Temporal variations in the surface hydrology across Antarctic ice shelves

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1. Background and Aims

- Surface and subsurface melting, and the ponding, drainage and movement of meltwater across ice shelves have all been identified as factors contributing to past **ice shelf collapse.**
- For example, the Larsen B Ice Shelf likely collapsed due to the chain reaction drainage of ~ 3000 melt ponds in < 6 weeks.
- Recent studies have identified **pervasive meltwater systems** (i.e. rivers, streams and lakes) across Antarctic ice shelves (Kingslake et al., 2017; Dell et al., 2020).
- In addition, Antarctic ice shelves are often covered by vast **areas of slush and shallow water**.
- Slush is a spectrally ambiguous class (Moussavi et al., 2020), and can often be confused with blue ice and re-frozen meltwater. Identifying slush using a simple band thresholding approach is therefore likely to lead to significant errors.
- Here we use **machine learning** in the form of a k-means clustering algorithm (Arthur and Vassilvitskii, 2007) to train a supervised classifier on Landsat 8 imagery (Halberstadt et al., 2020), to assess seasonal variations in the **proportion of slush vs. deep water bodies** on ice shelves from 2013 to present day.

2. Scene Selection

- 14 image scenes across 7 ice shelves (Nivlisen, Roi Baudouin, Amery, Shackleton, Nansen, Bach, George VI), distributed across Antarctica were selected to train the unsupervised classifier (Fig.1). These ice shelves were selected as they are spatially distributed around the continent, and are characterised by a range of surface conditions.
- Image scene dates spanned the full Landsat 8 record (2013-2020), to account for temporal variations in surface conditions.
- Image scenes acquired at a range of solar angles > 20° were incorporated into the training data, following Halberstadt et al. (2020).

3. Identifying Slush, Shallow Water and Deep Water

- All scenes (see Section 2) were clipped using the rock and cloud thresholding methods from Moussavi et al. (2020).
- In Google Earth Engine (GEE) we then used an unsupervised clustering algorithm (k-means) to identify clusters with statistically different spectral properties for bands 1-7 in each image.
- We then manually interpreted these clusters in order to identify our classes of interest: (i) slush and shallow water, (ii) deep water.
- To accurately identify: (i) slush and shallow water, (ii) deep water, we have separated out and identified visually ambiguous classes such as: blue ice, cloud and rock shadow, re-frozen meltwater.
- Figure 2 provides an example of an output from the unsupervised k-means algorithm (Fig 2c), alongside an interpretation of the clusters to classify pixels as either (i) slush and shallow water or, (ii) deep water (Fig 2d).

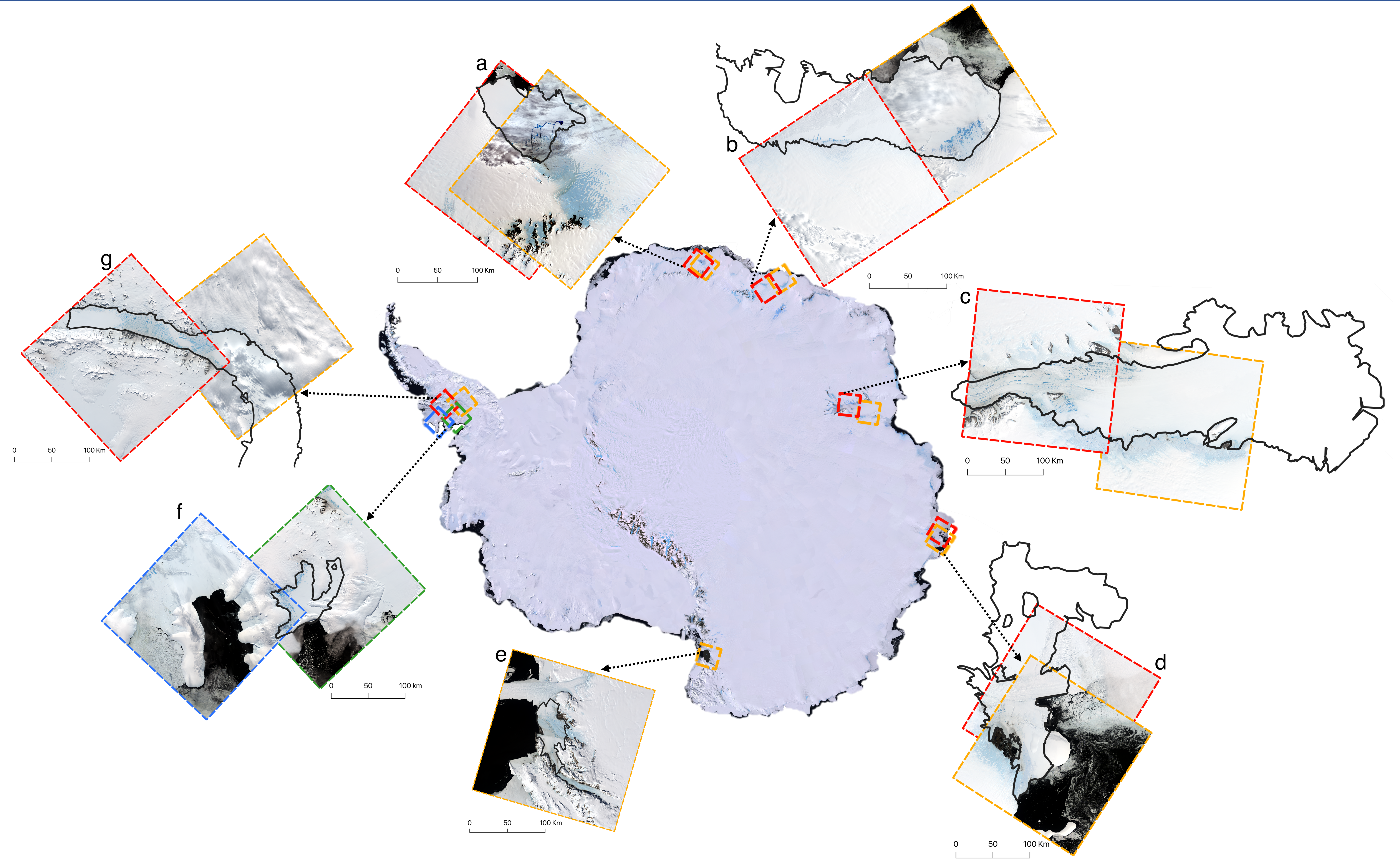

Figure 1: Selected training sites for the unsupervised k-means clustering algorithm. The central map of Antarctica is the Center-Filled LIMA Mosaic (Bindschadler et al., 2008). Dashed coloured boxes indicate the location of the surrounding Landsat-8 images for a) Nivlisen (166-110, 2019-02-19 (red)), (165-110, 2020-01-14, orange)), b) Roi Boudouin (154-110, 2017-01-24 (red)), (154-109, 2015-02-04, orange)), c) Amery (128-111, 2019-01-08 (red)), (127-110, 2019-01-17, orange)), d) Shackleton (113-106, 2020-01-18 (red)), (112-106, 2020-02-28, orange)), e) Nansen (063-113, 2014-01-02, orange)), f) Bach (221-110, 2020-02-23 (blue)), (218-111, 2020-01-17, green)), g) George VI (218-110, 2020-01-17 (red)), (215-111, 2018-02-07, orange)).

4. Future Work

- Develop the k-means clusterer to identify: (i) slush and shallow water, (ii) deep water across all training sites.
- Use the classes identified from the k-means clusterer to train a supervised classifier (e.g. Halberstadt et al., 2020).
- Create a validation dataset to quantify classification error (e.g. Dirscherl et al., 2020; Halberstadt et al., 2020; Moussavi et al., 2020).
- Use validated supervised classifier to quantify areas of slush and shallow melt vs. deep surface melt across Antarctica from 2013 to present day.

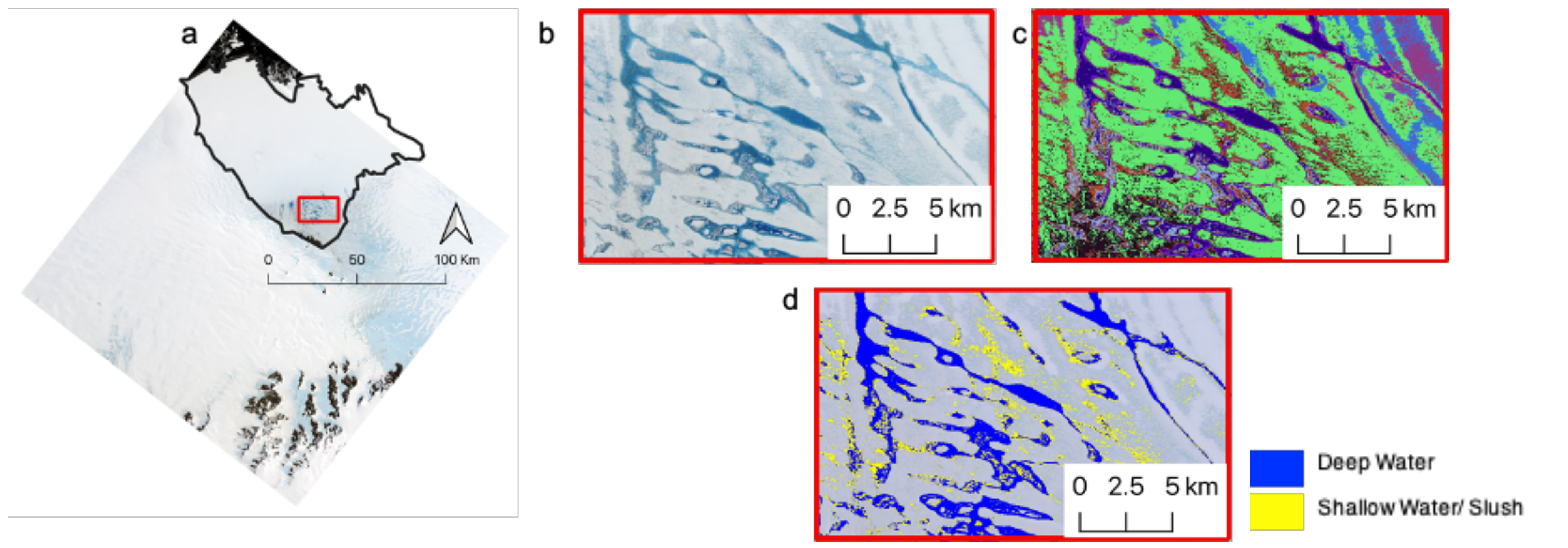

Figure 2: Example products from the k-means clusterer over the Nivlisen Ice Shelf (Landsat 8 image, 166-110, 2016-12-27). a) Base image of the Nivlisen Ice Shelf, the solid black line marks the ice shelf area, the red box shows the zoomed area featured in b,c, and d. b) True Colour composite, c) k-means classes identified, d) interpreted deep water and shallow water/slush classes, extracted from the k-means clusters in Fig. 2c.

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