applications such as avalanche forecasting, where both spatial detail and temporal consistency are critical, especially for capturing the onset of snow wetting across different slope aspects (Cluzet et al., 2024). With the community increasingly moving towards the provision of large-scale LRW datasets such as already available from *e.g.* (Copernicus Data Space Center, 2026), making use of this data will become more efficient and operational applicability more feasible.

6.4 Extracting avalanche release conditions (wet vs dry) from S1-based wet snow ratio

To assess the applicability of SAR-based wet snow detection for the retrieval of the avalanche release conditions, we compared the wet snow ratios derived from both the multi-track LRW product and the standard ~~S1 wet snow dataset~~ Copernicus SWS to the DAvalMap wet snow avalanche catalogue. This approach provides an indication of how well remotely sensed wet snow conditions may provide indication on avalanche type occurrence.

The available DAvalMap ~~library contains manually observed and recorded~~ catalogue contains field-based observations of avalanches and their type (wet, dry, unknown). ~~This dataset~~ Even though this dataset is not without limits, it provides a valuable opportunity to relate ~~observed~~ avalanche activity to SAR-derived snow wetting. ~~However, the avalanche inventory is not without limitations and several aspects~~ In the following, we discuss a few aspects which must be considered when interpreting the wet snow ratio in relation to this dataset. The catalogue does not permit a full evaluation of the detection performance beyond the observed avalanche sample ~~(no avalanche)~~ In other words, a lack of record does not necessarily mean ~~no~~ that wet snow avalanche conditions were ~~present~~ not present. Also, the DAvalMap perimeter is smaller than the study area used for LRW

production, meaning that avalanches outside of this region were not systematically recorded. As a result, elevation bins above approximately 2 800 m a.s.l. contain little to no documented avalanche activity. ~~Furthermore, all-~~

~~All~~ avalanches included in the dataset were classified into wet, dry or unknown-type snow avalanches, ~~implying where the~~
455 ~~classification pertained to~~ the conditions in the starting zone. However, this classification is challenging from a distance, and
some events may have been misclassified, particularly ~~where-in cases when~~ avalanches started as dry snow avalanches, but
developed ~~wet-deposits-into wet snow avalanches~~ during their descent (Köhler et al., 2018). Lastly, the inventory is based on
in-situ observations that depend on good visibility and are biased towards days with lower avalanche risk, as observations are
less likely to be made during hazardous conditions (Schweizer et al., 2020; van Herwijnen and Schweizer, 2011). This can
460 lead to uncertainties in the assigned release dates of up to several days (avalanches are reported when they have been observed
instead of when they have been triggered (Schweizer et al., 2020)) ~~but-~~. ~~However, this issue~~ is less pronounced for wet snow
avalanches occurring on sunny days ~~with-the-during~~ warming. Given the applied six-day temporal resolution of our product,
the impact of these timing uncertainties is expected to be limited. However, such misclassifications are likely to have a stronger
effect on the daily temporal matching to the SWS product. Even with these ~~observations'-observational~~ shortcomings, this
465 dataset is one of the most comprehensive avalanche activity datasets (Schweizer et al., 2020).

~~No clear dependency between wet snow avalanche occurrence and measured rainfall was found, with correlation values not
exceeding 0.2 at an average daily rainfall of 17 kg/m², suggesting that rain-on-snow had a limited influence on wet snow
avalanche release in this dataset (see Appendix Fig. A9). Despite the mentioned limitations, DAvalMap remains a unique
dataset for comparing observed avalanche activity with snow wetting derived from S1 data.-~~

470 The initial ~~surges-clusters~~ of wet snow avalanches in spring 2019 and 2020 did not coincide with a pronounced increase in
the wet snow ratio across ~~two-of-the-investigated those two~~ seasons (see Fig. 4). These events were ~~both~~ the most susceptible to
misclassification ~~as wet snow avalanches~~ in the DAvalMap dataset ~~and-~~, ~~given their higher potential at the start of the melting
season to initiate as dry releases before transitioning into wet snow avalanches. Furthermore, they are~~ the most likely to occur
during short-lived wetting phases that may go undetected ~~due-to-given~~ the temporal resolution of S1 imagery ~~-Furthermore~~
475 ~~with-the-temporal-binning-performed, the wet snow avalanches have partly occurred during the days, where no image was
acquired and therefore there would be no change of detection, if the conditions were shortlived or fast changes (see (shown in~~
daily grid and unavailable images in Fig. A8). ~~These limitations underscore Rainfall showed no significant dependency with
wet snow avalanche occurrence over the time series ($r < 0.2$; mean daily rainfall: 17 kg/m²; Appendix Fig. A9), indicating that
rain-on-snow events had limited influence on wet snow avalanche releases in this dataset, excluding this as potential factor.~~
480 ~~This underscores~~ the need for improved temporal coverage ~~of the SAR mission~~ to enhance the timing accuracy of remotely
sensed snowpack transitions.

All these effects impact the threshold extraction which marks the ~~switch-of-transition from~~ dry to wet snow avalanche release
conditions. ~~We-Additionally, we~~ found an aspect dependency on the sensitivity of ~~avalanche type-classification-the thresholds~~
(appendix Fig. A7). This can be attributed for one to a) the difference in melting, since the north-facing slopes are typically
485 later in melting and then more intensive (visible in the elevation dependent melting diagrams (appendix Fig. A6), but also b)

the inherent flight geometry of the sensor, which covers the south facing slopes the best, and offers least coverage for north facing slopes.

Ideally, a clear threshold of the wet snow ratio ~~threshold would be identifiable at~~ would identify the transition between dry and wet snow avalanche release conditions, indicating that the ratio provides a robust measure to differentiate between these conditions. ~~In this study, we derived such a threshold for the dataset based on multi-track LRW S1 data.~~ To mark the uncertainty range, we also provide a threshold ~~on for~~ wet-dominated ~~, where still mixed conditions can~~ conditions, where wet snow avalanches prevail but dry snow avalanches can still occur. However, the use of the SWS product showed increased noise and lower reliability with a transition to ~~dry-only~~ wet-only conditions at a very late stage. This highlights the dependency of the threshold on the underlying radar data processing. Consequently, the thresholds derived in this study should be interpreted as a range that needs to be selected according to the specific product used in practical applications.

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 liquid water content and not only the presence of liquid water.

500 7 Conclusions

This study shows that S1 LRW multi-track composites provide useful information on snowpack wetting in complex alpine terrain and can support the identification of conditions associated with wet snow avalanche releases. We found a consistent relationship between decreasing SAR backscatter and increasing liquid water content in the snowpack as well as runoff, thereby linking RTC images to snowpack characteristics. The use of the LRW multi-track compositing approach allowed us to derive a relationship between the wet snow ratio and avalanche observations, which revealed a transition from conditions dominated by ~~dry-snow~~ dry snow avalanches to conditions where wet snow avalanches became predominant. At a wet snow ratio of 0.35 only wet snow avalanches were recorded. Compared with the Copernicus SWS product, the LRW-based approach provided a clearer separation of avalanche-release conditions, highlighting the benefit of multi-track compositing in steep terrain.

The approach remains limited by the revisit time of S1 and uncertainties in avalanche timing, which may affect the detection of short wetting phases. Despite these limitations, the results suggest that S1 multi-track composites may assist the evaluation of snowpack wetting across large areas and provide additional information on the development of conditions prone to wet snow avalanches.

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Code and 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 (Gamma Remote Sensing, 2025). The SNOWPACK data including the forced IMIS station information can be found under Bavay (2026a) with further information on the model under Bavay (2026b). The code used in this study is publicly available on the GitLab repository: <https://gitlabext.wsl.ch/alpineremotesensing-public/ccamm-wetsnow>. This GitLab repository also contains information used from the DAvalMap catalogue (original dataset described in Hafner et al. (2021)).

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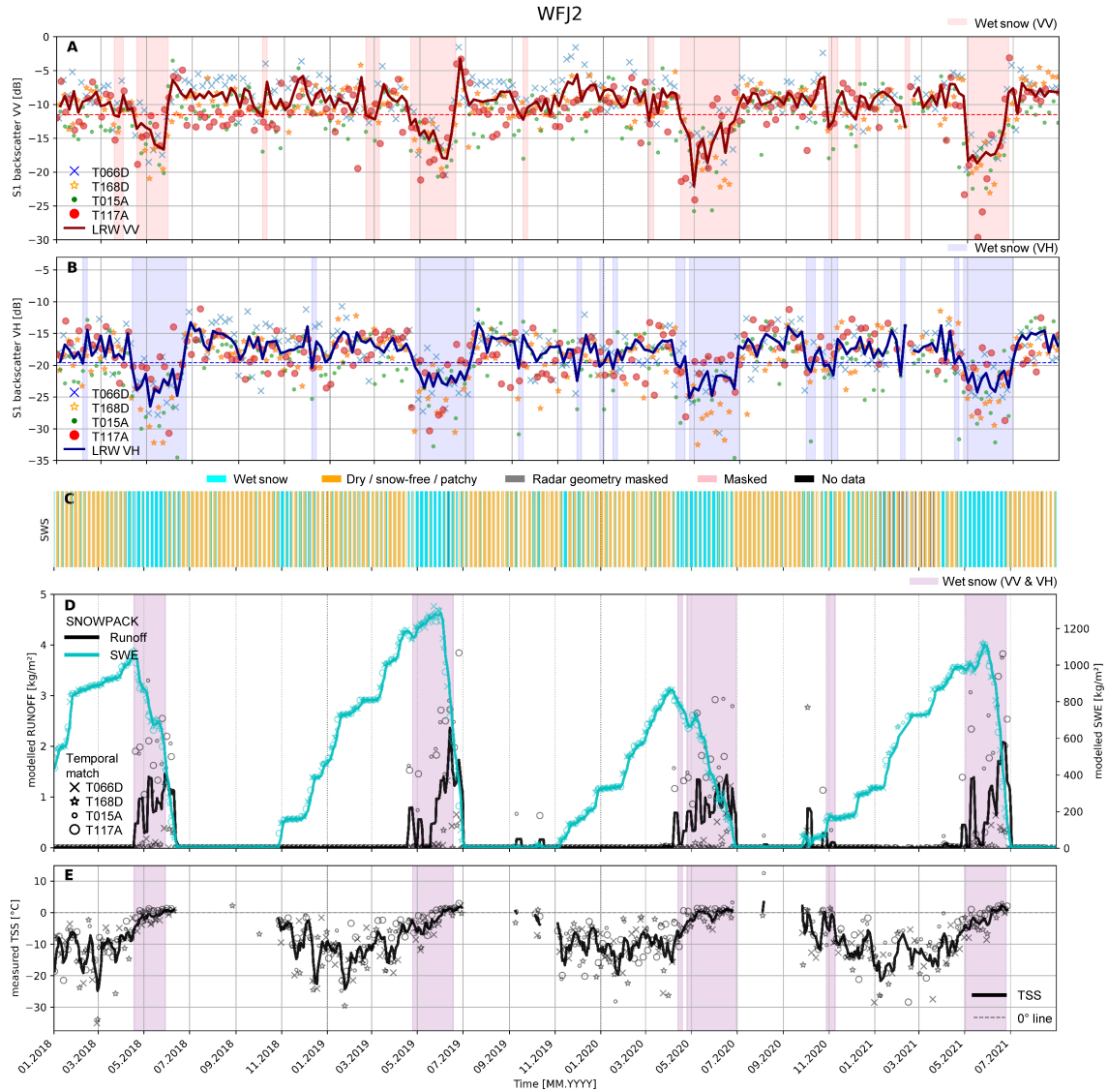


Figure 2. Time series of ~~wet-snow~~ wet snow evolution over four melting seasons from January 2018 until August 2021 at Weissfluhjoch (WFJ2). A) and B) show the time series extracted from the pixel within which the IMIS station is situated in (A) co- and (B) cross-polarised S1 data ([contains modified Copernicus S1 data](#)). The horizontal line indicates the time series median including the 2 dB threshold and the shading background displays the times during which the backscatter falls below this and wet snow is detected. C) SAR Wet Snow classified layer from Copernicus per track over the station area. D) Modelled time series of virtual lysimeter (MS RUNOFF) and ~~measured-snow height-water equivalent (HSSWE)~~ at the station as extracted from SNOWPACK data with markers indicating the corresponding time of S1 acquisition and ~~the line being the mean values between those four times indicated via connecting lines~~. Similarly, E) shows the local measured snow surface temperature (TSS), masked to when snow height at IMIS station was measured non-zero. In D) and E), the applied purple shading corresponds to our wet snow combined polarisation product.

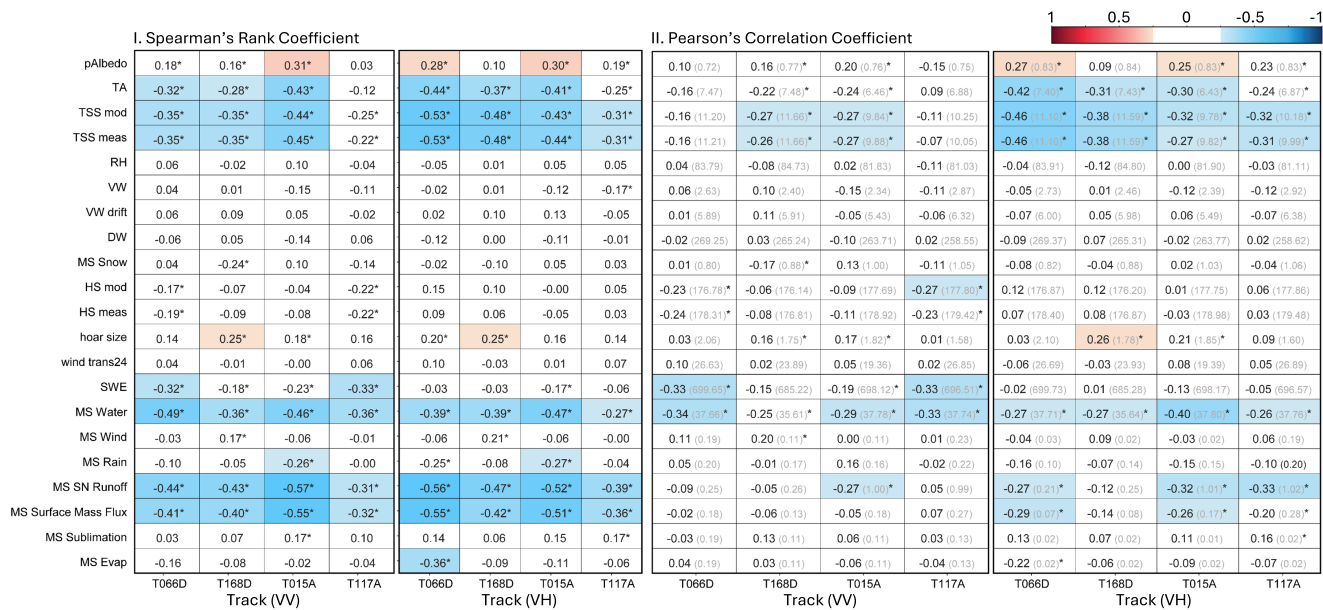


Figure 3. Correlation of analysed SNOWPACK variables compared to the median Sentinel-1 backscatter time series at the WFJ2 station per track (location see Fig. 1). The table includes the results per polarisation state for ~~3x3 window-size~~ 3 x 3 pixel-window. Included are the Spearman's (I) and Pearson's (II) correlation ~~coefficient~~ coefficients and the root mean square error (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 1 and the correlation of the other stations in appendices A4 and A5.

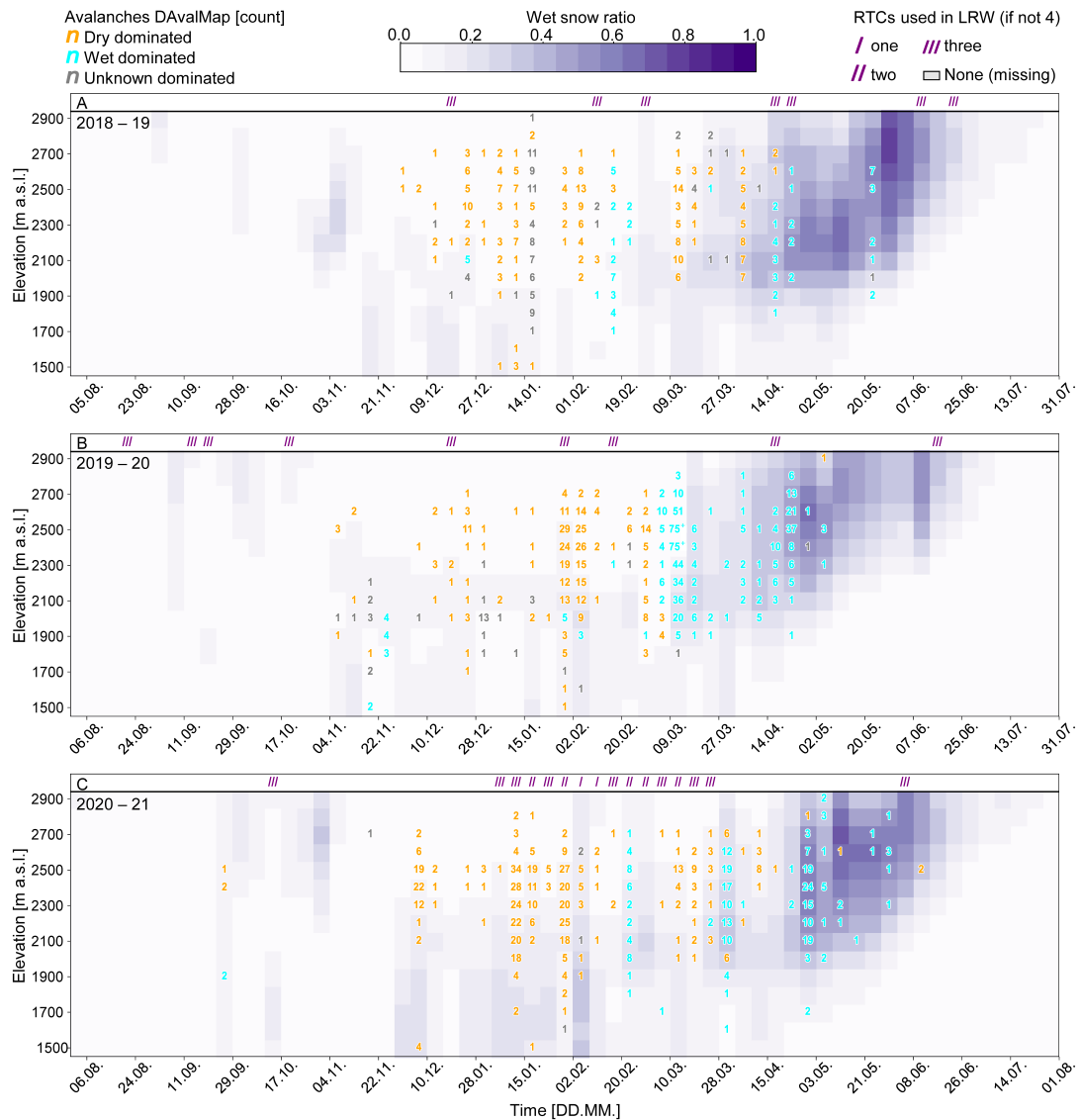


Figure 4. Time-elevation plots of wet snow ratio evolution for combined polarised product across three melting seasons (A: 08.2018–07.2019, B: 08.2019–07.2020 and C: 08.2020–07.2021) featuring the area of Davos as indicated in Fig. 1, resolved at discrete 100 m elevation bands. The wet snow ratio is the percentage of pixel per elevation band that was detected as indicating wet snow using S1 data. The number of / lines indicates the amount of tracks used, when less than the max. of four tracks were used for the LRW creation. Coloured numbers indicate the count of recorded snow avalanches per time step according to the DAvalMap data set at the corresponding elevation band and coloured according to the dominant avalanche type dry (orange), wet (cyan) and unknown (gray) (Hafner et al., 2021). In case of equal amounts of avalanches, "wet" snow was given priority followed by "unknown" and then "dry" snow avalanches. Plot design was inspired by Karbou et al. (2021) and Karbou et al. (2022).

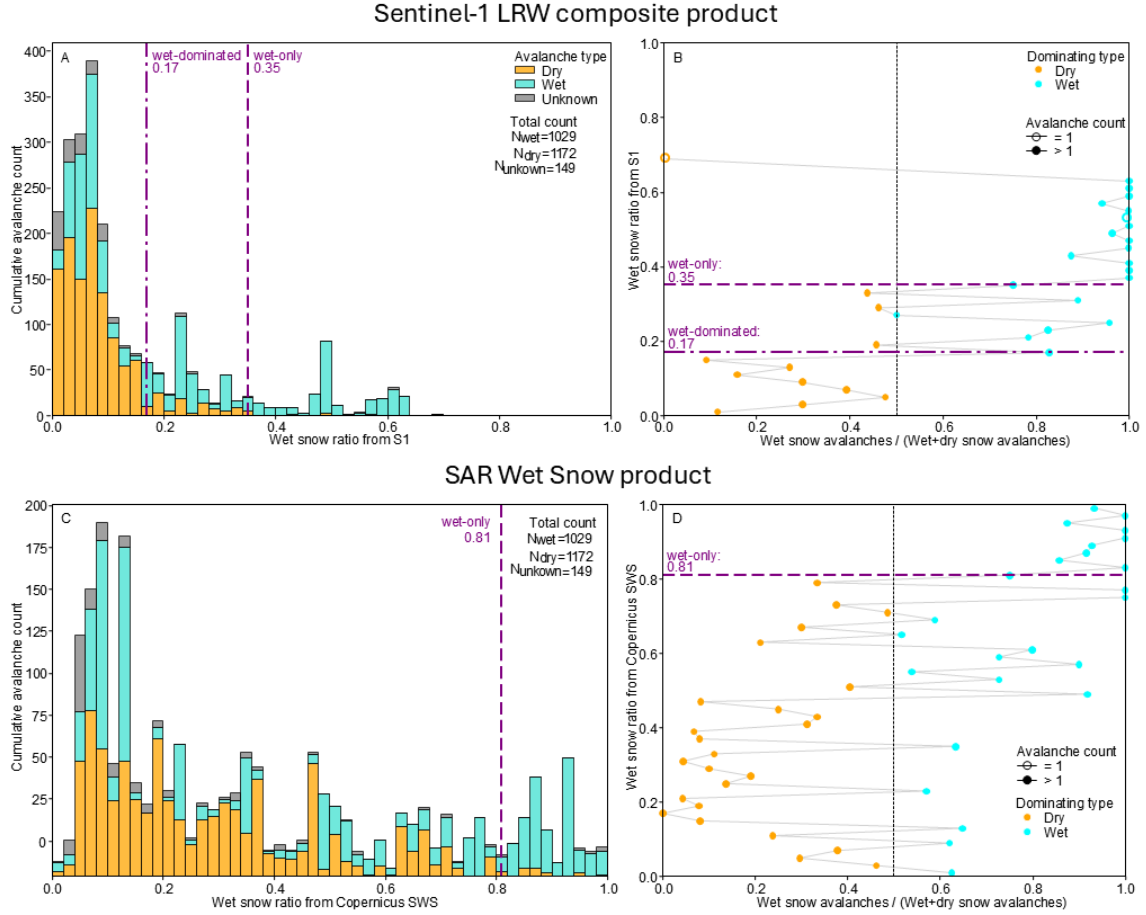


Figure 5. Extraction of wet snow ratio thresholds from S1 I) using our LRW approach and II) SWS product. A: Total avalanche count per type in comparison to wet snow ratio and the extracted wet-dominated and wet-only transition lines after applying Gaussian distribution. B: ~~Wet~~wet snow ratio in comparison to dominating type. The extracted thresholds only consider wet and dry snow (unknown, excluded) and entries when more than one avalanche was present. In cases of equal amount wet and dry snow avalanches, wet snow was given priority.

A1 Temporal binning of avalanche data

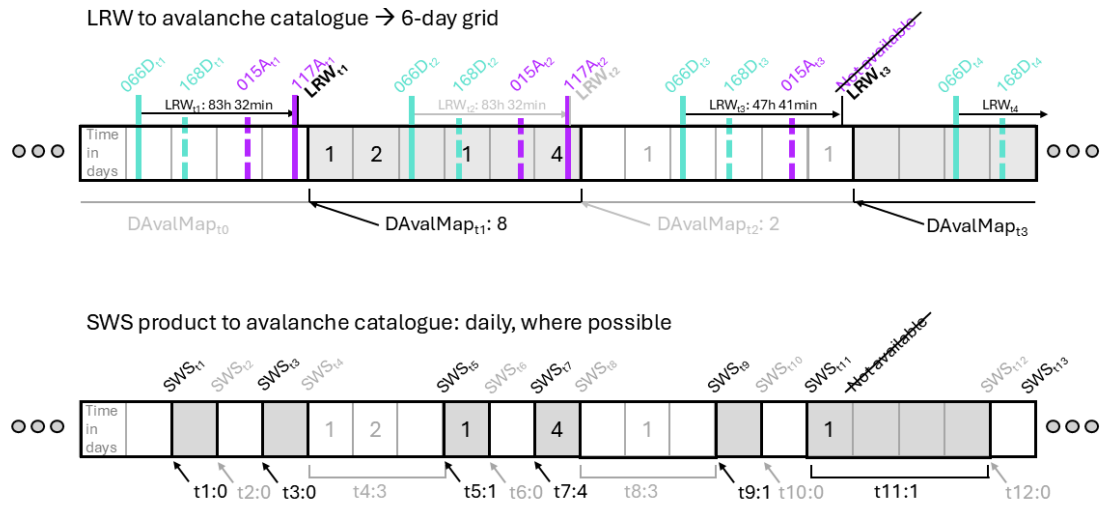


Figure A1. Exemplary illustration of performed temporal binning featuring the SAR acquisition times in descending and ascending tracks to corresponding local resolution composites (shading) in combination with the summed wet snow avalanches. Binning has been optimised to include all recorded wet snow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

A2 Timeseries time series of stations DAV5 and SLF2

A2.1 DAV5 station

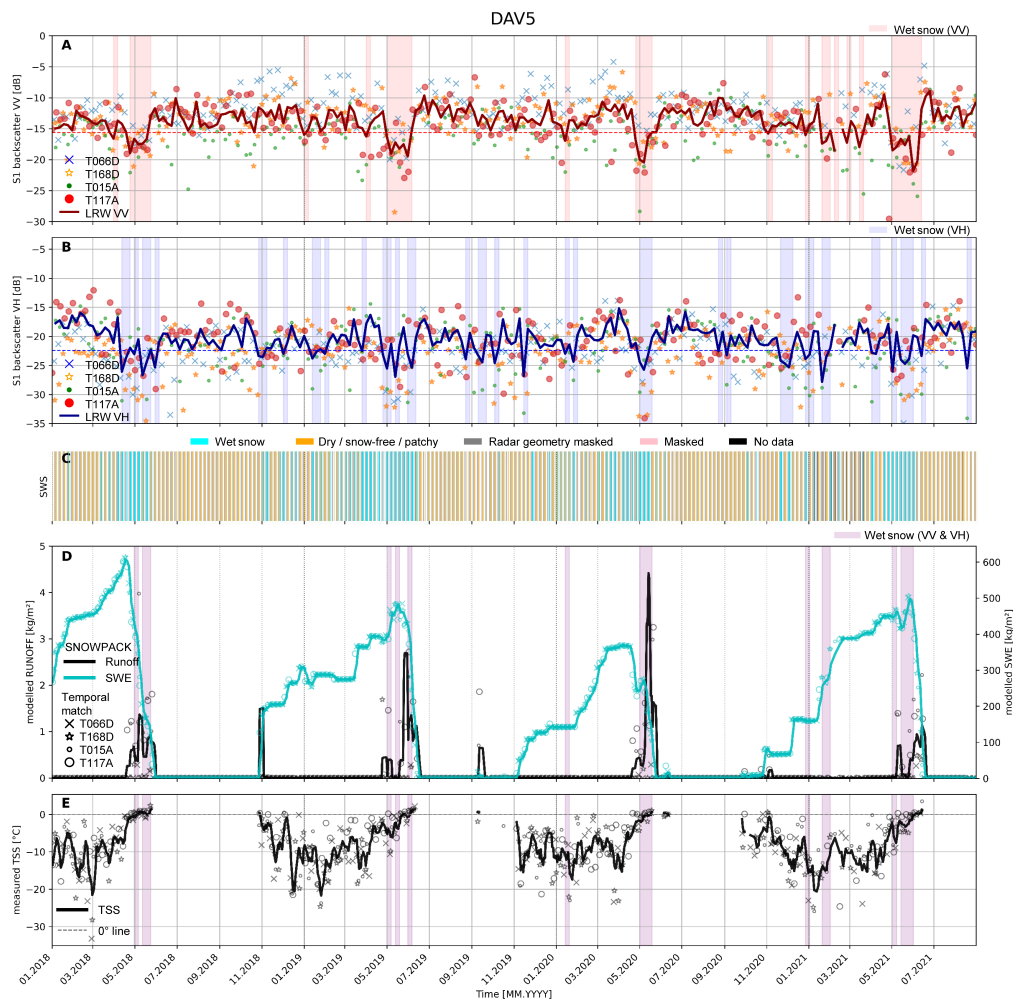


Figure A2. Time series of wet-snow wet snow evolution over four melting seasons from January 2018 until August 2021 at DAV5 station. A) and B) show the time series extracted from the pixel within which the IMIS station is situated in co- (A) and cross-polarised (B) S1 data. The horizontal line indicates the time series median including the 2 dB threshold and the shading background displays the times during which the backscatter falls below this and wet snow is detected. C) SAR Wet Snow classified layer from Copernicus per each track over the station area. D) Modelled time series of virtual lysimeter (MS SN RUNOFF) and measured-snow height-water equivalent (HSSWE) at the station as-extracted from SNOWPACK data with markers indicating the corresponding time of S1 acquisition and the line being the mean between those four times. Similar E) shows the local measured snow surface temperature (TSS) from IMIS, masked to when snow height as non-zero. In D) and E), the applied purple shading corresponds to our wet snow combined polarisation product.

A2.2 SLF2 station

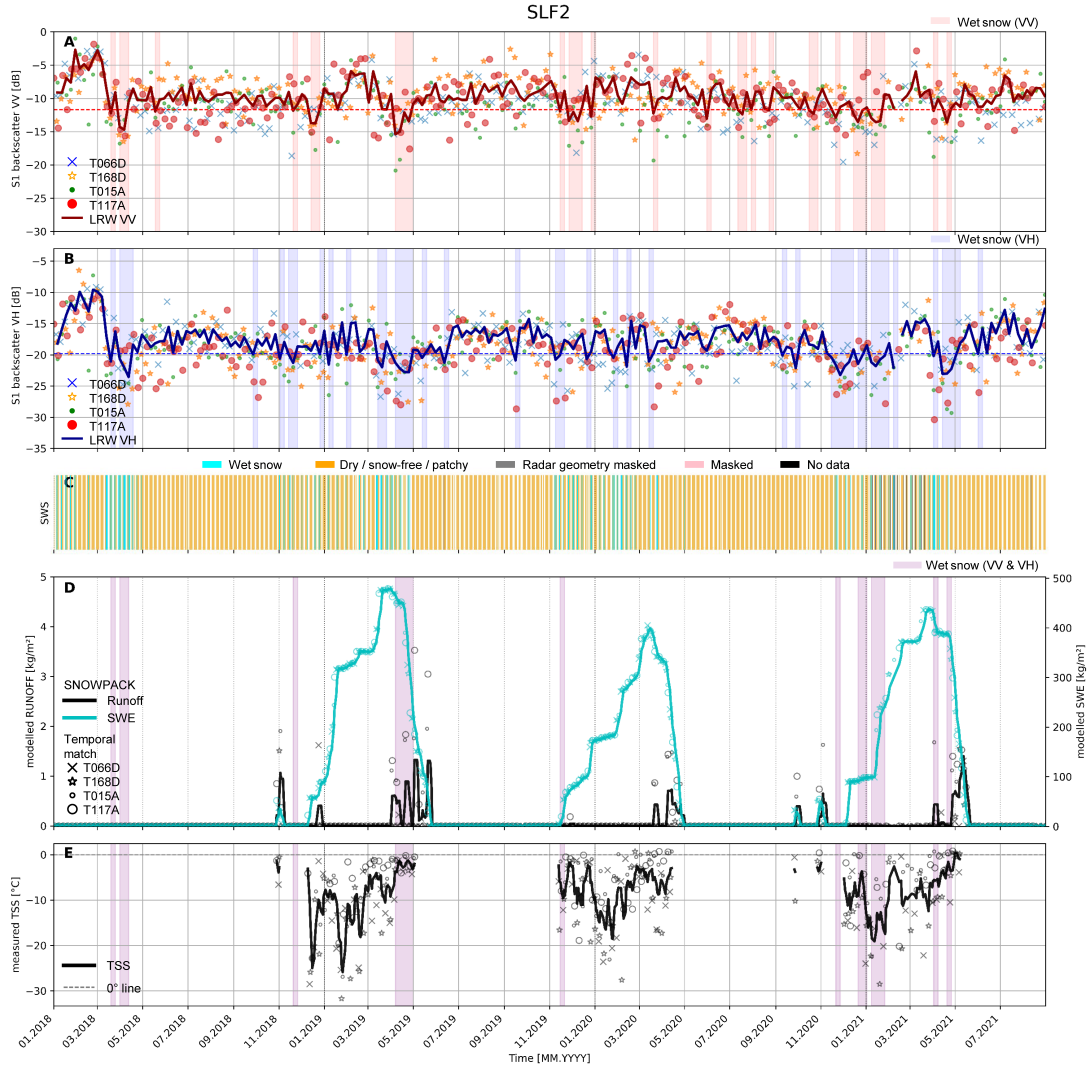


Figure A3. Time series of wet-snow-wet snow evolution over four melting seasons from January 2018 until August 2021 at SLF2 station. A) and B) show the time series extracted from the pixel within which the IMIS station is situated in co- (A) and cross-polarised (B) S1 data. The horizontal line indicates the time series median including the 2 dB threshold and the shading background displays the times during which the backscatter falls below this and wet snow is detected. C) SAR Wet Snow classified layer from Copernicus per each track over the station area. D) modelled time series of virtual lysimeter (MS SN RUNOFF) and measured-snow height-water equivalent (HSSWE) at-the-station as-extracted from SNOWPACK data with markers indicating the corresponding time of S1 acquisition and the line being the mean between those four times. Similar E) shows the local measured snow surface temperature (TSS), masked to when snow height as non-zero. In D) and E), the applied purple shading corresponds to our wet snow combined polarisation product. D and only available from September 2018 due to a sensor failure before.

A3.1 DAV5 station

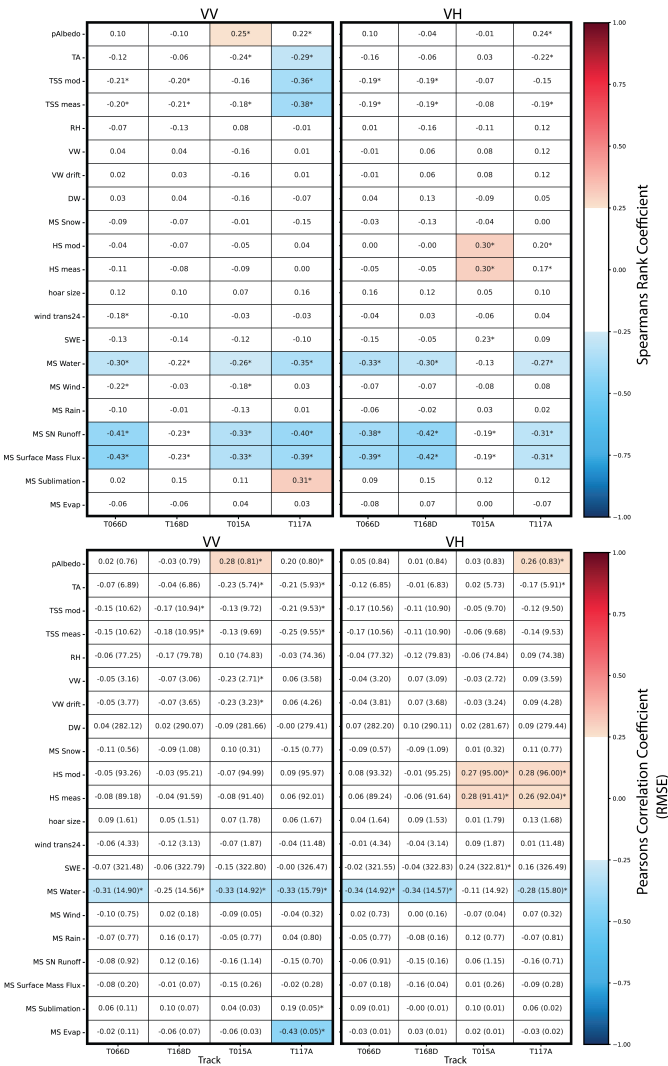


Figure A4. Correlation of analysed SNOWPACK variables compared to the median VV and VH S1 backscatter time series at the DAV5 station per track (location see Fig. 1). The table includes the results per polarisation state for 3x3 window size. Included are the Spearman's (top) and Pearson's (bottom) correlation 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.

A3.2 SLF2 station

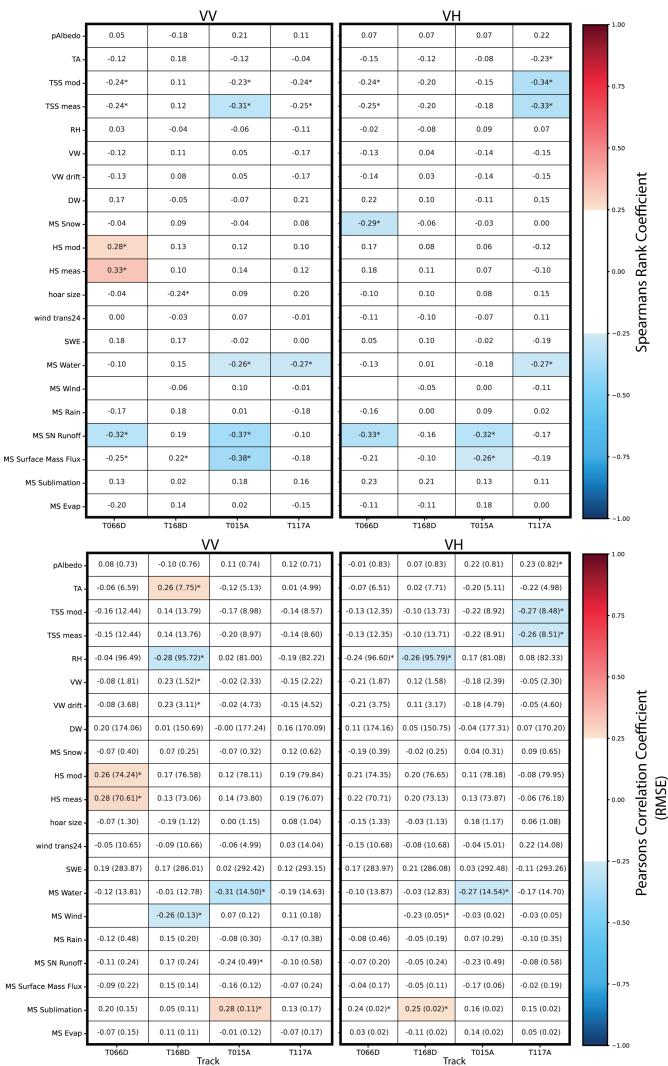


Figure A5. Correlation of analysed SNOWPACK variables compared to the median VV and VH S1 backscatter time series at the SLF2 station per track (location see Fig. 1). The table includes the results per polarisation state for 3x3 window size. Included are the Spearman's (top) and Pearson's (bottom) correlation 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 1.

A4 Aspect dependency of wet snow ratio time-elevation plots and thresholds

A4.1 Aspect dependent time-elevation based melting evolution

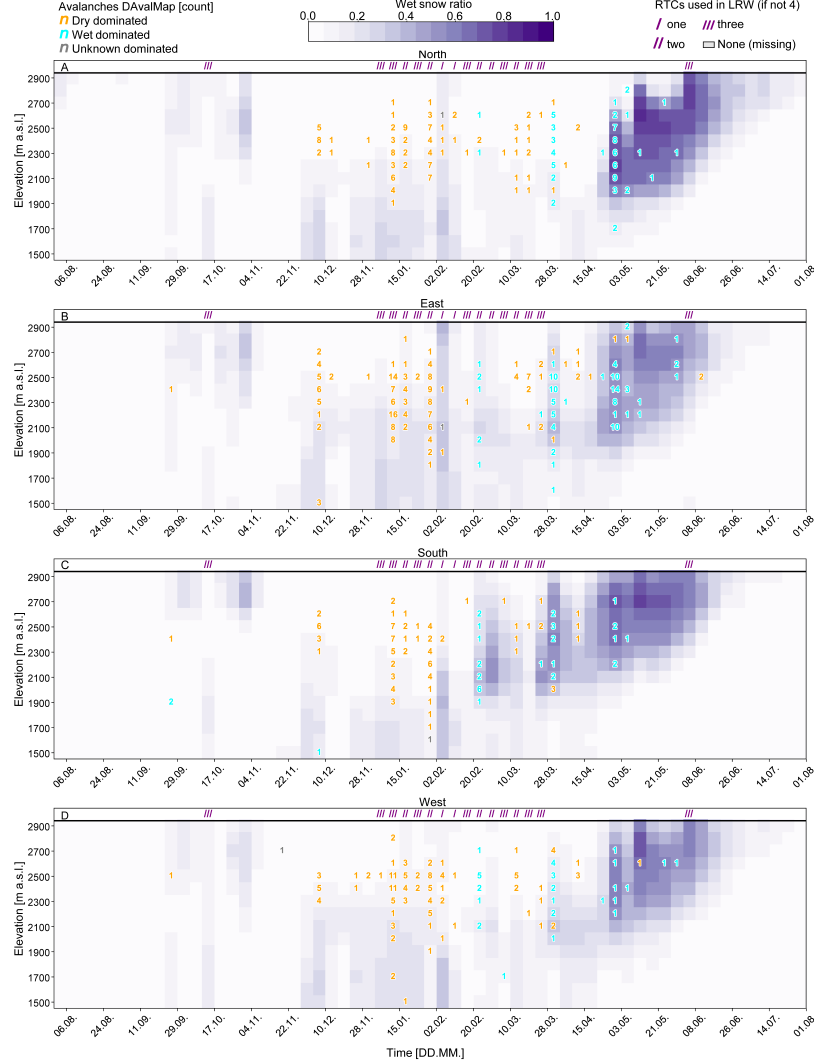


Figure A6. Time-elevation plots of wet snow ratio evolution for combined polarised product for the exemplary seasons of 2020–2021. Displayed are the time series resolved into the different slope aspects: A: North, B: South, C: East and D: West. The plot encompasses data featuring the area of Davos as indicated in Fig. 1, resolved at discrete 100 m elevation bands. The wet snow ratio is the percentage of pixel per elevation band that was 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).

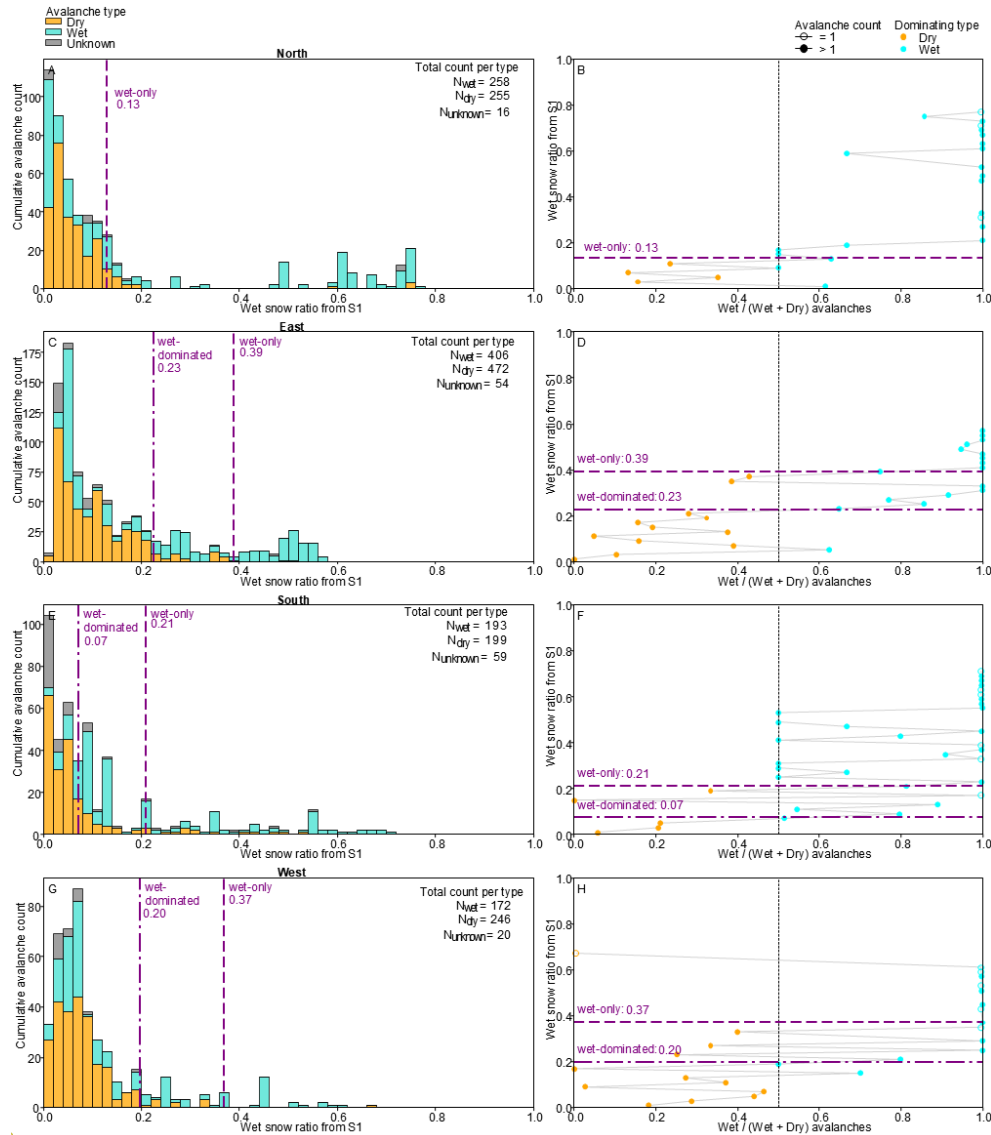


Figure A7. Extraction of wet snow ratio thresholds from S1 D using the [here-presented LRW approach](#) and [SWS product](#). [A Left column:](#) Total avalanche count per type in comparison to wet snow ratio and the extracted wet-dominated and wet-only transition lines after applying gaussian distribution. [B Right column:](#) Wet snow ratio in comparison to dominating type. The extracted thresholds only consider wet and dry snow (unknown, excluded) and entries when more than one avalanche was present. In case of equal amount wet and dry snow avalanches, wet snow was given priority. [The four rows show the data parsed by aspect ranges.](#)

A5 Time-elevation evolution of wet snow ratio derived from SWS product

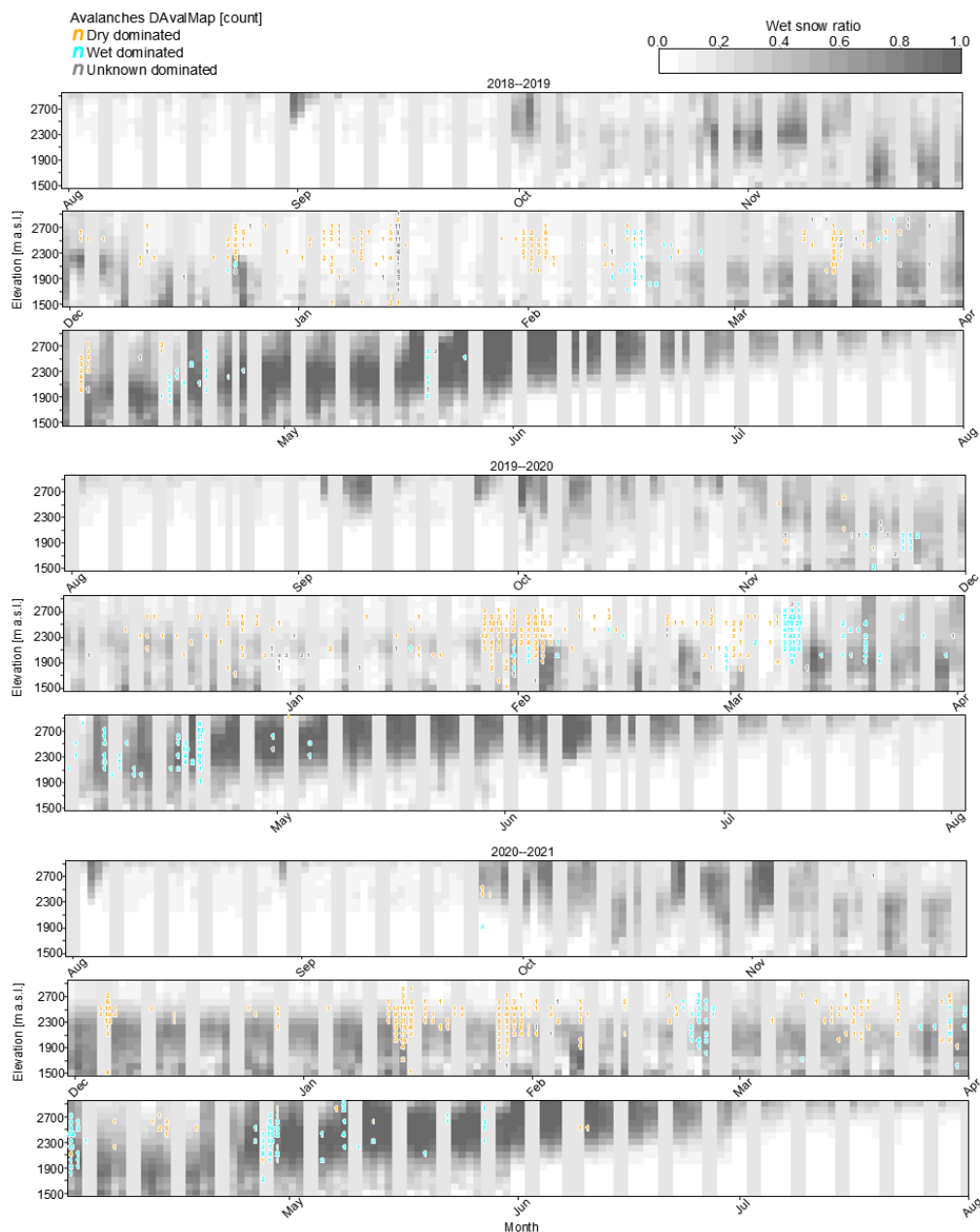


Figure A8. Wet snow ratio evolution extracted from the SWS product (Copernicus land monitoring service, 2025) over time per elevation on a daily grid across the three melting seasons. Recorded avalanches are superimposed on the plot, with the colours indicating the dominant type of avalanche recorded. Empty columns of no available data are displayed in light gray.

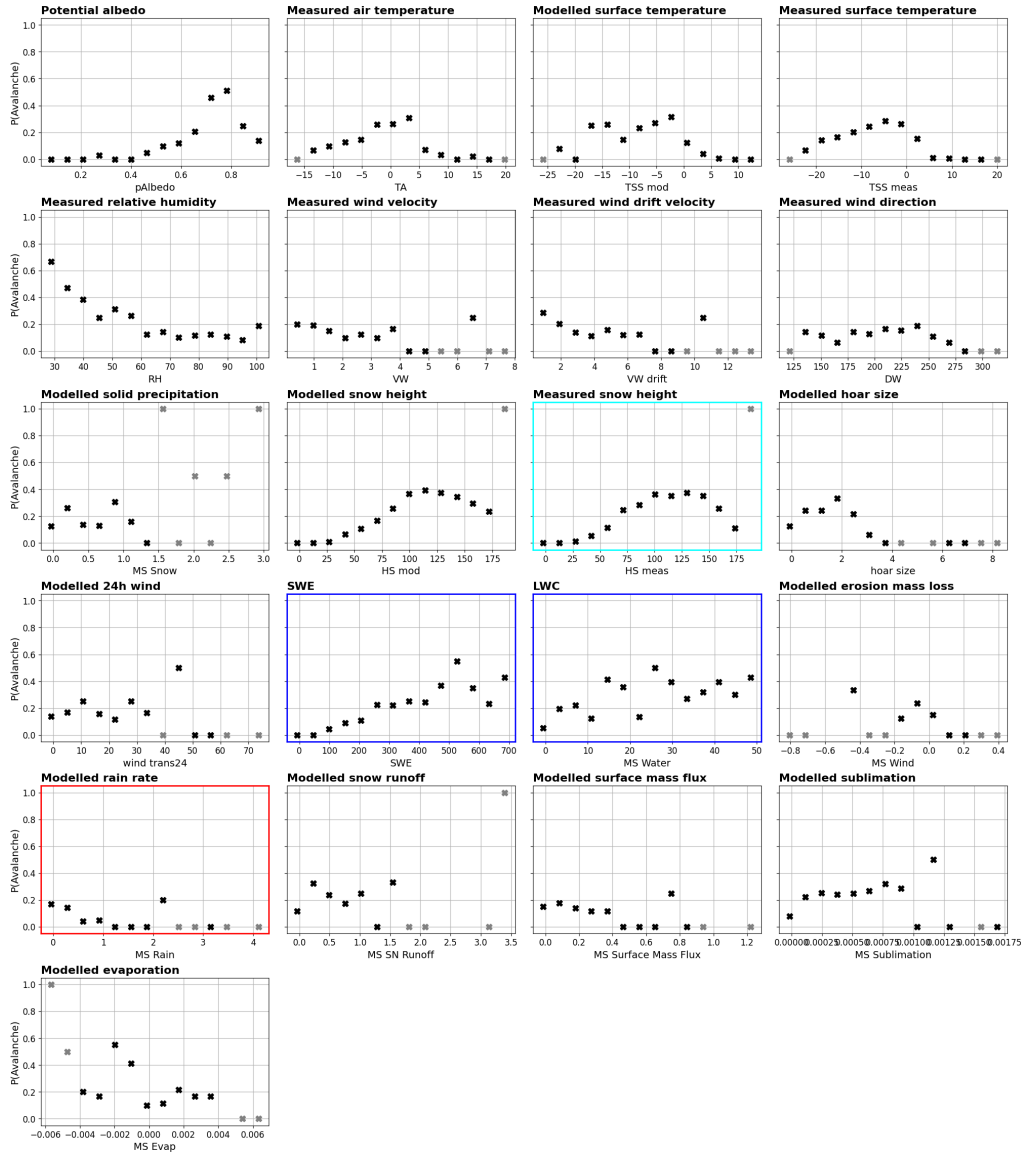


Figure A9. Probability of ≥ 1 avalanche report from the DAvalMap dataset as a function of SNOWPACK variables. Each subplot shows the conditional probability of at least one avalanche occurring on a day given a range of values for a specific variable (*e.g.*, "On days with X mm of rain, what's the chance 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. 2).

A7 Visualisation LRW-product to SWS and optical false colour imagery

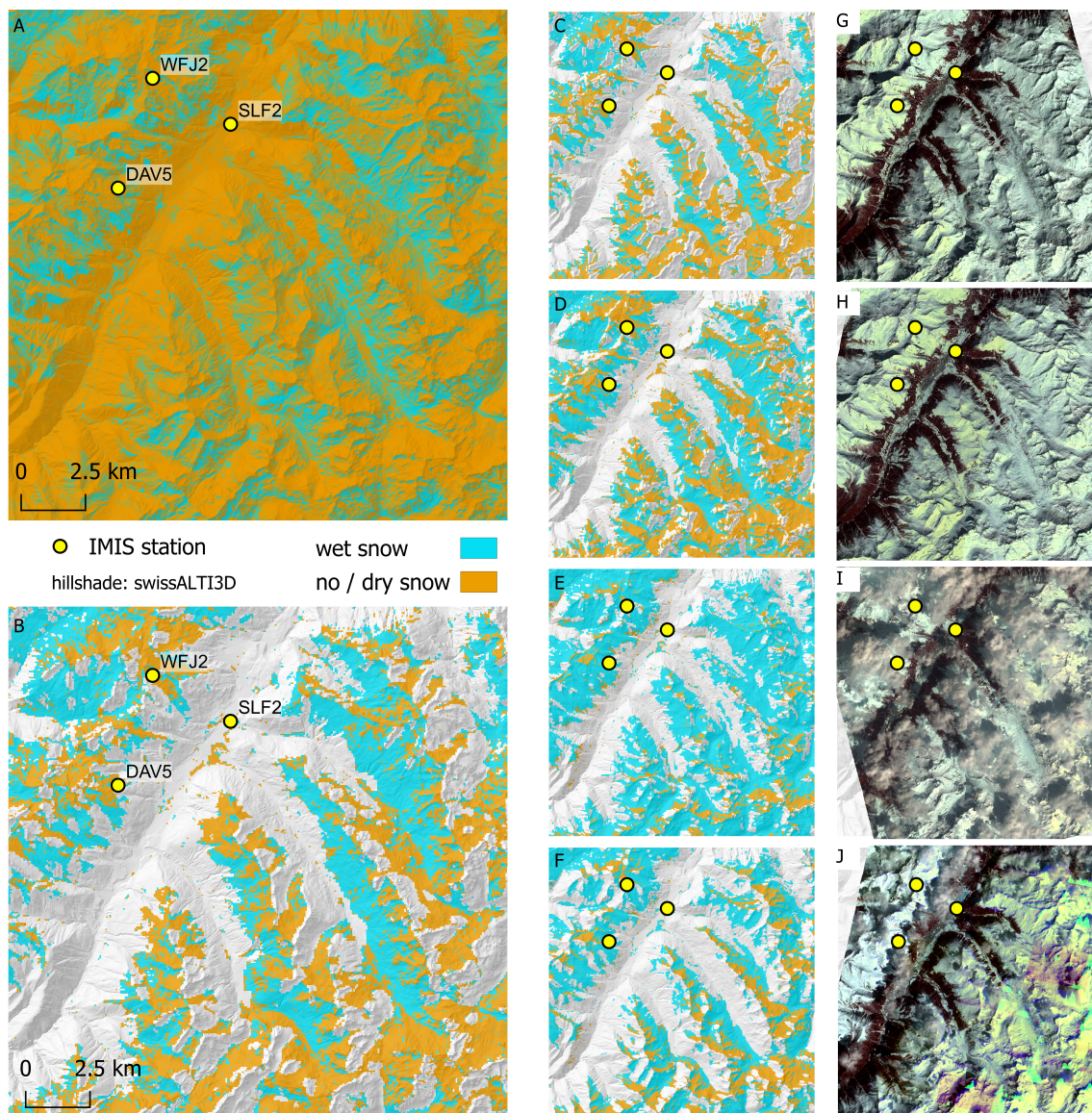


Figure A10. Example case ([220210331-20210403](#)[31.03.2021-03.04.2021](#)) of wet snow detection on a visual comparison. The outline of all the images is the same as the research site displayed in Figure 1.B. [1.A](#)) Based on our processing using LRW, whereas [1.B](#) shows pixels usable from SWS layer on the first acquisition day (Copernicus land monitoring service, 2025). [1.A-D-C-F](#) show SWS product for the four acquisitions which were used for creating the LRW based product ([A-C](#) (same as [B](#) in different scale): 31.03. [B-D](#): [1.401.04.](#), [C-E](#): [2.402.04.](#), [D-F](#): [3.403.04.2021](#)) and [1.H-A-D-G-J](#) show the corresponding optical imagery from ©Planet Labs PBC. Imagery using false colour infrared (Red: NIR, Green: red, Blue: green). [Image contains modified Copernicus Sentinel-1 data \(2021\).](#)

675 *Author contributions.* Conceptualisation: AM, MJ; Data Curation: AM, GD, VB, MR; Formal Analysis, Investigation, Software, Visual-
ization: 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, 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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