Automated Image Classification of Greenlandic Outlet Glaciers using Deep Learning: A Case Study on Helheim Glacier.

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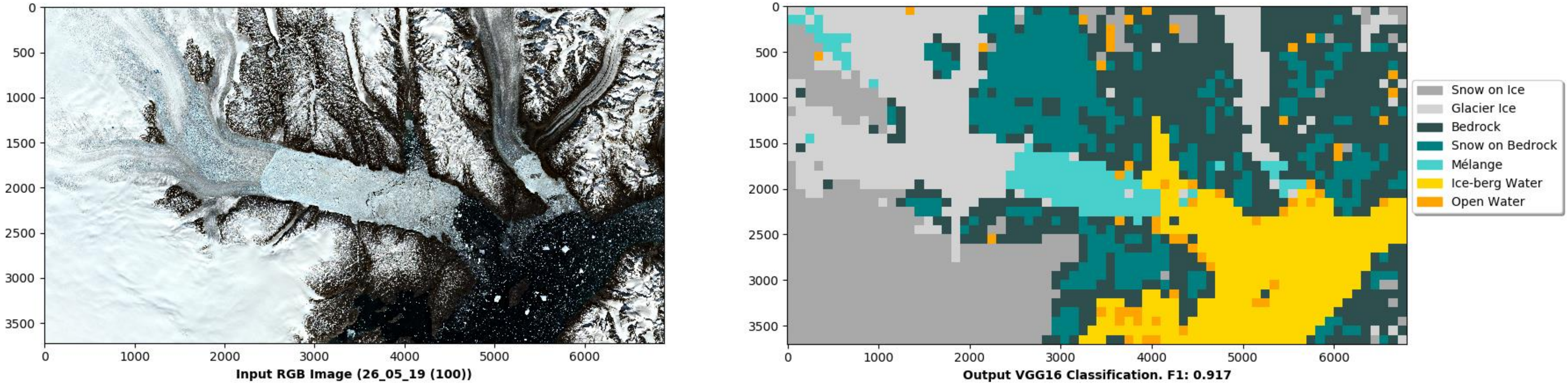

Sentinel-2 Image of Helheim Glacier, Greenland (26/05/2019) and corresponding CNN classification using the VGG16 architecture with a patch size of 100 pixels.

Outline:

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- Methods: Image Classification with Deep Learning
- Results: Initial CNN Classification of Helheim Glacier
- Results: Pixel-based Self-Supervised Classification of Helheim Glacier
- Conclusions and Further Work
- References

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Introduction:

- A wealth of research in recent decades has focused on elucidating the key controls on the mass loss of the Greenland Ice Sheet and its response to climate forcing, specifically in relation to the drivers of spatio-temporally variable outlet glacier change (Catania *et al.*, 2018; Vieli and Nick, 2011).

- Advances in deep learning applied to image processing have opened up a new frontier in the area of automated delineation of glacier termini with an aim to increase the efficiency of analysing outlet glacier change (e.g. Zhang *et al.*, 2019; Mohajerani *et al.*, 2019; Baumhoer *et al*. 2019).

- However, at this stage, there remains a paucity of research on the use of deep learning for image classification of outlet glacier landscapes. Such image classification permits not only automated terminus delineation, but also facilitates the efficient analysis of numerous processes controlling outlet glacier behaviour, such as fjord geometry, subglacial plumes, and supra-glacial lakes.

Aims:

- Despite the increasing availability of medium resolution satellite imagery, image classification of glacial landscapes remains challenging.

- Thus, our aim is to adapt a supervised learning workflow called Self-Supervised Classification (SSC), a method originally developed for fluvial environments (Carbonneau *et al*. (in revision), for glacial landscapes.

- We aim to adapt this method, based on the VGG16 convolutional neural network (CNN), to classify Sentinel-2 images of outlet glaciers in Greenland.

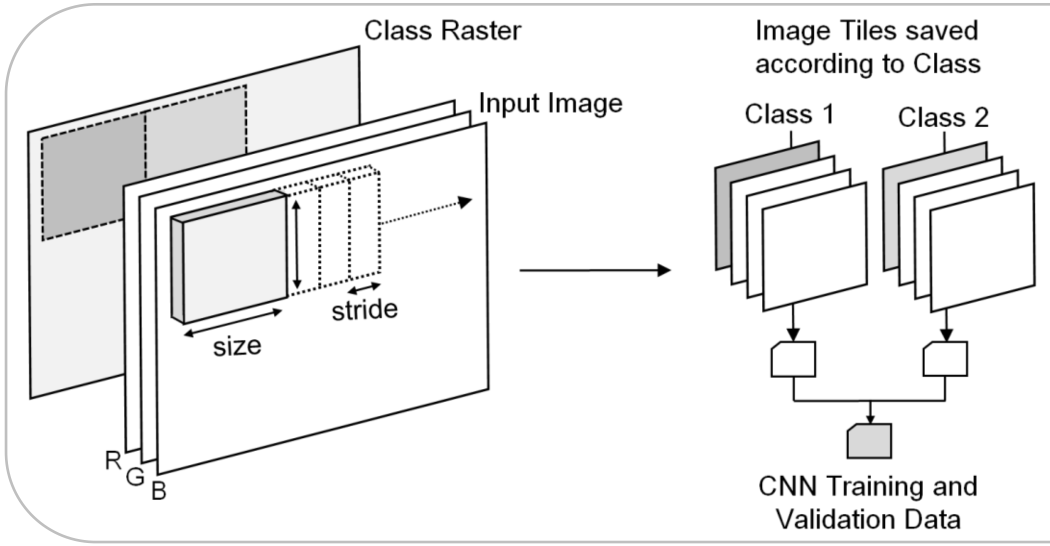
- SSC uses a pre-trained CNN to replace the human operator's role in traditional supervised classification by automatically producing new label data to train a pixel-level neural network classifier for any new image.

- We train the pre-trained CNN using images of Helheim Glacier, a major outlet of the Greenland Ice Sheet and test the overall SSC technique using an unseen image of Helheim as a case study.

Methods: Image Classification with Deep Learning

CNN Model Training:

- The CNN is trained on 13 Sentinel-2 images of Helheim Glacier which are labelled according to 7 classes.
- The images are tiled (according to a specified tile size and stride) with class labels (based on manually drawn class polygons) and augmented (rotation and flipping) to create ~200,000 training tiles (Figure 1).
- These tiles are then used as training data for the CNN, in this case using the VGG16 architecture.



Classes:
1. Open water
2. Ice-berg water
3. Mélange
4. Glacier ice
5. Snow on ice
6. Snow on rock
7. Bare bedrock

Figure 1: Conceptual diagram of tiling process used to create training data.

Self-Supervised Classification seeks to replace a human operator with a pre-trained CNN, and is a 2 phase workflow (Figure 2):

- Phase 1: Input image is tiled and fed into the pre-trained CNN.
- Phase 2: The resulting CNN predictions are used as labelled pixels and, along with RGB features, are fed into a multilayer perceptron (MLP) to train a model specific to the input image. The MLP then predicts the class of each pixel in the input image.

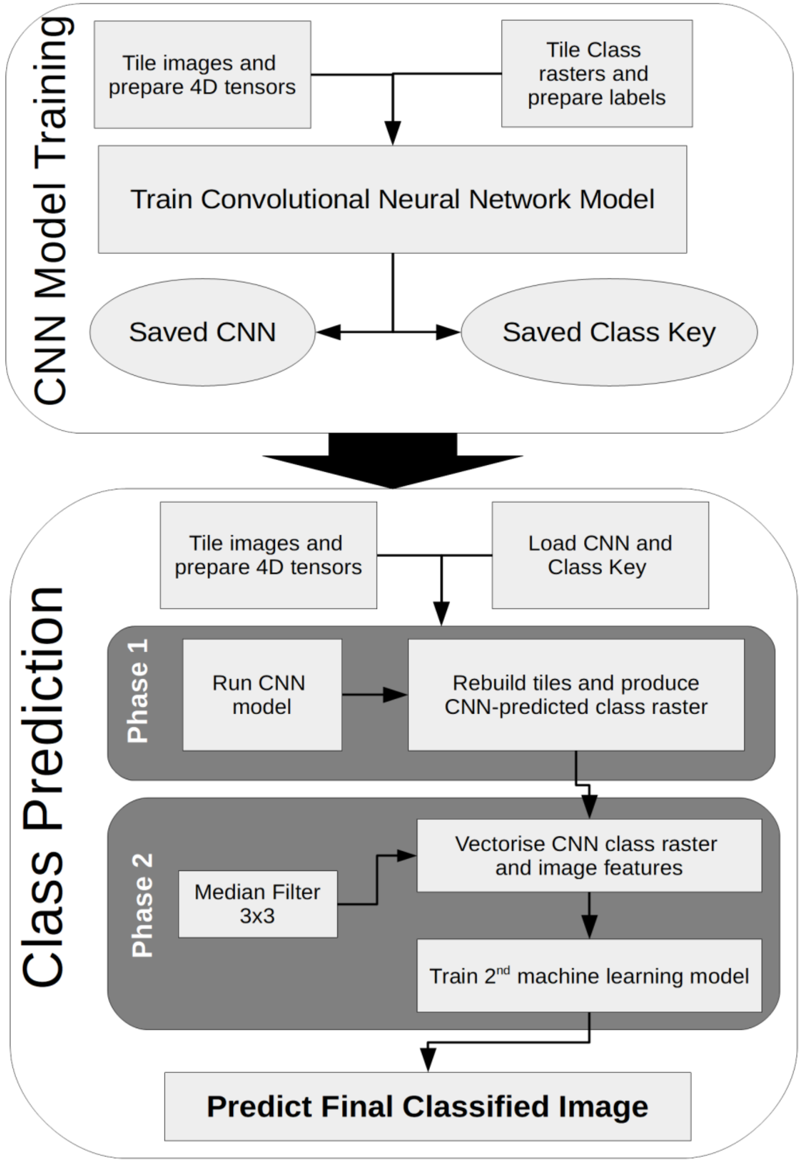


Figure 2: Self-Supervised Classification Workflow (Source: Carbonneau et al (in revision) for Remote Sensing of Environment).

Results: Initial CNN Classification of Helheim Glacier

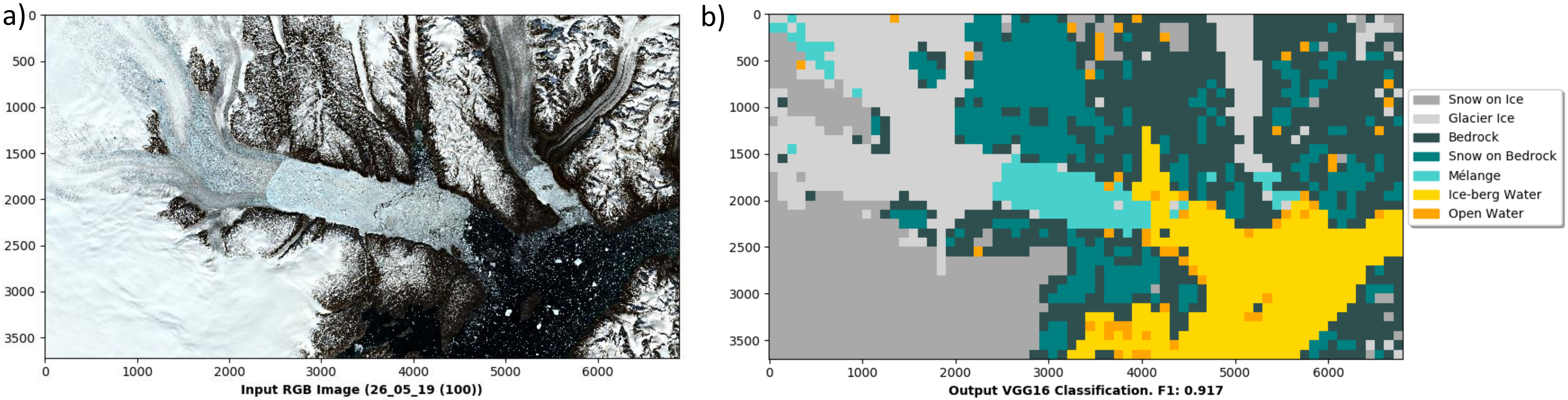


Figure 3: The pre-trained CNN with VGG16 architecture was applied to a) an unseen image of Helheim Glacier. B) shows the classification output.

- Figure 3 shows the results of the first pre-trained CNN classifier (VGG16) in the workflow.
- The classifier was applied to a previously unseen Sentinel-2 image of Helheim Glacier (26/05/2019) (Figure 3a).
- The accuracy of the classifier is assessed using a common validation metric called an F1 score (Chinchor, 1992). This model yielded an F1 score of 92% (Figure 3b).

The CNN:

- The CNN was trained using 197800 input tiles belonging to 7 classes.
- The tiles had a size of 100 pixels and stride of 30 pixels.

Results: Pixel-based Self-Supervised Classification of Helheim Glacier

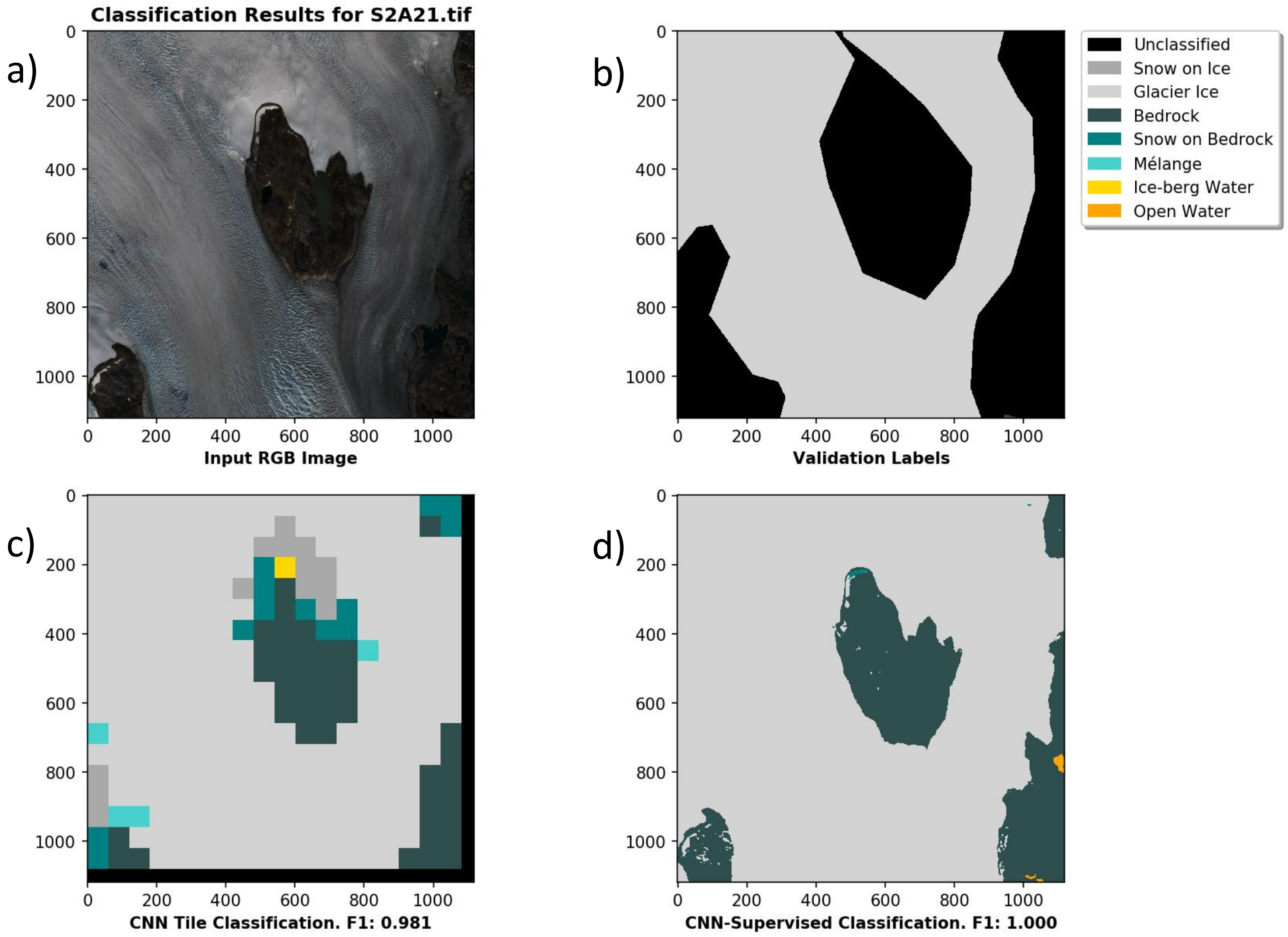


Figure 4: First example of the classification results from Self-Supervised Classification, applied to a 1120x1120 pixel tile extracted from an unseen Sentinel-2 image of Helheim Glacier.

The following 3 examples (Figure 4, 5, and 6) show the final pixel-based classification output of the SSC workflow.

- The workflow was applied to tiles with a size of 1120x1120 pixels.

Figures 4, 5, and 6:
- A) shows the input image.
- B) shows the validation data used to produce the output F1 score.
- C) shows the first CNN output used as training for the SSC.
- D) shows the final classification of the input image tile at the scale of each individual pixel.

Results: Pixel-based Self-Supervised Classification of Helheim Glacier

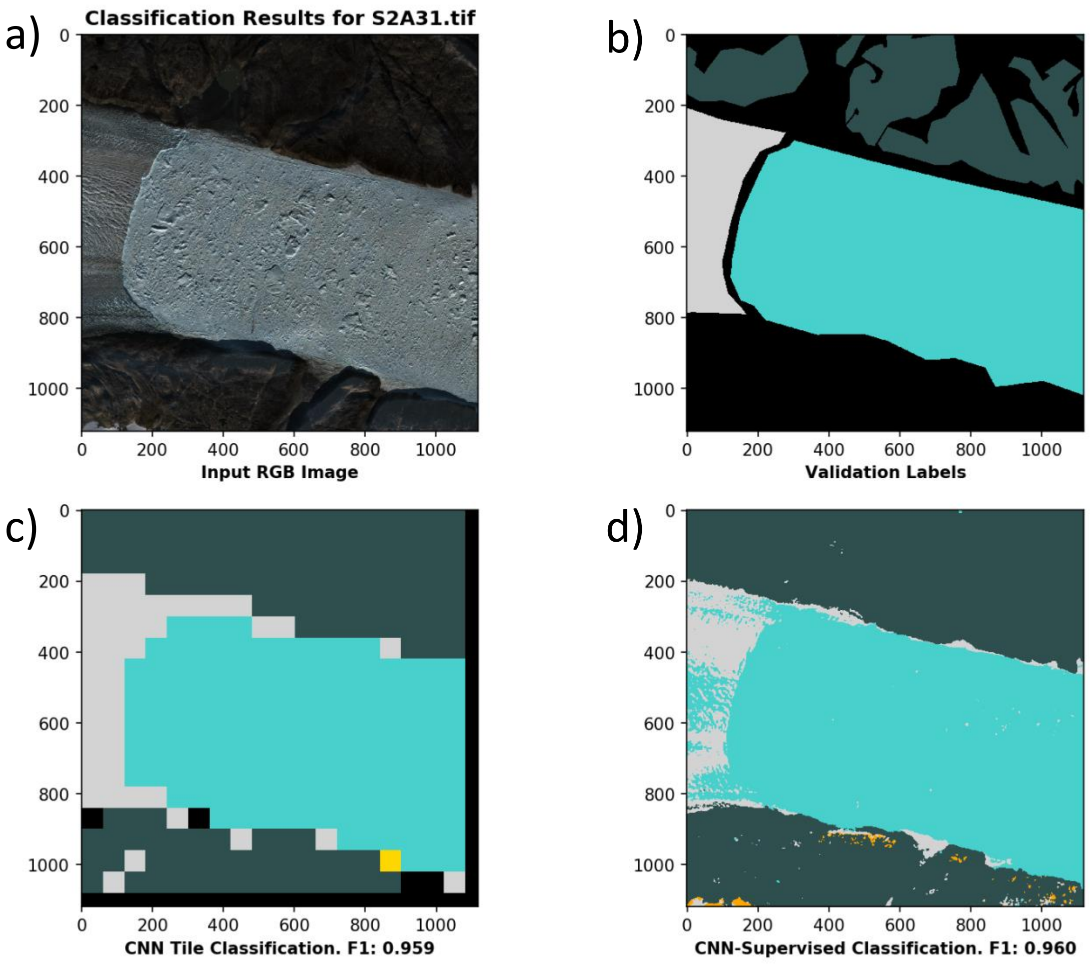


Figure 5: Second example of the classification results from Self-Supervised Classification, applied to a 1120x1120 pixel tile extracted from an unseen Sentinel-2 image of Helheim Glacier.

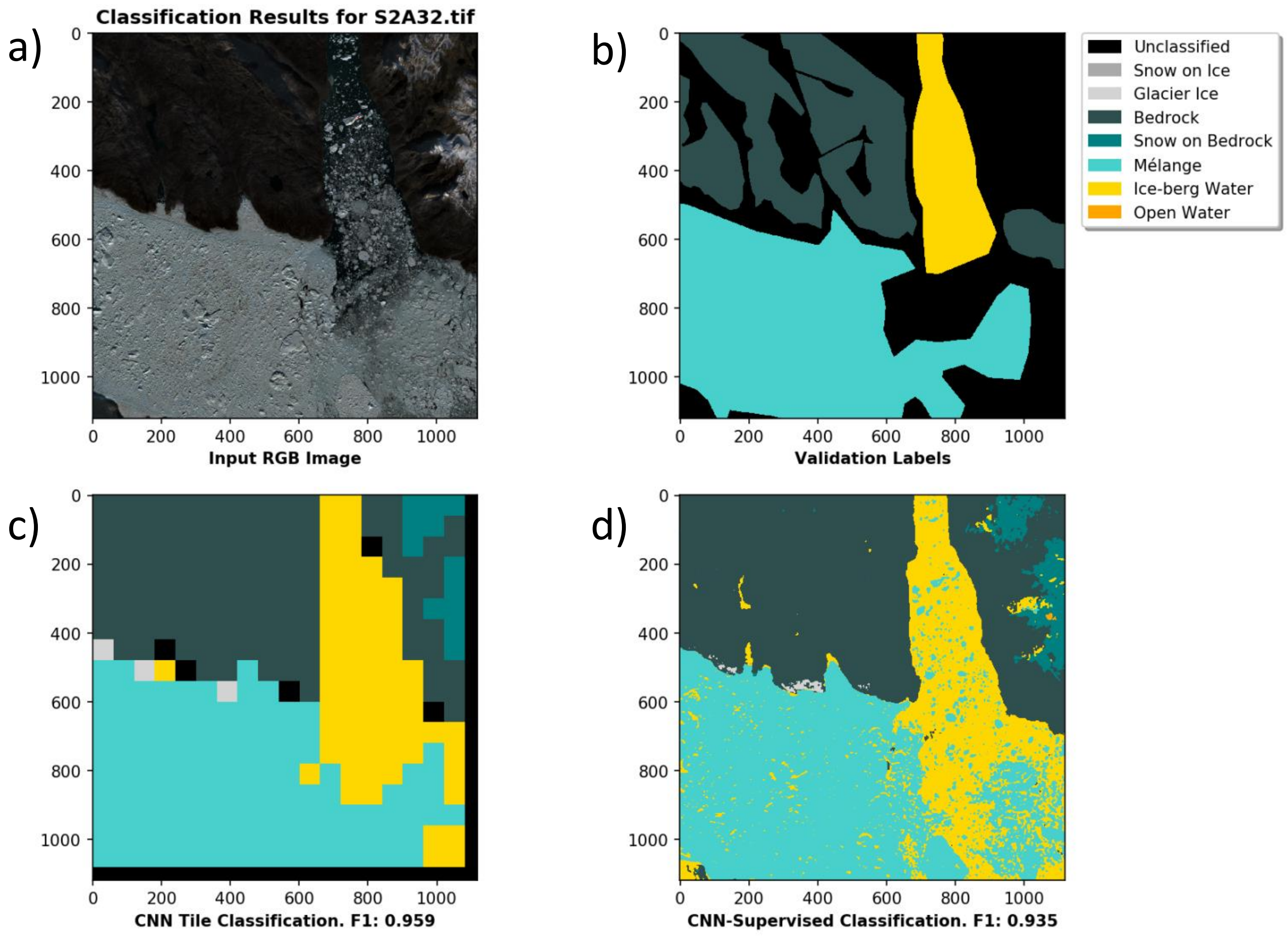


Figure 6: Third example of the classification results from Self-Supervised Classification, applied to a 1120x1120 pixel tile extracted from an unseen Sentinel-2 image of Helheim Glacier.

Conclusions and Further Work

- The initial results of the Self-Supervised pixel-based classification indicate that the workflow is able to produce F1 scores of >90% on an unseen image of the glacier used to train the CNN.
- It is also apparent that, in most cases, the CNN-MLP step in the workflow improves the F1 score in comparison to the initial output classification of the VGG16 CNN.
- In the next steps of this research we intend to apply a novel patch-based technique which uses a window of surrounding pixels to determine the class of each individual pixel in the classification.
- The transferability of the approach will also be tested by applying the workflow to unseen images of different glacial landscapes in Greenland.
- Overall, these initial results indicate that deep learning has the potential to significantly improve our ability to accurately and efficiently classify satellite images of complex glacial landscapes, providing an avenue for wider use in glacial research.

References

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The Python code for SSC is available on GitHub at: https://github.com/geojames/Self-Supervised-Classification

Thank you for your interest!