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2 Satellite Detection of Snow Avalanches using Sentinel-1 in a

3 Transitional Snow Climate

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16 Snow avalanches endanger lives and infrastructure in mountainous regions worldwide.
17 Consistent and accurate datasets of avalanche events are critical for improving hazard forecasting
18 and understanding the spatial and temporal patterns of avalanche activity. Remote sensing-based
19 identification of avalanche debris allow for the acquisition of continuous and spatially consistent
20 avalanches datasets. This study utilizes expert manual interpretations of Sentinel-1 synthetic
21 aperture radar (SAR) satellite backscatter images to identify avalanche debris and compares

22 those detections against historical field records of observed avalanches in the transitional snow
23 climates of Wyoming and Utah, USA. We explore and quantify the ability of an expert using
24 Sentinel-1 (a SAR satellite) images to detect avalanche debris on a dataset comprised exclusively
25 of dry slab avalanches. This research utilized four avalanche cycles with 258 field reported
26 avalanches. Due to individual avalanches appearing in multiple overlapping Sentinel-1 images
27 this resulted in 506 potential detections of avalanches in our SAR images, representing the
28 possibility of multiple detections of a single avalanche event in different images. The overall
29 probability of detection (POD) for avalanches large enough to destroy trees or bury a car (i.e.,
30 $\geq D3$ on the destructive size scale) was 65%. There was a significant variance in the POD among
31 the 13 individual SAR image pairs considered (15 – 86%). Additionally, this study investigated
32 the connection between successful avalanche detections and SAR-specific, topographic, and
33 avalanche type variables. The most correlated variables with higher detection rates were
34 avalanche path lengths, destructive size of the avalanche, incidence angles for the incoming
35 microwaves, average path slope angle, and elapsed time between the avalanche and a Sentinel-1
36 satellite image acquisition. This study provides a quantification of the controlling variables in the
37 likelihood of detecting avalanches using Sentinel-1 backscatter temporal change detection
38 techniques, as specifically applied to a transitional snow climate.

39

40 Keywords: Remote Sensing, Snow avalanches, Terrain, Synthetic Aperture Radar

41

42 Highlights:

- 43 • Dry slab avalanches $\geq D3$ had a detection rate of 65%;

- 44 • Improved quantification of controlling variables on SAR based avalanche detection;
- 45 • Path length, D size, and average slope correlated with higher detections;
- 46 • Incidence angle and time between event and image acquisition also correlated with higher
- 47 detections;

48

49

50 **1 Introduction**

51 Snow avalanches are a complex mountain hazard that endangers lives, threatens infrastructure,
52 and closes transportation corridors (e.g. McClung and Schaerer 2006, Hendrikx et al., 2014,
53 Birkeland et al., 2017). Timely knowledge about when and where avalanches occur is vital for
54 avalanche risk assessment and forecasting (McClung, 2002a, 2002b). Currently, gathering data
55 about the spatial distribution and magnitude of avalanche events most typically relies on human
56 field observers and is consequently spatially and temporally limited. Other sources of avalanche
57 records, such as airborne surveys or infrasound arrays, are cost prohibitive to implement
58 consistently over large regions. However, human observations rarely cover an entire mountain
59 range, are limited by low visibility or high danger conditions, and are biased towards accessible
60 locations and convenient collection periods (Eckerstorfer and Malnes, 2015).

61 Recent research has shown promising results from radar satellite-based avalanche detections as
62 an alternative method to provide near real-time, consistent data about avalanche occurrences
63 (Eckerstorfer et al., 2019; Leinss et al., 2020). Radar satellite-based detections provide a valuable
64 supplement to field-based observations due to their large spatial coverage and the temporal
65 consistency with which avalanches can be observed, allowing for more reliable comparisons of

66 avalanche activity. A sensor that has demonstrated specific utility in detecting avalanche debris
67 is Synthetic Aperture Radar (SAR) (Eckerstorfer et al., 2016; Leinss et al., 2020; Yang et al.,
68 2020). SAR sensors emit energy in the microwave spectrum (wavelengths of 1 – 300 mm) which
69 are not affected by cloud cover or darkness, allowing for temporally and spatially consistent
70 remote sensing.

71 SAR-equipped satellites have been used to detect avalanche debris since the early 2000s
72 (Wiesmann et al., 2001). However, the recent introduction of freely available imagery from the
73 Sentinel-1 SAR satellite constellation has vastly expanded opportunities for SAR-borne
74 avalanche detection. Multiple studies exploited Sentinel-1 imagery to map avalanche cycles and
75 create automatic detection systems (Abermann et al., 2019; Eckerstorfer et al., 2019; Leinss et
76 al., 2020). Eckerstorfer et al. (2019), working in a maritime snow climate, provided one of the
77 few studies comparing manual detections using SAR backscatter change detection against
78 avalanche field observations. Their study compared field-observed datasets of avalanche activity
79 against manual interpretations of SAR images and automated detections. They reported an
80 overall probability of detection (POD) of 77.3%. Multiple factors, however, influenced the
81 overall detectability of avalanches. Large avalanches resulted in a 100% POD and were more
82 detectable than small avalanches (64.9%), as a consequence the spatial resolution of the Sentinel-
83 1 SAR sensor. Wet snow avalanches were more detectable than dry snow avalanches due to
84 higher relative backscatter from rougher wet snow avalanche debris. Leinss et al. (2020)
85 provided an important first exploration of the utility of Sentinel-1 in detecting avalanches in a
86 transitional snow climate in Switzerland during a major avalanche cycle from January 2018.
87 However, they did not quantify the accuracy of Sentinel-1 borne avalanche detections due to a

88 lack of field-based validation data. They manually delineated 104 avalanches in Sentinel-1 data
89 compared to 164 in higher resolution TerraSAR-X data. They suggested a minimum detectable
90 Sentinel-1 avalanche debris size of 2000 m². They, moreover, noted that avalanches that
91 descended “below the wet-snow line were much more visible than avalanches from the dry
92 snow-zone”, suggesting that dry slab avalanches may be harder to detect. Finally, they suggested
93 that higher incidence angles should provide higher detection rates, but did not test this theory
94 directly. More recent research has explored this relationship between incidence angle and
95 increased backscatter. Tompkin and Leinss (2021), exploring a dataset of exclusively wet snow
96 avalanches, found that, compared to an optimal incidence angle of ~55°, backscatter was reduced
97 by 4 dB for incidence angles below 40° in VV polarization (vertically transmitted and received
98 signal). They also found that backscatter intensity also decreased for incidence angles over 70
99 degrees. This study showed the importance of incidence angles and the utility of local resolution
100 weighting that prioritizes higher incidence angles in multi-image composites. However, more
101 research is necessary to confirm this relationship in other snow conditions and study sites.
102 Building on the avalanche detections in Switzerland, Hafner et al. (2021) detected avalanches
103 using Sentinel-1 and the optical Sentinel-2 and SPOT-6. Using Sentinel-1 imagery they were
104 able to detect 90% of avalanches large enough to destroy substantial forest, but only 4% of those
105 harmless to people. Conversely to other studies Hafner et al. (2021) found higher detection rates
106 for the dry-snow conditions relative to the mixed wet and snow avalanche cycle. They suggested
107 that in scene-wide dry-snow only conditions the “avalanches were the most prominent changes
108 in the backscatter signal”. The larger scene-wide backscatter changes in wet to dry snow
109 conditions could make detections more challenging.

110 While backscatter change detection is valuable for detecting avalanche debris, important
111 questions remain about the strengths and limitations of this technique. Without a thorough
112 understanding of the benchmark avalanche detection rate and how it varies as a function of
113 topographic and SAR-specific variables, we cannot accurately communicate the global utility of
114 this technique or accurately assess the performance of automated detection systems.

115 Therefore, the purpose of this study is to compare Sentinel-1 SAR manual detections to field-
116 observations of exclusively dry slab avalanches in a transitional snow climate in two different
117 regions of the western United States. We address the following questions:

- 118 1. What are the manual detection rates of dry slab avalanches using change detection techniques
119 on Sentinel-1 SAR backscatter images in the transitional snow climates of Utah and
120 Wyoming, U.S.A.?
- 121 2. How do topographic (elevation, path length, slope, curvature, tree coverage), SAR (incidence
122 angle, layover, shadow, and days between images) and avalanche characteristics (destructive
123 size) affect SAR avalanche detection rates?

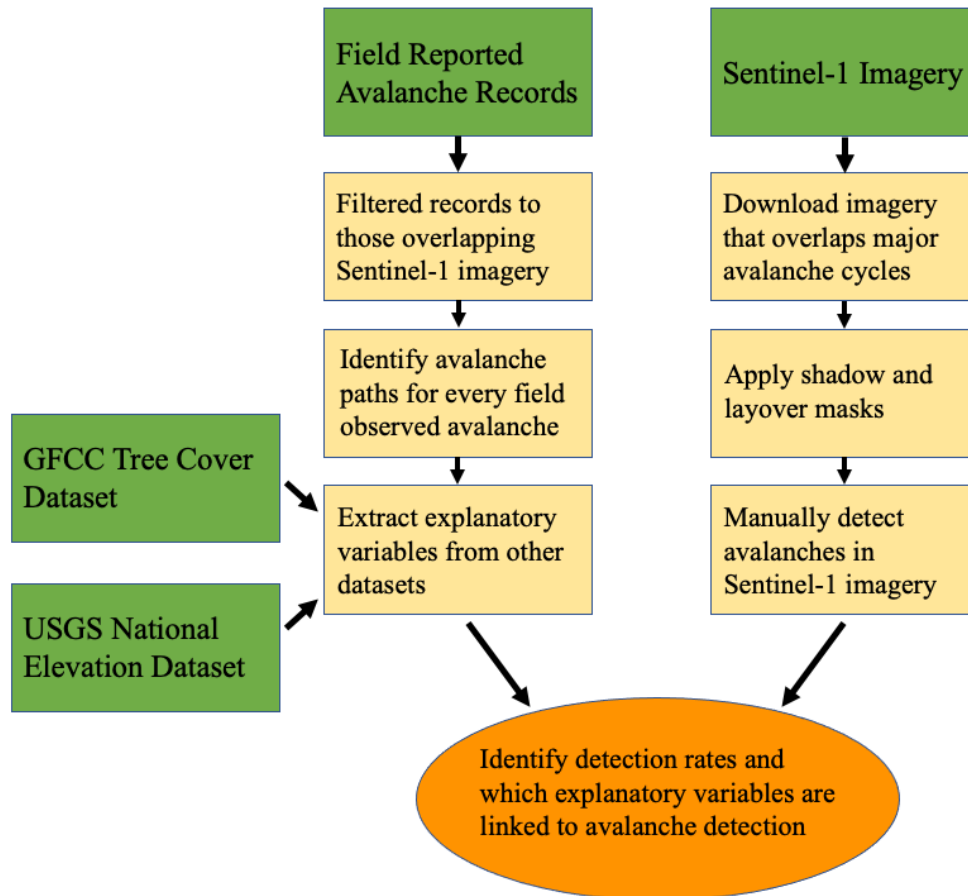
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126 2 Methods and datasets

127 To answer our research questions, we consider two primary sources: 1) field observations of
 128 avalanches, and 2) manual detections in Sentinel-1 data (Figure 1). For processing and analysis,
 129 we consider three ancillary data sources: Global Forest Cover Change Tree Cover (Sexton et al.,
 130 2013), USGS National Elevation Dataset (Gesch et al., 2002), and auto-Avalanche Terrain
 131 Exposure maps (Larsen et al., 2020) (Figure 1).

132



133

134 Figure 1: Flowchart of data collection and processing steps. Green shows input datasets, yellow
 135 shows processing and analysis steps, and orange shows statistical analysis steps.

136

137 2.1. Sentinel-1 datasets:

138 The Sentinel-1 constellation is a pair of polar-orbiting, sun-synchronous satellites with a 6-day
139 orbit repeat interval. Due to overlapping image footprints between orbital geometries at higher
140 latitude this image frequency can be as little as 1 day at higher latitudes. Both satellites are
141 equipped with C-band SAR sensors (wavelength ~ 5.54 cm) that acquire SAR images with
142 roughly 20 m pixel resolution in interferometric wide swath mode (IW) in both co-polarized (e.g.
143 VV) and cross-polarized (e.g. VH) polarization.

144

145 We downloaded Sentinel-1 backscatter intensity images (ground range detection – GDR
146 products) from Google Earth Engine (GEE) (Gorelick et al. 2017) that matched the timing of
147 major avalanche cycles (see section below) and processed them as follows:

- 148 - Sentinel-1 imagery was preprocessed by GEE via the application of a precise orbit file,
149 removal of border and thermal noise, application of radiometric calibration, and terrain
150 correction (Gorelick et al., 2017).
- 151 - For each Sentinel-1 image, we created and applied layover and shadow masks using the
152 United States Geological Survey's (USGS) National Elevation Dataset at 1/3 arc-second
153 resolution (Gesch et al., 2002). During this step, we also extracted local incidence angles
154 for each pixel. This processing workflow used a python script adapted from Vollrath et
155 al. (2020) (please refer to the supplemental materials).

156

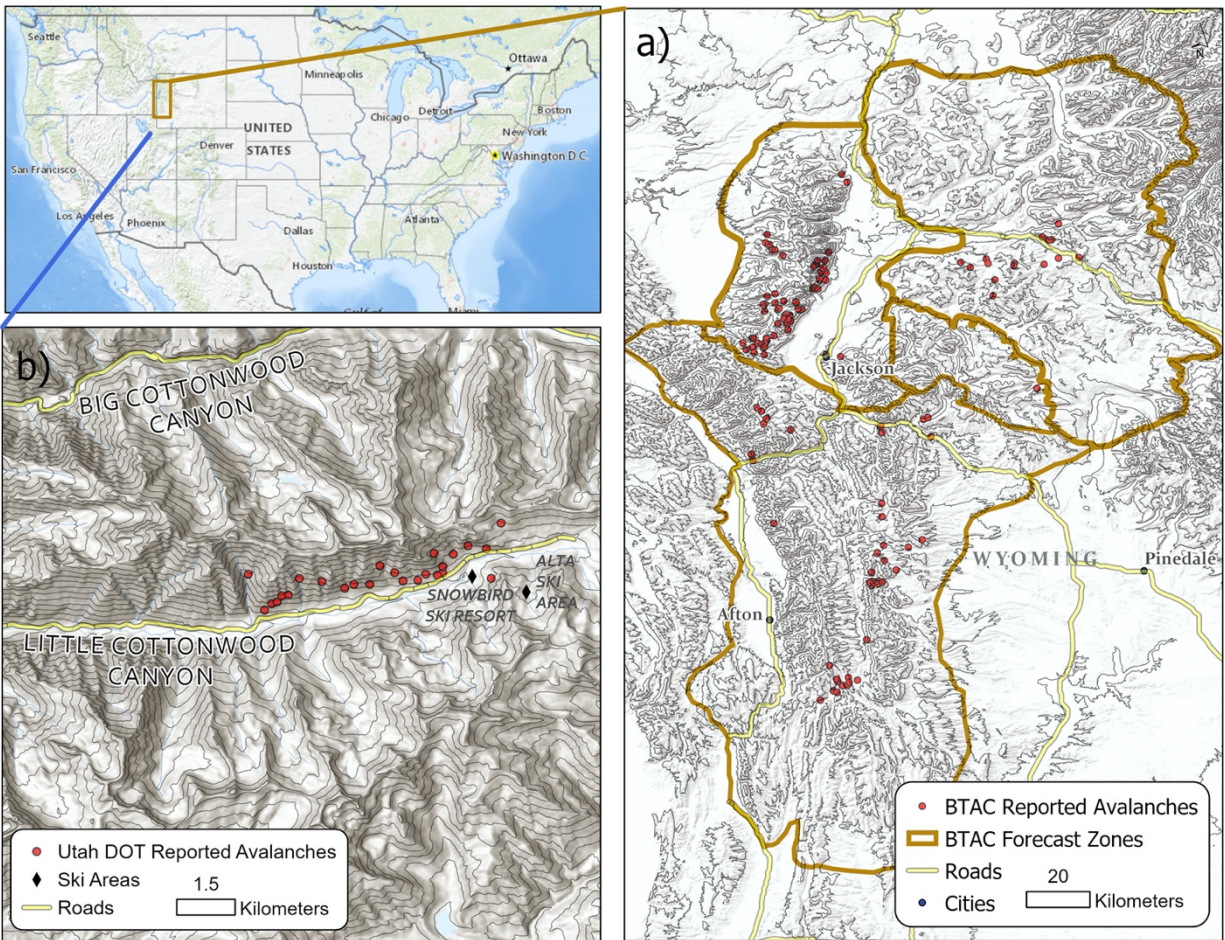
157 To visualize temporal backscatter intensity change necessary for manual avalanche detection, we
158 paired Sentinel-1 images of same orbital geometry (ASC- ascending or DES – descending) and

159 track number (e.g. DES 100). Sentinel-1 image pairs contained a reference and an activity image.
160 For our study these are 12 or 24 days apart instead of 6 due to lower imaging frequency over
161 these areas in the ESA's operational plan.

162

163 2.2 Field-observed avalanche datasets

164 We used records of field-observed avalanches in a transitional snow climate in the USA (Mock
165 and Birkeland, 2000), from the Utah Department of Transportation (UDOT) and the Bridger
166 Teton Avalanche Center (BTAC). The BTAC records covered their avalanche forecasting region
167 near Jackson, Wyoming. UDOT avalanches were from Little Cottonwood Canyon outside of Salt
168 Lake City, Utah (

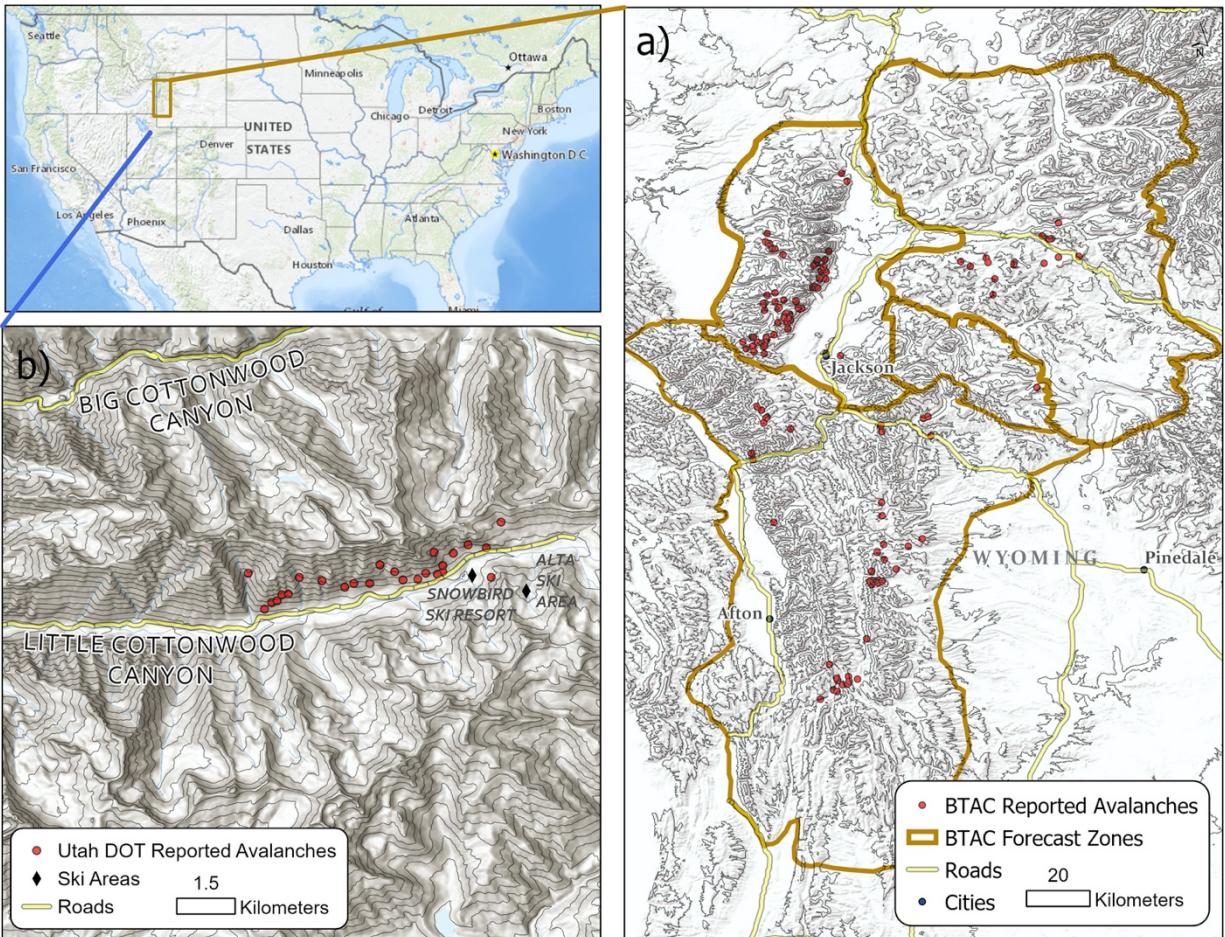


169

170 Figure 2).

171 These records included written descriptions of location, date, avalanche type, and destructive (D)
 172 size. The records were predominantly dry (88% for BTAC and 87% for UDOT) and slab (95%
 173 for BTAC and 85% for UDOT) avalanches. Slab avalanches result from the failure of an
 174 underlying weak layer and the release of a cohesive “slab” of snow, compared to loose
 175 avalanches where surface snow loses cohesion (Gaume et al., 2017). To focus our analysis
 176 exclusively on dry slab avalanches we filtered the records to only those avalanche types. We
 177 examined only avalanche records between 2016–2020, covering the operational period for both
 178 satellites of the Sentinel-1 constellation.

179



180

181 Figure 2: Avalanche locations for the a) BTAC (n = 134) and b) UDOT (n = 124) avalanche
 182 databases.

183

184 We calculated avalanche activity indexes (AAIs) according to Schweizer et al. (2003) for each

185 database to identify significant avalanche cycles. The AAI is the sum of observed avalanches

186 weighted by their destructive size (D1: 0.01, D2: 0.1, D3:1, D4:10) for each day (Figure 3). Our

187 study investigated the two most significant cycles using AAI scores from the BTAC (Figure 3(a):

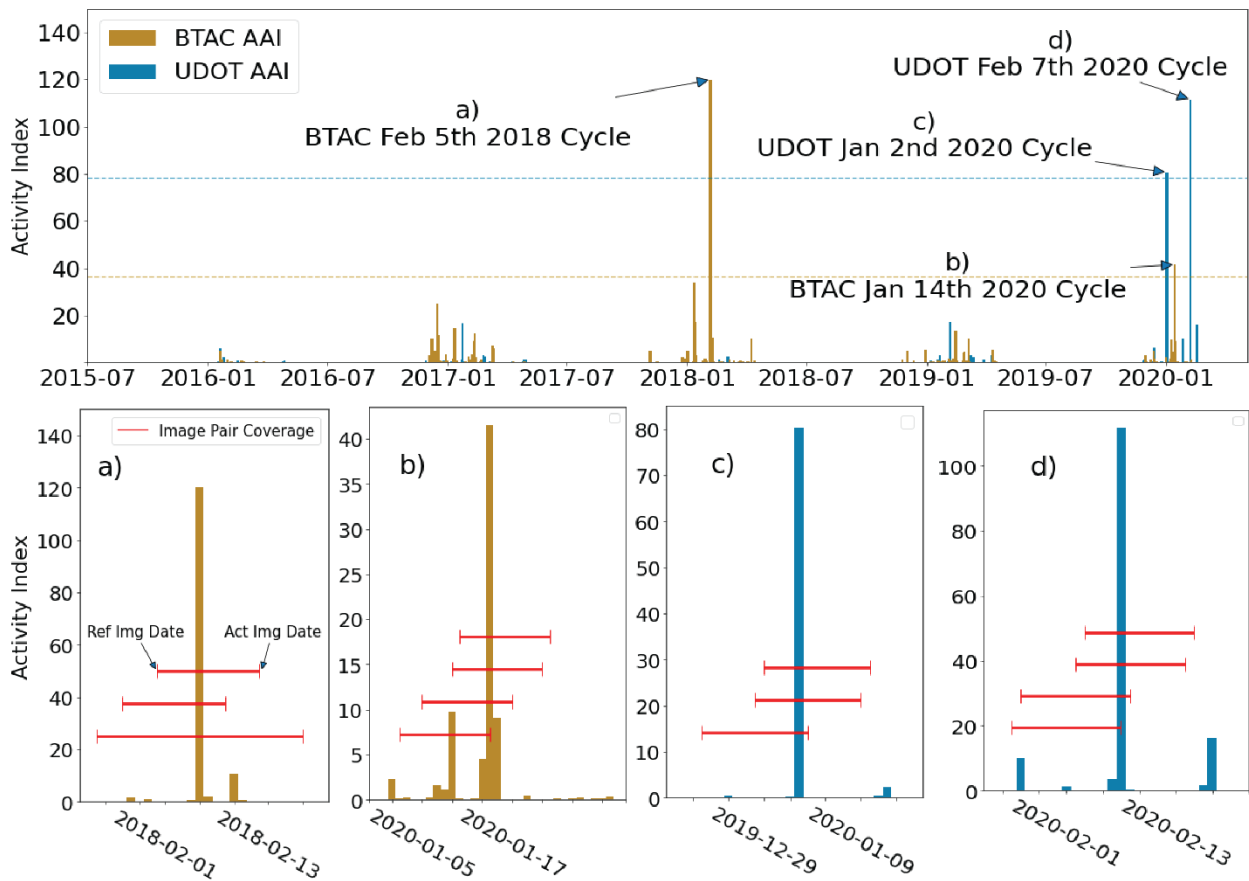
188 AAI = 120; (b): AAI = 41) and UDOT (Figure 3 (c): AAI = 80; (d): AAI = 111). These cycles'

189 AAI scores exceed the 99th percentile for each respective dataset.

190

191 2.3 Comparison between Sentinel-1 avalanche detections and field-observed avalanche
 192 activity

193 We downloaded 14 Sentinel-1 image pairs. 7 image pairs spatially and temporally overlapped the
 194 BTAC avalanche cycles and 7 overlapped the UDOT avalanche cycles (Figure 3). The image
 195 pairs with matching orbital geometries and paths were all either 12, or 24 days apart.



196

197 Figure 3: Avalanche activity index for the two databases from 2016-2020 with the two largest
 198 cycles for each region (four total) noted. The dashed lines show 99th percentile of the avalanche
 199 activity index for BTAC (AAI = 36) in beige, and UDOT (AAI = 78) in blue, showing the
 200 extreme nature of these events. Insets show each avalanche cycle with capped lines showing the
 201 imagery dates of all utilized Sentinel-1 image pairs. Note that insets a-d have different y-axes.

202

203 We analyzed all the avalanches that released between a reference and activity Sentinel-1 image.

204 In total, we used 7 descending and 7 ascending Sentinel-1 image pairs in this study (

205 Table 1). Within the time periods these Sentinel-1 image pairs covered, a total of 258 field
206 reported avalanches were recorded in the two study regions. There were 124 UDOT avalanches.
207 Of the UDOT avalanches, 23 (19%) were natural avalanches, and 101 (81%) were artificially
208 triggered. For the BTAC dataset, there were 134 avalanches. Ninety-four were naturally
209 triggered (69%), and 40 (31%) were artificially triggered. The destructive size distribution of
210 both the UDOT and BTAC was centered on D2 (53%) and D3 (23%) (please refer to the
211 supplementary material). Given the temporal overlap of the satellite orbits, these 258 field
212 reported avalanches had the potential to be detected and counted in multiple pairs of images.
213 This resulted in a final dataset of 506 potentially detectable avalanche events, representing
214 multiple opportunities to count the 258 unique field observed events.

215

216

217 Table 1: Studied avalanche cycles from both study regions and orbit direction and satellite path
 218 number of the Sentinel-1 image pairs that match in space and time. The final column shows the
 219 total field reported avalanches that could have been detected in each pair of images. This number
 220 varies due to the varying spatial footprints and temporal coverage of each pair of images relative
 221 to the field reported avalanches and adds up to 506 total possible avalanche detections.

Activity Image Date	Reference Image Date	Orbit Direction	Sat. Path #	Possible Avalanche Detections
BTAC Feb. 5th, 2018 Cycle				
February 8 th , 2018	January 27 th , 2018	Ascending	49	31
February 12 th , 2018	January 31 st , 2018	Descending	27	43
February 17 th , 2018 ¹	January 24 th , 2018 ¹	Descending	100	19
BTAC Jan. 14th, 2020 Cycle				
January 14 th , 2020	January 2 nd , 2020	Descending	100	41
January 17 th , 2020	January 5 th , 2020	Ascending	49	28
January 21 st , 2020	January 9 th , 2020	Descending	27	41
January 22 nd , 2020	January 10 th , 2020	Ascending	122	40
UDOT Jan. 2nd, 2020 Cycle				
January 3 rd , 2020	December 22 nd , 2019	Ascending	20	44
January 9 th , 2020	December 28 th , 2019	Descending	27	18
January 10 th , 2020	December 29 th , 2019	Ascending	122	42
UDOT Feb. 7th, 2020 Cycle				
February 7 th , 2020	January 26 th , 2020	Descending	100	41
February 8 th , 2020	January 27 th , 2020	Ascending	20	45
February 14 th , 2020	February 2 nd , 2020	Descending	27	26
February 15 th , 2020	February 3 rd , 2020	Ascending	122	47

222 ¹ Only pair with 24 days instead of 12 days between imaging dates

223 2.4 Avalanche path identification

224 Avalanche paths, defined here as the potential region affected by a 1 in 100-year avalanche from
 225 a specific start zone, were necessary to extract spatial averages of Sentinel-1 backscatter change
 226 and potential explanatory variables (Mears, 1992). For the UDOT region we used a pre-existing
 227 catalog of avalanche paths. An avalanche atlas was not available for the BTAC region.

228 Consequently, we delineated avalanche paths for each BTAC event based on the field recorded
229 location, written descriptions and photographs of the avalanche and automatic Avalanche Terrain
230 Exposure (auto-ATES) maps of the regions (Larsen et al. (2020)). The starting zone and track
231 were defined using the field description and photographs of the avalanche when available and
232 otherwise following topographic constraining features (ridgelines). We drew the runout extent
233 using auto-ATES maps to terminate the path at a 23-degree alpha angle from the starting zone
234 (Larsen et al. 2020). These auto-ATES maps use alpha angles from the nearest starting zones to
235 map potential avalanche hazard and were used to identify likely runout extent using the
236 workflow in Larsen et al. (2020). We drew these avalanche paths before SAR debris detections
237 to avoid biasing of the path characteristics.

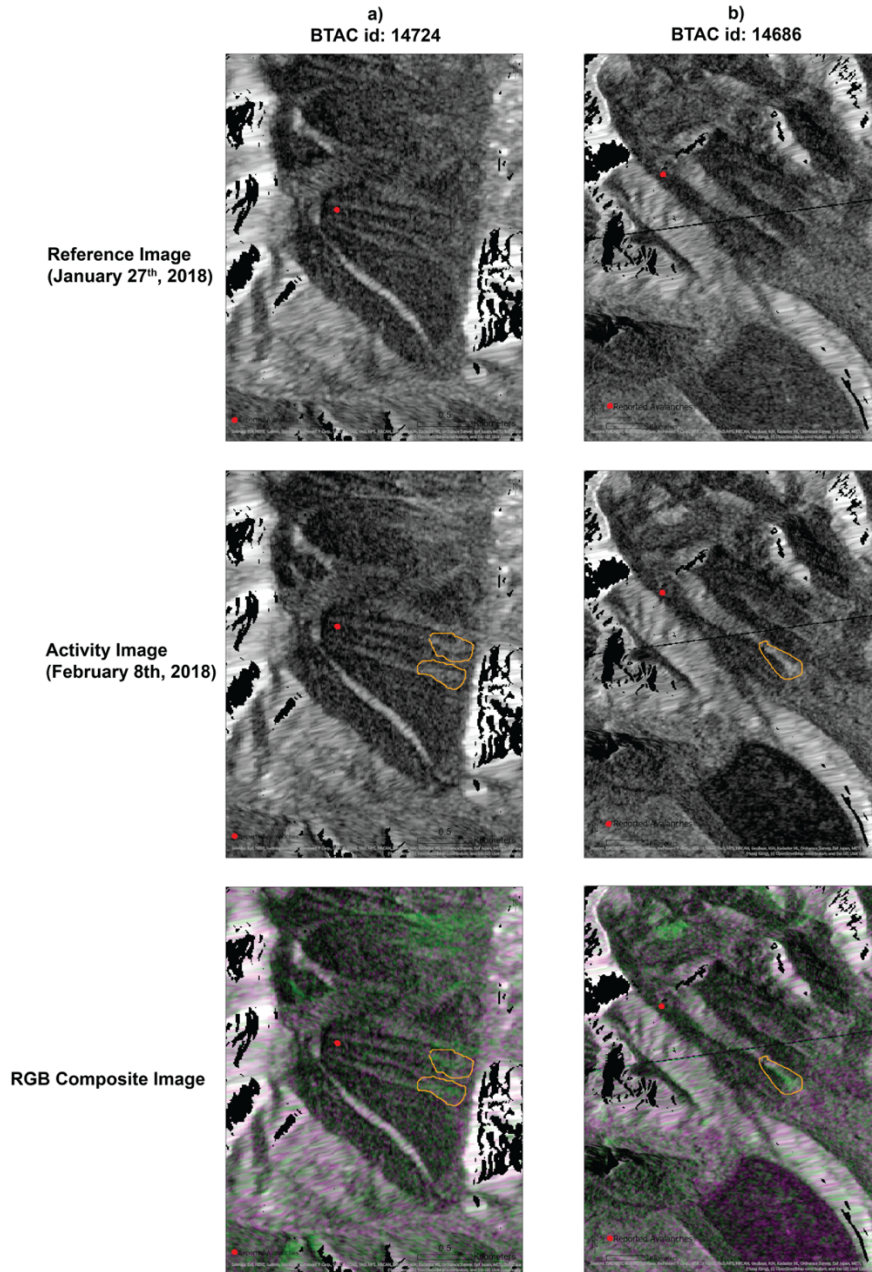
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239 2.5 Manual avalanche detection

240 To facilitate manual interpretation of the SAR images we created RGB composites, where we
241 put the reference image in the red and blue channels and the activity image in the green channel
242 (Figure 4). A temporal backscatter increase appears in green while a decrease appears in purple
243 in these RGB composites. The RGB composites contained SAR images with the same geometry
244 and path number, ensuring changing scattering properties resulted from changes in surface
245 conditions and not from different incidence angles (Wynne and Campbell, 2011).

246 According to Eckerstorfer and Malnes (2015) avalanche debris exhibits higher backscatter than
247 the surrounding undisturbed snow due to a higher contribution from the rougher surface-air
248 interface, as well as some higher contribution from increased volumetric scattering within a
249 thicker snowpack. Thus the occurrence of avalanche debris covering a pre-existing snowpack

250 leads to increase in backscatter that is visible as green, elongated features in the RGB composites
251 (Figure 4) (Leinss et al., 2020; Malnes et al., 2013; Wiesmann et al., 2001). We examined all the
252 RGB images for regions with increased backscatter within the marked avalanche paths. If these
253 regions of localized backscatter increase matched the description and photos of the field-
254 observed avalanches, and had at least a 2–3 decibels backscatter increase across the likely debris
255 zone, then we marked them as ‘detected’. The UDOT dataset included multiple reported
256 avalanches per avalanche path, while the BTAC dataset did not. These overlapping avalanches
257 were either all marked "Detected" or "Not detected". The average avalanches per path in the
258 UDOT dataset was 2.3.



259

260 Figure 4: Reference, activity, and RGB composite images for (a) two and (b) one field reported
 261 avalanches in the BTAC region. Red dots show the field reported crown locations, polygons
 262 represent the manually detected debris outlines. Temporal change analysis compares the
 263 reference image to the activity image to identify increased backscatter areas. The diagonal black
 264 line across (b) is an artifact of merging two Sentinel-1 images into one. Other regions of
 265 significant increases in (a) and (b) are likely more avalanche debris that was not reported from
 266 the field due to their distance from roads or ski areas, though other possibilities include wind-
 267 drifted snow, ground roughness changes, and freezing or unfreezing of lakes or snow.

268 2.6 Explanatory variables for manual avalanche detection

269 We extracted possible explanatory variables for every recorded avalanche event, regardless of
270 SAR detection. The avalanche databases from the BTAC and UDOT contained standard
271 avalanche descriptive data, including dates, D-size, wet vs. dry debris, slab vs. loose type, and
272 natural vs. artificial release for all included avalanche observations (Greene et al., 2016). In order
273 to focus on dry slab avalanches we began by filtering out all wet and loose snow avalanches
274 from these databases. To explore topographic effects on detection rates, we extracted: ‘average
275 elevation of the avalanche path’, the ‘average slope’, ‘average profile curvature’, ‘path length’,
276 and ‘path width’ (using a minimum bounding geometry on the paths from step 2.4) (Gesch et al.,
277 2002). The Global Forest Cover Change Tree Cover Multi-Year Global Dataset (GFCC), i.e. the
278 horizontal percentage of ground covered by woody vegetation greater than 5 meters in height in
279 2015, provided the average tree coverage within each avalanche path (Sexton et al., 2013). C-
280 band SAR backscatter is heavily affected by tree cover, so we chose this variable to explore if
281 tree cover in the debris zone negatively affected the detection rates (Vreugdenhil et al., 2018).
282 Finally, we extracted the ‘percentage of the path affected by radar layover effects’ (phenomena
283 that occur in steep topography due to the side-looking geometry of the SAR sensor), ‘percentage
284 affected by radar shadow’ (no-data zones from lack of returning SAR energy), ‘lag time’ (the
285 number of days between the avalanche’s field observation and the acquisition of the activity
286 image), and the ‘average local incidence angle’ (angle between the incoming microwave energy
287 and the normal to the ground surface) within each avalanche path from the Sentinel-1 image pair
288 (Table 2). Geometric terrain correction cannot unfold layover areas so that successful avalanche
289 debris detection is limited in heavily affected regions.

290

291 Table 2: Explanatory Factors with data sources, spatial resolutions, and shortened names.

Explanatory Factor	Source	Resolution	Alias	Range
Destructive size of avalanche	BTAC, UDOT		D-size	1–4.5
Mean tree coverage percentage in the path	GFCC	30 m	Tree Perc	0–47%
Average elevation of avalanche path	USGS NED	10 m	Elevation	1857–3823 m
Average slope in the path	USGS NED	10 m	Slope Angle	15–55°
Avalanche path length	USGS NED	10 m	Path Length	0.19–3.2 km
Avalanche path width	USGS NED	10 m	Path Width	0.13–1.8 km
Average profile curvature in the path	USGS NED	10 m	Curvature	0–0.175
Average local incidence angle within the path	USGS NED, Sentinel-1	20 m	Incidence Angle	11–83°
Percentage of the path affected by radar layover	Sentinel-1	20 m	Layover Perc	0–77%
Percentage of the path affected by radar shadow	Sentinel-1	20 m	Shadow Perc	0–54%
Days between avalanche and the activity image acquisition	Sentinel-1	1 day	Lag Days	1–11

292

293 2.7 Statistical analysis

294 For our statistical analysis, we used the entire dataset of possible detections from all 14 image
295 pairs. This resulted in 506 potential detections for the 258 field reported dry avalanche events.
296 The increased number of possible detections relative to field reported avalanches is due to the
297 combined effects of multiple opportunities to detect a unique event and the varying spatial
298 footprint and temporal coverages of the different image pairs. The varying spatial and temporal
299 footprints means that a single unique event could be included in one or more image pairs, hence
300 resulting in a final dataset of 506 detectable avalanche events. Table 1 details the possible field
301 reported avalanches that could have been detected in each pair of images. We calculated the

302 covariance of our quantitative variables using Spearman's rank correlation test (Wilks, 2019). If
303 two variables were strongly correlated ($p < 0.05$ or $|r_s| > 0.5$), we retained the variable that
304 appeared most directly in the conceptual model of avalanche debris backscatter (Eckerstorfer and
305 Malnes, 2015). We also performed Shapiro Wilk's test for normality on all quantitative
306 variables. All variables failed the test for normality.

307 We then identified explanatory variables with significant variance between the detected and
308 undetected avalanches. We used thresholds of $p < 0.05$ as significant and $p < 0.1$ for marginally
309 significant. Since all variables failed the test for normality, we performed the non-parametric
310 equivalent of the Student t-test: the Mann Whitney U (MWU) test. We use the MWU to analyze
311 if values from each explanatory variable from our detected avalanches were larger or smaller
312 than values from our non-detected avalanches (Wilks, 2019).

313 We split the full dataset ($n = 506$) of potential detections into those appearing in either ascending
314 or descending image pairs. We again used the MWU to compare detection rates, destructive size,
315 and average local incidence angles between our different directions (Wilks, 2019).

316 Finally, we wanted to investigate the dataset for non-linear variable importance. Consequently,
317 we trained a random forest model to identify detectable vs. non-detectable avalanches (Breiman,
318 2001). The random forest used the entire dataset of possible detections with 10-fold cross-
319 validation ($n = 506$). Additionally, we inserted a random variable to assess which variables were
320 more important than a random variable. We tuned the hyperparameter based on maximizing
321 validation accuracy to optimize the number of decision trees (250) and the network's max depth
322 (3). The random forest's performance was assessed with an accuracy score and F1 score, a

323 weighted average of precision and recall (Liu et al., 2014). We finished by extracting feature

324 importance from the trained random forest.

325

326 **3 Results**

327 3.1 Image pairs and field location detection rates

328 Overall, we achieved a POD of 49% by successfully identifying 250 of our potential
329 opportunities to detect avalanche debris and missing 256. This total set is larger than the 258
330 field observed avalanches, as a single avalanche can be observed, or not observed, in multiple
331 temporally overlapping images. However, the detection rates varied between the two field
332 locations and between image pairs.

333 The average POD of avalanches in the BTAC dataset was 41% and of avalanches in the UDOT
334 dataset 57%. As mentioned earlier, the UDOT dataset contained multiple avalanche reports per
335 path. Since we did not know which avalanche debris was detected in the Sentinel-1 images, all
336 field-observed avalanches in a particular path were marked either as 'detected' or 'not detected'.
337 When extracting avalanche paths that had only one avalanche observation (N=48), the POD of
338 this subset of single UDOT avalanches was 46%.

339 POD for individual image pairs for both regions ranged from 15% up to 86%. The number of
340 avalanches in individual image pairs ranged from 18 to 47. There were significant differences
341 between the two orbit directions of the image pairs. Ascending image pairs averaged a POD of
342 54%, while descending image pairs averaged 41% ($p = 0.0058$). There were also significantly
343 higher incidence angles in ascending image pairs (53°) vs descending images (42°) pairs ($p <$
344 0.0001). Finally, the mean destructive size of the avalanches was also significantly higher ($p =$
345 0.01) in ascending images (2.3 vs 2.5). We extracted the following explanatory variables for

346 analysis of image pair variability further below: the number of avalanches, median destructive
 347 size of avalanches, and the median local incidence angle (Table 3).

348 Table 3: Image Pairs with PODs. Darker colors show larger incidence angles or higher POD.

Site	Ref Date	Act Date	Direction	Orbit	# aval.	D-Size	Incidence Angle	Detection %
BTAC	1/24/18	2/5/18	Descending	100	19	2.0	36	21
BTAC	1/27/18	2/8/18	Ascending	49	31	2.5	50	52
BTAC	1/31/18	2/12/18	Descending	27	43	2.5	38	47
BTAC	1/2/20	1/14/20	Descending	100	41	2.0	32	20
BTAC	1/5/20	1/17/20	Ascending	49	28	2.0	51	39
BTAC	1/9/20	1/21/20	Descending	27	41	2.5	40	54
BTAC	1/10/20	1/22/20	Ascending	122	40	2.5	56	48
UDOT	12/22/19	1/3/20	Ascending	20	44	2.5	59	87
UDOT	12/28/19	1/9/20	Descending	27	18	2.5	50	50
UDOT	12/29/19	1/10/20	Ascending	122	42	2.5	51	52
UDOT	1/26/20	2/7/20	Descending	100	41	2.0	48	78
UDOT	1/27/20	2/8/20	Ascending	20	45	2.5	59	80
UDOT	2/2/20	2/14/20	Descending	27	26	2.5	50	15
UDOT	2/3/20	2/15/20	Ascending	122	47	2.5	51	19

349

350

351 3.2 Covariation between explanatory variables for manual avalanche detection

352 We evaluated quantitative variable covariance with a Spearman's rank correlation test. Three
 353 pairs of variables (Table 2) showed correlations over our threshold ($p < 0.05$ or $|r_s| > 0.5$): 1) the
 354 'percentage of the path in shadow' with 'local incidence angle' ($r = 0.65$), 2) 'average elevation'
 355 with 'tree percentage' ($r = 0.50$), and 3) 'path width' with 'path length' ($r = 0.59$). For the first

356 pair we retained ‘path length’ due to its higher correlation with detection rates. For the second
357 pair we retained ‘tree percentage’ also due to its higher correlation to detection rates.
358 For the ‘percentage of the path in shadow vs. local incidence angle’ – we retained ‘local
359 incidence angle’ because the ‘percentage of path in shadow’ was less correlated to detection rates
360 and had a seemingly nonintuitive sign of correlation. As the ‘percentage of the path in shadow’
361 increased, the detection rates also increased, which is not a logical trend for these two variables.
362 However, when considering the positive relationship between higher incidences angle and
363 detection rates this relationship between shadow percentage and detection rates is clarified. The
364 higher incidence angles that led to increased detection rates would also lead to greater
365 percentages of the path being affected by radar shadow.

366

367 3.3 Importance of explanatory variables on detection rates

368 We performed the non-parametric MWU tests on the full dataset and separate subsets for BTAC
369 and UDOT regions since our variables were not normally distributed (please refer to
370 supplementary material). The significant variables between our detected and undetected
371 avalanches were generally the same between our full and regional datasets with ‘destructive
372 size’, ‘incidence angle’, ‘path length’, and ‘lag days’ being the most important variables (

373 Table 4).

374

375

376 Table 4: Mann Whitney U test results for the full dataset, UDOT, BTAC. For all marginally
 377 significant or significant results, the detected and undetected median relative values are noted
 378 below the p-value. Darker green shows higher significance.

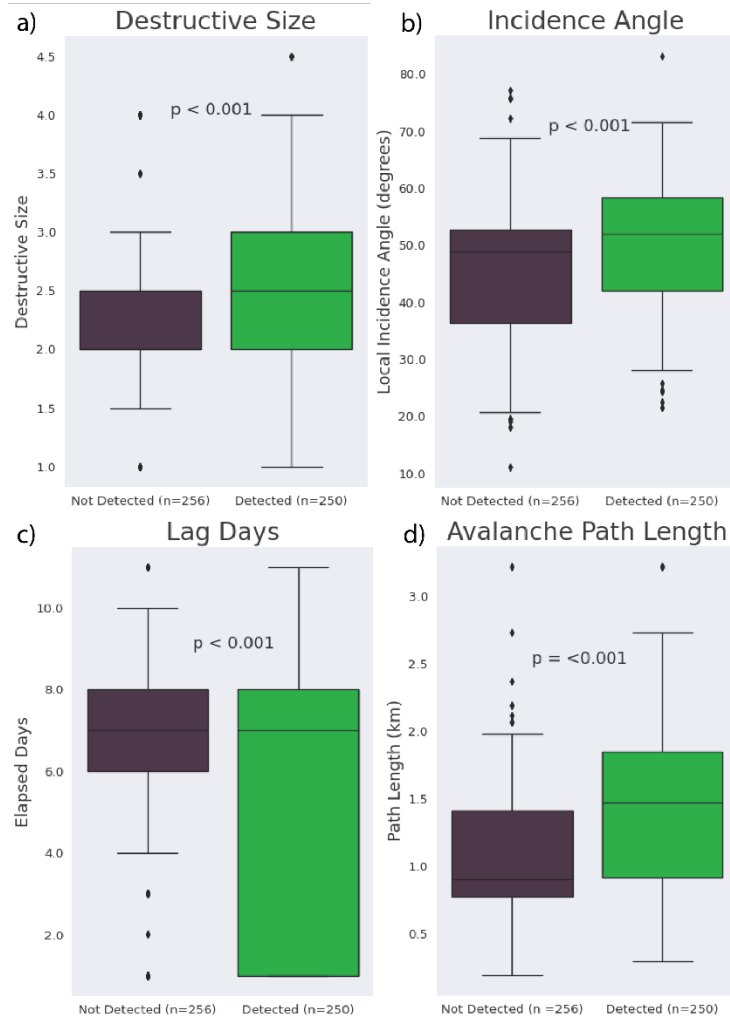
379

Variable	D-Size	Tree Perc	Incidence Angle	Slope	Curvature	Path Length	Layover Perc	Lag Days
Full Dataset								
p-value	7.3E-11	0.39	2.2E-05	0.0038	0.61	1.9E-16	0.97	2.5E-06
	det > undet		det > undet	det > undet		det > undet		det = undet
BTAC								
p-value	1.3E-13	0.76	0.0099	0.64	0.068	1.7E-07	0.15	0.43
	det > undet		det > undet			det > undet		
UDOT								
p-value	0.07	0.33	0.019	0.0052	0.032	3.4E-09	0.16	1.4E-05
			det > undet	det > undet	det < undet	det > undet		det < undet

380

381

382 For the four explanatory variables with significant variance, we show the difference between
 383 ‘detected’ and ‘non detected’ in Figure 5 for the entire dataset. Our individual regional datasets
 384 showed similar patterns to the overall dataset. There is considerable overlap in the interquartile
 385 range for all explanatory variables with significantly higher medians for ‘detected’ vs ‘non
 386 detected’.



387

388 Figure 5: Boxplots showing the median, interquartile ranges, whiskers, and outliers for detected
 389 and undetected avalanches in the full dataset. Whiskers extend to the last data point that is within
 390 1.5 times the interquartile range above (below) the upper (lower) quartile, and outliers are data
 391 points beyond that 1.5 times the interquartile range from the lower or upper quartile.

392

393 Previous research has established destructive size as a controlling variable on detection rate
 394 (Eckerstorfer et al., 2019, Hafner et al. 2021). We also found a strong relationship between
 395 increased POD and larger avalanches for the BTAC dataset and a marginal relationship for the
 396 UDOT (Table 5). When we consider avalanches large enough to destroy trees or bury a car, or

397 larger (i.e., $\geq D3$) we obtained a POD of 65% ($n = 164$). Those smaller than D3 had a POD of
 398 42%.

399

400 Table 5: Detection rates by destructive size. Darker green represents higher detection rates. Bold
 401 horizontal line marks the threshold between smaller ($<D3$) from relatively larger avalanches
 402 ($\geq D3$).

403

Destructive Size	# Detected	# Not	Detection Rate	
1	4	23	15%	
1.5	26	43	38%	
2	78	100	44%	< D3: 44%
2.5	60	47	56%	
3	56	41	58%	
3.5	17	2	89%	$\geq D3$: 65%
4	31	15	67%	
4.5	2	0	100%	

404

405

406 3.4 Random forest feature importance in detection rates

407 Following hyperparameter tuning, the random forest attained a validation accuracy of 64% with
 408 10-fold cross-validation. The feature importance from the random forest results aligned with the
 409 findings from the MWU analysis with ‘path length’, ‘incidence angle’, ‘lag days’, and
 410 ‘destructive size’ as the most significant variables (Table 6).

411

412 Table 6: Feature individual and cumulative importance in the random forest model.

Feature	Individual Importance	Cumulative
Path Length	33%	33%
Lag Days	19%	52%
Incidence Angle	13%	65%
D- Size	12%	77%
Slope	6%	83%
Curvature	5%	88%
Tree Percentage	5%	93%
Layover Percentage	4%	97%
Random Variable	3%	100%

413

414 **4 Discussion**415 4.1 Manual avalanche detection using Sentinel-1 in a transitional snow climate

416 Our study is the first to provide a large-scale analysis of detection rates for Sentinel-1 images

417 relative to field observed datasets in the continental United States, which has a markedly

418 different topography and snow climate from previous SAR avalanche detection studies.

419 Our POD was 49% from two field locations utilizing SAR temporal change analysis on a dataset

420 of dry slab avalanches (with 248 unique avalanche events, and 506 opportunities to detect in the

421 images). However, when considering avalanches equal to or larger than D3 the manual detection

422 rate rises to 65%. SAR temporal change analysis is effective for most avalanches large enough to

423 do substantial damage to infrastructure or vegetation. However, we still miss around 35% of

424 even these large avalanches.

425 The detection rate for the UDOT avalanches (POD = 53%) is substantially higher than for the

426 BTAC avalanches (POD = 41%). Considering only UDOT avalanche paths with single events,

427 the detection rate dropped to 46%, thus much closer to the BTAC POD, suggesting fairly similar
428 results. Both field locations are in a transitional snow climate where wet and dry snow avalanche
429 cycles can be expected. However, the vast majority of observed avalanches were dry snow
430 avalanches, which is the focus of this study.

431 Previous research on wet snow avalanches detected 100% of avalanches D3 and larger
432 (Eckerstorfer et al., 2019). Our study, focused solely on dry snow avalanches, found a much
433 lower detection rate (64%) for comparably sized avalanches. While there are topographic and
434 climatic factors that may be influencing these results, our results suggest that a maritime snow
435 climate dominated by wet snow avalanche activity may be better suited to Sentinel-1 temporal
436 change analysis techniques.

437

438 4.1.1 How did detection rates vary between image pairs?

439 Detection rates differed between Sentinel-1 image pairs, with the lowest detection rate being
440 15% and the highest being 87% (Table 3). This means that certain pairs of images are more
441 suitable for detecting avalanche debris than others. A trend in detection rates was that ascending
442 image pairs had higher detection rates (54%) compared to descending image pairs (41%) ($p =$
443 0.0058). While there was a skew towards larger avalanches in ascending image pairs ($p = 0.01$)
444 the difference in medians was only 0.5 and probably doesn't fully account for the observed
445 differences in detection rates.

446 A more likely explanation for varying detection rates might be the trends in aspect of the active
447 avalanche paths relative to the SAR sensor. Ascending image pairs had higher median incidence
448 angles (53.2°) relative to descending image pairs (42.2°) ($p < 0.001$). In Wyoming and Utah, due

449 to prevailing wind direction and less solar warming, more avalanches are noted in field
450 observations on east facing aspects. This predominance of east facing avalanches means that in
451 ascending images, there were more paths that faced away from the sensor leading to higher
452 incidence angles and, based on this study and Tompkin and Leinss (2021), to higher detection
453 rates. Generally, this relationship suggests that depending on the predominant aspects of
454 avalanches in a region, either flight direction (ascending or descending), will yield higher
455 detection rates.

456

457 4.2 Which explanatory factors correlated with successful detections?

458 Several explanatory factors reached high significance in our MWU tests for one or more of the
459 datasets. We present these explanatory factors in descending order of significance and the
460 associated reason for an increased detection rate in

461 Table 7. Then we discuss each of the explanatory factors separately below.

462

463

464 Table 7: Summary of explanatory factors related to increased detection rates sorted by Mann-
 465 Whitney U (MWU) test p-values.

Explanatory factors	Increased Detection Rates	MWU P-Value	RF Importance
Path length	Longer path length	<0.001	1 st
Lag Days	Fewer days elapsed	<0.001	2 nd
Local incidence angle	Increased local incidence angles	<0.001	3 rd
Destructive size	Larger destructive size	<0.001	4 th
Slope angle	Steeper average slope angle	0.0038	6 th
Curvature	More convex curvature	0.032 (UDOT only)	5 th
Layover Percentage		>0.1	8 th
Tree Coverage		>0.1	7 th

466

467 4.2.1 Destructive size

468 Our results show a strong and positive correlation between the field reported destructive size and
 469 Sentinel-1 based POD for our whole dataset and for the BTAC subset ($p < 0.001$) (Table 5). The
 470 marginal significance of destructive size in the UDOT dataset may have been due to overlapping
 471 avalanches in paths causing increased detections of smaller avalanches that occurred
 472 simultaneously with larger avalanches. This matches previous results reported by Eckerstorfer et
 473 al. (2019) and Hafner et al. (2021). Both studies found PODs around 90–100% for D4 and D5
 474 avalanches dropping off rapidly for smaller avalanches, with Hafner et al. (2021) reporting
 475 detection rates of only 4% for D1s. Our results match this general trend, with a 29% detection
 476 rate for avalanches D1.5, 47% for D2 to D2.5 and 65% for all D3 and larger. A probable
 477 explanation for our lower detection rates of large avalanches is our dataset was only dry

478 avalanches, unlike the dataset in Eckerstorfer et al. (2019) that was over 90% wet avalanches and
479 Hafner et al. (2021) that was composed of a mixture of dry and wet snow avalanches.

480 The correlation between destructive size and POD is likely due to the spatial resolution of the
481 Sentinel-1 sensor. Larger avalanches will typically result in wider and deeper debris piles. These
482 expanded debris piles are easier to detect with the relatively coarse resolution of the Sentinel-1
483 sensor. Leinss et al. (2020) suggested a smallest detectable size of 2000 m² for avalanche debris
484 in their Sentinel-1 automated avalanche detection system, while Eckerstorfer et al. (2019) use a
485 minimum cut-off size of 4000 m².

486 Avalanche inventories using Sentinel-1 are biased towards larger avalanches. Higher resolution
487 sensors may improve the ability to detect smaller avalanches, as shown by Eckerstorfer and
488 Malnes (2015) using very high resolution Radarsat-2 ultrafine data for avalanche detection.
489 However, if infrastructure damage is the primary concern, accurate mapping of more significant
490 avalanches with Sentinel-1 will be sufficient in most applications.

491

492 4.2.2 Avalanche type

493 Compared to previous studies, our results provide further supporting evidence that dry
494 avalanches are more difficult to detect than wet avalanches. Our dataset was entirely dry
495 avalanches and we consistently found lower POD rates than those in previous research on the
496 detection rates for wet snow avalanches (Eckerstorfer et al. 2019, Hafner et al. 2021).

497 Consequently, SAR-based avalanche detections may be best suited to regions dominated by wet
498 snow avalanches. An overall lower POD can be expected in transitional or continental snow
499 climates.

500 Dry snow is mostly transparent for C-band SAR, which means that an unknown contribution
501 from the ground surface can be expected to the total backscatter signal. This results in minor
502 relative backscatter difference between avalanche debris and surrounding undisturbed snow in
503 dry snow conditions. In case of wet snow avalanches, the SAR signal does not penetrate the
504 snow, leading to the majority of the backscatter signal stemming from the air-surface interface,
505 that is typically rough in wet snow avalanches. A major difference in backscatter between the
506 debris and the surrounding snow can thus be expected, which is more likely detectable in wet
507 snow than in the case of dry snow.

508

509 4.2.3 Path length

510 Previous studies have not investigated the relationship between detection rates and ‘path length’.
511 We found a strong relationship (MWU p-value <0.001 and first in the random forest feature
512 importance), with longer paths having higher detection rates. Intuitively, longer paths may
513 produce larger avalanches. However, we did not find path length to be significantly correlated
514 with destructive size, suggesting that path morphology rather than total mass of the avalanche is
515 more important. Future research is needed to confirm our findings, but our study suggests that
516 certain regions with longer path lengths might lead to higher detection rates.

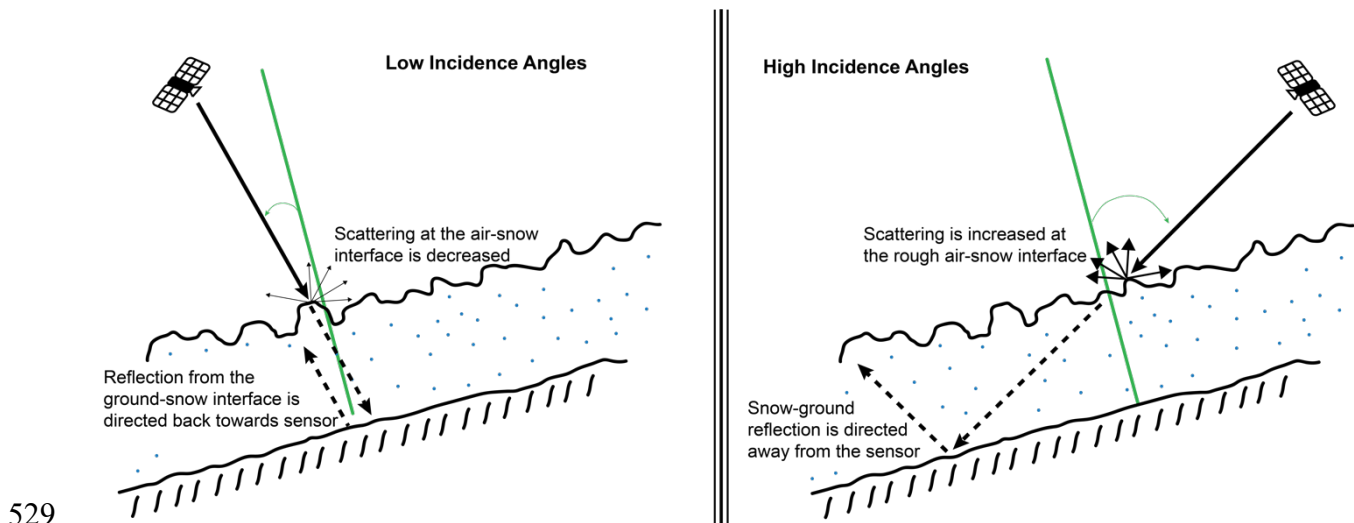
517

518 4.2.4 Local incidence angle

519 The average local incidence angle was significant in the MWU comparisons for every dataset
520 ($p < 0.02$, Table 4) and was the second most important feature in our random forest model (Table
521 6). This relationship between high local incidence angle and high detection rates is based on a

522 few factors. First, due to the geometry of SAR images there is higher resolution in areas where
 523 the incidence angle is farther from zero. Also, this limits the effects of layover, which can
 524 obscure avalanche debris. This result matches the findings of Tompkin and Leinss (2021) whose
 525 work with exclusively wet snow avalanches showed a 4 dB increase in avalanche debris
 526 backscatter change for incidence angles between 40–70° for VV polarization and 2 dB for VH
 527 polarization. (Figure 6).

528



529

530 Figure 6: Proposed conceptual model explaining the increased detection rates of avalanche debris
 531 at higher incidence angles.

532

533 Future applications could also use this knowledge to differentiate paths with a high chance of
 534 detecting avalanches from those with a relatively low probability. Identifying paths with a high
 535 POD is valuable for suggesting when avalanches are not occurring instead of just being missed
 536 by this technique.

537

538 4.2.5 Lag days

539 The elapsed days between the avalanche field observation and the acquisition of the Sentinel-1
540 activity image was highly significant for our complete and UDOT datasets ($p < 0.001$, Table 4),
541 with fewer lag days correlated with higher detections. The median lag days for detected
542 avalanches in the UDOT dataset was 2 compared to 8 for the undetected UDOT avalanches.
543 Additionally, it was the 3rd most important variable in our random forest.
544 This connection between fewer days elapsed and higher detection rates makes intuitive sense.
545 The increased number of days leads to greater exposure to ablative meteorological factors such
546 as: 1) increased temperatures that might reduce the chances of detection due to melting and
547 smoothing of the rough avalanche surface, 2) increased cumulative precipitation, which might
548 cover the rough surface of the debris and lead to a less dramatic contrast between the increased
549 volumetric backscatter from the deeper avalanche debris and the surrounding snowpack, and 3)
550 more exposure to wind redistribution, which might smooth the avalanche debris surface. In
551 regions with less frequent Sentinel-1 imaging or high repeat frequencies (such as lower latitudes
552 and outside of Europe), atmospheric weathering will likely cause lower detection rates.
553 It is unclear why the BTAC did not have a significant effect from lag days. Potentially the
554 atmospheric conditions of Little Cottonwood Canyon, Utah (generally warmer and less frequent
555 intense storms) lead to greater reductions in detectability relative to Wyoming (generally more
556 continually snowy, colder average temperatures) for these cycles. Future research into the
557 specific meteorological conditions that lead to lower PODs with increased days of exposure may
558 be valuable for understanding these underlying causes.

559

560 4.2.6 Layover percentage

561 The percentage of the path affected by layover did not result in significant MWU results ($p =$
562 0.42, Table 4) and was only slightly more important than a random variable in our random forest.
563 Thus, our results do not provide evidence for a connection between layover effect and detection
564 rates. However, layover can effectively obscure large portions of an avalanche path, leading to
565 missed detections. Therefore, the conclusion that paths highly affected by layover would have
566 lower detection rates seems reasonable. While this study did not find evidence for a relationship
567 between layover and detection rates, we did note a few outliers, where layover did impact
568 detection. The low significance of layover on detection rates may have been because our sample
569 only had a median layover percentage of 3% suggesting that our paths may have had limited
570 impacts from layover.

571

572 4.2.7 Avalanche slope angle

573 The average slope (across the entire path) was significant in the overall and UDOT dataset ($p =$
574 0.0038, Table 4) and the fifth most important feature in our random forest (Table 6). The median
575 slope was 33 degrees for detected avalanches and 31 degrees for the undetected avalanches.
576 These results suggest a slight relationship between steeper slopes and higher detection rates but
577 may also be due to steeper slopes generally having higher incidence angles in this study. The
578 weaker relationship between slope and POD for the BTAC may be explained by the relatively
579 larger spatial extent of the avalanche observations in the BTAC dataset, rather than the single,
580 steep canyon for the UDOT data.

581

582 4.4 Limitations and future work

583 This study assessed the detectability of avalanches in Sentinel-1 images in a transitional snow
584 climate in the United States. We noted several limitations that may help guide future research:

585 1) Our avalanches datasets covered only two regions of a similar snow climate. Expanding
586 to other regions within the transitional snow climate, as well as purely continental or
587 maritime snow climates in the United States would be useful. An excellent potential
588 study area would be Alaska, which receives more Sentinel-1 overflights, reducing lag
589 days and thus atmospheric influence on avalanche debris. The coastal climate and large-
590 scale topography with long avalanche paths in Alaska may also improve avalanche
591 detectability.

592 2) This research utilized only four avalanche cycles with 258 field reported avalanches,
593 resulting in 506 potentially detections of avalanches in our SAR images. These four
594 avalanche cycles were selected to maximize the number of avalanches in each pair of
595 Sentinel-1 images but choosing events from these extreme avalanche cycles may have
596 introduced other factors that skewed our results (e.g. more long runouts). Studies in the
597 future with additional avalanche cycles may help to clarify if our findings hold for less
598 extreme avalanche cycles. Additionally, exploring spring avalanche cycles will be
599 valuable, considering also wet snow avalanche activity.

600 3) We utilized avalanche records that were opportunistically collected. The BTAC records
601 may have been incorrect due to non-expert public sources reporting. These records were
602 potentially also skewed towards accessible locations, periods of high visibility, and larger
603 events. Future studies could limit these biasing effects by performing randomized
604 observations or confirming complete coverage of a region.

- 605 4) We focused exclusively on backscatter analysis of a single sensor. Future studies could
606 explore other SAR sensors for avalanche detection, operating at different frequencies
607 (e.g. X-band) and spatial resolutions.
- 608 5) We carried out manual detections, which are currently considered the gold standard of
609 avalanche detection using SAR imagery (Bianchi et al., 2021). However, since only one
610 person (the first author) performed the manual detections, there may have been biases
611 that systematically or randomly affected the results. Future studies may want to compare
612 multiple people independently detecting avalanche debris in SAR image to explore the
613 variability of expert interpretation.
- 614 6) Our techniques relied on manual detection but monitoring seasonal avalanche activity or
615 a larger dataset of avalanche cycles will require automatic detection methods. Currently,
616 classification of SAR images using neural networks shows promising results (Tompkin
617 and Leinss, 2021, Bianchi et al., 2021). Future research combining these manual
618 detections with machine learning techniques to explore automatic detections of dry snow
619 avalanches will be valuable. This future machine learning work would also benefit from
620 the establishment of a community-recognized dataset of manual detections and imagery
621 to test new models against. This study and others have shown the wide range in site and
622 event-specific PODs, so improvements in model performance are only meaningful if
623 done against a common set of images and detections.
- 624 7) While we assessed whether a single manual observer could use SAR imagery to detect an
625 avalanche that had been observed in the field (our Probability of Detection or POD), we
626 did not assess how often that manual observer might have identified an avalanche that did

627 not occur in the field (the false alarm rate or FAR). Doing this requires the observer to
628 start with SAR imagery with no knowledge of avalanche activity, and then to identify all
629 areas that appear to be avalanche debris. It would also require a spatially and temporally
630 complete data set of avalanche activity for the area, which was unavailable to us.
631 Obtaining such datasets is critically important for furthering this research because
632 quantifying this manual FAR is critical to provide context for automating future
633 avalanche detection, which often relies on manually labeled training data.

634

635 **5 Conclusion**

636 This study examined the manual avalanche detection rates in Sentinel-1 backscatter intensity
637 data relative to datasets of field observed dry snow avalanches from two locations in a
638 transitional snow climate in the western United States. For the 506 potentially observable
639 avalanche events in the SAR images, 250 (49%) were manually detectable in the Sentinel-1
640 images, which were derived from the 248-field observed unique events examined in this study.

641 This POD increased to 65% when considering only avalanches large enough to bury cars or
642 break trees ($\geq D3$). Thus, most dry snow avalanches larger than D3 can be detected by SAR-
643 based change detection analysis, though this technique still missed about 35% of these
644 avalanches in our combined database.

645 The primary variables showing a strong correlation with detection rates (both in our MWU and
646 random forest analysis) are local incidence angle, path length, destructive size, slope angle, and
647 elapsed days between the avalanche and the activity image. We also established a much weaker,
648 and statistically insignificant relationship for the percentage of path affected by layover. Tree

649 coverage, average slope steepness, and the slope's curvature failed to reach a marginal
650 significance.

651 With further refinements, our methods may provide a first step toward automated avalanche
652 detection using remote sensing. This, in turn, would give avalanche practitioners in the United
653 States much-needed feedback and researchers spatially extensive and relatively complete
654 datasets of avalanche occurrences for machine learning techniques and trend analysis. Though
655 the lower latitudes of the United States only have revisit intervals of ~2–4 days instead of the
656 daily revisit interval near the poles, there is still reasonable temporal coverage for detection of
657 major avalanche events in a reasonably timely manner. Within the United States there are
658 specific regions, in particular Alaska, that may be better suited to immediate applications of this
659 technology including manual mapping of major cycles and automated near-real time detection
660 techniques.

661

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