



Diverse C-Band Radiometric Signatures of Buried Supraglacial Lakes on the Greenland Ice Sheet

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Abstract. On the Greenland Ice Sheet, buried supraglacial lakes modulate surface mass balance through water storage and dynamic mass loss through drainage events. These buried lakes are typically mapped using C-band synthetic aperture radar (SAR) data, but to date, there has been no comprehensive validation of the radiometric signatures used for their detection. Here, we use ice-penetrating radar (IPR) to create a ground-truth catalog of buried lakes in spring 2017. We compare this catalog to coincident imagery from Sentinel-1 and investigate how lake geometry and environmental setting influence the radiometric signatures observed in the SAR imagery. We find that Sentinel-1 can directly sense buried water when the depth to the water table is less than 5 m thick. However, only 23-27% of buried lakes in our IPR catalog show clear negative anomalies in the HV polarization and those lakes are preferentially located in the lower accumulation zone. This suggests that current buried lake detection algorithms are spatially biased and significantly underestimate the total number of buried lakes. We show that incorporating multiple polarization metrics, particularly the difference between HH and HV backscatter, can reduce both spatial bias and missed detections. Our analysis provides a quantitative assessment of the strengths and limitations of C-band SAR for mapping buried lakes and offers a basis for improving detection algorithms and uncertainty quantification.

1 Introduction

The Greenland Ice Sheet (GrIS) is currently the largest individual contributor to barystatic global sea level rise and is projected to continue to lose mass through the end of the century (Frederikse et al., 2020; Fox-Kemper et al., 2021). Since approximately 2000, about 50% of that mass loss has been attributed to declining surface mass balance (SMB) and the remaining 50% to increasing dynamic mass loss (Mouginot et al., 2019). This decline in SMB has been driven by an increase in surface meltwater runoff (Van Den Broeke et al., 2016; Bevis et al., 2019; Glaude et al., 2024), a process that can also modulate the rate and timing of dynamic mass loss if that water drains into the subglacial system (Bartholomew et al., 2012; Moon et al., 2014; Andrews et al., 2014). As a result, translating the total surface melt volume into surface mass loss and projecting ice-velocity changes in response to hydrology requires an accurate accounting of the rate, timing, and mechanisms of meltwater transport and storage through the ice sheet.

Buried supraglacial lakes are one common mode of temporary water storage. These features form when supraglacial lakes partially refreeze over the winter, leaving behind a pocket of buried liquid water beneath an ice lid a few meters thick (Law et al., 2020; Lampkin et al., 2020). Initially, these buried lakes impound meltwater and reduce runoff. However, they can



eventually drain englacially, sometimes after multiple years of storage (Benedek and Willis, 2020; Schröder et al., 2020; Dean et al., 2026; Wei et al., 2026), causing a sudden influx of water into the subglacial system that is decoupled from the timing of seasonal melt and interannual variations in meltwater production. Winter lake drainages, where water enters a largely inefficient and unchannelized subglacial system, have been shown to temporarily increase ice velocity by 10-86% and may contribute to reconfiguring the subglacial hydrologic network (Maier et al., 2023; Wei et al., 2026).

As a result, there has been significant interest in mapping the extent and volume of buried supraglacial lakes across the GrIS and tracking their drainage dynamics over time. The first pan-Greenland catalog of buried supraglacial lakes identified lakes using airborne ice-penetrating radar (IPR) data collected in the springs of 2009-2012 by NASA's Operation IceBridge (Koenig et al., 2015). IPR generates a cross-sectional image of the interior structure of the ice sheet and can directly image the buried water table beneath the ice lid. However, this airborne data has limited spatial and temporal coverage, insufficient to capture the full spatial distribution of buried lakes or to observe their drainage dynamics.

Later studies leveraged C-band synthetic aperture radar (SAR) observations from satellites to map buried supraglacial lakes and detect drainage events at the ice-sheet scale. Early studies manually delineated lakes based on expert judgment (Johansson and Brown, 2012; Miles et al., 2017), while later studies developed automated detection methods based on quantitative backscatter thresholding (Zheng et al., 2023), Bayesian classification schemes (Schröder et al., 2020), or deep learning approaches (Dunmire et al., 2021; Jiang et al., 2022). All of these studies assumed that buried supraglacial lakes are characterized by low horizontal-vertical (HV) backscatter (σ_{HV}), either in an absolute sense or relative to their surroundings, since the thin, newly formed ice lid is relatively homogeneous and smooth, and water strongly absorbs radio frequency energy. Schröder et al. (2020) also considered horizontal-horizontal (HH) backscatter (σ_{HH}) and the difference between HH and HV backscatter (σ_{HH-HV}) in their classification scheme, but the use of multiple polarization metrics is otherwise uncommon. In all of these studies, optical images of lake locations at the end of the melt season were used to validate the SAR buried lake detections. Numerous other studies have focused on identifying lake drainage events rather than automatically detecting lakes. These studies generally identify lakes in late summer using optical imagery, then track the evolution of C-band backscatter through the winter over known lakes to identify drainage events (Benedek and Willis, 2020; Dunmire et al., 2025; Wei et al., 2026; Dean et al., 2026). Drainages are assumed to be characterized by a sudden sustained increase in σ_{HV} , indicating a transition from a smooth lake lid overlying absorptive water to a dry basin filled with ice rubble from the collapsed lid (Benedek and Willis, 2020; Dunmire et al., 2025; Wei et al., 2026; Dean et al., 2026).

Although IPR is the most reliable way to detect buried lakes at scale, only two studies have validated their putative SAR-detected buried lakes with IPR data. Miles et al. (2017) compared the qualitative distribution of their SAR-detected lakes to the IPR-derived map from Koenig et al. (2015) and found good agreement, but they could not quantitatively validate their mapping since the SAR and IPR data were collected in different years. Schröder et al. (2020) used Snow Radar data to validate SAR lake detections where they intersected flight lines and found that 90.5% of those detections were associated with subsurface water signatures in the airborne IPR data. However, there has been no comprehensive comparison of an IPR catalog of buried supraglacial lakes with spatially and temporally coincident SAR signatures. As a result, the conditions under which buried



60 lakes are detectable by C-band SAR and the fraction of lakes we would expect to detect remain unquantified. Similarly, the assumption that buried lakes always characterized by negative local anomalies in σ_{HV} is not well-validated.

Here, we build a new catalog of buried supraglacial lakes using Accumulation Radar data collected over the GrIS in spring 2017. This time period overlaps with collection by the Sentinel-1 SAR constellation, allowing us to directly investigate the SAR signatures of the IPR-detected lakes. We analyze lake detectability using multiple SAR polarization metrics and then
65 assess the degree to which lake lid roughness, the depth to the water table, and the local environmental setting can explain the diversity of SAR radiometric signatures that we observe.

2 Data and Methods

2.1 Airborne Ice-Penetrating Radar Data

To create a catalog of buried supraglacial lakes, we used Accumulation Radar data collected as part of NASA's Operation
70 IceBridge from 22 March to 11 May 2017 over the GrIS (Fig. 1). The Accumulation Radar (AR) operated at a center frequency of 750 MHz with 300 MHz of bandwidth, giving a range resolution in firn and ice of 0.51 - 0.43 m (Lewis et al., 2015; Rodríguez-morales et al., 2014). This is conservatively sufficient to detect lakes where the water table buried is 1 m or more below the surface of the ice sheet. The only previous paper to catalog buried supraglacial lakes with IPR data used the Snow Radar, an ultrawideband system that operates from 2-6 GHz, and achieves a range resolution of ~ 4 cm (Rodríguez-morales
75 et al., 2014; Koenig et al., 2015). We chose to use the AR instead because the lower center frequency and higher transmit power lead to deeper penetration of the radar signal, higher signal to noise ratio, and less scattering and clutter from surface features and crevasses. This makes it easier to reliably interpret the radargrams and ensures that deep lakes will not be missed. Koenig et al. (2015) found that most lake lids are a meter or more thick, and modeling work by Law et al. (2020) suggests that 1.3-3.4 m of refreezing are typical over the winter period, indicating that the AR has sufficient range resolution to identify most buried
80 lakes.

We manually reviewed all radar data frames at elevations below the upper limit of the percolation zone as defined by the Surface Microwave Active Passive (SMAP) radiometer (Miller et al., 2022a, b) to locate buried lakes. Following Koenig et al. (2015), we defined the signature of buried lakes as a strong, localized subsurface reflector below which the radar signal is almost completely attenuated. The reflection occurs at the interface between the ice lid and buried liquid water, so the reflectivity of
85 this interface typically exceeds that of the ice-air interface, due to the larger dielectric contrast. The rapid attenuation of radio waves in liquid water leads to a characteristic absence of deeper reflections. We required both signatures to be present to categorize a feature as a buried lake. The reflector also needed to form a coherent interface, rather than being a collection of point scatterers, and be limited in horizontal extent to a few kilometers or less. This reduced the risk of false positive detections from water storage in crevasses or firn aquifers. Examples of buried lakes detected in the AR data are shown in Fig. 2a & d.

90 For each lake identified in the AR data, we manually digitized the left and right limits of the water table and automatically tracked the water table's location by finding the point of maximum reflectivity below the surface in each trace. All water table picks were manually reviewed for correctness. Along each water table reflector, we calculated two metrics: abruptness and

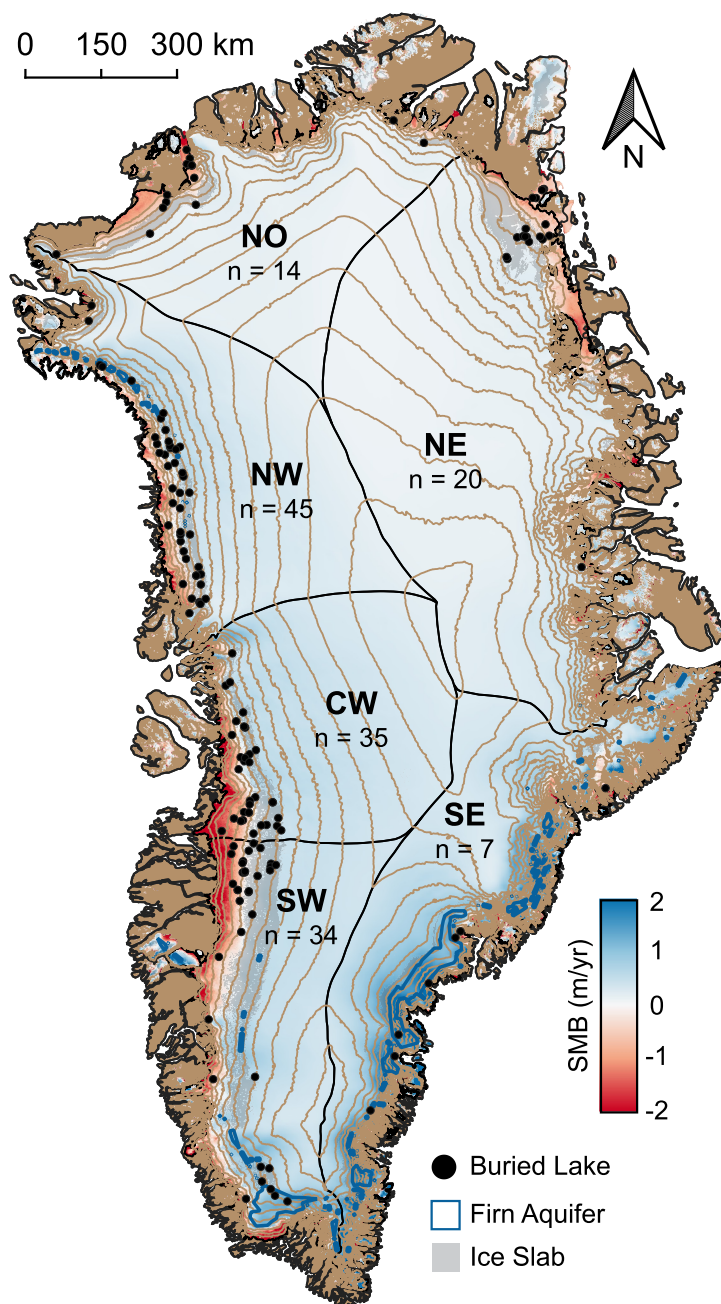


Figure 1. Study area on the GrIS. The surface mass balance (SMB) in meters of water equivalent per year from RACMO2.3p2 is shown in the red to blue color map, with the ablation zone denoted in red and accumulation zone in blue. The locations of firn aquifers and ice slabs are overlaid in dark blue and transparent gray outlines respectively. The locations of buried supraglacial lakes identified in Accumulation Radar data collected from March-May 2017 are shown in black dots. The IMBIE region labels and the total lake count within region are also shown.

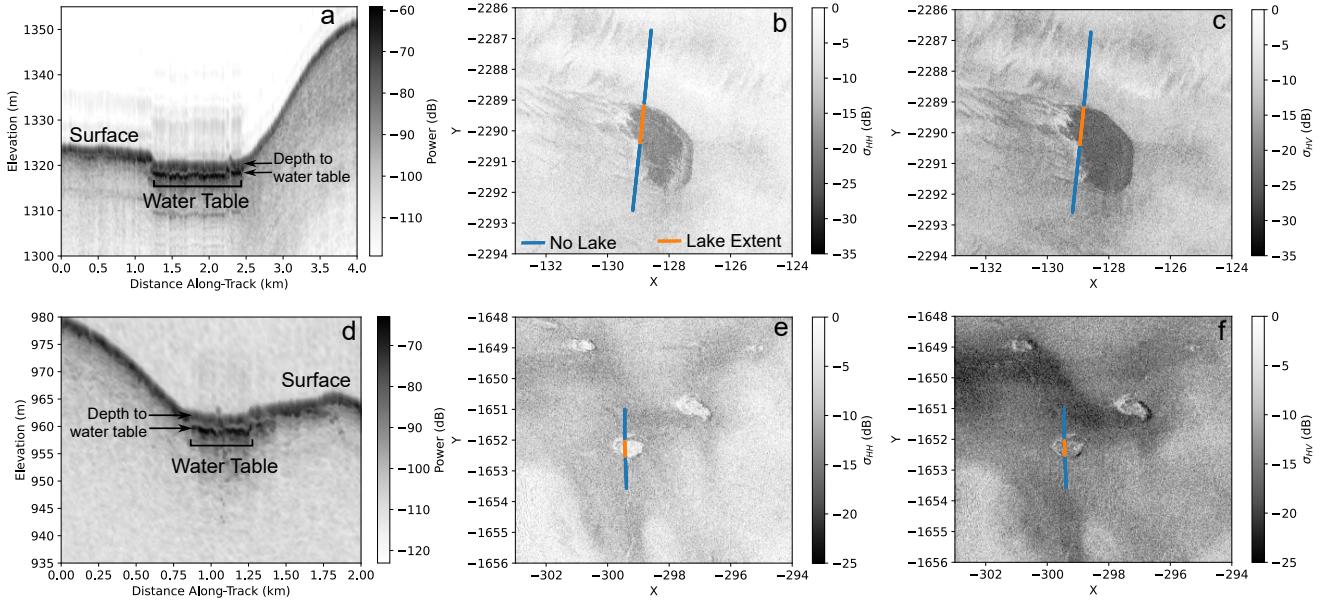


Figure 2. Examples of buried supraglacial lakes in radar data. a) Accumulation Radar data showing a cross-sectional profile through Lake # 78 in central-west Greenland. b) Sentinel-1 σ_{HH} over the same region. The orange line shows the portion of the IPR flight line where subsurface water was detected. The blue lines show the surrounding flight line segments defined as the "no lake" region . c) Sentinel-1 σ_{HV} over the same region. d) Accumulation Radar data showing a cross-sectional profile through Lake # 137 in central-west Greenland. e) Sentinel-1 σ_{HH} over the same region. f) Sentinel-1 σ_{HV} over the same region. Contains Copernicus Sentinel data [2017].

depth to the water table. Abruptness is the ratio of peak to aggregate power, where aggregate power is calculated by integrating all returns from 1 m above the water table to 15 m below the water table (Oswald and Gogineni, 2008; Jordan et al., 2016).

95 Abruptness quantifies the sharpness of the reflected waveform and is a proxy for interface roughness (Oswald and Gogineni, 2008; Jordan et al., 2017). If the ice-water interface is smooth, the waveform will be dominated by specular reflection and will approach the ideal impulse response of the system. We normalized our abruptness values by the abruptness of the system impulse response, estimated from coherent reflections from the surface of the open ocean, meaning that for very smooth surfaces, abruptness is equal to 1. However, if the ice-water interface is rough or geometrically complex, off-nadir scattered
100 energy will reduce the peak reflected power and increase the scattered power at greater time delays, leading to abruptness values significantly less than 1. Depth to the water table captures the depth of the buried water below the surface, and is calculated from the difference in two-way travel time between the surface and water table at each trace, assuming a refractive index of 1.78 for ice. The AR range resolution is not sufficient to separate a surface snow layer from the refrozen lake lid and lake ice may have a refractive index of less than 1.78 due to bubble entrainment, so these thicknesses represent a minimum value.

105 We expect depth to the water table and abruptness to be correlated with SAR observables for a number of reasons. First, SAR has a limited depth of sensitivity, likely in the range of 1-10 m for C-band observations of ice and firn (Rignot et al.,



2001; Fischer et al., 2019; Culberg et al., 2024). We hypothesize that shallow buried lakes may have strong expressions in the Sentinel-1 surface backscatter, whereas deeper lakes may lie outside the radar sensitive volume and, as a result, produce little to no observable change in backscatter. Abruptness as a proxy for interface roughness provides information on how side-looking SAR signals may interact with the lake surface. For high abruptness (smooth) lakes, the signal will undergo specular reflection away from the satellite line of site and minimal depolarization, leading to anomalously low backscatter values over the lake area in both HH and HV channels. For low abruptness (rough) lakes, significantly more energy will be backscattered to the radar and more depolarization will occur, leading to higher backscatter in both HH and HV channels, potentially reducing the radiometric detectability of the lake relative to its surroundings.

2.2 Satellite Synthetic Aperture Radar Data

Sentinel-1 is a series of C-band synthetic aperture radar satellites launched and maintained by the European Space Agency. In 2017, the constellation consisted of Sentinel-1A and Sentinel-1B, operating in Extra Wide Swath (EW) and Interferometric Wide Swath (IW) modes over the GrIS (ESA, 2023b). In 2017, both HH and HV polarization data were collected in EW mode at 40 m resolution with a 400 km swath width (ESA, 2023b). This wide swath produced a sufficiently high revisit rate that we were able to retrieve EW images collected in both polarizations within ± 1 day of the AR data collection date for all lakes in our catalog. We used Google Earth Engine (GEE) (Gorelick et al., 2017) to retrieve and process these images. The Sentinel-1 GRD data provided in GEE underwent thermal noise removal, radiometric calibration, and orthorectification using the ASTER GDEM (ESA, 2023a). Unfortunately, a previous study has reported geolocation errors of up to 1 km in some sectors of Greenland for the Sentinel-1 data in GEE, due to localized vertical errors of up to ~ 1000 m in the ASTER GDEM used for terrain correction (Tedstone et al., 2025). We manually checked the extent of our IPR-detected lake against the EW Sentinel-1 images from GEE and found no clear evidence of major geolocation errors in our areas of interest. However, the moderate spatial resolution and potentially reliable geolocation of the EW data are notable disadvantages of this particular dataset.

Given this, we also analyzed the IW data. The Alaska Satellite Data facility provides radiometric terrain corrected (RTC) IW data at a spatial resolution of 30 m through the OPERA project. These data are orthorectified and radiometrically terrain corrected using the Copernicus GLO-30 DEM, which is more reliable than ASTER over the GrIS. As a result, the IW data provides more reliable geolocation and better spatial resolution than the EW data. However, the IW data is focused on the ice sheet margins with a ~ 6 day repeat cycle, and HV collection did not begin until 1 May 2017 in this mode. As a result, there are significant temporal offsets, varying from 0-31 days, between the AR data and the nearest dual-polarization IW image for each lake. At lower elevations, some of these images were also collected during the beginning of the melt season, which biases the lake backscatter statistics. Therefore, in the IW dataset we discarded a total of 20 lakes where either no IW data was available or where the images were collected after the onset of consistent melt.

To ensure a consistent comparison of lake backscatter across all the lakes, we normalized the backscatter in all images to a viewing angle of 35° . Observed backscatter is a function of both surface properties and the satellite viewing angle, which varies between 19° - 47° for EW imagery and 29° - 46° for IW imagery. This can lead to backscatter variations on the order of



~3-4 dB between lakes that are not related to physical differences in lake structure or setting. Backscatter has been shown to vary linearly with viewing angles over ice sheets (Long and Drinkwater, 1994; Ashcraft and Long, 2005; Lindsley and Long, 2016; Long and Miller, 2023), so we use a linear model for this correction.

For the EW data, we followed the viewing angle correction procedure from Culberg et al. (2024), which assumes that during winter, temporal variations in backscatter within a given pixel are primarily the result of different viewing angles during different orbital passes. For each pixel in an image of interest, we collected every observation of backscatter at that pixel between 1 Oct 2016 and 30 Mar 2017, as well as the associated viewing angle for each observation, and regressed backscatter on viewing angle. We then used the slope of this relationship to calculate a backscatter correction for that pixel. This correction added to the observed backscatter to estimate the theoretical backscatter at a viewing angle of 35°. The correction was calculated separately for σ_{HH} and σ_{HV} within each pixel.

The IW data did not have a sufficiently long winter time series in both polarizations to apply this method, since IW σ_{HV} collection did not begin until May 2017. Instead, we selected two calibration sites in the dry snow zone near the Camp Century and NEGIS ice core sites. At these sites, we assumed that the surface is sufficiently homogeneous that spatial variations in backscatter are driven primarily by variations in viewing angle across the radar swath. We used all available pixels within the full radar swath along with the associated viewing angle at each pixel to regress backscatter on viewing angle. As with the EW data, we then used the slope of this linear relationship to calculate and apply a backscatter correction for each pixel in our images of interest over the lakes. The correction was calculated separately for σ_{HH} and σ_{HV} .

To summarize, the EW dataset provides imagery over all our IPR-detected lakes within ± 1 day of the IPR collection. Additionally, the GEE computing framework makes it easy to compile massive time series to calculate the most robust viewing angle corrections. However, EW has moderate spatial resolution and, in select areas, may have significant geolocation errors. On the other hand, the IW images do not cover all lakes and have significant time offsets from the IPR collection, during which time lake structure may have changed. The limited data availability means that the viewing angle correction must be calculated using dry snow zone calibration sites, whose scattering properties are different from lakes in the lower accumulation and ablation zones. However, the IW data has relatively high spatial resolution and very reliable geolocation. Given the complementary advantages and disadvantages of the two datasets, we chose to analyze both. Trends that remain strong across both datasets can be more confidently ascribed to the physical system rather than data errors.

For each lake identified in the AR data, we used nearest neighbor interpolation to extract the corrected σ_{HH} and σ_{HV} values from the nearest EW and IW images along the portion of the IPR flight line where the lake was identified. For each lake, we also defined a "no lake" region, consisting of segments of the flight line to either side of the lake, equal in total length to 3 times the width of the lake itself (see Fig. 2b, for example). We manually reviewed these flight line segments to ensure that they did not intersect with other surface features in the SAR data that might also be lakes. From σ_{HH} and σ_{HV} , we also calculated the linear polarization ratio, σ_{HH-HV} , for the lake and no lake regions.



2.3 Analysis Methods

To understand if and how lake geometry and structure impact the Sentinel-1 observables, we looked for any correlation between abruptness, depth to the water table, and σ_{HH} , σ_{HV} , or σ_{HH-HV} . We also investigated whether the depth to the water table or abruptness could explain the relative radiometric detectability of our observed lakes. We defined three polarization metrics to investigate lake detectability:

- ΔHH is the median σ_{HH} over the lake minus the median σ_{HH} in the "no lake" region surrounding each lake.
- ΔHV is the median σ_{HV} over the lake minus the median σ_{HV} in the "no lake" region surrounding each lake.
- $\Delta[HH - HV]$ is the median σ_{HH-HV} over the lake minus the median σ_{HH-HV} in the "no lake" region surrounding each lake.

These metrics quantify how much each lake's radiometric signature differs from the surrounding ice and firn in each polarization channel. A positive value indicates that the lake is brighter than its surroundings, a negative value indicates that the lake is darker than its surroundings, and a value near zero indicates that the lake is very similar to its surroundings. We chose these metrics to quantify detectability because most studies that automatically detect buried supraglacial lakes in C-band SAR imagery have used some form of backscatter thresholding. These studies typically assume that lakes are significantly darker than their surroundings in σ_{HV} . Here, we explore the full range of polarization metrics to assess the validity of that assumption. Finally, we assess whether lake detectability can be predicted by environmental setting, specifically ice sheet region (based on the IMBIE basin definitions), surface elevation from BedMachine v4 (Morlighem et al., 2017), or annual surface mass balance (SMB) averaged over 1958-2018 from RACMO2.3p2 (Noël et al., 2019). RACMO is a polar regional climate model that has been extensively validated against historical observations of atmospheric variables and SMB in Greenland (Ettema et al., 2010). We use modeled SMB from the latest operational version of RACMO which is forced at the boundaries with ERA5 reanalysis and run at 5.5 km spatial resolution, with offline statistical downscaling to 1 km resolution (Noël et al., 2019).

3 Results and Discussion

3.1 Buried Lake Catalog

In total, we cataloged 155 buried supraglacial lakes in the Accumulation Radar data. Most lakes were found on the west coast, with 114 of the lakes located in the northwest (NW), central-west (CW), or southwest (SW). An additional 14 lakes were found in the north (NO), 20 in the northeast (NE), and 7 in the southeast (SE) (Fig.1). Depth to the water table ranged from 0.84 m to 16.6 m, with a median depth of 2.2 m, similar to the average depth of 1.88 m reported in Koenig et al. (2015). 92% of these detections have depths to the water table of less than 9.43 m, the maximum depth reported by Koenig et al. (2015). Twelve of the 155 buried lakes are significantly deeper, with depths to the water table ranging from 10.7 m to 16.6 m. Six of these deep water tables were found within previously cataloged ice blobs in Northwest Greenland, where Culberg et al. (2022) found that



they were likely formed by surface lakes or streams draining through crevasses in the overlying ice slab. An additional two of these features had similar morphologies to the ice blobs identified in Northwest Greenland. The remaining four features had indeterminate morphologies and could represent either true buried supraglacial lakes or water reservoirs formed by surface water drainage in near-surface void space. Ultimately, we retained all of these detections for the satellite data analysis because they compose a small part of the dataset, have similar water table morphology as true buried lakes, and still represent shallow subsurface impoundment of surface meltwater that is important for surface mass balance. For convenience, we will refer to all features in the cataloged as "buried lakes" in this study, while acknowledging that these deeper features may have been formed by drainage rather than top-down refreezing. Our overall spatial distribution of lakes is consistent with past catalogs from both ice-penetrating radar (Koenig et al., 2015) and SAR (Dunmire et al., 2021; Zheng et al., 2023).

3.2 Lake Structure and Backscatter

First, we investigated whether Sentinel-1 is able to directly sense buried water by assessing the degree to which the observed backscatter is correlated with the geometry of the buried lakes, as quantified by water table abruptness and depth to the water table. We find that σ_{HH} is uncorrelated with abruptness, while σ_{HV} shows a statistically significant negative correlation with abruptness (Fig. 3a-b,d-e). This suggests that σ_{HH} may respond primarily to the structure of the ice-air interface (e.g. surface roughness), whereas σ_{HV} is also influenced by the roughness of the ice-water interface. In regions of low abruptness, where the ice-water interface is rough or geometrically complex, σ_{HV} is high due to significant depolarization of the signal. In contrast, regions of high abruptness are associated with smooth ice-water interfaces that produce minimal depolarization and reflect the incoming signal away from the radar, leading to much lower values of σ_{HV} . These trends produce a statistically significant positive correlation between abruptness and σ_{HH-HV} (Fig. 3c,f), indicating that returns from high-abruptness lakes are dominated by surface scattering and returns from low-abruptness lakes are more influenced by rough surface or volume scattering.

All polarization metrics show some correlation between backscatter and depth to the water table when the water table is buried less than 5 m deep (Fig. 4). Both σ_{HH} and σ_{HV} increase as the depth to the water table increases, while σ_{HH-HV} decreases. When the water table is shallow, the return is likely dominated by specular reflections at the ice-water interface due to the high dielectric contrast. This process scatters energy away from the radar leading to low backscatter in both polarization channels. As the depth to the water table increases, the return is increasingly dominated by volume scattering from heterogeneity within the ice lid itself and by scattering at the ice-air interface, since relatively little power reaches the ice-water interface after absorptive and scattering losses in the lid. This leads to a commensurate increase in backscatter in both polarizations. Additionally, deeper water tables are associated with lower abruptness values and more complex ice-water geometries, likely due to the longer freezing period under variable conditions, which increases both backscatter from the ice-water interface and depolarization of the signal.

Once the depth to the water table exceeds 5 m, backscatter and depth to water table are no longer correlated. This suggests that the C-band SAR penetration depth is limited to about 5 m depth in these settings. The high σ_{HV} and low σ_{HH-HV} values

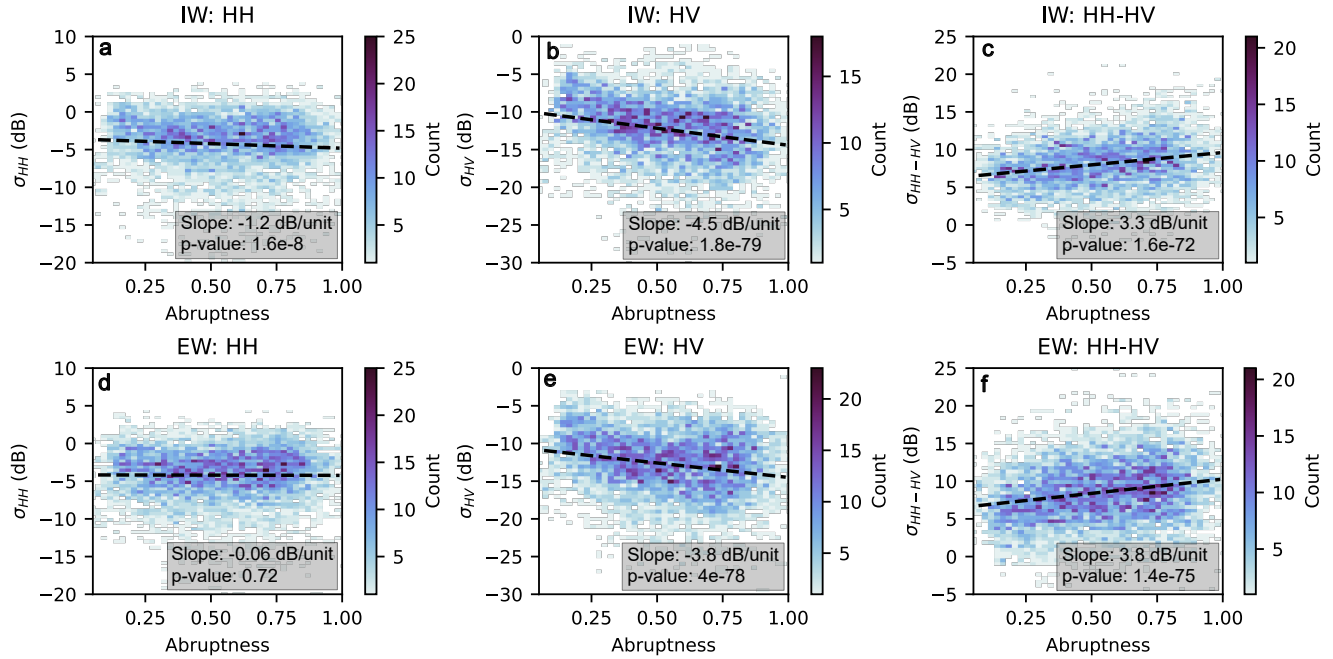


Figure 3. Relationship between Sentinel-1 backscatter and the abruptness (A) of the Accumulation Radar waveform reflected from the lake water table. The first row shows results from the IW imagery. a) Relationship between σ_{HH} and A. b) Relationship between σ_{HV} and A. c) Relationship between σ_{HH-HV} and A. The second row shows the results from the EW imagery. d) Relationship between σ_{HH} and A. e) Relationship between σ_{HV} and A. f) Relationship between σ_{HH-HV} and A. Contains modified Copernicus Sentinel data [2017].

for these deep lakes suggest that the return is dominated by some combination of rough surface scattering at the ice-air interface and volume scattering within the lake lid.

Altogether, our results show that C-band backscatter, particularly σ_{HV} , is modulated by the geometry of the buried lake. This suggests that, when the depth to the water table is less than 5 m thick, Sentinel-1 is directly sensing the buried water, rather than responding to some surface roughness proxy correlated with buried lake formation. However, deeper buried lakes may leave no discernible imprint in the SAR backscatter as the ice-water interface is not within the radar sensitive volume at C-band.

3.3 Lake Detectability

Next, we investigated whether buried lakes have consistent radiometric signatures that make them distinguishable from the surrounding ice and firn by assessing the difference in median backscatter between each lake and its surroundings for all three polarization metrics (ΔHH , ΔHV , and $\Delta[HH - HV]$). Figure 5 shows histograms of ΔHH , ΔHV , and $\Delta[HH - HV]$ for all lakes using both IW and EW imagery. In this paper, we consider a lake to be radiometrically undetectable if its median backscatter anomaly does not exceed one standard deviation of the backscatter over the surrounding non-lake area. This is

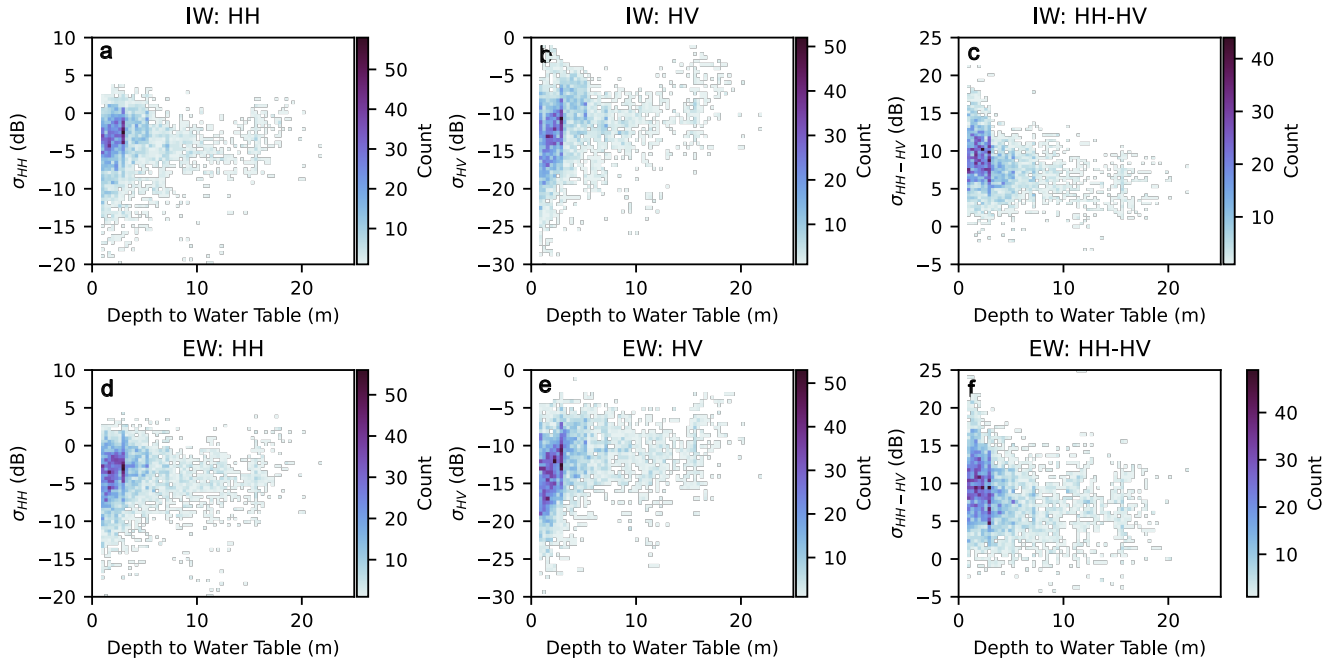


Figure 4. Relationship between Sentinel-1 backscatter and depth to water table (d) as measured by the Accumulation Radar. The first row shows results from the IW imagery. a) Relationship between σ_{HH} and d. b) Relationship between σ_{HV} and d. c) Relationship between σ_{HH-HV} and d. The second row shows the results from the EW imagery. d) Relationship between σ_{HH} and d. e) Relationship between σ_{HV} and d. f) Relationship between σ_{HH-HV} and d. Contains modified Copernicus Sentinel data [2017].

equivalent to saying that the lake's signal to noise ratio (SNR) should exceed 1 if we define SNR as the ratio of average target
 250 (lake) power to the standard deviation of the noise (the backscatter from surrounding ice and firn) (Ulaby and Long, 2014). This condition is shown with gray shading in Fig. 5, indicating lakes whose radiometric signatures are very similar to their surroundings.

We find that radiometric detectability is complicated and inconsistent. For any given polarization metric, around 60% of lakes do not meet our detection threshold. For lakes that do, the sign of the radiometric anomaly is inconsistent. Lakes are somewhat
 255 more likely to be brighter than their surroundings in σ_{HH} , but many lakes are also darker. Similarly, lakes are somewhat more likely to be darker than their surrounding in σ_{HV} , but many are also brighter. $\Delta[HH - HV]$ shows the most consistent pattern, with most detectable lakes having positive values, indicating that lakes are more dominated by surface scattering than their surrounding environments.

Most other studies identify buried supraglacial lakes based on negative anomalies in σ_{HV} . Our results show that this criterion
 260 would detect only 37 (27%) IPR-detected lakes in the IW data and 36 (23%) IPR-detected lakes in the EW data. Considering both positive and negative σ_{HV} anomalies for lake detection raises the detection rate to 36% for IW data and 38% for EW data. If instead we consider a lake to be detectable if the absolute value of its SNR exceeds 1 in any of the three polarimetric

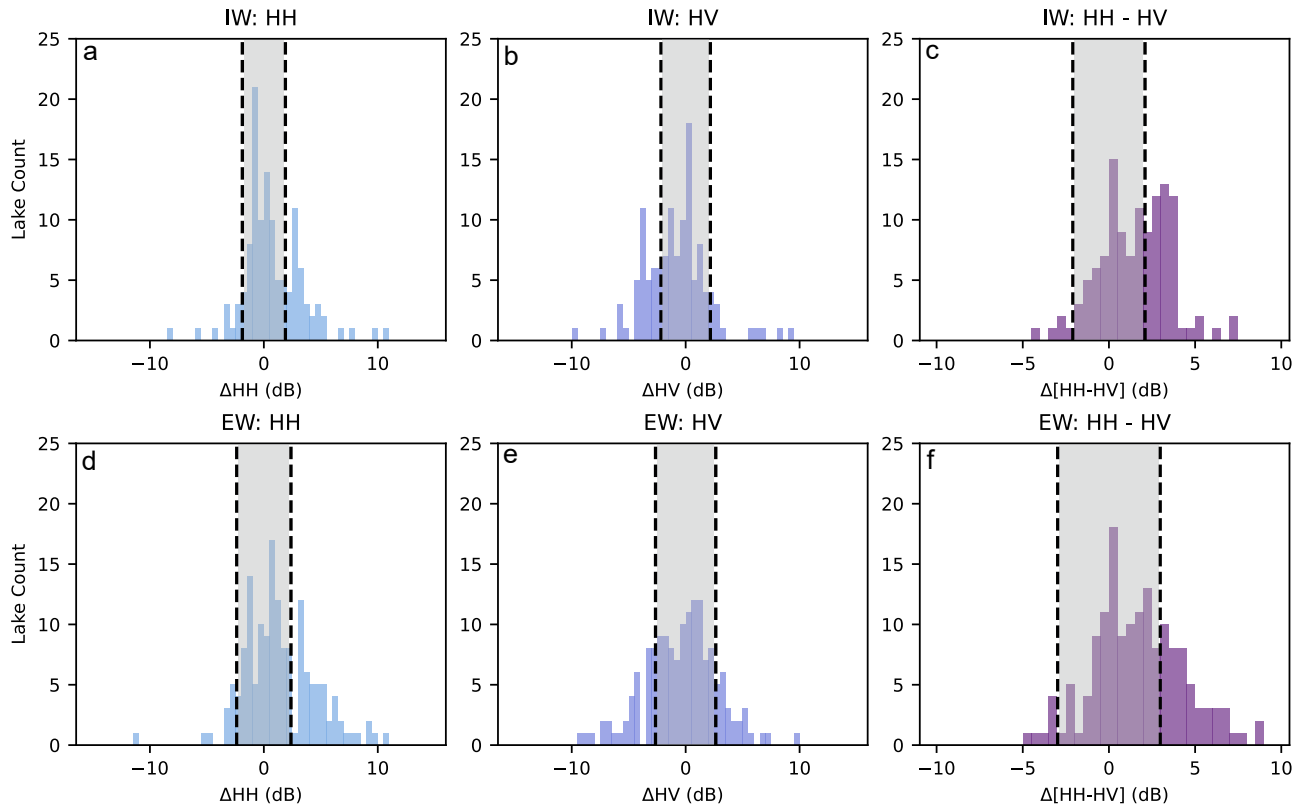


Figure 5. Lake detectability as quantified by the difference in median Sentinel-1 backscatter between the lake and surrounding non-lake areas. A positive value indicates that the lake is brighter than the surrounding region and a negative value indicates that the lake is darker. The gray region between the dashed black lines in each histogram shows areas where the difference in median power between lake and non-lake pixels does not exceed the standard deviation of the backscatter in the non-lake pixels. We assume that lakes which fall within this zone are radiometrically undetectable. The first row shows results from the IW imagery. a) Difference in σ_{HH} between lake and non-lake pixels. b) Difference in σ_{HV} between lake and non-lake pixels. c) Difference in σ_{HH-HV} between lake and non-lake pixels. The second row shows results from the EW imagery. d) Difference in σ_{HH} between lake and non-lake pixels. e) Difference in σ_{HV} between lake and non-lake pixels. f) Difference in σ_{HH-HV} between lake and non-lake pixels. Contains modified Copernicus Sentinel data [2017].

metrics, we would be able to identify up to 83 (61%) of the lakes in the IW data and 96 (62%) in the EW data. Using ΔHH and $\Delta[HH - HV]$ together produces the best two-metric results across both datasets, capturing 93% of the detectable lakes in the IW data and 91% of the detectable lakes in the EW data. The remaining 7% (IW) and 9% (EW) of detectable lakes are detectable only in ΔHV . In both datasets, only 4-9% of lakes are detectable in only one metric. This result is broadly consistent with Schröder et al. (2020), which found that combining σ_{HH} , σ_{HH-HV} , and the averaged σ_{HH} and σ_{HH-HV} anomalies was most effective for discriminating buried lakes in northeast Greenland. However, the common approach of relying solely

**Table 1.** Lake detectability across polarization metrics.

	IW	EW
Total Lakes	135	155
Detectable	83	96
Not Detectable	52	59
Detectable Only in ΔHH	11	14
Detectable Only in ΔHV	6	9
Detectable Only in $\Delta[HH - HV]$	8	9
Detectable in Any Two Metrics	47	48
Detectable in All Three Metrics	11	16

on σ_{HV} or ΔHV to identify buried lakes clearly leads to a significant underestimate of the extent of buried water on the ice sheet.

3.4 Controls on Lake Detectability

To explain why the radiometric signatures of buried lakes vary so widely across our dataset, we investigated whether lake structure or environmental setting can explain these variations. We find that ΔHH , ΔHV , and $\Delta[HH - HV]$ all have complex relationships with abruptness and the depth to the water table. Figure 6 shows abruptness and depth to water table plotted against $\Delta[HH - HV]$, which has the strongest relationship with these structural metrics. As abruptness increases, the maximum possible value of $\Delta[HH - HV]$ also increases. However, while most detectable lakes have abruptness values > 0.4 , there are many lakes with abruptness values > 0.4 that remain undetectable. Similarly, detectability declines rapidly as the depth to the water table increases. Almost all detectable lakes are shallower than 5 m, although there are many shallow lakes that are not detectable.

Figure 7 shows that shallow ($d < 5$ m) and smooth ($A > 0.4$) lakes (purple histogram) comprise the majority of lakes that are detectable in the $\Delta[HH - HV]$ metric. ΔHH shows a similar separation between the distributions for smooth, shallow lakes and all other lakes. This is physically consistent, since these lakes will be dominated by specular reflections at the air-ice and ice-water interfaces, with minimal contributions from volume or rough-surface scattering, leading to a surface scattering dominated regime that is well captured by these polarimetric metrics. Interestingly, ΔHV detectability alone is less strongly related to the depth to the water table and smoothness than $\Delta[HH - HV]$ or ΔHH , suggesting that ΔHV provides additional independent information when detecting lakes. HV backscatter might be modulated in part by the internal heterogeneity of the lake lid ice, which forms by refreezing of lake water and therefore has a different structure than the meteoric ice or icy firn surrounding a lake.

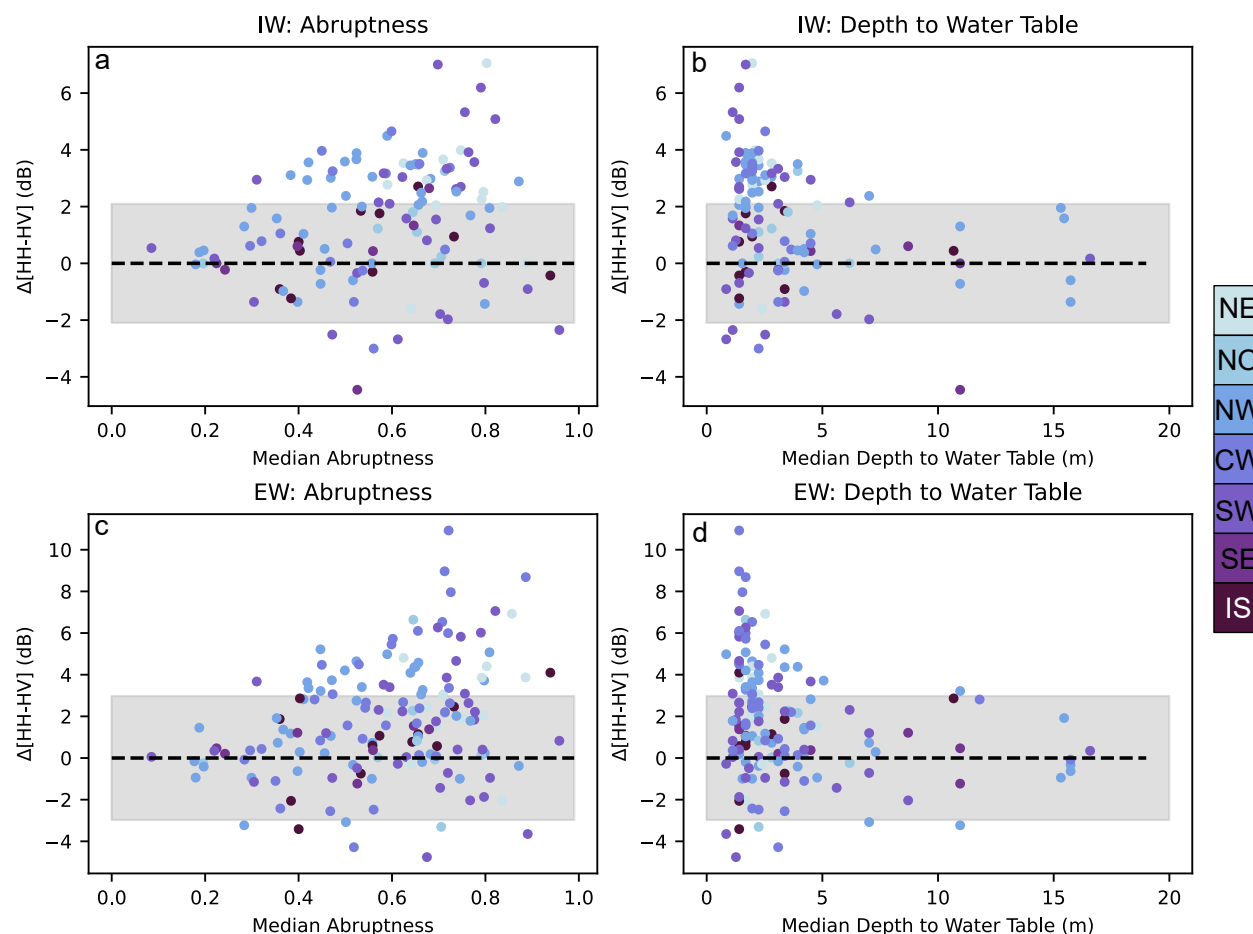


Figure 6. Relationship between lake detectability and lake structure. One dot represents one lake and dots are color-coded by the ice-sheet region in which the lake is found (note that "IS" indicated lakes found in floating ice shelves). The gray patch in each plot shows the region in which lakes are radiometrically undetectable. The first row shows results from the IW imagery. a) Scatterplot of the median abruptness of the Accumulation Radar waveform reflected from the water table versus the difference in median σ_{HH-HV} between lake and non-lake pixels for each lake. b) Scatterplot of the median depth to water table versus the difference in median σ_{HH-HV} between lake and non-lake pixels for each lake. The second row shows results from the EW imagery. c) Scatterplot of the median abruptness of the Accumulation Radar waveform reflected from the water table versus the difference in median σ_{HH-HV} between lake and non-lake pixels for each lake. d) Scatterplot of the median depth to water table versus the difference in median σ_{HH-HV} between lake and non-lake pixels for each lake. Contains modified Copernicus Sentinel data [2017].

To further investigate why the detectability of lakes with similar abruptness and depths to the water table varies so significantly, we tested whether lake detectability is related to ice-sheet region, elevation, or SMB. We find no relationship with ice-sheet region or elevation, but both ΔHH and ΔHV have statistically significant negative linear relationships with SMB

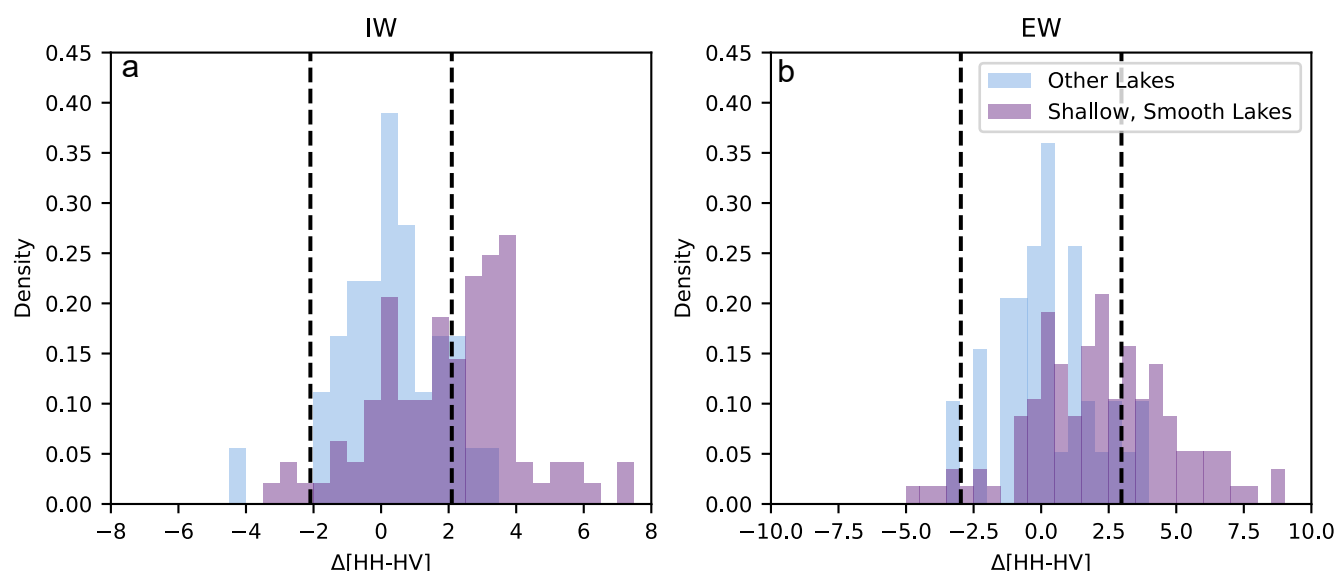


Figure 7. Histogram of the difference in median σ_{HH-HV} between lake and non-lake pixels for shallow, smooth lakes ($d < 5$ m, $A > 0.4$) in purple and all other lakes in blue. Lakes that fall between the two dashed black lines are considered to be radiometrically undetectable. a) Results from IW imagery. b) Results from EW imagery. Contains modified Copernicus Sentinel data [2017].

(Fig. 8). Our data show that in the ablation zone, buried lakes are characterized by positive anomalies in both σ_{HH} and σ_{HV} , while in the accumulation zone, they are characterized by negative anomalies in σ_{HH} and σ_{HV} . Buried lakes at the equilibrium line altitude are the least detectable, with near-zero backscatter anomalies in both polarizations.

295 In the ablation zone, the radiometric signatures of buried water may largely reflect the differences in ice composition and roughness between the homogeneous exhumed meteoric ice surrounding the lake (low backscatter) and the bubblier lake ice that was formed by refreezing (higher backscatter). In the accumulation zone, lakes form on top of ice slabs, so the background substrate is a complex mixture of superimposed ice and icy firn. Here, lakes appear as negative backscatter anomalies since the refrozen lake lid is smoother and less heterogeneous in composition than the surroundings. Lakes near the ELA may be
300 challenging to detect because they have similar levels of heterogeneity to their surroundings, since both largely consist of superimposed ice. This interpretation is consistent with past work which has shown that superimposed ice has an intermediate backscatter signature in SAR data, brighter than meteoric ice in the ablation zone and darker than icy firn in the wet snow and percolation zones, likely due to the scattering from clusters of large bubbles (König et al., 2002; Parrella et al., 2021; Langley et al., 2008, 2009).

305 As a result, using the standard lake detection metric of a negative σ_{HV} anomaly will produce a clear spatial bias in lake detection, where the classifier will miss most buried lakes in the ablation zone, while preferentially detecting high-elevation buried lakes in the ice slab regions. However, our results show that lake detectability in $\Delta[HH - HV]$ is not correlated with SMB (Fig. 8c,f), suggesting that regardless of environmental setting, lake returns have a stronger surface scattering component

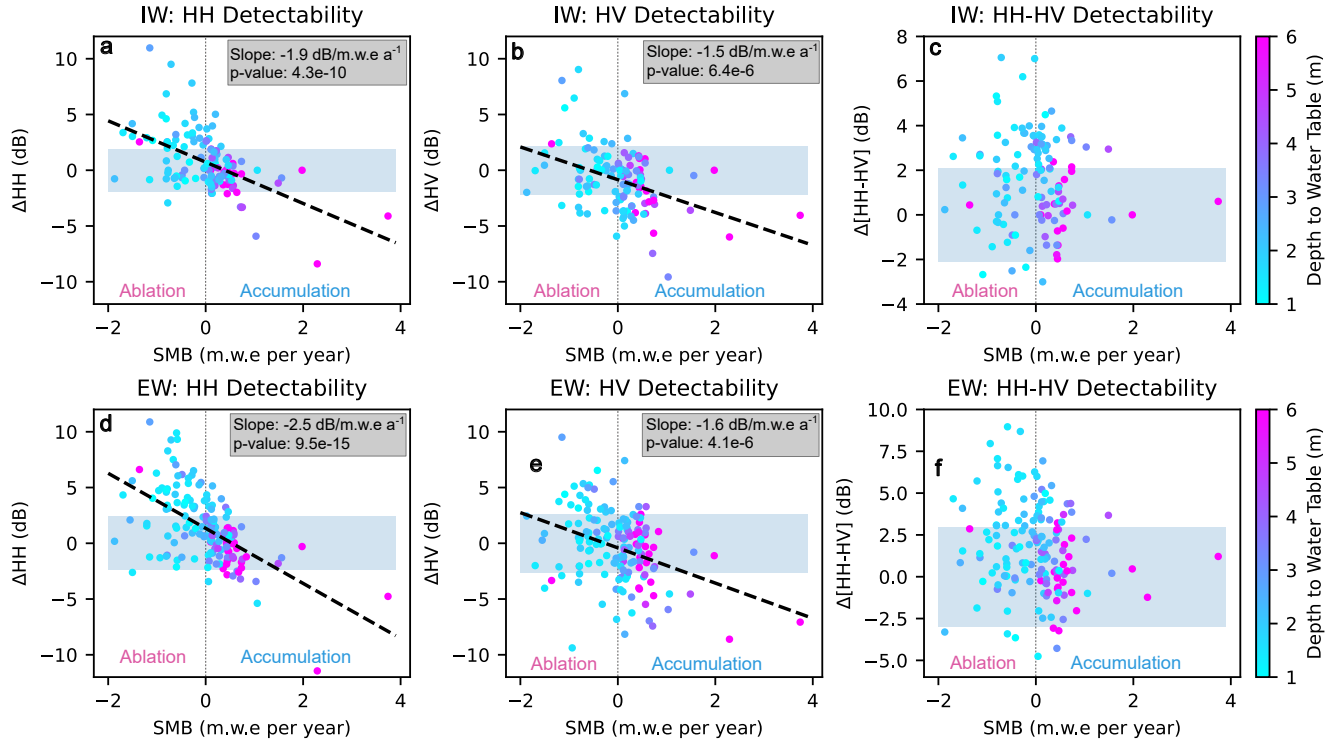


Figure 8. Relationship between surface mass balance (SMB) and Sentinel-1 backscatter over lakes identified by the Accumulation Radar. Each dot represents one lake and lakes are color-coded by depth, with shallow lakes in shades of blue and deep lakes in shades of pink. The shaded blue region in each plot shows the area where lakes are radiometrically undetectable. Dashed black lines show the best linear fits to the data. The first row shows results from the IW imagery. a) Scatterplot of SMB versus σ_{HH} . b) Scatterplot of SMB versus σ_{HV} . c) Scatterplot of SMB versus σ_{HH-HV} . The second row shows results from the EW imagery. d) Scatterplot of SMB versus σ_{HH} . e) Scatterplot of SMB versus σ_{HV} . f) Scatterplot of SMB versus σ_{HH-HV} . Contains modified Copernicus Sentinel data [2017].

than their surroundings. Our results demonstrate that considering either σ_{HH-HV} or $\Delta[HH-HV]$ in buried lake classification algorithms is important for reducing spatial bias.

4 Conclusions

Our results confirm that C-band SAR is a valuable tool for quantifying the spatial extent and temporal dynamics of buried lakes across the GrIS. For shallow lakes that fall within the radar-sensitive volume, σ_{HV} is directly modulated by lake structure, particularly the depth to the water table and the smoothness of the ice-water interface. HH backscatter (σ_{HH}) is likely controlled by the roughness of the air-ice interface and, to a lesser extent, the thickness of the ice lid. This demonstrates that, for shallow lakes, C-band SAR is able to directly sense buried water, and both polarization channels provide information on the presence of liquid water and its structure in the englacial system.



However, our analysis also identifies some significant limitations in this technique. First, the limited penetration depth of the C-band signal means that lakes buried deeper than 5 m are largely undetectable. In our data set, 23 of the 155 lakes, or 15%, are too deep to be detected. Second, the radiometric signatures of buried water are inconsistent from lake to lake, in part due to correlation with local SMB. As a result, the most common detection metrics in the literature, which are based on either absolute or relative anomalies in σ_{HV} , will fail to detect many buried lakes. In our dataset, only 23-27% of lakes appeared as negative anomalies in ΔHV , demonstrating that this metric severely underestimates the total extent and volume of water stored across the ice sheet by this mechanism. The detections were also strongly biased towards buried lakes in the accumulation zone.

Our results show that all three polarimetric metrics should be considered in SAR lake detection algorithms. In particular, including σ_{HH-HV} can significantly reduce spatial bias in the results since $\Delta[HH - HV]$ is not correlated with SMB. Additionally, considering both positive and negative backscatter anomalies as indicative of buried water increases the lake detection rate. New L-band observations from ALOS and NISAR may also be able to improve the detection of deep lakes with their deeper penetration depth.

Our study does not address how these expanded criteria for lake detection might change the false positive detection rate, an issue that deserves further study. Full quad-polarimetric data, additional polarization metrics such as entropy and alpha angle, or interferometric properties such as volume decorrelation not considered here may also provide additional information that can further constrain buried lake extent. It is also the case that many of the buried lakes that were not radiometrically detectable by the standard defined in this paper could still be visually identified in the SAR imagery based on surface morphology. For example, some buried lakes were marked by a dark (low backscatter) moat around the edges of the topographic basin in which they formed, or by bright (high backscatter) ridges along the edges of the refrozen lid. Ultimately, our results demonstrate that buried lake detection would benefit from SAR data with a diversity of polarization channels and frequencies, as well as deep learning approaches that can consider both morphological and radiometric information in the classification problem. Our new catalog of IPR-detected buried lakes provides an important ground truth dataset for further investigation of these approaches.

Code and data availability. Data required to reproduce these results and code to reproduce Figures 3-8 from the final data are available at <https://zenodo.org/records/21652205> (Steinmetz and Culberg, 2026). 2017 Accumulation Radar data (Paden et al., 2014) are available from the National Snow and Ice Data Center (NSIDC) at <https://nsidc.org/data/iracc1b/versions/2>. Sentinel-1 GRD Extra Wide Swath data are available through Google Earth Engine at https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S1_GRD. Sentinel-1 OPERA RTC Interferometric Wide Swath data (NASA/JPL/OPERA, 2023) are available through the Alaska Satellite Facility at <https://search.asf.alaska.edu>. IMBIE ice sheet basins are available from <https://imbie.org/imbie-2016/drainage-basins/>. Ice sheet surface elevation is available from Greenland BedMachine v4 (Morlighem et al., 2017; Morlighem and et al, 2021) via NSIDC at <https://nsidc.org/data/idbmg4/versions/4>. Surface mass balance from RACMOv2.3p2 (Noël et al., 2019) is available upon request to Brice Noël (bnoel@uliege.be) due to data volume, or through the QGreenland Project: <https://qgreenland.org/>.



Author contributions. RC conceived the study. JS conducted the data processing and analysis and produced and interpreted the results. RC
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