environmental sciences proceedings

MDPI

Proceedings

Spatiotemporal Variations of Glacier Surface Facies (GSF) in Svalbard: An example of Midtre Lovénbreen †

Shridhar D. Jawak [1,2,3], Sagar F. Wankhede [3,4,*], Prashant H. Pandit [5,6], Keshava Balakrishna [3]

1 Atmosphere and Climate Department, The Climate and Environmental Research Institute NILU, PO Box 100, NO-2027 Kjeller, Norway; shridhar.jawak@nilu.no
2 Svalbard Integrated Arctic Earth Observing System (SIOS), SIOS Knowledge Centre, Svalbard Science Centre, P.O. Box 156, N-9171, Longyearbyen, Svalbard, Norway
3 Department of Civil Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal 576104, Karnataka, India; sagar.wankhede@learner.manipal.edu; k.balakrishna@manipal.edu
4 Department of Geography and Research Centre, Parvatibai Chowgule College of Arts and Science (Autonomous), Gogol, Margao 403602, Goa, India; sfw000@chowgules.ac.in; sagar.wankhede@learner.manipal.edu
5 Department of Information Engineering and Computer Science, University of Trento, 38123 Trento, Italy; prashant.pandit@unitn.it
6 Institute for Earth Observation, Eurac Research, Viale Druso 1, 39100 Bolzano, Italy; prashant.pandit@eurac.edu
* Correspondence: sagar.wankhede@learner.manipal.edu
† Presented at the 5th International Electronic Conference on Remote Sensing, 7–21 November 2023; Available online: https://ecrs2023.sciforum.net/.

Abstract: Glacier surface facies (GSF) are visible glaciological regions which can be distinguished and mapped at the end of summer using optical satellite data. GSF maps act as visual metrics of glacier health when assessed independently or correlated with in situ mass balance measurements. Literature suggests that the spatiotemporal distribution of all accumulation and ablation facies are important inputs to 3D mass balance models because the GSF trends enhance the precision of models. For example, the progressive increase in area and distribution of melting ice and decrease in area and distribution of glacier ice as estimated by satellite data may signal potential mass loss without significant change in overall area of the ablation zone. Tracking the evolution of GSF in Svalbard is important for predictive assessment of the cryosphere in the Arctic. This will further facilitate robust methods for monitoring GSF on a planetary scale. In this context, we present a regional spatiotemporal analysis of GSF of Midtre Lovénbreen, Ny Ålesund, Svalbard. We used openly available Landsat 8 Operational Land imager (OLI) and Sentinel 2A imagery from 2017-2022, to track the occurrence and variations in GSF via machine learning. Current results suggest that ablation facies such as melting ice and dirty ice are increasing over time. Sentinel 2A provides finer resolution but is limited by its temporal coverage. Although Landsat is suitable for long-term trend analysis, its coarser resolution can lead to errors such as over/underestimation of smaller patches of facies on relatively smaller glaciers. As the spectral properties of GSF are consistent over time, a robust set of spectra depicting variations in physical appearance of facies may be used to train machine learning algorithms, thereby improving efficacy. In forthcoming studies, our objective is to expand the temporal scope spanning decades and to trace facies evolution over longer time series.

Keywords: Glacier Surface Facies; Machine Learning; Landsat; Sentinel; Arctic

Citation: To be added by editorial staff during production.

Academic Editor: Firstname Lastname

Published: date

1. Introduction

Glacier facies are the natural zones of a glacier's evolutionary cycle. These zones are formed as result of the precipitation, metamorphosis, and discharge of snow. The entrainment and deposition of debris plays a key role in determining facies of the ablation zone. Facies are distinct due to their varying spatial and spectral properties. These properties can be used to map facies via satellite images. When mapped using Synthetic Aperture Radar (SAR), these facies are called radar facies and when mapped using optical data, they are called surface facies. Glacier surface facies (GSF) therefore, are the surface expressions of glacier facies as mapped by optical sensor (satellite/airborne) data.

GSF maps provide the opportunity to calibrate distributed mass balance models for improving their predictive performance [1], for tracking the development of streams and lakes for disaster management [2], and for assessing the overall hydrological resources of the glacial body [3]. Garg et al. [4] conducted spatiotemporal mapping of radar facies in Ny-Ålesund. However, radar facies and optical facies cannot be directly compared on account of the inherent differences in both the mechanism and nomenclature used to generate the maps. Although spatiotemporal variations using optical data have not been tested in Ny-Ålesund, snapshot classification of facies have been performed for selected glaciers from the same region [5–9]. Current literature for mapping facies does not address the challenges and requirements for performing a long-term spatiotemporal analysis for larger study sites. In the current study, we present a preliminary experiment for monitoring spatiotemporal variations of facies for the Midtre Lovenbreen glacier in Ny-Ålesund, Svalbard.

2. Materials and Methods

2.1. Study Area and Data Used

Ny-Ålesund, Svalbard lying within 75° and 82° N presents an accelerated warming high Arctic environment. The rate of warming experienced here is twice the global average. This region is comprised of some of the most well-studied glaciers. The Midtre Lovenbreen (ML) glacier (Figure 1) is well monitored with a long mass balance record [10]. ML has been utilized for mapping facies by several studies [9]. This provides a working repository of literature for the current study.

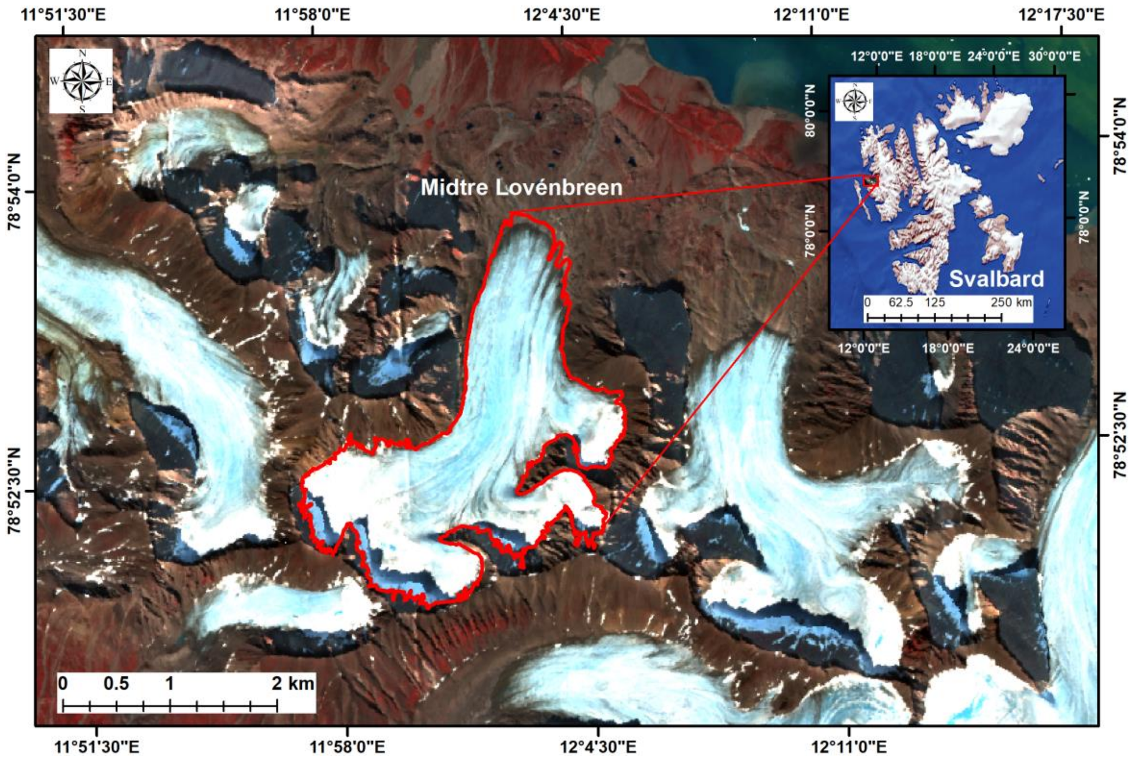

Figure 1. Geographic location of the Midtre Lovenbreen glacier. The background image of the inset of Svalbard was obtained from Natural Earth: Free vector and raster map data: naturalearthdata.com. The Sentinel 2A Level 2A imagery of ML was acquired on 17 July 2022.

The current study aims to assess the spatiotemporal variations of glacier facies. As a preliminary experiment, we downloaded Level 2A Sentinel 2A (S2AL2A) and Level 2 Collection 2 Landsat 8 OLI (L8C2L2) images from 2017 to 2022. These products provide calibrated reflectance data. Table 1 provides the image acquisition dates of the respective images. For this experiment we utilized only the 10 m high resolution bands from S2AL2A. The bands comprise of blue (490 nm), green (560 nm), red (665 nm), and near infrared (NIR) (842 nm). The corresponding four spectral bands from L8L2 were blue (482 nm), green (562 nm), red (655 nm), and NIR (865 nm). S2AL2A images were downloaded from https://dataspace.copernicus.eu/ and L8C2L2 images were downloaded from https://earthexplorer.usgs.gov/.

Table 1. Date of image acquisitions and corresponding sensors. OLI: Operational Land Imager.

Date of Image Acquisition	Sensor
02 August 2017	Landsat 8 OLI
30 July 2018	Sentinel 2A
27 July 2020	Landsat 8 OLI
01 August 2020	Sentinel 2A
17 July 2022	Sentinel 2A

2.2. Experimental Methodology

To focus on the spatiotemporal variations of the facies maps, we circumvented preprocessing of the satellite data and downloaded cloud free reflectance products from each respective sensor. We analysed data from 2017 to 2022 as a preliminary assessment for testing short term changes. ML glacier extents were digitized over a 3D surface generated using an Arctic DEM [11]. The extents were used to extract individual glacier subsets from the overall datasets. Facies were then identified by assessing the visual and spectral properties of the images according to Jawak et al. [7,12]. Facies identified comprise of dry snow, wet snow, melting snow, saturated snow, glacier ice, melting ice, dirty ice, and shadowed snow. Subsequently, training data were generated for each glacier and used as input to the traditional soft machine learning Maximum Likelihood (MXL) algorithm. MXL was selected for this study as it is well tested for its efficacy for mapping glacier facies [7,13]. Total area per facies per year was then calculated to determine trends and variability.

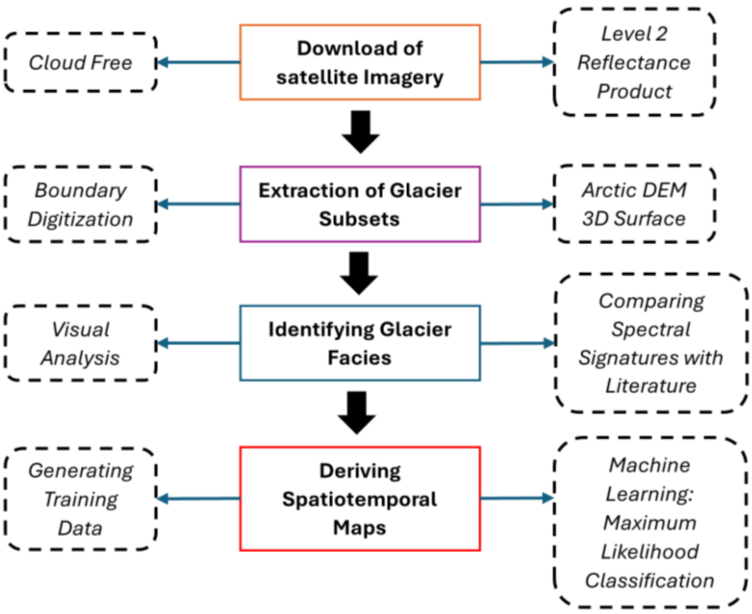

Figure 2. Methodology protocol for the practical implementation of current study. DEM: Digital Elevation Model.

3. Results and Discussion

In the current analysis, we mapped glacier facies using L8C2L2 and S2AL2A imagery for assessing spatiotemporal variations from 2017-2022. Five GSF maps were produced yielding different distributions of facies for each year. Table 2 displays the area per facies in percentage.

Table 2. Area per facies in percentage for each year. 2020_L/S represent the individual Landsat/Sentinel sensor derived imagery for the year 2020.

Facies	Year-wise Area per Facies (in %)				
	2017	**2018**	**2020_L**	**2020_S**	**2022**
Dirty Ice	8.37	6.66	8.99	8.81	7.85
Dry Snow	11.46	4.04	2.42	3.60	3.72
Glacier Ice	26.68	11.76	10.31	13.95	11.23
Melting Ice	14.12	35.80	23.76	18.28	30.17
Saturated Snow	20.82	15.17	8.39	17.27	18.99
Shadowed Snow	10.85	11.79	9.27	12.91	9.40
Wet Snow	7.70	9.70	23.96	13.33	7.99
Melting Snow	0.00	5.07	12.91	11.87	10.66

From 2017 to 2022 we observe an overall increase in ablation facies. Melting ice and melting snow have increased in area by 16.05% and 10.66% respectively. Most of this change can be suggested to have occurred because of the loss of glacier ice area to melting ice and a reduction in dry snow area to melting snow. This suggests that ML is increasing in melt facies and may most likely discharge this mass if the current trend continues to advance. For the year 2020, we analysed both L8C2L2 and S2AL2A images. Interestingly, we find that while wet snow and melting ice show a decrease in area by 10% in S2AL2A data, glacier ice and saturated snow show an overall increase in area. Saturated snow being the most affected with an 8% increase in area. As the spectral bands of both sensors are almost similar, we speculate that spatial resolution plays a key role in determining final maps of facies. In the case of very high resolution (VHR) imagery, we have observed that spatial resolution improves object-based mapping, because pixels can be combined to enhance homogeneity [8]. In the current study, we find that Sentinel 2A provides better visualization and characterizability of facies. However, this may have occurred because ML is a relatively small glacier. On smaller glaciers, coarser pixels obscure much of the detail that can help identify training data for classification.

As the current study is a preliminary experiment for long term spatiotemporal mapping of glacier facies, we highlight key features for future research.

1. Spectral signatures of facies are consistent and can be used across time to map facies [5,6]. However, spatial resolution is critical for determining the visibility of facies especially for smaller glaciers. Although the Landsat archive provides an unparalleled repository for long-term monitoring, its spatial resolution can be challenging for targeting local, small, alpine glaciers.
2. Although Landsat data can be pansharpened, we have observed in previous experiments that pansharpening distorts the spectral information within the pixel [7–9]. Thus, while enhancing spatial resolution may improve identification of facies, the distorted spectral information may misrepresent the facies causing misclassification.

3. In Sentinel 2A, only four spectral bands are of 10 m spatial resolution, this suggests that the entire spectral range cannot be used as one dataset for mapping facies without resampling of pixel dimensions. Another alternative could compile individual bands with common spatial resolutions in separate datasets to map facies to avoid misrepresentation from spectral distortion.
4. A limitation of the current study is lack of field data for validation of the thematic maps. However, our future research includes field validation of the thematic maps. Presently, we are focused on determining the challenges with upscaling these methods at a Svalbard-wide scale.
5. Availability of VHR data at the Svalbard-wide scale may help establish facies maps at fine resolution and generate validation data for open-source thematic maps. Figure 3 displays the thematic classification of the present study.
6. When performing long term spatiotemporal analysis, cloud cover and illumination conditions will determine the final set of images. In the current study, we could not obtain cloud free data for 2019. Illumination at the time of scene capture will determine the extent of shadow on the glacier body. Facies lying within shadow regions are difficult to identify as the signature is distorted and can lead to misclassification [8]. Thus, we labelled this region as shadowed snow.

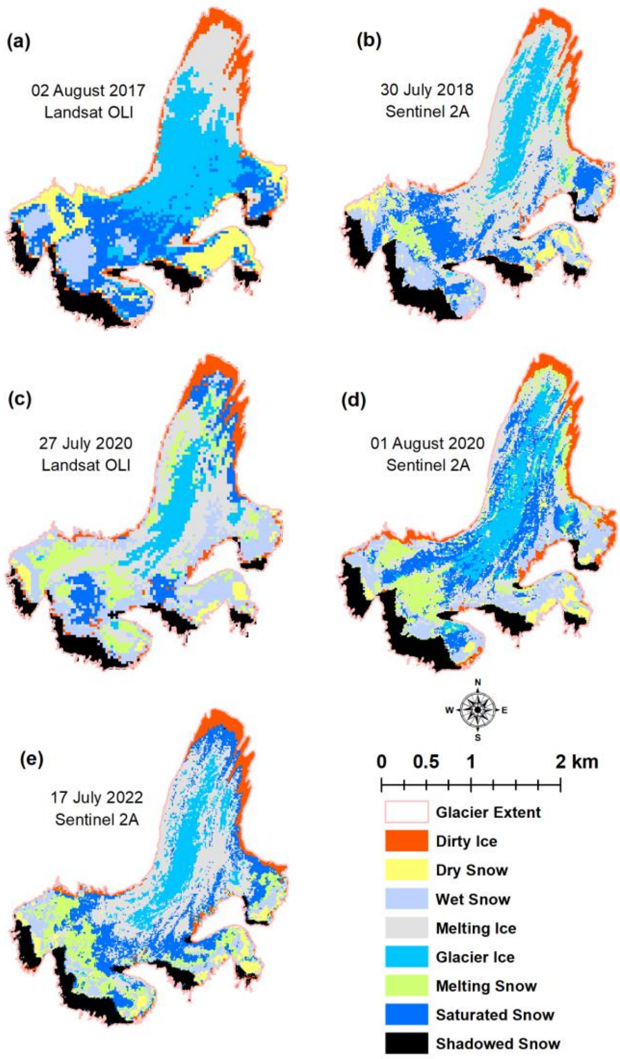

Figure 3. GSF maps. (a) Landsat OLI map for 2017, (b) Sentinel 2A map for 2018, (c) Landsat OLI map for 2020, (d) Sentinel 2A map for 2020, (e) Sentinel 2A map for 2022.

4. Conclusion

Spatiotemporal analyses of facies are important because the precision of distributed mass balance models relies on accurate spatial properties. The trends of accumulation and ablation facies act as reliable indicators of the evolution of a glacier. Mapping facies across time provides a robust assessment of the overall health of the glacier in addition to tracking the development of features such as supraglacial lakes and streams for resource and disaster management. Here, we presented a preliminary experiment to outline the challenges for conducting a long-term analysis of glacier facies. Utilizing Sentinel 2A Level 2 and Landsat OLI Collection 2 Level 2 data we identified and characterized facies for the Midtre Lovenbreen glacier in Ny-Ålesund, Svalbard. Facies identified comprise of dry snow, wet snow, melting snow, saturated snow, shadowed snow, glacier ice, melting ice, and dirty ice. Overall trends suggest that ablation facies such as melting ice and melting snow are increasing in area. The occurrence of facies needs to be monitored for a longer time span to identify robust trends. The challenges for spatiotemporal mapping comprise of cloud cover, scene illumination, spatial resolution, spectral resolution, and availability of field data. Our future research involves mapping facies across larger time periods. The current results highlight important factors for conducting long term analysis of facies and will play a critical role in upcoming experiments.

Author Contributions: Conceptualization, S.D.J. and S.F.W.; methodology, S.D.J. S.F.W. P.H.P. and K.B.; software, S.D.J. S.F.W. P.H.P. and K.B.; validation, S.D.J. S.F.W. P.H.P. and K.B.; formal analysis, S.D.J. S.F.W. P.H.P. and K.B.; investigation, S.D.J. S.F.W. P.H.P. and K.B.; resources, S.D.J. S.F.W. P.H.P. and K.B.; data curation, S.D.J. S.F.W. P.H.P. and K.B.; writing—original draft preparation, S.D.J. S.F.W. P.H.P. and K.B.; writing—review and editing, S.D.J. S.F.W. P.H.P. and K.B.; visualization, S.D.J. and S.F.W.; supervision, S.D.J. and K.B.; project administration, S.D.J. and K.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: All Sentinel-2 data are freely available from the Copernicus Data Space Environment. Sentinel 2A Level 2A Data download: https://dataspace.copernicus.eu/. Landsat 8 OLI data is available from the U.S. Geological Survey. See USGS Visual Identity System Guidance (https://www.usgs.gov/information-policies-and-instructions/copyrights-and-credits) for further details.

Acknowledgments: We thank HOD, Department of Civil Engineering, MIT, and Director MIT for their encouragement. We also thank HOD, Department of Geography and Research Centre, PCCAS, and Principal, PCCAS for their support.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Braun, M.; Schuler, T.V.; Hock, R.; Brown, I.; Jackson, M. Comparison of remote sensing derived glacier facies maps with distributed mass balance modelling at Engabreen, Northern Norway. *IAHS Publ. Ser. Proc. Rep.* **2007**, *318*, 126–134.
2. Mitkari, K.V.; Arora, M.K.; Tiwari, R.K.; Sofat, S.; Gusain, H.S.; Tiwari, S.P. Large-Scale Debris Cover Glacier Mapping Using Multisource Object-Based Image Analysis Approach. *Remote Sens.* **2022**, *14*, 3202. https://doi.org/10.3390/rs14133202.
3. Haq, M.A.; Alshehri, M.; Rahaman, G.; Ghosh, A.; Baral, P.; Shekhar, C. Snow and glacial feature identification using Hyperion dataset and machine learning algorithms. *Arab. J. Geosci.* **2021**, *14*, 1525. https://doi.org/10.1007/s12517-021-07434-3.
4. Garg, V.; Thakur, P.K.; Rajak, D.R.; Aggarwal, S.P.; Kumar, P. Spatio-temporal changes in radar zones and ELA estimation of glaciers in Ny-Ålesund using Sentinel-1 SAR. *Polar Sci.* **2022**, *31*, 100786. https://doi.org/10.1016/j.polar.2021.100786.
5. Pope, A.; Rees, G. Using in situ spectra to explore Landsat classification of glacier surfaces. *Int. J. Appl. Earth Obs. Geoinf.* **2014**, *27*, 42–52. https://doi.org/10.1016/j.jag.2013.08.007.
6. Pope, A.; Rees, W.G. Impact of spatial, spectral, and radiometric properties of multispectral imagers on glacier surface classification. *Remote Sens. Environ.* **2014**, *141*, 1–13. https://doi.org/10.1016/j.rse.2013.08.028.
7. Jawak, S.D.; Wankhede, S.F.; Luis, A.J.; Balakrishna, K. Impact of Image-Processing Routines on Mapping Glacier Surface Facies from Svalbard and the Himalayas Using Pixel-Based Methods. *Remote Sens.* **2022**, *14*, 1414. https://doi.org/10.3390/rs14061414.

8. Jawak, S.D.; Wankhede, S.F.; Luis, A.J.; Balakrishna, K. Effect of Image-Processing Routines on Geographic Object-Based Image Analysis for Mapping Glacier Surface Facies from Svalbard and the Himalayas. *Remote Sens.* **2022**, *14*, 4403. https://doi.org/10.3390/rs14174403.
9. Jawak, S.D.; Wankhede, S.F.; Luis, A.J.; Balakrishna, K. Multispectral Characteristics of Glacier Surface Facies (Chandra-Bhaga Basin, Himalaya, and Ny-Ålesund, Svalbard) through Investigations of Pixel and Object-Based Mapping Using Variable Processing Routines. *Remote Sens.* **2022**, *14*, 6311. https://doi.org/10.3390/rs14246311
10. King, E.; Smith, A.; Murray, T.; Stuart, G. Glacier-bed characteristics of midtre Lovénbreen, Svalbard, from high-resolution seismic and radar surveying. *Journ. Glacio.* **2008**, *54*, 145-156. https://doi.org/10.3189/002214308784409099
11. Porter, C.; Morin, P.; Howat, I.; Noh, M.-J.; Bates, B.; Peterman, K.; Keesey, S.; Schlenk, M.; Gardiner, J.; Tomko, K.; et al. "ArcticDEM", Harvard Dataverse, V1. 2018. Available online: https://www.pgc.umn.edu/data/arcticdem/ (accessed on 13 March 2022).
12. Jawak, S.D.; Wankhede, S.F.; Luis, A.J. Explorative Study on Mapping Surface Facies of Selected Glaciers from Chandra Basin, Himalaya Using World, View-2 Data. *Remote Sens.* **2019**, *11*, 1207. https://doi.org/10.3390/rs11101207.
13. Shukla, A.; Ali, I. A hierarchical knowledge-based classification for glacier terrain mapping: A case study from Kolahoi Glacier, Kashmir Himalaya. *Ann. Glaciol.* 2016, *57*, 1–10. https://doi.org/10.3189/2016aog71a046.