GI_Forum 2021, Issue 1
Page: 46 - 52
Research Paper
Corresponding Author:
zahra.dabiri@sbg.ac.at
DOI: 10.1553/giscience2021_01_s46

Comparing the Applicability of Sentinel-1 and Sentinel-2 for Mapping the Evolution of Ice-marginal Lakes in Southeast Iceland

Zahra Dabiri[1], Daniel Hölbling[1], Lorena Abad[1] and Snævarr Guðmundsson[2]
[1]University of Salzburg, Austria
[2]South East Iceland Nature Research Center, Iceland

Abstract

Monitoring ice-marginal lakes is important for glaciological and geomorphological studies, as well as hazard and risk assessment. Sentinel-1 synthetic aperture radar (SAR) and Sentinel-2 optical data opened a new era for multi-temporal analysis and studying geomorphological changes. The purpose of this study is to compare the applicability of Sentinel-1 and Sentinel-2 data for mapping the changes in ice-marginal lake areas at the southern margin of the Vatnajökull ice cap, southeast Iceland, between 2016 and 2020. We semi-automatically mapped the ice-marginal lakes with object-based image analysis (OBIA) and based on image time series using 1) the polarization products derived from Sentinel-1 data, and 2) the spectral information of Sentinel-2 data, and compared the results. Our results show that Sentinel-1 performed better regarding the detection of the number of ice-marginal lakes, whereas Sentinel-2 performed better regarding lake delineation. Moreover, we discuss the applicability of optical and SAR data for mapping and monitoring the evolution of ice-marginal lakes.

Keywords: Sentinel-1, Sentinel-2, ice-marginal lake, object-based image analysis, Iceland

1 Introduction

Monitoring of ice-marginal (or proglacial) lakes is important for glaciological and geomorphological studies, as well as hazard and risk assessment. Ice-marginal lake development is a result of deglaciation, where changes in the lake area and appearance are visible consequences of climate change (Dell, Carr, Phillips, & Russell, 2019; Shugar et al., 2020). In recent years, freely available Copernicus data, including Sentinel-1 C-band Synthetic Aperture Radar (SAR) data and Sentinel-2 optical data, opened a new era for multi-temporal monitoring and analysing, for example, changes in lake ice (Tom et al., 2020) or glacial lakes (Wangchuk & Bolch, 2020). SAR data has a nearly all-weather imaging capability that facilitates the monitoring of ice-marginal lakes, especially in areas where frequent cloud cover limits the availability of optical imagery. However, the potential of SAR data for mapping ice-marginal lakes needs to be further exploited. Usually, mapping of the glacial geomorphology is largely done by manual techniques, while (semi-)automated mapping approaches are still relatively rare (Robb, Willis, Arnold, & Gudmundsson, 2015). Object-based image analysis (OBIA) provides a set of suitable tools for semi-automated delineation and classification of geomorphological phenomena (Hölbling et al., 2017). It has been used for mapping various glacial and geomorphological features, for example, glaciers (Robson, Hölbling, Nuth, Strozzi, & Dahl, 2016), rock glaciers (Robson et al., 2020), supraglacial lakes (Mitkari, Arora, & Tiwari, 2017), drumlins (Eisank, Smith, & Hillier, 2014), and landslides (Hölbling et al., 2012). The purpose of this study is to compare the applicability of Sentinel-1 and Sentinel-2 data for multi-temporal analysis of yearly changes in the ice-marginal lake area between 2016 and 2020 using OBIA.

2 Materials and Methods

2.1 Study Area

We focused on ice-marginal lakes at the southern margin of the Vatnajökull ice cap in southeast Iceland, which have shown a constant evolution over the last years (Guðmundsson et al., 2019), in particular the ice-marginal lakes of the outlet glaciers Breiðamerkurjökull and Fjallsjökull, i.e. Jökulsárlón, Breiðárlón, and Fjallsárlón (Figure 1).

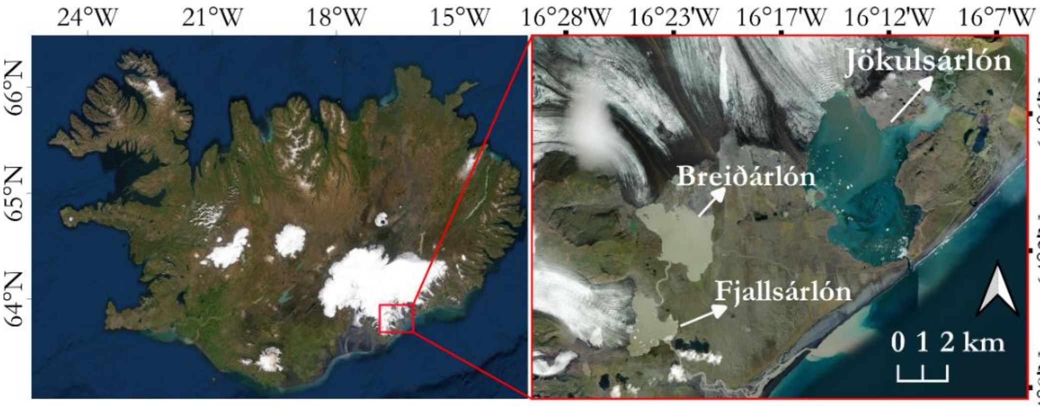

Figure 1: The study area located in southeastern Iceland (left), and the location of the Jökulsárlón, Breiðárlón, and Fjallsárlón ice-marginal lakes. Background images © ESRI.

2.2 Data and Data Preparation

We used multi-temporal Sentinel-1 and Sentinel-2 data from 2016 to 2020 (Table 1) and considered only summer images (one for each year) to avoid snow-cover on the ground. To facilitate comparability of the mapping results, we selected Sentinel-1 and Sentinel-2 images from the same or, when not possible, from similar acquisition dates per year. We selected Sentinel-1 Interferometric Wide Swath Level-1 Ground Range Detected georeferenced imagery with 10 m spatial resolution, with Vertical-Horizontal (VH) and Vertical-Vertical (VV) polarisations from the ascending orbit (track 145). The Sentinel-2 top of atmosphere reflectance images were selected based on the visibility of lakes, using the Google Earth Engine (GEE) platform.

Table 1: Acquisition dates of Sentinel-1 and Sentinel-2 data used in this study.

Sentinel-1 data	2016/06/06	2017/06/18	2018/06/01	2019/06/21	2020/06/15
Sentinel-2 data	2016/06/06	2017/06/18	2018/06/01	2019/06/23	2020/06/17

The pre-processing of the Sentinel-1 data included updating the orbit state vectors using the Sentinel precise orbit file provided by the European Space Agency (ESA) (Filipponi, 2019), and data calibration by calculating the backscatter coefficient (i.e. sigma nought) so that the pixel values represent the SAR backscatter of the reflecting surface. We applied the Range Doppler Terrain Correction operator available in the Sentinel Application Platform (SNAP) to correct the topographical variations of the scenes using the freely available Global Earth Topography And Sea Surface Elevation at 30 arc-second resolution (GETASSE30) digital elevation model (DEM). We converted sigma values from linear units to decibel (dB).

2.3 Object-based Image Analysis

The OBIA classification was performed on Sentinel-1 and Sentinel-2 data separately using eCognition (Trimble) software. First, we applied the multiresolution segmentation (MRS) algorithm to create homogenous image objects. Then the lakes were semi-automatically classified based on spectral and spatial information.

Sentinel-1 Data

First, we created three new layers: namely a mean (VH+VV/2), and two ratios (VV/VH and VH/VV, respectively). We then applied the MRS with a Scale Parameter (SP) set to 50, and the homogeneity criteria, i.e. shape and compactness were set to 0.1. The "mean" layer was used for the classification of the water bodies, by applying a classification threshold of < -19 dB for the backscatter coefficient. The classified water objects were merged and then assigned to the class "lake", considering the size of the merged polygons.

Sentinel-2 Data

First, we calculated the normalised difference vegetation index (NDVI), the normalised difference water index (NDWI), the normalised difference snow index (NDSI), as well as a brightness layer based on the mean reflectance of the visible spectral bands. Next, we applied the MRS using the spectral bands, the NDVI, NDWI, and NDSI indices, and the brightness layer with an SP of 500, and the shape and compactness criteria were set to 0.3 and 0.4, respectively. However, after visually assessing the segmentation results, we adapted the settings for 2018 (SP: 800, shape and compactness criteria: 0.5 and 0.4, respectively) to better delineate the lakes. We used the NDWI >= 0.3 to classify water areas and the NDVI layer and size criteria for classification refinement.

2.4 Validation

We used reference data from Guðmundsson et al. (2019), which was created by digitizing the ice-marginal lakes on pan-sharpened Landsat imagery (15 m) from 2018/05/28 for validation of the lake area delineation and the number of detected lakes (cf. section 3.2). Due to the absence of complete reference data, we assessed the accuracy of the OBIA classification results only for the year 2018.

3 Results

3.1 Object-based Image Analysis Classification Results

The OBIA classification results based on Sentinel-1 and Sentinel-2 are shown in Figure 2. We were able to classify all three major ice-marginal lakes and several small lakes semi-automatically. Visual inspection of the results using Sentinel-1 and Sentinel-2 data shows no major errors.

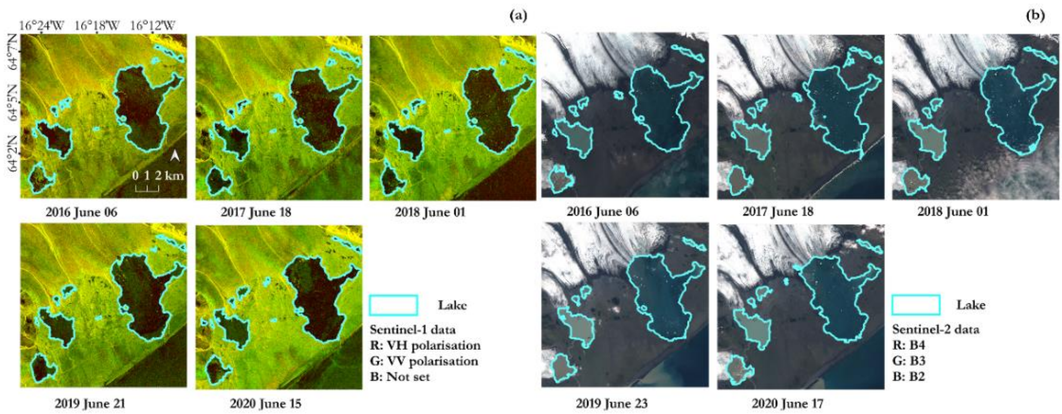

Figure 2: The OBIA classification of the ice-marginal lakes (cyan colour) using (a) the multi-temporal Sentinel-1 data, and (b) the multi-temporal Sentinel-2 data.

3.2 Validation Results

The reference data contained fourteen ice-marginal lakes, ten of which were identified using Sentinel-1, and six were identified using Sentinel-2. Moreover, we used the intersection over union (IoU) metric to compare the semi-automatically derived lake areas of the three main ice-marginal lakes (i.e. Jökulsárlón, Breiðárlón, and Fjallsárlón) to the reference (Table 3).

Table 3: Accuracy assessment of the OBIA classification for Sentinel-1 and -2 (2018/06/01).

		Jökulsárlón	Breiðárlón	Fjallsárlón
Sentinel-1	IoU (%)	84	83	86
Sentinel-2	IoU (%)	94	95	94

The comparison shows that the ice-marginal lakes were accurately identified. In general, the classification based on Sentinel-2 produced better results than the classification based on Sentinel-1, with the best IoU for Breiðárlón (95%). The best classification result using Sentinel-1 data was achieved for Fjallsárlón, with an IoU of 86%. The lake outlines derived from Sentinel-1 and Sentinel-2 for June 2018 as well as the reference data are shown in Figure 3. The lower accuracy using the IoU metric of the Sentinel-1 mapping results can partly be explained by slight shifts in lake position in comparison to the reference layer due to the side-looking geometry of SAR imagery and the usage of the default GETASSE30 DEM for terrain correction in SNAP. The use of a more accurate and higher resolution DEM would likely help to overcome the SAR geometric distortion, however, in this study, we aimed at a fully automatic and transferable SAR pre-processing workflow using SNAP.

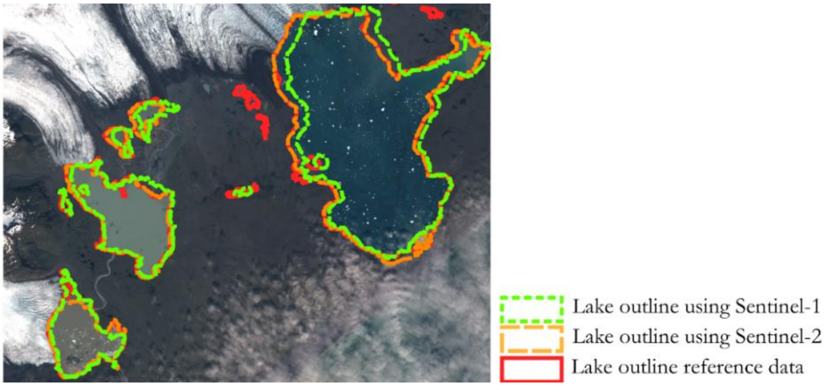

Figure 3: Illustration of the classification results using Sentinel-1 (green), Sentinel-2 (orange), and the reference data (red). Background image: Sentinel-2 image from 2018/06/01.

3.3 Lake Area Change From 2016 to 2020

We compared the change in area per lake as shown in Figure 4. The mapping results using Sentinel-1 show that Jökulsárlón gradually increased from 2016 to 2020, whereas, the mapping results derived from Sentinel-2 show a significant increase from 2016 to 2017, followed by a stable period until 2020. The lake areas of Breiðárlón and Fjallsárlón increased from 2016 to 2018 for both mapping results, followed by a slight decrease revealed by the Sentinel-1 results from 2018 to 2020. Sentinel-2 mapping results show an abrupt decrease from 2018 to 2019 and an increase from 2019 to 2020 for these two lakes. This can partly be explained by the existence of clouds on the Sentinel-2 image from 2019 which partially obscured the shore of the Breiðárlón lake and affected the segmentation and classification. A comparison to the reference data from 2018 shows that, except for the Sentinel-1 result for Breiðárlón, the semi-automated mapping results underestimated the lake area. Potential classification errors might be explained by the existence of ice blocks on the lake surface and by high soil moisture at the lakeshores. Another reason for differences compared to the reference data might be that the reference data was created based on different imagery with coarser spatial resolution.

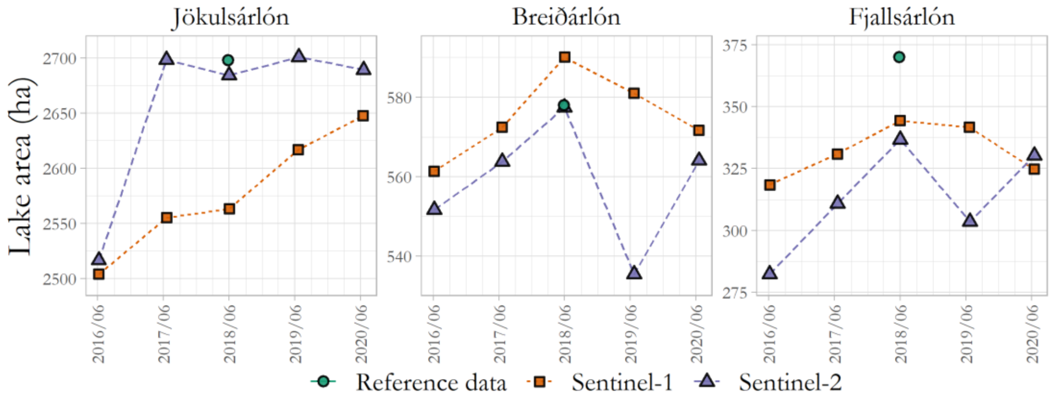

Figure 4: Change in area per lake from 2016 to 2020 for the Sentinel-1 and Sentinel-2 results.

4 Discussion and Conclusions

Sentinel-1 and Sentinel-2 show great potential for multi-temporal monitoring of ice-marginal lakes. These sensors offer high temporal and high spatial resolution data, while Sentinel-1 can be particularly useful for multi-temporal monitoring of ice-marginal lakes, regardless of weather and illumination conditions. We developed a semi-automated OBIA workflow and achieved good accuracy values for both sensors. Guðmundsson et al. (2019) describe that most of the large ice-marginal lakes in front of outlet glaciers at the southern margin of the Vatnajökull ice cap continuously grow, particularly due to recent climate change. However, our mapping results do not show such a trend for Breiðárlón and Fjallsárlón after 2018. Further investigations are needed to confirm this and to assess how classification errors influence these findings. Moreover, a combined analysis of both, Sentinel-1 and Sentinel-2 data, could offer further opportunities for analysing geomorphological changes (Dabiri et al., 2020).

Acknowledgements

This research has been supported by the Austrian Science Fund (FWF) through the Doctoral Collage GIScience (DK W 1237-N23) and the project MORPH (Mapping, monitoring and modelling the spatio-temporal dynamics of land surface morphology; FWF-P29461-N29).

References

Dabiri, Z., Hölbling, D., Abad, L., Helgason, J. K., Sæmundsson, Þ., & Tiede, D. (2020). Assessment of Landslide-Induced Geomorphological Changes in Hítardalur Valley, Iceland, Using Sentinel-1 and Sentinel-2 Data. *Applied Sciences*, *10*(17), 5848. https://doi.org/10.3390/app10175848

Dell, R., Carr, R., Phillips, E., & Russell, A. J. (2019). Response of glacier flow and structure to proglacial lake development and climate at Fjallsjökull, south-east Iceland. *Journal of Glaciology*, *65*(250), 321–336. https://doi.org/doi:10.1017/jog.2019.18

Eisank, C., Smith, M., & Hillier, J. (2014). Assessment of multiresolution segmentation for delimiting drumlins in digital elevation models. *Geomorphology*, *214*, 452–464. https://doi.org/10.1016/j.geomorph.2014.02.028

Filipponi, F. (2019). Sentinel-1 GRD Preprocessing Workflow. *Proceedings*, *18*(1), 11. https://doi.org/10.3390/ECRS-3-06201

Guðmundsson, S., Björnsson, H., Pálsson, F., Magnússon, E., Sæmundsson, Þ., & Jóhannesson, T. (2019). Terminus lakes on the south side of Vatnajökull ice cap, SE-Iceland. *Jökull*, *69*(April), 1–34. https://doi.org/10.33799/jokull2019.69.001

Hölbling, D., Eisank, C., Albrecht, F., Vecchiotti, F., Friedl, B., Weinke, E., & Kociu, A. (2017). Comparing Manual and Semi-Automated Landslide Mapping Based on Optical Satellite Images from Different Sensors. *Geosciences*, *7*(2), 37. https://doi.org/10.3390/geosciences7020037

Hölbling, D., Füreder, P., Antolini, F., Cigna, F., Casagli, N., & Lang, S. (2012). A Semi-Automated Object-Based Approach for Landslide Detection Validated by Persistent Scatterer Interferometry Measures and Landslide Inventories. *Remote Sensing*, *4*(5), 1310–1336. https://doi.org/10.3390/rs4051310

Mitkari, K. V., Arora, M. K., & Tiwari, R. K. (2017). Extraction of Glacial Lakes in Gangotri Glacier Using Object-Based Image Analysis. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *10*(12), 5275–5283. https://doi.org/10.1109/JSTARS.2017.2727506

Robb, C., Willis, I., Arnold, N., & Gudmundsson, S. (2015). A semi-automated method for mapping glacial geomorphology tested at Breidamerkurjökull, Iceland. *Remote Sensing of Environment*, *163*, 80–90. https://doi.org/10.1016/j.rse.2015.03.007

Robson, B. A., Bolch, T., MacDonell, S., Hölbling, D., Rastner, P., & Schaffer, N. (2020). Automated detection of rock glaciers using deep learning and object-based image analysis. *Remote Sensing of Environment*, *250*(July), 112033. https://doi.org/10.1016/j.rse.2020.112033

Robson, B. A., Hölbling, D., Nuth, C., Strozzi, T., & Dahl, S. O. (2016). Decadal scale changes in glacier area in the Hohe Tauern national park (Austria) determined by object-based image analysis. *Remote Sensing*, *8*(1), 67. https://doi.org/https://doi.org/10.3390/rs8010067

Shugar, D. H., Burr, A., Haritashya, U. K., Kargel, J. S., Watson, C. S., Kennedy, M. C., … Strattman, K. (2020). Rapid worldwide growth of glacial lakes since 1990. *Nature Climate Change*, *10*(10), 939–945. https://doi.org/10.1038/s41558-020-0855-4

Tom, M., Aguilar, R., Imhof, P., Leinss, S., Baltsavias, E., & Schindler, K. (2020). Lake Ice Detection from Sentinel-1 SAR with Deep Learning. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *V-3–2020*(3), 409–416. https://doi.org/10.5194/isprs-annals-V-3-2020-409-2020

Wangchuk, S., & Bolch, T. (2020). Mapping of glacial lakes using Sentinel-1 and Sentinel-2 data and a random forest classifier: Strengths and challenges. *Science of Remote Sensing*, *2*, 100008. https://doi.org/10.1016/j.srs.2020.100008