

Classification of Radar Zones on Selected Glaciers in Ny-Ålesund, Svalbard

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Abstract

Glacier facies are characteristic properties of glaciers that are an observable and mappable determinant of their health. The occurrence and distribution of facies depend upon several contributing factors such as climatic shifts, sudden events, temperature, precipitation, overall deglaciation, *etc.* Seasonal variations of facies in one year and annual variations across several years are effective markers of seasonal and long-term glacial evolution. Synthetic aperture radar (SAR) allows for efficient generation of seasonal data within multilayer composites which can be exploited for mapping facies. In this study, we utilized Sentinel-1 data to create seasonal composites from 2016-2023 and mapped facies of selected glaciers, in Ny-Ålesund, Svalbard. We utilized unsupervised classification to obtain facies maps in a data-centric approach. This involved modulating the number of output thematic classes across sets of 3, 5, and 7, as well as changing the spatial extent from multiple glaciers to a single glacier in the classification workflow. Thematic classification revealed mixed clusters across all years and polarizations. Our analysis suggests that seasonal variability of facies leads to mixed signals within a single pixel causing misclassification. Additionally, the spatial extent of the input data drives fluxes in thematic mapping, suggesting that changes in local and global raster statistics can limit spatial scale transferability of a mapping workflow. The present results place thematic classification of glacier facies into a practical context for future applications. Our upcoming experiments will include a longer time-series, various polarizations, and advanced information extraction methods, leading to improved understanding of the operational applications of seasonal SAR data for mapping glacier facies.

Key words: radar zones, glacier facies, ISODATA, thematic mapping, seasonal facies, glacial time series, spatiotemporal variations

DOI: 10.5817/CPR2026-1-4

Received August 25, 2025, accepted June 26, 2026.

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Acknowledgements: The authors thank HOD, Civil Engineering, and Director, MIT for encouraging the present research.

Introduction

Glaciological zones are areas of differentiated snow and ice formed by natural accumulation and ablation. When observed on the supraglacial terrain using optical sensors, they can be called glacier surface facies (GSF). GSF are valuable and sensitive indicators of climate change. Global adaptations occurring due to climate change present an urgent requirement for mapping GSF using existing open-source data (Jawak *et al.* 2019). Monitoring changes in GSF are important because of their valuable input in assessing glacier mass balance (Pope and Rees 2014a). Radar zones are backscatter sequences of GSF in synthetic aperture radar (SAR) signals that vary according to surface roughness and moisture. These are called radar zones (Garg *et al.* 2022).

SAR uses microwave signals to penetrate the surface and map sub-surface features of glaciers. Therefore, radar zones can bypass surface mixture classes causing confusion in optical data (Barzycka *et al.* 2023). Commonly observed radar zones are dry snow, percolation refreeze, lower percolation or wet snow, superimposed ice, and clean ice (Partington 1998). Optical data is used to map the GSF mainly because of its high resolution, spectral richness, visible detailing and color (Pope and Rees 2014b). In Arctic regions with unique climatic conditions like extreme weather, high cloud cover and variable illumination conditions, SAR provides more utility than optical data (Beamish *et al.* 2020).

Jawak *et al.* (2024) mapped GSF on the Midtre Lovénbreen glacier in Svalbard using optical satellite imagery. Their analysis demonstrated the utility of GSF maps as graphical signs of the health of glaciers. The authors faced difficulties in differentiating facies due to limited selection of images based on cloud cover and changing illumination conditions. SAR, by and large, can overcome these challenges, permitting

a wider range of data selection, application, and information extraction. Zhang *et al.* (2019) applied a Random Forest algorithm to Landsat-8 imagery to classify GSF automatically in the Parlung Zangbo Basin. Although the authors were able to differentiate between debris and clean ice zones, the spectral resemblance between supraglacial debris and nearby bedrock along with cloud cover, added to image-based challenges.

Partington (1998) employed multi-temporal European remote sensing (ERS)-1 SAR data to differentiate radar zones in Greenland and Alaska. Their results suggest that seasonal backscatter changes could efficiently demarcate facies. The spatial dimensions of facies vary with seasonal and overall climatic changes including variations in the equilibrium line altitude (ELA) which affects the rate of expansion and contraction.

Kundu and Chakraborty (2015) mapped the variations in spatial distribution of facies in the Himalayas from July 2012 to June 2013 using dual-polarized Indian Radar Imaging Satellite-1 (RISAT-1) data and a linear decision rule equation. While their results deliver key insights into backscatter behavior of specific facies across different seasons and along the altitude of the glacier, adaptive multi-year investigations with the same methodology require multi-data analysis from ablation to accumulation. Overcoming the data intensive requirements for spatiotemporal mapping, Pandey *et al.* (2022) mapped Himalayan facies via supervised classification of a three-layer composite generated from individual intensity images from each season – winter, spring, and summer. This approach merges seasonal variations of facies in a single multi-band raster. Additionally, by generating a false color composite of the multilayer raster, each facies obtains a unique tonal variation according to its backscatter. This provides a visually aided iden-

tification of radar facies. Garg et al. (2022) mapped facies of selected glaciers in Ny-Ålesund, using supervised classification on three-layered SAR composites and found only three facies on these glaciers – middle percolation/wet snow, lower percolation/wet snow, and clean ice. Multispectral delineations of facies in this region find at least four distinct facies, in addition to mixture classes (Jawak et al. 2022a). This presents a curious requirement to ascertain the operator-algorithm divide.

Unlike multispectral data, multilayer SAR composites do not provide a natural-colored view of the glacier’s surface. The tonal variations observed in SAR composites are derived from backscatter signals of the polarization used for each layer (Pandey et al. 2022). Collection of training data for supervised classification often relies on an analyst/operator’s ability to differentiate between features using visual distinctions, specific data-derived properties (reflectance/backscatter), knowledge of the area, and availability of comparative data (Jawak et al. 2022a). Moreover, facies have varying spatial dimensions, implying that assignment of the same number of

pixels for each identifiable class may not be practically possible. In such cases, training a knowledge-driven supervised classification can unintentionally lead to erroneous results.

Unsupervised classification is characterization based on backscatter, texture, and polarimetric properties rather than analyst training. This method can yield data-centric results. This data-first approach when assessing facies in SAR composites may allow an analyst to identify previously uncharacterizable patterns. To this effect, radar facies have been previously mapped using K-means clustering and ISODATA (iterative self-organizing data analysis techniques algorithm) classification (Ayma et al. 2019) with acceptable results. However, it is necessary to conduct an analysis into misclassifications induced by unsupervised methods to understand variations, reliability, and challenges within a data-centric approach. Such an analysis can provide operational reference material to an analyst seeking to extract maximum information from SAR composites to map radar facies.

Research aim

In the present study, we aim to characterize radar facies for selected glaciers in Ny-Ålesund, Svalbard using ISODATA classification from 2016-2023 on Sentinel-1 data. We provide a robust assessment of the classification using the thematic clusters and calculated area. Additionally, we examine the differences in

classification clusters attained when mapping all glaciers *vs.* a single glacier by masking the non-target areas. This was performed to understand the overall impact of spatial extent and local *vs.* global contextual variance on thematic classification.

Study area

Svalbard is a Norwegian archipelago (Fig. 1) consisting of nine islands surrounded by the Norwegian Sea, Barents Sea, and the Arctic Ocean (Kar et al. 2018). It has a mountainous topography

with around 1668 glaciers, covering approximately 57% of its landmass (Kar et al. 2018, Nuth et al. 2013) Svalbard is among the fastest warming regions on Earth with peak warming rates at its south-

ern and central regions. It has observed a warming rate twice the global average (Isaksen et al. 2016). This warming can be attributed to Arctic amplification, changes in ocean currents, and feedback mechanisms (Isaksen et al. 2016). This results in varying glacier mass balance across the archipelago. Existing data on long term monitoring of the region reveals a negative mass balance trend indicating an increased amount of melting since 2000 (Bhattacharjee et al. 2023). Adverse outcomes of this warming include glacier melting and retreat, alternating topographies, and a significant volume of freshwater discharge into marine systems. Thus, Svalbard is a key location for conducting climatic change, glaciological, and oceanographic studies.

Ny-Ålesund is an international research town located on the island of Spitsbergen in the Svalbard archipelago. It serves as a working base for international settlements and environmental observation due to its accessibility to the high Arctic, supporting glacier mass balance and climate change studies (Jawak et al. 2022b). Botnfjellbreen (Fig. 1) is one of the seven major glaciers of the Ny-Ålesund peninsula which lies at the eastern most end. Access to the glacier is limited because of the surrounding rugged Arctic landscape. Kongsfjorden, near the Ny-Ålesund peninsula is a major hotspot for research on climate change and marine ecosystem studies (Bennett et al. 2000).

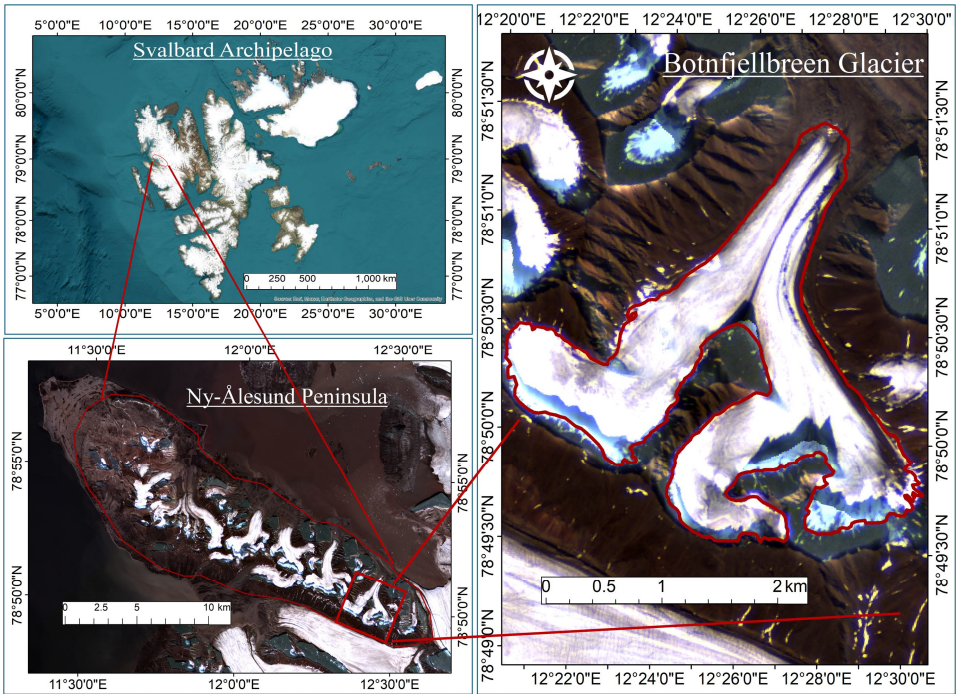


Fig. 1. Location of (a) Svalbard, (b) Ny-Ålesund, and (c) Botnfjellbreen. The Svalbard inset is created using Esri, World Imagery basemap (Accessed via ArcGIS online). The insets of Ny-Ålesund and Botnfjellbreen are prepared using Sentinel-2A data acquired on 18th August 2023.

Data and Methodology

Data used

Sentinel-1 operating in C band (5.4 GHz) can acquire imagery in all-weather, and illumination conditions. The instrument operates in four exclusive imaging modes the wave, strip map, extra wide (EW) swath, and interferometric wide (IW) swath modes, with different resolutions and coverage. Sentinel-1 operates with a single polarization (VV or HH) for the wave mode, and dual polarization (VV+VH or HH+HV) for other modes (Nagler et al.

2016). In this research, we have utilized the IW ground range detected (GRD) products from 2016 to 2023^[1] with HH, HV, VH and VV polarizations. Data from three seasons, *i.e.*, Winter-January, Early summer-May and Late summer-August were collected to obtain seasonal variation of facies. Corresponding optical imagery for the late summer season was downloaded for visual comparison between SAR and optical data.

Year	Season	Date of acquisition	Polarization
2016	Winter-January	17 January 2016	HH
	Early summer-May	16 May 2016	HH
	Late summer-August	20 August 2016	HH
2017	Winter-January	23 January 2017	HV
	Early summer-May	23 May 2017	HH
	Late summer-August	27 August 2017	HH
2018	Winter-January	24 January 2018	VH
	Early summer-May	22 May 2018	HV
	Late summer-August	22 August 2018	HV
2019	Winter-January	25 January 2019	VH
	Early summer-May	23 May 2019	HV
	Late summer-August	23 August 2019	HV
2020	Winter-January	20 January 2020	HH
	Early summer-May	7 May 2020	VH
	Late summer-August	21 August 2020	HV
2021	Winter-January	20 January 2021	HV
	Early summer-May	26 May 2021	VV
	Late summer-August	22 August 2021	HH
2022	Winter-January	21 January 2022	VH
	Early summer-May	19 May 2022	VV
	Late summer-August	23 August 2022	HV
2023	Winter-January	26 January 2023	HV
	Early summer-May	16 May 2023	VV
	Late summer-August	18 August 2023	VH

Table 1. Complete list of the season, date of acquisition, and polarization of the data used in the present study.

Methodology

A. Pre-processing

We first performed thermal noise removal to remove additive noise in the polarization channels, referred to as swath-induced error. The process normalizes backscatter signals and minimizes sub-

swath discontinuities during acquisition modes (Mascolo et al. 2022). Fig. 2 presents the data processing methodology of the current study.

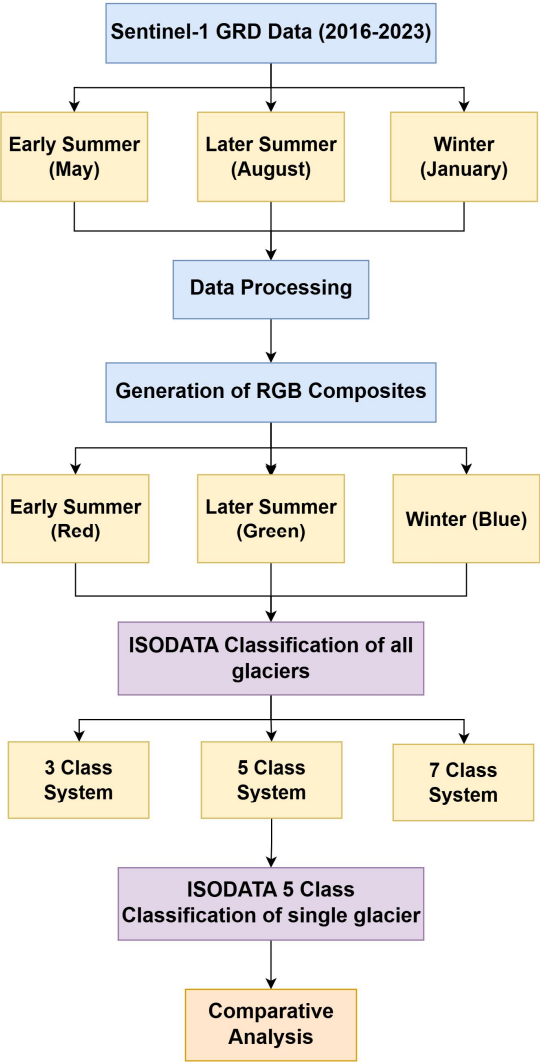


Fig. 2. The data processing methodology of the present study. GRD: ground range detected. ISODATA: iterative self-organizing data analysis techniques algorithm.

Next, we applied an orbit file which establishes a precise orbit for accurate satellite position and velocity information. Subsequently we removed GRD border noise to reduce low-intensity noise and incorrect data present at the edges of the scene, thereby addressing the impact of the earth's curvature, which can cause radiometric distortions. Radiometric calibration was then applied to obtain the corrected backscatter. Backscatter intensities were computed using sensor calibration parameters.

The interaction between waves from the outer phase and the target often results

in grainy salt and pepper pattern in radar imagery. This adversely affects image quality. We used speckle filtering to address this. Subsequently, terrain correction was performed using a Copernicus 30 m digital elevation model (DEM) to address the distortions and variations present in data captured from an angle greater than 0. The DEM corrects distortions caused by topography, such as foreshortening and shadow, and adjusts the location of each pixel. Lastly, we separated the individual polarizations into individual layers, which were reprojected to UTM WGS 84 33 N (Filipponi 2019).

B. Creation of multilayer composites and masking

Several three-layer composites were created using the Early summer (red), Late summer (green) and Winter (blue) polarizations, *e.g.* HH_HV_HH. These composites present multi-temporal signatures via visual hues, aiding the analysis of radar facies (Partington 1998). Additionally, three layered rasters are operationally efficient

for classification. Subsequently, we digitized the Botnfjellbreen glacier extent using a 2016 Sentinel-2A image, acquired on 20 August 2016 close to the date of acquisition of the late summer SAR data. This extent was then used to mask every year's data to understand evolution of facies from 2016 onwards.

C. ISODATA Classification

ISODATA is a widely used pixel-based unsupervised classification method. The algorithm classifies pixels based on their spectral properties without having any prior knowledge of the number of classes and characteristics. Iterative classification repetitively refines clusters that are initially grouped together, calculates the mean and then reassigns pixels based on the new mean, allowing pixels to combine and separate during the iterative process. It is widely used for land cover mapping (Lemenkova 2021), image analysis (Lemenkova and Milton 2009), and environmental monitoring. ISODATA can identify and sort distinct radar facies based on their backscatter properties. After analyzing the multilayer composites, we found five distinct tonal variations. However, these variations were not consistent across each com-

posite. Therefore, to identify the natural affinities of each pixel and the clustering propensities of each facies in this configuration, we adopted a multi-class approach.

Classification was applied to generate 3 thematic classification cluster systems: 3 classes, 5 classes, and 7 classes. These thematic clusters were assessed to determine the facies grouped within each cluster based on literature (Garg et al. 2022) and assessment of the composites themselves. Additionally, upon evaluation of the classification results, and the visible tonal variations, the 5-class system was selected to be applied to a single glacier. This was performed to document the variability induced when utilizing global vs. local statistics in an unsupervised clustering.

Results and Discussion

Multi-class thematic mapping

The goal of this experiment is to provide an assessment of these variations across the study using selected composites to extract meaningful information without needlessly increasing the length of this chapter. Therefore, we present the ISODATA classification cluster schemes for the 2016_HHHHHH (*see* Fig. 3), the 2018_VHHVHV (*see* Fig. 4), the 2021_HVVVHH (*see* Fig. 5), and the 2023_HVVVVH (*see* Fig. 6) composites. The 3-class, 5-class, and 7-class cluster schemes were designed to provide a similar structure to the multispectral ISODATA assessment. However, the class settings for each composite did not exactly deliver the desired number of thematic clusters. Therefore, we present these results using the composites themselves rather than the cluster schemes. Additionally, by using only selected composites we can draw inferences across the entire dataset as these fluctuations are representative of the variability across all the tested data.

2016_HHHHHH: In the current experiment, we find that when set at a 3-class limit, the ISODATA algorithm delivers two classes for this composite with only a minor portion of the glacier allocated to Class 2, and the rest of the glacial bodies grouped into class 1. In the 5-class scheme, we retrieve only three classes, representing similar distributions. In the case of the 7-class scheme, all test glaciers deliver only a marginally larger distribution of other classes than the previous schemes with Class 1 still dominating the larger scheme.

2018_VHHVHV: For this composite, while the 3-class scheme retrieved three

classes, the 5-class scheme delivered four classes. In both schemes, only the upper reaches of the accumulation region of the glaciers were differentiated leaving the rest of the glacier allocated to class 1. The 7-class cluster retrieved only six classes with improved discernment across the glacial bodies suggesting potential for greater differentiation.

2021_HVVVHH: In this composite, only the 3-class scheme delivered the designated number of classes, while the 5-class and 7-class scheme yielded four and five classes each. Across all three schemes, maximum differentiation occurred in the upper reaches of the accumulation zone with the rest of the glacier being allocated to Class 1.

2023_HVVVVH: For this composite, we found greater differentiation across the glacial bodies. While the 3-class and 5-class schemes delivered the designated number of thematic clusters, the 7-class scheme delivered only six. In this composite, maximum differentiation was attained in the ablation zone.

Such a differentiation across time and data can be attributed to polarimetric variations, surface properties, presence of moisture, and even to the limitations of the ISODATA classifier itself. However, it is worth noting that in this experimental set up, we did not attempt to fit any single class across all the composites into a thematic facies category. The purpose of this experiment was to test pixel affinities and output class clusters. To that effect, we found that the ISODATA classifier did not yield the designated number of classes in most scenarios.

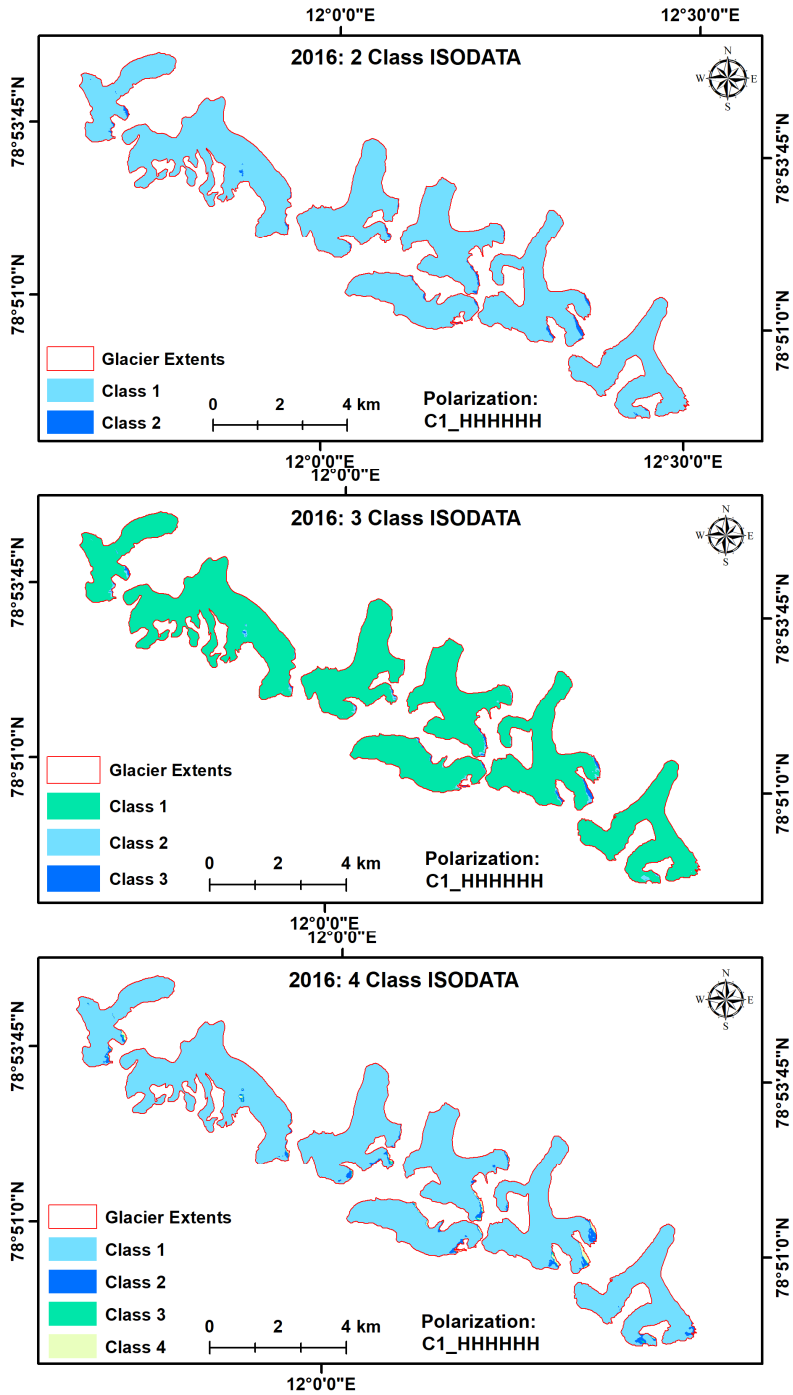


Fig. 3. ISODATA classification of the 2016 HHHHHH composite, using the delimitations of 3, 5, and 7 classes. The mapped classes and panel titles reflect the exact number and distribution of the unsupervised thematic classes.

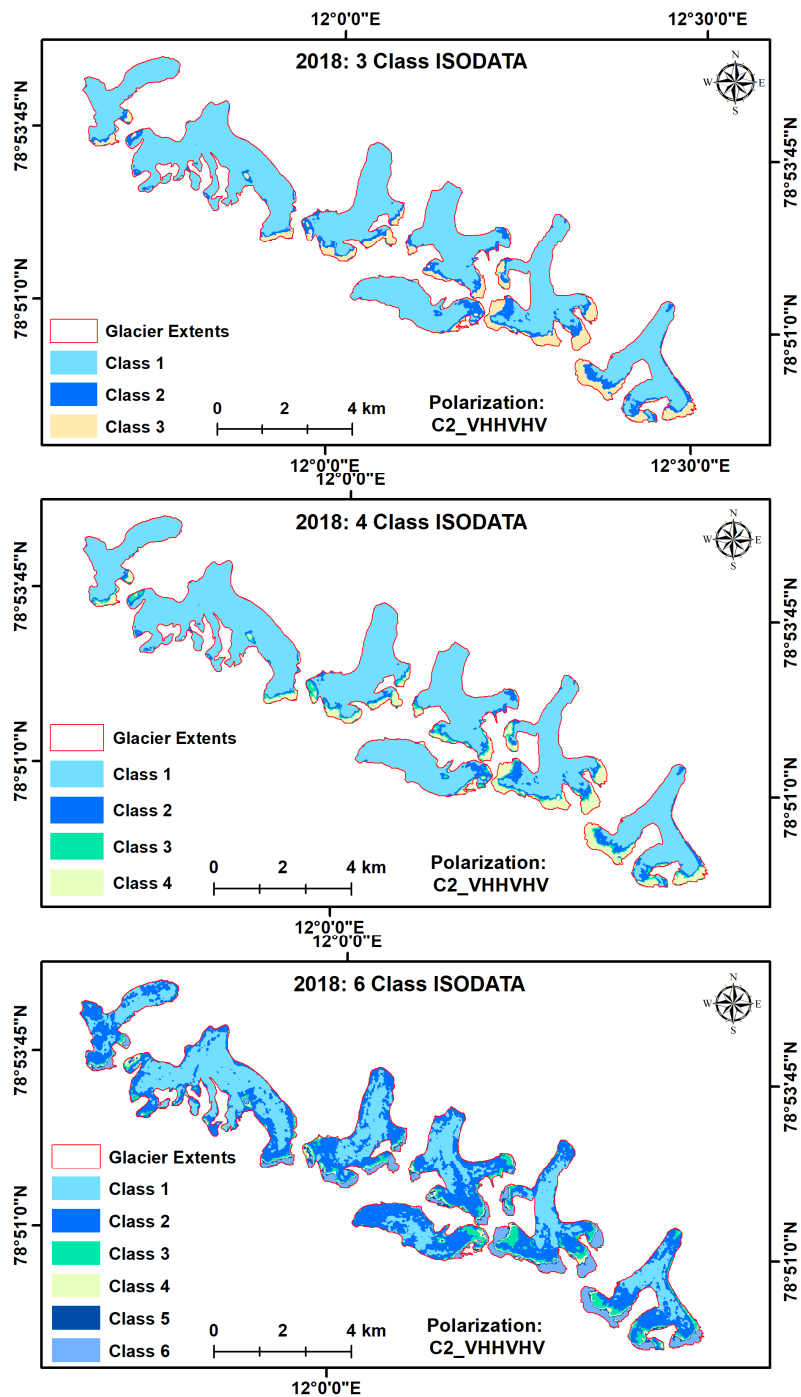


Fig. 4. ISODATA classification of the 2018 VHHVHV composite, using the delimitations of 3, 5, and 7 classes. The mapped classes and panel titles reflect the exact number and distribution of the unsupervised thematic classes.

The lower number of returned classes through ISODATA is fundamentally a function of its algorithmic mechanisms. Primarily, if the natural statistical variations of the composite do not support the maximum number of separable classes, ISODATA will merge the nearest (via Euclidean distance) clusters and delete the smallest ones, *i.e.* with the least number of pixels, to deliver a statistically stable output (Richards 1986). In our experiment, we speculate that this lack of variance may also be attributed to the stacked multiple varying polarizations. In cases with a single raster with the same propagation and return polarization (either HH or VV), it is noted that ISODATA has delivered comparable performance even against the maximum likelihood classifier (Andrade et al. 2024). In the specific case of Andrade et al. (2024), the authors utilized 5 TerraSAR-X HH composites to classify three glacier facies classes in Antarctica from 2014-2016. While this is not directly comparable with the present results, it lends evidence to the capability of ISODATA in specific scenarios. However, even this speculation of multiple polarizations causing a lack of variance stands in

contrast to the results of the 2023 data (Fig. 6).

This contrast demonstrates that the statistical variability within the 2023 dataset was large enough to accommodate up to 6 classes, with 5 classes being the most interpretable. Therefore, although single polarization data (Andrade et al. 2024) and multiple polarization data stacks (Garg et al. 2022) can be used to map glacier facies, a more comprehensive experiment is necessary to determine and understand the exact advantages and disadvantages of both methods in varying contexts. Additionally, if the statistical variance across a dataset determines its clustering and total output classes, any process that changes the spatial extent of the dataset will invariably alter the total variance within the dataset. Therefore, a classifier's output on a global dataset for the same phenomena/feature will differ from the output of local dataset and vice versa. This implies that the present results hold true for the case of the current seven glaciers in this scenario. Altering the spatial extent by reducing the number of glaciers can yield differing results.

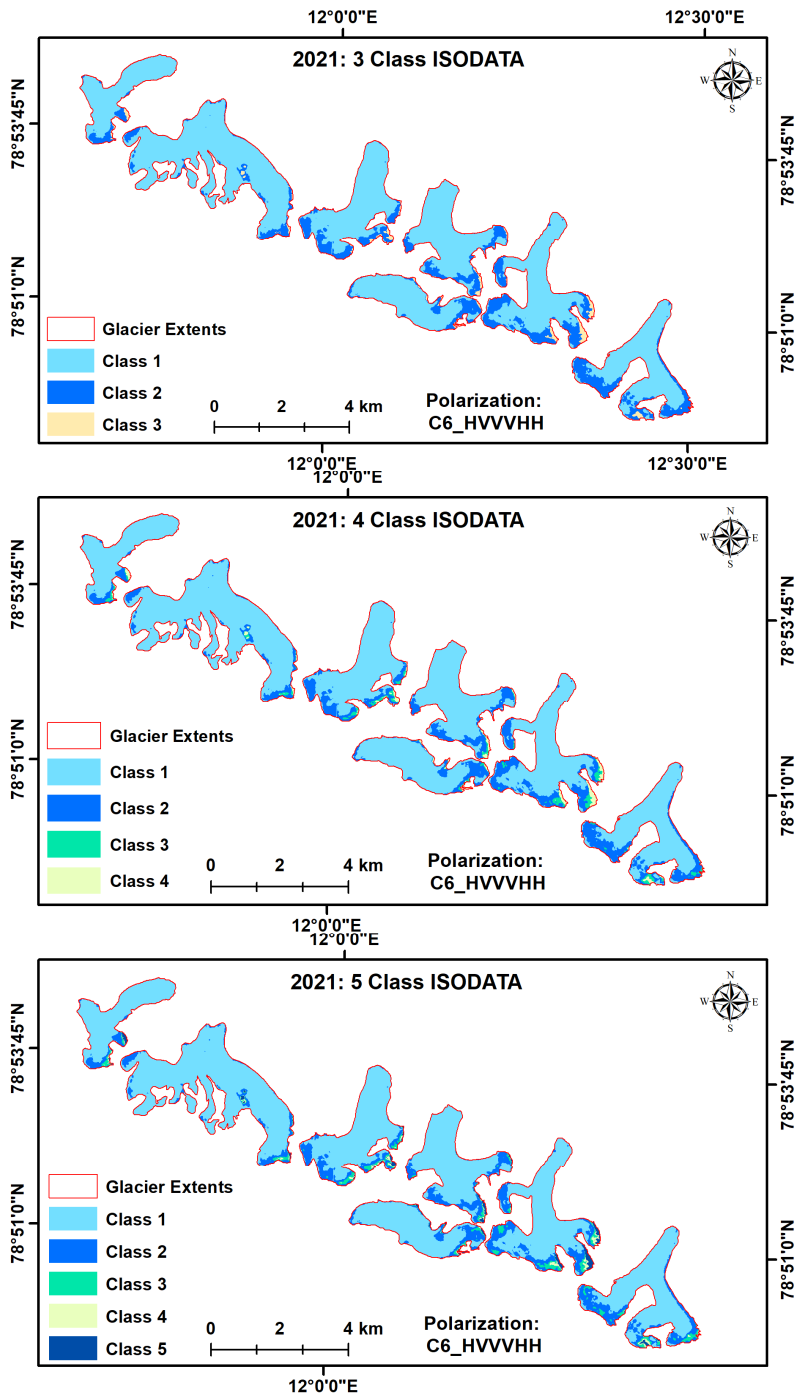


Fig. 5. ISODATA classification of the 2021 HVVVHH composite, using the delimitations of 3, 5, and 7 classes. The mapped classes and panel titles reflect the exact number and distribution of the unsupervised thematic classes.

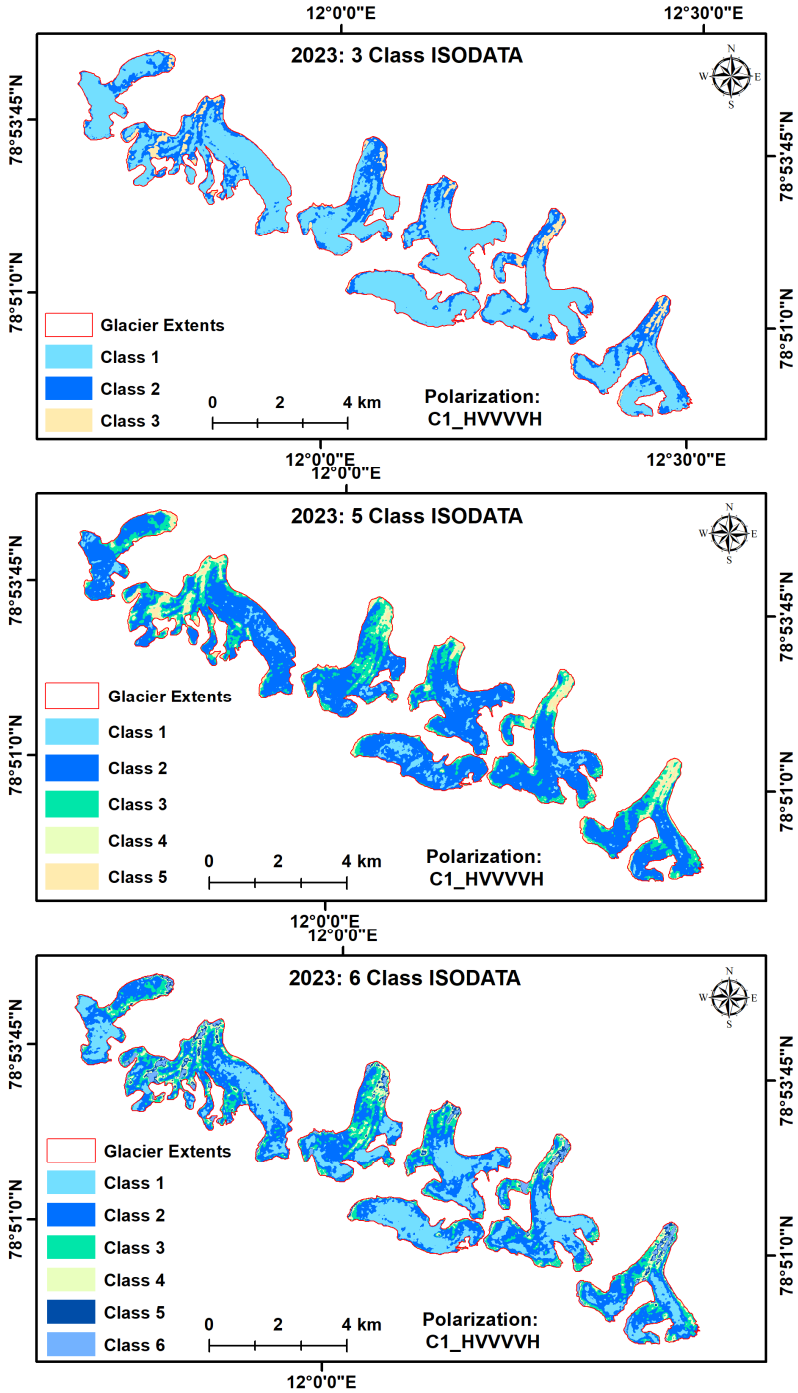


Fig. 6. ISODATA classification of the 2023 HVVVVH composite, using the delimitations of 3, 5, and 7 classes. The mapped classes and panel titles reflect the exact number and distribution of the unsupervised thematic classes.

Divergent classification from multiple glaciers to a single glacier

Every glacier within a basin or a sub-basin possesses its own structure, micro-climate, and consequently its own slightly differing physical characteristics of facies. For example, the percolation zones of several glaciers in the same basin may vary in backscatter signal causing each zone to present itself differently from its neighboring glaciers (Steffen and Heinrichs 2001). Across a composite of seven glaciers, this variability is often ignored in unsupervised classification as it is forced to generalize signatures that apply universally across the dataset; the variance between percolation zone and debris warranting a separation of clusters rather than that between percolation zone and clean ice. This generalization leads to enlarged clusters and

fewer classes.

Figure 8 presents the results for the isolated classification of the Botnfjellbreen glacier for the 2016 and 2023 data. We masked the entire composite and only performed ISODATA on the extent of the Botnfjellbreen glacier for our temporal period. In this scenario, we found that the ISODATA algorithm delivers interpretable classes along with the desired number of classes. Once the statistics of the dataset are reduced from seven to a single glacier, the algorithm can now split the clusters according to the variability of the limited feature space. Even in this case, unsupervised classification delivered thematic class mixtures.

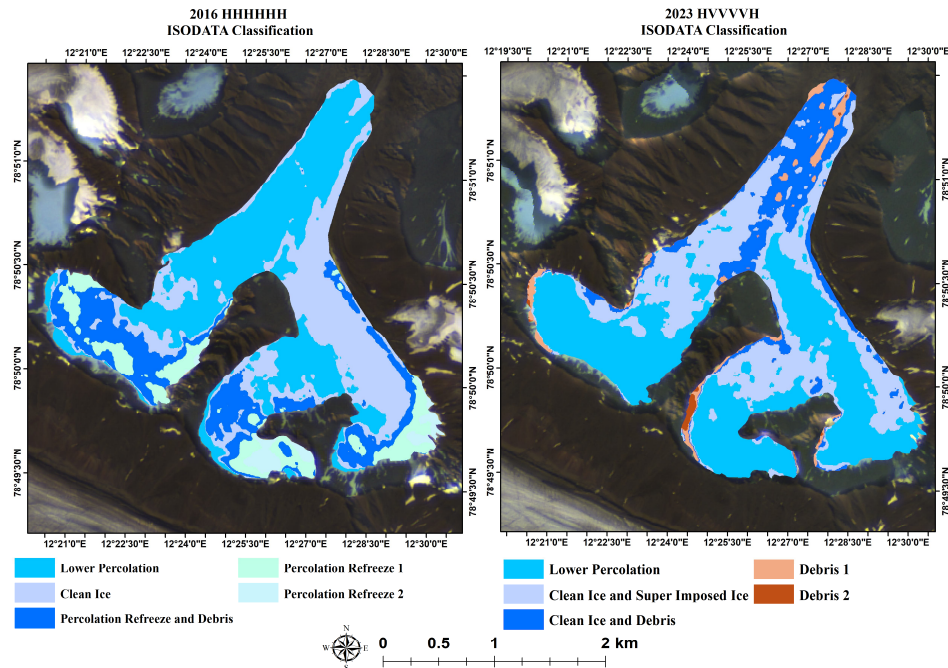


Fig. 7. Comparison of the 2016 (left) and 2023 (right) classification maps of the Botnfjellbreen glacier.

Mixed classification

Garg et al. (2022) provide a descriptive guide on the hue and tonal variations of each radar facies in multilayer SAR composites. Based on these guidelines, the composites, and the ISODATA clusters, we identified percolation refreeze, lower percolation/wet snow, superimposed ice, clean ice, and debris. However, from 2016

to 2023, while most thematic classes were easily identifiable through visual properties and backscatter, specific classes displayed mixed clustering among each other. Table 2 presents the Botnfjellbreen facies classification from each composite according to the mixed and unmixed clusters.

Composite	Mixed classes	Unmixed classes
2016_HHHHHH	Percolation Refreeze and Debris	Percolation Refreeze 1 Percolation Refreeze 2 Lower Percolation Clean Ice
2017_HVHHHH	Percolation Refreeze and Debris Lower Percolation and Clean Ice Clean Ice and Superimposed Ice	Percolation Refreeze 1 Percolation Refreeze 2
2018_VHHVHV	Superimposed Ice and Debris	Percolation Refreeze 1 Percolation Refreeze 2 Lower Percolation Clean Ice
2019_VHHVHV	Lower Percolation and Debris Clean Ice, Superimposed Ice, and Lower Percolation	Percolation Refreeze 1 Percolation Refreeze 2 Percolation Refreeze 3
2020_HHVHHV	Lower Percolation and Superimposed Ice Percolation Refreeze and Debris	Percolation Refreeze 1 Percolation Refreeze 2 Clean Ice
2021_HVVVHH	Clean Ice and Superimposed Ice Clean Ice and Debris Debris and Percolation Refreeze	Percolation Refreeze 1 Percolation Refreeze 2
2022_VHVHVH	Percolation Refreeze and Debris Clean Ice and Percolation Refreeze Lower Percolation and Superimposed Ice	Percolation Refreeze 1 Percolation Refreeze 2
2023_HVVVVH	Clean Ice and Superimposed Ice Clean Ice and Debris	Wet Snow Debris 1 Debris 2

Table 2. Mixed and unmixed classes of the ISODATA classification for each composite.

Among the mixed and unmixed classes from 2016-2023, only in the 2018 and 2019 classifications do we find no overlap between mixed and unmixed classes. Classification of the other years, even with unmixed classes such as percolation refreeze 1/2/3, produces mixed classes that group together percolation refreeze along with clean ice or debris. In the case of 2023, we find no percolation refreeze but mixing between debris and clean ice. Lower percolation, superimposed ice, and debris are among the most consistently misclassified facies. This mixing suggests that separation of spectrally distinct facies in optical differentiation such as dry/wet snow and debris, presents mixing challenges in SAR, *i.e.* percolation refreeze and debris. This mixing caused severe distortions for tracking the spatial dimensions of facies making spatiotemporal analysis severely challenging.

Facies have distinct backscatter signals according to their surface roughness, moisture content, and scattering properties. These are inherent properties of facies in the microwave spectrum. Additionally, polarization plays a critical role in the appearance and signal of specific facies (NASA-ISRO SAR Mission). For example, percolation refreeze presents strong backscattering from refrozen ice due to intense volume scattering in cross-polarized channels. Lower percolation, located in proximity to percolation refreeze presents a sharp drop in volume scattering, but higher surface scattering. This explains the non-existence of a mixed class between percolation refreeze and lower percolation. The contrast between volume and surface dominant scattering (Partington 1998) prevents this cluster.

When incorporating seasonal variations into a single composite via one layer each from a distinct season, the signal and boundaries of facies become transient and relative based on the layer and polarization. For example, clean ice which

would be solid during winter, has a surface melt layer in summer (Huang *et al.* 2013). Backscatter intensities of clean ice would then resemble the lower percolation zone, creating the lower percolation and clean ice mixed class. Additional confusion can be created by the spring layer which presents a clean ice pixel with ‘little’ melt. Figure 8 presents the area of the classified classes from 2016-2023.

Superimposed ice has shown consistent challenges in unsupervised classification (Barzycka *et al.* 2023). The backscatter signal of superimposed ice is determined by the density and air-bubble distribution of the ice layers. As this property of the facies is transient across seasons, a multi-layer seasonal composite will have varying signals of superimposed ice based on the condition of the facies itself. This causes significant mixing of superimposed ice with other classes, leading to its mixture with nearly every facies in our analysis. However, the most interesting mixture in our analysis occurs with debris and all other non-debris classes. Usually, debris presents such a stark contrast to other glacier facies that it is often used to differentiate between debris-covered ice and clean ice (Yao *et al.* 2022). In winter, snow cover would envelop any debris. In spring or early summer, we would find a mixture of debris, ice, dust, and partial melt. In late summer, with maximum ablation, we would find debris mixed with snowmelt. The backscatter within a debris pixel for each season would vary considerably due to these variations. Notably, 2023 was the only year when there was at least one separately classified debris class. However, an analysis on the glaciers in this region from 2000 to 2020 reports that debris cover has been steadily increasing (Murugesan *et al.* 2021). Misinterpretations can arise when attempting to separate debris covered ice from the surrounding terrain (Yao *et al.* 2022). Kundu and Chakraborty (2015) delineated the glacier

boundary using DEM derived terrain curvature. In contrast, our mechanism of us-

ing optical Sentinel-2A data to delineate the boundary is far simpler and efficient.

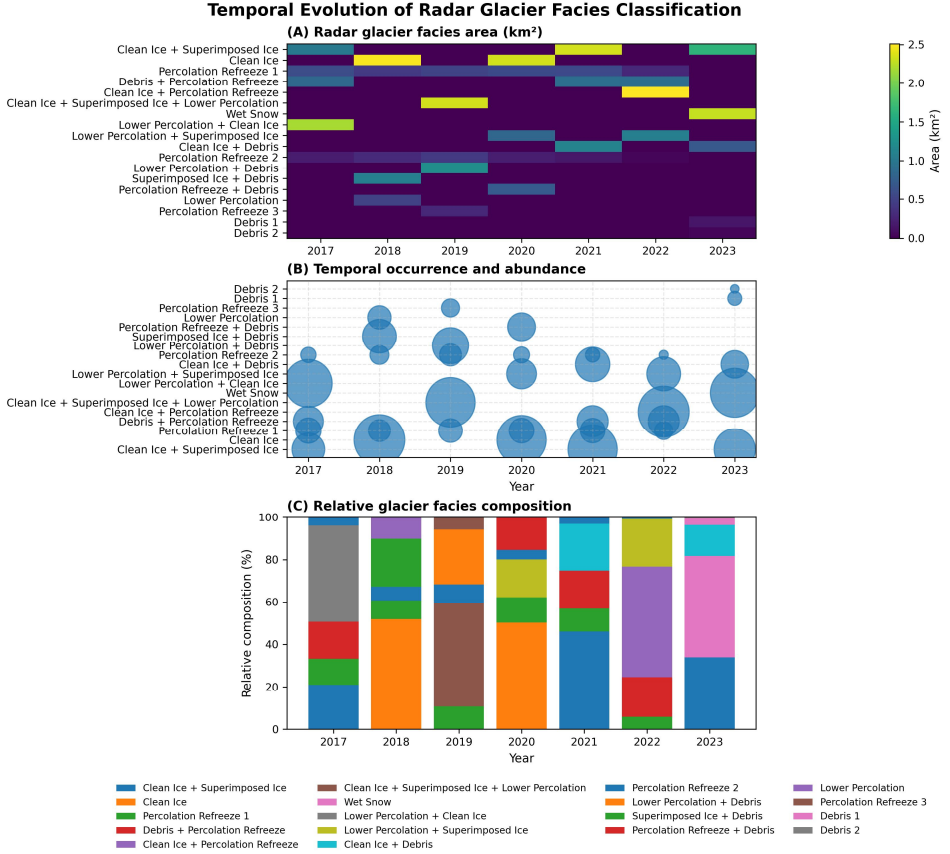


Fig. 8. Calculated area per facies, per year from the ISODATA classification of the Botnfjellbreen glacier. (A) Facies–Year Heatmap: shows absolute area (km²) for each radar glacier facies through time. (B) Bubble Plot: wherein the bubble sizes are proportional to facies area. (C) 100% Stacked Composition Chart: Shows relative facies composition of the glacier each year.

SAR is sensitive to observation geometry, leading to backscatter variability across polarizations. However, even the use of a single type of polarization in a multilayer seasonal stack still leads to mixture. Our 2016 classification utilized only HH polarization for all three seasons. Despite the single polarization, percolation refreeze, and debris were mixed into one class. This suggests that seasonal drifting

and overlapping of backscatter signals for a given facies exerts a strong influence on thematic mapping. Nonetheless, the SAR classification displays a crucial benefit of avoiding misclassification errors occurring due to shadows in optical data (Jawak et al. 2022b).

The current results open a necessary discussion for effective utilization of seasonal SAR layers to map glacier facies.

Our analysis suggests that seasonal multi-layer stacks while offering operational utility can lead to severe misclassification with unsupervised methods. This paves the way for advanced information extraction techniques, from conventional supervised methods (Jawak et al. 2022a) to object-based image analysis (Jawak et al. 2022a),

and advanced deep learning methods (Lu et al. 2021). This potential, however, comes with a necessary question- which method can delineate seasonal variations, and deliver a reliable facies map without leading to misclassifications arising from those variations themselves?

Significances and Limitations

The statistical scaling challenges observed in this study directly inform the architecture and deployment of modern Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) models used for cryospheric monitoring. As modern image processing and information architecture are increasingly adapting to generate global-level datasets and products, phenomena such as glacier facies present practical challenges. If classification from a single to a regional scale delivers widely different outputs because of a dataset's native properties, training data derived across a limited number of scenes may not be sufficient to derive large spatial scale products. This is primarily because supervised classifiers such as the maximum likelihood, random forest, and even artificial neural networks (Wankhede et al. 2025) generally accommodate all variances within the training dataset. This implies that the thematic classification is often the best result of the training dataset and the imagery within that methodological context.

In our previous experiments (Jawak et al. 2022a, 2022b, and 2022c; Wankhede et al. 2025), we demonstrated the variability induced in thematic classification by testing multiple image preprocessing pipelines

on very high resolution (VHR) optical satellite data. Those methods and classification algorithms cannot directly be transferred to a SAR-based experiment because testing the native dataset's properties and its own affinities is necessary before contextualizing training data to drive supervised classification. The present experiment delivers two key takeaways: (1) SAR experiments that deliver facies maps often present a methodology that may be hyper-suited to only that experiment, and (2) Testing multi-polarization stacks, single rasters, and statistical scaling experiments are crucial to create truly transferable methods for mapping glacier facies globally. Our future experiments will involve testing advanced image analysis methods on SAR data for mapping facies, discussing data-based challenges and providing solutions to existing methodological hurdles.

Due to logistical constraints, field data could not be acquired to determine the true glaciological zones within the glacier. However, the present experiment focuses on identifying native challenges that present experimental potential. These results can be used to contextualize mapping procedures and avoid exaggerated claims of transferability and reproducibility.

Conclusion

In this study, we applied unsupervised ISODATA classification to multilayer seasonal SAR data to map glacier facies from 2016 to 2023. Focusing on the glaciers near Ny-Ålesund, Svalbard, we used Sentinel-1 IW GRD data to generate three-layer composites comprising of early summer, late summer, and winter scenes. These composites were classified, and the resultant thematic clusters were assessed to determine facies across 3, 5, and 7 class outputs. This structure delivered large thematic clusters without interpretable facies for every year's data except 2023. We then mapped facies only for a single glacier (Botnfjellbreen) while masking the rest of the data and found thematically interpretable facies classes. While observable facies on the composites include percolation refreeze, lower percolation, superimposed ice, clean ice, and debris, we found mixed classification for every year indicating high unreliability. Analysis suggests that

seasonal drifting of facies caused overlapping of unrelated backscatter within the same pixel, leading to confusing data for the algorithm. Additionally, we created composites with different polarizations and found that even with the same polarization across all three layers, mixing of unrelated classes occurs due to overlapping signals arising from seasonal distribution of facies. Additionally, the change in interpretable thematic clusters with different global and local statistical variances suggests that there is a practical challenge in creating methods that can truly transfer from a local to regional and vice versa scale. The present results require further experimentation to determine an appropriate mechanism for minimising these variations. Our future experiments involve testing more polarizations, with advanced information extraction methods, across multi-temporal periods to accurately map glacier facies.

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