

Article

Understanding Landslide Expression in SAR Backscatter Data: Global Study and Disaster Response Application

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Highlights

What are the main findings?

- A global analysis of 1000+ landslides revealed consistent patterns in SAR backscatter change.
- Empirical findings were integrated into a physical conceptual model linking SAR backscatter to landslide surface changes.

What is the implication of the main finding?

- The conceptual model fills a key gap in understanding landslide signatures in SAR backscatter, enabling more reliable interpretation across diverse environments.
- It provides a foundation for advancing rapid landslide detection and automated methods, supporting disaster response and climate resilience in areas where optical satellite data are limited.



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Abstract

Cloud cover can delay landslide detection in optical satellite imagery for weeks, complicating disaster response. Synthetic Aperture Radar (SAR) backscatter imagery, which is widely used for monitoring floods and avalanches, remains underutilised for landslide detection due to a limited understanding of landslide signatures in SAR data. We developed a conceptual model of landslide expression in SAR backscatter (σ^0) change images through iterative investigation of over 1000 landslides across 30 diverse study areas. Using multi-temporal composites and dense time series Sentinel-1 C-band SAR data, we identified characteristic patterns linked to land cover, terrain, and landslide material. The results showed either increased or decreased backscatter depending on environmental conditions, with reduced visibility in urban or mixed vegetation areas. Detection was also hindered by geometric distortions and snow cover. The diversity of landslide expression illustrates the need to consider local variability and multi-track (ascending and descending) satellite data in designing representative training datasets for automated detection models. The conceptual model was applied to three recent disaster events using the first post-event Sentinel-1 image, successfully identifying previously unknown landslides before optical

imagery became available in two cases. This study provides a theoretical foundation for interpreting landslides in SAR imagery and demonstrates its utility for rapid landslide detection. The findings support further exploration of rapid landslides in SAR backscatter data and future development of automated detection models, offering a valuable tool for disaster response.

Keywords: pattern recognition; conceptual model; change detection; time series; landslide detection; land cover; SAR; backscatter; Google Earth Engine; Sentinel 1

1. Introduction

Landslides pose an increasing risk to humans due to urban expansion into unstable areas and an increasing frequency of extreme precipitation events [1–3]. Landslides frequently occur with other types of natural hazards, including earthquakes, floods, volcanic eruptions, and tsunamis, particularly in areas with high hydrological or seismic risk [4]. Consequences may include fatalities, damage to infrastructure and property, blocked transport routes, and dammed rivers, which create a further risk of flash flooding to downstream areas [5]. Landslides vary greatly in materials, size, and failure mechanisms [6]. Here, we use the term ‘landslide’ to include all types of mass movements of soil and rock and focus on fast-moving landslides (occurring in less than a day).

Technological developments, including more frequent satellite image acquisition, cloud-based high-performance computing capabilities, and automatic image detection methods, can greatly improve the efficiency of extracting useful information from satellite images. Accordingly, there has been significant progress in automated landslide detection models, e.g., [7–10]. Preliminary studies have yielded promising results at a local scale, particularly with deep learning methods. However, further development is needed to achieve automatic landslide detection models that perform well in diverse environments [11].

Most automatic landslide detection models use optical images [10,12], requiring cloud-free images and sufficient light conditions. This can be a critical limitation, where persistent cloud cover, or seasonal darkness, can lead to delays of weeks or months before changes to the ground surface are observable in optical satellite images [13–15]. Cloud cover can be a problem for the rapid detection of both rainfall- and seismically triggered landslides (e.g., Nepal, 2015) [16]. The authors argue that optical satellite imagery alone should not be relied upon for rapid landslide detection in emergency situations due to the potential delays from clouds and darkness.

Synthetic Aperture Radar (SAR), on the other hand, is cloud-penetrating and an active sensor, sending pulses of microwave radiation towards the Earth and recording the properties of the returned signal. Ground surface reflectance properties can be measured irrespective of cloud cover or illumination from the sun [17]. Previous studies have demonstrated the potential for detecting landslides in SAR backscatter images, albeit with reduced clarity and detection rate compared to optical images [12,18–21]. In addition, SAR images are more complex to process, and interpretation is less intuitive. This is due to a complex backscatter signal, speckle noise, and geometric distortions [22]. In addition, the variety of landslide types and landscapes and land cover types in which they occur makes the interpretation of these features in SAR imagery non-trivial. This presents an obstacle for geoscientists and other operators in the development of operational systems using SAR backscatter images for rapid landslide detection [19,23].

SAR satellites measure two components of the returning backscatter signal, the phase and the amplitude (or intensity). Differences in the phase component between two images

are commonly used to monitor millimetre- to centimetre-scale ground movements using SAR interferometry (InSAR) methods [24–27]. Coherence is a measure of similarity between radar signals reflected from the same location between two SAR images. Areas with low coherence could indicate significant changes in scattering properties or decorrelation. Coherence methods also have potential for rapid detection of landslides [28]. The present article focuses specifically on landslide detection using the backscatter intensity component of the returned SAR signal. Changes in ground cover properties due to landslides are associated with changes in scattering mechanisms. This can be exploited to differentiate the disturbed landslide surface from the undisturbed surroundings using the intensity component [21,29,30].

In a previous work by the authors [20], it was observed that in SAR backscatter change images, landslides were expressed as an increase in backscatter intensity. Possible reasons for this were discussed in the referenced article. However, the author of a related study [23] expressed surprise that there was an increase in backscatter intensity, given that the landslides observed in their similar study were showing a decrease in intensity. In trying to understand the reasons for the differences in the results between the two studies, a knowledge gap was identified: what are the main factors that control landslide expression in SAR backscatter imagery?

In a review of 54 journal articles about landslide failure detection using SAR imagery, published between 1995 and 2020, Ref. [24] found that the literature on the exploitation of SAR amplitude data for landslide event detection remains limited. The review concluded that available SAR amplitude images are well suited for landslide detection and mapping as the wavelength of the microwave SAR sensors is comparable to the length scales of morphometric elements typical of landslides. However, there remains a lack of understanding of the physical basis of backscatter response. The present article will attempt to address this knowledge gap.

In previous studies, SAR polarimetry methods, mainly with matrix decomposition, have been used for identifying landslides with fully polarised SAR data [31]. Recently, an increasing number of studies have begun to investigate SAR backscatter intensity change images for landslide detection and mapping using Sentinel-1 C-band SAR backscatter images. Ref. [19] investigated landslide detection using Sentinel-1 backscatter change images for 32 case studies. Ref. [18] explored how accurately two large single landslide events could be mapped using such images. Others have used multi-temporal composites to improve landslide visibility in change images [20] and create heat maps of landslide density [23]. Ref. [31] used Sentinel-1 time series to backdate monsoon-triggered landslides and explored the performance of different bands. There have also been a few studies demonstrating the potential to automate this process using locally trained deep learning models [11,32].

While most of the studies using SAR intensity data test the performance of multiple band combinations (VV and VH) and orbit geometries (ascending or descending), interpretation of the spatial and temporal expression of landslides in images and time series data is still somewhat limited in detail (e.g., [32]). Most of these studies focus on whether it is possible to detect, map, and backdate landslides using SAR imagery. They do not systematically quantify changes in backscatter intensity or relate this to the landslide type, morphometric elements, or environmental conditions. Most investigations of landslides are in densely forested areas, while areas with herbaceous or little to no vegetation, especially polar regions, are poorly represented [24]. Landslides are observed to produce both increases and decreases in backscatter intensity [19]; however, a physically based explanation for these observations in relation to the ground properties is lacking.

In this study, we aim to improve the understanding of how SAR imagery can be used as an alternative to optical images for rapid landslide detection, where timely detection is critical. Using well-documented and diverse case studies, we identify patterns in the expression of landslides in SAR backscatter change images. This study differs from previous works, which have focused on detectability, in that we (a) seek to highlight variation in the expression of landslides in SAR backscatter images and (b) attempt to provide a physical explanation for the observed patterns based on quantitative and qualitative analyses of a variety of controlling factors. Through a multidisciplinary literature review and discussions with experts, we seek to explain how physical changes to the ground surface relate to the change in scattering mechanisms and backscatter intensity, which determine the expression (pattern of increase or decrease) of landslides observable in SAR imagery. We then synthesise the patterns and theory into a conceptual model that can be used to aid interpretation. Finally, the findings are applied to recent disaster events, with the aim of manually detecting previously undetected landslide events. The findings contribute towards developing an understanding of the variability in how landslides may appear and be interpreted in SAR backscatter images, depending on local environmental conditions and properties of the landslides, as well as sensor properties. This is relevant for training deep learning models that use SAR imagery for automatic landslide detection, as such models rely on diverse training datasets that capture the range of expected landslide types and land cover in a given region.

The research questions are as follows:

1. What patterns and trends in the spatial and temporal expression of landslides in SAR backscatter intensity data can be identified from the 30 case studies?
2. Which factors control the visibility and expression of landslides in SAR data?
3. What can be learnt by applying these findings to detect landslides in real disaster scenarios using SAR imagery before optical images are available, and how could these insights support future automated detection approaches?

2. Materials and Methods

An iterative process was followed to answer the research questions as illustrated in Figure 1. This included compiling a diverse selection of landslide case studies and producing change images for each case. We examined the spatial and temporal signatures of landslides in each case using time series data and collected the change images in the Supplementary Materials. A GitHub repository containing the scripts used to produce the change images and time series, along with a PDF (Supplementary Materials) showing all change images produced for the 30 case studies, is available (<https://github.com/erin-ntnu/Understanding-Landslide-Expression-in-SAR---change-images-in-GEE-.git> (accessed on 17 September 2025)).

From this collection of images, patterns in the landslide expression (increases and decreases in backscatter intensity) were identified. Quantitative analyses of the case studies were performed to investigate temporal and spatial variations in the expression of landslide failures. To understand which factors were relevant in controlling this expression, a multidisciplinary literature review was performed, and discussions were held with several experts. The relevant concepts were summarised as a theory review and a conceptual model. Finally, the findings were applied to manually detect landslides that were not known previously, in three recent disaster events.

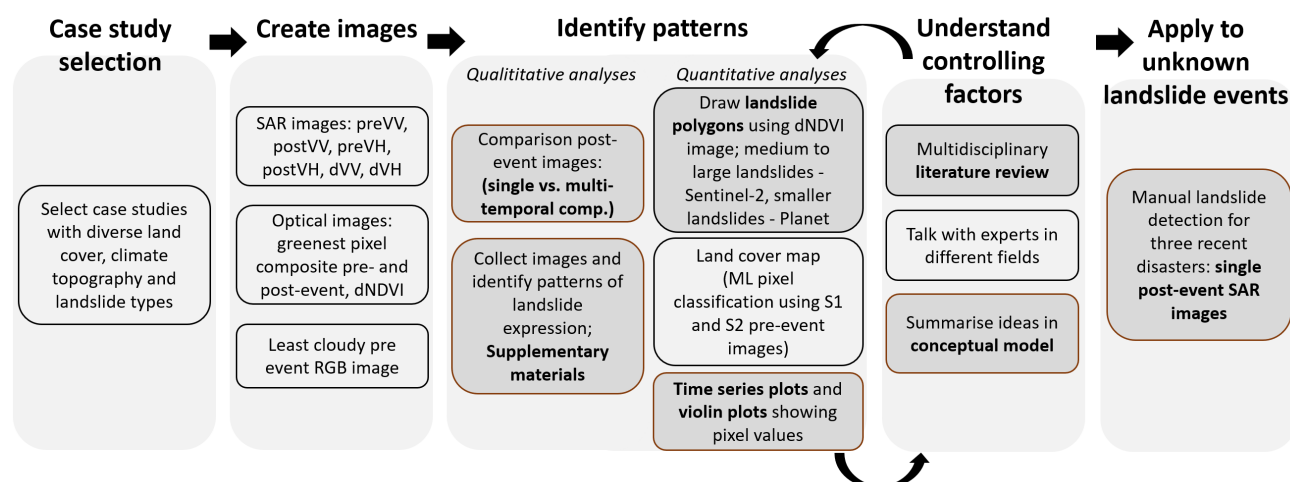


Figure 1. Flow chart showing methodology. The darkened boxes show the main results that are presented.

2.1. Study Areas

A selection of 30 study areas, with varying terrain types, orientation and size, ground cover, climate zones, geological materials, and failure mechanisms, was systematically analysed. The case studies were identified from reports in *The Landslide Blog* [33] and from news reports or journal articles found by internet search. The location and dates of the investigated landslide events are shown in Figure 2, while the properties of the landslides and local environment are shown in Table 1.

Table 1. Properties of the investigated landslides and their local environment. For clarity, the visibility set assigned to the landslides in the Sentinel-1 multi-temporal composites (see Supplementary Materials) is also presented here. Following the approach by [19], these include Set 1: not visible, Set 2: partially visible, recognisable only knowing a priori the location, and Set 3: clearly visible.

Landslide						Environment			Set
Location	Type	T	Size L × W [km]	Aspect	Geology	K.G. Climate	Rainfall [mm/yr]	Land Cover GI/EU	1. No 2. Part. 3. Yes
1. Iceland	DS	R	0.8 × 0.1	E	V	Cfc	672	Herb./Moor	3
2. Ireland	PF	R	0.58 × 0.7	NW	S	Cfb	1358	Herb./Peat	3
3. N. Zealand	DS	R	0.13 × 0.05	W	S	Cfb	1508	Herbaceous	2
4. Ecuador	EF	R	1.5 × 1.5	W-NW	S-V	Cfb	918	F Unknown	3
5. Norway	DF, DA	R	0.11 × 0.03	mixed	M	Dfc	2285	Herbaceous	3
6. Sth. Africa	DF	R	0.5 × 0.2	W	M	Cfa	940	Herbaceous	1
7. Vanuatu	DS-DF	R	0.8 × 0.2	S	V	Af	3440	F Broadleaf	2
8. Brazil	DF	R	1.6 × 0.02	NE	S	Cfa	1547	F Broadleaf	2
9. China	DS-DF	R	1.34 × 0.92	S	S	Cwb	1297	F Broadleaf	3
10. Philippines	MF	R	2.1 × 0.7	SW	S	Af	2915	F Broadleaf	3
11. Japan	DS, DF	ER	0.22 × 0.13	mixed	S-V	Dfb	1131	F Broad. dec.	3
12. USA	DA	R	1.7 × 0.18	N	P	Dsb	1282	F Needle	3
13. China	DS	R	1.2 × 0.3	S	S	Cfa	1409	F Unknown	3
14. N. Zealand	RA	R	1.8 × 0.28	SE	S	ET	4222	Snow	3
15. Iceland	RA	R	2.4 × 1.7	SE	V	Cfc	829	Herb./Grass	3
16. India	RF	R	0.68 × 0.15	SW	M	Cwb	824	Herbaceous	1
17. India	DS	R	0.34 × 0.2	SE	S	Cwa	2183	F Unknown	2
18. Norway	SF	S	1.35 × 0.95	E	V	Dfc	974	Herb./Rock	1
19. India	DF	R	1.2 × 0.12	S	P	Am	2848	F Needle	3
20. Peru	EF	U	0.6 × 1	NE	S-V	Dsb	506	Herbaceous	3
21. Kyrgyzstan	CCS-EF	RS	5 × 0.6	NE	S	ET	394	Herbaceous	2
22. Italy	DF	R	0.35 × 0.07	SE	S	Dfc	886	Agriculture.	2
23. Indonesia	DF	E	6 × 0.3	NE	V	Af	2775	F Broadleaf	2
24. Brazil	DS	R	0.06 × 0.03	SE	S	Am	1678	Urban	1
25. Canada	DF	R	0.85 × 0.32	SE	S-V	Cfb	1712	F Needle	3
26. USA	RF	U	0.09 × 0.06	W	P	Csb	1560	Shrub	1
27. Burundi	DS, DF	R	0.4 × 0.3	mixed	M	Aw	1519	F Unknown	2

Table 1. Cont.

Location	Type	Landslide				Environment			Set
		T	Size L × W [km]	Aspect	Geology	K.G. Climate	Rainfall [mm/yr]	Land Cover GI/EU	1. No 2. Part. 3. Yes
28. Australia	DS, DF	R	0.8 × 0.04	S	S	Cfa	2031	Agriculture	2–3
29. Indonesia	SLS	E	2.1 × 1.1	W	P	Af	1534	Urban	2
30. Turkey	RS	U	0.5 × 0.3	SE	S-V	Cfb	626	Agriculture	3

Acronyms: Type [6]: RF—rock fall, RS—rock rotational slide, DS—gravel/sand/debris slide, CCS—clay/silt compound slide, SLS—sand/silt liquefaction spread, RA—rock avalanche, DF—debris flow, MF—mud flow, DA—debris avalanche, EF—Earth flow, PF—peat flow, and SF—slush flow. **Trigger (T):** R—rainfall, E—earthquake, S—snow melt, and U—unknown. **Geology:** S—mainly sedimentary terrain, P—plutonic terrain, M—metamorphic, S-V—mixed sedimentary–volcanic terrain, and V—mainly volcanic terrain. **K.G. Climate zone:** A (tropical) + f (rainforest), m (monsoon) w (savanna, dry winter), and s (savanna, dry summer); C (temperate) + w (dry winter), f (no dry season), s (dry summer), l l a (hot summer), b (warm summer), and c (cold summer); D (continental) + w (dry winter), f (no dry season), s (dry summer), l l a (hot summer), b (warm summer), c (cold summer), and d (very cold winter); E (polar) + T (tundra) and F (eternal frost (ice cap)). **Land Cover: GI (Copernicus Global Land Cover):** F—forest, dec.—deciduous, broadleaf. **Land cover: EU (CORINE Land Cover):** Grass—natural grassland, Moor—moors and heathland, Rock—bare rocks, and Peat—peat bogs.

The data used to describe the landslide properties was retrieved from the following sources:

- Location and date: Literature (various sources, see Appendix A).
- Landslide type and trigger: From the reports describing the article or classified from the descriptions and images according to [6]. It should be noted that there can be uncertainty associated with both the classification of landslide types, given that these were not observed directly by the authors, and in determining triggers, especially if there were multiple triggers involved.
- Landslide size and aspect: The length and width of the largest landslide in the study area were measured, and the slope aspect was estimated manually.

For each set of coordinates in Figure 2, values from the following maps were extracted:

- Geology: Generalised Geology of the World, WMS V 1.3.0 [34].
- Climate zone: World Map of the Köppen-Geiger climate classification [35].
- Mean annual rainfall: WorldClim BIO Variables V1 [36].
- Land cover classification: CORINE [37] and Copernicus Global Land Cover [38].

As shown in Table 1, of the 30 events included in this report, the most common types were debris slides and debris flows, with eight in each category. Half of the events had rapid flow-type failure mechanisms. The next most frequent failure mechanism was sliding, including 10 events. The majority of the landslides were reported as rainfall-triggered (25/30), with the remaining being earthquake-triggered or unknown. In terms of size, 10 were less than 0.1 km³, and 12 were between 0.1 and 1 km³. The remaining eight events were between 1 and 5 km³. A total of 12 different climate classes were included, with seven case studies in tropical (A), 15 in temperate (C), six in continental, and two in polar (E) climates. For geology, 13 cases were located in sedimentary bedrock, five in volcanic, and four cases each had metamorphic, plutonic, or mixed sedimentary–volcanic terrain bedrock. The mean annual rainfall varied from 394 mm/yr in Kyrgyzstan (#21) to 4222 mm/yr in New Zealand (#14). The land cover types using the Copernicus Global Land Cover map included 15 cases in forest, 12 in herbaceous, cropland, or shrubs, two in urban areas, and one in snow/ice.

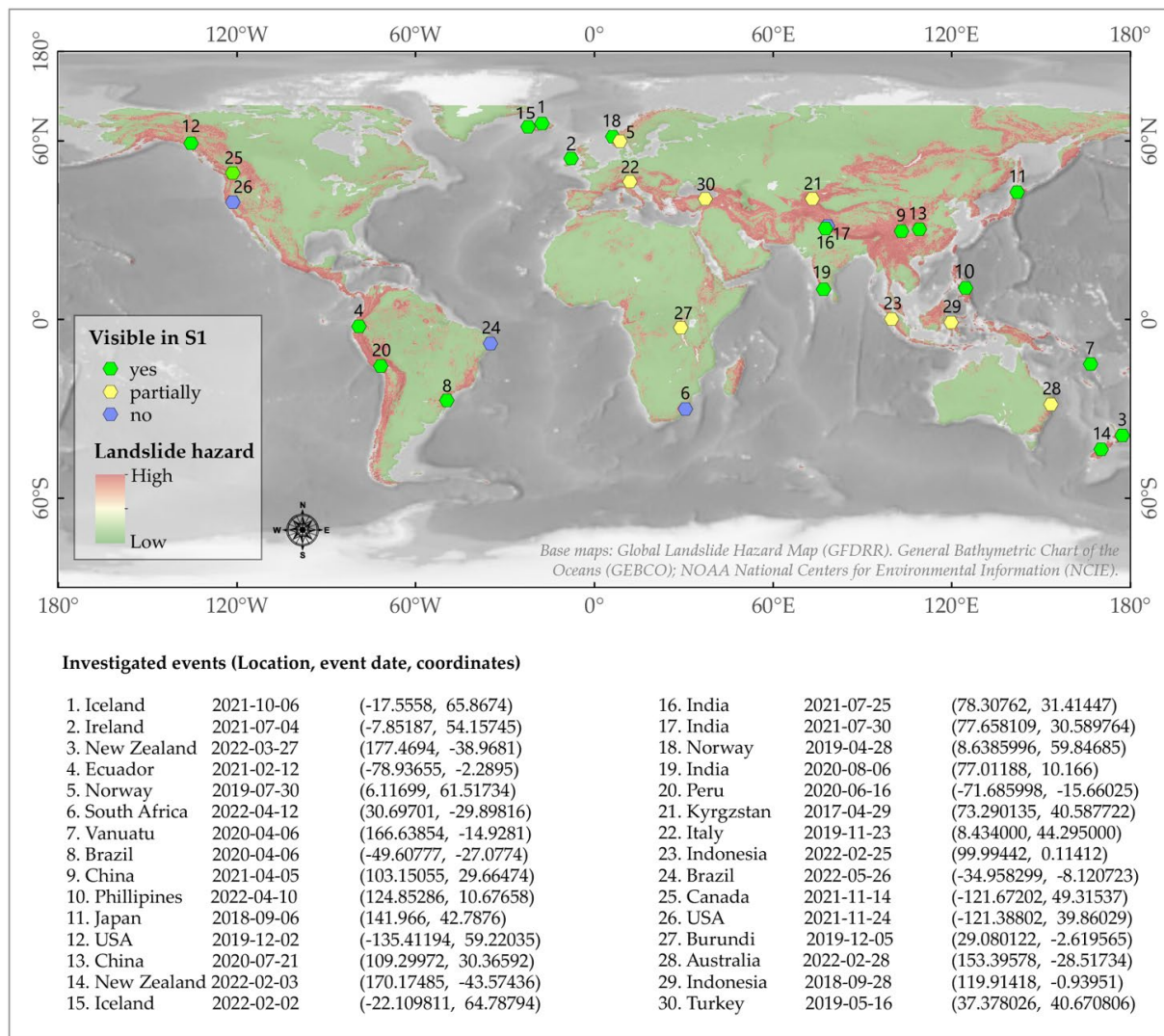


Figure 2. Map of study area locations and event dates (for events triggered over multiple days, only the last date is given). Base map: Landslide Hazard Map [39].

2.2. Image Processing

The input data, pre-processing, visualisation and interpretation methods are described in the following section. The script available from ref. [1] for reducing speckle noise was adapted for producing change images. Two approaches were used for two separate purposes using Google Earth Engine (GEE) [40]. These approaches are shown in Figure 3.

Sentinel-1 Level-1 Ground Range Detected (GRD) scenes pre-processed to backscatter coefficient (σ^0) in decibels (dB) were used. The Sentinel-1 images on GEE are available pre-processed (calibrated and ortho-corrected) in 10 m resolution [41]. Image stacks were produced by filtering for ascending or descending orbit pass, VV or VH receiver polarisation, and Interferometric Wide (IW) instrument swath mode. A terrain correction [42] was applied to each image in the stack using either a volumetric or a surface model, depending on the land cover type (volumetric was used for forested areas, surface for non-woody vegetation and bare surfaces). For most cases, the 30 m resolution Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) available within GEE was used. However, local DEMs were needed for the Icelandic case (link: https://gee-community-catalog.org/projects/iceland_dem/, accessed on 11 December 2022) and Norwegian cases (<https://www.kartverket.no/api-og-data/terrengdata>, accessed on 17 September 2025). The Sentinel-1 composites were created by taking the

median of the terrain-corrected image collections and change images (the post- minus the pre-event image composite) produced from these.

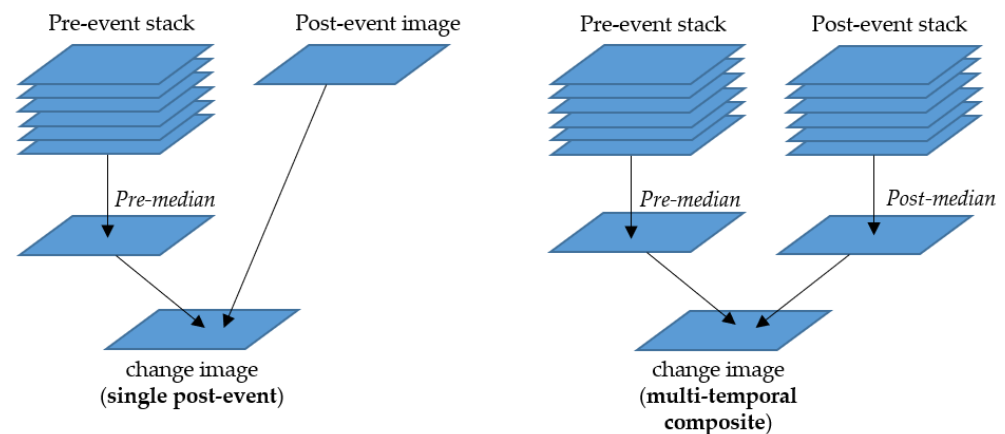


Figure 3. The two approaches for making change images used in this article. **Left:** Using a single post-event image for rapid detection. **Right:** Using multi-temporal median composites for the post-event image for identifying patterns in landslide expression. Median composites are used when practical to reduce speckle noise. The script is available at <https://github.com/erin-ntnu/Understanding-Landslide-Expression-in-SAR---change-images-in-GEE-.git> (accessed on 27 August 2025).

In addition, an alternative visualisation was used, which gives the viewer a more intuitive sense of the topography and can help to locate landslides in the terrain. This RGB composite visualisation is preferred for manual detection for this reason over the change images, which appear two-dimensional. The change images are preferred for showing absolute changes in intensity (dark blue as a decrease exceeding -10 dB, dark red as an increase exceeding 10 dB) and patterns in landslide expression and are expected to perform better in automatic detection models. An example of an SAR RGB composite is shown in Section 3.3 in the results from Lake Helin in Norway. The SAR RGB composite uses Pre-Post-Pre Sentinel-1 median composite images in the R-G-B bands, respectively. Strong changes associated with landslides may present as bright green (increased intensity) or dark purple (decreased intensity) [20].

For the multi-temporal composite change images, date ranges for the pre- and post-event image collections, and coordinates of the approximate event location were used as filter conditions to produce pre- and post-event image stacks of both Sentinel-1 GRD and Sentinel-2 (Level 2A) images. Time periods of one, two, or 12 months, either side of the event date, were used, depending on the local image acquisition frequency and seasonality. The date ranges and coordinate locations used for each case study (along with the change images produced) are provided in the Supplementary Materials. Pre- and post-event image composites were produced from the image stacks for a 4 km^2 area around the defined point. For rapid detection, the same method was followed, except only a single post-event image was used.

Sentinel-2 images (10 m resolution) were used for verification and manually digitising outlines of the landslides. Care was taken to accurately distinguish landslide signatures from other vegetation loss processes, including construction, deforestation, and agriculture, as well as seasonal changes in vegetation or snow cover. A Normalised Difference Vegetation Index (NDVI) band was added to each image in the pre- and post-event stacks, and then a greenest-pixel composite was created (maximum NDVI) using the quality-mosaic tool [43]. A difference in NDVI (dNDVI) image was produced (the post- minus the pre-event image composite). These are shown in Figure 4. The background high-resolution satellite images in GEE were used for further verification.

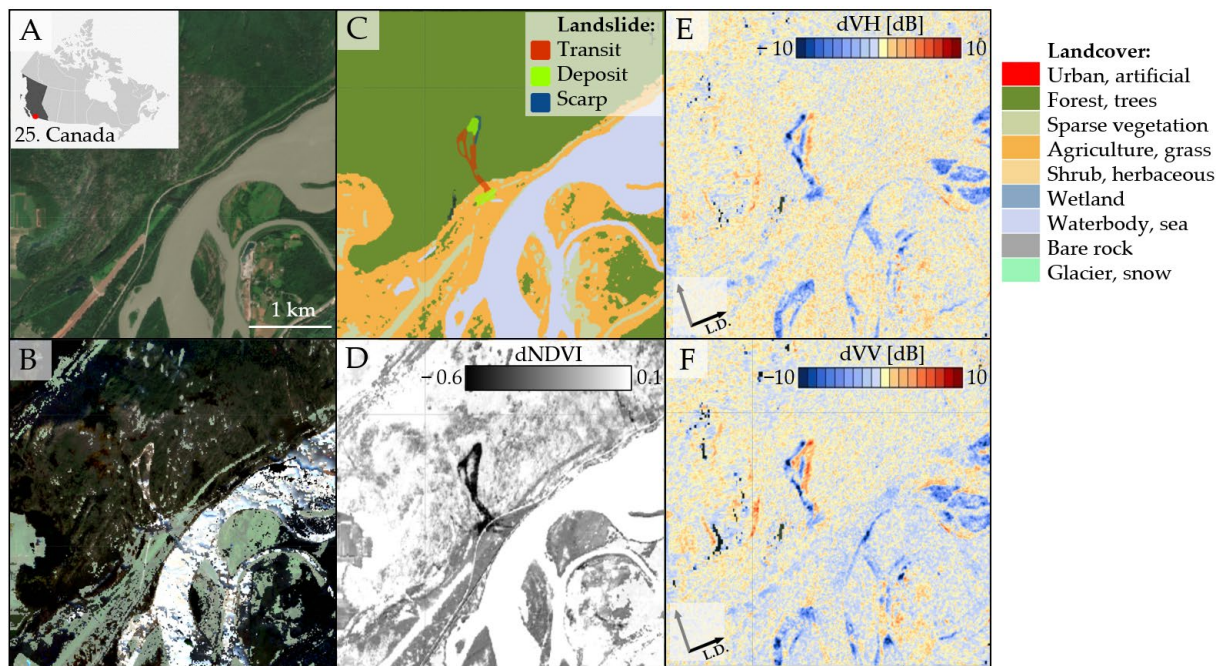


Figure 4. Input data for statistical analyses showing case study 25. Ruby Creek landslide, British Columbia, Canada (14 November 2021). Similar images are available for all case studies in the Supplementary Materials. Input images, including (A) Sentinel-2 pre-event least cloudy image; (B) Sentinel-2 post-event greenest-pixel composite; (C) pre-event land cover produced using a machine learning classifier, with pre-event Sentinel-1, -2, and DEM as input; (D) change in Normalised Difference Vegetation Index (dNDVI); (E) Sentinel-1 change in backscatter intensity (ascending VH); and (F) Sentinel-1 change in backscatter intensity (ascending VV).

For the land cover class, existing land cover maps (Copernicus Global Land Cover, CORINE, and Dynamic World) were first examined. These were deemed to be not of high enough accuracy at the pixel level for statistical analyses. Therefore, we produced our own locally trained land cover maps. For each case study, a machine learning-based land cover classification was performed using the ee.smile. CART algorithm (Classification and Regression Tree) in GEE [44]. These were trained using a Sentinel-2 image with minimal cloud cover from before the event, along with the DEM, and pre-event Sentinel-1 composite images (VV and VH polarisation). The classifier was trained by manually selecting points within the following classes: ‘urban, artificial’; ‘forest, trees’; ‘scrub, herbaceous’; ‘pasture, grass’; ‘sparsely vegetated’; ‘water body, sea’; ‘wetland’; ‘bare rocks’; and ‘glacier, snow’. A minimum of 10 points was selected in each of the classes present. Then the images were sampled at the selected points, and the classifier was trained. The classification was thereafter performed over the entire area of interest, and the results were viewed. If the classification was not satisfactory (judged by visual comparison of the results with the higher resolution base satellite images), then additional training points were added, or input data was modified. The process was repeated until a satisfactory land cover map was achieved.

Finally, for each case study, the following data was exported: (1) landslide polygons; (2) Geotiff raster images, including the pre-processed Sentinel-1 bands from ascending and descending mode where available (preVV, postVV, dVV, preVH, postVH, and dVH) along a band of the land cover class. The pixel values within each of the landslide polygons were extracted to produce a dataset consisting of approximately 300,000 pixels. Using Seaborn (version 0.12.2), violin plots were produced to display the distribution of the data. The default settings were used [45,46].

2.3. Landslide Detection in SAR Images

Landslide detection was performed manually as described in [20], with a slight modification; ascending and descending images were not combined here, to avoid averaging out the strongest change signals that were not aligned in the different images. Landslides can be identified as clusters of pixels showing significant changes in backscatter intensity (and NDVI) that can be differentiated from the surrounding undisturbed areas. The shape of the pixel clusters depends on the type of landslides; flow types and slides are usually elongated in the downslope direction, possibly with a clear deposit area, while rotational landslides may show clusters of strong change that are elongated across the slope, representing the appearance of a scarp. Whether landslides can be differentiated from surrounding undisturbed areas depends on whether other changes occurred in the same period, including changes in snow cover, seasonal changes in vegetation, agricultural activities, or saturation of soil. If landslides were not visible using images from within one month before and after the event, alternative date ranges were tested (usually summer months before and after the event) to see if the landslide signal was obscured by other seasonal changes.

Depending on the information available about the selected case studies (see Appendix A), the landslide location was either known precisely with coordinates or only approximately (e.g., along a highway between two towns). In the latter cases, a larger buffer region was used. For each investigated landslide, Sentinel-1 and Sentinel-2 change images were produced as described in Section 2.2. The SAR RGB composites (from both ascending and descending modes where available) were examined first to assess whether the landslide was clearly visible using only Sentinel-1. Next, Sentinel-2 dNDVI and RGB images—and, in some cases, with smaller landslides, Planet images, or the high-resolution satellite base map from Google Earth Engine—were inspected to verify detections and digitise landslide outlines (see Figure 4D). Finally, the visibility of each landslide was classified following [19] into three sets: Set 1—not visible; Set 2—partially visible, recognisable only with prior knowledge of the location; and Set 3—clearly visible.

2.4. Identifying Patterns: Qualitative and Quantitative Analyses

After the landslides were detected, further analysis of the absolute changes and identification of patterns in landslide expression was undertaken using the absolute (multi-temporal median composite) change images, dVV and dVH [19]. Patterns in landslide expression were identified gradually throughout the study, as case studies were investigated in detail.

For landslides that were visible (Sets 2 or 3), time series plots were produced for the point within the landslide (scarp, transit, or deposit area) that showed the strongest change. From these points, 30 m² square polygons were generated using a buffer function, and five years of terrain-corrected S1 time series data, with median backscatter intensity [dB] for ascending VV and VH, and descending VV and VH, were exported. The purpose of extracting and analysing the time series data was to determine the local seasonality due to snow cover or changes in vegetation, in order to understand whether the periods being compared in the change images were ‘temporally homogenous’. If not, then the changes in the images could not be assumed to be related to the landslide. Furthermore, we were interested in inspecting the values of backscatter intensity within the pre- and post-event periods in which the median composites were created, to see if there was significant variation within those periods.

Next, in order to investigate the factors that influence the expression of landslides in the change images, plots of land cover class and backscatter intensity values were made. This involved manually mapping the landslide polygons for each case study, exporting the Shapefiles along with Geotiff raster images for each case study, and finally extracting

and plotting the pixel values from within the polygons. Where possible, landslides were mapped according to morphometric feature class (scarp, transit, or deposit zone). Additional ground-based or drone images (from internet searches or journal articles) showing the shape of the landslide were used to identify these separate features, although there remained uncertainty in the exact boundaries. If no additional information was available to identify the morphometric features, then the entire landslide body was mapped in the transit zone class as the default, as this includes both erosion and deposition.

2.5. Theory Review and Conceptual Model

As patterns in landslide expression emerged during the investigation period, a literature review and discussion with experts (see acknowledgements) were conducted iteratively to understand the physical explanation behind the observed patterns. The literature review included journal articles and textbooks on fundamental SAR backscatter theory and multidisciplinary applications of change detection, including forestry, geomorphology, and agriculture. The findings are illustrated in the conceptual model. This was produced based on cross sections taken from representative examples to show patterns of increased and decreased intensity due to landslides, according to the physical changes to the ground surface.

2.6. Application to Disasters

The previous methods were applied to manually detect landslides in three disasters using the first available Sentinel-1 post-event image. The events included landslides triggered by the Turkey earthquakes (2023), Cyclone Gabrielle in New Zealand (2023), and the ‘Hans’ storm in southern Norway (2023), see Table 2. This was conducted without prior knowledge of landslide locations and with no optical imagery available for confirmation (initially). Background information was used where available to target areas where landslides were more likely to be found, including terrain data, high-resolution base optical images (pre-event), landslide susceptibility maps, and rainfall data. These areas were searched semi-systematically until signs of possible landslides were detected. The potential landslides or areas of interest were marked with points or polygons and then revisited when optical imagery became available for verification.

Table 2. Recent disaster events were investigated using the first available Sentinel-1 images prior to optical images becoming available.

Landslide			Images		Environment			Set	
Location	T	Event Date	1st S1 Image	1st Cloud-Free S2 Image	Geology	K.G. Climate	Rainfall [mm/yr]	Land Cover GI	
Turkey	E	2023-02-06	2023-02-09	2023-02-09	S-V	Cfa/Dsb	~800	Mixed	1
N. Zealand	R	2023-02-12/16	2023-02-14	2023-02-17	S	Cfb	1358	F Needle	2
Norway	R	2023-08-07/09	2023-08-10	2023-09-07	V	Dfc	861	F Broadleaf	3

Acronyms: Trigger (T): R—rainfall, E—earthquake. **Geology:** S—mainly sedimentary terrain, S-V—mixed sedimentary–volcanic terrain, and V—mainly volcanic terrain. **K.G. Climate zone:** C (temperate), f (no dry season), l a (hot summer), b (warm summer); D (continental), f (no dry season), s (dry summer), l l b (warm summer), and c (cold summer); **Land Cover: GI (Copernicus Global Land Cover):** F—forest. **Set:** 1—no LS detected, 2—LS detected with low confidence, and 3—LS detected with high confidence.

3. Results

This section presents the patterns of landslide expression observed in SAR backscatter intensity change images and the controlling factors identified in the literature review, followed by insights from applying the methods to identify new landslides in recent disasters. Landslides selected from the 30 case studies analysed that best represent the identified patterns are also shown. Change detection images and time series data for these landslides are presented in the following sections.

3.1. Patterns Identified

3.1.1. Comparison of Single vs. Multi-Temporal Composite Post-Event Images

The landslides presented in the following section, are introduced first with context images in Figure 5. More images and contextual information about each individual case study can be accessed with the links provided in Appendix A, and in the Electronic Supplements.

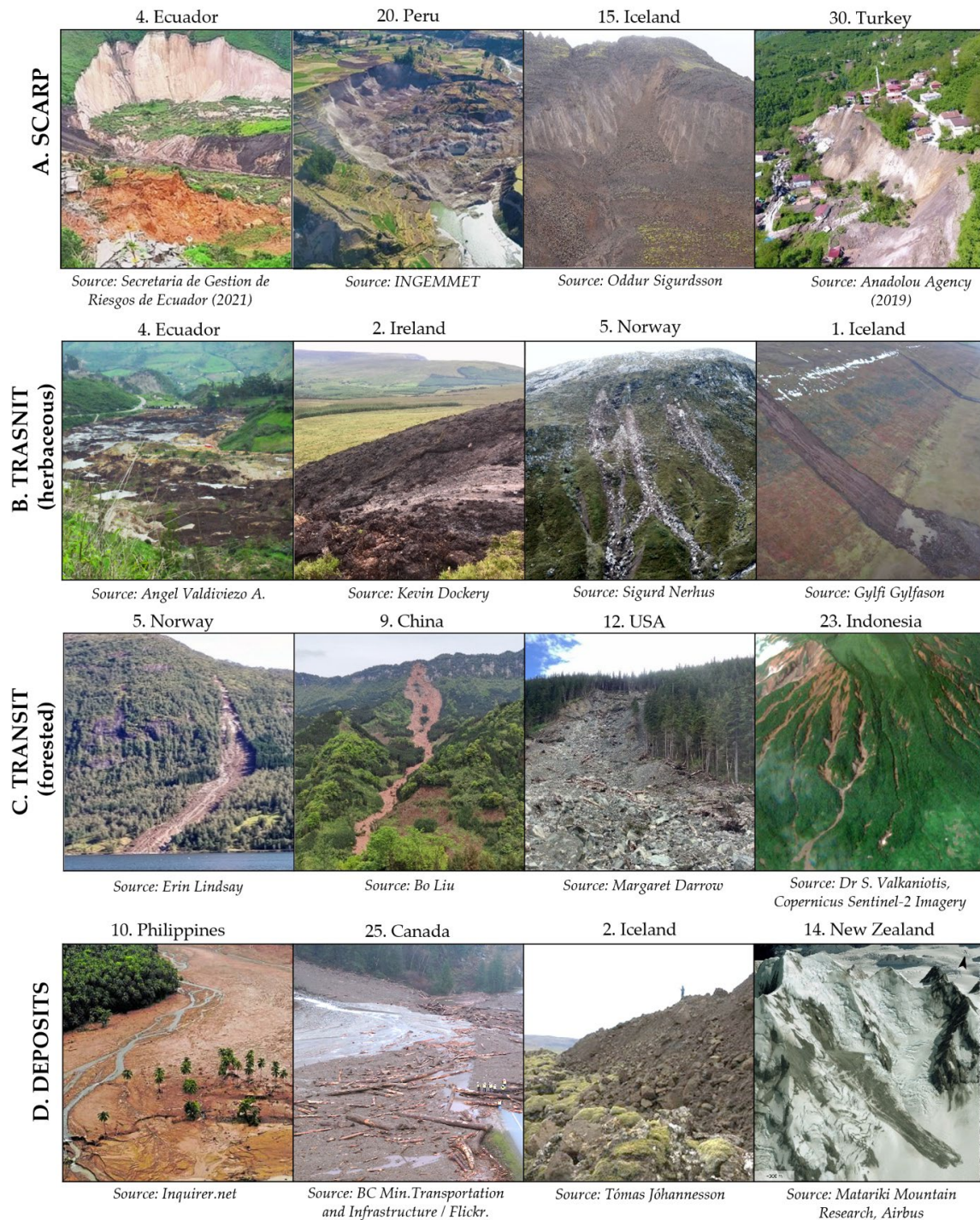


Figure 5. Context images corresponding to the landslides are presented with change images and time series shown in subsequent figures, grouped according to similar morphology or environmental settings. (A) Includes landslides with prominent back scarps, (B) landslides in herbaceous vegetation, (C) landslides in forested areas, and (D) landslides where the deposits were either smooth (mud or silt deposits, Philippines and Canada) or rough (rock avalanche deposits, Iceland and New Zealand).

Figures 6 and 7 show the difference in the two image processing approaches for creating SAR change post-event images for a selection of landslides using a multi-temporal median composite for the pre-event image, together with, firstly, a single (earliest possible) post-event image (Figure 6) and, secondly, a multi-temporal (at least one month of images post-event) median composite image (Figure 7). Visual comparison of the two approaches shows that background noise is reduced when using the post-event median composites, relative to a single post-event image, especially for those affected by seasonal changes related to autumn vegetation loss and changes in snow cover (e.g., 5. Norway, 12. USA, and 14. New Zealand).

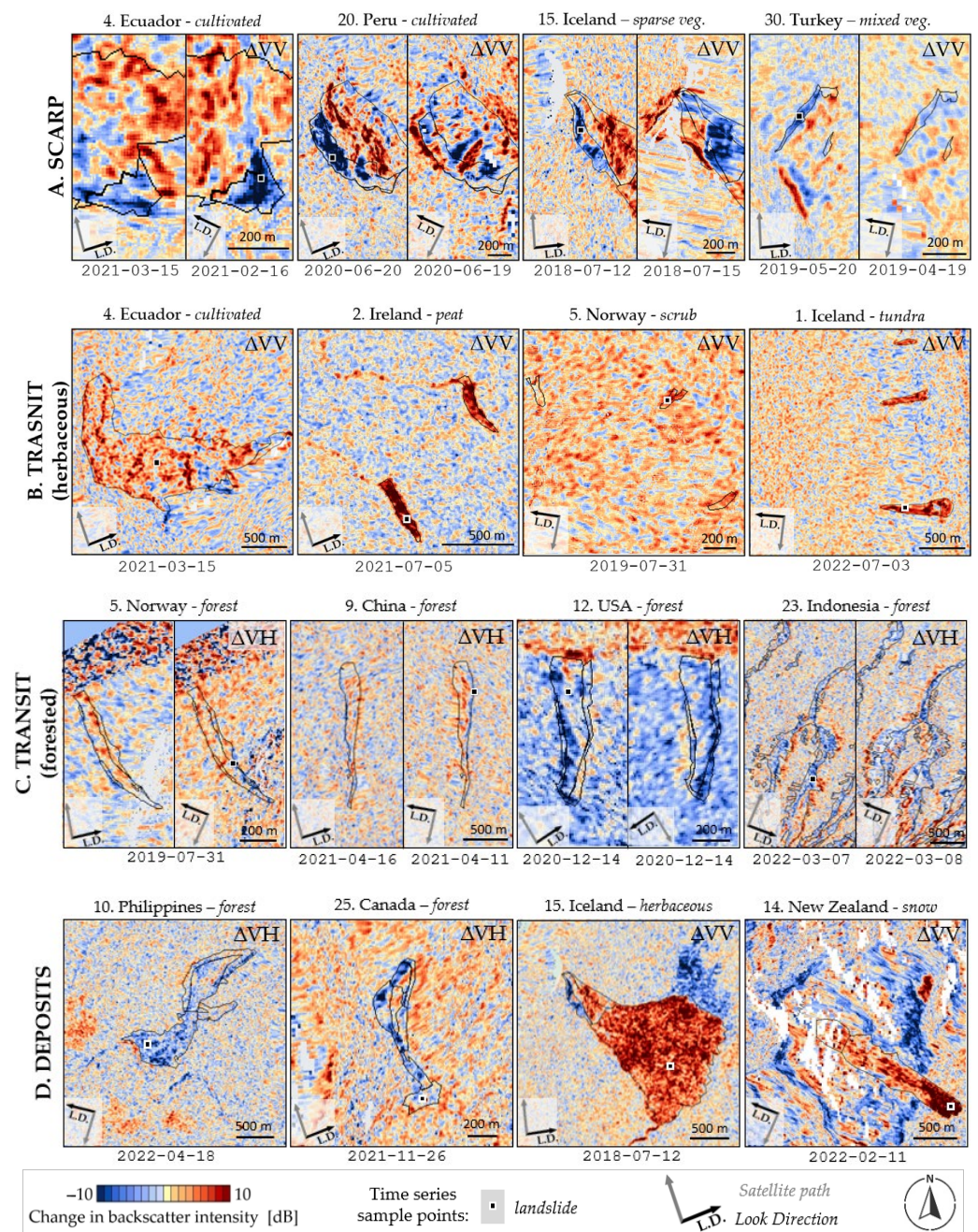


Figure 6. Change images with a single post-event image. The backscatter intensity change images are produced from pre-event median composites (from stacks consisting of 1 to 12 months of images, see Appendix A for details) of terrain-corrected Sentinel-1 SAR images and the first available post-event image (note: date label shows image date, not event date). Centre coordinates and dates of the landslides are provided in Figure 2. The black outlines were mapped from optical images, with scarp, transit, and deposit zones mapped separately.

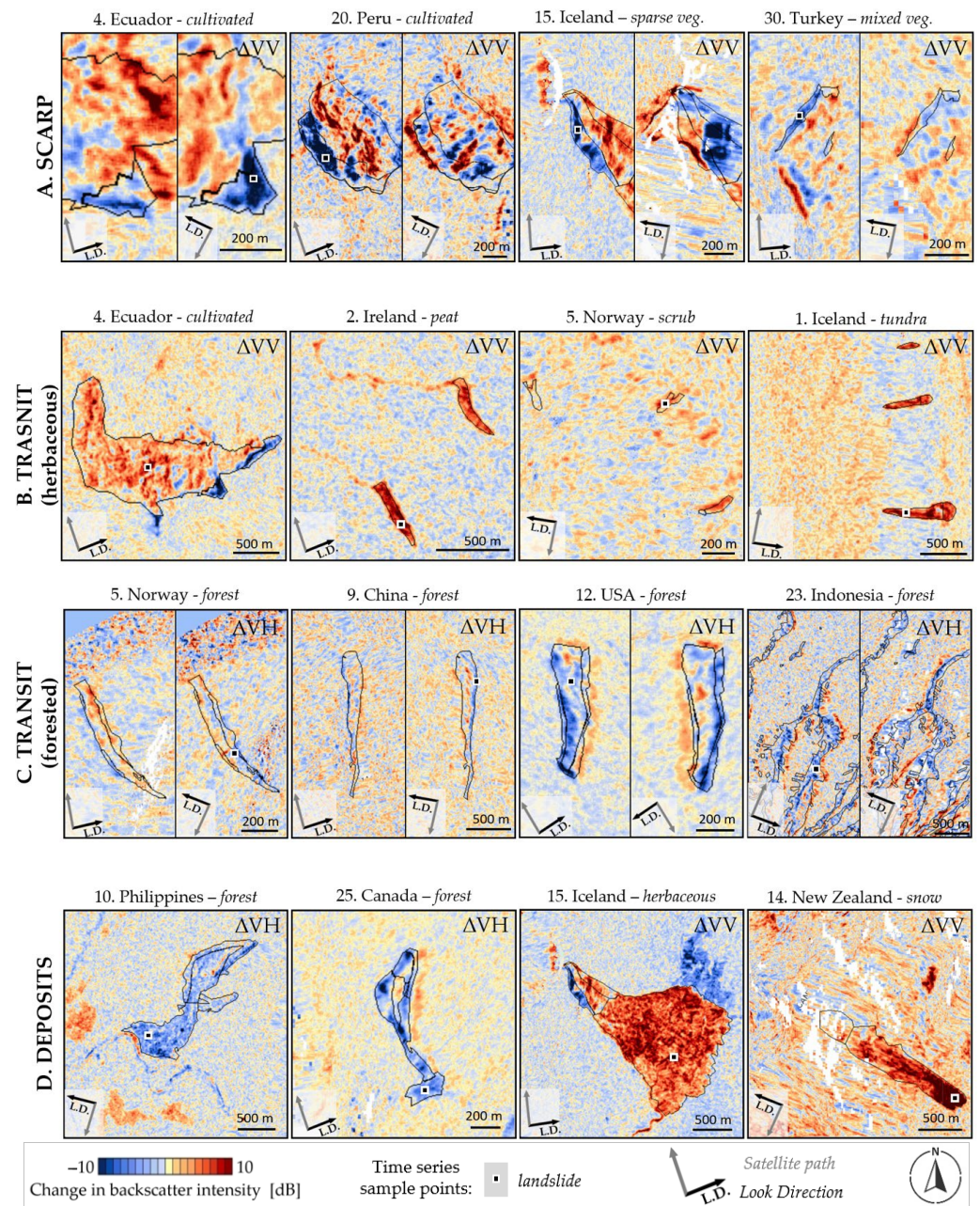


Figure 7. Change images with a multi-temporal composite post-event image. The change images are produced from pre- and post-event median composites (from stacks consisting of 1 to 12 months of images, see Appendix A for details) of terrain-corrected Sentinel-1 SAR images. A selection of landslides is presented, demonstrating the patterns identified during systematic mapping of landslides in all 30 case studies shown in Figure 2. Centre coordinates and dates of the landslides are provided in Figure 2. The black outlines were mapped from optical images, with scarp, transit, and deposit zones mapped separately.

This article focuses firstly on identifying patterns that landslides produce in change images in different conditions. Therefore, the median composite change images in Figure 7 were used for the pattern identification and in developing the conceptual model, as the signal-to-noise ratio is reduced, and it is easier to identify the patterns in landslide expression. However, despite the increased noise with only a single post-event image, in most of the illustrated cases, the landslide signal is still visible, and in a few cases, an even stronger change signal is seen (e.g., 2. Ireland). In practice, change images using the first available post-event image would be used for rapid landslide identification after a triggering event.

Therefore, the second approach was used for manually detecting previously unknown landslides in recent disaster situations, as presented in Section 4.3.

3.1.2. Patterns in Landslide Expression

Through systematic mapping, over 1000 landslides were digitised and qualitatively and quantitatively analysed from the 30 case studies. During this process, we identified predictable patterns in the expression of landslides in SAR backscatter change images related to the different morphometric features of the landslides (scarp, transit zone, and deposit zone) and land cover type, see Figure 7. A generalised conceptual model illustrating the following four observed patterns is also shown in Section 4.2.2. These include the following:

- **(A) Scarp:** The expression of lateral and back scarps varied depending on the sensor look direction, with scarps angled away from the sensor look direction producing an abrupt decrease in backscatter intensity in both dVV and dVH images, while scarps facing towards the sensor produced slightly to moderately increased backscatter intensity. In some cases (seen quite clearly in case 20 in Peru), an edge of increased backscatter intensity was also observed slightly behind the scarp on the far side of the landslide from the sensor. Rock fall scarps were not clearly distinguishable in the cases we examined.
- **(B) Transit zone in herbaceous vegetation:** The most easily distinguishable landslides were those that occurred in herbaceous vegetation. These cases showed moderate to strong increases in backscatter intensity that correlated well with the observed position of the landslide from optical images. Very clear examples were obtained from within the tundra in Iceland and the peatland in Ireland. Less clear examples were observed in the grassland in New Zealand, where the small size of the landslides and geometric distortions, due to the rugged terrain, limited the visibility of the landslides in the Sentinel-1 images.
- **(C) Transit zone in forested area:** A more complex, but quite distinct, pattern of backscatter intensity change was observed in most of the landslides that occurred in forested areas, which is seen most clearly in VH polarisation. As with the scarps, the pattern depends on the look direction of the sensor. For the cases shown in Figure 7 (including cases 5, 9, 10, 12, 23, and 25), it can be seen that moving away from the sensor, there is a sequence with first decreased backscatter intensity along the edge of the landslide closest to the sensor, and increased backscatter intensity on the far edge of the landslide. The best example of this was seen in case 12 from Haines, Alaska (USA), where the landslide occurred on a north-facing slope where the signal was not significantly affected by geometric distortions. For wider landslides, there may be a zone with moderately increased or decreased backscatter intensity in the centre of the transit zone, as seen in case 12.
- **(D) Deposits:** In most of the cases we observed, deposits were observable by a moderately to strongly increased backscatter intensity (in VV polarisation) as seen in cases 2 and 14, which show rock avalanche deposits in Iceland and New Zealand. Although in some specific cases, the deposits were observable by areas of decreased backscatter intensity, as illustrated in cases 10 and 25, which show a mudflow in the Philippines and a debris flow in Canada.

3.1.3. Time Series Plots Showing Magnitude of Change and Seasonal Variations

A five-year time series of terrain-corrected Sentinel-1 data was extracted from points manually selected within the landslides showing strong change. The time series are presented in Figure 8, and the locations that they were extracted from are shown in Figure 6,

indicated by the black squares. The time periods were selected to show approximately three years before and two years after the landslides, so that the change due to landslides could be observed in relation to the seasonal changes in the pre- and post-event land cover.

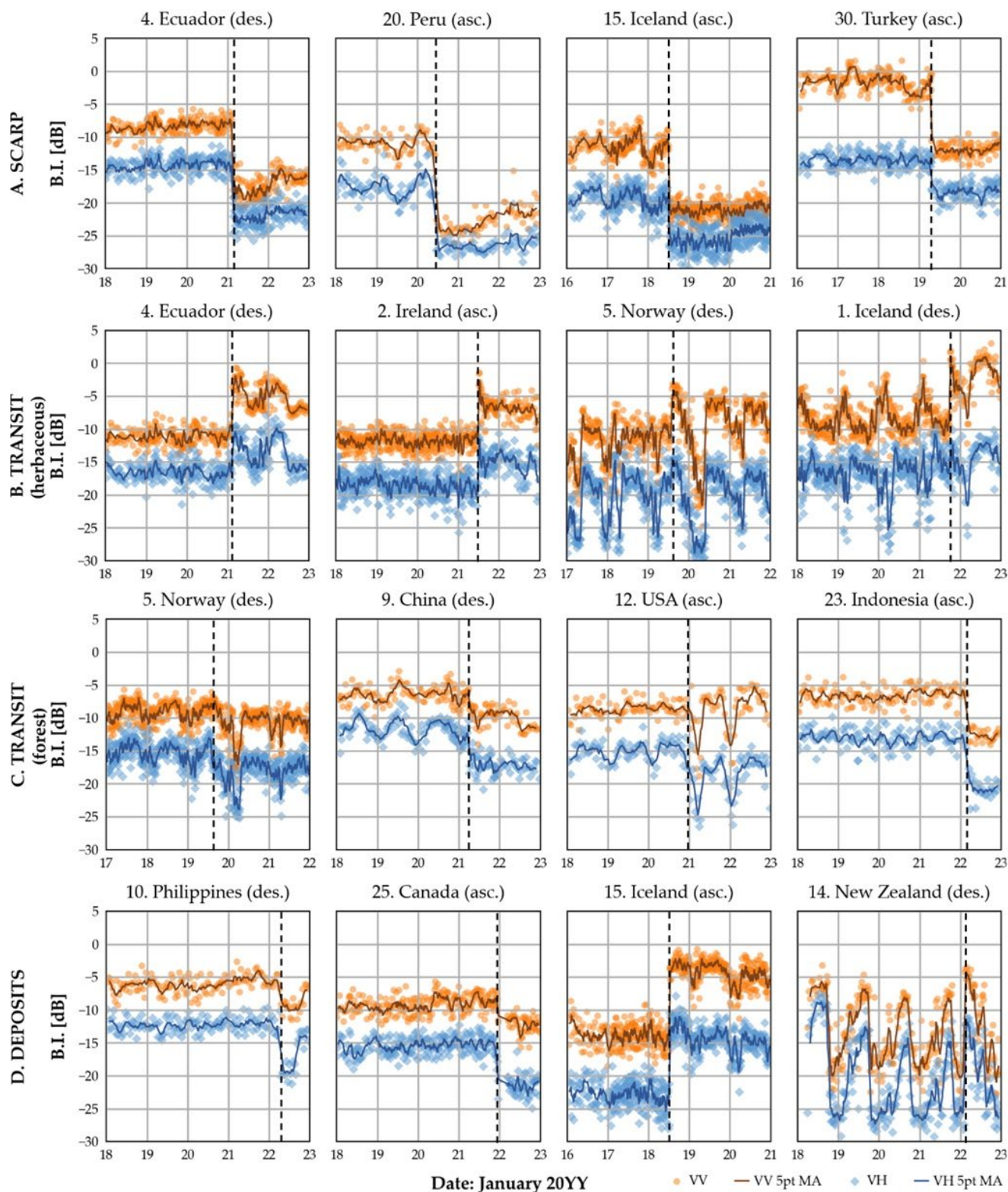


Figure 8. Five-year time series plots of mean backscatter intensity in VV and VH polarisation, sampled from a 30×30 m patch within the landslide body. The location of the sample patches is shown in Figure 7. Landslides can be observed by an abrupt break in the seasonal cycle of backscatter intensity. The black dashed lines show when the landslide occurred. Event dates for each case are provided in Figure 2.

- **(A) Scarp:** The time series plots taken from the scarps show strong decreases, particularly in VV polarised data, with magnitudes of 7 to 12 [dB].
- **(B) Transit zone in herbaceous vegetation:** The time series plots show strong increases in backscatter intensity, most clearly seen in VV polarised data, in the order of 7 to 10 dB.
- **(C) Transit zone in forested area:** Although the landslides in forested areas show both decreases and increases in backscatter intensity, the strongest changes were associated with the decrease in the edge closest to the sensor. The decreases shown in the time series plots are around 4 to 8 dB.
- **(D) Deposits:** Cases 10 and 25 from the Philippines and Canada occurred in forested areas and had flat deposits, showing decreases in backscatter intensity of around 6 to 8 dB in VH. Conversely, cases 15 and 14, which occurred in Iceland and New Zealand in the tundra and on a glacier, showed very strong increases of around 13 to 18 dB in VV.

The case studies presented represent a wide range of climatic conditions and land cover types. The time series from locations with tropical climates show relatively stable values, those with seasonal changes in vegetation show moderate variation, and those from alpine or polar regions show strong seasonal variations associated with snow cover. In some cases, seasonal variation appears to decrease following the landslide, while in others it increases. In general, for vegetated areas, the backscatter intensity is higher in summer and lower in winter. While in tropical areas, the backscatter intensity is relatively constant throughout the year, and in sub-polar or alpine regions, winter snowfalls produce strong decreases (in the order of 10 to 20 dB) in intensity. In most cases, the change due to landslides appears unambiguous, and a clear difference in the seasonal cycle is observable. However, in cases with seasonal snow cover (e.g., 5B. Norway, 1B. Iceland, and 14D. New Zealand), the changes due to landslides are of a lower magnitude than the change due to snow cover change, and therefore less clear.

Most of the inter-annual variability in the pre- and post-event seasonal cycles is likely caused by fluctuations in moisture content. Although we do not have access to soil moisture measurements to confirm this, some trends can be inferred. The effect of moisture content is seen most clearly in case 14 from a high alpine environment in New Zealand (Mt Tasman, approx. 2500 m a.s.l.). Here, in spring at the onset of snowmelt, the backscatter intensity drops abruptly, with a magnitude of approximately 15 dB. In several cases, in the transit and deposit zones, it is seen that following the initial change in backscatter intensity, there is a period over several weeks where the backscatter intensity decreases slightly. This is seen in cases 4, 2, and 5 in the herbaceous transit zone, and in 23 in the forested transit zone. It is possible that this pattern is due to decreasing moisture content after the rainfall triggered landslides. In contrast, the values increase in the deposit zone in case 15 in Iceland.

The cases presented show some of the clearest examples. In other cases, which can be viewed in the Supplementary Materials, particularly case 21 from Kyrgyzstan, changes in snow cover around the time of landslide occurrence in spring made it difficult to minimise background noise. For case 12 from Alaska, USA (shown), the landslide occurred in December, and it was unclear if the changes in the time series were due to the landslide, snow cover, or both.

3.1.4. Violin Plots Showing Values of Pre- and Post-Event Land Cover

Figure 9 shows the distribution of pixel values within the mapped landslide polygons according to land cover class, for pre-event values and the change in backscatter intensity. The pre-event backscatter intensity values have a combined median of -9.9 and -17.6 dB for VV and VH, respectively. Urban and forest land cover classes have slightly higher initial

values relative to the median in VV and VH polarisations, while wetland and water bodies have slightly lower values in both. In VH, non-vegetated land cover types, including bare rocks and snow, also show values lower than the median.

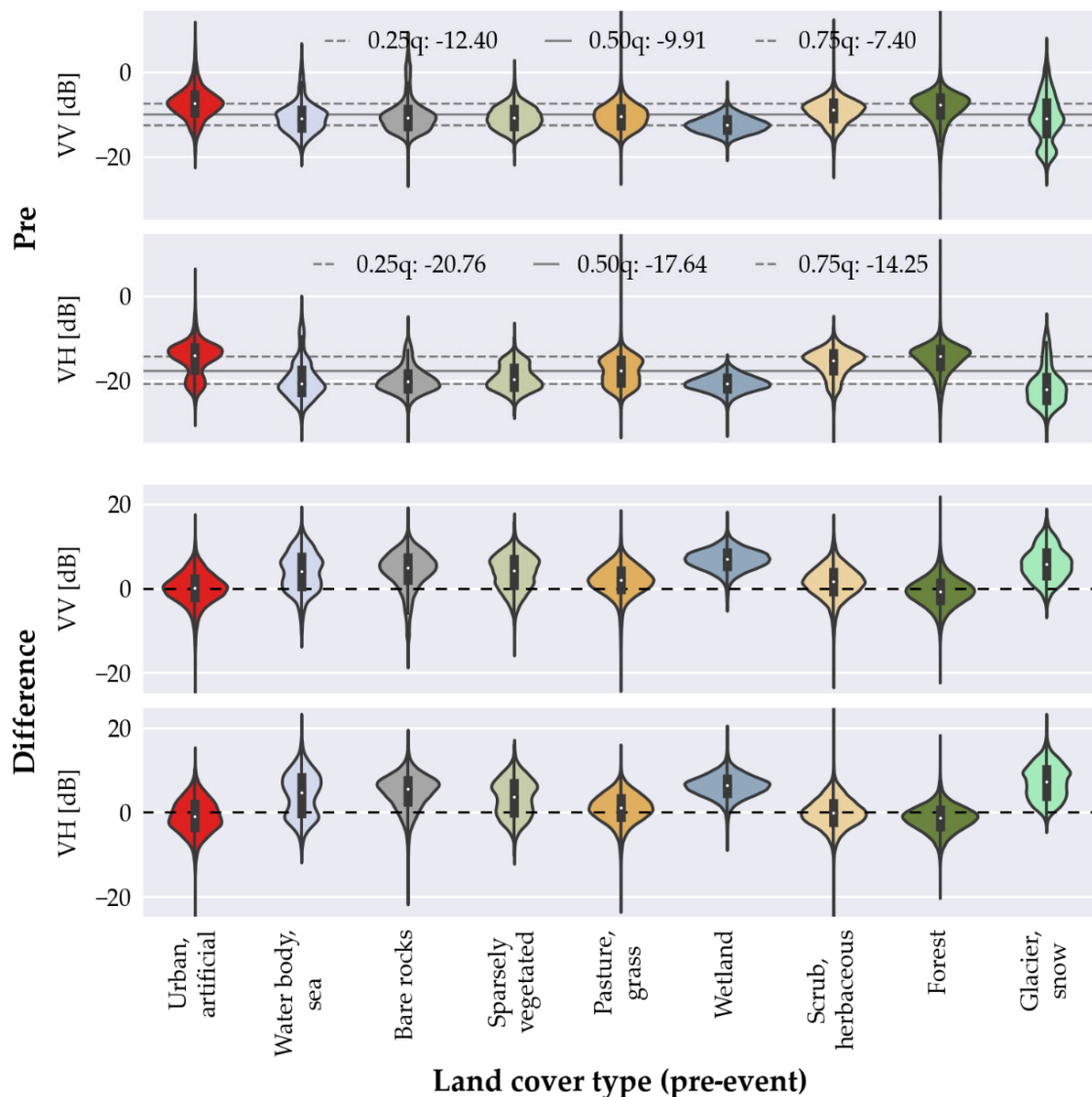


Figure 9. Distribution of sampled pixel values within mapped landslides from the pre-event and difference images, shown as violin plots with boxplots and kernel distribution. The upper and lower quartiles and the median are indicated by the black box plot with a central white dot. These are separated according to pre-event land cover types and polarisation.

The differences in backscatter intensity are mostly positive, except for pixels within the forest class, which show a mean decrease of -2 dB in both VV and VH polarisation. The strongest increases are observed for landslides that occurred in wetland and snow with average difference values of ~ 4 dB. Slightly negative changes are also seen for scrub and urban land cover classes in VH polarisation.

Figure 10 shows the increasing backscatter intensity of deposits from four cases. Post-event deposits show variation depending on the material, with a variation between the medians of 4 dB. The backscatter intensity increases with increasing material size (10. mainly fines, 5. mixed fine and coarse, 9. mixed with vegetation debris, and 11. rock and boulders). Note that the deposits in cases 5, 10, and 11 occurred mainly on flat or shallowly sloping

areas, while those in 14 are from a slope with a lower incidence angle; therefore, the values may be slightly higher due to this.

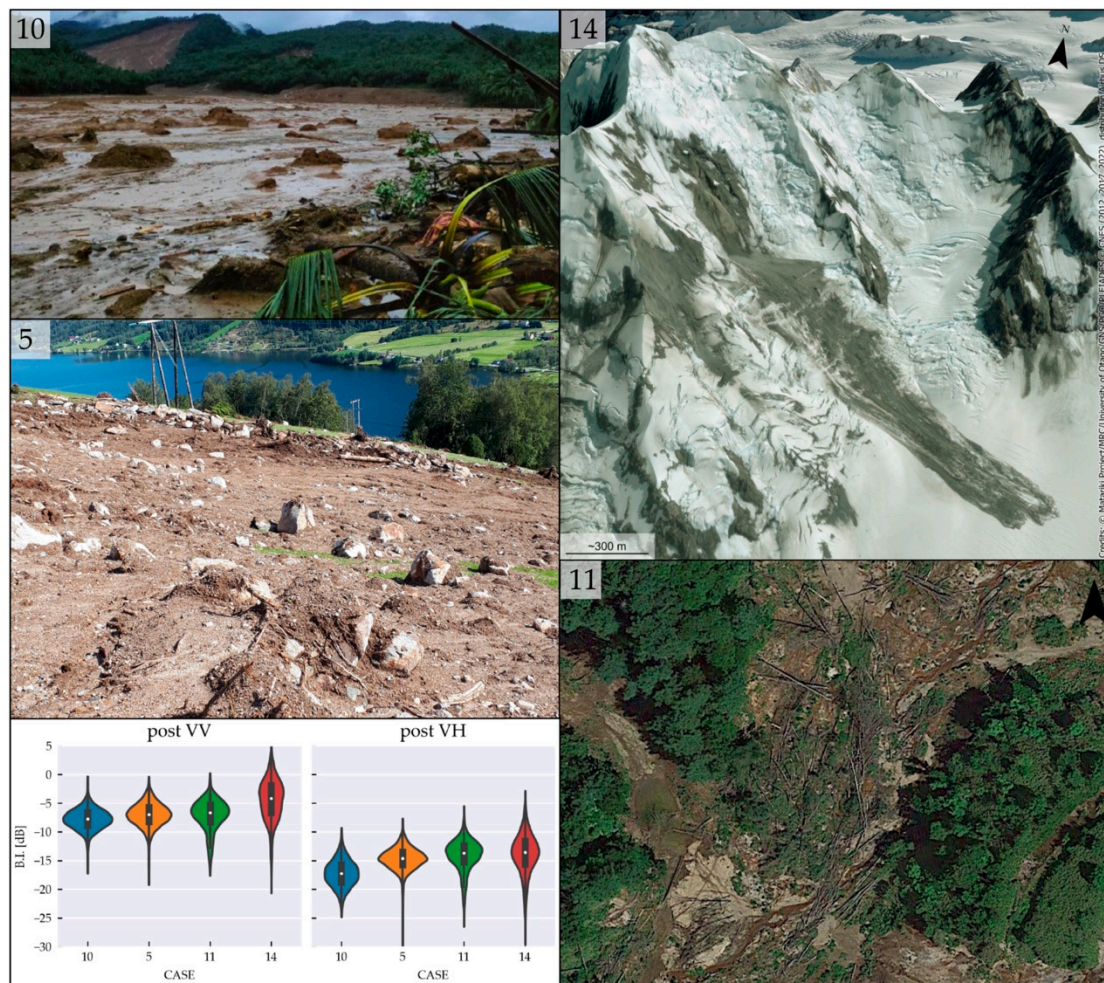


Figure 10. Different deposit material types and the distribution of the pixel values from the four different case studies are shown. These include smooth, flat deposits from mudflow near Baybay City, Philippines (10) (source: Philippines Coast Guard, AP); a mixture of soil and rocks in a debris flow deposit in Vassenden, Norway (5); rock avalanche deposits at Mt Tasman, New Zealand (14) (© Matariki Project/MRC/University of Otago/GNS/PGO/PLEIADES © CNES (2022), distribution Airbus DS); and (11) forest debris from landslides in Hokkaido, Japan (© Maxar (2018)). Bottom left: Violin plots of post-event backscatter intensity distribution from the different deposit material types. The upper and lower quartiles and the median are indicated by the black box plot with a central white dot.

In the contextual photos in Figure 5, it is shown that the deposits with decreased backscatter intensity relate to cases where fine sediments settled from still water caused by drainage blockage, whereas those showing increased backscatter intensity appear to relate to deposits consisting of coarser materials inferred to be deposited more rapidly from the turbulent landslide flow.

3.2. Controlling Factors Identified

The main factors affecting landslide detectability and expression discussed in this section are summarised in Table 3. This study investigates the effects of the landslide characteristics and surrounding environment, while the sensor properties and image pre-processing remained fixed (with the exception of ‘volumetric’ or ‘surface’ models used in the terrain correction, depending on land cover type).

Table 3. Factors affecting landslide detectability and expression in SAR change images.

Landslide Characteristics	Surrounding Environment	Sensor Properties	Image Processing
• Type and morphology • Size • Material (fine, coarse) • Vegetation preserved, relocated, or removed	• Land cover type(s) • Seasonal variability • Terrain ruggedness, geomorphology • Slope aspect and angle • Moisture content of soil or vegetation • Presence of snow • Anthropogenic activities	• Image resolution • Wavelength • Polarisation (VV, VH) • Orbit direction (ascending, descending) • Look angle • Instrument mode • Revisit frequency	• Calibration • Ortho-correction • Correction of geometric distortions • Noise filtering

3.2.1. Literature Review: SAR Backscatter Theory Applied to Landslides, Controlling Factors

The following section presents the factors considered relevant to controlling the expression of landslides in SAR backscatter images, identified through the multidisciplinary literature review and synthesised to apply specifically to landslides. Along with the observed patterns described above, these results form the basis for the conceptual model presented in the following section.

Changes to the ground surface caused by landslide erosion and deposition may change the surface roughness and dielectric properties of the ground surface and thus the intensity of backscatter. This information can be used to detect and map landslides. Several factors that can affect the visibility and expression of landslides in SAR backscatter intensity data are illustrated and described in this section. These include radar properties (wavelength (λ), polarisation and incidence angle), and surface properties (terrain elevation and geometric distortions, local incidence angle (LIA), roughness (relative to λ), and land cover type) [47]. Seasonal variations in vegetation or snow cover, and changes in moisture content, can also affect the backscatter intensity.

- (A) **Terrain and geometric distortions:** In Figure 11A, it is shown how the position of a landslide in the terrain relative to the sensor determines whether the landslide signal will be affected by geometric distortions (including layover, shadow and foreshortening). It is seen that Landslide-I would be visible to the sensor; however, it would be distorted due to layover, while Landslide-II would not be visible to the sensor, as it is in the shadow zone. The distortion of Landslide-I can be corrected with a terrain correction, while the distortion of Landslide-II can be detected if images from both ascending and descending orbits are available.
- (B) **Local Incidence Angle (LIA):** In Figure 11B, the effect of the orientation of the landslide surface, relative to the sensor line of sight (LOS), is considered. Here, it is shown that the LIA affects the strength of the received backscatter signal, with surfaces with lower LIA generally returning stronger intensity signals than those with high LIA. The strength of the returned signal also depends on the ground surface properties, with surface scatters being more sensitive to the LIA than volumetric scatters.
- (C) **Wavelength:** Figure 11C illustrates how the wavelength of the sensor determines the height of irregularities (h [cm]) that the signal will be sensitive to, as well as the degree of penetration of vegetation and the elements of vegetation that the signal will interact with. Shorter wavelength signals (i.e., X- and C-band) are more sensitive to smaller changes in surface roughness (<5 cm) and are mainly reflected from the canopy. Longer wavelengths (i.e., L-band) are sensitive to larger-scale changes in roughness (>10 cm) and penetrate leaves, and thus are reflected from woody structures and the ground.

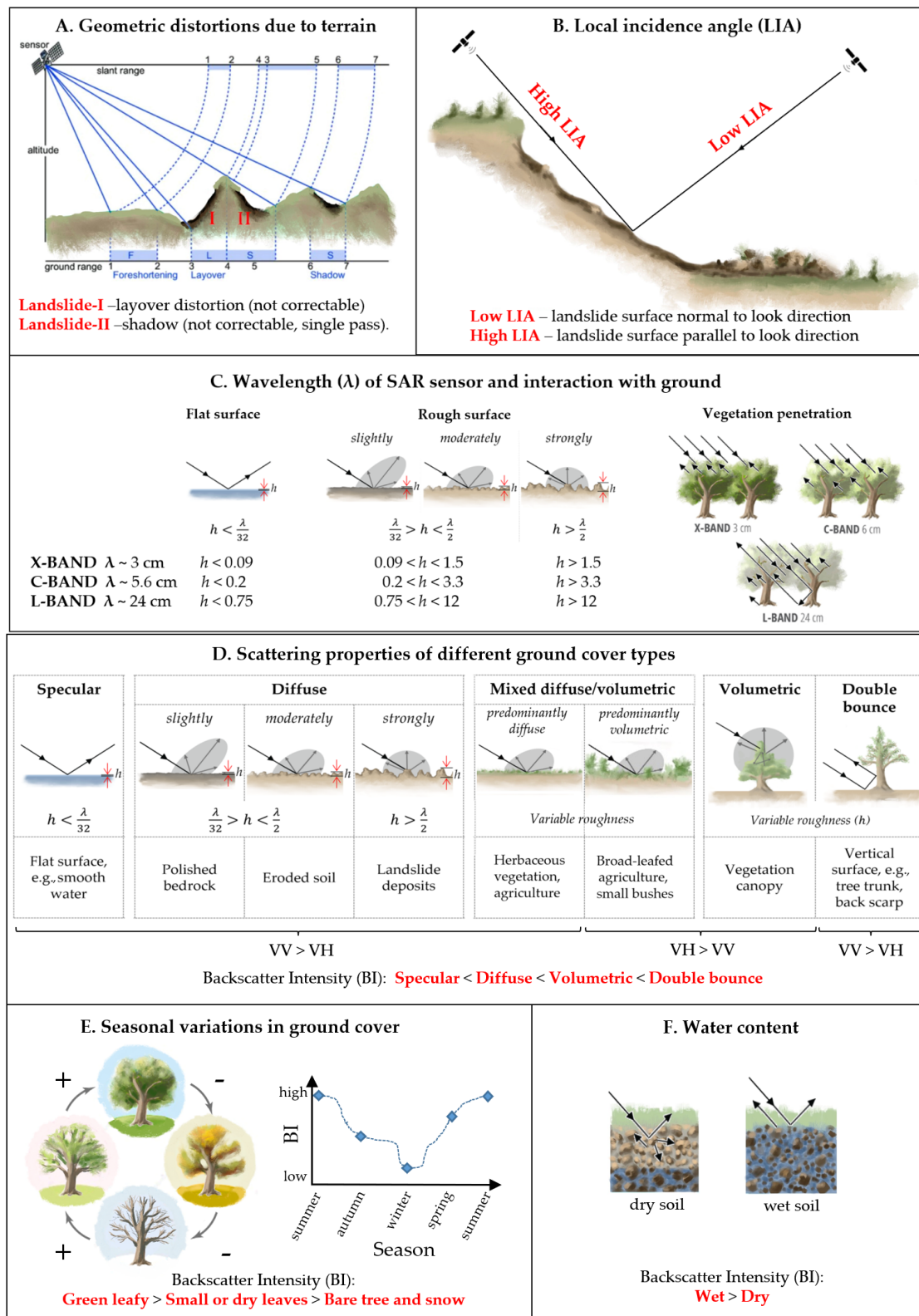


Figure 11. Factors affecting the expression of landslides in SAR data. These factors include the position of the landslide within the terrain relative to (A) terrain features, (B) the sensor line of sight (LOS), and (C) the wavelength of the SAR signal (λ). Modified from (A) [48], (B) [20], and (C) [49]. The roughness is relative to the wavelength, and h is the height of surface irregularities. The lower half shows factors that may vary over time. These factors include (D) the type of ground cover and associated scattering mechanisms, (E) seasonal variations in ground cover, including vegetation changes and snow cover, and (F) water content.

- (D) **Scattering mechanisms of different ground cover types:** In Figure 11D, different ground cover types and their associated scattering mechanisms are shown. Here we see that the intensity of the received backscatter increases with increasing surface roughness, with flat surfaces (e.g., still water or snow) with oblique LIAs reflecting the signal specularly in accordance with Snell's law [50]. As surface roughness increases, diffusivity increases, and more of the signal is reflected in all directions, including back towards the sensor. Co-polarised bands (e.g., VV) are more sensitive to variation in surface roughness. For volumetric scattering as occurs in vegetation, in C-band, the canopy provides a strongly reflective surface, with most of the energy received reflected volumetrically within the upper few cm of the canopy. Cross-polarised bands (e.g., VH) are more sensitive to variation in vegetation (volume scattering). For areas with mixed types of scatters, i.e., herbaceous vegetation, agriculture, or areas with both herbaceous and woody vegetation, the strength of the received signal depends on (i) the degree to which the signal penetrates the vegetation and (ii) the roughness of the underlying soil surface. For thin herbaceous vegetation (e.g., grass, peat, or low-biomass crops), the underlying surface roughness determines the intensity of the backscatter received, while for ground with predominantly volumetric scatterers (e.g., dense leafy crops, small bushes), the biomass of the vegetation will have a stronger effect on the intensity. Finally, double bounce scatterers (near-vertically inclined surfaces, e.g., cliffs or exposed tree trunks) produce the highest received backscatter intensity, and as surfaces, these features are most strongly observed in co-polarised bands.

It is the change between the different types of ground cover that determines the change in the observed intensity. For instance, a change from a volumetric scatterer (e.g., forest canopy) to a surface scatterer (e.g., soil surface) will result in a decrease in intensity, and the edges of the remaining forest may also produce radar shadow [51]. While for surfaces, an increase in roughness caused by deposition or erosion of the weathered soil surface will produce an increase in intensity.

- (E) **Seasonal variations in ground cover:** In Figure 11E, we see that for a given ground cover type, the intensity can vary significantly if there are strong seasonal variations. For instance, intensity is highest when the leafy canopy reflects the SAR signal volumetrically and is lower in autumn and spring when leaves are small or dry. Smooth snow reflects the signal away specularly, resulting in lower intensity for periods when snow cover is present.
- (F) **Water content:** In Figure 11F, we see that increased water content (of soil, snow, or vegetation) produces higher intensity than dry ground covers, due to increased conductivity, decreased penetration of the wave into the ground surface, and thereby increased reflectivity. The magnitude of intensity change that a landslide produces will increase or decrease depending on seasonal variations in the pre-existing ground cover.

3.2.2. Conceptual Model

To improve understanding of the physical basis for the identified patterns, we present the generalised conceptual model shown in Figure 12, relating the change in scattering behaviours to the observed change in backscatter intensity. This is described as follows, referring to the numbers illustrated:

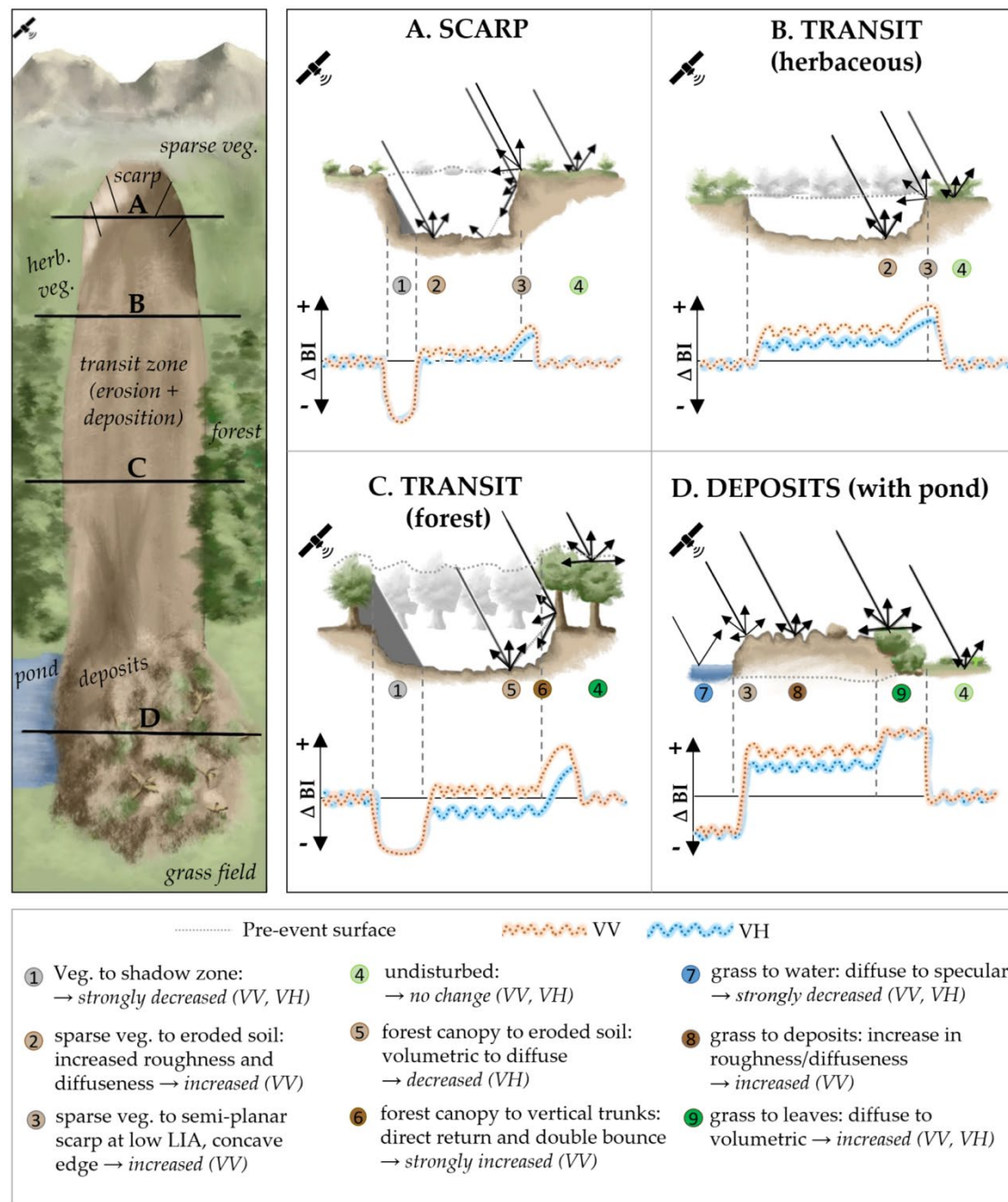


Figure 12. Patterns identified are represented by representative generalised landslide profiles with the relative changes in backscatter intensity (B.I.).

- (A) SCARP:** The sudden change in topography, usually expressed by a steep surface, results in a strongly decreased intensity for scarps facing away from the sensor (1). This is attributed to radar shadow, which occurs when the slope angle is steeper than the radar incident angle. The base of the scarp beyond the shadow zone may show increased intensity due to an increase in surface roughness (2), as in the conceptual model. However, this will vary depending on the specific pre-event land cover and post-event surface roughness and orientation. For scarps facing towards the sensor (3), if the LIA is decreased, more energy will be reflected back towards the sensor, resulting in increased intensity. In addition, the concave top edge of the scarp will also give strongly increased reflectivity relative to a flat pre-event surface, producing strongly increased values on the outer edge of the scarp. These patterns are seen most

clearly in VV, due to the greater sensitivity to changes in surface roughness. Similar changes have been documented in relation to changes in the topography of a volcanic crater following an explosive eruption [52].

- **(B) TRANSIT (herbaceous):** The trend of predominantly increased backscatter intensity in these areas is due to an increase in surface roughness of the landslide surface compared to a weathered pre-event surface (2). This results in increased diffusivity and stronger reflection back towards the sensor. Minor scarps and concave features within transit zones of larger landslides are identifiable based on the same principles as described for the main scarp. There are numerous examples of agricultural studies relating increasing roughness of non-vegetated surfaces to increasing backscatter intensity [48,53,54].
- **(C) TRANSIT (forested):** The pattern illustrated for landslide transit zones in forest is very similar to the pattern described by [55] from drainage canals that are constructed within rainforests prior to deforestation. The changes relate to (1) radar shadow on the edge nearest to the sensor. Then at (5), a change from forest to bare soil produces a decrease in VH due to the reduction of volumetric scattering, and possibly a slight increase in VV, depending on the roughness of the surface. Finally, at (6), increased backscatter intensity on the farthest edge from the sensor occurs due to a change from forest to a new near-vertical surface of the scarp and tree-trunks, which produces direct and double bounce scattering, increasing the energy returned to the sensor.
- **(D) DEPOSITS (with ponding):** The example illustrated shows firstly a strong decrease caused by a new pond, related to a change from grass to water (7), which has a very low intensity due to specular reflection. From the case studies, we observed that new lakes or ponds caused by landslide dams showed stronger signals than the landslides themselves and are very easy to detect in the change imagery. Although they can be difficult to distinguish from scarps without contextual information, as can be seen in the Ecuador case, where there first seemed to be three large scarps, one of them was actually a lake. Detecting newly formed lakes is important in disaster response, as these may occur in unpopulated areas; however, they can pose serious threats to people downstream if the landslide dam bursts suddenly [56]. The signal is the same as that used to detect flooding [57]. Conversely, changes from ground to water result in strongly increased backscatter intensity, which was observable in cases 10, 15 and 20 from the Philippines, Iceland, and Peru.

The landslide deposits themselves were most frequently observed in change images by increased backscatter intensity (8), as is illustrated in the conceptual model. This is due to increased surface roughness and possibly also the presence of concave structures for landslides with a large volume, both of which produce increased diffusivity. However, as shown in Figures 7, 8 and 10, cases that appeared to have smooth deposits formed by fine materials (mud or silt) produce lower backscatter intensity post-event, and this may result in decreased backscatter intensity in VH change images. Such deposits can indicate that the sediments were deposited by still or slow-moving water, related to blocked drainage.

3.2.3. Limitations and Variability: The Impact of Geometric Distortions and Look Direction

While the results shown above represent the clearest of the cases seen, not all cases are equally clear. One of the most common reasons was geometric distortions due to rugged terrain. Figure 13 shows an example where the landslides were clearly visible in the Sentinel-2 NDVI image but were barely visible in the Sentinel-1 image due to geometric distortions and unfavourable mixed vegetation conditions.

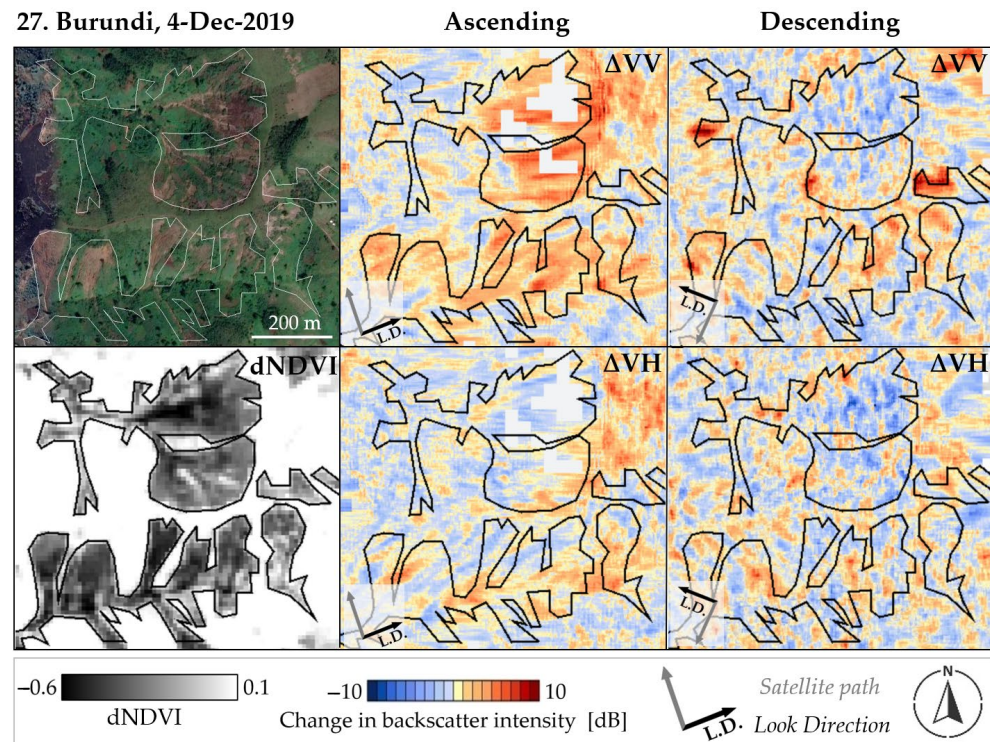


Figure 13. Landslide visibility was reduced in the Burundi case due to geometric distortions, as well as unfavourable mixed vegetation conditions. Black areas show shadow distortion, while the stretched pixels are presumably affected by foreshortening. Outlines were drawn based on the Sentinel-2 dNDVI image. Note: The RGB image is from later after the event and shows some vegetation recovery.

It is also important to understand how significantly the expression of the landslides in SAR backscatter images can vary depending on whether ascending or descending images are used. This is observed for landslides with significant scarps and those that occur in forested areas, where the appearance of the landslide varies significantly depending on the sensor direction, as illustrated in Figure 7. The landslides triggered by the earthquake in Hokkaido, Japan, shown in Figure 14, show how strongly the expression of landslides can vary, particularly in VV.

The landslide scarps to the west of the central valley are mainly sloping down towards the east, in a similar direction to the look angle of the sensor on the ascending path (high LIA). In both the dVV and dVH ascending images, these western landslides show decreased backscatter intensity at the location of the back scarps. While the landslides to the east of the central valley, facing approximately normal to the sensor (low LIA), show a strong increase in the dVV image at the location of the back scarp and a moderate increase in the mid slope. By contrast, in ascending dVH, these eastern landslides show moderately decreased backscatter intensity in both the mid-slope and towards the back scarps. A similar but reversed pattern can be observed in the descending images. The LIA appeared to be less relevant for landslides that occurred in herbaceous vegetation and for deposit zones. In Figure 14, the deposit zone in the centre of the valley shows an increase in all the change images.

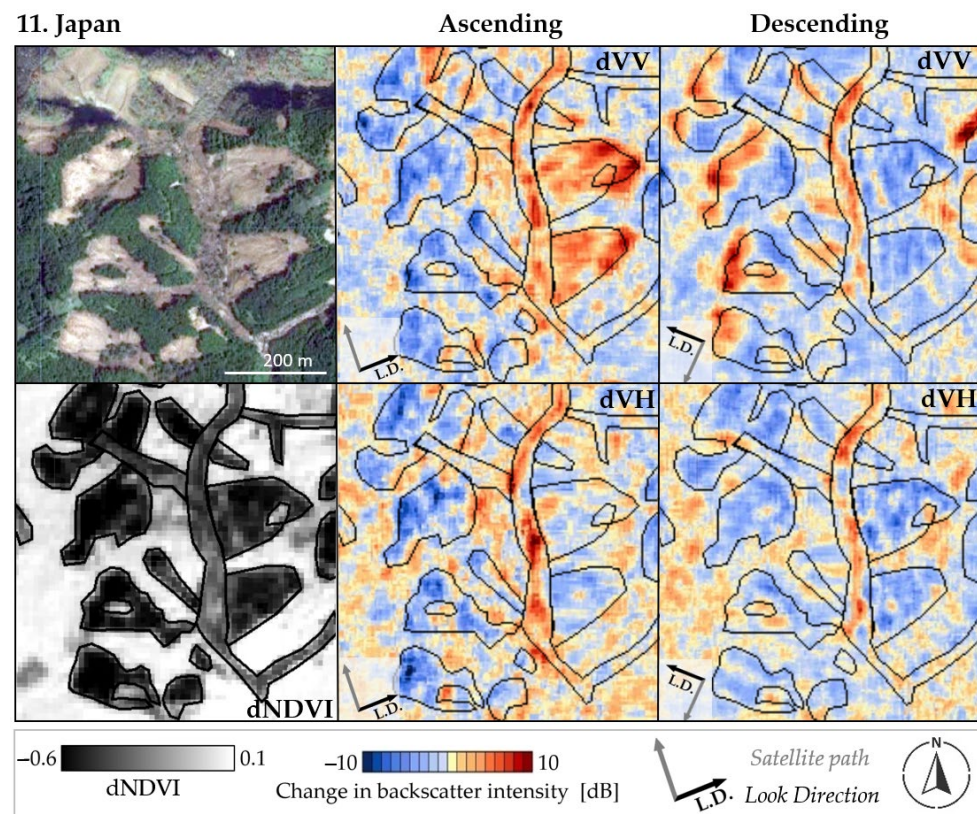


Figure 14. Landslides in forested areas from Hokkaido, Japan (case 11), showing strong variation in expression in backscatter intensity change images depending on the orientation of the landslide surface. Outlines were drawn based on the Sentinel-2 dNDVI image.

3.3. Application: Manual Detection of Landslides in SAR Images in Recent Disasters

The previous findings were applied to manually detect landslides from three disaster events using the first available post-event images, without prior knowledge of landslide locations and with no optical imagery available for confirmation (initially).

Cyclone Gabrielle in the Hastings District of New Zealand (12–16 February 2023) triggered hundreds of thousands of landslides in the North Island of New Zealand [58]. In this case, strong, mainly increased intensity change signals gave an indication of many small landslides on hilly slopes with pine forest land cover, as shown in Figures 15 and 16. However, it was challenging to confidently identify individual small landslides before optical imagery was available for confirmation. This was partially due to the small size of landslides relative to the ruggedness of the terrain, and that detectability was also limited on slopes facing away from the sensor, and possibly by increases in soil moisture in surrounding undisturbed areas, which can also create increased backscatter intensity. Landslide dams were investigated and due to the strong negative change in the backscatter signal in the dammed area, these could be easily identified.

The investigations following the Turkey earthquake (6 February 2023) using this method were not successful. There was a large area affected, the investigator had little knowledge of where to look for landslides beyond coarse-scale slope and susceptibility maps, and snow fell on hilly slopes, which made it difficult to detect any landslides.

For the ‘Hans’ storm in Norway (7–9 August 2023), previously unknown landslides were confidently detected alongside Lake Helin before optical imagery was available from the first post-event image on 10 August 2023. For manual detection, a different visualisation was preferred, as shown in Figure 17. It was up to six weeks after the event before cloud-free optical satellite imagery was available for parts of the affected area. Subsequent systematic

mapping with optical imagery and field work identified 648 landslides [15]. Only the largest of these could be easily identified using a single-post event Sentinel-1 SAR image.

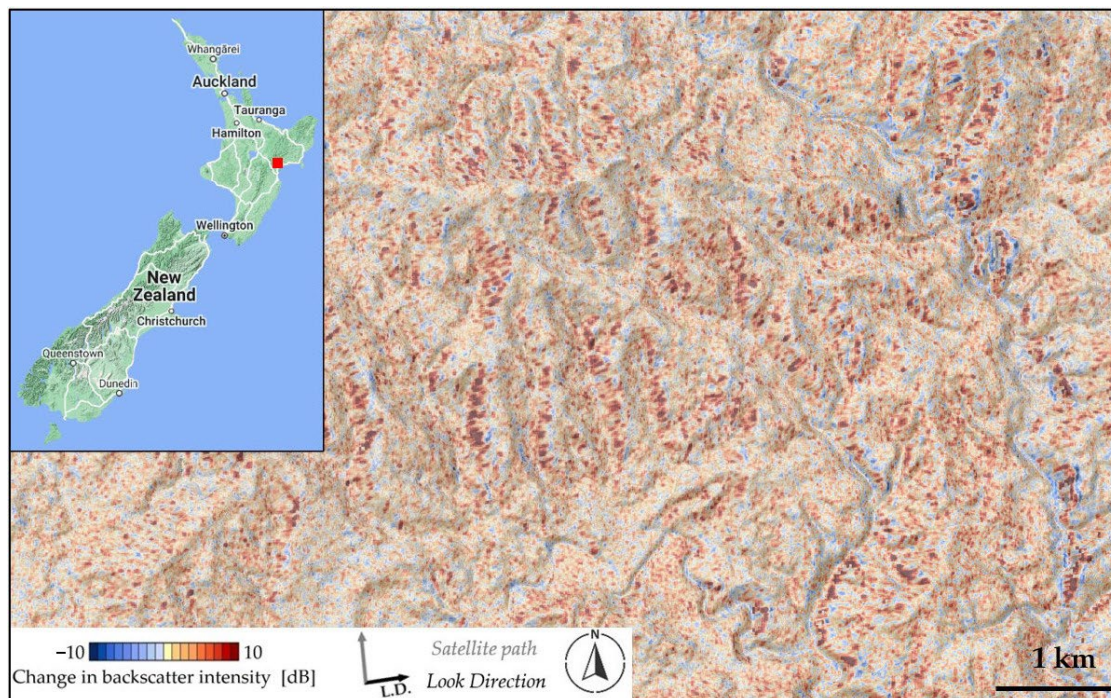


Figure 15. Single post-event SAR change image showing hundreds of possible small landslides (dark red), triggered by Cyclone Gabrielle (12–16 February 2023), west of Kotemaori, Hastings, New Zealand (176.94656, −39.075). Landslides are mainly visible on west-facing slopes.



Figure 16. Screenshot from Google Earth Engine of the satellite base map for the region shown in Figure 14. The landslides shown here are relatively shallow and mainly located within a commercial pine forest plantation.

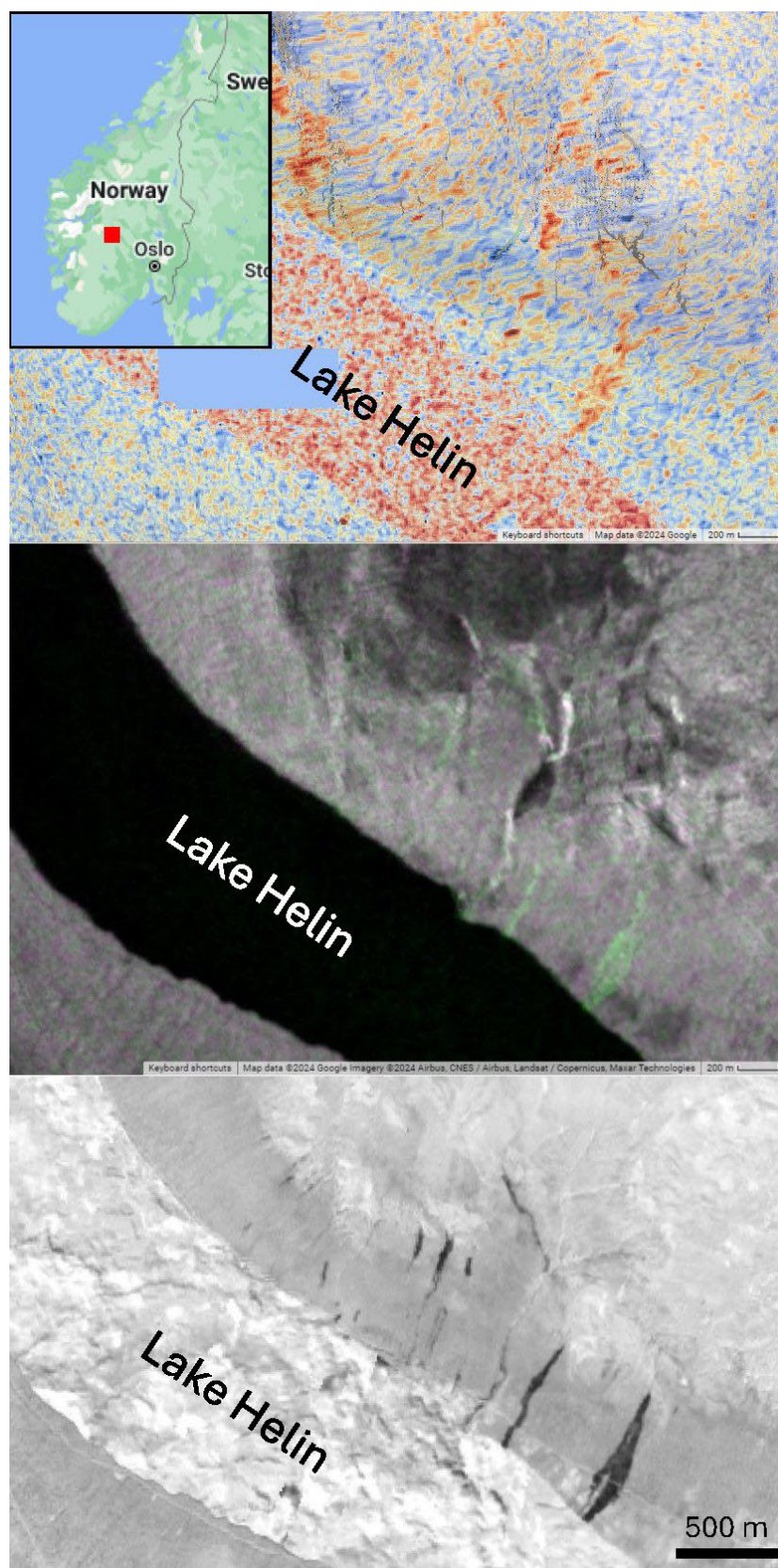


Figure 17. Screenshots from Google Earth Engine of landslides identified alongside Lake Helin in Norway (8.66598, 61.04546), showing **(top)** a single post-event SAR change image (10 August 2023), **(middle)** the SAR RGB composite, which is an alternative visualisation of the pre- and post-event images (bands: R: pre, G: post, and B: pre), and **(bottom)** a dNDVI (change in Normalised Difference Vegetation Index) image using Sentinel-2 images.

The experience has shown that indications of both medium and large landslides and landslide dams can be detected from single post-event Sentinel-1 images. However, a significant limitation for applying these methods in disaster situations is the lack of daily images freely available (revisit frequency in Europe is 1–3 days; in equatorial regions, it can be up to 12 days). For the Turkey earthquakes, snow and a large search area were also major limitations for landslide detection. Geometric distortions also provide challenges for mapping the exact location of landslides, as there will be slight offsets and stretching. However, it is still possible to obtain an indication of the location of large landslides with an accuracy of 50 m, which can provide potentially useful information for emergency response.

4. Discussion

4.1. Patterns

In the analysis of prior known landslide case studies, the overall detection rate was 87% (n. test cases = 26/30) in this study. This is similar to that reported by Mondini et al. (2019) of 83% (n. test cases = 27/32) [19], yet it differs significantly from the rate reported by Lindsay et al. (2022) of less than 10% (n. test cases = 9/120) [20]. The difference between these reported rates lies in the method of case study selection and the size of landslides investigated. In the former two, the examples selected came mostly from news reports and are biased towards larger, more catastrophic events, whereas in Lindsay et al. (2022) [20], the reported rate was in comparison to a set of previously mapped landslides from a single case study and included mainly smaller landslides.

The first aim of this study was to identify patterns in the expression of landslides in SAR change imagery through systematic analyses of diverse individual case studies, and to perform quantitative analyses of time series data and pixel values within the mapped landslide areas. Four patterns were observed in change images and time series data relating to landslide morphology, land cover, and LIA. While the landslide literature mentions increased or decreased intensity related to landslides, such descriptions are rare, and the observations have not been collected before in a way that would allow one to predict how a landslide may be expressed in a given environment, along with some expectation of the type of landslides that might occur in that area. The patterns observed in this study, combined with the theoretical background and conceptual model, contribute towards building the foundational knowledge needed to develop operational SAR-based systems for rapid landslide detection in the aftermath of a disaster or for continuous monitoring systems.

No fixed threshold values were applied for landslide detectability, as detectability depends on multiple factors that can vary significantly within a landslide and between case studies. Speckle noise and unrelated surface changes can generate false positives both inside and outside the landslide area. Moreover, a single landslide may cause both increased and decreased signal intensity, as shown in the conceptual model. Any landslide-related change must also be distinguishable from background variations in undisturbed areas (e.g., seasonal effects or changes in soil moisture). These findings suggest that automated detection models based on pattern recognition across pixel patches are better suited to separate landslide signals from random noise than traditional pixel-by-pixel classification methods, as discussed in ref. [11].

4.2. Controlling Factors

The second aim was to investigate which factors control the visibility and expression of landslides in SAR backscatter change images. Based on the theoretical review, the factors that were expected to control the visibility and expression of landslides in backscatter intensity change images included geometric distortions, LIA, ground cover, seasonal

variations, and water content. Wavelength is also considered relevant; however, it was not investigated in this study as we used only C-band images.

4.2.1. Landslide Type

The cases that were undetectable in this study (Table 1, Set 1) included two rock fall events, one slush flow, and one case with mixed vegetation type. In the rock fall events, it was determined that the change in the ground surface texture was not significant, or in the case where deposition occurred on a road, it is likely that the deposits were removed before an image was acquired. The slush flow was not detectable due to changes in the surrounding area caused by snowmelt. While for the mixed vegetation case, where deposition occurred without removing the pre-existing trees, the change produced by the landslide did not significantly alter the backscatter response, which included both diffuse and volumetric scatterers, before and after the event. This is in line with the findings of [21]. In cases where landslides were only partially visible or detectable only with a priori knowledge (Set 2), the main limiting factors included small or narrow landslide geometry, geometric distortions that obscured or warped the landslide signatures, snow melt in the surrounding area, deposition in an urban area, and only a single orbit pass available. Large-scale topography, in particular high mountains, was not as problematic as expected.

4.2.2. Large-Scale Terrain Features and Geometric Distortions

Geometric distortions were considered to have been a major limitation to landslide visibility in six of the cases (including 7. Vanuatu, 8. Brazil, 14. New Zealand, 26. USA, 27. Burundi, and 28. Australia). This was particularly problematic if only one orbit pass was available. In the Burundi case, although two orbit passes were available, a significant area was affected by foreshortening in both the ascending and descending images (see Figure 7), which appears as stretched pixels when corrected and distorts the landslide signatures significantly. This is problematic for areas with steep, narrow valleys. Shadow zones were not as problematic as expected for large-scale terrain features (e.g., the 4000 m high mountains in case 14 from New Zealand, see Figure 4. Most of the shadow zones were related to the presence of medium-scale topographic features, such as cliffs.

4.2.3. Local Incidence Angle

The influence of the LIA was clearly observable when looking at the differences in the landslide expression between individual cases. The variability in landslide expressions in relation to the LIA was clear in the qualitative analyses, as shown in Section 3.2.3. This was particularly important in cases where landslides produced an abrupt change in surface height, whether due to the removal of materials in the scarp area or the removal of trees in the transit or deposition zones. The pattern of shadows from steep or vertical surfaces facing away from the sensor, and bright edges facing towards the sensor, is highly dependent on the sensor's look direction (ascending or descending orbit path). Shibayama et al. (2015) expected a trend of increased intensity at high LIA on rough bare surfaces based on theory [30], but this was not observed in the results. However, the LIA has been shown to affect the backscatter intensity to different degrees, in experimental data from other fields where the sampled areas were more homogenous (e.g., agriculture [54] and canals in areas to be deforested [55]). Using post-event DEMs to estimate the LIA would probably give clearer trends, especially for the scarp. However, this data is not readily available in most cases [59]. Furthermore, there may be sampling bias, with landslides oriented at a very high or low LIA being possibly less likely to be visible in the first place.

4.2.4. Ground Cover

The change in the ground cover type was very important in determining the expression of the landslides. In the change images, time series data, and statistical analyses, it was clear that landslides in forest tend to produce an overall decrease in backscatter intensity, while those in herbaceous and non-vegetated areas tend to produce an increase. In addition, changes to water bodies were very clear in the change images. Differences in the post-event backscatter intensity sampled within deposit zones were also observed depending on the material size (fine or coarse).

4.2.5. Seasonal Variations and Water Content

Understanding the seasonal variation in backscatter intensity values at the location of interest is important for two reasons. Firstly, if making changes to images to detect landslides, one should choose periods to compare where the background values are similar, so that the change due to the landslide is easier to distinguish. Changes due to landslides in time series were clearer for cases with tropical and temperate climates, where the vegetation showed limited background seasonal variation. Cases with changes in snow cover showed abrupt changes in backscatter intensity values that were not related to landslides. It was observable that the timing of landslides in relation to the underlying seasonal cycle, either enhanced (i.e., 14. New Zealand) or reduced (i.e., 5. Norway), was associated with the change in backscatter intensity. These variations in seasonal conditions are important to be aware of when designing an operational landslide detection system based on time series data. The effect of changes in water content was not clear due to a lack of ground data.

4.3. Application and Future Research Directions

The final aim was to investigate what insights can be gained with relation to the future development of automated detection approaches from attempting to manually detect landslides in three real disaster scenarios using SAR imagery before optical images are available.

For the recent events where the location of landslides was not known a priori, new landslides were detected in two out of three events. For Cyclone Gabrielle in New Zealand, these were mainly smaller landslides, and it was difficult to distinguish them individually with confidence until optical imagery later became available. Higher resolution SAR data and DEMs would be desirable to improve the results. For the Hans storm in Norway, large landslides were detected with confidence. However, many of the smaller landslides that were later mapped with optical images were not clearly visible in the SAR change images. This was due mainly to mixed vegetation conditions, small landslides, and unfavourable terrain features. Future research could investigate whether different wavelength SAR images are more effective at detecting landslides where there are mixed vegetation conditions.

The dataset produced in this study provides a diverse training dataset that can be used for developing generalised automatic detection models. Previous studies have shown that locally trained deep learning models, such as U-Net, can detect landslides with good accuracy from Sentinel-1 images due to their ability to differentiate random speckle noise from clusters of pixels related to changes to the ground surface [11]. The results of this study can be used to improve the design of deep learning models through understanding how to ensure representative training cases and relevant input data are included. A challenge for such models will be to differentiate signals of non-landslide-related vegetation loss from landslides, as is an ongoing problem for landslide detection using optical data [8]. More investigations could also be carried out using this dataset for improving the understanding of how land cover affects the generation of post-event DEMs [59]. Then, automated

estimation of the volume of material would also be possible. This would enable disaster responders to estimate the magnitude of the problem and send appropriate resources.

The frequency of freely available SAR images will double with the launch of the NISAR (NASA-ISRO SAR) satellites in 2025. However, it will take some time to build up a set of new landslide observations in the S- and L-band, after the satellite becomes operational. Future work can also investigate how coherence data (the similarity in radar reflections between two SAR images) and backscatter data can be used together to improve landslide detection. Automatic detection and consequence analyses (for instance, highlighting the intersection of automatically detected landslides with buildings or infrastructure) could also be useful for improving situational awareness during disaster response.

Commercial high-resolution SAR data is currently available at a daily frequency from commercial providers (e.g., ICEYE, Spacety, and TerraSAR-X). The use of high-resolution imagery will likely improve the visibility of landslides in SAR imagery, especially with regard to smaller landslides and potentially for those that occur in urban environments or with mixed vegetation conditions. Research should be conducted into combining imagery from multiple sensors with varying wavelengths, view angles, and resolutions to be prepared to rapidly utilise whatever information is available.

5. Conclusions

Through systematic analysis of over 1000 landslides from 30 diverse global case studies, we found that landslides produce predictable patterns of increased and decreased backscatter intensity in Sentinel-1 change images. Four main trends were identified: (A) the scarp shows strongly decreased intensity on the side closest to the sensor, and increased intensity on the far side; (B) landslides in herbaceous or non-vegetated land cover types show increased intensity; (C) landslides in forested areas show a striped pattern with the edges showing the most extreme change values, with decreased intensity on the edge closest to the sensor and increased intensity on the far edge; and finally, (D) the deposits show generally increased intensity, with some exceptions. These patterns have not been documented collectively in relation to landslides previously; however, they have similarities to signals produced by features described in the literature in relation to volcanic eruptions, agriculture, deforestation, canal building, and floods.

Through qualitative and quantitative image analyses and a multidisciplinary literature review of SAR backscatter theory, the observed patterns were related to factors including, depending on the local environment, landslide type and orientation and sensor properties (look direction and polarisation). Seasonal changes, particularly vegetation loss in autumn and snow cover, urban land cover, and geometric distortions, can limit visibility. The findings were summarised in a generalised conceptual model illustrating the observed patterns and associated scattering mechanisms. SAR change images were produced for three recent disaster case studies prior to optical imagery being available, when new SAR images became available online. Previously unknown landslides were detected in two of three cases using manual detection and later verified when cloud-free optical imagery became available.

The patterns observed in this study illustrate the variety in landslide expression in C-band SAR backscatter images. This can improve understanding of how landslides are likely to appear in different environments and gives insight into what should be considered a 'representative' dataset for training an automatic landslide detection model. Additionally, we demonstrated the potential for using a single post-event SAR image for landslide detection. These findings, combined with knowledge of the controlling factors, are foundational for developing robust, multi-sensor automatic detection models and continuous monitoring systems. By leveraging satellite radar images, these models

can address critical needs in disaster scenarios, where rapid landslide detection takes precedence over detailed mapping—particularly when optical images are hindered by clouds or darkness. Providing timely, actionable information on landslide events and their consequences can enhance situational awareness during disaster response efforts, ultimately improving outcomes for affected communities.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/rs17193313/s1>.

Author Contributions: Conceptualization, E.L.; methodology, E.L., J.R. and R.F.; software, E.L.; validation, E.L.; formal analysis, E.L.; investigation, E.L. and A.J.G.; resources, E.L.; data curation, E.L. and A.J.G.; writing—original draft preparation, E.L.; writing—review and editing, E.L., G.D., J.R., S.N. and R.F.; visualization, E.L., G.D., R.F. and A.J.G.; supervision, G.D. and S.N.; project administration, E.L.; funding acquisition, S.N. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The Google Earth Engine scripts and the Supplementary Materials showing change images produced for all case studies are available at <https://github.com/erintnu/Understanding-Landslide-Expression-in-SAR---change-images-in-GEE-.git>, accessed on 27 August 2025.

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Conflicts of Interest: Author Erin Lindsay was employed by the company SINTEF. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Table A1. Links for landslide case study reports. Accessed: 11 December 2022.

Location	Link
1. Iceland	https://blogs.agu.org/landslideblog/2021/10/08/multiple-landslides-in-thingeyjarsveit-and-in-kinnarfjall-in-iceland/
2. Ireland	https://blogs.agu.org/landslideblog/2021/07/23/benbrack-1/
3. New Zealand	https://blogs.agu.org/landslideblog/2022/04/21/wairoa-1-2/
4. Ecuador	https://blogs.agu.org/landslideblog/2021/02/16/chunchi-a/
5. Norway	https://blogs.agu.org/landslideblog/2019/08/01/sogn-og-fjordane-1/
6. Sth. Africa	https://blogs.agu.org/landslideblog/2022/04/22/durban-1/
7. Vanuatu	https://hazmapper.org/2020/05/20/cyclone-harold-defoliation-and-mass-wasting-in-vanuatu/
8. Brazil	https://blogs.agu.org/landslideblog/2021/05/17/the-17-18-december-2020-landslide-disaster-in-presidente-getulio-southern-brazil/

Table A1. Cont.

Location	Link
9. China	https://blogs.agu.org/landslideblog/2021/10/28/the-21-july-2020-shaziba-landslide-at-mazhe-village-in-en-shi-china/
10. Philippines	https://blogs.agu.org/landslideblog/2022/04/14/three-very-large-landslides-triggered-by-tropical-storm-megi-agaton/
11. Japan	https://link.springer.com/article/10.1007/s10346-019-01206-7
12. USA	https://blogs.agu.org/landslideblog/2022/08/03/haines/
13. China	https://blogs.agu.org/landslideblog/2021/10/26/the-5-april-2021-tiejiangwan-landslide-in-sichuan-province-china/
14. N. Zealand	https://www.otago.ac.nz/surveying/potree/pub/mrc/projects/matariki/changing-landscape
15. Iceland	https://blogs.agu.org/landslideblog/2018/07/26/fagraskogarfall-landslide/
16. India	https://link.springer.com/article/10.1007/s10346-021-01802-6
17. India	https://link.springer.com/article/10.1007/s10346-021-01802-6
18. Norway	https://www.regobs.no/Registration/193067
19. India	https://link.springer.com/article/10.1007/s10346-020-01598-x
20. Peru	https://blogs.agu.org/landslideblog/2020/06/30/achoma-landslide-1/
21. Kyrgyzstan	https://earthobservatory.nasa.gov/images/90255/landslide-in-southern-kyrgyzstan
22. Italy	https://blogs.agu.org/landslideblog/2019/11/25/savona-landslide-1/
23. Indonesia	https://blogs.agu.org/landslideblog/2022/03/29/mount-talakmau-1/
24. Brazil	https://blogs.agu.org/landslideblog/2022/05/31/recife-1/
25. Canada	https://blogs.agu.org/landslideblog/2021/11/16/bc-1/
26. USA	https://twitter.com/bclemms/status/1452333926949822468?lang=en
27. Burundi	https://hazmapper.org/2020/04/27/mass-wasting-in-burundi-december-2019/
28. Australia	https://blogs.agu.org/landslideblog/2022/03/11/main-arm-1/
29. Indonesia	https://link.springer.com/article/10.1007/s10346-021-01700-x
30. Turkey	https://blogs.agu.org/landslideblog/2019/05/17/ordu-1/

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