



Sentinel-1 SAR for historical avalanche activity reconstruction and probabilistic runout modelling under variable snow conditions

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Abstract. Accurate records of snow avalanche activity are crucial for hazard assessment, avalanche forecasting, and estimating the probability of extreme runout distances, yet such datasets are limited in many mountain regions. This study combines dual-
15 polarization Sentinel-1 Synthetic Aperture Radar (SAR) imagery with a deep learning model to automatically detect avalanche deposits in the Central Rhaetian Alps over a ten-year period. Two independent SAR image series, acquired at different times of day, are analysed to assess the effects of acquisition timing and snow conditions on detection performance. An Avalanche Activity Index, derived from both SAR and manual observations, allows us to classify scenes according to valid, false-positive, or false-negative predominance, mitigating gaps in manual datasets. Both dry and wet snow avalanche cycles are reproduced
20 without significant preferential performance, while systematic detection errors are mainly associated with snow conditions at the time of post-event acquisition, and snow and weather evolution during SAR revisits. False negatives are related to snowmelt and the presence of dry, spread deposits, with new snow in the scene. On the other hand, false positives primarily result from general snow refreezing and, more rarely, from wet snow on tree canopies. A comparison with potential avalanche paths simulated with a dynamic model reveals recurrent biases in areas such as lakes, ski slopes, and anthropic terrain. Finally, we
25 conduct the first probabilistic runout distance estimation based on avalanche annual maximum Runout Ratios automatically extracted from SAR data and fitted to a generalized extreme value distribution. This pilot study demonstrates that the combination of SAR imagery and deep learning reliably reconstructs historical avalanche activity, complements traditional records, and supports probabilistic hazard assessment in regions with sparse ground-based monitoring.

1 Introduction

30 To mitigate snow avalanche risk, forecasting procedures and spatial hazard zonation are essential (Statham et al., 2018). Both approaches rely fundamentally on an accurate characterization of avalanche activity (Schweizer, 2003), which is defined as the spatio-temporal distribution of avalanche events within a given region, including their number, location, and main physical characteristics (McClung and Schaerer, 2006). This information, it is used to assess avalanche danger levels and to interpret



possible avalanche scenarios (Schweizer, 2003), as well as to calibrate and validate potential release area models (Bühler et al., 2018). Beyond forecasting and operational hazard assessment, avalanche activity information is also crucial for land-use planning and site-specific avalanche warning. To this end, the European Avalanche Warning Service (EAWS) elaborated a set of recommendations for avalanche warning services that target specific users defined avalanche paths within a forecasting region (Site specific avalanche warning, 2026). In the EAWS report, the site-specific avalanche hazard is defined in terms of impact probability, which is obtained as the product between the release probability, depending on the snow in(stability), and the runout probability along the avalanche path.

To estimate the runout probability, it is essential to estimate extreme avalanche runout distances (i.e., the farthest locations reached by avalanches), commonly complemented by an assessment of the expected destructive effects along the avalanche path (McClung et al., 2022). In this context, two main approaches have been developed. The first approach relies on physical avalanche dynamics models (Voellmy, 1955; Salm, 1993; Christen et al., 2010; Tonnel et al., 2023b). The second approach comprises empirical or statistical methods, which exploit historical avalanche records within a probabilistic framework to estimate extreme runout distances and their associated return periods (McClung and Hoeller, 2025). Dynamic modelling, often coupled with probabilistic nivometeorological analyses to estimate the release thickness, is widely adopted in several European countries as a guideline for avalanche hazard zonation (Massimiliano Barbolini et al., 2005; Salm et al., 1990). The advantages of these procedures are that 2-D or 3-D avalanche modelling is now possible, and that the physical properties of the moving snow mass can be represented as a function of space and time. However, these models require numerous assumptions and often involve parameters that are unmeasurable or unverified (McClung and Hoeller, 2025). For this reason, despite offering less detailed outputs, the probabilistic runout distance estimation approach, based on real avalanche events, remains essential. This method, firstly proposed by Lied and Bakkehoi (1981), is based on collections of extreme avalanche runout distances (Δ_x) which are then fitted to a probabilistic model. In the work of Lied and Bakkehoi, Δ_x is measured as the horizontal distance between the farthest point reached by the avalanche deposits (the α -point) and a reference point along the path (the β -point). The method became known as the α - β model.

Given that extreme avalanches are rare events (McClung and Schaerer, 2006), it is usually difficult to obtain enough Δ_x records for probabilistic modelling from a single avalanche path. For this reason, data from similar sites at different locations, known as distributional data, are often used (McClung et al., 2022). This approach is analogous to the regional index-value method commonly employed for hydrological extreme events (Kottegoda et al., 1997), and has been applied to estimate release thickness for avalanche dynamic modelling aimed to hazard mapping by Barbolini et al. (2002) and Bocchiola et al. (2006). For the distributional data approach, the choice of a parameter independent of individual path characteristics is mandatory to aggregate observations at the regional scale within a common statistical framework. Since the quantity Δ_x clearly strongly depends on the chosen mountain a parameter statistically independent of individual path morphology was defined by McClung and Lied (1987) with the Runout Ratio (RR). This is obtained by normalizing Δ_x by the horizontal distance between the β -point



and the avalanche starting zone (X_{β}). More recently, McClung and Hoeller (2025) showed that the generalized logistic (GLO) and the generalized extreme value (GEV) distributions provide the best goodness of fit of RR values.

Traditionally, near-real-time avalanche activity has been documented through direct observations conducted from safe locations, whereas historical extreme events have been reconstructed from archival records or dendrochronological analyses (Butler and Sawyer, 2008). However, historical archives are available only in a limited number of regions, and dendrochronological methods are expensive and mainly applicable near the treeline (McClung and Hoeller, 2025). To overcome the limitation of near-real time manual observations, terrestrial and satellite remote sensing techniques have increasingly been investigated.

Examples of terrestrial approaches include geophones buried in the snowpack (Van Herwijnen and Schweizer, 2011), infrasound sensors (Scott et al., 2007), Interferometric Doppler Radar (Viviani et al., 2020), and optical time-lapse cameras (Portenier et al., 2020). Although effective, these systems are difficult to deploy in remote areas and provide limited spatial coverage. Satellite remote sensing overcomes these constraints by enabling observations over large regions through optical and Synthetic Aperture Radar (SAR) sensors (Eckerstorfer et al., 2016; Hafner et al., 2021; Hafner et al., 2022). In particular, SAR operates independently of cloud cover and illumination conditions, although only avalanche deposits can be detected. Subsequent studies extended these capabilities to different SAR systems, with Bühler et al. (2014) applying change detection to X-band TerraSAR-X data. The advent of freely available Sentinel-1 C-band imagery further facilitated SAR-based avalanche mapping, and Malnes et al. (2015) demonstrated the detection of avalanche deposits from single backscatter images. A first physical interpretation of avalanche-deposit backscatter was proposed by Eckerstorfer and Malnes (2015) using Radarsat-2 C-band data, showing reliable detection for avalanches with avalanche size class (ASC ; Avalanche size, 2026) greater than 2. Under dry-snow conditions, increased backscatter mainly results from enhanced volume scattering associated with greater snow depth and, to a lesser extent, from increased surface roughness. Under wet-snow conditions, reduced microwave penetration caused by the higher dielectric constant of wet snow (Mätzler, 1987), makes surface scattering the dominant mechanism. Subsequent studies highlighted the influence of the Local Incidence Angle (LIA) on avalanche signatures (Tompkin and Leinss, 2021; Keskinen et al., 2022), while Yang et al. (2020) demonstrated the potential of polarimetric and interferometric parameters for avalanche characterization.

The first application of SAR for reconstructing historical avalanche activity was reported by Eckerstorfer et al. (2017) who reconstructed two years of avalanche records in Norway using Sentinel-1 imagery. Since then, both near-real-time and historical SAR-based avalanche detection have been successfully applied in several regions worldwide (Leinss et al., 2020; Abermann et al., 2019; Kapper et al., 2023; Kneib et al., 2024b), making SAR one of the most practical tools for monitoring avalanche activity in remote areas.

Because avalanche activity often occurs as widespread avalanche cycles, automatic detection methods are required. Early approaches relied on thresholding (Wesselink et al., 2017), unsupervised object-based classification (Vickers et al., 2016), and principal component analysis (Liu et al., 2021). More recently, machine-learning and deep-learning methods have substantially improved detection performance (Bianchi and Grahn, 2025; Gatti et al., 2026).



100 Based on the liquid water content of the release snow, avalanches are generally classified as dry or wet. However, frictional heating during the flow may cause dry-snow avalanches, especially large events ($ASC = 4$), to melt and refreeze (McClung and Schaerer, 2006). Previous studies reported contrasting results regarding the detectability of dry and wet avalanche cycles, with some favouring dry snow conditions and others wet snow conditions, highlighting the need for a better understanding of the conditions under which SAR-based avalanche detection may fail (Eckerstorfer et al., 2019; Hafner et al., 2021; Keskinen et al., 2022; Malnes et al., 2015; Tompkin and Leinss, 2021).

105 This study aims to combine automatic avalanche detection with probabilistic runout modelling. Specifically, we use the Change Detection Neural Network based on the Swin Transformer, specifically designed in Gatti et al. (2026) for avalanche segmentation, to automatically delineate avalanche deposits from two independent Sentinel-1 image time series acquired over the Central Raethian Alps. The model is used to reconstruct ten years of historical avalanche activity from the SAR data. The SAR-based avalanche activity is then compared with in situ observations over a dedicated comparison area to identify conditions leading to recurrent detection failures and to investigate whether dry or wet snow avalanches are more reliably detected. Furthermore, the suitability of SAR-based avalanche deposits for this purpose is tested using a regional (distributional) approach, and avalanche runout distance probabilities are mapped along the main avalanche paths of the study region.



115 2 Study area and data

2.1 Study area

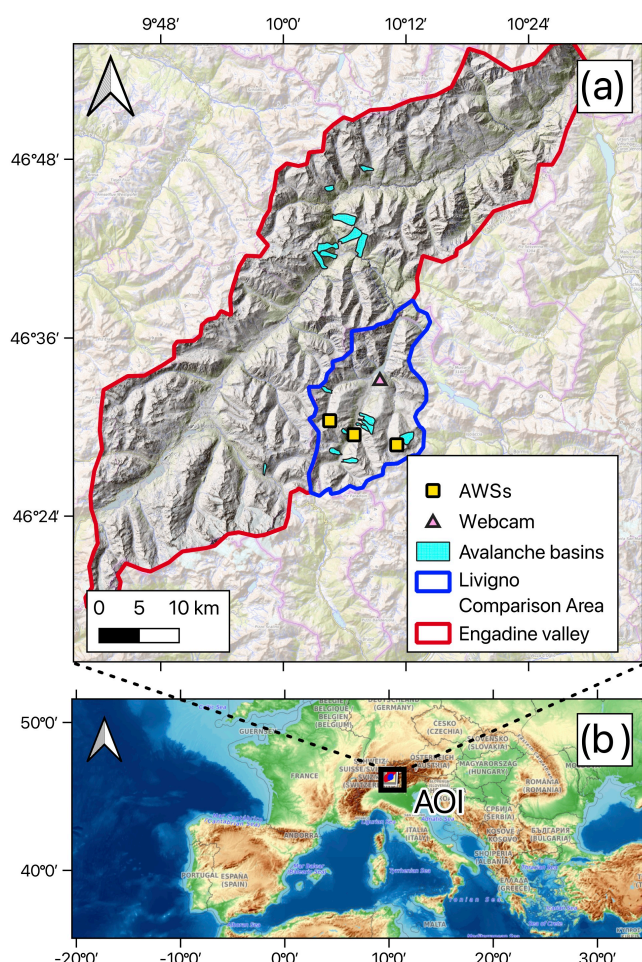


Figure 1. Spatial framework of the study area. (a) The Livigno and Engadine valleys, showing the avalanche basins selected for the return period analysis. (b) Location of the study area within Central Europe.

120 The area of interest is in the Central Rhaetian Alps along the Italian–Swiss border and includes two major Alpine valleys: the Engadine Valley – Switzerland and the Livigno Valley – Italy (Figure 1). The region is highly anthropized, hosting several villages with populations of up to approximately ten thousand inhabitants, as well as multiple ski resorts and related infrastructures. Elevation ranges from about 1000 m a.s.l. on the valley floors of the Lower Engadine to 4049 m a.s.l. at the summit of Piz Bernina. The regional climate is typically Alpine, with snow regimes that gradually shift from predominantly
125 continental conditions in the northern sector to more maritime influences toward the south (McClung and Lied, 1987). Land cover varies markedly with altitude. High elevation zones are mainly characterized by alpine meadows and talus slopes, and host numerous glaciers above approximately 2500 m a.s.l., whereas elevations below roughly 2200 m a.s.l. are largely



dominated by coniferous forests interspersed with anthropogenic land use. Across both valleys, several avalanche paths threaten critical infrastructure, including settlements, roads, railways, alpine and cross-country ski facilities. Extreme
130 avalanche events have been documented in the past (Latenser and Ammann, 2001). Avalanche forecasting is managed by different regional services on the two sides of the border. In Switzerland, public avalanche forecasts are issued by the WSL Institute for Snow and Avalanche Research (SLF), while in Italy forecasting activities are coordinated by the AINEVA association (EAWS, 2026).

The area used to compare SAR-based avalanche detections with in situ observations correspond to the municipality of Livigno
135 (Italy). Owing to its intense tourist activity and distinct climatic conditions compared to surrounding Italian regions, Livigno operates a dedicated local avalanche forecasting system supported by several automatic weather stations (AWSs) equipped with standard meteorological sensors (Monti et al., 2014). Hereafter, this area is referred to as the Livigno area.

2.2 SAR data

This study relies on Level-1 Ground Range Detected products acquired by the Sentinel-1 mission, which carries a dual-
140 polarization C-band synthetic aperture radar (SAR) sensor operating at 5.405 GHz. Data acquisition takes place in Interferometric Wide Swath mode, yielding a native spatial resolution of 5 m in range and 20 m in azimuth. The sensor, mounted on a right-looking platform, delivers imagery in both VV and VH polarizations. Each satellite acquires images over a given area using specific acquisition geometries (AGs), each defined by a relative orbit number, which are repeated over a certain revisit period. The first satellite of the constellation, Sentinel-1A, was launched in 2014 and was paired with Sentinel-
145 1B between 2016 and 2021, and with Sentinel-1C starting from April 2025. The revisit time is 6 days when a two-satellite configuration is available and 12 days with Sentinel-1A alone. Nevertheless, in the historical archive some acquisitions over the area of interest are missing for reasons unknown to us, resulting in sporadically longer revisit times (up to a maximum of 24 days).

Over the area of interest there are four different AGs: two with ascending orbits, which acquire data in the early morning
150 (around 5 a.m. UTC), and two with descending orbits, which acquire data in the afternoon (around 5 p.m. UTC). To reconstruct the historical avalanche activity, we selected the AG 168 (descending, early morning) and the AG 15 (ascending, afternoon). The different acquisition times provided valuable information for monitoring snow-related features such as avalanche deposits, as snow properties can vary significantly between morning and afternoon at this latitude.

Based on the climatic characteristics of the area, this study focuses on the period between November 1st and May 15th,
155 covering ten full snow seasons from 2015 to 2025. A total of 136 and 132 images were downloaded for AG 168 and AG 15, respectively, in Cloud Optimized GeoTIFF format (Copernicus Data Space Ecosystem, 2026).

2.3 Field avalanche observations

Systematic avalanche observations in specific mountain regions are generally scarce, and their reliability is often difficult to verify (Kapper et al., 2023). For the Livigno area, an avalanche dataset is available, comprising more than 600 avalanche



160 release areas precisely mapped in vector format by at least two avalanche experts independently, based on in situ observations and associated photographs, since December 2015.

For each event, the database provides information on the release date (with a maximum uncertainty of approximately two days), the avalanche size class (*ASC*) estimated by the local forecasters (Avalanche size, 2026), the daily avalanche danger level (Avalanche danger scale, 2026), the main avalanche problem (Avalanche problems, 2026), the avalanche type
165 (Avalanche types, 2026), and information regarding the triggering mechanism (i.e., natural or artificial).

Due to the inherent difficulties in observing avalanches manually from a safe distance, the main limitations of the database are missing data in specific areas or periods. Notable gaps occur during the COVID-19 pandemic (from February to May 2020), during particularly severe weather events that limited near-real-time observations, and prior to 2017. Regarding spatial coverage, avalanche records are more reliable in the main valley and areas visible from ski resorts, while lateral valleys and
170 high alpine terrain likely have a higher proportion of unrecorded events.

Hereafter, we will refer to this dataset as the Livigno avalanche dataset. Across the full study period (2015–2025), this dataset reports 61 dates with avalanche events. Among these, 43 dates contain only dry-snow avalanches, 10 dates only wet-snow avalanches, and 8 dates a combination of dry and wet events.

2.4 Supplementary data

175 In this study, a DEM was generated by merging a 2 m resolution DEM covering the Swiss portion of the area of interest (Wiederkehr and Möri, 2013) with a 5 m resolution DEM for the Italian sector (Regione Lombardia, 2015). The resulting DEM was subsequently resampled to a 4 m spatial resolution using bilinear interpolation and used to compute Potential Release Areas (PRAs; see Sect. 3.1).

To investigate the conditions associated with recurrent failures in SAR-based avalanche detection, meteorological records
180 from the AWSs located within the Livigno area were analysed. In addition, archived images from a webcam installed in the area and overlooking the main valley were examined (PANOMAX 360° System, 2026), together with historical public avalanche forecast archives (Monti et al., 2014) and field observations collected during major avalanche events.

3 Methods

3.1 Potential release areas and avalanche dynamic simulations

185 To spatially evaluate the performance of the SAR-based historical avalanche detection and to identify potentially invalid areas, a spatial representation of potential avalanche flow paths over the Livigno area is required. To this end, we first computed avalanche Potential Release Areas (PRAs) using the algorithm developed by Mariani et al. (2024). In this work individual PRA polygons were obtained by segmenting the PRA raster using a lower threshold value of 0.4, to account for larger avalanches. Avalanche dynamic simulations were then performed for each release polygon. Since the purpose of the resulting
190 avalanche flow layer was limited to the visual identification of portions of the Livigno area that are not potentially affected by



avalanche flows or deposits, for the dynamic simulations we adopted the com1DFA module of the AvaFrame framework (Oesterle et al., 2025), using the SamosAT friction model and the default parameter settings proposed in Tonnel et al. (2023b). A uniform release thickness of 0.5 m was prescribed for all simulations.

3.2 SAR data preprocessing and automatic avalanche classification

195 The entire standard preprocessing chain applied to the Sentinel-1 Ground Range Detected products, together with the extraction of the local incidence angle (LIA), was carried out using the open-source SNAP software. We first updated the products with the precise orbit state vectors distributed by the satellite operator, followed by radiometric calibration according to the beta-nought (β_0) convention. Topographic effects on radiometric variability were then corrected through the Radiometric Terrain Correction approach described by Small (2011), yielding the gamma-nought (γ_0) backscatter coefficient. Finally, this
200 coefficient underwent geometric terrain correction and speckle reduction via a Lee filter (9×9 pixel window, 2 looks), following Yommy et al. (2015). Finally, both images of the backscatter coefficients γ_0^{VV} and γ_0^{VH} , with the same 10 m resolution of the original Ground Range Detected product, were saved for further elaborations.

To automatically classify avalanche deposits in each scene, we employed the Change Detection Neural Network model based on the Swin Transformer, presented in Gatti et al. (2026). The architecture follows a Siamese design, with two identical
205 encoders that process pre- and post-event SAR images within a change detection framework. The LIA and the slope raster, taken from the Copernicus GLO-30 digital elevation model (European Space Agency, 2024), are included as input variables. Avalanche deposits are detected for each acquisition pair and provided both as binary rasters and polygonal outputs. Given the number of Sentinel-1 products downloaded, the avalanche detection was performed on 135 dates for AG 168 and 131 dates for AG 15.

210 3.3 SAR-based reconstruction of historical avalanche activity

In this section, the methodology adopted to evaluate the spatial and temporal reliability of the SAR-based historical avalanche detection dataset is presented. The analysis aims to identify and characterize potentially invalid scenes and areas (i.e., scenes and locations affected by systematic detection failures), and to investigate the main factors controlling the performance and reliability of the SAR-based avalanche detection.

215 3.3.1 Spatial assessment for invalid areas identification

To assess the spatial reliability of the historical detection of avalanche deposits, we generated a deposit frequency layer by summing all single prediction binary rasters, considering only the Livigno area. In the resulting layer, each pixel indicates the number of times it was affected by an avalanche deposit during the study period. To substantially clean the results, predicted avalanche deposits with an area smaller than the Sentinel-1 minimum resolution were not considered, as they correspond to
220 ASC 1 avalanches non detectable from the neural network model (Gatti et al., 2026). The results were visually compared with the flow thickness raster obtained from the AvaFrame::com1DFA simulation. This allowed us to identify recurrent avalanche



deposits detections in non-avalanche terrain (i.e., where no simulated avalanches are present), resulting in the identification of land features significantly affecting SAR-based avalanche deposits retrieval.

3.3.2 Temporal assessment for invalid scenes identification

225 To assess the temporal reliability of the historical avalanche detection, we computed the Avalanche Activity Index (AAI) from the SAR-based detections and compared it with the one computed from the Livigno avalanche dataset. The AAI is defined by Schweizer et al. (2020) as a measure of the temporal evolution of avalanche activity over a given area. In this work, we propose a modification of the original index by not considering the triggering mechanism, which cannot be inferred from SAR observations. Specifically, we define:

$$230 \quad AAI = \sum_{i=1}^N w_{ASC}(i), \quad (1)$$

where N is the number of avalanches observed within a given temporal interval and $w_{ASC}(i)$ is the weight associated with the ASC of the i -th avalanche (Schweizer et al., 2020). We denote the AAI computed from SAR detections as AAI_{sar} and the AAI computed from the Livigno avalanche dataset as AAI_{obs} . Both indices refer to the same temporal interval, corresponding to the period between each pre- and post-event SAR acquisition. This temporal aggregation ensures consistency in the comparison
235 between remotely sensed detections and in situ observations.

The ASC in the Livigno avalanche dataset was estimated by the local forecasters based on a rough approximation of the volumes involved from observing the release area. For avalanches detected via SAR, volumetric information of the deposits is not available, so we approximated the ASC based on the deposit area. Specifically, deposits with an area less than 500 m² were assigned ASC 1, those with an area between 500 m² and 5000 m² were assigned ASC 2, deposits between 5000 m² and
240 50000 m² were assigned ASC 3, and deposits larger than 50000 m² were assigned ASC 4. ASC 1 avalanches, non-detectable by the neural network model (Gatti et al., 2026), were excluded from the Livigno avalanche dataset to ensure consistency between the two datasets.

To avoid the manual inspection of every single scene, we automatically identified potentially invalid scenes based on discrepancies between AAI_{sar} and AAI_{obs} , considering the limitations of the Livigno avalanche dataset. Specifically, for each
245 date we computed

$$\Delta_{AAI} = AAI_{sar} - AAI_{obs}. \quad (2)$$

A scene was considered potentially invalid, and thus visually inspected, if it fell into one of the following cases:

- Case A: dates for which Δ_{AAI} is negative. Since SAR observations cover a wider area than what can be manually observed, this scenario suggests the presence of false negatives in the corresponding scenes.
- Case B: dates for which Δ_{AAI} lies between the 75th and 95th percentiles of all Δ_{AAI} values. In this case, AAI_{sar} is
250 significantly larger than AAI_{obs} , indicating potential false positives in the corresponding scenes. However, the AAI_{sar} values remain realistic, so the mismatch may also reflect limitations in the reference database.



- Case C: Dates for which Δ_{AAI} exceeds the 95th percentile of all Δ_{AAI} values. Here, Δ_{AAI} shows extremely high values, most likely due to a strong presence of false positives in the corresponding scenes.

255 Once all potentially invalid scenes were identified, each of them was analysed exploiting the data reported in Sect. 2.4. For Case A (negative Δ_{AAI}), the following sub-categories were distinguished:

- A1: Avalanches detected by SAR correspond to documented events in the database but differ in terms of assigned ASC . Given the weighting scheme of the AAI , even minor misclassifications of ASC may result in substantial discrepancies between AAI_{sar} and AAI_{obs} .
- 260 • A2: Scenes affected by missed detections of many small avalanches not excluded a priori (release area between 500 m² and 1000 m²). Although classified as ASC 2, these events may produce relatively small deposition areas that are close to the detection limit of the neural network model and are therefore expected to be underrepresented from Sentinel-1 images.
- A3: Scenes affected by missed detections of avalanches with area > 1000 m². In this case, missed detections cannot
265 be attributed to SAR resolution constraints and are instead likely caused by external interferences.

For Cases B and C (positive Δ_{AAI}), two main sub-categories were defined:

- B/C1: Probable lack of observations in the reference database. These scenes contain avalanche deposits that are plausible in terms of size, shape, and locations, and occur under meteorological and snowpack conditions favourable for avalanche activity. Such events typically affect areas or period that are difficult to observe manually, for instance
270 due to persistent adverse weather conditions or during the Covid-19 period (see Sect. 2.3).
- B/C2: Scenes characterized by non-plausible avalanche detections, either in terms of size, shape, or spatial location, or occurring under meteorological and snow conditions that preclude avalanche release. These cases are therefore interpreted as dominated by false positive detections.

Based on this classification, scenes were flagged as invalid and excluded from the final AAI_{sar} timeseries if they were affected
275 by true false negatives, involving avalanches with $ASC \geq 2$ (Case A3), or a dominance of non-plausible detections interpreted as false positives (Case B/C2). Scenes affected solely by ASC misclassification in the database (case A1), by detection limitations inherent to Sentinel-1 spatial resolution (Case A2), or by plausible avalanche activity likely missing from the reference database (Case B/C1), were retained. Finally, the percentage of scenes with a reliably predicted AAI , before and after this data cleaning, was assessed for both the AGs.

280 3.3.3 Analysis of the conditions leading to systematic detection failures

While the scene classification allowed the identification and removal of clearly unreliable SAR acquisitions, a deeper understanding of the mechanisms leading to detection failures was required to assess the reliability of SAR-based historical avalanche activity reconstruction. The overarching objective of this analysis was to identify recurring interferences external to SAR data resolution that may compromise the detection. Ultimately, this approach aimed at supporting a semi-automatic pre-



285 screening of SAR acquisitions, enabling the identification of potentially unreliable scenes even in the absence of reference in situ avalanche observations.

Using again the data reported in Sect. 2.4, we analysed the snow and weather evolution between pre- and post-event conditions, as well as at the time of the SAR acquisitions, for all scenes flagged as invalid, looking for systematic processes potentially contributing to scene invalidation. Representative invalid scenes were then selected for more detailed analysis. Variations
290 between pre- and post-event backscatter were visualized using color composite images, in which the pre-event image was assigned to the red and blue channels, and the post-event image to the green channel, following the approach proposed by Wiesmann et al. (2001). Next, we examined the distributions of co- and cross- polarization backscatter coefficients variations within the SAR revisit period, comparing it either with those of the surrounding areas or with those of correctly detected avalanche deposits from a reference, reliable scene. Note that the surrounding area was selected with a 500 m buffer around
295 the deposits' outlines, excluding other neighbouring deposits eventually present.

The selected valid reference scene corresponds to the acquisition of 3 April 2024, acquired in AG 168 (early morning). This scene was chosen as a benchmark for the comparative backscatter analysis because part of the training dataset for the neural network model, after checking the detections validity through a field survey conducted after a major dry snow avalanche cycle occurred on April 1st, 2024. In this cycle, multiple *ASC* 4 avalanches were documented within the Livigno area and correctly
300 reproduced by the neural network model.

3.4 Probabilistic analysis of avalanche runout from SAR data

After excluding all invalid scenes and areas following the methodology described in Sect. 3.3, we used the historical avalanche deposits detected in the AG that led to the best performances to model the avalanche runout distance probabilities. The aim of this analysis was to assess the potential of SAR-derived avalanche deposits as a dataset for probabilistic runout distance
305 analysis, complementing traditional field-based approaches.

To this end, we selected 17 avalanche basins located between the Livigno and Engadin valleys (Figure 1). These basins were manually delineated based on local topography and represent sub-catchments of the main valleys where at least one SAR-based avalanche deposit with *ASC* = 4 was detected. The conditions for the choice of the avalanche basins are a well-defined avalanche path, typically confined within gullies or couloirs reaching the main valley floor, avalanche runouts primarily
310 controlled by natural energy dissipation rather than by morphological constraints, and no artificial release performed within the slopes. Only avalanche deposits detected within the boundaries of the selected basins were considered for the probabilistic modelling.

According to McClung et al. (2022), the most suitable parameter for probabilistic runout distance modelling with distributional data is the Runout Ratio (*RR*), which is defined as

$$315 \quad RR = \frac{\Delta x}{x_{\beta}}, \quad (3)$$



where Δ_x is the avalanche runout distance, defined as the maximum horizontal reach of the avalanche from a zero-reference point along the path, known as the β -point, and X_β is the horizontal length of the avalanche path from the starting zone to the β -point (McClung and Lied, 1987). The β -point is usually defined as the location along an avalanche path where the slope angle permanently decreases below a given threshold when moving downslope from the release area (where typically
320 avalanches starts to decelerate). In practice, avalanche experts typically identify the β -point at the 10° slope angle using topographic maps, disregarding local benches or short-scale slope variations occurring upstream of the deposition zone (McClung et al., 2022).

Often, multiple individual PRAs can generate flows that merge downstream along a common path, terminating in the same deposition zones. Consequently, even when selecting avalanche basins where all potential paths feed into a single main channel
325 before the deposition zone, the SAR sensitivity only to the deposits makes it impossible to determine which specific path the avalanche followed in the upper basin. Therefore, we derived X_β as the average of all the single paths. The centroid of each PRA was then used as the origin of the potential avalanches occurring within a basin, simulating the corresponding flow paths with the GRASS GIS tool r.drain (GRASS Development Team, 2025).

To identify the β -point along the flow paths, we computed a representative elevation profile for each avalanche basin. This
330 was obtained by averaging the elevations of all individual flow paths which originates from the different PRA centroids within the basin, at equal distances from a common outlet located downstream to the SAR-based deposits detected within the basin. A spatial step of 4 m, consistent with the DEM resolution, was used. The average slope profiles were then derived as the gradient of the average elevation profiles smoothed using a moving window of size 7 to reduce the influence of local sharp slope variations and DEM limitations. The β -point was then automatically located along the representative profile. Multiple
335 candidate β -points at 10° , 15° , 20° , 25° , and 30° were initially identified. The final β -point was selected based on visual inspection, requiring it to be located downstream of the convergence of the individual flow paths and to exhibit spatial consistency between SAR-based deposits and the simulated flow paths.

To model the RR distribution, we assumed that the annual maxima observed on each avalanche path $i \in \{1, \dots, 17\}$ are independent and identically distributed (i.i.d.) random variables $G_i \sim \text{GEV}(\mu, \sigma, \xi)$, where $\text{GEV}(\mu, \sigma, \xi)$ denotes a
340 generalized extreme value distribution with location $\mu \in \mathbb{R}$, scale $\sigma > 0$, and shape $\xi \in \mathbb{R}$ (McClung et al., 2022). However, not necessarily an avalanche with $ASC \geq 2$ occurred on each slope every year. Hence, G_i would allow us to derive the conditional probability that *the largest RR observed during a year on path i (RR_i) exceeds a threshold $x \in \mathbb{R}$, provided that at least one qualifying avalanche occurred on that path during that year*, namely

$$P(RR_i > x \mid \exists \text{ avalanche on path } i). \quad (4)$$

345 Hence, the unconditional annual exceedance probability on path i is obtained as

$$P(RR_i > x) = P(RR_i > x \mid \exists \text{ avalanche on path } i) \cdot P(\exists \text{ avalanche on path } i). \quad (5)$$



Since the G_i are i.i.d., Eq. (4) does not vary globally (i.e., it does not depend on the avalanche path in the study area). On the other hand, Eq. (5) has a local validity since $P(\exists \text{ avalanche on path } i) =: p_i$ depends on the individual path. Indeed, some paths are more prone to large avalanches than others.

350 To estimate the common GEV distribution, all available annual maxima of RR from the 17 paths were pooled together, similar to what Bocchiola and Rosso (2008) proposed for the three days cumulative snowfall parameter. This distributional approach increases statistical robustness by maximizing the effective sample size, consisting of 76 annual maximum RR values. The parameters μ , σ , and ξ were estimated by maximum likelihood estimation (Myung, 2003). On the other hand, the occurrence probabilities p_i were estimated as the ratio between the number of years in which path i experienced a significant avalanche
355 and the total number of years considered in the study. However, recall that only 10 years of SAR acquisitions have been considered, hence leading to a less reliable estimate than the one of the GEV distributions.

Notice that Eqs. (4) and (5) provide estimates of the runout probability and the impact probability, respectively, following the definitions adopted in the site-specific avalanche warning recommendations of the EAWS (Site specific avalanche warning, 2026).

360 4 Results

4.1 Spatial distribution of SAR-based detections

In general, the avalanche deposits detected over the Livigno area visually correspond to the lower portions of the simulated avalanche paths (Figure 2a). However, the visual inspection revealed specific areas characterized by recurrent false positives such as ski-domain infrastructures, including alpine ski slopes, cross-country tracks, and other winter sport facilities (Figure
365 2b). as well as the artificial Livigno lake (Figure 2c). Based on in situ observations, ski slopes are generally groomed every night, while the Livigno lake remains generally frozen between late December and early April, with a continuously varying water level due to hydropower operations. False deposits within the ski areas are mainly detected in early or late season, while false deposits within the lake in winter. Frequent small deposits (i.e., in the order of few pixels) are detected in backcountry non-avalanche areas often characterized by slopes change, bowls, or gullies. Small areas with deposit frequencies larger than
370 1 were also detected along the main roads.

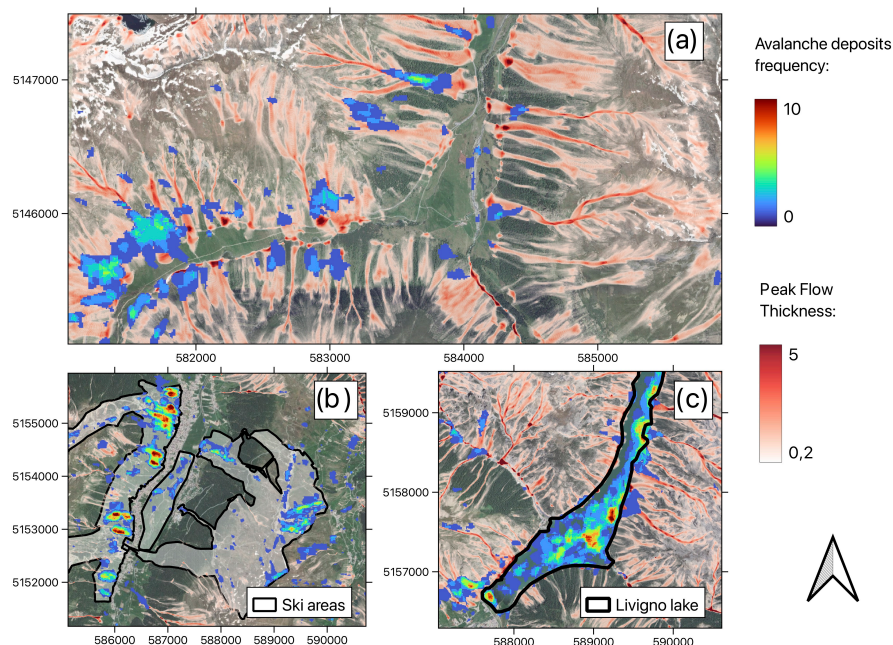


Figure 2. Avalanche deposit frequency raster representing the number of hits in the last ten years together with different land features and AvaFrame::com1DFA simulations. (a) Avalanche deposits frequency in backcountry terrain potentially interested by simulated avalanches. (b) Avalanche deposits frequency in non-avalanche ski areas. (c) Avalanche deposits frequency within the Livigno lake, which is a non-avalanche area.

4.2 Comparison between SAR-based and observed avalanche activity

For AG 168, 24 scenes (17.8 % of the total) presented substantial differences between AAI_{sar} and AAI_{obs} . According to the classification scheme defined in Sect. 3.3.2, they were thus classified as follows: 13 scenes as B1 (plausible avalanche activity likely missing in the Livigno avalanche dataset), 3 scenes as C2 (dominance of non-plausible detections interpreted as false positives), 2 scenes as A1 (ASC misclassification between datasets), 1 scene as A2 (missed detections attributable to Sentinel-1 resolution limits), and 2 scenes as A3 (missed detections not attributable to resolution or ASC mismatch). For AG 15, the classified scenes were 28 (21.3 % of the total). Of these, 8 scenes were classified as B/C1, 13 as B/C2, 1 as A1, and 6 as A3. In both avalanche groups, scenes classified as B1 or B/C1 were generally associated with deposits detected in remote areas or in periods characterized by limited ground-based observations in the Livigno avalanche dataset (recall Sect. 2.3). Scenes classified as A1 or A2 mainly involved channelized avalanche deposits correctly detected by SAR but associated with underestimated ASC values in the Livigno avalanche dataset, likely due to their elongated geometry and locally enhanced deposit thickness. In addition, A2 scenes included multiple missed detections corresponding primarily to avalanches manually classified as ASC 1.

Based on this assessment, only 5 scenes were considered invalid for AG 168 (3.8% of the total), compared to 19 scenes for AG 15 (14.5%). According to the information reported in the Livigno avalanche dataset, 95 % of the total number of dry



avalanche cycles, 99 % of the total number of wet avalanche cycles, and 100 % of the total number of mixed avalanche cycles have a corresponding valid scene. Following Sect. 3.3.3, scenes classified as invalid (class A3 or B/C2) were further analysed to identify external processes potentially contributing to scene invalidation.

4.2.1 Snow, weather, and avalanche conditions of the invalid scenes

395 As reported in Table 1, most invalid scenes dominated by false negatives (class A3) were associated with increasing air temperatures and significant melting episodes affecting the avalanche deposits during the SAR revisit period, resulting in enhanced snow wetness under post-event conditions. In some cases, new snow accumulated over the deposits before the melting episodes. This behaviour was observed in two scenes for AG 168 and four scenes for AG 15. Conversely, in one scene for AG 168 and two scenes for AG 15, missed detections occurred over dry, thin, and spread deposits, combined with
400 approximately 50 cm of dry new snow accumulation during the SAR revisit period. Regarding invalid scenes dominated by false positives (class B/C2), two cases for AG 168 and twelve cases for AG 15 were characterized by wet snow conditions at the pre-event acquisition time, followed by decreasing air temperatures during the SAR revisit period, which promoted substantial snow refreezing before the post-event acquisition. In these cases, false positives frequently affected entire slopes or corresponded to old avalanche deposits accumulated earlier in the same season. In only one case for AG 168, false positives
405 were mainly located within patchy coniferous forest areas, where snow-free canopies at the pre-event acquisition became covered by a significant amount of wet snow in the post-event acquisition.

Table 1. Summary of the main causes that potentially led to scene invalidation, together with the error type and the relative class.

Probable failure cause	Number of scenes (AG 168)	Number of scenes (AG 15)	Type and class
Thin and spread deposits with new snow	1	2	False negative (A3)
General snow wetting	1	4	False negative (A3)
General snow refreezing	2	12	False positive (B/C2)
Wet snow on the forest	1	0	False positive (B/C2)
Unknown	0	2	False positive (B/C2)

410 After excluding potentially invalid scenes and areas from the SAR-derived dataset, a total of 130 scenes were retained for AG 168, representing 96.2 % of the total. Similarly, 112 scenes were retained for AG 15, corresponding to 85.5 % of the total. Considering both AGs, the median AAI_{sar} of scenes flagged as B/C2 (false positives) was 41.7, compared to a median AAI_{sar} of 1.5 for the valid scenes. Scenes classified as A3 exhibited a median AAI_{sar} of 2.31 (see Figure 3).

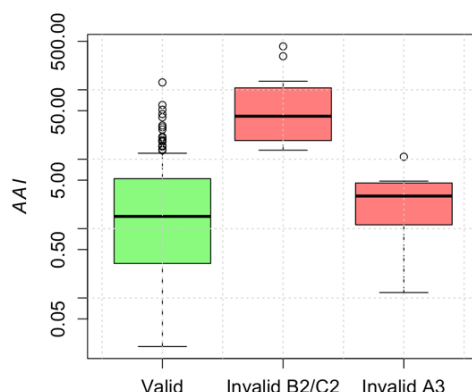


Figure 3. Boxplot of the AAI for all valid scenes, invalid scenes of class B/C2 (large false positive presence), and invalid scenes of class A3 (large false negative presence).

4.2.2 Backscatter characteristics of the invalid scenes

We are now ready to compare the backscatter characteristics related to the different causes of failure in the invalid scenes with the backscatter characteristics of the reference valid scene.

Figure 4 represents the scene of 3 April 2024 from AG 168, assumed as valid (recall Sect. 3.3.3) and considered as the reference for analysing the backscatter variations in the ones classified as invalid. The avalanche deposits classified in this scene clearly appear as green tongue-shaped features, visually distinguishable by the human eye from the surrounding areas. The distribution of backscatter coefficient variations between pre- and post-event acquisitions is also clearly distinguishable for both γ_0^{VH} and γ_0^{VV} , with deposits presenting a marked increase in backscatter with respect to the surrounding and limited overlap between the two histograms.

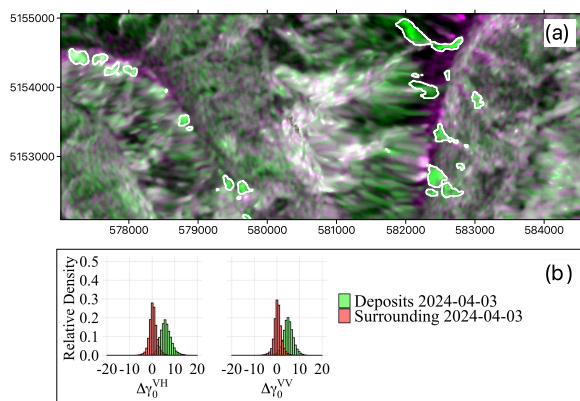


Figure 4. Reference valid scene of 2024-04-03 acquired in AG 168. (a) Color Composite Image of the scene together with the deposits correctly detected by the neural network model. (b) Co- and Cross- polarization backscatter variations distributions within the ground-truth deposits (green) and the surrounding area of the Livigno area (red).

430 Figure 5 shows the color composite image of 4 April 2024 from AG 15 (afternoon), when snow wetting occurred leading to false negatives, with the superimposition of the valid-scene deposits (acquired with AG 168 in the early morning of 3 April 2024). Between the two acquisition times, temperatures significantly increased leading to a significant increase in snow wetness at the post-event acquisition. Looking at Figure 5a, avalanche deposits are no longer clearly distinguishable from the surrounding and appear in purple rather than green. Consistently, Figure 5b shows that the variations of backscatter between

435 pre- and post-event conditions are distributed around zero, instead of the clear positive variations observed within the valid-scene deposits.

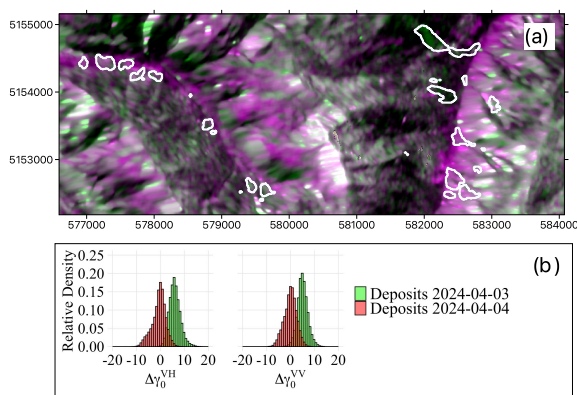


Figure 5. Invalid scene of 2024-04-04 acquired in AG 15 affected by snow wetting. (a) Color Composite Image of the scene together with ground truth deposits from Gatti et al. (2026). (b) Co- and Cross- polarization backscatter coefficients variations distributions within the correctly detected deposits of the valid reference scene (green) and within the same deposits for the invalid scene (red).

440

Figure 6 focuses on the scene of 10 March 2024, where dry snow avalanches with $ASC > 2$ produced spread deposits expanded laterally outside the main flow path, with an average thickness estimated from field survey of about 100 cm. Around 50 cm of



new dry snow had recently accumulated in the surrounding area, partially covering the deposits. As can be seen from the color
445 composite image (Figure 6a), the deposits exhibit very low contrast with respect to the surrounding area, which is also evident
from the backscatter coefficients variation distributions reported in Figure 6c.

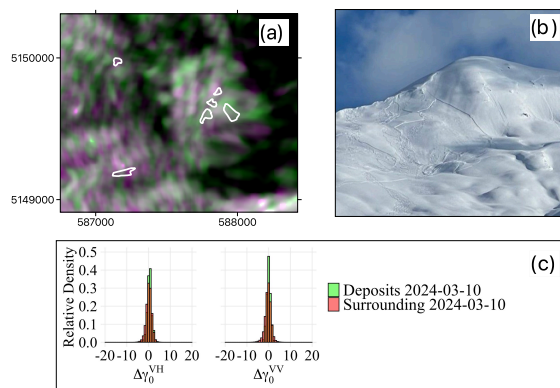


Figure 6. Invalid scene of 2024-03-10 acquired in AG 168 affected by spread and relatively thin deposits with new dry snow presence. (a)
450 Color Composite Image of the scene together with ground-truth deposits from field observations conducted after the avalanche events. (b)
Picture acquired during the field survey. (c) Co- and Cross- polarization backscatter coefficients variations distributions within the ground-
truth deposits of the invalid scene (green) and the surrounding area (red).

Figure 7 represent the scene of 27 March 2024 from AG 168, characterized by the presence of wet snow on the ground at the
time of the pre-event acquisition, with a consistent snow refreeze for the time of the post-event acquisition. Looking at the
color composite image reported in Figure 7a, the false positive occupies large slope portions, with a marked green color
455 indicating backscatter increase. As reported in Figure 7b, the distribution of the backscatter coefficients variations in these
areas is positive and similar to the variation occurred within the deposits of the valid scene (3 April 2024, AG 168).
Furthermore, old avalanche deposits which undergoes the same melting-refreezing process within the SAR revisit period were
classified again by the neural network model as new avalanche deposits.

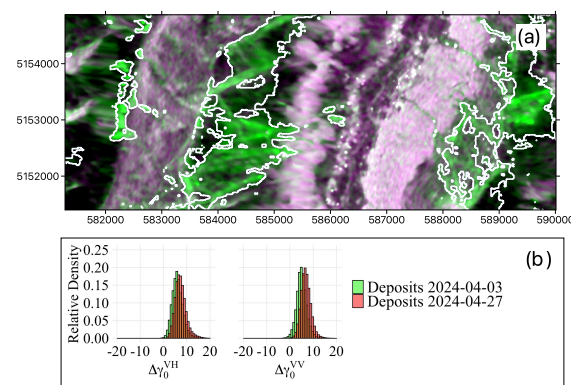


Figure 7. Invalid scene of 2024-04-27 acquired in AG 168 affected by snow refreezing. (a) Color Composite Image of the scene together
460 with false positives detected by the neural network model. (b) Co- and Cross- polarization backscatter coefficients variations distributions
within the false positives of the invalid scene (red) and within the correctly detected deposits of the valid reference scene (green).



Figure 8 represents the scene of 28 January 2025, where false positives appeared in patchy forested areas which canopy was covered by wet snow. Looking at the color composite image reported in Figure 8a, these areas present a marked green color, indicating backscatter increase. Similarly to the case of snow refreezing, the backscatter coefficients variations distributions reported in Figure 8c is positive and similar to the one of the valid reference scene (3 April 2024, AG 168).

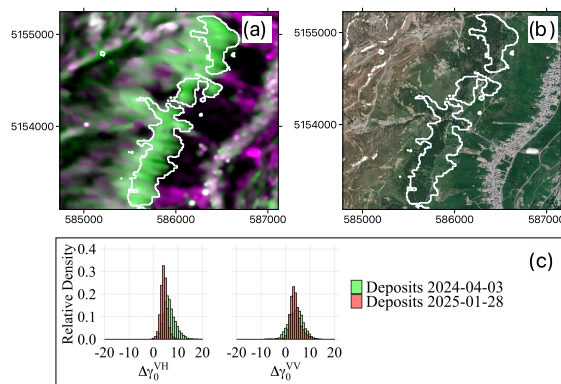


Figure 8. Invalid scene of 2025-01-28 acquired in AG 168 affected by wet snow on tree canopies. (a) Color Composite Image of the scene together with false positives detected by the neural network model. (b) False positives outlines superimposed to an optical satellite image. (c) Co- and Cross- polarization backscatter coefficients variations distributions within the false positives of the invalid scene of 2025-01-28 (red) and within the correctly detected deposits of the valid reference scene (green).

4.3 Probabilistic Runout Ratio modelling

The analysis of the candidate β -point locations led to the selection of the 25° slope as the most representative configuration. Indeed, β -points associated with the 10° slope were not consistently present along the selected avalanche paths and were, in most cases, located downstream of the mapped deposits. The 15° and 20° β -points were frequently situated within the debris fan area that characterize the avalanche deposit zones. In this sector, a significant discrepancy between the simulated flow paths and the SAR-detected deposit trajectories was frequently observed, potentially leading to errors in the computation of Δx . Conversely, the location of the 30° β -points was generally considered too far upstream along the flow paths, often above the zone where the flow paths merge into a single channel (see Figure 9).

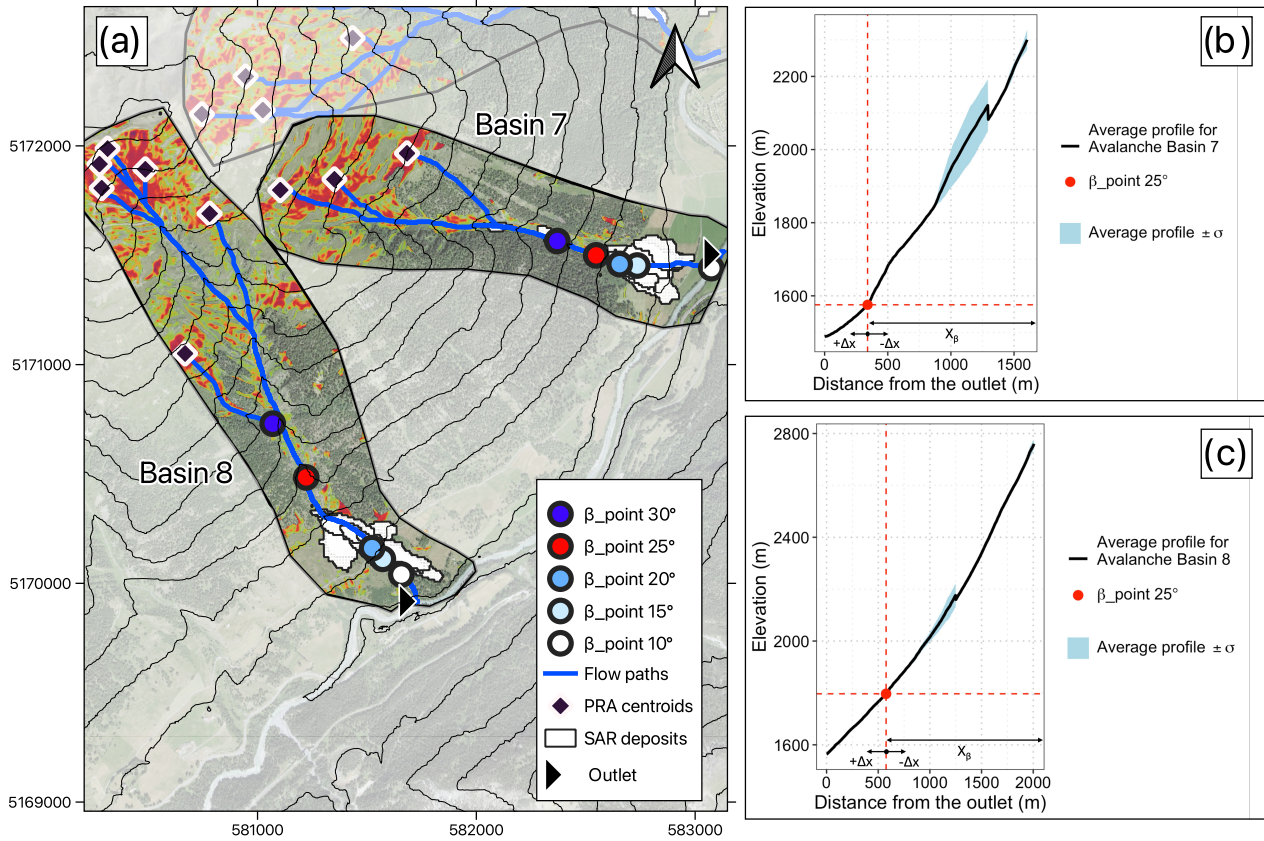


Figure 9. Example of flow paths and β -points location for two of the 17 selected avalanche basins. (a) Avalanche basins 7 and 8 with the simulated flow paths, the PRA layer, the PRA centroids, the SAR-based avalanche deposits, the β -points locations, and the location of the common outlets of the multiple sub-paths. (b) Average flow profile for Basin 7 together with the β -point for 25°. (c) Average flow profile for Basin 8 together with the β -point for 25°.

Figure 10a shows the cumulative distribution function (CDF) and Figure 10b the probability density function (PDF) of the estimated GEV distribution, whose parameters are reported in Table 2 together with their 95 % confidence intervals. The negative value of the shape parameter ξ indicates a Weibull-type GEV distribution, implying a bounded upper tail for the RR , and the confidence interval of ξ does not include zero, providing statistical evidence that the tail behavior significantly departs from the Gumbel and Fréchet cases. The Q-Q plot related to the GEV model reported in Figure 10c shows a generally good agreement between empirical and theoretical quantiles, with deviations mainly observed in the lower tail (i.e., at small RR values). Formal goodness-of-fit tests further support the adequacy of the GEV model: the Kolmogorov–Smirnov test does not reject the null hypothesis that the data follow the fitted distribution (KS statistic of 0.10), similarly the Anderson–Darling test indicates no strong evidence against it ($A^2 = 0.83$). However, note that the reliability of these two statistical tests is limited by the relatively small dataset (76 data). Finally, the results of the two different RR models are shown in Figure 11.

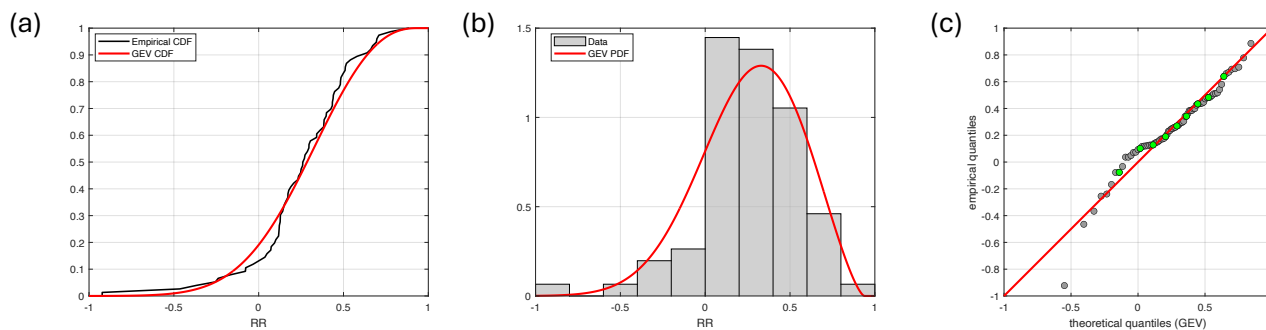


Figure 10. Results of the GEV model fitting. (a) Empirical and modelled cumulative distribution function (CDF). (b) Modelled probability density function (PDF) compared to the empirical data. (c) Q–Q plot, the deciles are highlighted in green.

500 **Table 2.** Parameters of the fitted GEV model, together with their 95 % confidence intervals (CIs).

Parameter	Value	95 % CI
μ (location)	0.1774	[0.1016, 0.2533]
σ (scale)	0.3159	[0.2682, 0.3721]
ξ (shape)	-0.4160	[-0.5114, -0.3205]

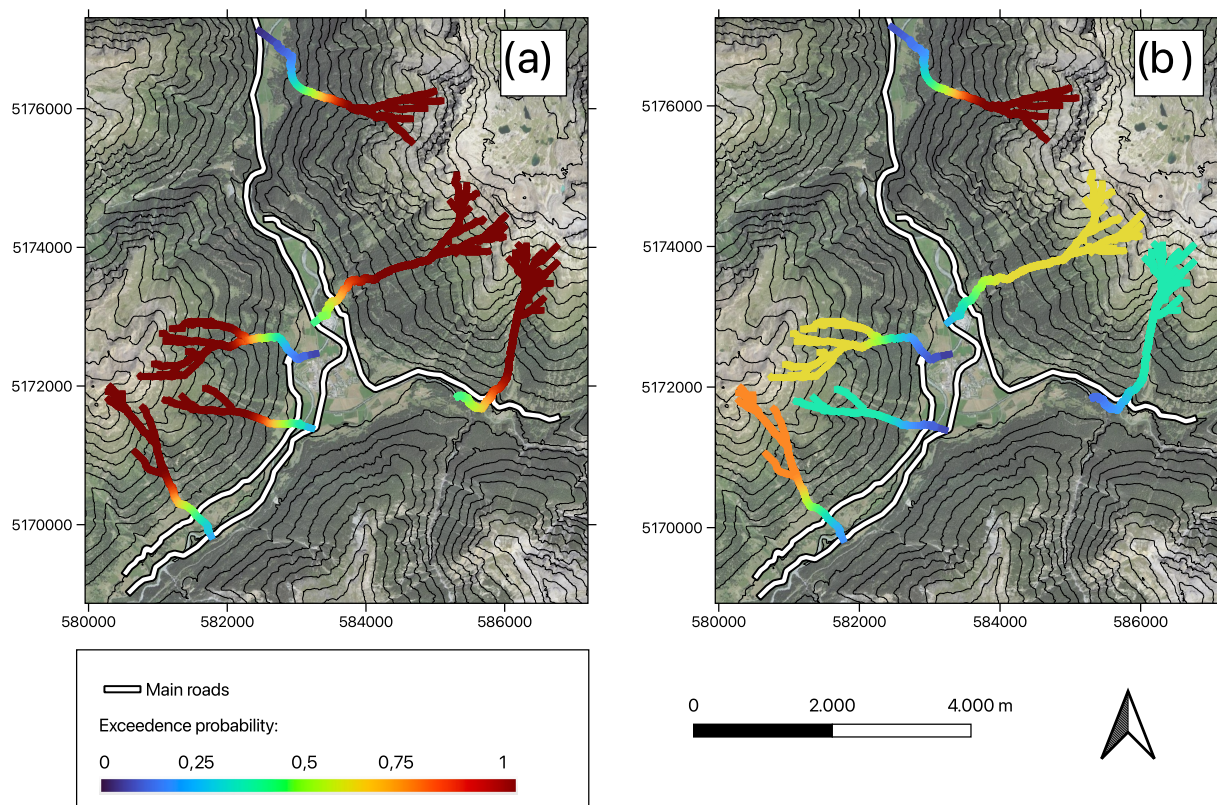


Figure 11. Runout distance exceedance probability along the flow paths of six avalanche basins located in the Engadine valley, together with the main roads. (a) Conditional exceedance probability (i.e., Eq. (4)). (b) Non-conditional exceedance probability (i.e., Eq. (5)).

505 5 Discussion

5.1 Influence of land surface features on SAR-based avalanche detection

The visual inspection of the SAR-based avalanche deposit frequency over the Livigno area revealed the presence of specific land features where recurrent false-positive detections are present. Patchy zones characterized by non-null detection frequencies in non-avalanche alpine terrain are primarily associated with preferential wind-accumulation features, such as bowls and gullies. Wind redistribution plays a key role in controlling spatial snow-depth variability throughout the winter season, and zones of snow accumulation and erosion tend to recur systematically within a given region (Föhn and Meister, 1983). This spatially structured redistribution significantly influences radar backscatter signals, due to variations in snow depth and land surface roughness (Nandan et al., 2023). Other small false detections, typically spanning only a few pixels, frequently occur along main roads, where snow-clearing operations generate snow piles or in anthropogenic areas due to local land cover modifications.



False avalanche detections along ski slopes may be primarily associated with surface roughness variations induced by grooming activities. Snow grooming machines produce characteristic ridges and corrugations with heights on the order of 2 or 3 cm. Given the ~5.6 cm wavelength of the C-band signal emitted by Sentinel-1, variations in the height and the orientation of these surface undulations between pre- and post-event acquisitions can significantly modulate the radar backscatter response, potentially explaining the false detections (Flores-Anderson et al., 2019). Areas surrounding the ski slopes, characterized by intense anthropogenic activity and frequent skier traffic, also exhibit multiple small false detections, which can be attributed to temporal snow properties variations.

False detections associated with the Livigno lake likely arise from the complex microwave backscatter response of ice-covered water bodies (Wakabayashi et al., 2019). Additionally, many false detections occur near the shoreline, where fluctuations in water level due to hydropower operations expose terrain between pre and post event acquisitions, leading to strong backscatter increases in these areas (i.e., typically water bodies as the lower backscatter values of the entire scenes). Occurrence of false positives on iced lakes was also reported in Eckerstorfer and Malnes (2015), in addition to misclassification in active debris flow tracks, not present in our study area.

Finally, false detections can also occur in forested areas. However, this effect is not systematic and is observed only under specific snow conditions; it is therefore discussed in detail in the following section.

5.2 Influence of snowpack and weather variations on SAR avalanche detections

Detection failures associated with thin and spread dry deposits can be attributed to their low backscatter contrast relative to the surrounding snow cover (Figure 6). Similar difficulties in detecting dry avalanche deposits have already been reported by Eckerstorfer et al. (2019) and Malnes et al. (2024). Dry snow avalanches are often characterized by smoother deposits with finer granules compared to wet-snow avalanches (Bartelt and McArdell, 2009). Thus, according to the avalanche backscatter mechanism proposed by Eckerstorfer and Malnes (2015), if the deposit depth is not significantly larger than that of the surrounding snow cover, a small contrast in snow volumetric backscatter should be expected. Furthermore, the limited increase in both γ_0^{VV} and γ_0^{VH} between pre- and post-event conditions may be related to the negligible surface backscatter produced by dry snow (Mätzler, 1987; Strozzi et al., 1997). Finally, new dry snow deposited during the SAR revisit period can lead to a general increase in γ_0^{VH} over the scene, while γ_0^{VV} remains mainly influenced by the relatively stable properties of the underlying soil, further limiting the contrast between avalanche deposits and the surrounding (Lievens et al., 2022; Mariani et al., 2026).

Snow wetting represented another reason for false negatives. In this scenario, detection failures are attributed to a general decrease in backscatter relative to pre-event conditions in the areas where avalanche deposits should have been located. Snow wetting occurring after avalanche release may smooth the surface roughness of the deposits, leading to a less pronounced surface backscatter increase. Furthermore, both γ_0^{VV} and γ_0^{VH} decrease with increasing liquid water content, reflecting the well-known effect of differing complex dielectric constants between dry and wet snow (Mätzler, 1987). For example, Nagler and Rott (2000) reported a decrease of at least 3 dB between dry and wet snow conditions, which can compensate the expected



backscatter increase over avalanche deposits in the case of smoothed snow surface. This failure mechanism is further enhanced when new snow accumulates over the deposits prior to snow wetting, as the SAR signal can no longer penetrate sufficiently to interact with the buried avalanche debris under post-event conditions.

Failures in avalanche deposit detections, leading to many false positives, were mainly attributed to general snow refreezing between pre- and post-event acquisitions. In these areas, the increase in both γ_0^{VV} and γ_0^{VH} , is very similar to that of valid avalanche deposits. Because wet snow backscatter is typically very low, refreezing causes the backscatter to increase. This effect is further enhanced by the presence of the melt-freeze crust at the time of post-event acquisitions, which has been shown to further increase both co- and cross-polarization backscatter coefficients (Carletti et al., 2025). A positive aspect of this interference mechanism is that snow refreezing is generally widespread across homogeneous slopes, producing very large false positives that can be discriminated by an expert and enabling the automatic flagging of potentially invalid scenes based on AAI_{sar} ; this will be further discussed in Sect. 5.3. It is also important to note that general snow refreezing was the main cause of scene invalidation and should therefore be considered carefully when mapping avalanche deposits from SAR data.

Regarding the false positives associated with the presence of wet snow on the tree canopy, these areas exhibited a notable increase of both γ_0^{VV} and γ_0^{VH} , again with a distribution of backscatter coefficients variations closely resembling that of valid avalanche deposits. Chauhan et al. (2022) identified that the complex dielectric constant of tree leaves at microwave frequencies increases with moisture content, similarly the presence of wet snow on the branches during the post-event acquisition likely contributed to increased backscatter and reduced signal penetration. Chang et al. (2025) showed a gain up to 7 db in the reflection coefficients of vegetated surface after rainfall events. Additionally, double-bounce scattering mechanisms between branches or between the wet snow at the ground and the tree trunks could have further amplified the backscatter signal (Oh et al., 2002). Notably, Chauhan et al. (2022) also highlighted that the backscatter increase with leaf humidity depends on the LIA and, in our case, false positives were observed predominantly on one side of the Livigno valley (Figure 8). While SAR-based avalanche deposits misclassifications due to changing snowpack properties was already noticed in Eckerstorfer and Malnes (2015), to our knowledge, ours is the first report of such an effect in avalanche remote sensing, and further targeted studies are needed to fully characterize and address this phenomenon.

From a theoretical perspective, another potential interference mechanism not directly observed in this study is the transition from wet snow cover, characterized by low backscatter values in the pre-event acquisition, to bare soil conditions, which is known to significantly increase backscatter thus leading to false positives (Flores-Anderson et al., 2019; Carletti et al., 2025).

5.3 Reliability of SAR-based avalanche activity reconstruction

The comparison between the AAI computed from SAR-based avalanche deposit detections and the one derived from manual observations allowed us to account for the limitations inherent to manual avalanche records. The larger number of invalid scenes for AG 15 compared to AG 168 is related to increased detection failures attributed to general snow refreezing or snow wetting. Since AG 15 acquires images in the afternoon, this behaviour is likely linked to more favourable conditions for snow wetting during that time of day (Kneib et al., 2024a). For this reason, we consider the choice of using AG 168 detections for



reconstructing a historical avalanche deposit series for probabilistic analysis appropriate. Furthermore, we conclude that early-morning SAR acquisitions are advantageous for historical avalanche reconstructions at these latitudes.

Based on the avalanche cycles nature reported in the Livigno avalanche dataset, both wet and dry snow avalanche activity was well reproduced, and no clear detection pattern was observed. Although the studies of Keskinen et al. (2022) and Eckerstorfer et al. (2019) reported limitations in monitoring dry snow avalanches, we believe that the wet or dry nature of avalanches has a negligible influence on detection performances, assuming that the avalanche deposits are of sufficient size. Instead, successful detection is primarily affected by the state of the snow in and around the avalanche deposits at the time of post-event acquisitions, as well as by the snowpack and weather evolution during the SAR revisit period.

Only a small percentage of scenes (3.8 % for AG 168 and 14.5 % for AG 15) were completely invalid due to the predominance of both false positives and false negatives. In contrast, in 24 scenes for the two AGs, SAR identified avalanche cycles that were missed or underestimated in the Livigno avalanche dataset. This, together with the significantly higher total AAI derived from SAR-based detections, supports the findings of Eckerstorfer et al. (2016, 2017, 2019), demonstrating that SAR represents an effective tool for comprehensive avalanche monitoring over forecasting regions, complementing traditional manual observations. Moreover, it demonstrates the reliability of reconstructing historical avalanche activity using Sentinel-1 SAR data with the neural network model presented in Gatti et al. (2026).

As shown in Figure 3 invalid scenes characterized by consistently high false positives can be automatically flagged for manual inspection based on their elevated AAI_{sar} values. This procedure identifies both valid large avalanche cycles and invalid scenes with large false positives detections. Avalanche experts can then decide whether to retain or exclude individual scenes, without analysing the entire historical series, as general snow refreezing produces clearly distinguishable deposit shapes.

5.4 Modelling avalanche runout distance probabilities from SAR data

The definition of the β -point is a key step in the computation of the RR parameter used for probabilistic modelling of avalanche runout distances. Although the β -point is commonly defined at a slope angle of about 10° (Lied & Bakkehoi, 1981; McClung & Lied, 1987; McClung & Mears, 1991; McClung et al., 2022), our results suggest that this assumption is not always appropriate when the analysis relies on automatically derived flow paths in an Alpine context. Indeed, some of the flow paths used in this study never reach 10° of slope before the outlet, while 15° and 20° thresholds tended to place the β -point within or even downstream of the observed deposition zones. The spatial distribution of SAR-detected avalanche deposits and the underlying DEM morphology indicate that starting of avalanche retardation is more consistently represented by a slope threshold of about 25° in our study area, supporting the choice of the β -point for this value.

The significance of the GEV model fitting demonstrates the potential of using SAR-based avalanche detections for probabilistic modelling of the conditional probability of avalanche runout distance. In particular, the distributional approach based on the RR helps compensate for the limited temporal record of SAR observations by exploiting their wide spatial coverage and the large number of avalanche basins potentially observed across a broad area. The Weibull-type nature of the GEV suggests the existence of a theoretical upper limit to extreme runout distances in the analysed dataset, consistent with



615 physical constraints imposed by topography and energy dissipation processes (McClung and Hoeller, 2025). The deviations in
the lower tail of the Q–Q plot related to the GEV model suggest that this reproduces the central and upper portions of the
empirical distribution well, while the smallest observations are less accurately captured. Since the primary interest in extreme
value analysis typically concerns the upper tail, this behaviour does not substantially affect the interpretation of extreme runout
probabilities. Moreover, these discrepancies can be explained by the difficulties in measuring precisely small avalanches with
620 SAR data.

The mapping of the unconditional annual exceedance probability reveals the limitations of using only 10 years of data to
compute the probability of annual avalanche occurrence on each path. Indeed, from a visual inspection of the results reported
in Figure 11, neighbouring avalanche basins with similar morphological characteristics present very different values in terms
of existence probability. Since no climatic or morphological properties of these basins is found to justify this behaviour,
625 differences in the unconditional exceedance probability are probably related to the low number of observation years available,
together with SAR-based avalanche detection limitations.

Relating the proposed methodology in the context of the site-specific avalanche warning recommendations written by the
EAWS (Site specific avalanche warning, 2026), we conclude that SAR data are effective for estimating the conditional
probability of avalanche runout, i.e., assuming conditions favourable to large avalanche releases.

630 5.5 Main limitations and future work

Firstly, we did not analyse the influence that snowpack properties (e.g., density, grain and particle size, the presence of ice
lenses, and debris surface roughness) have on detection performance. Moreover, even if the main snow and weather variations
affecting the detections identified in this study are believed to represent general processes occurring in mountainous snow
climates worldwide, additional studies in different regions are required.

635 In the automatic definition of the flow paths associated with the SAR-based detections, as well as in the identification of the
 β -point along them, difficulties mainly arose from discrepancies between the SAR-derived deposits and the simulated
hydrological paths within the deposition zones. To our knowledge, no studies have yet combined remotely sensed avalanche
deposits with avalanche dynamic simulations to fully reconstruct avalanche event morphology. Therefore, improved methods
are needed to relate the detected deposits to the avalanche events that generated them.

640 6 Conclusions

In this work, we combined dual-polarization Sentinel-1 SAR imagery with the deep learning Convolutional Neural Network
algorithm presented in Gatti et al. (2026) to automatically detect snow avalanche deposits between December 2015 and May
2025 in an area located in the Central Rhaetian Alps. The main snow and weather conditions affecting detection reliability
were evaluated, and the resulting SAR-based avalanche deposit dataset was tested for runout distance modelling. Two



645 independent image series acquired with different acquisition geometries, in the early morning and in the afternoon, were considered to assess the influence of acquisition time and variable snow conditions on detection performances.

Focusing on a portion of the study area, we first computed the Avalanche Activity Index (*AAI*) from both the SAR- and manual-based datasets, over the same temporal intervals. A pre-classification of each detection scene based on the *AAIs* was then performed, distinguishing between valid and invalid scenes. Recurrent patterns leading to false negatives were attributed to
650 snow melting after the avalanche events at the deposit locations, as well as to thin and spread deposits combined with the presence of new dry snow in the area. In contrast, false positives were attributed to general snow refreezing at the slope scale during the SAR revisit period and, in one case, to the presence of wet snow on the tree canopies. The potential of describing both dry and wet snow avalanche cycles without preferential performances was demonstrated, particularly for images acquired in the early morning. While previous studies often attributed differences in detection rates to the dry or wet nature of
655 avalanches, our results demonstrated that the main causes of detection invalidation were related to snow conditions at the time of post-event acquisition, as well as to snow and weather evolution occurring during the SAR revisit periods.

To model the runout distance exceedance probability from the historical SAR-based avalanche deposits, our analysis focused on 17 avalanche basins, selected for their morphological characteristics prone to extreme avalanche events. For each basin, potential avalanche flow paths were simulated, and times series of annual maximum Runout Ratios (*RRs*; McClung and Lied
660 (1987)) were automatically derived from SAR detections. Finally, following a distributional approach (Bocchiola and Rosso, 2008), these data were aggregated and successfully fitted with a Weibull-type GEV model.

Overall, this work demonstrates that Sentinel-1 SAR data and deep learning can reliably reproduce the historical evolution of the avalanche activity within a region and support probabilistic runout assessment across multiple basins. It also complements traditional avalanche records and provides valuable information for hazard management in remote or poorly monitored areas,
665 where remote sensing may represent the only feasible data source.

Data availability

The Livigno avalanche dataset is available from the corresponding author. Automatic Weather Station (AWSs) data are available from ARPA Lombardia: <https://www.arpalombardia.it/temi-ambientali/meteo-e-clima/form-richiesta-dati/>. Historical webcam images for the Livigno area are available at <https://livigno.panomax.com/>. The Livigno public avalanche
670 forecast archive is available at <https://www.livigno.eu/bollettino-valanghe>. Sentinel-1 SAR data were downloaded from the Copernicus Open Access Hub (Copernicus Data Space Ecosystem, 2026).

Author contributions

AM: Conceptualization, Investigation, Formal analysis, Methodology, Validation, Visualization, Writing (original draft preparation). JB: Formal analysis, Methodology, Validation, Visualization, Writing (original draft preparation), Writing



675 (review and editing). MG: Data curation, Investigation, Writing (review and editing). GG: Data curation, Writing (review and editing). PS: Data curation, Writing (review and editing). MM: Data curation. LD: Data curation. FL: Supervision, Writing (review and editing). GI: Writing (Review and Editing). FM: Supervision, Writing (review and editing).

Competing interests

The contact author has declared that none of the authors has any competing interests.

680

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685 **References**

- Abermann, J., Eckerstorfer, M., Malnes, E., and Hansen, B. U.: A large wet snow avalanche cycle in West Greenland quantified using remote sensing and in situ observations, *Nat. Hazard.*, 97, 517–534, <https://doi.org/10.1007/s11069-019-03655-8>, 2019.
- Abhinav, A. and Sattar, A.: Snow avalanche susceptibility, hazard, and exposure assessment in the Western Himalaya using machine learning and numerical modelling, *Sci. Rep.*, 15, 38093, <https://doi.org/10.1038/s41598-025-22051-w>, 2025.
- 690 Barbolini, M., Natale, L., and Savi, F.: Effects of Release Conditions Uncertainty on Avalanche Hazard Mapping, *Nat. Hazard.*, 25, 225–244, <https://doi.org/https://doi.org/10.1023/A:1014851705520>, 2002.
- Bartelt, P. and McARDell, B.: Granulometric investigations of snow avalanches, *J. Glaciol.*, 55, 829–833, <https://doi.org/https://doi.org/10.3189/002214309790152384>, 2009.
- Bocchiola, D. and Rosso, R.: Application of a regional approach for hazard mapping at an avalanche site in northern Italy, *Adv. Geosci.*, 14, 201–209, <https://doi.org/https://doi.org/10.5194/adgeo-14-201-2008>, 2008.
- 695 Bocchiola, D., Medagliani, M., and Rosso, R.: Regional snow depth frequency curves for avalanche hazard mapping in central Italian Alps, *Cold Reg. Sci. Technol.*, 46, 204–221, <https://doi.org/https://doi.org/10.1016/j.coldregions.2006.07.004>, 2006.
- Bühler, Y., Bieler, C., Pielmeir, C., Wiesmann, A., Caduff, R., Frauenfelder, R., Jaedicke, C., and Bippus G.: All-weather avalanche activity monitoring from space?, in: *International Snow Science Workshop 2014*, 795–802, 2014.



- 700 Bühler, Y., von Rickenbach, D., Stoffel, A., Margreth, S., Stoffel, L., and Christen, M.: Automated snow avalanche release area delineation – validation of existing algorithms and proposition of a new object-based approach for large-scale hazard indication mapping, *Natural Hazards and Earth System Sciences*, 18, 3235–3251, <https://doi.org/10.5194/nhess-18-3235-2018>, 2018.
- Butler, D. R. and Sawyer, C. F.: Dendrogeomorphology and high-magnitude snow avalanches: a review and case study, *Nat. Hazards Earth Syst. Sci.*, 8, 303–309, <https://doi.org/10.5194/nhess-8-303-2008>, 2008.
- 705 Carletti, F., Marin, C., Ghielmi, C., Bavay, M., and Lehning, M.: Multitemporal analysis of Sentinel-1 backscattering during snow melt using high-resolution field measurements and radiative transfer modeling, *Cryosphere*, 19, 5579–5612, <https://doi.org/10.5194/tc-19-5579-2025>, 2025.
- Chang, J. G., Kraatz, S., Oh, Y., Gao, F., and Anderson, M.: Quality Assessment of Dual-Polarization C-Band SAR Data Influenced by Precipitation Based on Normalized Polarimetric Radar Vegetation Index, *Remote Sens. (Basel)*, 17, <https://doi.org/10.3390/rs17142343>, 2025.
- 710 Chauhan, P., Gadani, D. H., and Rana, V. A.: Study of variation of complex permittivity of tree leaves with moisture content, over microwave frequency range, *Mater. Today Proc.*, 67, 47–50, <https://doi.org/10.1016/j.matpr.2022.05.104>, 2022.
- Christen, M., Kowalski, J., and Bartelt, P.: RAMMS: Numerical simulation of dense snow avalanches in three-dimensional terrain, *Cold Reg. Sci. Technol.*, 63, 1–14, <https://doi.org/10.1016/j.coldregions.2010.04.005>, 2010.
- Copernicus Data Space Ecosystem : <https://dataspace.copernicus.eu/>, last access: 23 April 2026.
- EAWS: <https://www.avalanches.org/>, last access: 20 February 2026.
- Site specific avalanche warning: [https://www.avalanches.org/wp-content/uploads/2023/04/EN_Site-specific-final-](https://www.avalanches.org/wp-content/uploads/2023/04/EN_Site-specific-final-document_final.pdf)
- 720 [document_final.pdf](https://www.avalanches.org/wp-content/uploads/2023/04/EN_Site-specific-final-document_final.pdf), last access: 13 April 2026.
- Eckerstorfer, M. and Malnes, E.: Manual detection of snow avalanche debris using high-resolution Radarsat-2 SAR images, *Cold Reg. Sci. Technol.*, 120, 205–218, <https://doi.org/10.1016/j.coldregions.2015.08.016>, 2015.
- Eckerstorfer, M., Bühler, Y., Frauenfelder, R., and Malnes, E.: Remote sensing of snow avalanches: Recent advances, potential, and limitations, *Cold Reg. Sci. Technol.*, 121, 126–140, <https://doi.org/10.1016/j.coldregions.2015.11.001>, 2016.
- 725 Eckerstorfer, M., Malnes, E., and Müller, K.: A complete snow avalanche activity record from a Norwegian forecasting region using Sentinel-1 satellite-radar data, *Cold Reg. Sci. Technol.*, 144, 39–51, <https://doi.org/10.1016/j.coldregions.2017.08.004>, 2017.
- Eckerstorfer, M., Vickers, H., Malnes, E., and Grahn, J.: Near-real time automatic snow avalanche activity monitoring system using sentinel-1 SAR data in Norway, *Remote Sens. (Basel)*, 11, <https://doi.org/10.3390/rs11232863>, 2019.
- 730 Avalanche danger scale: <https://www.avalanches.org/standards/avalanche-danger-scale/>, last access: 13 April 2026.
- Avalanche problems: <https://www.avalanches.org/standards/avalanche-problems/>, last access: 13 April 2026.
- Avalanche size: <https://www.avalanches.org/standards/avalanche-size/>, last access: 19 February 2026.
- European Space Agency: Copernicus Global Digital Elevation Model, 2024.



- Flores-Anderson, A., Herndon, K., Thapa, R., and Cherrington, E.: The SAR Handbook: Comprehensive Methodologies for Forest Monitoring and Biomass Estimation, <https://doi.org/10.25966/nr2c-s697>, 2019.
- Föhn, P. and Meister, R.: Distribution of Snow Drifts on Ridge Slopes: Measurements and Theoretical Approximations, *Ann. Glaciol.*, 4, 52–57, <https://doi.org/10.3189/S0260305500005231>, 1983.
- Gatti, M., Mariani, A., Gallo, I., and Monti, F.: Large-Scale Avalanche Mapping from SAR Images with Deep Learning-based Change Detection, *arXiv [preprint]*, <https://doi.org/10.48550/arXiv.2603.22658>, 2026.
- GRASS Development Team: Geographic Resources Analysis Support System (GRASS GIS), <https://doi.org/10.5281/zenodo.5176030>, 2025.
- Hafner, E. D., Techel, F., Leinss, S., Bühler, Y., and Hafner, E.: Mapping avalanches with satellites-evaluation of performance and completeness, *Cryosphere*, 15, 983–1004, <https://doi.org/10.5194/tc-15-983-2021>, 2021.
- Hafner, E. D., Barton, P., Daudt, R. C., Wegner, J. D., Schindler, K., and Bühler, Y.: Automated avalanche mapping from SPOT 6/7 satellite imagery with deep learning: results, evaluation, potential and limitations, *Cryosphere*, 16, 3517–3530, <https://doi.org/10.5194/tc-16-3517-2022>, 2022.
- Van Herwijnen, A. and Schweizer, J.: Monitoring avalanche activity using a seismic sensor, *Cold Reg. Sci. Technol.*, 69, 165–176, <https://doi.org/10.1016/j.coldregions.2011.06.008>, 2011.
- Kapper, K. L., Goelles, T., Muckenhuber, S., Trügler, A., Abermann, J., Schlager, B., Gaisberger, C., Eckerstorfer, M., Grahn, J., Malnes, E., Prokop, A., and Schöner, W.: Automated snow avalanche monitoring for Austria: State of the art and roadmap for future work, *Front. Remote Sens.*, 4, <https://doi.org/10.3389/frsen.2023.1156519>, 2023.
- Keskinen, Z., Hendrikx, J., Eckerstorfer, M., and Birkeland, K.: Satellite detection of snow avalanches using Sentinel-1 in a transitional snow climate, *Cold Reg. Sci. Technol.*, 199, <https://doi.org/10.1016/j.coldregions.2022.103558>, 2022.
- Kneib, M., Dehecq, A., Gilbert, A., Basset, A., Miles, E. S., Jouvét, G., Jourdain, B., Ducasse, E., Beraud, L., Rabatel, A., Mouginot, J., Carcanade, G., Laarman, O., Brun, F., and Six, D.: Distributed surface mass balance of an avalanche-fed glacier, *Cryosphere*, 18, 5965–5983, <https://doi.org/10.5194/tc-18-5965-2024>, 2024a.
- Kneib, M., Dehecq, A., Brun, F., Karbou, F., Charrier, L., Leinss, S., Wagnon, P., and Maussion, F.: Mapping and characterization of avalanches on mountain glaciers with Sentinel-1 satellite imagery, *Cryosphere*, 18, 2809–2830, <https://doi.org/10.5194/tc-18-2809-2024>, 2024b.
- Kottegoda, N., Renzo, R., and Others: Statistics, probability and reliability for civil and environmental engineers, McGraw-Hill Publishing Company, 1997.
- Latenser, M. and Ammann, W. J.: The Avalanches in the Winter of 1951, *Schweizerische Zeitschrift für Forstwesen*, 152, 25–35, <https://doi.org/10.3188/szf.2001.0025>, 2001.
- Leinss, S., Wicki, R., Holenstein, S., Baffelli, S., and Bühler, Y.: Snow avalanche detection and mapping in multitemporal and multi-orbital radar images from TerraSAR-X and Sentinel-1, *Nat. Hazards Earth Syst. Sci.*, 20, 1783–1803, <https://doi.org/10.5194/nhess-20-1783-2020>, 2020.



- Lied, K. and Bakkehoi, S.: Empirical calculations of snow-avalanche run-out distance based on topographic parameters, Publikasjon - Norges Geotekniske Institutt, 165–177, <https://doi.org/10.3189/s0022143000010704>, 1981.
- Lievens, H., Brangers, I., Marshall, H.-P., Jonas, T., Olefs, M., and De Lannoy, G.: Sentinel-1 snow depth retrieval at sub-
770 kilometer resolution over the European Alps, *Cryosphere*, 16, 159–177, <https://doi.org/10.5194/tc-16-159-2022>, 2022.
- Malnes, E., Eckerstorfer, M., and Vickers, H.: First Sentinel-1 detections of avalanche debris, *Cryosphere*, <https://doi.org/10.5194/tcd-9-1943-2015>, 2015.
- Malnes, E., Vickers, H., Grahn, J., Jensen, R.-O. R., Ricker, R., and Lauknes, T. R.: Multi-frequency synthetic aperture radar observations of avalanches and snow parameters in Svalbard, in: International Snow Science Workshop 2024 (ISSW 2024),
775 2024.
- Mariani, A., Dellarole, L., Borsotti, J., Villa, G., and Monti, F.: A new operational approach for the daily assessment of potential avalanche danger, in: International Snow Science Workshop 2024 (ISSW 2024), 116–123, 2024.
- Mariani, A., Borsotti, J., Livio, F., Villa, G., Metzger, M., and Monti, F.: Influence of snowpack properties and local incidence angle on SAR signal depolarization: a mathematical model for high-resolution snow depth estimation, *Cryosphere*, 20, 963–
780 980, <https://doi.org/10.5194/tc-20-963-2026>, 2026.
- Massimiliano Barbolini, Luigi Natale, M Cordola, and G Tecilla: Linee guida metodologiche per la perimetrazione delle aree esposte al pericolo di valanghe, Pavia , 2005.
- Mätzler, C.: Applications of the interaction of microwaves with the natural snow cover, *Remote Sensing Reviews*, 2, 259–387, <https://doi.org/10.1080/02757258709532086>, 1987.
- 785 McClung, D. and Hoeller, P.: Probabilistic Estimates of Extreme Snow Avalanche Runout Distance, *Geosciences (Switzerland)*, 15, <https://doi.org/10.3390/geosciences15080278>, 2025.
- McClung, D. and Lied, K.: Ser Statistical and Geometrical Definition of Snow Avalanche Runout, *Regions Science and Technology*, 107–119 pp., 1987.
- McClung, D. and Mears, A.: Extreme value prediction of snow avalanche runout, *Cold Reg. Sci. Technol.*, 19, 163–175,
790 [https://doi.org/https://doi.org/10.1016/0165-232X\(91\)90006-3](https://doi.org/https://doi.org/10.1016/0165-232X(91)90006-3), 1991.
- McClung, D. and Schaerer, P. A.: The avalanche handbook, the Mountaineers Books, 2006.
- McClung, D., Höller, P., and Fischer, J. T.: The return period for land-use planning in snow avalanche terrain, *Nat. Hazard.*, 112, 783–806, <https://doi.org/10.1007/s11069-022-05205-1>, 2022.
- Monti, F., Steinkogler, W., and Mitterer, C.: Livigno (Italy) freeride project, in: International Snow Science Workshop (ISSW),
795 2014.
- Myung, I. J.: Tutorial on maximum likelihood estimation, *J. Math. Psychol.*, 47, 90–100, [https://doi.org/10.1016/S0022-2496\(02\)00028-7](https://doi.org/10.1016/S0022-2496(02)00028-7), 2003.
- Nagler, T. and Rott, H.: Retrieval of wet snow by means of multitemporal SAR data, *IEEE Trans. Geosci. Remote Sens.*, 38, 754–765, <https://doi.org/10.1109/36.842004>, 2000.



- 800 Nandan, V., Willatt, R., Mallett, R., Stroeve, J., Geldsetzer, T., Scharien, R., Tonboe, R., Yackel, J., Landy, J., Clemens-Sewall, D., Jutila, A., Wagner, D. N., Krampe, D., Huntemann, M., Mahmud, M., Jensen, D., Newman, T., Hendricks, S., Spreen, G., Macfarlane, A., Schneebeil, M., Mead, J., Ricker, R., Gallagher, M., Duguay, C., Raphael, I., Polashenski, C., Tsamados, M., Matero, I., and Hoppmann, M.: Wind redistribution of snow impacts the Ka- and Ku-band radar signatures of Arctic sea ice, *Cryosphere*, 17, 2211–2229, <https://doi.org/10.5194/tc-17-2211-2023>, 2023.
- 805 Oesterle, F., Wirbel, A., Fischer, J.-T., Huber, A., and Spannring, P.: AvaFrame, 25 November 2025.
Oh, Y., Jang, Y.-M., and Sarabandi, K.: Full-wave analysis of microwave scattering from short vegetation: an investigation on the effect of multiple scattering, *IEEE Trans. Geosci. Remote Sens.*, 40, 2522–2526, <https://doi.org/10.1109/TGRS.2002.805085>, 2002.
PANOMAX 360° System: <https://livigno.panomax.com/>, last access: 17 May 2026.
- 810 Portenier, C., Hüsler, F., Härer, S., and Wunderle, S.: Towards a webcam-based snow cover monitoring network: methodology and evaluation, *Cryosphere*, 14, 1409–1423, <https://doi.org/10.5194/tc-14-1409-2020>, 2020.
Regione Lombardia: DTM 5X5 – Modello Digitale del Terreno (ed. 2015), https://www.cartografia.servizirl.it/arcgis/services/wms/DTM5_RL_wms/MapServer/WMSServer?, 2015.
Salm, B.: Flow, flow transition and runout distances of flowing avalanches, *Ann. Glaciol.*, 18, 221–226, <https://doi.org/https://doi:10.3189/S0260305500011551>, 1993.
- 815 Salm, B., Burkard, A., and Gubler, H.: Berechnung von Fliesslawinen: eine Anleitung für Praktiker mit Beispielen, Davos, Switzerland, 41–41 pp., 1990.
Schweizer, J.: Rutschblock 73 – Verifikation der Lawinengefahr, *Bergundsteigen – Zeitschrift für Risikomanagement im Bergsport*, 12, 56–59, 2003.
- 820 Schweizer, J., Mitterer, C., Techel, F., Stoffel, A., and Reuter, B.: On the relation between avalanche occurrence and avalanche danger level, *Cryosphere*, 14, 737–750, <https://doi.org/10.5194/tc-14-737-2020>, 2020.
Scott, E. D., Hayward, C. T., Kubichek, R. F., Hamann, J. C., Pierre, J. W., Comey, B., and Mendenhall, T.: Single and multiple sensor identification of avalanche-generated infrasound, *Cold Reg. Sci. Technol.*, 47, 159–170, <https://doi.org/https://doi.org/10.1016/j.coldregions.2006.08.005>, 2007.
- 825 Small, D.: Flattening Gamma: Radiometric Terrain Correction for SAR Imagery, *IEEE Trans. Geosci. Remote Sens.*, 49, 3081–3093, <https://doi.org/10.1109/TGRS.2011.2120616>, 2011.
Statham, G., Haegeli, P., Greene, E., Birkeland, K., Israelson, C., Tremper, B., Stethem, C., McMahon, B., White, B., and Kelly, J.: A conceptual model of avalanche hazard, *Nat. Hazard.*, 90, 663–691, <https://doi.org/10.1007/s11069-017-3070-5>, 2018.
- 830 Strozzi, T., Wiesmann, A., and Mätzler, C.: Active microwave signatures of snow covers at 5.3 and 35 GHz, *Radio Sci.*, 32, 479–495, <https://doi.org/10.1029/96RS03777>, 1997.
Tompkin, C. and Leinss, S.: Backscatter Characteristics of Snow Avalanches for Mapping with Local Resolution Weighting, *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, 14, 4452–4464, <https://doi.org/10.1109/JSTARS.2021.3074418>, 2021.



- 835 Tonnel, M., Wirbel, A., Oesterle, F., and Fischer, J.-T.: AvaFrame com1DFA (v1.3): a thickness-integrated computational avalanche module – theory, numerics, and testing, *Geosci. Model Dev.*, 16, 7013–7035, <https://doi.org/10.5194/gmd-16-7013-2023>, 2023a.
- Tonnel, M., Wirbel, A., Oesterle, F., and Fischer, J. T.: AvaFrame com1DFA (v1.3): A thickness-integrated computational avalanche module-theory, numerics, and testing, *Geosci. Model Dev.*, 16, 7013–7035, <https://doi.org/10.5194/gmd-16-7013-2023>, 2023b.
- 840 Viallon-Galinier, L., Poussereau, M., Hagenmuller, P., and Lafaysse, M.: Machine learning for avalanche activity forecasting: combining the knowledge of past avalanche activity and snow modelling analysis, in: *International Snow Science Workshop 2024 (ISSW 2024)*, 449–456, 2024.
- Viviani, F., Michelini, A., and Mayer, L.: RockSpot: An Interferometric Doppler Radar for Rockfall/Avalanche Detection and Tracking, in: *IEEE National Radar Conference - Proceedings*, <https://doi.org/10.1109/RadarConf2043947.2020.9266677>,
845 2020.
- Voellmy, A.: Über die zerstörungskraft von lawinen, *Bauzeitung*, 73, 159–165, 1955.
- Wakabayashi, H., Motohashi, K., and Maezawa, N.: Monitoring Lake Ice in Northern Alaska with Backscattering and Interferometric Approaches Using Sentinel-1 Sar Data, in: *IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium*, 4202–4205, <https://doi.org/10.1109/IGARSS.2019.8900371>, 2019.
- 850 Wesselink, D. S., Malnes, E., Eckerstorfer, M., and Lindenberg, R. C.: Automatic detection of snow avalanche debris in central Svalbard using C-band SAR data, *Polar Res.*, 36, 1333236, <https://doi.org/10.1080/17518369.2017.1333236>, 2017.
- Wiederkehr, M. and Möri, A.: SwissALTI3D - A new Tool for geological Mapping, *Bulletin fuer Angewandte Geologie*, 18, 61–69, <https://doi.org/10.5169/seals-391140>, 2013.
- Wiesmann, A., Wegmuller, U., Honikel, M., Strozzi, T., and Werner, C. L.: Potential and methodology of satellite based SAR
855 for hazard mapping, in: *Scanning the Present and Resolving the Future. IEEE International Geoscience and Remote Sensing Symposium*, 3262–3264 vol.7, <https://doi.org/10.1109/IGARSS.2001.978322>, 2001.
- Avalanche types: <https://www.slf.ch/en/avalanches/avalanche-science-and-prevention/avalanche-types/>, last access: 21 April 2026.
- Yang, J., Li, C., Li, L., Ding, J., Zhang, R., Han, T., and Liu, Y.: Automatic detection of regional snow avalanches with
860 scattering and interference of C-band SAR data, *Remote Sens. (Basel)*, 12, <https://doi.org/10.3390/RS12172781>, 2020.
- Yommy, A. S., Liu, R., and Wu, A. S.: SAR Image Despeckling Using Refined Lee Filter, in: *2015 7th International Conference on Intelligent Human-Machine Systems and Cybernetics*, 260–265, <https://doi.org/10.1109/IHMSC.2015.236>, 2015.