

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

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**Abstract.** Information about snowpack ~~wetness at high temporal and spatial resolutions~~ at high spatio-temporal resolution is important for the timely identification of ~~pre-disposing conditions for wet~~ conditions favouring snow avalanche release. However, such information is often available only at specific instrumented locations. Spaceborne synthetic aperture radar (SAR) sensors can facilitate the acquisition of such information over large areas and in remote and challenging terrain. In this work, we ~~utilize-propose the use of ESA Copernicus~~ Sentinel-1 (S1) SAR multi-track composites to monitor ~~snow-wetness evolution over four melting seasons for a study site of 400 km<sup>2</sup> around Davos in the~~ snow-pack wetness evolution. We focus on a study area of 400 km<sup>2</sup> around Davos, eastern Swiss Alps. ~~We evaluate the performance of our method using both, where comprehensive~~ in-situ ~~measurements and modelled snowpack data. We compare snow wetness maps derived from dual-polarisation backscatter time series with wet avalanche records. We found statistically significant relationships between~~ information are available for validation of remotely sensed snow-pack conditions. We found statistically relevant anticorrelation between S1 SAR backscatter decrease in both polarisations and increase in liquid water content ~~expected in the snow-pack. By calculating the percentage of detected wet snow to dry/no snow per elevation (wet snow ratio) (VV: -0.42, VH: -0.38) and runoff (VV: -0.44, VH: -0.49). We calculate a wet snow ratio (0 referring to dry, the seasonal elevation-related melting can be tracked. Moreover, we show that a rise of dual-polarized~~ 1 to fully wet snowpack conditions) relying on dual-polarisation S1 backscatter time series. By comparing our indicator against the SAR Wet Snow (SWS) products, openly available from the Copernicus Land cover monitoring, we found clear benefit in terms of spatial performance. We also compare our wet snow ratio ~~above 30% coincides with~~ time series to a unique catalogue of snow avalanche, aiming to identify conditions that may precede an increase in wet snow avalanche ~~releases in corresponding elevation bands.~~ activity. We found a clear transition from dry snow avalanche dominated to wet snow avalanche dominated conditions when the S1 derived wet snow ratio reaches values of 0.17, while at 0.35 only wet snow avalanche were reported. Our results

suggest that ~~wet snow products derived from~~, despite current limitations in spatial and temporal resolution, S1 SAR data may assist in identifying regions featuring a potential increase of multi-track composites may assist wide area evaluation of snow-pack wetness conditions, and provide additional hints on the initiation of wet snow avalanche activity. However, the current temporal revisit release. Further availability of other satellite based radar products, combined with the continuation of

25 S1 does not allow us identifying potential precursors of wet avalanche occurrence, requiring sub-daily accuracy for operational monitoring mission, will allow increasingly accurate estimates of snow-pack conditions leading to wet snow avalanches, which are expected to be an increasing threat in alpine regions due to the changes associated to global warming.

## 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 ~~can have a high in~~ particular have a highly destructive potential, ~~however, they are still yet they are~~ difficult to predict (??). ~~This For one, this~~ difficulty can be attributed to the limited availability of ~~in-situ measurements of in-situ~~ measurements of the liquid water content in snow, 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 ;

35 ~~and in general and more broadly~~ for accurate run-off modelling (???). Currently, avalanche warning is based on information from weather forecasts, local observers, ~~weather forecasts, in-situ weather station measurements and spatial models~~ automatic weather stations and spatially distributed environmental models (*e.g.*, gridded snowpack and meteorological models) (?). Temporally and spatially ~~continual continuous~~ high-resolution monitoring of ~~wet snow on large spatial scales and in complex terrain could~~ snow wetting in complex and remote terrain could, therefore, help to improve ~~avalanche forecasting~~. Remotely

40 the forecasting of wet snow avalanches on large spatial scales. In this regard, remotely sensed data can help ~~to~~ overcome traditional challenges ~~in poorly accessible terrains, helping related to terrain accessibility and data continuity over space and time,~~ to provide cost-effective methods to efficiently monitor large and remote areas.

~~Spaceborne synthetic~~ Synthetic aperture radar (SAR) ~~from spaceborne~~ sensors, such as the ones onboard the ESA Copernicus Sentinel-1 (hereafter S1) ~~satellites, offer,~~ ~~offers~~ a promising approach to monitor the snowpack evolution at regional

45 scales. ~~Specifically, changes in the backscattered radar signal can be used to provide information on snow melt (????), but the interaction between snowpacks and microwave frequencies~~ 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 (????).~~ The presence of liquid water in the snowpack attenuates the SAR backscattered amplitude radar backscatter (???) ~~due to alterations in the mixture of contributing scattering mechanisms (?).~~ ? suggest that wet snow is

50 typically more cohesive than dry snow due to melting and refreezing processes, thereby altering scattering mechanisms at play. ~~The resulting signal loss is useful.~~ This attenuation results from changes in the scattering mechanisms and the dielectric properties of the snowpack (??).



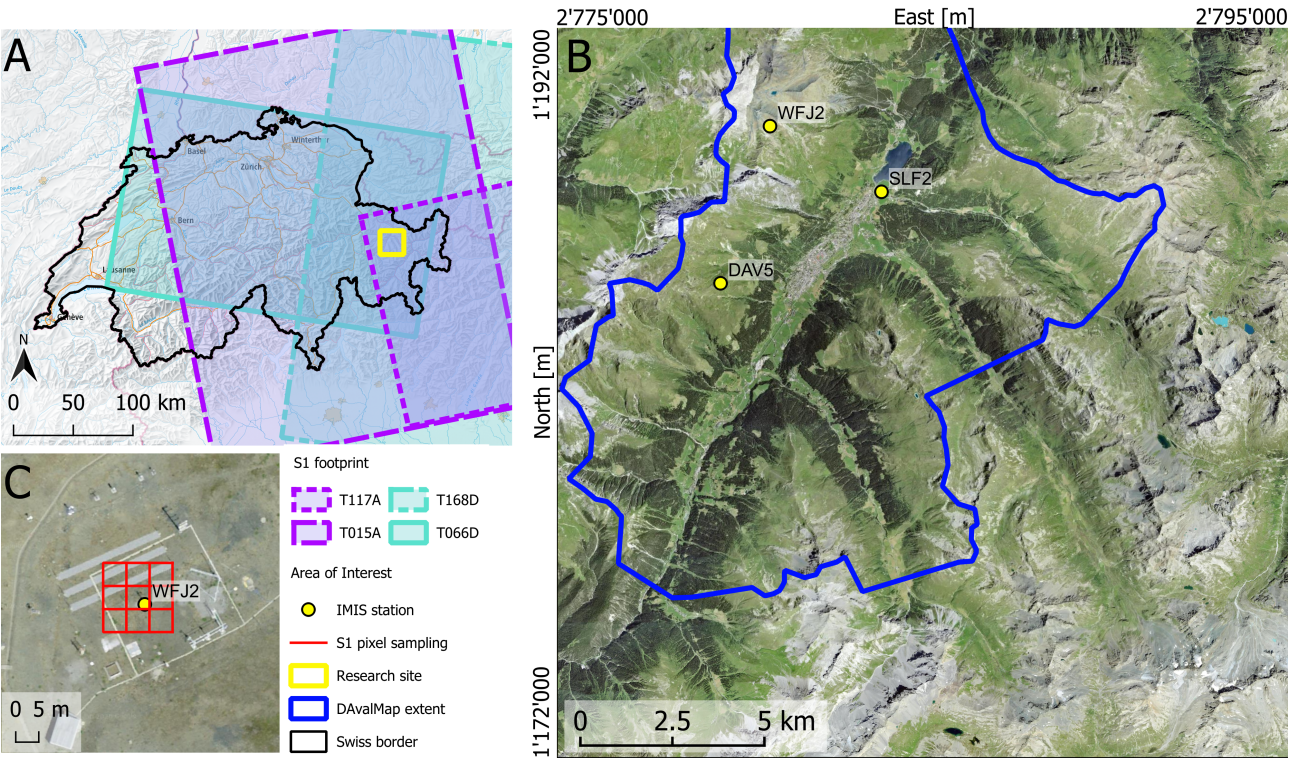
The resulting decrease in the backscatter amplitude can be leveraged to detect wet snow in SAR images by comparing signal backscatter amplitudes to it with a reference image without snow or with only dry snow (?). When the signal decreases below a pre-defined threshold compared to a known dry the threshold of 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 (?). ? showed that, in comparison with ground data-. The combination of co- and cross-polarisation has been found to be most effective for the detection of melt onset (?). 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 (?). By developing a representation style resolving the of detected wet snow maps in altitude-time and altitude-orientation diagrams, ? was able to efficiently show the behaviour of based on elevation-time and elevation-aspect diagrams, wet snow lines (elevation where melting begins) can be derived across large spatial scales aiming at avalanche prediction-(?, also in ?).

Publicly available products featuring wet snow coverage Radar-derived wet snow maps – such as the service provided by ? , currently have several drawbacks, i.e.: SAR Wet Snow (SWS) product provided by the ? – are nowadays publicly available, but (i) they are limited to a resolution of 60x60 relatively low spatial resolution of 60 x 60 m; and (ii) in mountainous terrains they are prone to topographic distortions caused by variable SAR acquisition geometries. Regarding the latter, in mountainous terrain, the the oblique, right-looking viewing geometry of the S1 satellites. This leads to foreshortening, lay-over, shadowing and highly varying ground resolution-. Shadowing a highly variable ground resolution (?). Topographic effects can be minimized minimised by producing composites of radiometrically terrain-corrected (RTC) images from ascending and descending orbits (?). We combine the To address these limitations, multi-track data following ? by taking local resolution available from each track into account. This S1 acquisitions can be combined in a way that accounts for locally varying ground resolution. The approach of generating local resolution weighting-weighted (LRW) composites makes use of multiple viewpoints on mountainous terrain to reduce missing data (shadow) from an individual orbit (?) , employing and employs the high ground resolution available when viewing backslopes. It further minimizes on backslopes. 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. Furthermore, it allows combination of information gathered from different orbits thereby potentially enabling higher temporal resolution than the exact repeat-orbit revisit interval-.

In this study, we used LRW composites to mitigate the restrictions of traditional SAR images such as geometric effects. By optimizing the The aim of our work is to assess the suitability of S1 processing workflow, we improved spatial resolution compared to current altitude-melting diagrams such as ??. We 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 composites and oversampled the SAR data to match all data to 5x5 m ground sampling distance (GSD) over the study region. We applied the LRW composites at a 5 x 5 m resolution and applied a wet snow detection approach on a regional-scale (400 km<sup>2</sup>) in the area of Davos, Switzerland, and compared it to a data set. Finally, we compared the wet snow distribution to a dataset of observed wet snow avalanches. We evaluated the reliability of our results by cross-correlating the time series with data recorded from

three weather stations as well as from the modelled snowpack information. This allowed us to perform validation assessment across the entire time series rather than only during cloud free days, a limitation endemic to optical missions (?) 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 [research study](#) on three scales. (A) Outline of the Sentinel-1 footprints in relation to the [research study](#) site of interest (Basemap © Esri, [Swiss border](#) © [swissBOUNDARIES3D](#)). (bB) 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 study](#) area extent)), and the IMIS stations used (yellow dots). (eC) Indication of the [3x3x3](#) pixel window used to calculate the Sentinel-1 backscatter median around the corresponding IMIS station (Basemap © Google Maps).

## 3 Data and methods

The study area is in the region of Davos, Switzerland. Davos's complex topography and dense monitoring network make this area an ideal study site for alpine wet snow dynamics (see Fig. ??), covering  $400\text{ km}^2$  and elevation ranges between 1542 and 3225 m ??). 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 (?).

The here assessed area covers 400 km<sup>2</sup> between 1 542 and 3 225 m a.s.l. (according to ?). The site is characterized by steep, mountainous terrain ~~, with slope values ranging from 0° to 86° and a median of 28°, and the presence of seasonal snow cover.~~  
100 ~~Mean values of daily temperature in the area and a pronounced winter season. Measured daily air temperature at the stations vary from min -27.4°C in winter (at WFIWFI2 station) to max +29.3°C in summer (SLF), with an average daily temperature range of 9.03C over the years 2019 to SLF2 station). At WFI2, 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. Approximately 15% of the study area is forested, with a median canopy height of ca.10 m~~

## 105 3 Data

### 3.1 In-situ automated weather station data

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 WFI2 (2 536 m a.s.l.), see Fig. ?? . These stations provide automatic measurements every 30 minutes of: snow depth, air and surface temperature, wind speed and wind direction,  
110 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 ~~dominated by coniferous species (??). 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).~~ WFI2. The variables indicated with "measured" in Tab. ?? are the ones we consider from the IMIS station measurement for this study.

### 115 3.2 Modelled data from SNOWPACK

To compare our data with relevant snowpack parameters, we used output data from the snow cover model SNOWPACK (?). This model was developed to support an operational avalanche warning service based on IMIS station data (?). 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,  
120 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 (?), phase changes, water transport in snow using a simplified model (?) or with full Richards Equations (?) and water vapour transport in snow (?). SNOWPACK is used by several countries for their operational avalanche warning services (?), but also in fundamental and applied research studies. SNOWPACK is provided alongside its meteorological preprocessor MeteoIO (?) and Graphical User  
125 Interface Inishell (?) 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 ?.

**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. Spaced 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.

|                                            |                |
|--------------------------------------------|----------------|
| relative humidity [measured]               | RH             |
| air temperature [measured]                 | TA             |
| surface temperature [measured]             | TSS_meas       |
| surface temperature [modelled]             | TSS_mod        |
| 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   |
| 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   |
| Parametrised snow albedo [modelled]        | pAlbedo        |

In this study, we used the output data from the SNOWPACK version of December 2022 (git version: 98a23cd, (?)) in an operational setup. The SNOWPACK output includes both measured data at the station, providing its meteorological forcings, 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. ?? shows all data provided by the model, including abbreviations and the information on which are measured at the three reference sites and which ones are modelled.

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### 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 polarisations ~~VV and VH~~ [polarizations vertical-vertical \(VV\) and vertical-horizontal \(VH\)](#). Over central Europe, S1 has [long had](#) an orbital repeat cycle ~~over central Europe every six days~~ [\(of six days, though this is not always maintained due to the failure of S1B outage of in December 2021, more recent projects have an extended time sampling of 12 days \(?\)\)](#). Our analysis is based on the SAR images acquired on the relative up to the launch of S1C (?).

We processed SAR data from the [descending](#) orbits 066 and 168 ~~(descending)~~ as well as [the ascending orbits](#) 015 and ~~177 (ascending; 117~~ (Fig. ??) [acquired](#) in interferometric wide (IW) swath mode. ~~Hereby, The~~ single-look-complex (SLC) data ~~have a~~ [has a native](#) pixel spacing of  $\sim 2.3$  m in slant range and  $\sim 14.1$  m in azimuth (?). ~~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~~ [Over Davos, the images](#) were acquired at 05:34 (track 066), 05:27 (track 168) ~~UTC on the descending tracks and at~~ 17:15 (track ~~088~~) [15](#)), and 17:07 (track 117) UTC ~~on the ascending tracks on consecutive days in this acquisition order (illustration in appendix over the course of four days (in consecutive order; see Appendix Fig. ??). This lead to a time difference within the resulting composites of less than 84 h.~~

~~We applied~~ 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°) (?).

Data from S1 is also the basis of the freely available Copernicus SAR Wet Snow (SWS) product. We downloaded the SWS products (version: 2025, ?) for the period between 1 January 2018 to 31 July 2021 via the WEkEO platform. This dataset has a resolution of 60 x 60 m and is based on ground range detected (GRD) imagery. 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 ?). This inventory was created by the avalanche warning service SLF through systematic mapping of field observations within a perimeter covering roughly 180 km<sup>2</sup> (see Fig. ??; ?). 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.



**Table 2.** Count of avalanches from DAvalMap sorted by type and season.

| Type per season [count] | 2018–19 | 2019–20 | 2020–21 |
|-------------------------|---------|---------|---------|
| Wet snow avalanche      | 77      | 723     | 261     |
| Dry snow avalanche      | 282     | 380     | 598     |
| Unknown avalanche       | 144     | 36      | 6       |

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 ?? and the used information as a subset of the database can be found in the supplementary material.

## 4 Methods

### 4.1 Sentinel-1 data processing

To create LRW composites from S1 data, we first performed a radiometric terrain correction ( $\gamma_0$ , following ?) to descending and ascending (RTC) ( $\gamma_0$ , following ?) on the S1 acquisitions and then combined the data into LRW composites. The latter products are calculated by considering These composites were calculated by applying a weighted function on to the RTC images based on the local incidence angle from at least two different flight tracks (here two descending, two ascending in our site we had a maximum of two descending and two ascending tracks). Weighting is was applied according to the local spatial resolution in the corresponding flight track (?). We masked out areas that lie lied in radar shadow in all tracks, following the processing chain by ? and ?. In cases where information was available in some track, i.e., unavailable in some tracks, i.e. lying in radar shadow in others, only the available orbit was orbits were considered (as in ?). In total, we produced 424 LRW composites. To maximise consistency, composites missing one of the four tracks were discarded (see Tab. ??). We also calculated LRW using only tracks 066 and 015 to assess the effect of using two instead of four tracks (420 RTC values below -30 dB were classified as noise below the sensor sensitivity threshold and were therefore not considered in the LRW calculation (?).

Images, where less than 75 % of the acquired scene was valid, were discarded. This resulted in 444 LRW composites (186 entailing all, 29 three-track, and 6 two-track LRW). To minimise noise and artifacts in the two-track LRWs, we calculated a temporal rolling median considering three samples for the time-series analysis, thereby executing a trade-off between a loss in detail and the influence of outliers composites per polarisation), as well as two dates where only one track was available (these images remained on RTC level). The maximum timespan covered by a composite was less than 84 h.

Wet snow maps were generated by comparing an acquisition potentially featuring wet snow with a reference without snow or with dry snow (?). ? defined a threshold 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 signal loss compared to a dry/no snow image for S1. In case of a stronger signal diminution, wet snow was assumed dB as an indication for the presence of wet snow (?). No standard approach for the selection of a reference image is yet has yet been established, leaving space for potential differences in results (?). ? used a single image from summer, where the least amount of (melting) snow was assumed to be present in the scene. Rather The revised version of the SWS product (?) 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" 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 and used this value as a "dry" reference (indicated in black in Fig. ??). With this approach, we cope with the challenge of finding a suitable reference image, which becomes less accurate the longer the timespan between time span between the 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.

We additionally used data of elevation, forest and water bodies to assess their influences on the data and potentially mask out areas where wet snow detection with S1 would be less reliable. A digital terrain model (DTM) provided by swisstopo with ground sampling distance 5x5 m was considered to perform aspect dependency analysis in four aspect categories (N: 315–45°, E: 45–135°, S: 135–225°, W: 225–315°) (?). Information on the distribution of water bodies was taken from the high resolution water and wetness (WAW) layer created by Copernicus (?). The data was provided at We then mapped wet snow on a 10x10 m grid scale, acquired between 2012 and 2018, and published in 2020. The land classes were resampled to match the DTM pixel grid using nearest neighbour to ensure class consistency. The land cover classes of permanent water, temporary water, permanently wet and temporarily wet were merged and used for masking. Information on forest cover in the study area was sourced from the forest mask of the Swiss national forest inventory (?). 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 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.



220 **4.2 Reference data** Two different validation data sets were used. First, we analysed the sensitivity of SAR backscatter to snowpack characteristics to identify the features influencing Timeseries analysis: 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 S1 to recorded wet snow avalanches. backscatter sensitivity to snow characteristics

#### 225 4.2.1 Modelled Snowpack characteristics from SNOWPACK

The SNOWPACK snow cover model was developed to support an operational avalanche warning service based on the international measurement and information system (IMIS) automatic weather station data (?). 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 (?), phase changes, water transport in snow with a simplified model (?) or with full Richards Equations (?) and water vapour transport in snow (?). SNOWPACK is used by several countries for their operational avalanche warning services (?) but also in research. SNOWPACK is provided alongside its meteorological preprocessor MeteIO (?) and Graphical User Interface Inishell (?) under an open source licence (LGPLv3).-

In this study, we used the SNOWPACK version from December 2022 (git version: 98a23ed) in an operational setup. This means that the simulations did not model soil, relying on a Dirichlet lower boundary condition (upper soil temperature). The upper boundary condition (energy exchange between the snow or soil and the atmosphere) relied on either a measured snow or soil surface temperature (Dirichlet when the surface temperature was less than  $-1^{\circ}\text{C}$ ) or a parameterized incoming long wave radiation (Neumann) relying on an atmospheric cloudiness estimated from the measured short wave radiation (?). These reanalyses additionally used a horizon computed from a 25 m resolution digital elevation model in order to distinguish shading by the terrain from cloudy sky, when parameterising the incoming long wave radiation. The SNOWPACK output includes both measured data at the nearest station as well as modelled parameters. The IMIS stations SLF2 (1563 m a.s.l.), at DAV5 (2315 m a.s.l.) and WFJ2 (2536 m a.s.l.) were within the boundaries of the research site. In order to test 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 over time (see Fig. ??, appendices ?? and ??). 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. ??C) in relation to diverse variables contained in SNOWPACK at three IMIS station locations (at

245 IMIS stations Fig. ??), the IMIS measurements were hence covering a variety of elevations within the region of interest in a flat field simulation. The timespan covered by available SNOWPACK data was September 2017 to August 2020. Due to a sensor failure, no SNOWPACK simulations could be performed at the SLF2 station for the 2018-19 season and hence the corresponding SNOWPACK data was not used in this analysis.

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

260 ~~Finally, and in order to test the factors influencing the SAR backscatter time series, we performed a cross-correlation analysis~~  
~~between diverse variables in SNOWPACK at the corresponding station locations over time (see Fig. ??, appendices ?? and ??).~~  
 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~~ minimise the correlation coefficient bias due to the effect of over-represented numerical values (~~e.g.~~  
 265 e.g. zero is used by SNOWPACK when void), correlations were only calculated during the snow cover period (defined as snow  
 height above zero within SNOWPACK). The significance level for both tests ~~were was~~ set to p-values below 0.05.

~~After detection~~ To quantify the time difference between the onset of the main melting season and its detection using S1 LRW  
data. We defined melt onset as the first date on which the 3-day median runoff exceeded the runoff threshold (set to 1 kg/m<sup>2</sup>).  
This was then compared to the current or first following composite on which wet snow was detected in the LRW timeseries.

## 270 4.3 Retrieval of wet snow avalanche preconditions

After the successful detection of wet snow across the study site based on the composite timeseries, wet snow was classified  
 into elevation bands, and ~~the its~~ relative occurrence was quantified using a modified plot design based on ? showing elevation-  
 dependent melting over time. Elevation bands were defined in 100 m increments, ranging from ~~1500 to 3000 m~~ 1 500 to  
3 000 m a.s.l. ,resulting in 15 elevation steps. Temporal classification followed the timing of ascending S1 acquisitions Temporal  
 275 classification was based on a six day grid, starting with the first LRW per season. Areas with slope angles below 28° were  
 excluded to focus on potential avalanche release zones (?). For homogeneity in the intercomparison with the coarser resolved  
SWS dataset, the latter has been oversampled using nearest neighbour onto the 5x5 m grid to minimise data-loss.

For each elevation band, we computed the wet snow ratio as:

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

280 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.

### 4.3.1 ~~Wet snow avalanche catalogue~~

~~As a further ground-reference, we considered data from the Davos Avalanche Mapping Project (DAvalMap, detailed description~~  
~~in ?). This data set was set up by the swiss avalanche warning service, designed to be an avalanche inventory covering about~~  
 285 ~~180 km<sup>2</sup>. Systematic mapping was performed within the illustrated perimeter in Fig. ?? (?) and is thus smaller than our study~~

area. A part of DAvalMap in the North was excluded to match the research area, fitted to be within Swiss national boundaries for data consistency. Mappings outside the DAvalMap were only sporadic. Spontaneous avalanches considered small according to their type (50 m for slab avalanche and glide-snow avalanche, 100 m for loose snow avalanches in either dimension) were not recorded in the catalogue, thereby setting a minimum size of avalanches within the data set. The data includes By comparing the wet snow detection from S1 with the event-based snow avalanche catalogue (DAvalMap), we retrieved information on the release date, the snow condition (wet/dry snow avalanche) and the elevation zone at release.

wet snow avalanche preconditions. For this study, we selected only the avalanches that were classified as wet snow avalanches situated within the research site (Fig. ??) inside the study's time range (January 2018 to August 2021). The recorded avalanches from DAvalMap were After discarding duplicates from the catalogue as well as data collected outside our study area, the avalanches were matched to wet snow ratio (see Equ. 1) plots according to the elevation of the release zone and the date of release (?). Temporal matching was performed by pooling the observed avalanches into one elevation-time bin by combining the avalanches occurring during the timerange one day before the LRW timespan to one day after (for illustration see 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. ??). This allowed coverage of a continuous time frame using a six day interval. This temporal matching also included avalanches after image acquisition. However, this is the most robust solution to approximate the wetness state of the snowpack and its corresponding proneness.

To assess the potential for this wet snow ratio to detect the transition from dry to wet snow avalanche dominated releases, we computed histograms and Gaussian distributions of recorded dry and wet snow avalanches in relation to the wet snow ratio. 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 avalanches, as it minimised temporal differences between avalanches and acquisitions. In the season 2019–20, the size restriction of the recorded avalanches was handled less strictly, also including smaller loose snow avalanches which would have been excluded in the other years. The used data from DAvalMap contained 77, 723 and 261 wet snow avalanches for the seasons 2018–19, 2019–20 and 2020–21, respectively avalanche prevalence only. This was defined as the transitioning point 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 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 the avalanches from the catalogue. Avalanches that occurred when no data was provided were carried over to the next available date (see Appendix ??). 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 ~~Polarisation dependent S1 backscatter time~~ Time series analysis

At WFJ2, the backscatter in For each season, the LRW backscatter signal fell below the threshold after the increase in runoff and the decrease in measured snow height (Fig. ??). The time difference between detection using S1 dual-polarisation approach and the increase of runoff above threshold was found to be within the 6 days of the LRW window (Fig. ??: -1, +1.6, +5.1, +5.6 days delay for 2017/18, 2018/19, 2019/20, and 2020/21 respectively). The backscatter in both polarisations (VV & VH) fell ~~clearly~~ ( $> 3$  dB) ~~reaching beyond the set threshold for wet snow or more below the time series median~~ in late spring/early summer in each season, ~~coinciding with snow melt at high alpine altitudes, and coincided with the snow melt occurring at high elevations~~ (shaded in Fig. ??) and temperatures around the freezing point (see Fig. ??E). Sporadic decreases of backscatter ~~reaching, dropping below the threshold were also observed, were observed in both polarisations,~~ where SNOWPACK data (*e.g. liquid water content or runoff*) did not suggest the presence of snow wetness. However, for all such spurious events, the results diverged depending on the polarisation ~~and they are accounted for when using the combined polarisation approach. So, while the, occurring in one polarisation but not in the other. The~~ combination of VV and VH polarisation (indicated by overlaid shadings in Fig. ??D and E) shortened the ~~timespan time-span~~ of detected wet snow ~~, it and resulted in delayed detections (especially in season 2020/21), but~~ minimised the potentially false detection during ~~off-season periods. When paired with a three-day rolling mean, the two-track composite (consisting of one ascending and one descending acquisition) produced a time series similar to that of the four-track composite, with the four-track LRW generally showing a more conservative behaviour (appendix ??). periods when snow melt should not occur.~~

Overall, similar results were observed at the DAV5 and SLF2 station locations (appendix ?? and ??). However, at SLF2 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 ??). The median backscatter of the DAV5 station was observed to be several dB lower than the other stations (Tab. ??).

Median of S1 backscatter per polarisations at the three different stations within the timeframe of 01.2018 to 08.2021. Polarisation SLF2 DAV5 WFJ2 VV -10.05 -13.49 -9.07 VH -17.92 -20.67 -17.30 Increasing Liquid Water Content (LWC) percentage coincided with a decrease in snow height (see Fig. ??c). In each melting season, an increase in LWC was found as well as sporadic peaks matching early snow melting events *e.g.* in November 2018. With a time shift of about a week, the backscatter signal diminished soon after the sudden increase in LWC and the decrease in snow height. This behaviour was found across all melting seasons (see Fig. ??).

~~Indication for~~ Statistical comparisons between the RTC level backscatter timeseries and the station measurements at all stations indicated negative correlation between S1 backscatter and SNOWPACK modelled ~~LWC liquid water content~~ as well as measured runoff ~~could be found at all stations, in most tracks. These correlations ranged, for LWC, between -0.12 over the full timespan (Jan. 2018 to Aug. 2021, Fig. ??). For runoff, the correlations ranged from -0.13 (VV; SLF2) to -0.42 (VV -0.49 (VH; WFJ2) in Spearmans rank and -0.16 (RMSE: 13.93) to -0.30 (RMSE: 37.20) from -0.28 to -0.26 for Pearsons~~

correlation, when averaged over the tracks per station per polarisation (Fig. ??, and appendices ?? and ??). ~~At WFJ2 station, a negative correlation with the temperature variables was indicated, and a~~ This and the correlation found with the liquid water content indicates the expected sensitivity of S1 to water within the snowpack (?). 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 ~~SNOWPACK's potential albedo, however neither could be found in the other station locations, 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 with early melt events (*e.g.* November 2018).

Time-elevation plots of wet snow ratio evolution for combined polarized product across three and a half melting seasons (A: 01.2018–07.2019, B: 08.2019–07.2020 and C: 08.2020–07.2021) featuring the area of Davos as indicated in Fig. ??, 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 (?). No spatial smoothing or filtering was applied (these effects can be found in the appendix ??). Dashed lines and letters a–d in panel C correspond to the timeframes of the wet snow maps displayed in Fig. ??. Plot design was inspired by ? and ?.

Time-elevation plots of wet snow ratio evolution for combined polarized product for the exemplary seasons of 2020–2021. Displayed are the time series resolved into the different slope aspects: A: North, B: South, C: East and D: West. The plot encompasses data featuring the area of Davos as indicated in Fig. ??, 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 (?). Plot design was inspired by ? and ?.

## 5.2 Spatial distribution and elevation dependent melting

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

Comparing our detection of wet snow to the SWS product suggested a general agreement on the main melting phases at all three stations (Fig. ??C for SWS and shadings in .D and .E for detected from LRW product, with the same in appendices ?? and ??). 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 ?? and ??).

Time-elevation-dependent melting seasonality was detected across the time series independent of polarisation and slope aspect

## 5.2 Retrieval of wet snow avalanche precondition

Overall the wet snow ratio decreased in elevation during the winter months and rose to higher elevations with the progression into summer (Fig. ??). ~~In the seasons~~. Across the three analysed seasons, the highest wet snow ratios occurred in 2018–19 and 2020–21, ~~the highest wet snow ratios were measured (mid March, classified into wet snow ratio of reaching 70–80 %).~~ The maximum ratios that were reached throughout the season ~~in mid or late March, whereas 2019–20 amounted to 50–~~ exhibited lower maximum values of about 60%. ~~Increasing ratio values (above %.~~ Both these two years saw a warm phase in February with wetting occurring quite early compared to other years. In 2020–21, elevated wet snow ratios (>30%) ~~were detected- %)~~ appeared earlier in the season of 2020–21 between November to February at elevations ranging from 1500 to 2200 m (November–February) between 1 500 and 2 200 m a.s.l. In 2020–21 (see Fig. ??), the wet snow ratio rose again, achieving, ~~followed by a second peak of up to 70–80% mid May- % in mid-May.~~

The wet snow ratio mainly diverged between polarisation states in late summer and autumn periods, where the VV polarisation indicated maximum wet snow ratio (see equ.1) values of up to 20 %, whereas the VH polarisation indicated a continuous time-elevation-dependent increase in

Fig. ??A, .C, .E and .G shows a histogram of avalanche types as a function of wet snow ratio with up to 40 % wet snow pixels per elevation class (appendix Fig. ?? and ??). VH indicated higher ratio values than VV polarized data at lower elevation classes (1500–1900 m a.s.l.). Based on this polarisation-dependent difference, only slight indications of late-autumn melt at higher elevations were visible; however, this period is of minor relevance due to the absence of avalanche-critical conditions and was therefore not the primary focus of this analysis. Fig. ??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 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. ??I).

Masking of land-cover classes such as forest and water bodies had little influence on the resulting time-elevation plots. Large water bodies such as lakes were mainly situated in the lowest classes and in flatlands, and were thereby already masked out by focusing on hillsides via the minimal slope threshold. On the other hand, the exclusion of forests resulted in measurable changes in elevation-based wet snow mapping (see appendix Fig. ??A 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 was mainly focused on a specific elevation range below 2000 m a. s.l. (see appendix Fig. ??A to B) Applying a moving median filter smoothed the time-elevation plots (see appendix Fig. ??A to C). The noise reduction had less impact in high alpine areas, likely because the original signal was already relatively undisturbed. In contrast, at lower elevations, the differences in classification between results with and without noise reduction can span two classes (from 0–10% to 30–40%

When resolving the data towards the four aspects (Appendix ??), we found the highest sensitivity (lowest wet snow ratio values), indicating a higher risk of also removing important signal components.



420 The time-elevation plots also clearly showed differences in aspects (see Fig. ??). South and East-facing slopes showed an earlier increase in wet snow ratio to values above 40 % in the season than did West and especially North-facing slopes (compare Fig. ??B and C to A and D). The highest ratios reaching 90–100 % wet snow ratio values 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 was found in VH-polarized data, also across all seasons. The aspect-dependency was more relevant when a minimal slope steepness, e.g. 45° (high avalanche danger according to ?) was defined (0.13). This indicated a slightly better performance in south and north-facing slopes than in east and west-facing slopes.

425 For the SWS product, the general transition between the avalanche release conditions was found to be less distinct (Fig. ??II). Although dry snow avalanches were more prevalent at lower wet snow ratios (below approximately 0.5), no period characterised exclusively by dry snow avalanche activity could be distinguished. The transition to conditions dominated solely by wet snow avalanches occurred at a higher threshold, when compared to the multitrack LRW-based product, i.e. 0.81 (Fig. ??I).

~~Wet snow ratios did not show relevant changes before the first surge of~~

## 435 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 for avalanche-related purposes. The product allowed a clear separation between conditions where dry snow avalanches dominate, wet snow avalanches recorded in DavalMap (see Fig. ??A, B and C). Instead, a second increase of avalanche occurrence observed in 2018–19 and 2020–21 ranging across various elevation classes (Fig. ??B) 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, coincided with wet snow ratio values of 25 to 30 % in altitudes from 2000–2200 m a.s.l.). After this second event, a further increase in wet snow ratio characterizes the melting season (Fig. ??). Events of multiple avalanche occurrences that were recorded in DavalMap coincided with dual-polarized wet snow ratios above 30 % (Fig. ??). DAV5, WFJ2; Fig. ?? and appendices ?? and ??). 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 (?). Adding modelled data, with all its inherent uncertainties, allowed us to assess the sensitivity of the radar signal to additional snowpack characteristics.

450 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 surface temperatures (TSS) provided an indication of the seasonal evolution of the snowpack and the timing of melt conditions. Periods with non-zero snow height together with temperatures around the freezing point can be interpreted as conditions favourable for snow wetting. However, the relationship between these variables and snow wetness remains indirect, explaining the rather low correlation statistics between S1 backscatter at WFI2 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 strong spatial variability of the alpine terrain.

Correlation of analysed SNOWPACK variables compared to the median VV Sentinel-1 backscatter time series at the WFI2 station per track (location see Fig. ??). The table includes the results per polarisation state for 3x3 window size. Included are the Spearmans (top) and Pearsons (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 ?? and ??. In contrast, additional parameters extracted from the SNOWPACK model showed stronger relationships with the SAR backscatter signal. Across all tests, liquid water content (MS Water) and snow runoff (MS SN Runoff) exhibited the strongest correlations with the SAR derived snow wetness (Fig. ?? and appendices ?? and ??). 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, resulting in low backscatter values (??).

## 7 Discussion

In this study, we analysed SAR-based wet snow maps by implementing a new processing chain and validating it with *in-situ* measurements and modelled information. By relying on LRW composites, Combining the two datasets, measured and modelled, at the station location allows us to define the best possible initiation of the main melting season and to extract a time difference between the snowpacks' main melt initiation and the wet snow detection. A time lag was observed between the decrease in the snow height, the increase in modelled liquid water content, and the detection of wet snow from S1 data was exploited to combine backscatter from different tracks. Thus, the information on snow wetness in our study is provided ready-to-use and was considerably less noisy compared with methods used previously (?).

The available S1-based snow cover products SAR Wet Snow or Wet/Dry Snow by Copernicus offer a spatial grid sampling distance of 60x60 m (?) and hence may not suffice to adequately resolve the variability of alpine topography (appendix Fig. ??). The discrepancy between the available products and our results is partly linked to the use of the more highly resolved SLCs rather than ground range detected (GRD) S1 ??. Most especially, by using LRW composites, the influence of typical SAR geometry effects, such as shadowing and layover, was mitigated (see appendix Fig. ??). Having fewer areas that lack data and potentially improving the temporal resolution is important, for example for avalanche forecasting where accurate timing of capturing the. However, the onset of runoff was matched within the timeframe of the LRWs (see Fig. ??). Compared

to results by ?, this suggests that the moistening and ripening phase was not fully captured. The study by ? also found the liquid water content to be the highest impact at the start of the wetting-of-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 snowpack (?), a key factor to estimate the hazard of wet-snow-avalanche releases applied reference and the thresholding approach (?), limited sensitivity of the sensor below a certain water content threshold, and diurnal variations in snowpack conditions.

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. 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 DAV5 station (Appendix Fig. ??). This measurement station is northwards oriented and on three sides surrounded by avalanche protection structures likely affecting backscatter signals. At SLF2, the snowmelt in spring 2020 is not captured when combining both polarisations, as no distinct drop in co-polarised backscatter was detected. 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. Also at SLF2, proximity to infrastructure (>15 m) and temporary constructions may have caused signal interference (e.g. the increase in backscatter observed early in the year (Appendix Fig. ??) coincided with the timing of the World Economic Forum, plausibly linked to temporary metal constructions for security around the nearby helicopter landing zone).

Validation of spatially continuous products providing information, where there was previously hardly any available, is challenging. Consequently, we relied on comparing data with *in-situ* measurements, where available, to minimise uncertainties related to the reference data. The SAR Wet Snow and Wet/Dry Snow layer were validated via a pixel-wise comparison to other remote sensing products such as snow cover maps from Landsat (?). Since the acquisition technique is still based on remote sensing approaches, the biases contained might also be similar, hence we believe our comparison to an independent product is less prone to bias. It further allows us to perform correlation assessments across the entire time series and not only under cloud-free conditions, a constant challenge when considering optical spaceborne imagery (?). Also, we compared the results to snowpack characteristics instead of snow extent, thereby more reliably approximating what actually influences the signal. Nevertheless, an example comparison of a wet snow mask from our multi-track LRW to the SAR Wet Snow layers and the best temporally matching false colour imagery from the same time range provided by Planet Labs Inc., showing a case of disappearance of snow during the time window of the LRW, can be found in appendix Fig. ??.

## 6.1 S1 based wet snow detection

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

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

~~As previously mentioned, no~~ No standard approach for the generation of a reference image ~~has been is~~ established. The ~~Copernicus SAR Wet Snow layer is~~ 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; ?). Other studies as well as the current SWS dataset calculate the mean over dry or no snow images (~~e.g., ??~~)(e.g., ???) or use a single reference image featuring either dry or no snow conditions (~~e.g., ?~~)(e.g., ?). Increasing temporal baselines between the image of interest and the reference image, results in greater errors due to changes over time. In the application of wet snow avalanche now- and forecasting, time efficiency and accuracy is of major importance. By choosing an "all season" median, we have wet snow contamination in the reference; however the results of our study indicate applicability of the method (see Fig. ??) and follow the process applied in ?. The advantage of reference image generation in that way is ~~lower processing costs, reduced input requirements~~, a high automation level, ~~and~~ no arbitrary reference selection and a simplified update-ability.

~~Validation was performed using SNOWPACK data at three IMIS stations SLF2, DAV5, WFJ2 (Fig. ?? and appendices ?? and ??). This allowed us to include both modelled and measured variables, thereby also allowing to check the validity of the gained results. The stations are all situated on mountain slopes but in rather flat areas. Hence, they are unlikely to accurately represent the conditions in highly variable topography limiting the possibility to validate LRW products in these areas. Additional limitations may come from the immediate surroundings of some of the stations having an impact on the radar backscatter. The mentioned signal instability at DAV5 is plausibly linked to interference from numerous nearby avalanche protection structures, which have stable backscatter properties and could thus bias the results. When seasonal transitions are less pronounced due to lower elevations, smaller melt events are often not captured. Which might explain that at SLF2 the snowmelt in spring 2020 is not captured when combining both polarisations, as no distinct drop in co-polarized backscatter could be detected. The SLF2 station's proximity to railway infrastructure suggests potential signal interference, with varying impact depending on the satellite track. Moreover, the increase in backscatter observed early in the year (appendix Fig. ??) coincided with the timing of the World Economic Forum, plausibly linked to temporary metal constructions for security around the nearby helicopter landing zone.~~

~~We tested the cross-correlation of values recorded on a single pixel in relation to diverse variables contained in SNOWPACK at IMIS station locations. However, single pixel analyses are prone to radar noise (e.g., speckle) and uncertainties, we therefore performed the same analysis on a 3x3 window (indicated in Fig. ??) and at three different locations. Across all tests, the liquid water content and the water runoff were among the strongest correlation values with the correlation assessment (Fig. ?? and appendices ?? and ??). This coincides with the ongoing understanding of the measured backscatter decrease being related to~~

~~the amount of liquid water within a snowpack (e.g., ???). Already with a LWC of 5 % in a snowpack, SAR penetration depth has been found to be minimized to one wavelength and hence SAR backscatter is already very low (??).~~

555 The selection of polarisation modes from S1 data has varied between wet snow observation studies. While ~~e.g. ?? used VV-polarized~~ e.g. ??? used VV polarised data, ? used VH ~~polarized-polarised~~ and ??? used a ~~dual-polarized-dual-polarised~~ approach. In our results, the correlation values showed similar trends between the different polarisation modes (Fig. ?? and appendices ?? and ??). In contrast to ? 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 ? on a dB scale on a ratio value as implemented by ?. The strongest divergence between the wet snow ratio extracted from VV and VH polarisation was observed in late summer / early autumn, whereby the VH polarisation indicated higher ratio values than VV. This might be related to a remaining influence of seasonal activity of vegetation (~~e.g. by-occurence~~ e.g. by occurrence of shrub forest), which is known to influence backscatter signal (?) or by the ripening which ? 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  
560 misclassification, however, the approach also results in a loss of ~~detail. In contrast to ? we performed analysis on separate polarisation states before combining the wet snow masks, this mitigated the issue of using a thresholding approach developed by ? on a dB scale on a ratio value as implemented by ?~~ sensitivity.

~~We observed a time lag between the decrease in snow height, the associated increase in LWC, and the detection of wet snow from S1 (see Fig. ??). Compared to the data from ? this indicates that we missed the moistening and ripening phase to measure the runoff. We believe this temporal gap might be attributed to the combination of four effects: i) the temporal gap between variables, as we made use of weighted S1 only every 6, or 12 days in case of a discharged composite (see appendix Table ??) ii) the potential filtering out of the onset of wetting in a snowpack as noise, iii) the limited sensitivity of the sensor up to a certain minimum water content threshold and iv) the dependence of~~

## 6.2 Benefit of using S1 multitrack LRW processing

575 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.

Commonly available S1-based snow products such as the Copernicus SWS or Wet/Dry Snow layers offer a grid sampling of 60 m (??), which may not sufficiently resolve the variability of mountainous topography. 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 representation of snow wetness patterns. Multi-track LRW allow 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 ~~abundance of the LWC on the acquisition time of the images, as the snowpack's characteristics change over the course of the day (as also the data by ? suggest). If and how these factors contributed to the miss of the first avalanche surge should be investigated further in the future, resulting product.~~ This is especially relevant in  
585 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.

Our results showed an earlier start of the melting season at lower elevation zones with increasing melting later in the season in higher elevation zones (see Fig. ??). This agrees with the station data, where at the more highly situated stations winter lasts longer, with a more pronounced and later melting season. Lower elevations typically have a shorter and warmer winter season. This leads to a shorter period of signal attenuation during the melting phase than at stations with more snow coverage in higher elevation zones. 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 (?). With the community increasingly moving towards the provision of large-scale LRW datasets such as already available from e.g. (?), making use of this data will become more efficient and operational applicability more feasible.

### 6.3 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 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 recorded avalanches within the area of the perimeter indicated in Fig. ?? (?). Multiple manually observed and recorded avalanches and their type (wet, dry, unknown). This dataset 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 must be considered when interpreting the wet snow ratio per elevation to this data set: i) The monitored in relation to this dataset. The catalogue does not permit a full evaluation of the detection performance beyond the observed avalanche sample (no avalanche does not necessarily mean no wet snow avalanche conditions were present). Also, the DAvalMap perimeter is smaller than the research site, so study area used for LRW production, meaning that avalanches outside of the perimeter this region were not systematically monitored and mapped. This results in recorded. As a result, elevation bins above approx. 2800 m approximately 2 800 m a.s.l. containing contain little to no recorded documented avalanche activity. ii) The avalanches used in the study were all wet. Furthermore, all avalanches included in the dataset were classified into wet, dry or unknown-type snow avalanches, so the snowpack implying the conditions in the starting zone of the avalanches was assumed to be wet. Since this classification of snow wetness in the starting zone. However, this classification is challenging from a distance, some avalanches might have been incorrectly included. We assume that this influenced the miss of the first wet snow avalanche surge in our analysis, where the avalanches had wet snow deposits even though they started out and some events may have been misclassified, particularly where avalanches started as dry snow avalanches and we only considered start zone coordinates. Later when the snowpack is wet from the valley to the mountaintops, this potential classification error becomes negligible. iii) The information was, but developed wet deposits during their descent (?). Lastly, the inventory is based on



~~in-situ observations dependent that depend~~ on good visibility ~~, so and~~ are biased towards days with lower avalanche risk, as observations are less likely to be made during hazardous conditions (??). This can lead to uncertainties in the assigned release date ~~might include uncertainties dates of~~ up to several days ~~. Keeping in mind our S1 timeframe of six days , the influence of potentially incorrectly recorded release date would be minimal~~ (avalanches are reported when they have been observed instead of when they have been triggered (?)) but is less pronounced for wet snow avalanches occurring on sunny days with the warming. Given the applied six-day temporal resolution of our product, the impact of these timing uncertainties is expected to be limited. However, ~~no clear dependency of wet snow avalanches~~ such misclassifications are likely to have a stronger effect on the daily temporal matching to the SWS product. Even with these observations' shortcomings, this dataset is one of the most comprehensive avalanche activity datasets (?).

No clear dependency between wet snow avalanche occurrence and measured rainfall was found, ~~overcoming with correlation values not exceeding~~ 0.2 at an average daily rainfall of  $17 \text{ kg/m}^{2-2}$  ~~averaged across the stations~~, suggesting that rain-on-snow had a limited ~~impact on influence on wet snow~~ avalanche release in this dataset (see ~~appendix Appendix~~ Fig. ??). ~~And despite mentioned challenges, DAvalMap provides a unique opportunity to compare observed~~ Despite the mentioned limitations, DAvalMap remains a unique dataset for comparing observed avalanche activity with snow wetting derived from S1 data.

The initial ~~surge surges~~ of wet snow avalanches ~~in spring 2019 and 2020~~ did not coincide with a pronounced increase in the wet snow ratio across ~~any two~~ of the investigated seasons (see Fig. ??). 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. ~~Furthermore 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 daily grid and unavailable images in Fig. ??).~~ These limitations underscore the need for improved temporal coverage to enhance the timing accuracy of remotely sensed snowpack transitions.

All these effects impact the threshold extraction which marks the switch of dry to wet snow avalanche release conditions. We found an aspect dependency on the sensitivity of avalanche type classification (appendix Fig. ??). This can be attributed for one to a) the difference in melting, since the north-facing slopes are typically later in melting and then more intensive (visible in the elevation dependent melting diagrams (appendix Fig. ??), 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 wet snow ratio threshold would be identifiable at 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 wet-dominated, where still mixed conditions can occur. However, the use of the SWS product showed increased noise and lower reliability with a transition to dry-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.

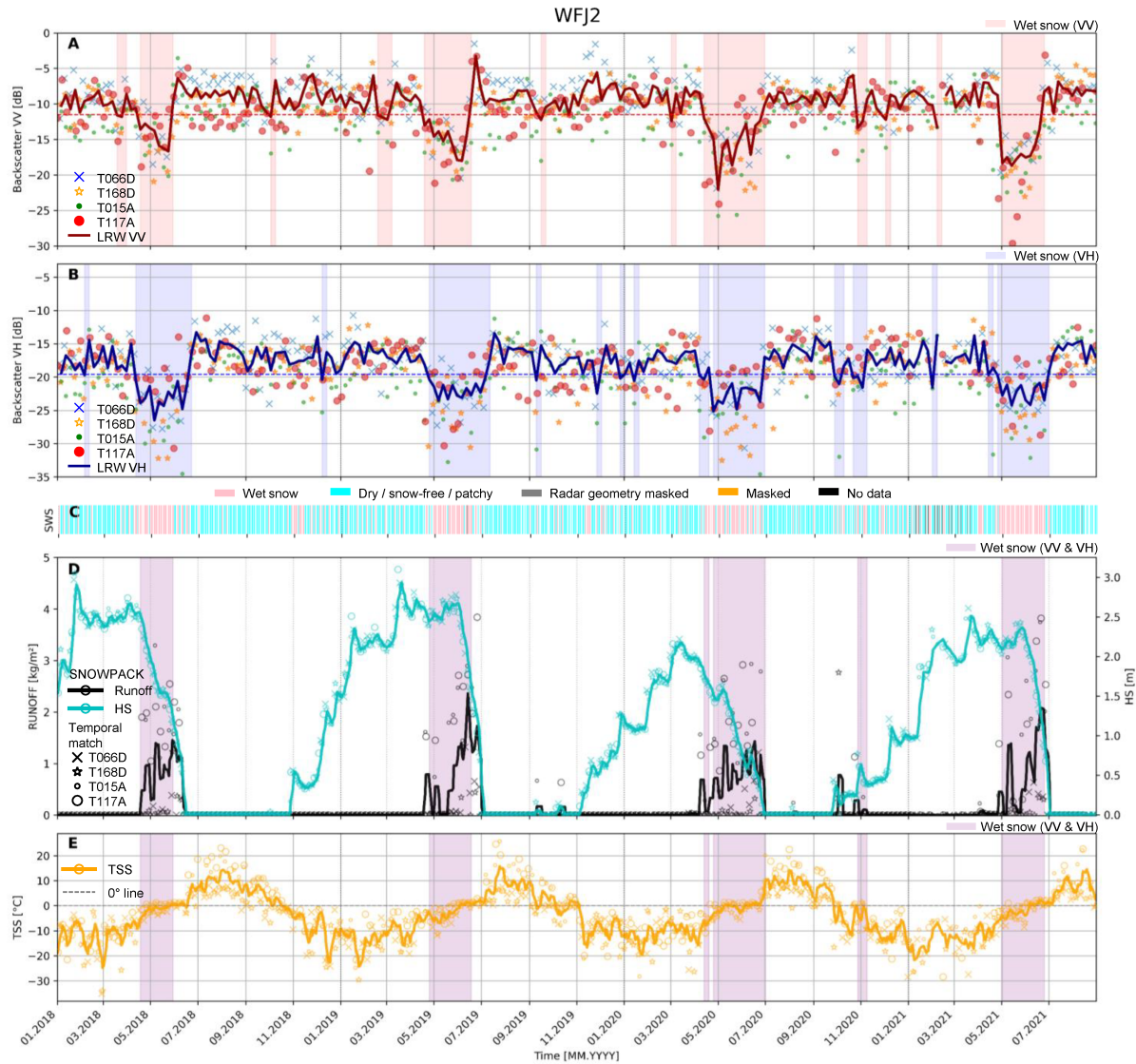
655 We encourage future research to make use of not only multi-platform but also multi-frequency data such as a combination of X- and L-band with ~~e.g. e.g.~~ the upcoming NISAR mission (?). This would allow the capture of different stages of the melting due to differences in sensitivity to water presence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

## 7 Conclusions

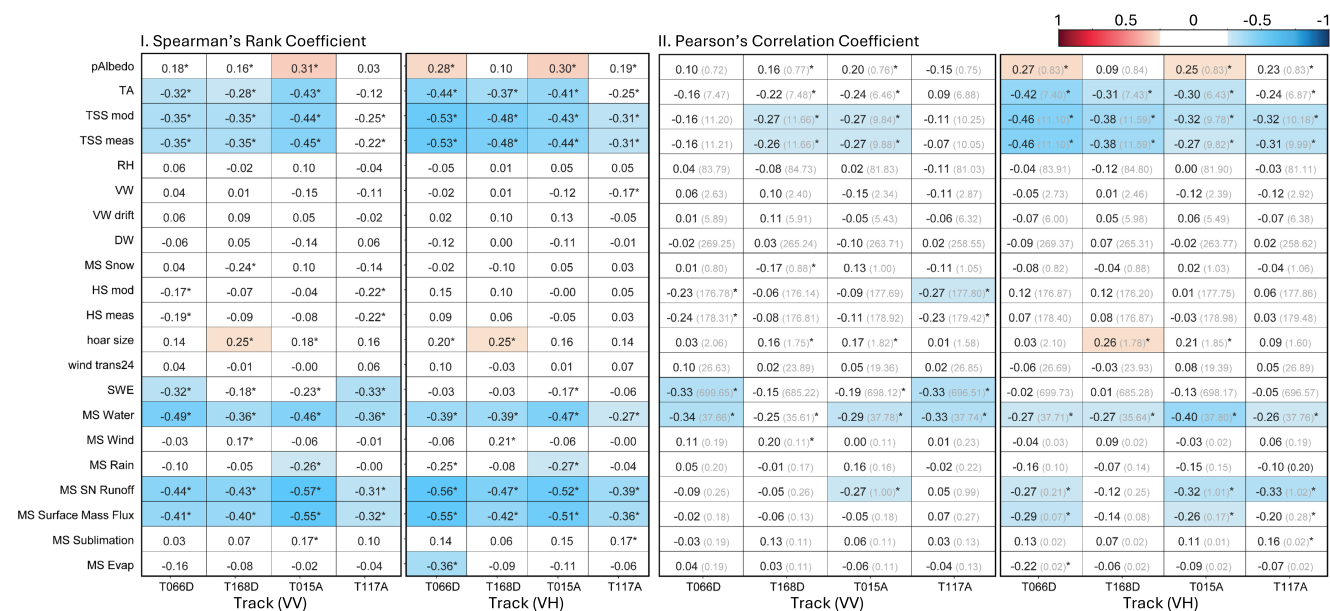
660 ~~We used~~ This study shows that S1 SAR-LRW multi-track composites ~~to derive snow wetness at different elevations and slope aspects around Davos. By exploiting LRW composites created from SLC products, we were able to more accurately resolve spatial variability of the snow wetness in alpine terrain than currently available products. We evaluated the performance of our approach by cross-correlating the data to in-situ measured and modelled snowpack variables as well as a~~ provide useful information on snowpack wetting in complex alpine terrain and can support the identification of conditions associated  
665 with wet snow avalanche ~~inventory, finding relevant correlation between S1 backscatter and modelled releases. We found a consistent relationship between decreasing SAR backscatter and increasing liquid water content ,in the snowpack as well as good agreement with the release of runoff, thereby linking RTC images to snowpack characteristics. The use of the 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 avalanches to conditions where wet snow avalanches became~~  
670 predominant. At a wet snow ratio of 0.35 only wet snow avalanches ~~coinciding with the wetting of the snowpack at the corresponding elevations, aside from an exception of~~ were recorded. Compared with the Copernicus SWS product, the very first surge of wet snow avalanches in spring. Our results indicated the potential of C-band SAR-based monitoring of wet snow avalanche preconditioning factors, provided the availability of data with higher spatiotemporal resolution than the current LRW-based approach provided a clearer separation of avalanche-release conditions, highlighting the benefit of multi-track  
675 compositing in steep terrain.

The approach remains limited by the revisit time of S1 orbit repeat interval offering. With the use of such 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 ,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  
680 wet-snow detection in alpine terrain, may assist the evaluation of snowpack wetting across large areas and provide additional information on the development of conditions prone to wet snow avalanches.

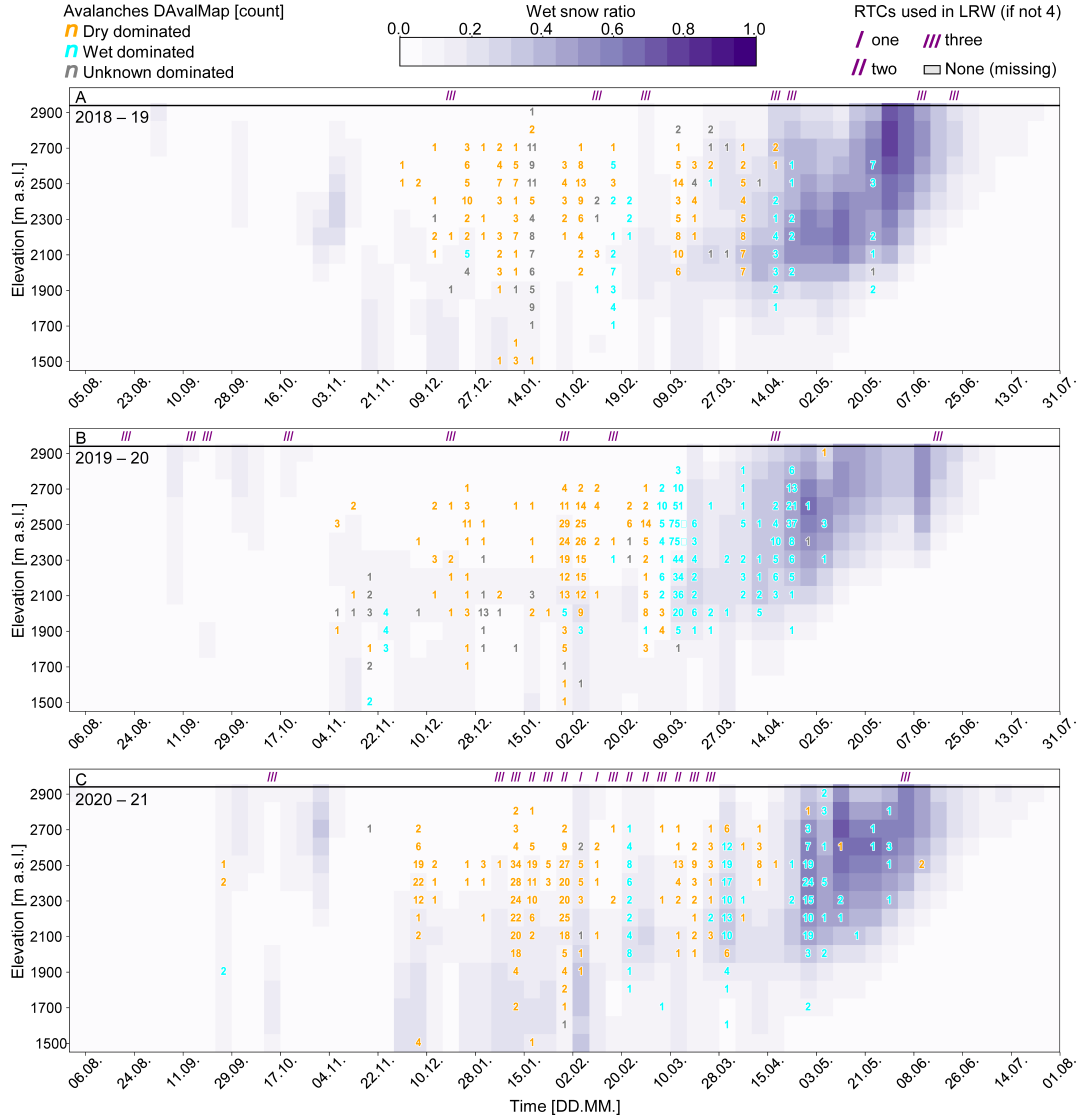
*Code and data availability.* SAR data can be downloaded from the Copernicus Open Access Hub or from the Alaska Satellite Facility. SAR processing has been performed using the gamma software (?). The SNOWPACK data including the forced IMIS station information can be found under ? with further information on the model under ?. The used information from the DAvalMap catalogue can be found in the  
685 supplementary data of this manuscript. The code used in this study is publicly available on the GitLab repository: <https://gitlabext.wsl.ch/alpineremotesensing-public/ccamm-wet-snow>.



**Figure 2.** Time series of 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 co-(A) co- and cross-polarized-(B) cross-polarised S1 data. The markers indicate the measured radar backscatter per RTC track, whereas the line indicates the corresponding LRW value. The horizontal line indicates the time series median including the 2 dB threshold and the shading background displays the times during which the backscatter falls lower than 2 dB below the calculated median in the corresponding polarisation this and wet snow is detected. C) shows SAR Wet Snow classified layer from Copernicus per track over the station area. D) time series of measured liquid water content virtual lysimeter (LWEMS RUNOFF) and measured snow height (HS) 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. In Similarly, E) shows the local measured snow surface temperature (ETSS). In D) and E), the applied purple shading indicates when VV and VH both fall underneath their corresponding thresholds and corresponds to our wet snow combined polarisation product.

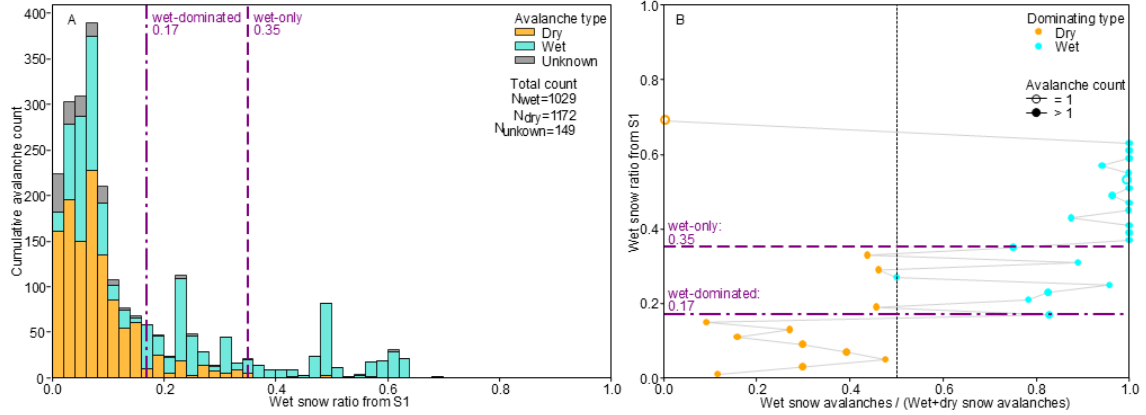


**Figure 3.** Correlation of analysed SNOWPACK variables compared to the median Sentinel-1 backscatter time series at the WFJ2 station per track (location see Fig. ??). The table includes the results per polarisation state for 3x3 window size. Included are the Spearman's (I) and Pearson's (II) correlation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

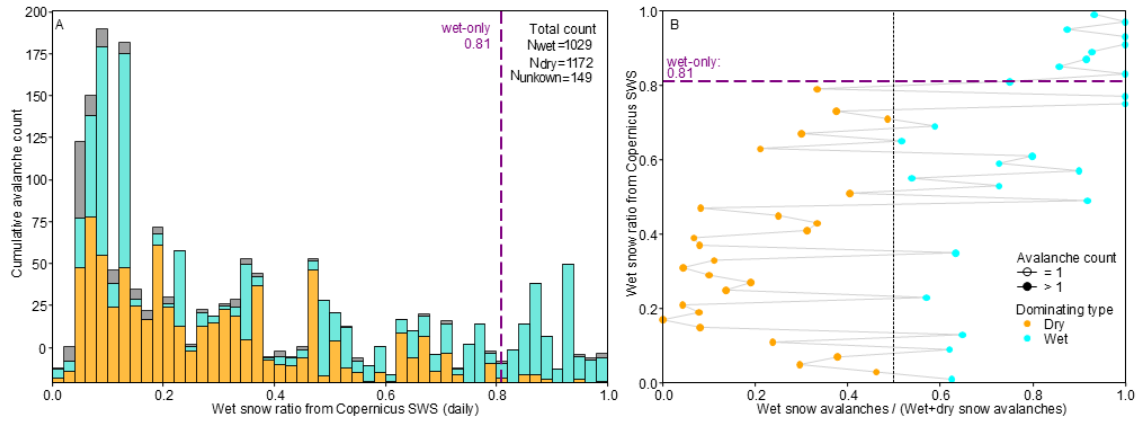


**Figure 4.** Time-elevation plots of wet snow ratio evolution for combined polarised product across three melting seasons (A: 08.2018–07.2019, B: 08.2019–07.2020 and C: 08.2020–07.2021) featuring the area of Davos as indicated in Fig. ??, resolved at discrete 100 m elevation bands. The wet snow ratio 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) (?). 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 ? and ?.

### I) Sentinel-1 LRW composites



### II) SAR Wet Snow product

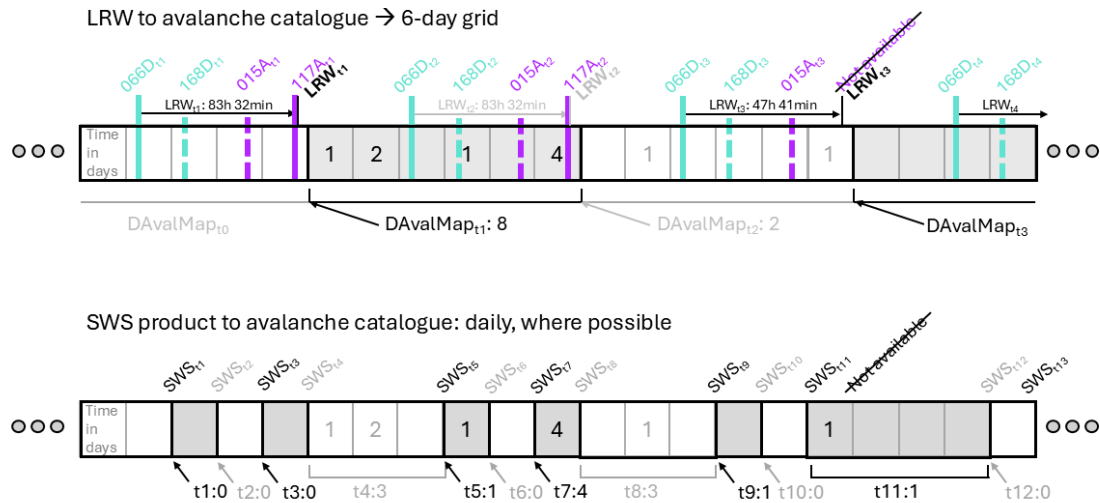


**Figure 5.** Extraction of wet snow ratio thresholds from S1 I) using our LRW approach and II) SWS product. A: Total avalanche count per type in comparison to wet snow ratio and the extracted wet-dominated and wet-only transition lines after applying Gaussian distribution. B: Wet snow ratio in comparison 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.



## Appendix A

### A1 Temporal binning of avalanche data

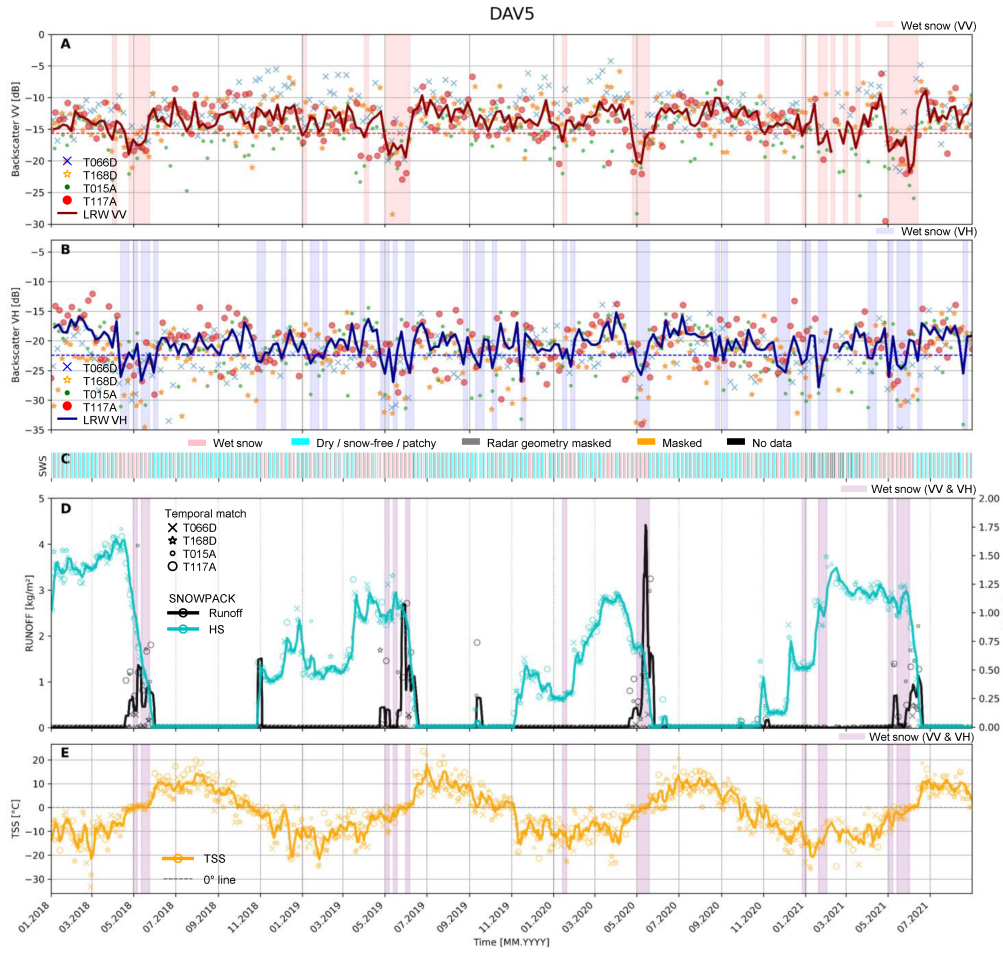


**Figure A1.** Exemplary illustration of performed temporal binning featuring the SAR acquisition times in descending and ascending tracks to corresponding local resolution composites (shading) in combination with the summed wet snow avalanches. Binning has been **optimized** optimised to include all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

Time-series of wet-snow evolution from January 2018 until August 2021 at Weissfluhjoch (WFJ2) for two-track rolling-mean  
690 (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  
695 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.

## A2 Timeseries of stations DAV5 and SLF2

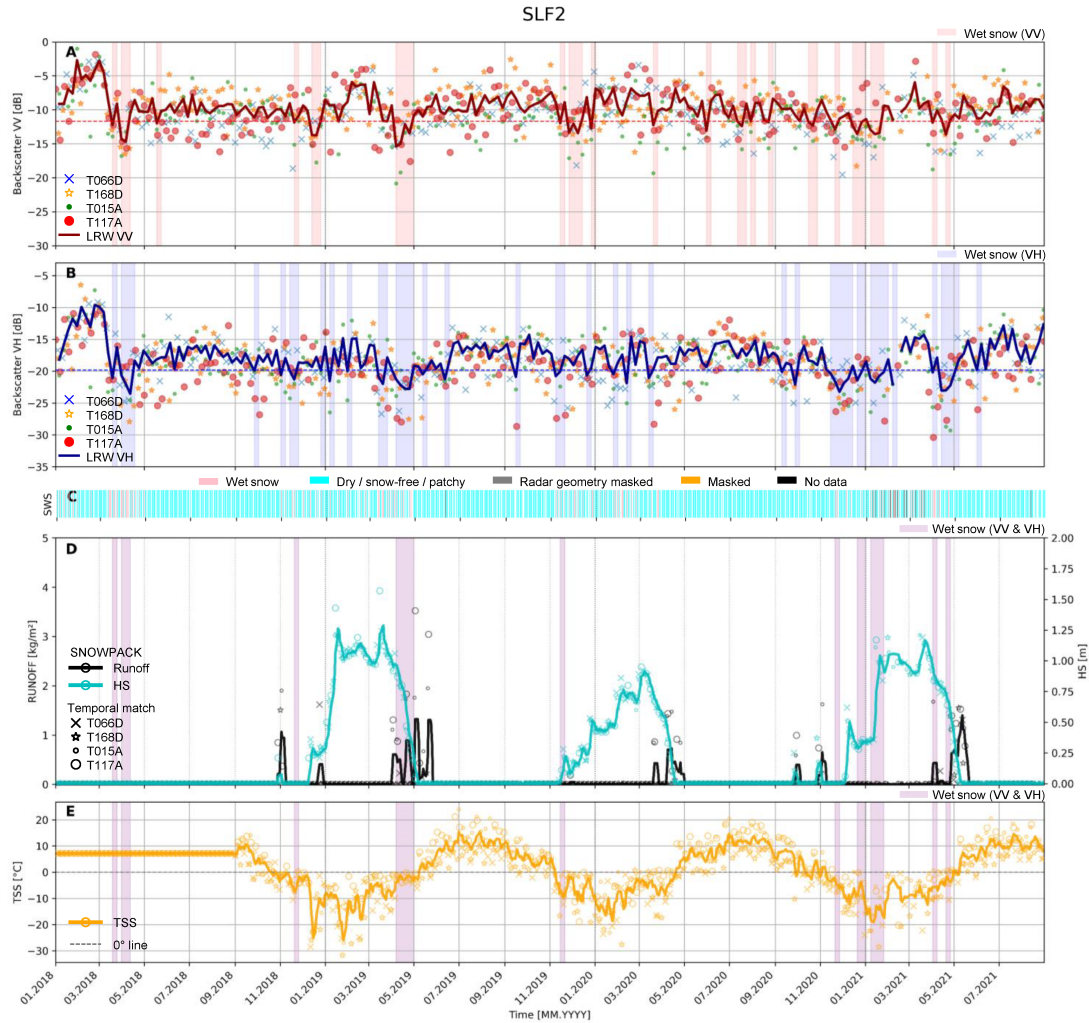
### 700 A2.1 DAV5 station



**Figure A2.** Time series of wet-snow evolution over four melting seasons from January 2018 until August 2021 at the DAV5 station for two-track rolling mean (a and b, A) and four-track LRW (c and d, B) in comparison to SNOWPACK data (e and f). The first two plots are show the time series extracted from the 3x3 window pixel within which the IMIS station is situated in co- (A) and cross-polarized Sentinel-1 cross-polarised (B) 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 horizontal line indicates the LRW value. The horizontal lines indicate the time series median including the 2 dB threshold and the shading background displays the times during which the backscatter falls lower than -2 dB below the median in the corresponding polarisation and wet snow is detected. The lower panels show C) SAR Wet Snow classified layer from Copernicus per each track over the station area. D) time series of measured liquid water content virtual lysimeter (LWCMS SN RUNOFF) and measured snow height (HS) and surface temperature (TSS) 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. The Similar E) shows the local measured snow surface temperature (TSS). In D) and E), the applied purple shading indicates when VV and VH correspond corresponds to our wet snow combined polarisation product. The different lines styles indicate the SNOWPACK data at the corresponding to the S1 matched acquisition.

## A2.2 SLF2 station

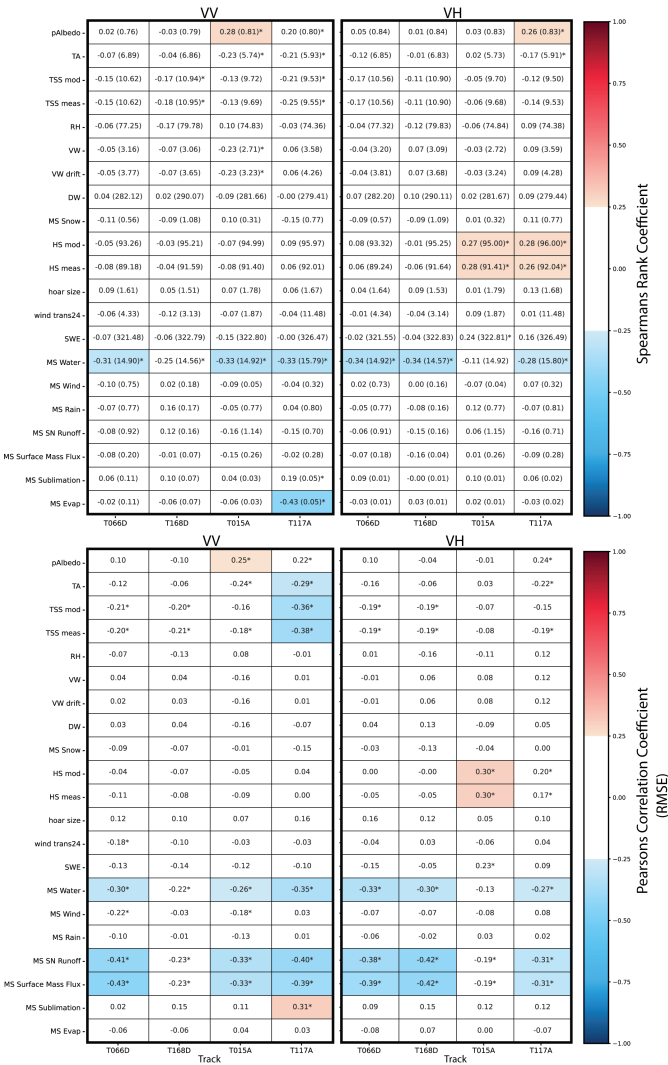
Time-elevation-plots of wet-snow-evolution following ? and ? for VV-polarisation for the exemplary seasons of 2020-2021. It shows the effect of filtering and masking: A) no filtering or masking applied, B: forest mask applied, C: spatial median filter with a window size of 3x3 applied, D: forest mask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



**Figure A3.** Time series of wet-snow evolution over four melting seasons from January 2018 until August 2021 at the SLF2 station for two-track rolling mean (a and b, A) and four-track LRW (c and d, B) in comparison to SNOWPACK data (e and f). The first two plots are show the time series extracted from the 3x3-window-pixel within which the IMIS station is situated in co- (A) and cross-polarized Sentinel-1 cross-polarised (B) 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 horizontal line indicates the LRW value. The horizontal lines indicate the time series median including the 2 dB threshold and the shading background displays the times during which the backscatter falls lower than 2-dB below the median in the corresponding polarisation this and wet snow is detected. The lower panels shows C) SAR Wet Snow classified layer from Copernicus per each track over the station area. D) time series of measured liquid water content-virtual lysimeter (LWEMS SN RUNOFF) and measured snow height (HS) and surface temperature (TSS) 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. The Similar E) shows the local measured snow surface temperature (TSS). In D) and E), the applied purple shading indicates when VV and VH correspond corresponds to our wet snow combined polarisation product. The different lines styles indicate the SNOWPACK data at the corresponding to the S1 matched acquisition.

A3 Correlation assessments between RTC timeseries and in-situ and modelled SNOWPACK data

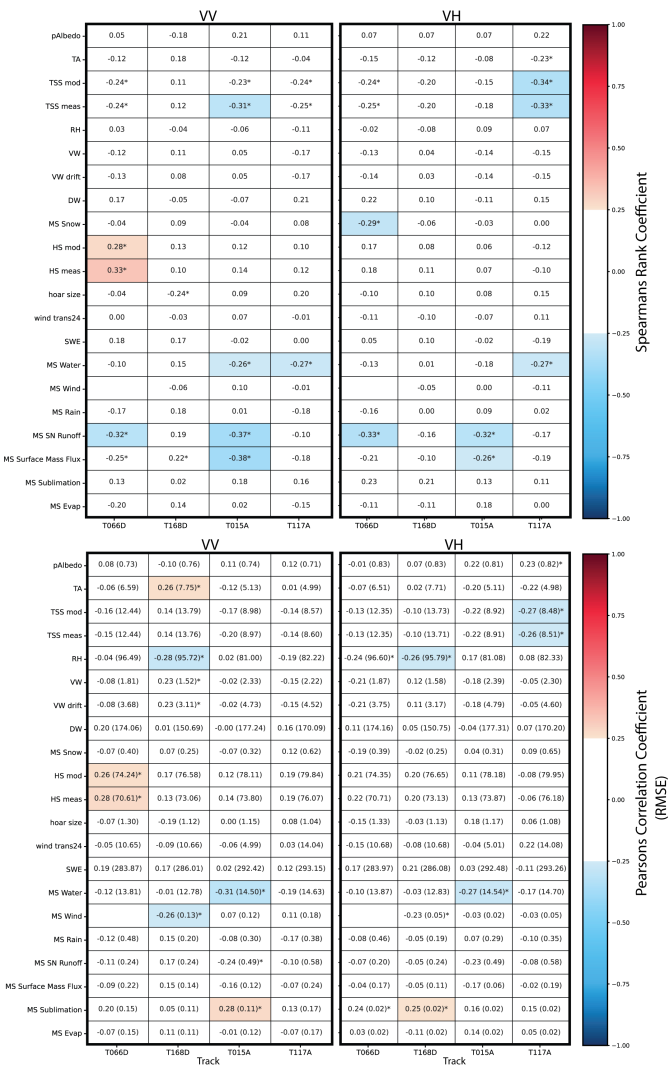
A3.1 DAV5 station



**Figure A4.** Correlation of analysed SNOWPACK variables compared to the median VV Sentinel-1 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.



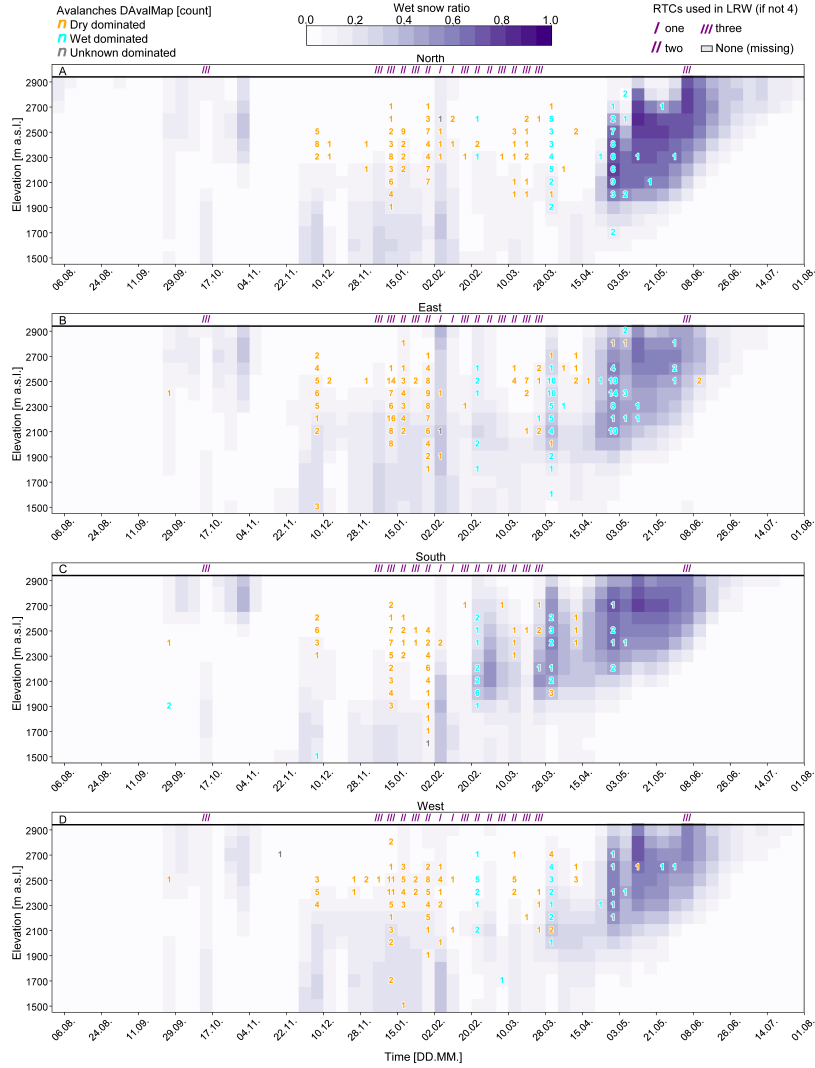
A3.2 SLF2 station



**Figure A5.** Correlation of analysed SNOWPACK variables compared to the median VV Sentinel-1 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 A2.1.

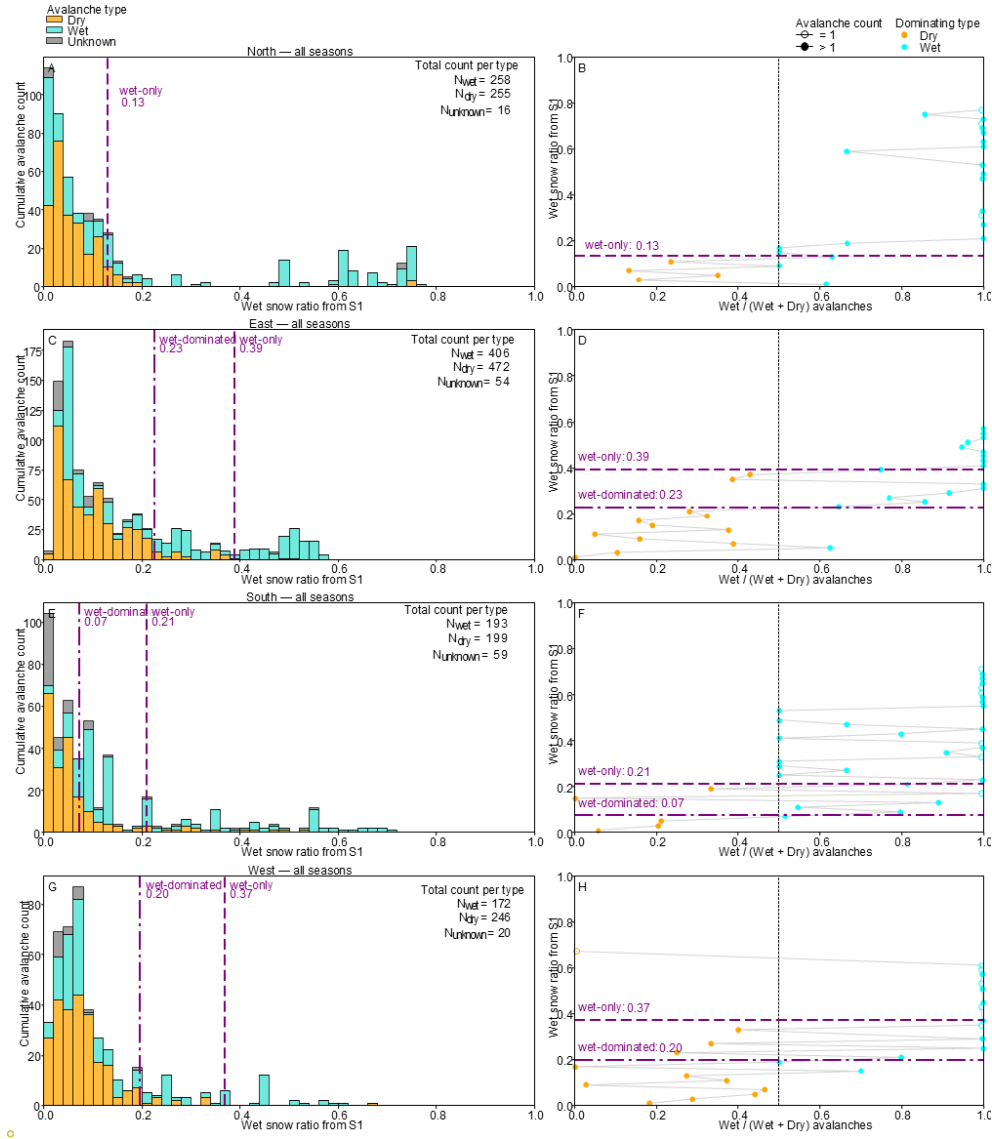
710 **A4** Aspect dependency of wet snow ratio time-elevation plots and thresholds

**A4.1** Aspect dependent time-elevation based melting evolution



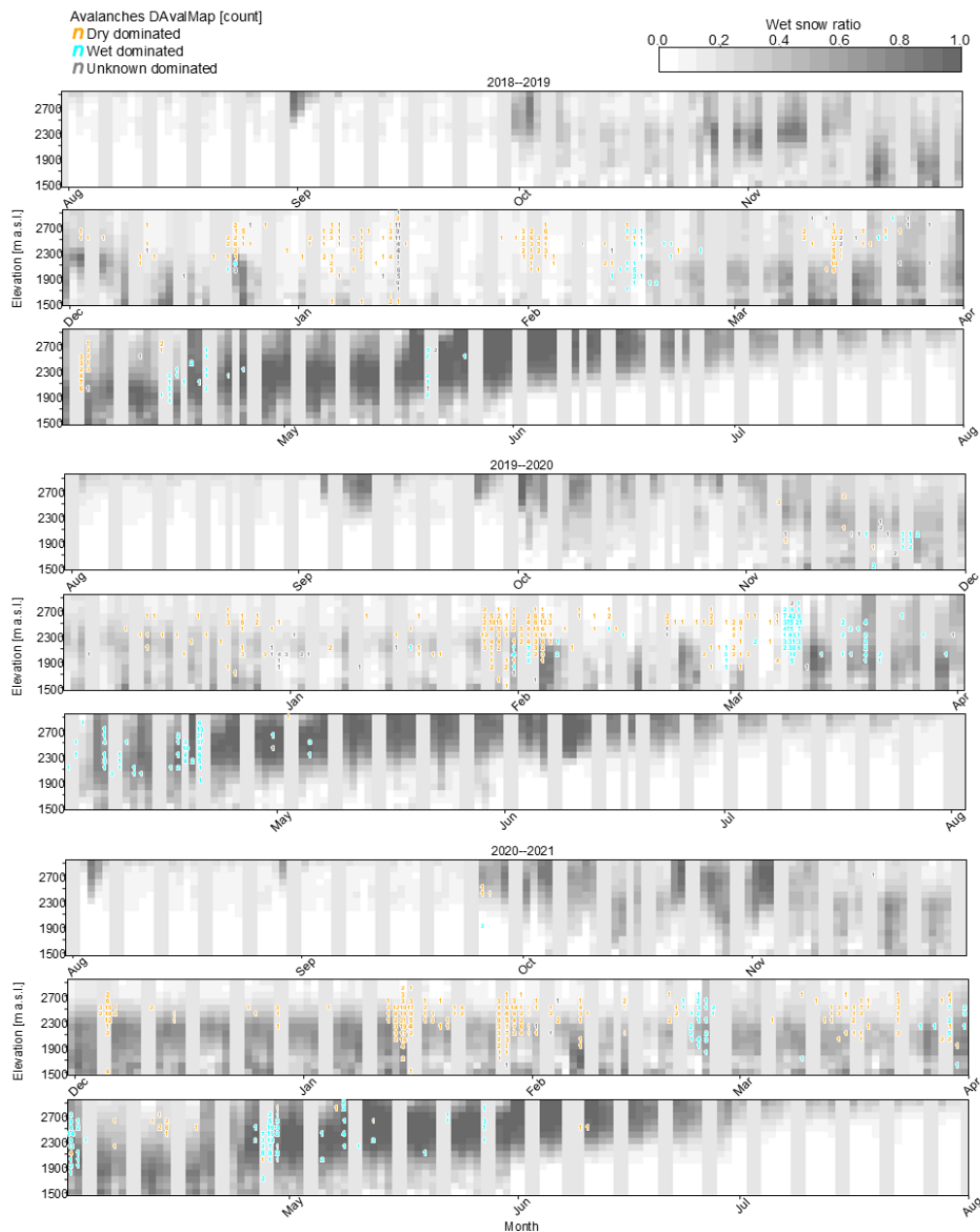
**Figure A6.** Time-elevation plots of wet snow ratio evolution for ~~VV-polarized wet snow detection across three and a half combined~~ polarised product for the exemplary seasons (of 2020-2021). Displayed are the time series resolved into the different slope aspects: A: 01.2018-07.2019 North, B: 08.2019-07.2020 and South, C: 08.2020-07.2021 East and D: West. The plot encompasses data featuring the area of Davos as indicated in Fig. ??, resolved at discrete 100 m elevation bands. The wet snow ratio is the percentage of pixel per elevation band that ~~were was~~ detected as indicating wet snow using Sentinel-1 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 (?). ~~No spatial smoothing or filtering was applied.~~ Plot design was inspired by ? and ?.

## A4.2 Aspect dependent threshold extraction

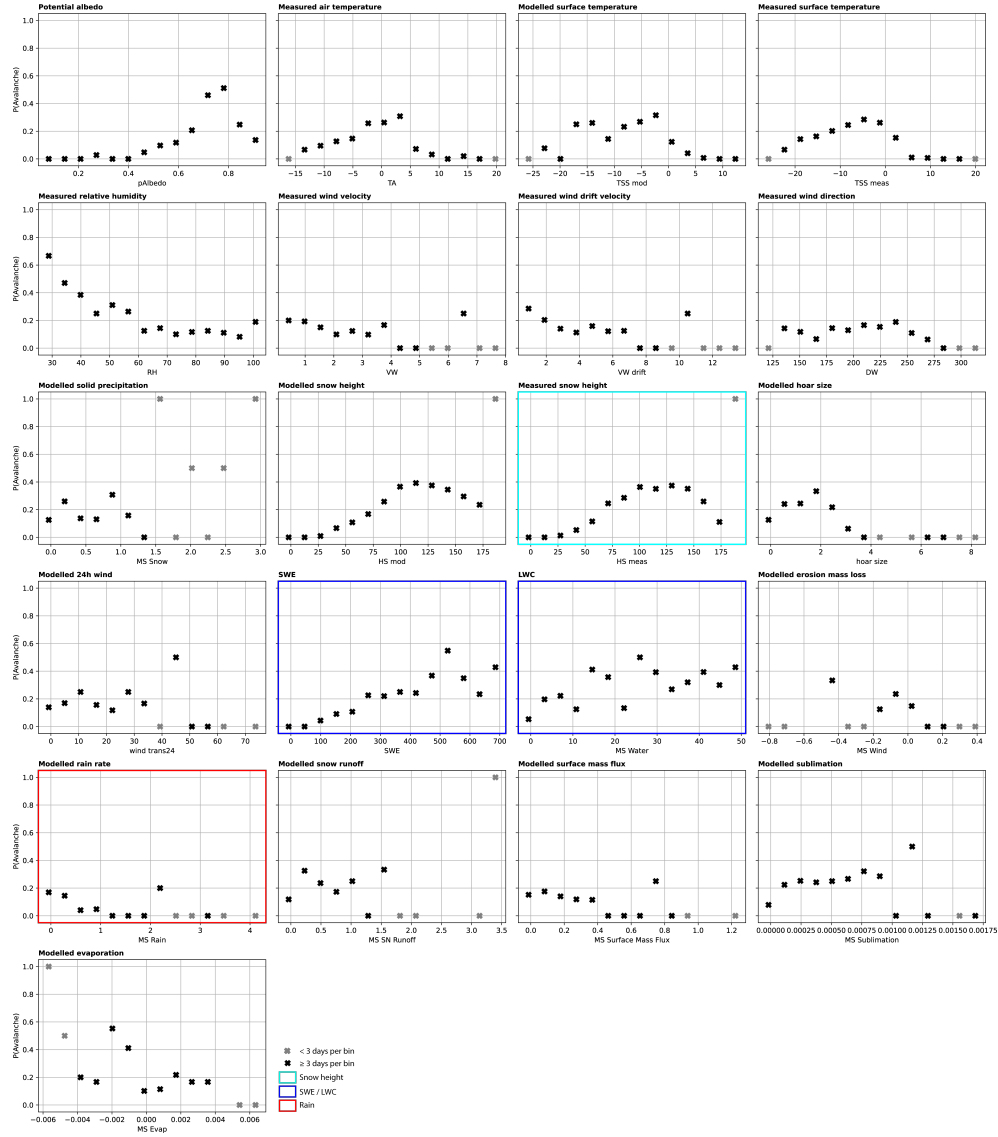


**Figure A7. Time-elevation-plots-Extraction of wet snow ratio evolution for VH-polarized wet snow detection across three thresholds from S1 I) using the here presented LRW approach and a half-seasons (II) SWS product. A: 01.2018–07.2019, B: 08.2019–07.2020–Total avalanche count per type in comparison to wet snow ratio and C: 08.2020–07.2021) featuring the area of Davos as indicated extracted wet-dominated and wet-only transition lines after applying gaussian distribution. B: Wet snow ratio in Fig comparison to dominating type. ??, resolved at discrete 100-m elevation bands. The extracted thresholds only consider wet and dry snow ratio is the percentage of pixel per elevation band that were detected as indicating wet snow using S1 data (unknown, excluded) and entries when more than one avalanche was present. Coloured numbers indicate the count In case of recorded equal amount wet and dry snow avalanches per time step according to the DAvalMap data set at the corresponding elevation band (?). No spatial smoothing or filtering, wet snow was applied given priority. Plot design was inspired by ? and ?.**

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

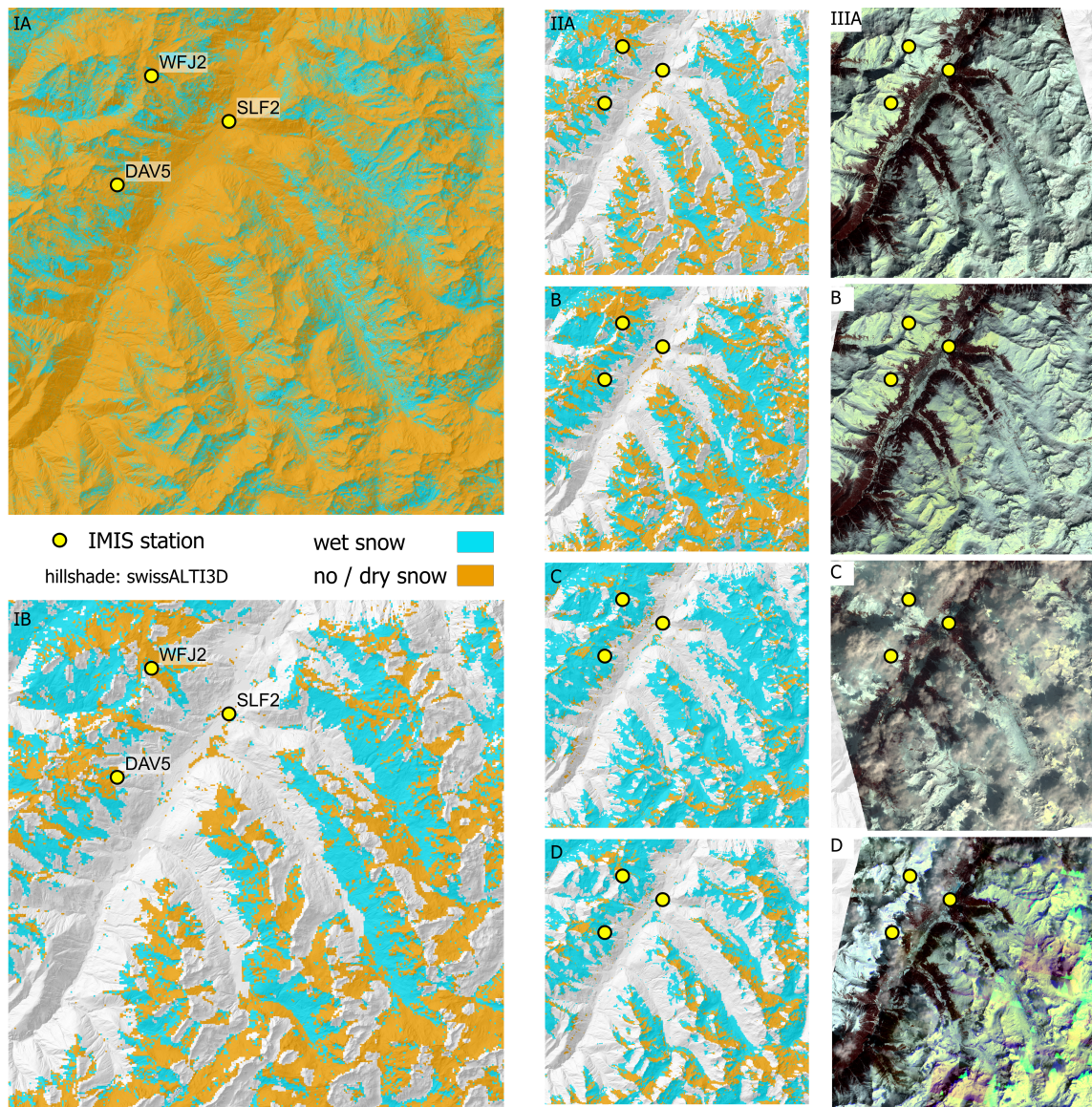


**Figure A8.** Wet snow ratio evolution extracted from the SWS product over time per elevation on a daily grid across the three melting seasons. Recorded avalanches are superimposed on the plot, with the colours indicating the dominant type of avalanche recorded (Data source: (?)). Empty columns of no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



**Figure A9.** Probability of  $\geq 1$  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.e.g., "On days with X mm of rain, what's the chance of  $\geq 1$  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. ???).





**Figure A10.** Example case (220210331-20210403) of wet snow detection on a visual comparison. The outline of all the images is the same as the research site displayed in Figure ??B. I.A) Based on our processing using LRW, whereas I.B shows pixels usable from SWS layer on the first acquisition day. II.A-D show SWS product for the four acquisitions which were used for creating the LRW based product (A: 31.03. B: 1.4., C: 2.4., D: 3.4.2021) and III.A-D show the corresponding optical imagery from ©Planet Labs PBC. Imagery using false colour infrared (Red: NIR, Green: red, Blue: green).

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

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

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

725 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  
730 Potential albedo pAlbedo

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