Using deep learning with CryoSat interferometric radar altimetry to adjust elevations and map surface penetration (CryoSurf)

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1 Background & Overview

Land ice is declining globally, raising sea levels and impacting glacial risks and access to fresh-water in high-mountain glaciers regions. Land-ice monitoring via Earth Observation methods in general, and altimetry in particular, are essential for tracking the current status of ice volume change and its evolution.

The **CryoSurf** project applied a Deep Neural Network to combine elevation measurements acquired by **ESA's CryoSat-2**, SARIn waveform parameters, **NASA's Operation Ice Bridge**, **IceSat-2**, and surface conditions over the **Greenland Ice Sheet** (GrIS). We explore the difference between radar and laser altimetry and its relationship with surface condition, the impact of penetration of radar waves into snow and firn, and the respective measurement uncertainties.

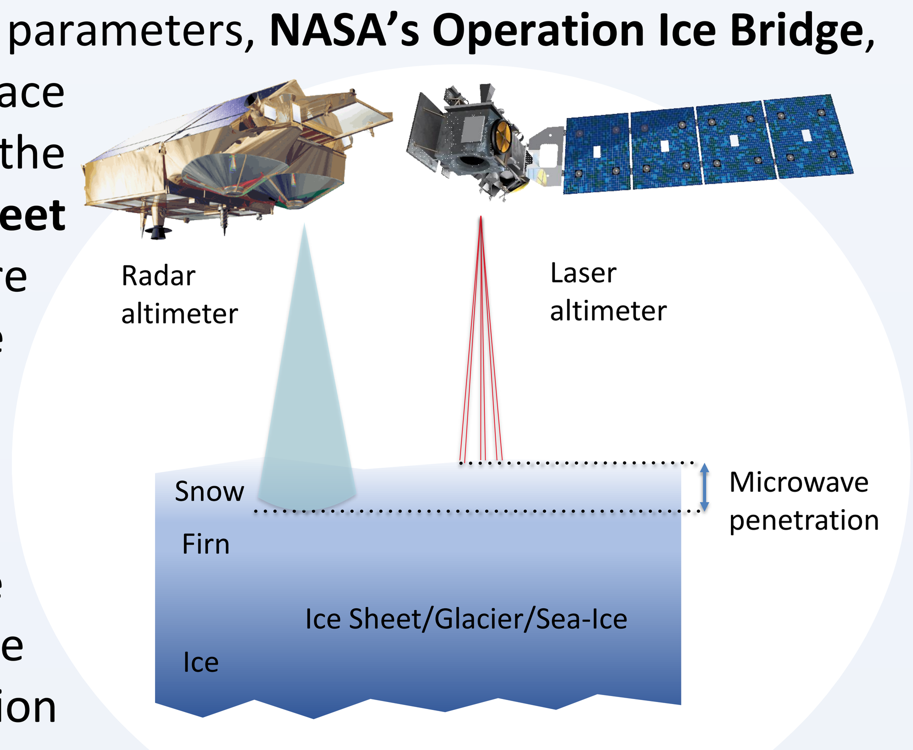

Figure 1. A representation of RADAR vs LIDAR surface penetration

2 Data & Methods

Data

Operation Ice Bridge (2011 – 2015) and IceSat2 (2018-2020) Lidar Altimetry was joined to CryoSat2 SARIn point data on a 50m spatial and 10 day temporal join for the whole of GrIS. Lower quality data was filtered from the dataset. The training and test data is split by time: 2015 (OIB) and 2020 (IS2) data is reserved as unseen test data and the remainder used for training.

Model Construction

A supervised regression Neural Network was constructed with flexible configurations to cater for variable inputs, neuron depth, layer width, and other features such activation function and layer normalisation.

Grid Search Optimisation

A traditional grid search was used to select the final models which optimised the Huber loss function.

Model Assessment

Simple model accuracy statistics were used to assess model accuracy on unseen test data. The model was run against all historic CryoSat-2 SARIn data and 2km, monthly gridded products were produced showing the model-predicted adjustment between Lidar and Ku-band SARIn altimetry.

3 Results & Discussion

Performance Against Unseen Test Data

Using the neural network, the mean adjustment was predicted to within 0.1cm (MAD 1.8m, RMSE 3.4m). Complex LIDAR-SARIn adjustments were better reproduced by the neural network when compared to a simple, multi-variate, ordinary least squares model.

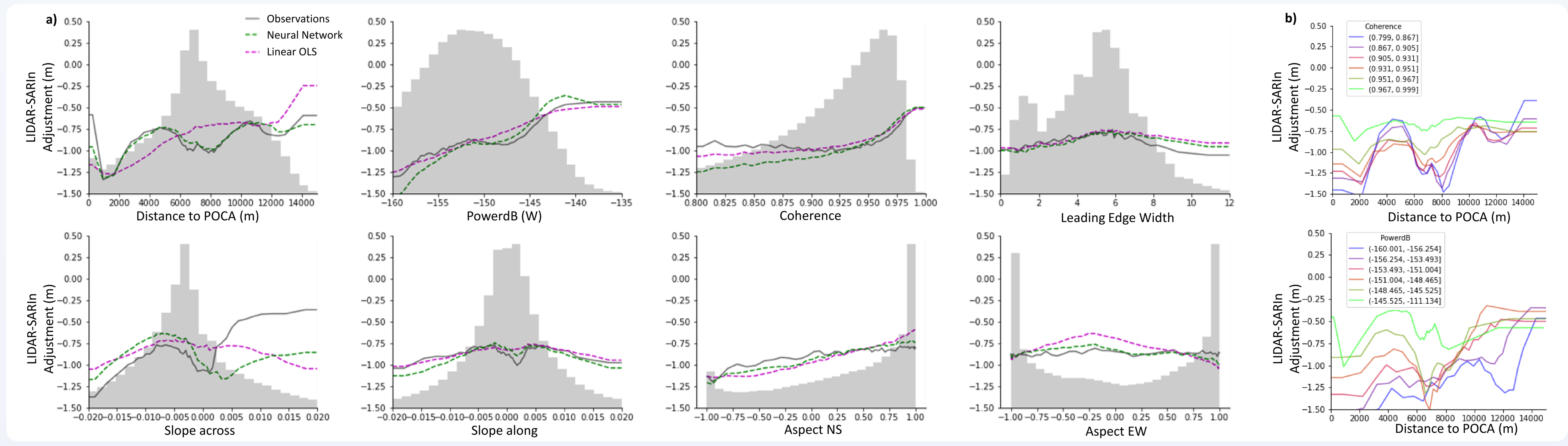

Figure 2. a) A summary of observed and modelled LIDAR-SARIn differences as a function of input parameters for unseen test data points across the GrIS. The distribution of observation counts per parameter is shown in the grey histogram for each plot. b) LIDAR-SARIn differences as a function of distance to POCA shown per quantile slice of coherence and powerdB

Spatial and Temporal Analysis

The trained model was used to predict **sub-waveform** level **LIDAR-SARIn** point adjustments and the resulting predicted adjustments were then converted into monthly, **2km gridded products**. These products, and the temporal changes therein, were then compared to the available observations and to a snowfall estimate from the MAR model.

Model predicted spatial trends were seen to broadly align to both observed and expected presence and absence of volume scattering from physical processes. E.g. general surface scattering on northerly aspects versus an increase in volume scattering on southern aspects. Similarly, an increase in surface scattering through months of reduced snowfall was both predicted and observed.

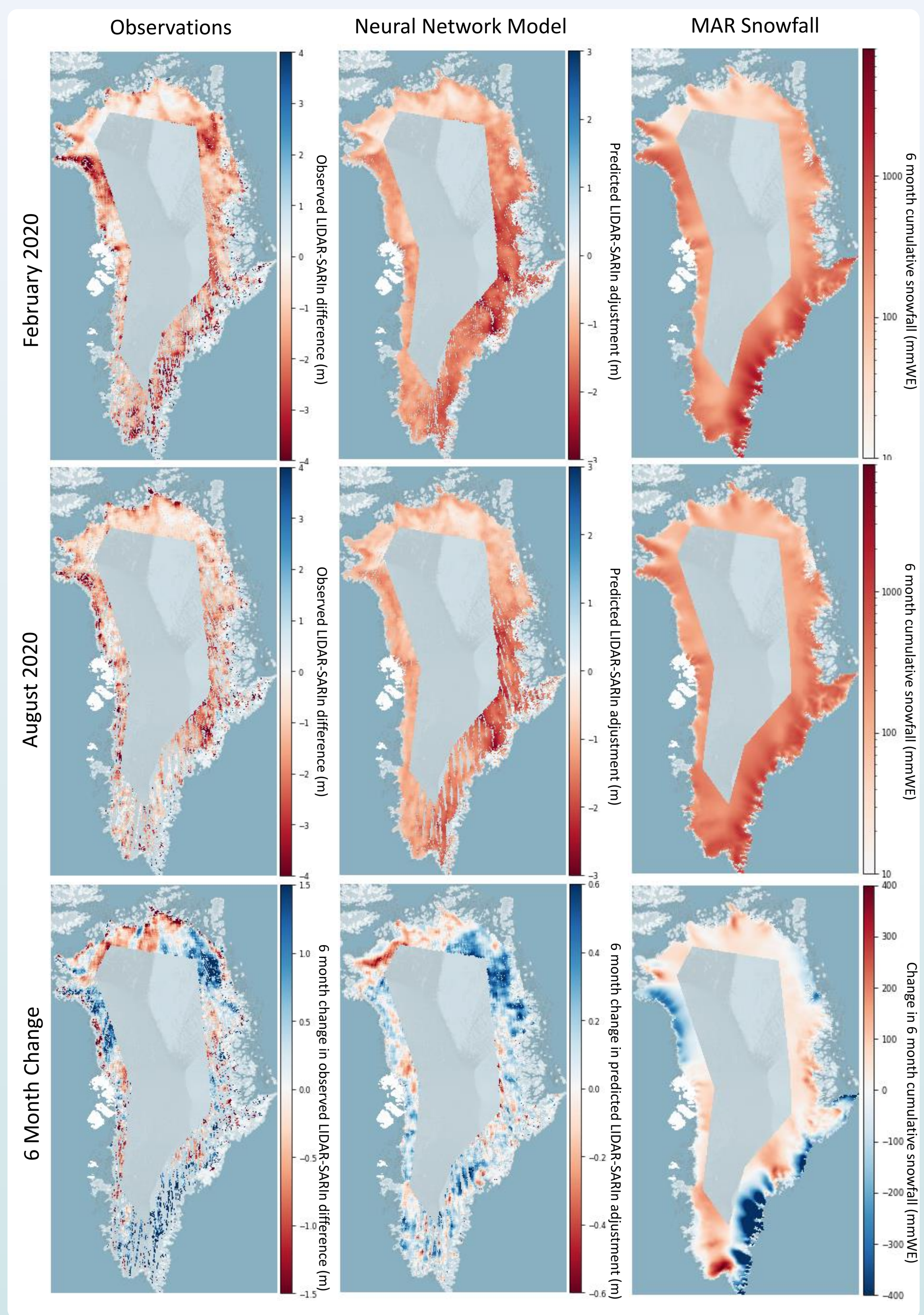

Figure 3. Observed and predicted LIDAR-SARIn differences from February 2020, August 2020, and their change over a 6 month window with a comparison to accumulated snowfall from the MAR model

Limitations

Not all localized observations recreated (e.g. King Frederick VIII Land). GrIS-wide magnitude of LIDAR-SARIn differences were not fully recreated for regional or seasonal trends. The exact source of limitation was not identified but most likely due to one of:

- The neural network lacking sufficient inputs to capture physical process
- Signal-to-systematic-error and signal-to—stochastic-error ratio too low (e.g. the magnitude of processing errors largely outweighs the magnitude of effects representative of penetration and volume scattering)

4 Conclusions & Roadmap

- A neural network was used to predict sub-waveform level LIDAR-SARIn adjustments
- Mean observations were predicted to within 1cm (MAD 1.8m, RMSE 3.4m)
- Broad spatial and temporal trends were recreated
- Further studies required to address limitations
- A myriad of potential applications to existing and future missions such as:
    - **CRISTAL**
    - **Cryo2Ice**
    - Airborne campaigns
    - Other multi-band sensor data

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