



Deep Learning for mapping retrogressive thaw slumps across the Arctic

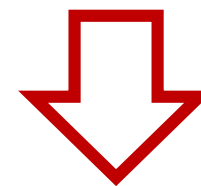
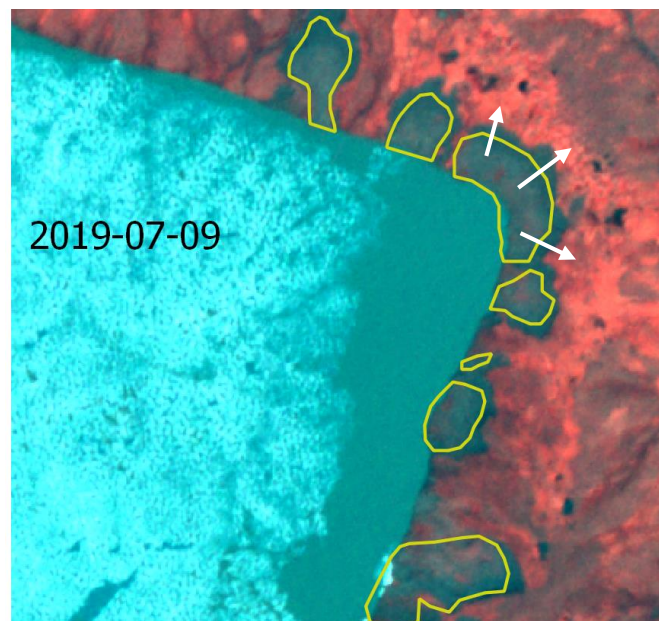
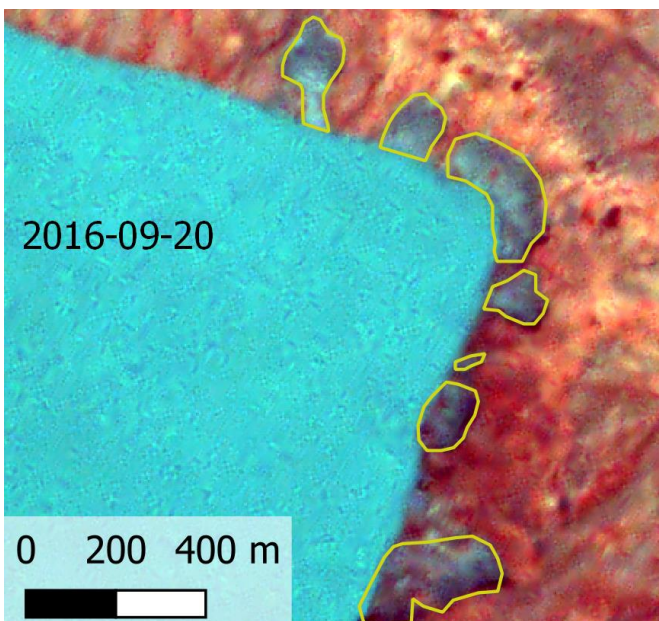


2022-05-19- International Circumpolar Remote Sensing Symposium (ICRSS)
I.Nitze, K.Heidler, S.Barth, G.Grosse

Retrogressive Thaw Slumps

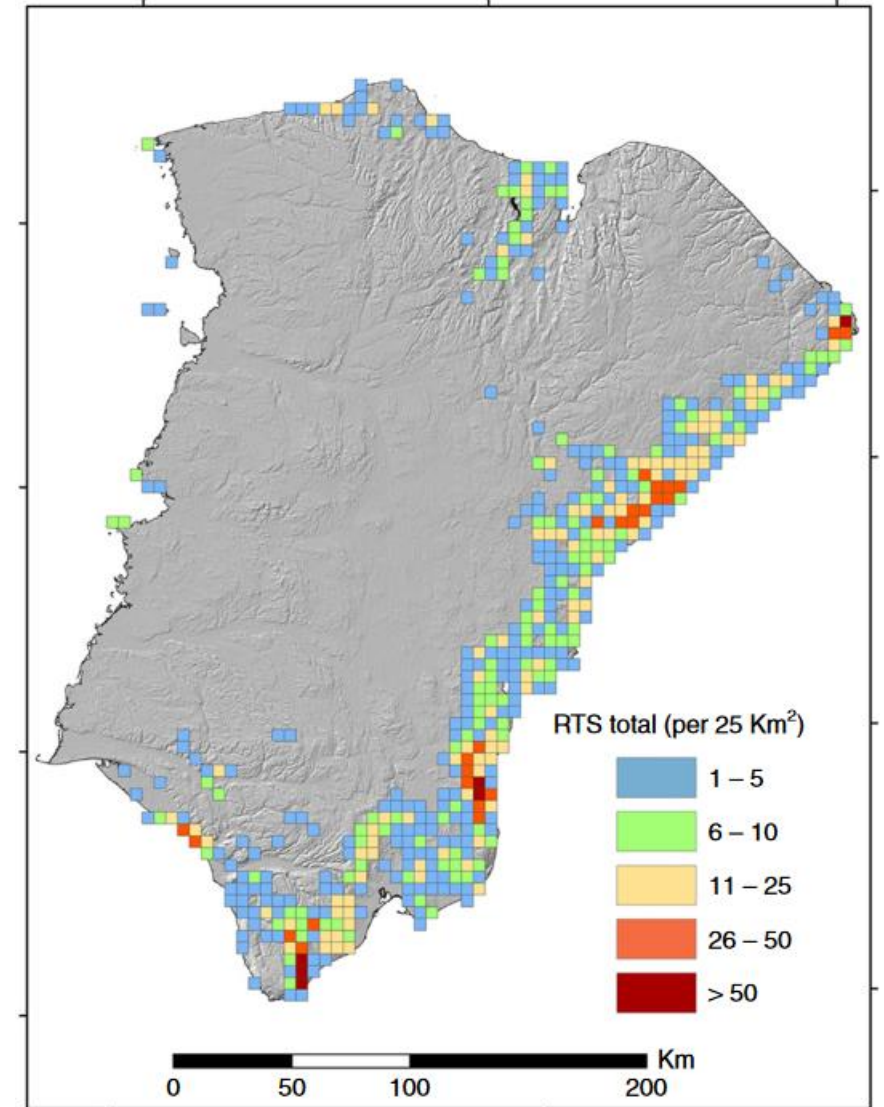
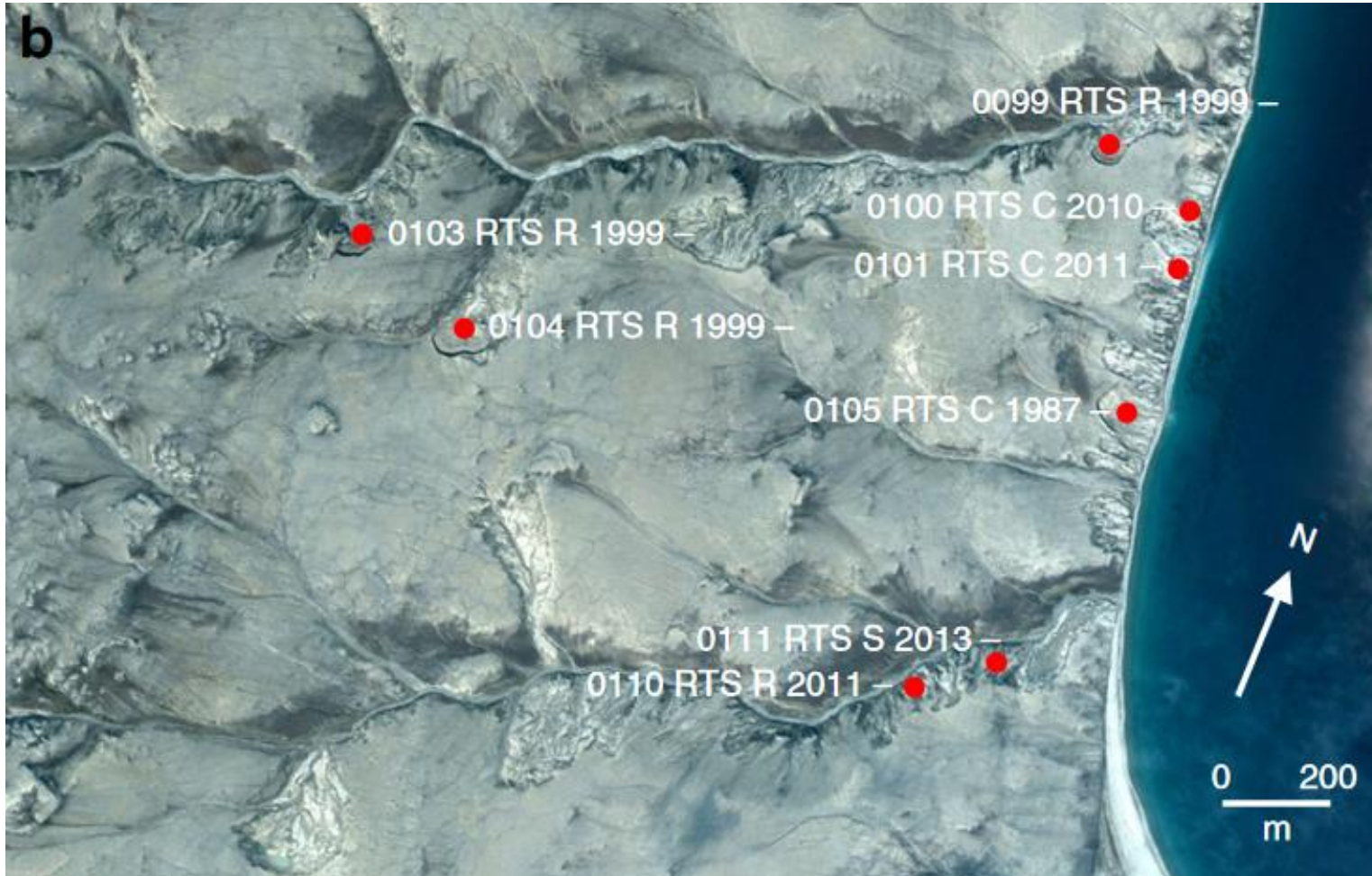


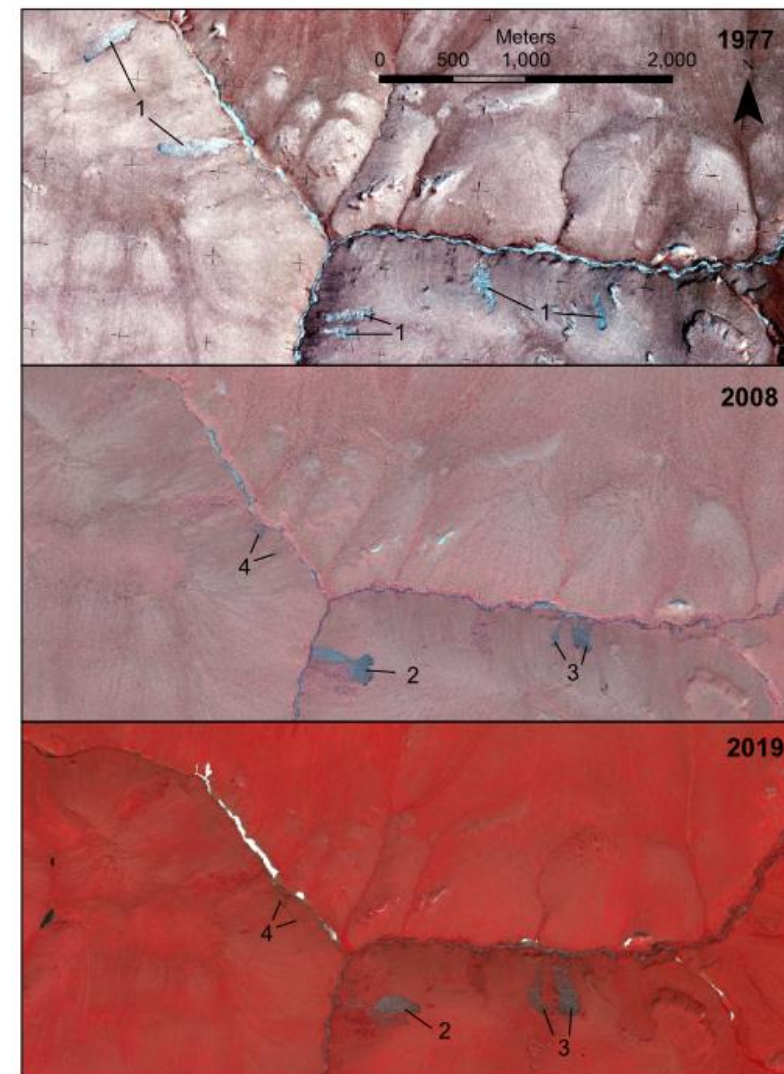
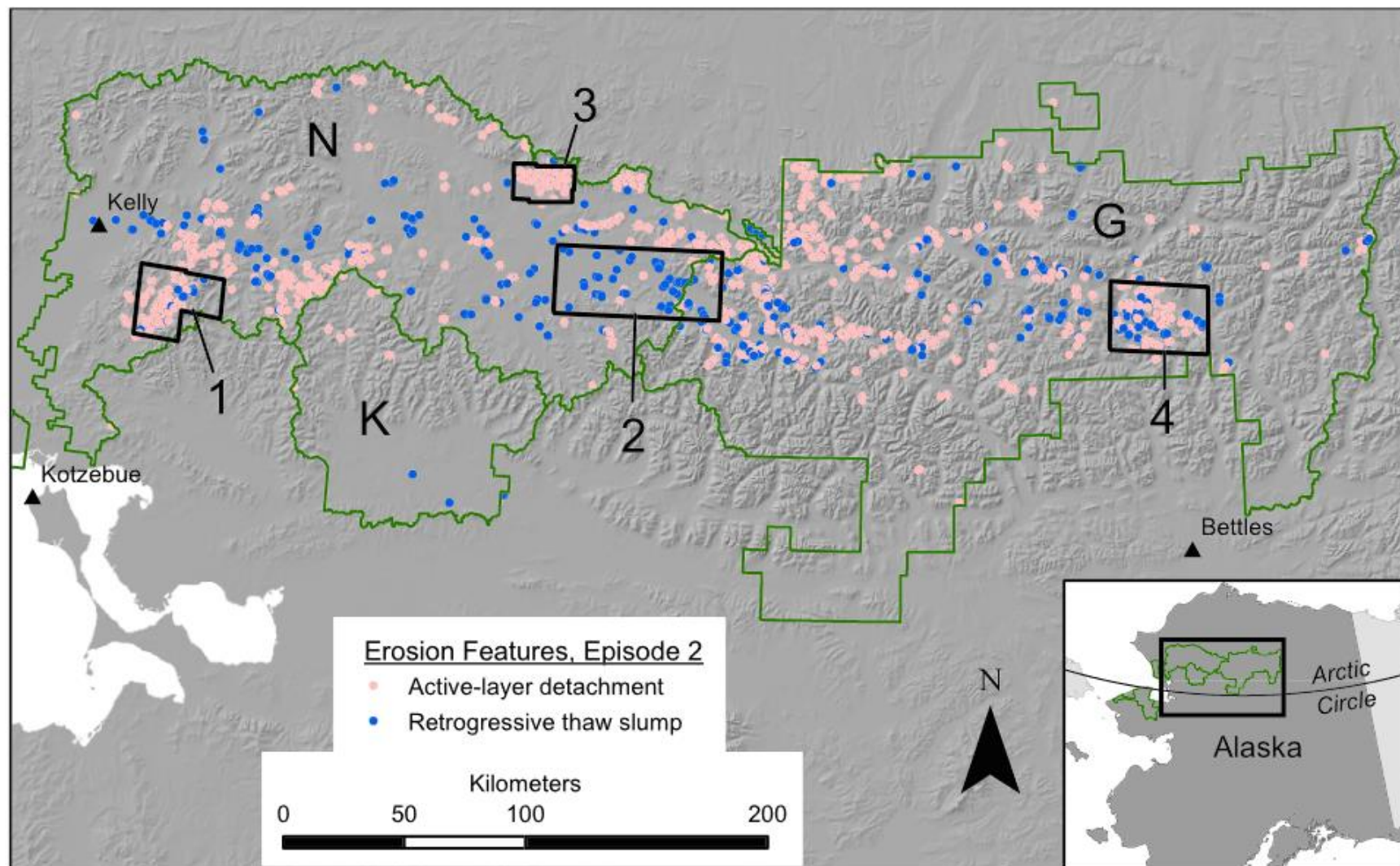
- Erosion
- Dynamic
- Progressive/Polycyclic
- Small (m^2 - $<1 km^2$)
- Often undetected
- Clustered Distribution

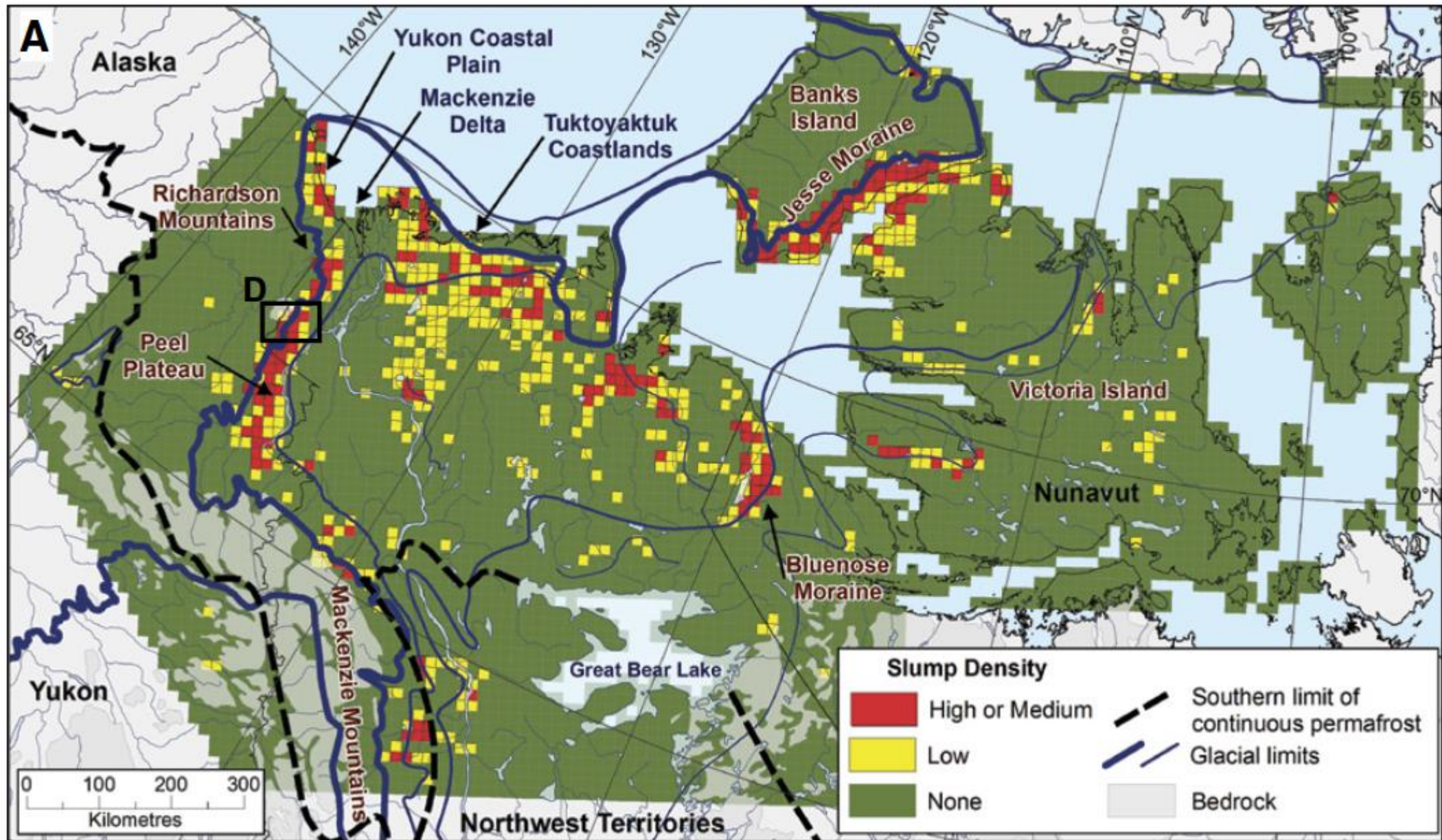


Segmentation Problem

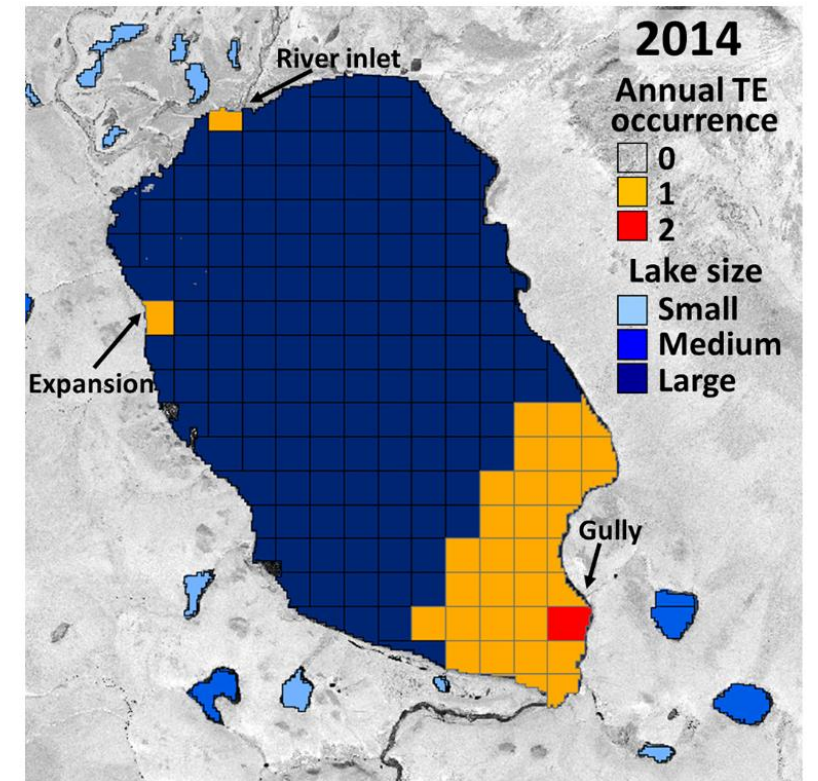
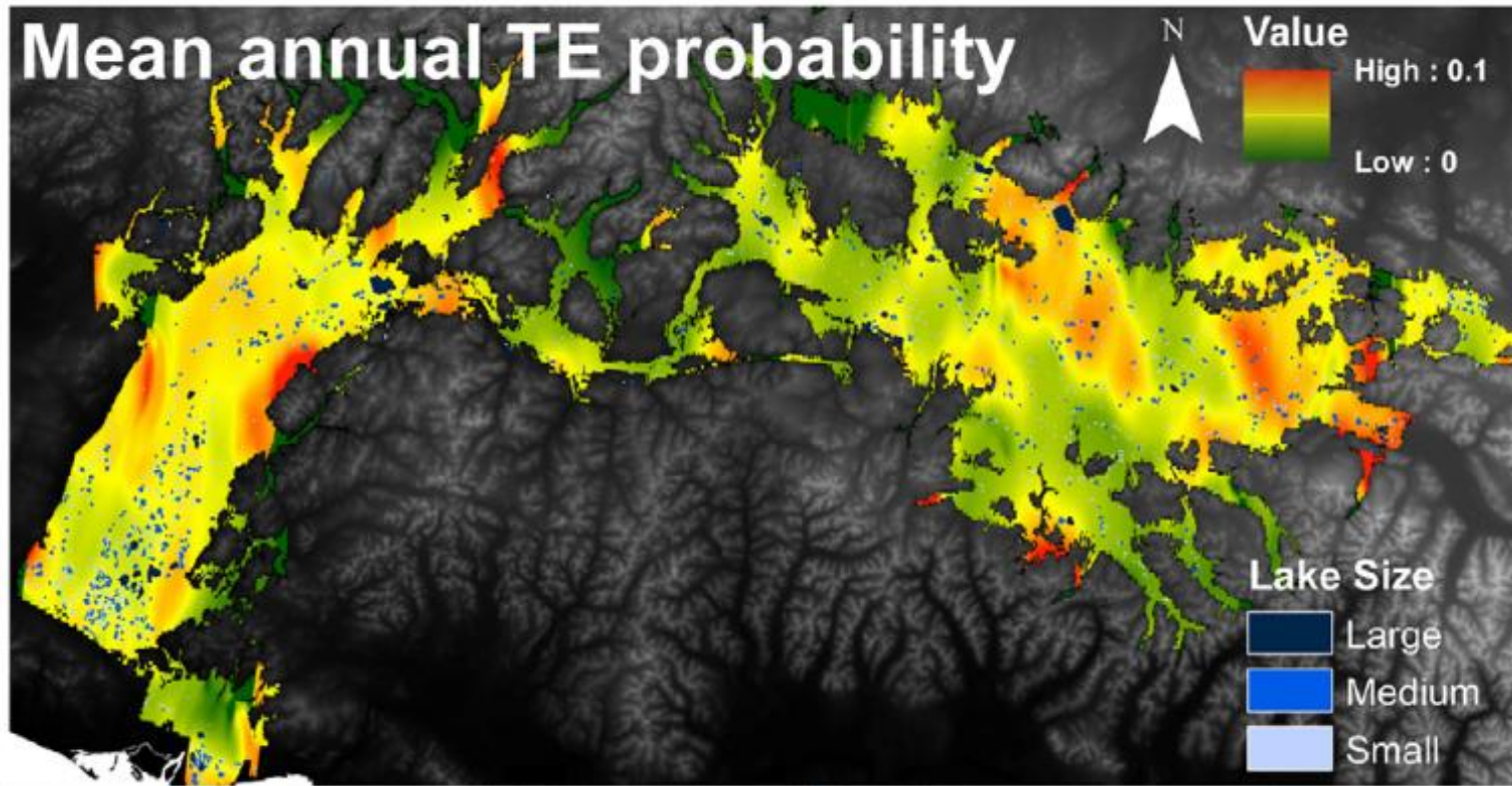
Manual RTS mapping





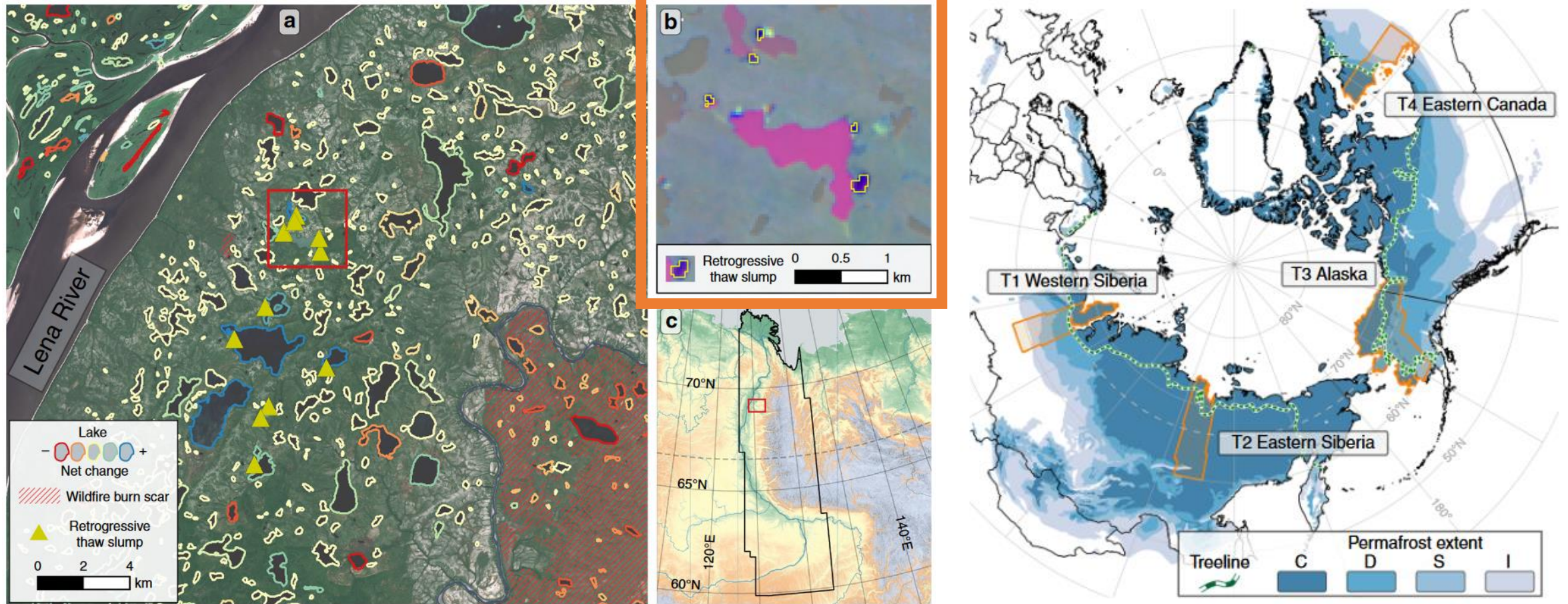


More automated approaches



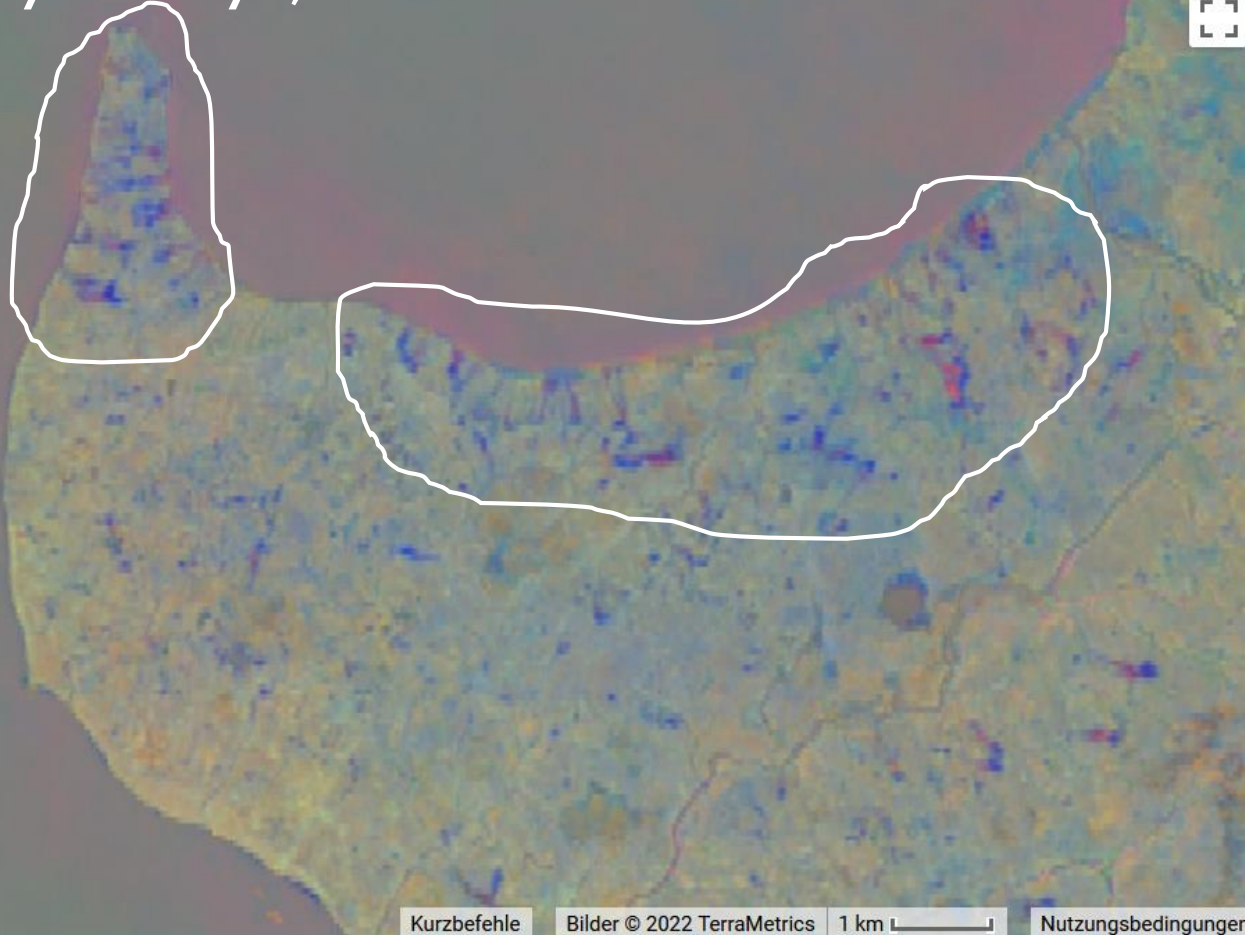
Lara et al., 2019

More automated approaches



Nitze et al., 2018

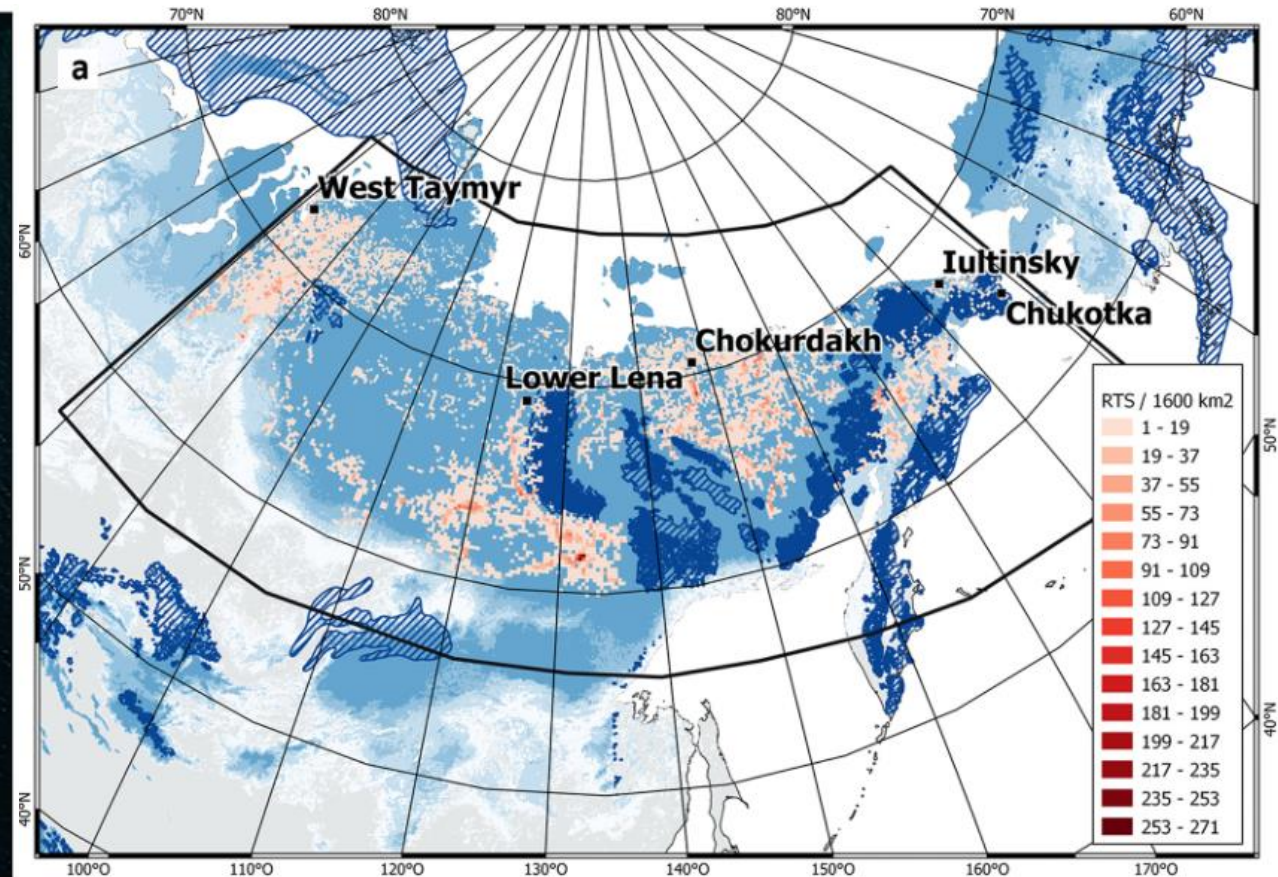
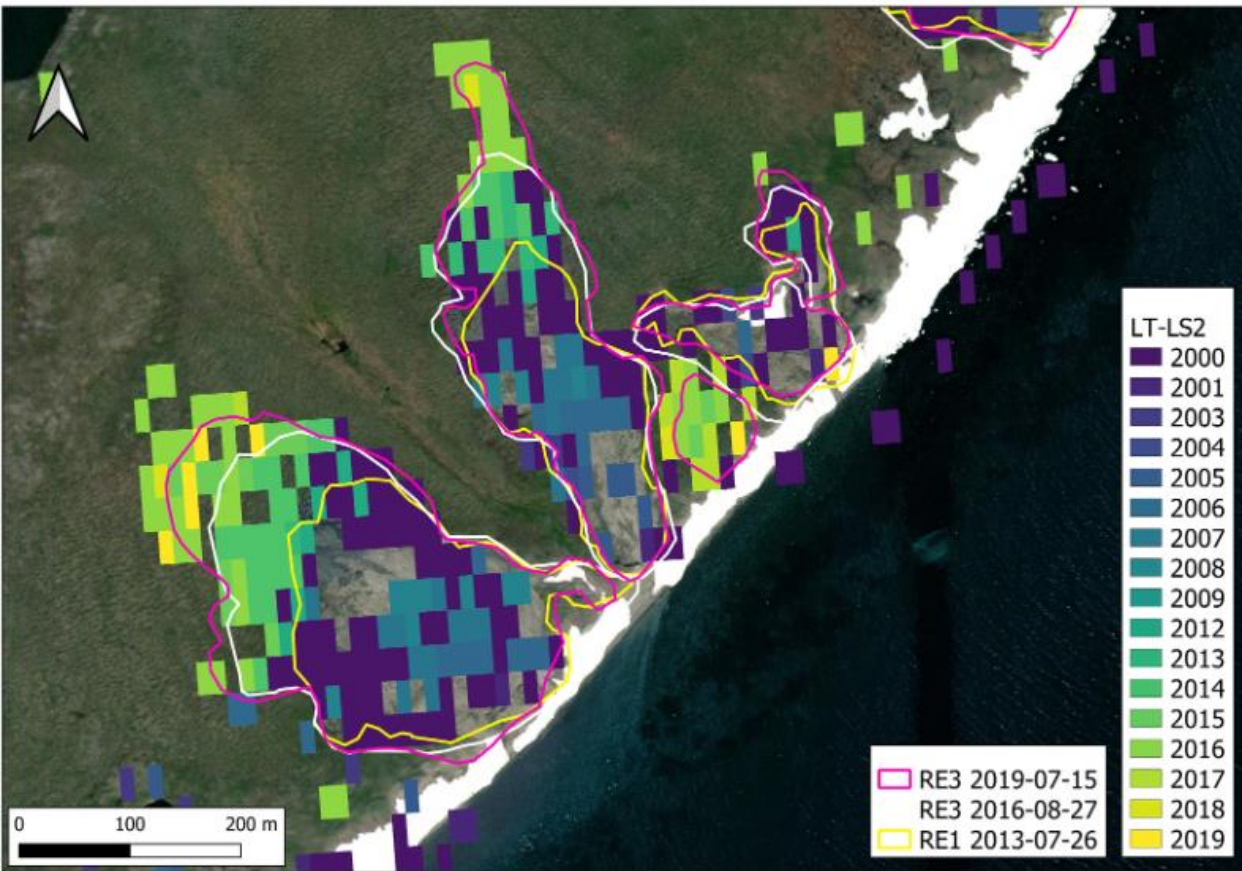
Sukhoy Nos, Novaya Zemlya, Russia



Explore by yourself !

<https://ingmarnitze.users.earthengine.app/view/hotspottcvisapp>

More automated approaches



Runge et al, 2022

Scale and Automation

Spatial Scale

Automation

Spatial Resolution

Accuracy

Local to regional

Low

Very High



Pan-arctic/
continental

High

Moderate



Scale and Automation

Spatial Scale **Automation** **Spatial Resolution** **Accuracy**

Local to regional

More Data

Low

Very High

Better/more suitable Data

Pan-arctic/
continental

New Detection Techniques

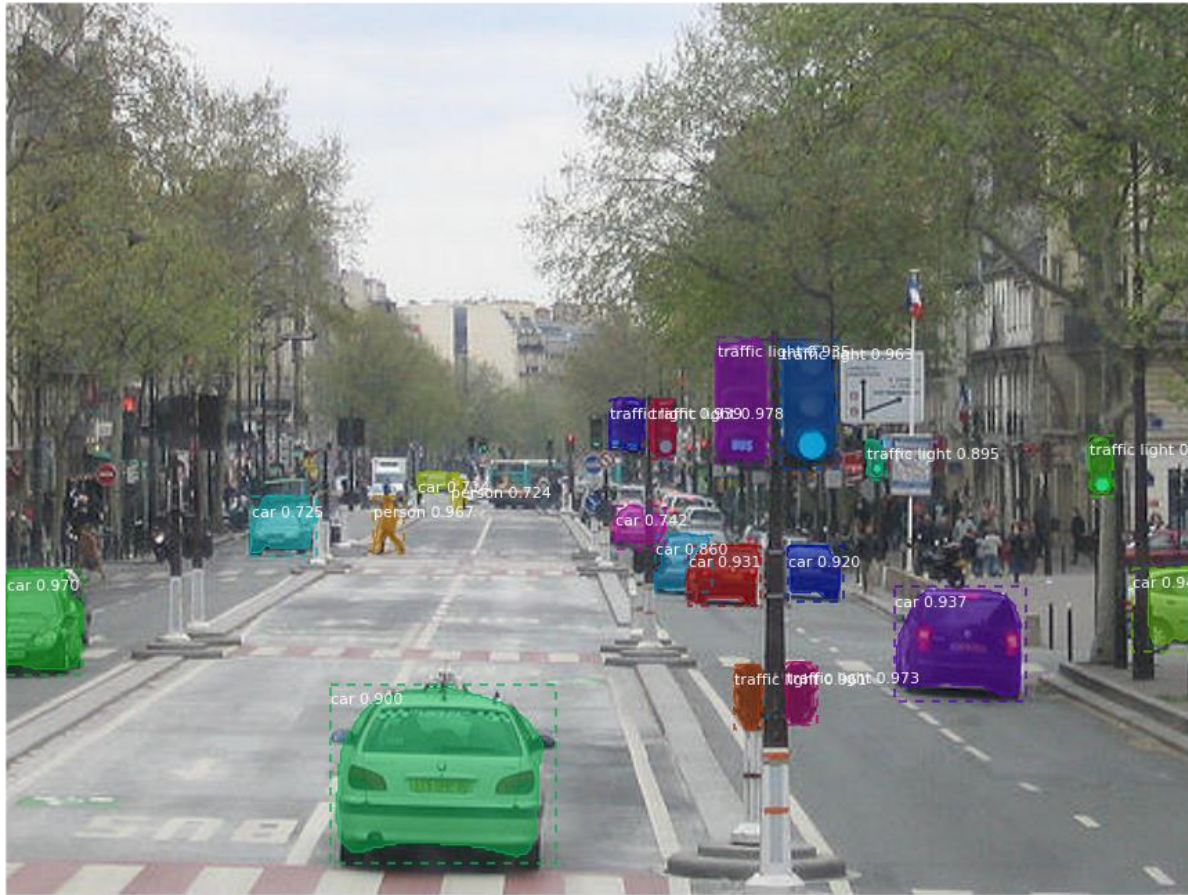
High

Moderate

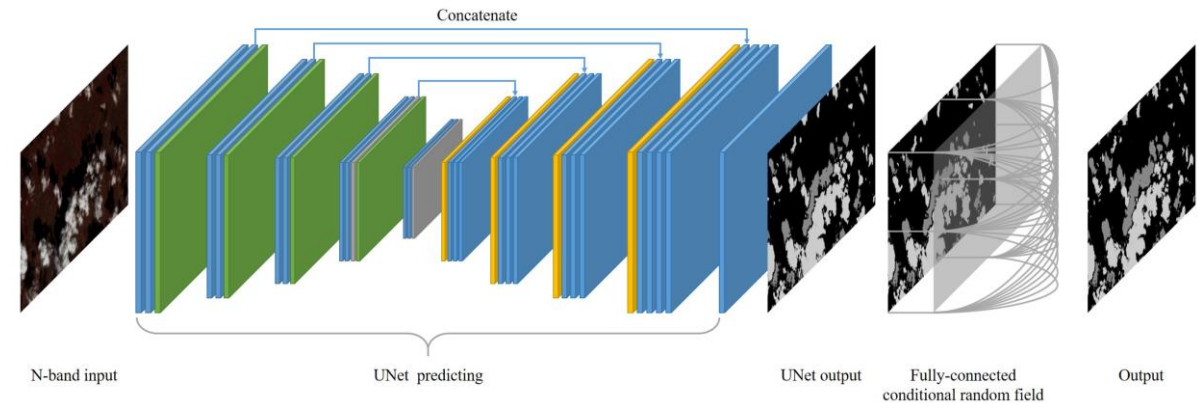
Processing Capabilities



Deep Learning and Image Segmentation



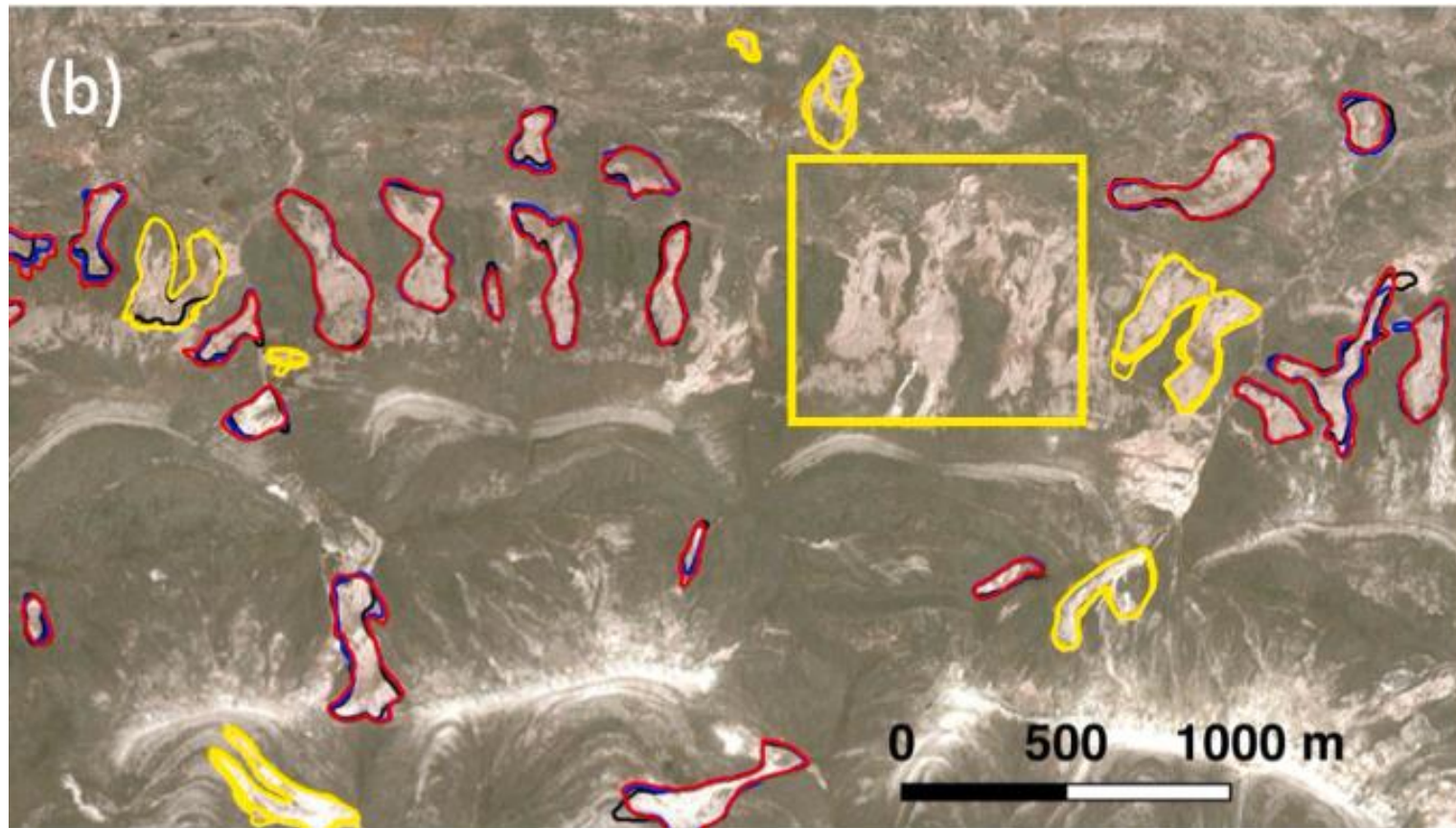
K.Majek.



Jiao et al., 2020

- Image segmentation
- Takes spatial context into account
- Computationally intensive (GPU)

Deep Learning for Object Segmentation



Only few permafrost deep learning studies

Even fewer for Thaw Slumps

Currently focussed on Tibetan Plateau

Huang et al., 2021

DL Model Framework

Input data → DL model → RTS footprints



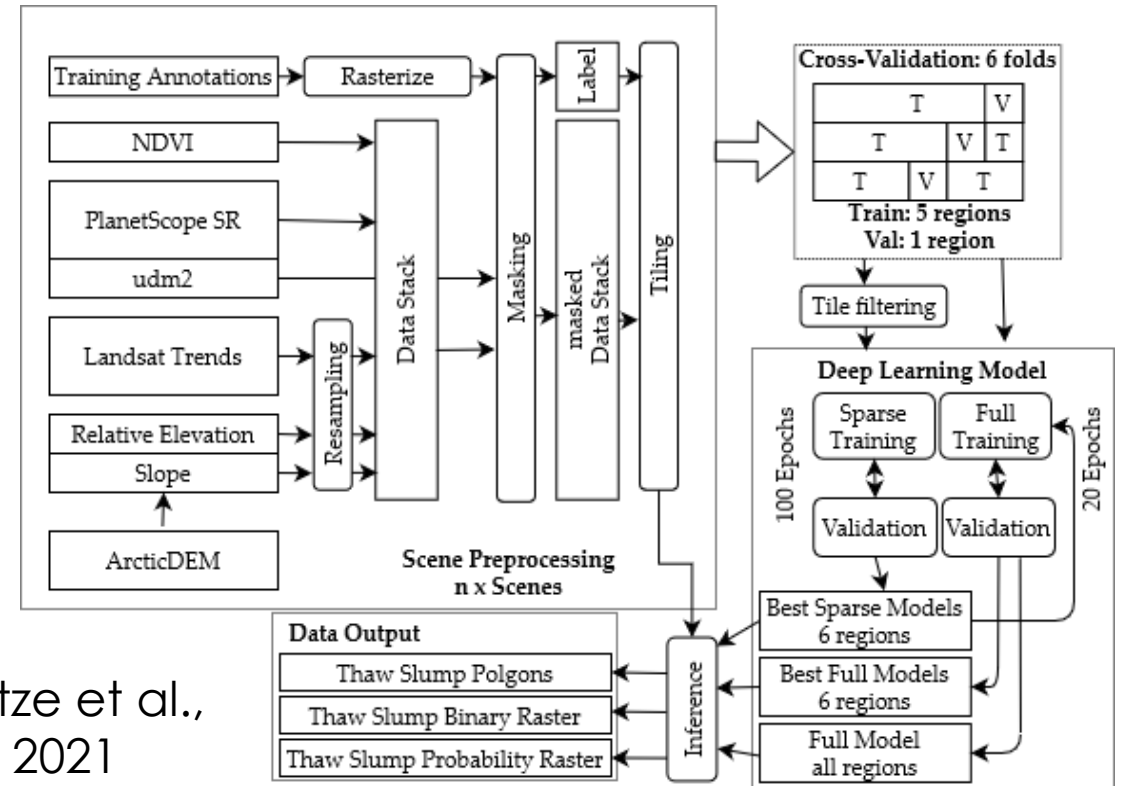
Automated Processing

- Flexible configuration with yaml files
- Target can be any object

Flexible Model Architecture

- Segmentation architecture
- Encoder/backbone network
- Loss functions

Data Augmentation Pipeline



Data

1. Planet SR Scenes (2018-2021) – 3m SR

- Multispectral (B-G-R-Nir) (A)
- NDVI (B)

2. Landsat Trends

- TCB, TCG, TCW (C)

3. ArcticDEM

- Relative (detrended) elevation (D)
- Slope (E)

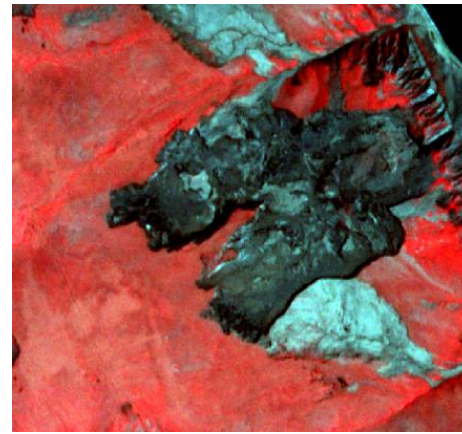
4. Training Data (polygons) $n=2182$

- How to delineate RTS?

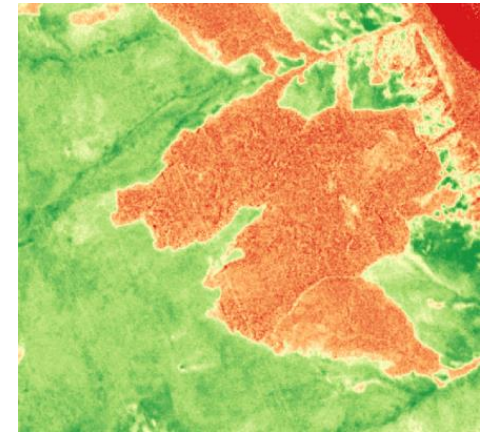
Output

- Raster (binary + probability)
- Vector (footprint)

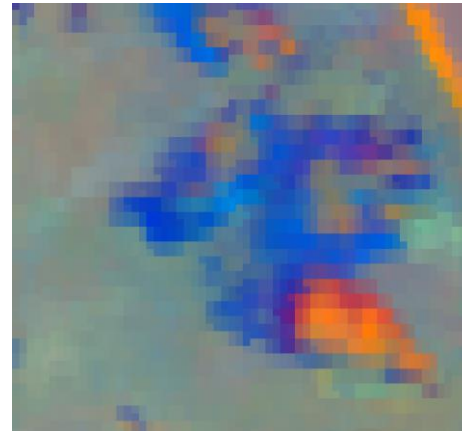
A



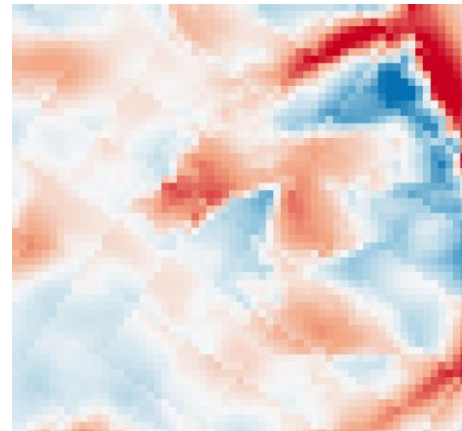
B



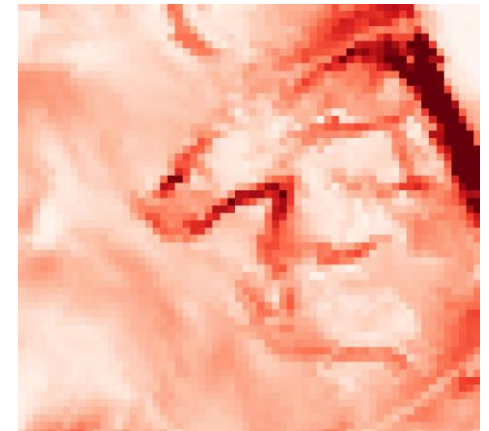
C

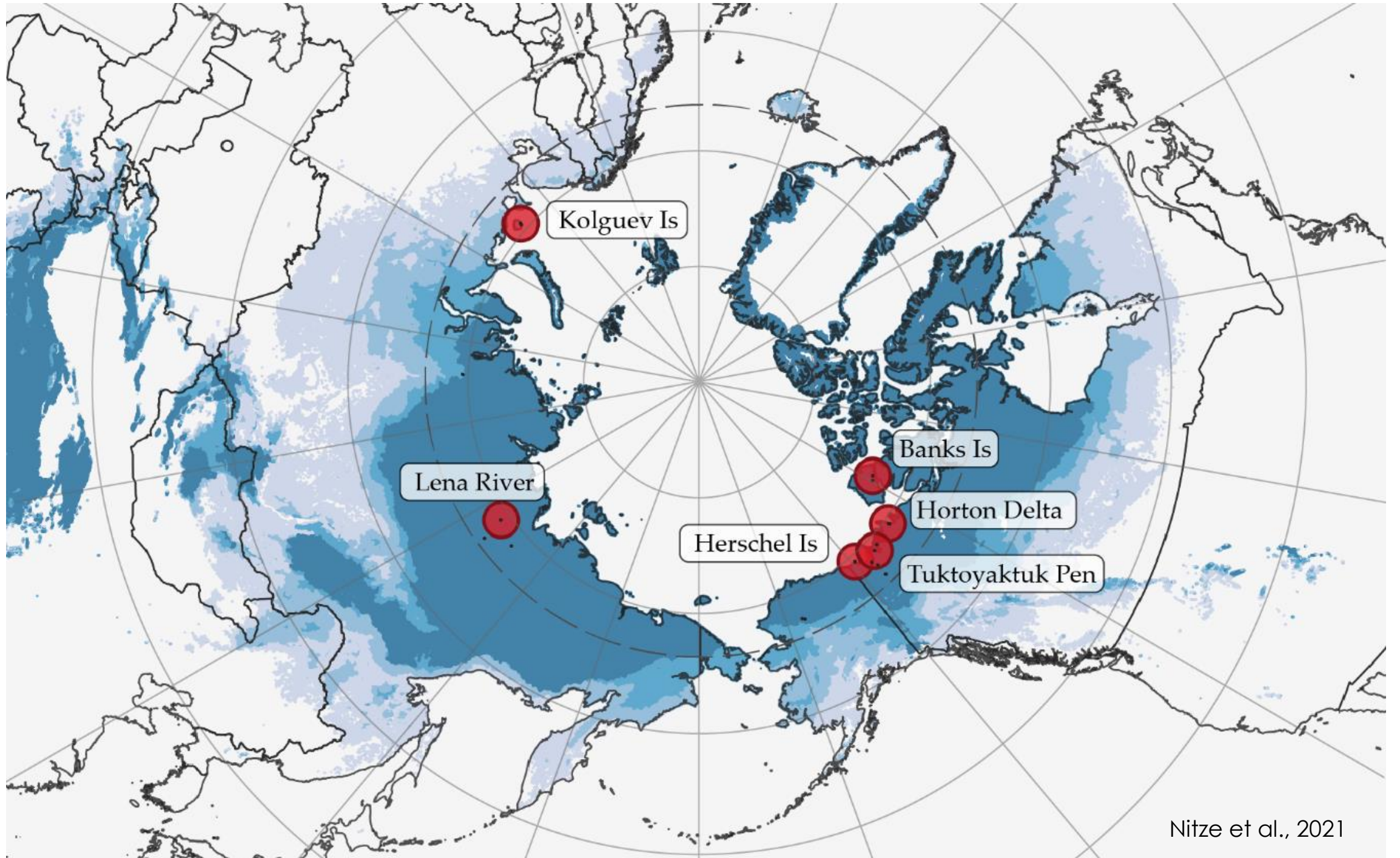


D

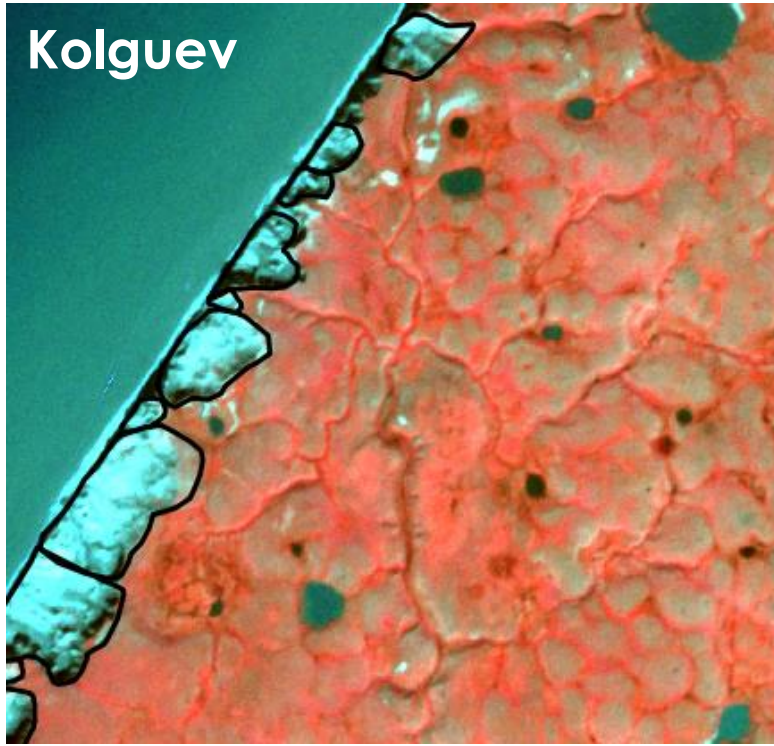


E





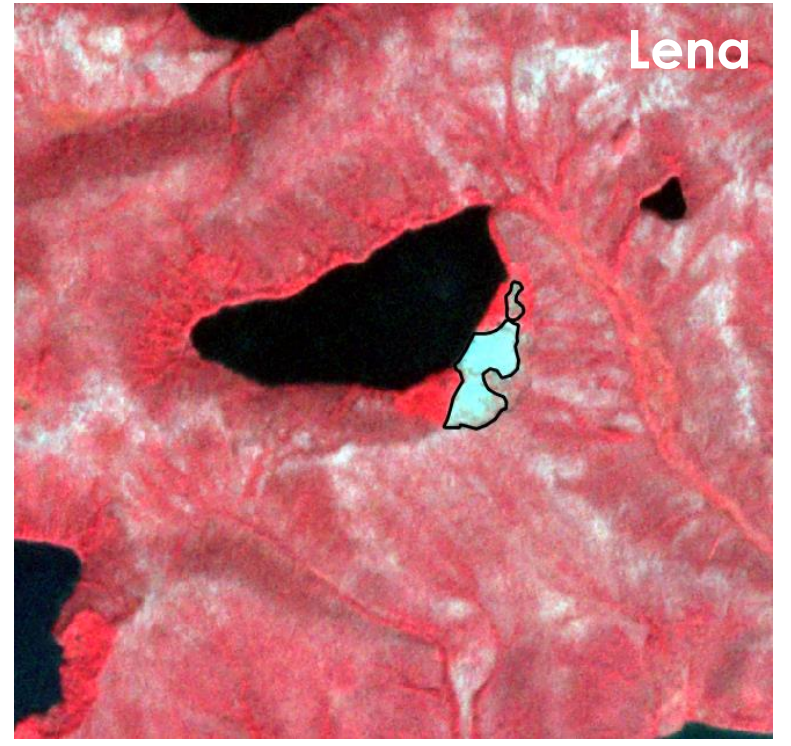
Kolguev



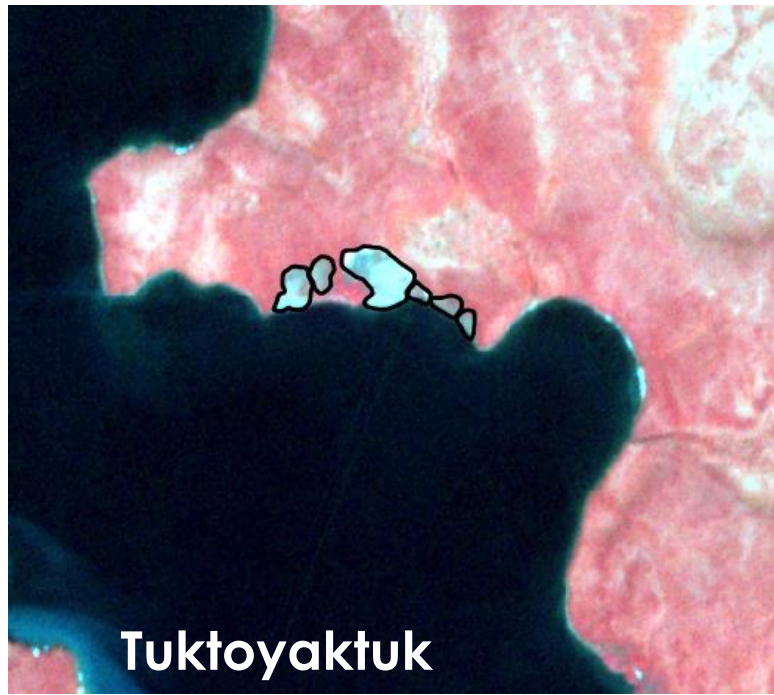
Banks Island



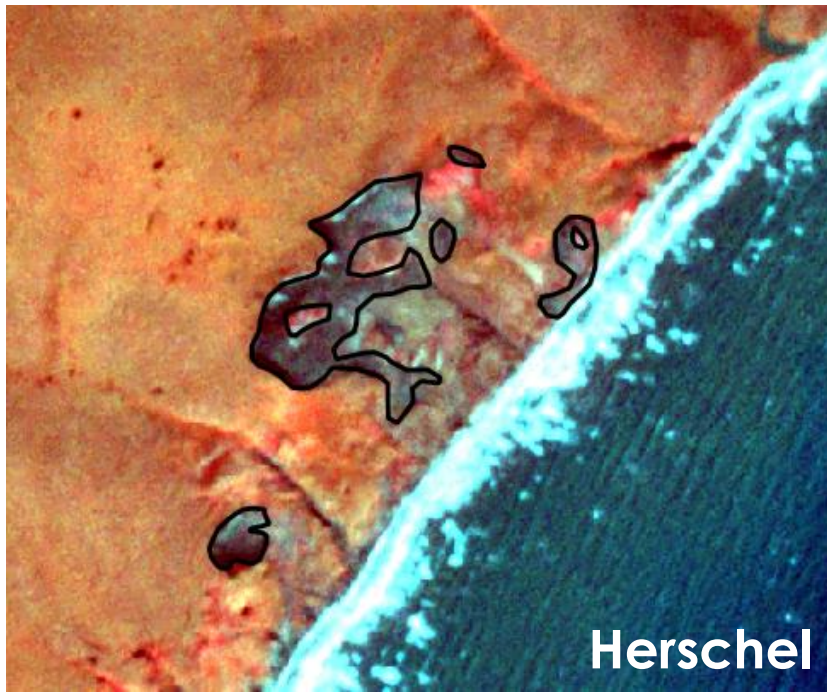
Lena



Tuktoyaktuk

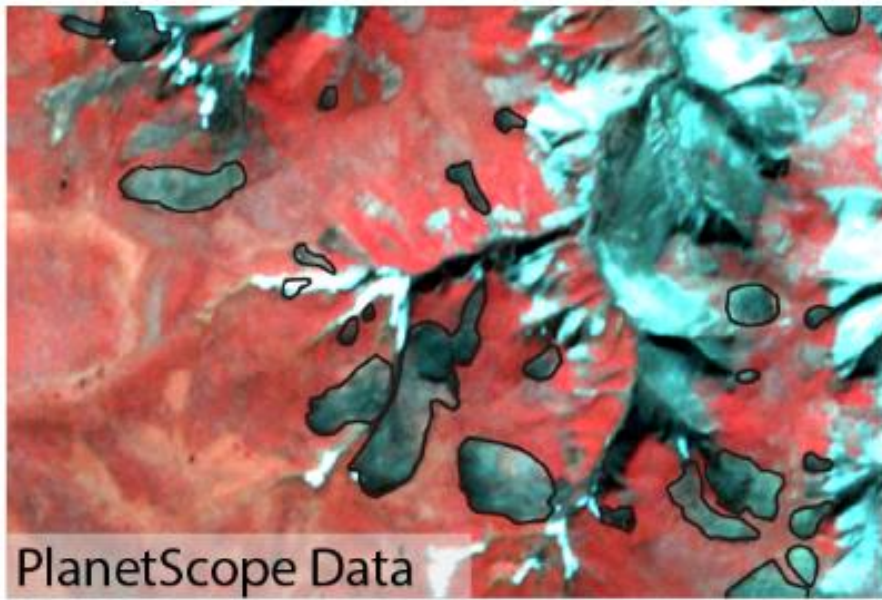


Herschel



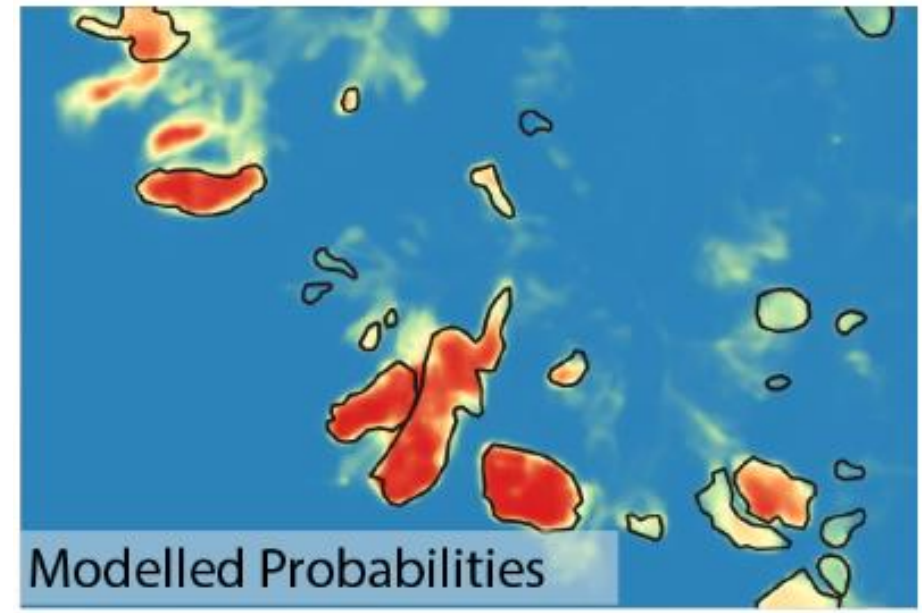
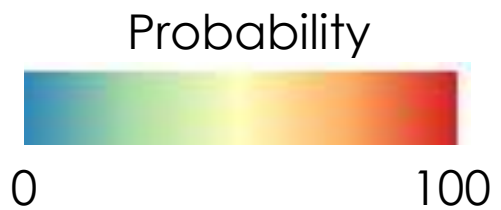
Horton



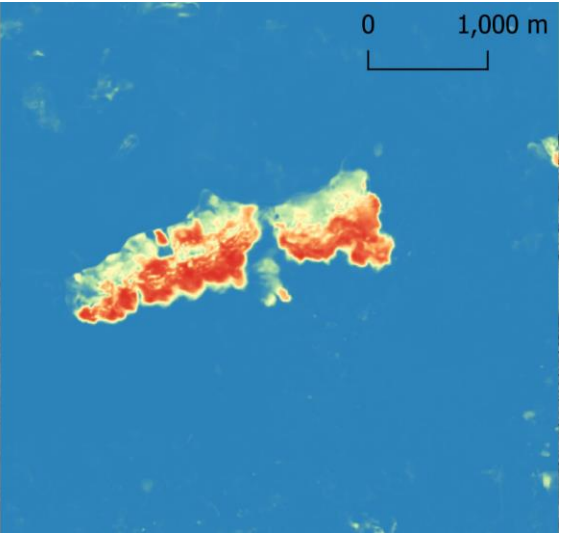
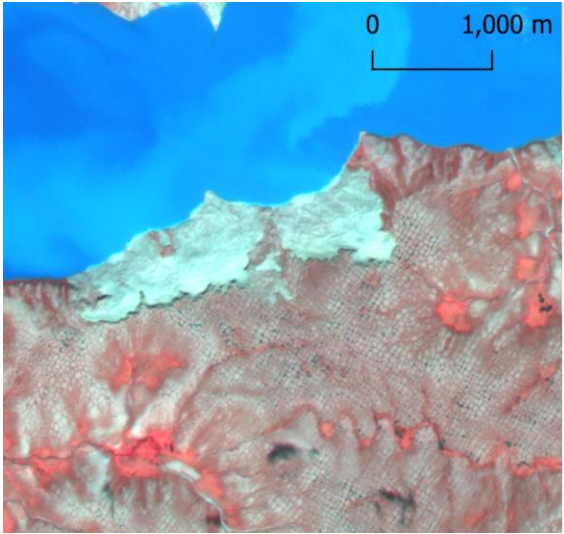


Adapted after Nitze et al., 2021
(Remote Sensing)

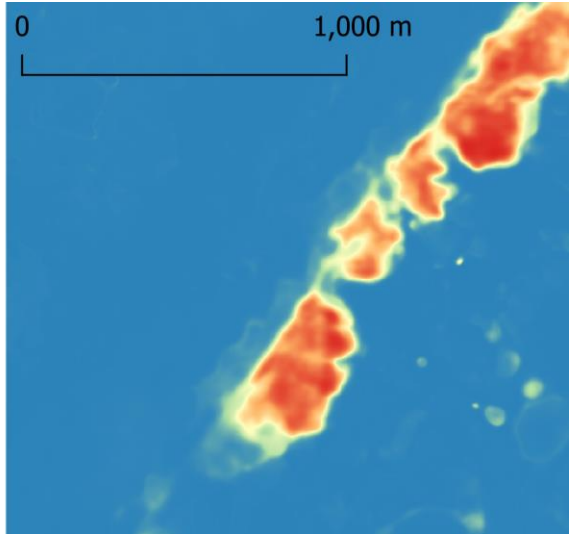
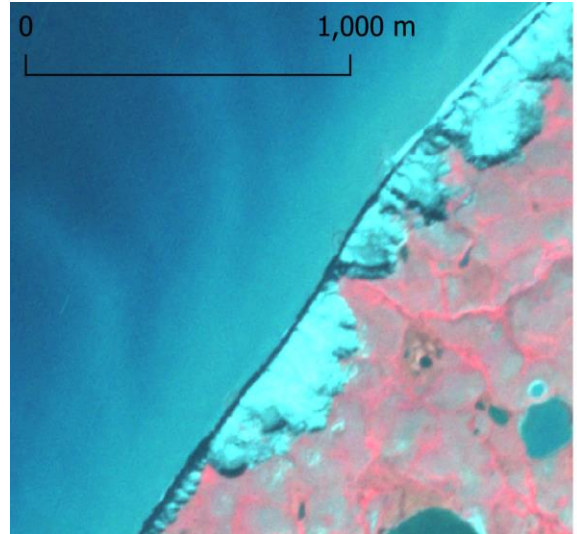
Deep Learning Model



Banks Island



Kolguev



Key Results

Good model performance for 3 sites (Horton, Lena, Kolguev)
High variability between regions

Consistently best architecture: Unet++

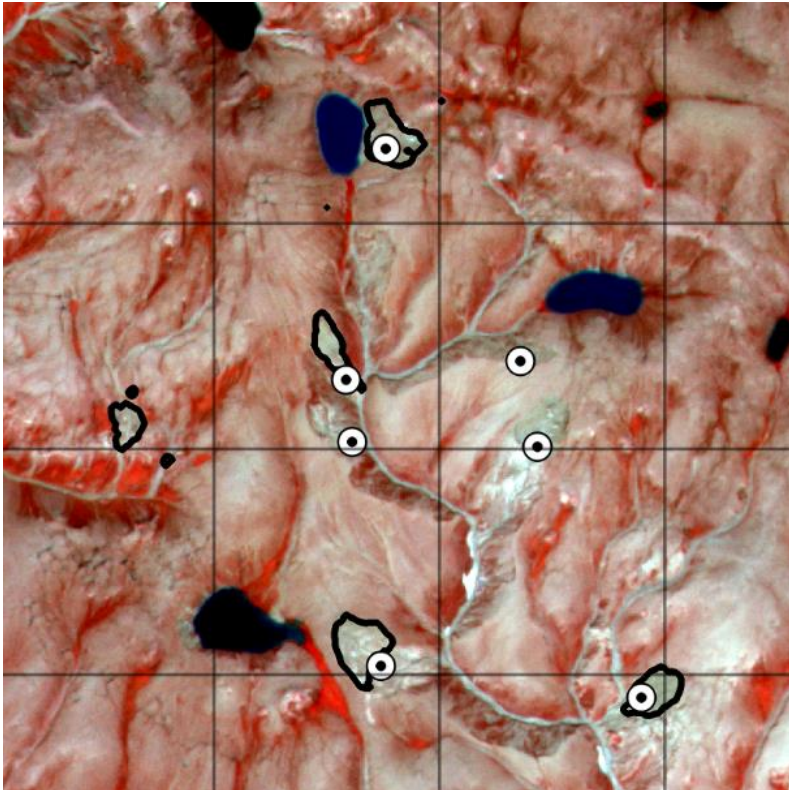
Training data quite limited

More and better standardized data across the Arctic required

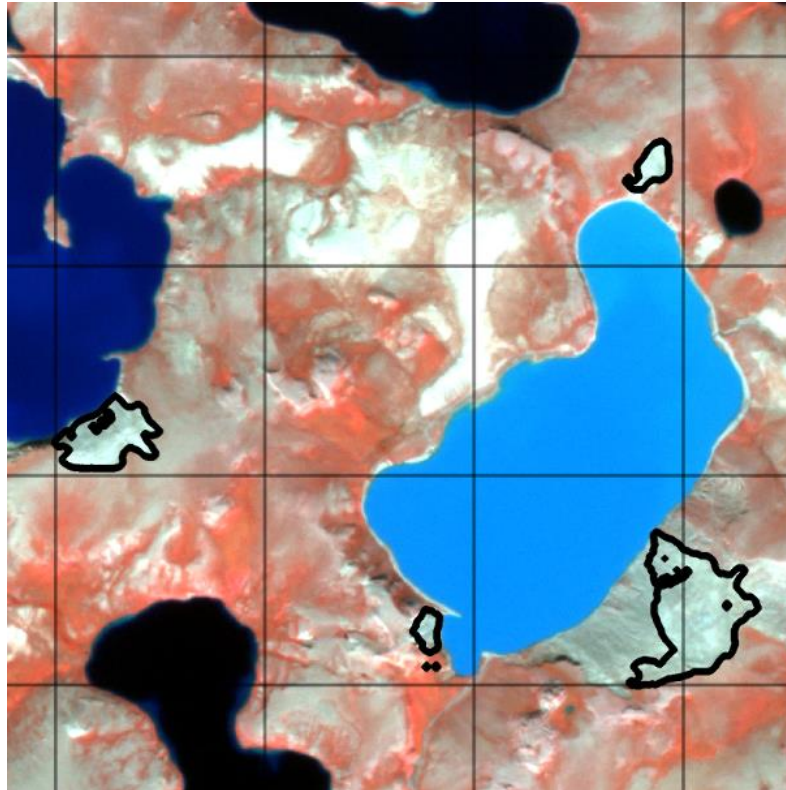
Inference + Scaling

The good ones !

Banks Island, Canada

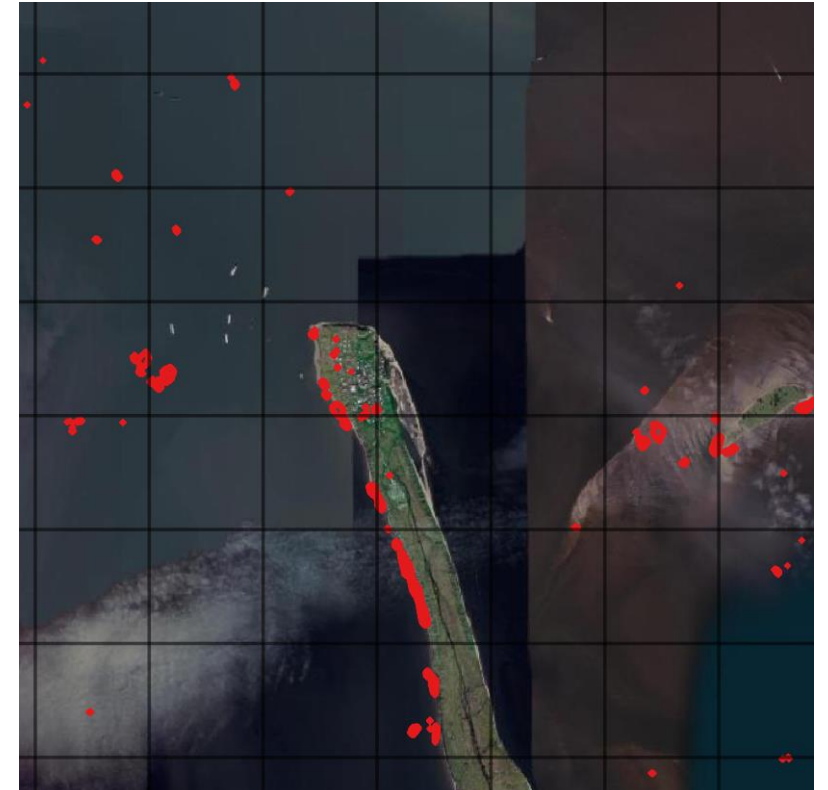


Bluenose Moraine, Canada

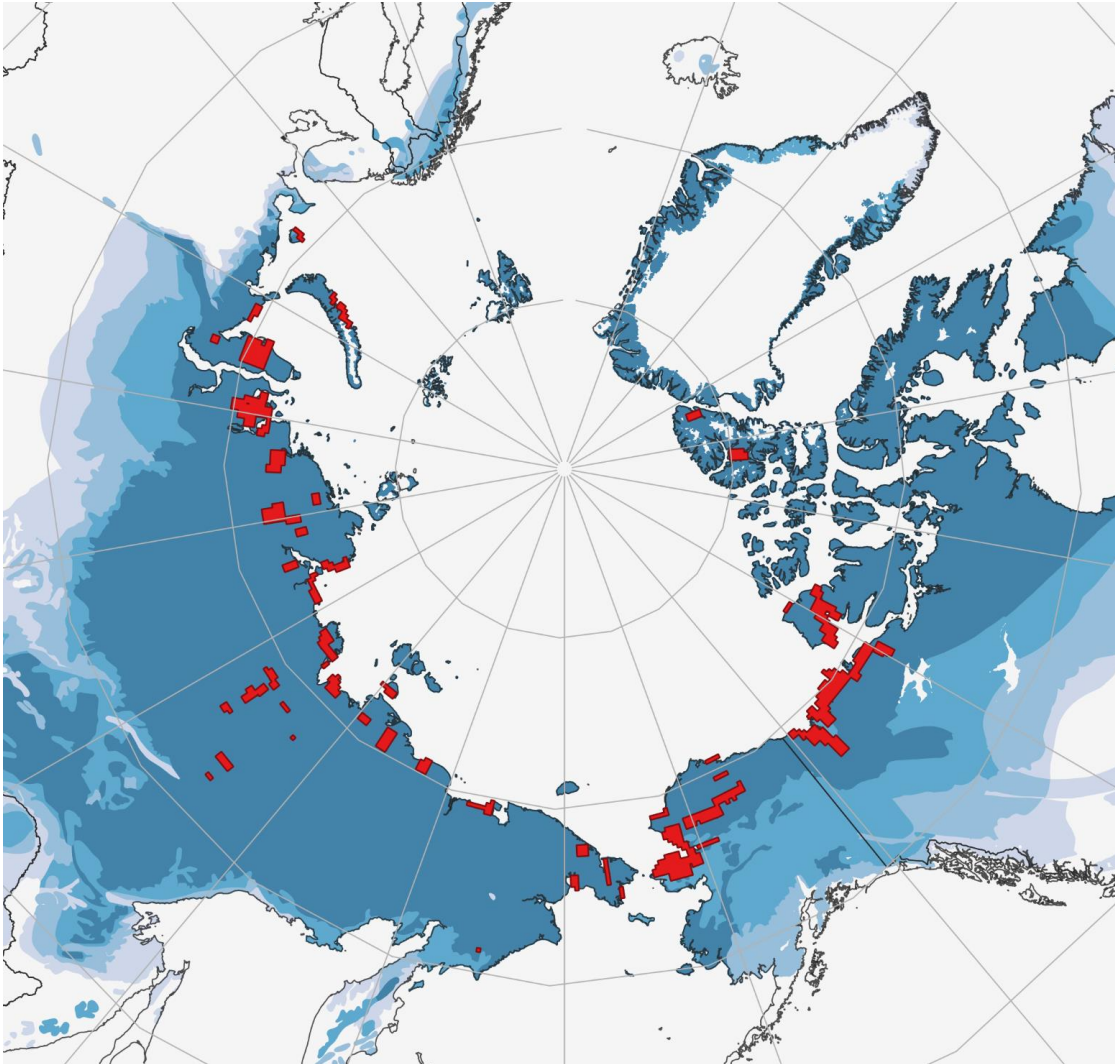


Not so good

Bykovsky Peninsula, Russia



Spatial Expansion + Operationalization



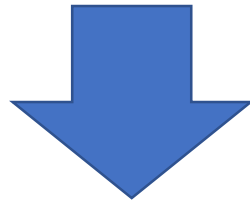
Requirements

- Improved (automated) data ordering
- More sophisticated (raster) data management (3k scenes atm)
- Operationalization (Auto-processing)
- More training data
 - RTSInAction Group

Current data footprint

Summary

- Automated configurable DL workflow to map RTS
- Planet input data + other *free* data sources
- Good results but variable transferability



- More + standardized training data required
- Upscaling next step
- Continuous monitoring and model improvement

Thank You

Contact: ingmar.nitze@awi.de

Github repo code: <https://github.com/initze/thaw-slump-segmentation>

Github repo data: https://github.com/initze/DL_RTS_Paper

Twitter: @i_nitze, @Permafrost_RS

Landsat Trend App: <https://ingmarnitze.users.earthengine.app/view/hotspottcvisapp>

References

Nitze, I., Heidler, K., Barth, S., & Grosse, G. (2021). Developing and testing a deep learning approach for mapping retrogressive thaw slumps. Remote Sensing. <https://doi.org/10.3390/rs13214294>

