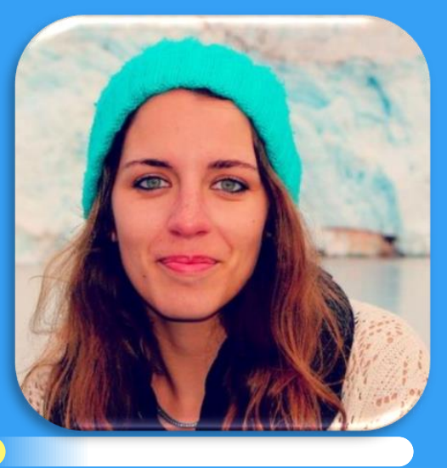
Sea ice Melt pond retrievals using AI-based Earth observation methods



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MIT Portugal 2023 Annual Conference

I. BACKGROUND

Melt ponds form in sea ice during summer and spring as a consequence of **melting** ice. Their darker color drastically reduces the ice albedo, increasing the flux of absorbed solar radiation playing a pivotal role in the **Artic energy budget**. Despite their relevance in the climate context, melt ponds are **poorly** represented in sea ice models[1] and are **not explicitly** represented in climate models[2]. Their scarce information is in fact pointed as a **source of uncertainty** for the underestimations of sea ice extent extension in climate models projections[3]. Furthermore, current melt pond products are based in optical data (and thus impacted by cloud coverage) and have a coarse resolution[4].

Melt Ponds

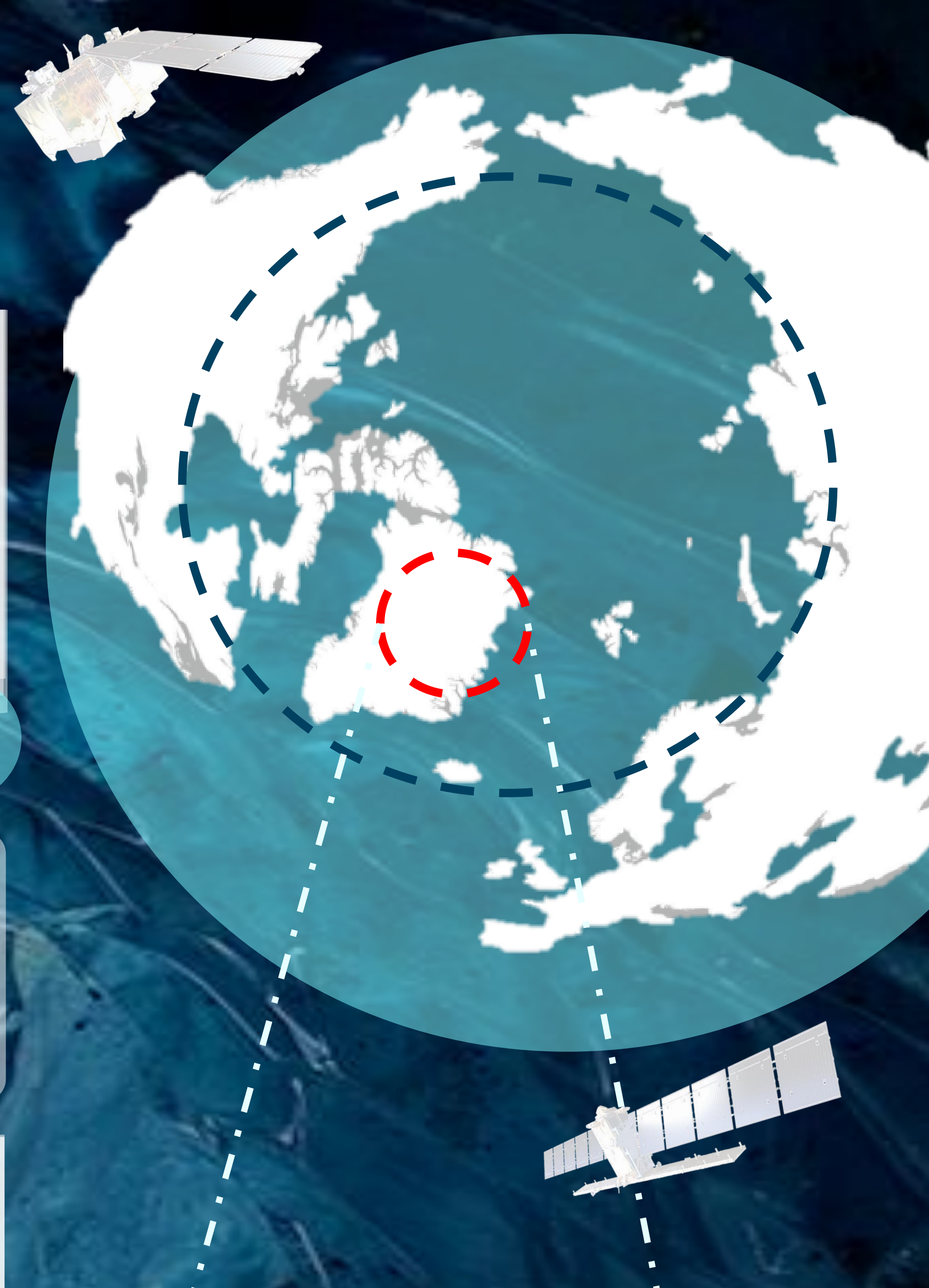
Credit: NASA Goddard Space Flight Center

II. OBJECTIVES

To **enhance temporal and spatial** accuracy of detection and characterization of melt pond by retrieving **daily melt pond fractions (MPF)** with the following characteristics:

- coverage of the entire Arctic region
- higher resolution than existing products (which have 500m resolution)
- using radar-based sensors which are not impacted by presence of clouds
- generated through an autonomous approach, applying Artificial Intelligence (AI) algorithms

III. AREA OF INTEREST

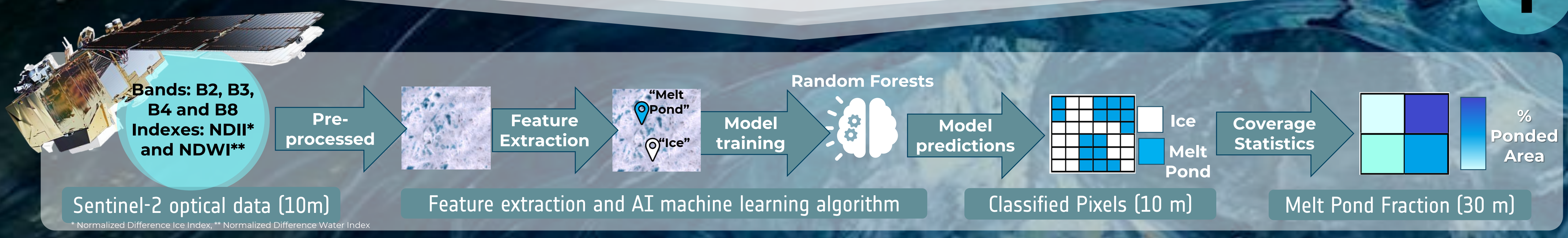


First trials in NE Greenland Coast

IV. METHODOLOGY

The workflow has **two main steps**. The first consisted in the generation of an optical-based MPF, that will be used as training data on the second step. This dataset was generated after selecting **Sentinel-2** (S2), an optical satellite, cloud-free areas. The data was processed by removing land pixels and atmospheric corrected and new bands/indexes were generated with some of its 13 spectral bands. A **Random Forest** (of 15 trees) was trained to predicts pixels the S2 bands/indexes as belonging to classes ice or melt pond (which were priorly humanly extracted). The resulting predicted **binary maps**, were then converted into a MPF by estimating percentage (%) of melt pond pixel per total pixel area, resulting in a dataset of **melt pond fractions - MPF**.

1



* Normalized Difference Ice Index, ** Normalized Difference Water Index

On the second step, Sentinel-1 (S1) Synthetic Aperture Radar (SAR) bands were used as input/predictor and MPF maps as target/output to teach a deep learning algorithm. The **Convolutional Neural Network (CNN)** created has **three** convolutional layers using **ReLu activation** followed by two **MaxPooling** layers, a **Flatten** layer and two **Dense** layers (i.e., fully connected layers) with **ReLU** and **linear activations**. A CNN was chosen, as it does not require manual feature extraction and in addition it can learn from the pixel's geospatial correlation.

2

V. PRELIMINARY MAIN RESULTS

- First step generated a dataset of 64x64 pixel MPF images with a size of 30k samples, with an overall accuracy of 0.87
- Second step generated a dataset of MPF with a Mean Absolute Error (MAE) of 0.0721

VI. CONCLUSIONS

In order to enhance the results from the second step, i.e., to generate MPF based on radar images, aiming at achieving a lower MSA value as possible, the training dataset size (generated from step 1 of methodology) needs to be increased and the deep learning model could be subject to improvements. As such the next steps are:

- Increase training dataset generated on step 1 by the order of tens of thousands (e.g.: image augmentation)
- Fine-tune hyperparameters of the deep learning model (CNN) on step 2
- Include wind and temperature daily datasets as part of training data on step 2
- Explore Generative Adversarial Networks (GANs) for the generation of synthetic MPF from Sentinel-1

VII. REFERENCES

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BACKGROUND IMAGE CREDITS: Katarzyna Stachniak

Funded by:

fct Fundação para a Ciência e a Tecnologia

MIT Portugal

under the Doctoral Grant PRT/BD/154506/2022| Earth Systems: Oceans to Near Space