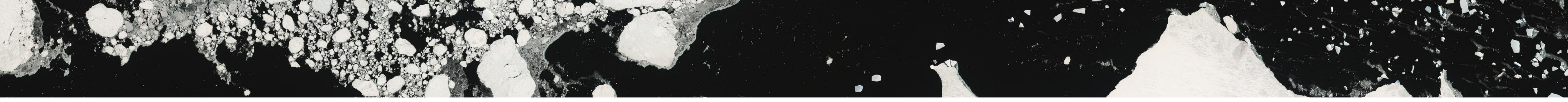

The Potential of Artificial Intelligence and Remote Sensing for Cryospheric Research

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Motivation

Recent advances in artificial intelligence, especially in the field of deep learning (DL), have allowed new insights into cryospheric systems. Nowadays, an abundance of satellite imagery, new developments in deep learning algorithms and easy accessibility to computational power enable new potentials for data processing and analysis. Here, we present a variety of deep learning applications for cold and polar regions providing new possibilities for observing and monitoring the cryosphere with remote sensing data. The presented examples showcase how dynamics of permafrost features, glacial lakes, glacier and ice shelf fronts, as well as supraglacial lakes are revealed from earth observation data and artificial intelligence.

I. Mapping Permafrost Disturbances

The changing climate of the Arctic has a significant impact on permafrost stability. Retrogressive thaw slumps (RTS) are an indicator of degrading hillslope permafrost but difficult to detect with earth observation data because RTS are small (<10 ha), highly dynamic and scattered across a large and remote area. Therefore, the potential of DL was tested to detect RTS in high-resolution PlanetScope satellite data in combination with auxiliary datasets. For this task, the DL architecture Unet++ performed best compared to other state-of-the-art models (Unet, DeepLabv3). The approach was tested for six different regions located in Russia and Canada. Good results (maxIoU: 0.39 to 0.58) were achieved for four areas whereas no satisfying results were derived for the remaining two areas. Hence, this requires improvement of the fully automated DL-approach by including more diverse and high-quality training datasets to increase spatial transferability. Current implementations also include the upscaling to RTS hot-spots across the Arctic by testing the approach for Sentinel-2 data providing full Arctic coverage and free data access [2].

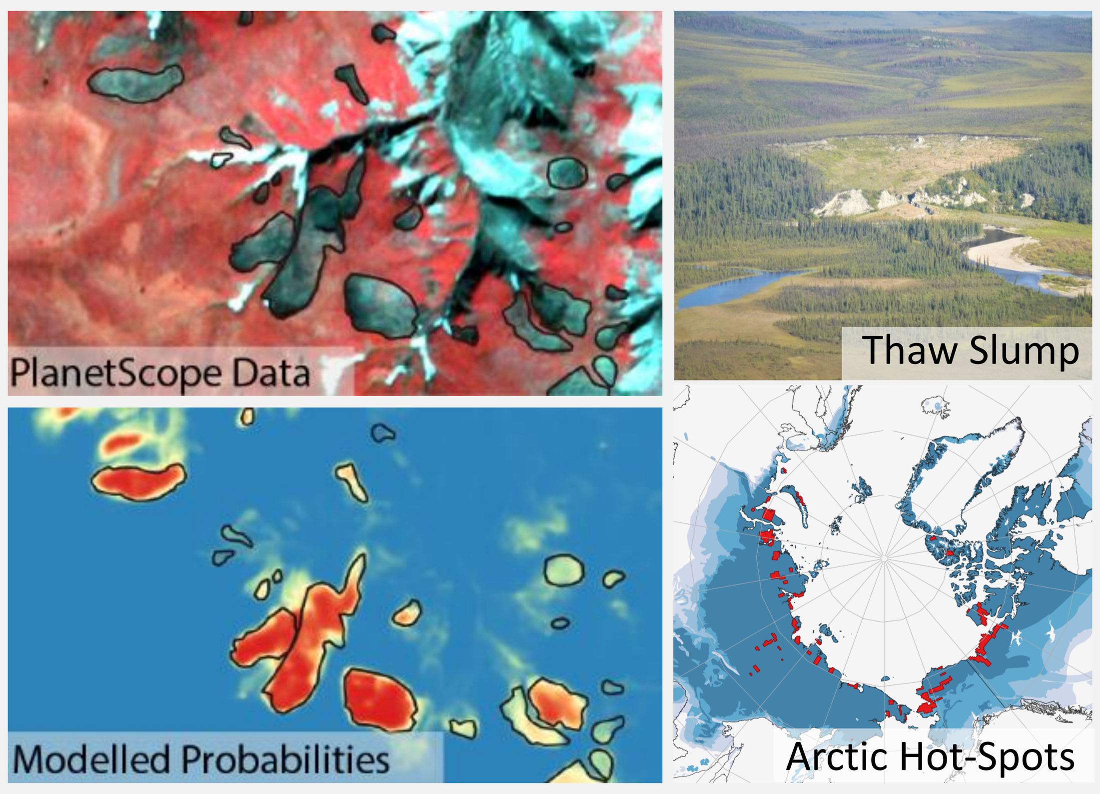

Abb. 2 Retrogressive Thaw Slumps (RTS) in PlanetScope satellite data (black boundaries) and in the field (upper). Classification probabilities of the model output and Arctic hot-spot regions for RTS (lower). [Nitze]

II. Glacial Lake Detection

Glacial lakes can be an indicator for glacier retreat, ice mass loss, changes in ice flow and risk by Glacial Lake Outburst Floods (GLOF). Automated mapping of glacial lakes in high mountain areas is limited by manual an semi-automated approaches. Therefore, the deep convolutional neural network GLNet was designed to automatically detect glacial lakes from multi-source remote sensing data including optical, SAR and elevation information. The neural network was trained on 660 images selected from twelve sites across the Himalaya. The classification results achieved an F1-score between 0.70 and 0.97 depending on the four test regions scattered across the Himalaya. The promising results are a first step towards the generation of a consistent glacial lake dataset for the entire Himalaya [3].

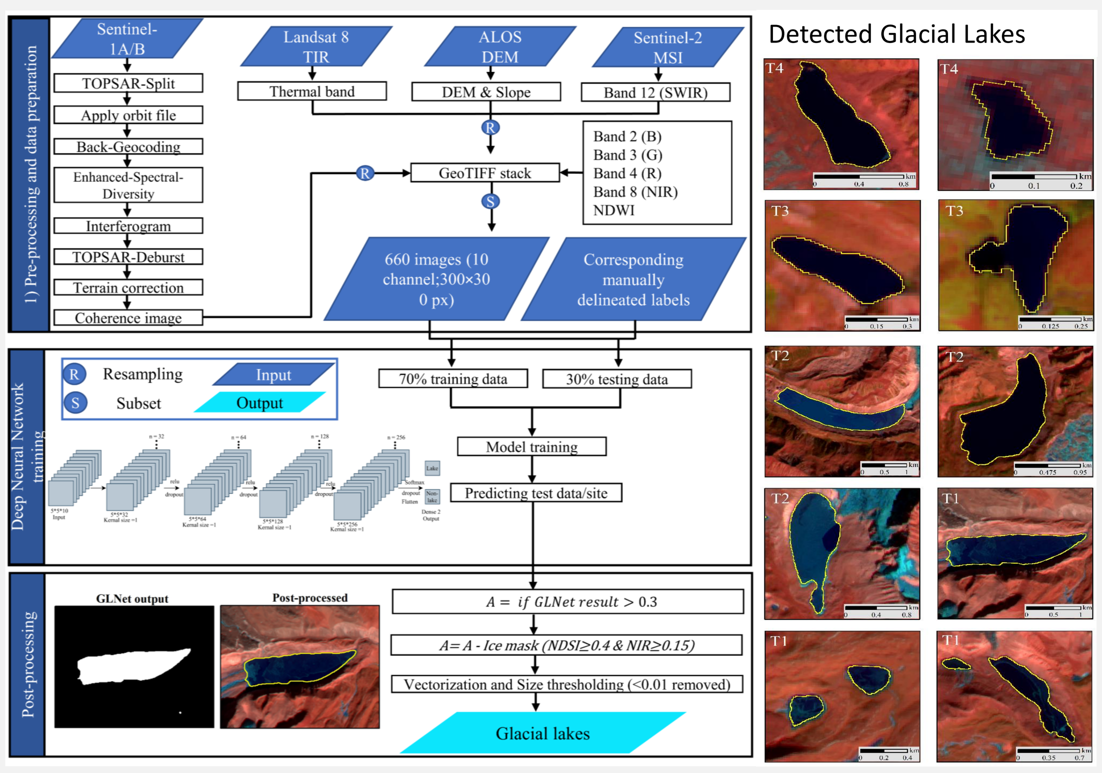

Abb. 3 Workflow for automated glacial lake detection with GLNet and examples of detected lakes (yellow boundaries) [Kaushik]

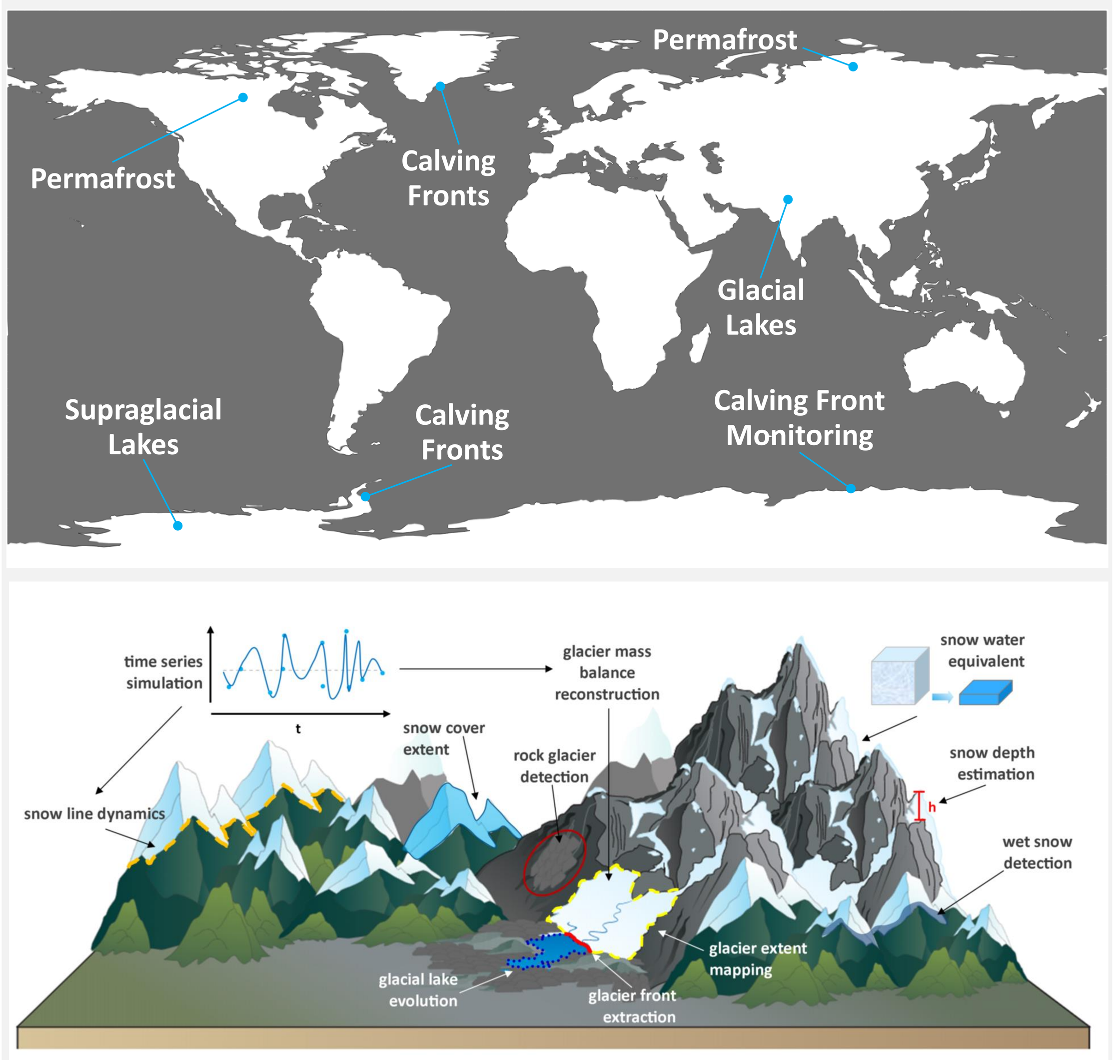

Abb. 1 Study area locations (upper) and potential artificial intelligence applications to the mountain cryosphere based on remote sensing data (lower) [1, Baumhoer].

III. Calving Front Extraction

Continuously tracking glacier front change is essential to understand glacier dynamics and for constraining ice sheet models. The abundance of satellite imagery enables continuous and automated mapping of calving front locations. Ice mélange, clouds and difficult illumination conditions complicate the automated extraction of tidewater glacier calving fronts with traditional image processing techniques. Therefore, a DL-based approach was chosen by training the convolutional neural network UNet with different input data derived from Landsat-8 imagery (e.g. single band, multi-spectral, textural features). The model was trained on 585 calving front positions from 18 different glaciers (2013-2019) and tested against 143 fronts from 25 glaciers (2020, 2021) in Greenland and Antarctica. It was shown that the integration of multi-spectral bands leads to more accurate predictions but textural and topographical inputs can easily lead to overfitting and do not show improvements for all glaciers. Overall, a mean distance error of 52.7 ± 2.2 m and a F1-score of 99 % was achieved for multi-spectral input data [4].

Current developments go even one step further by creating direct front predictions instead of solving a segmentation task. This deep snakes approach called 'COBRA' creates direct line predictions by combining DL and active contour models. This results in more accurate front delineations for glaciers in Greenland and quicker calculations as post-processing can be skipped. Still, some drawbacks remain as training time increases compared to segmentation models and a generalization to Antarctica is not yet possible.

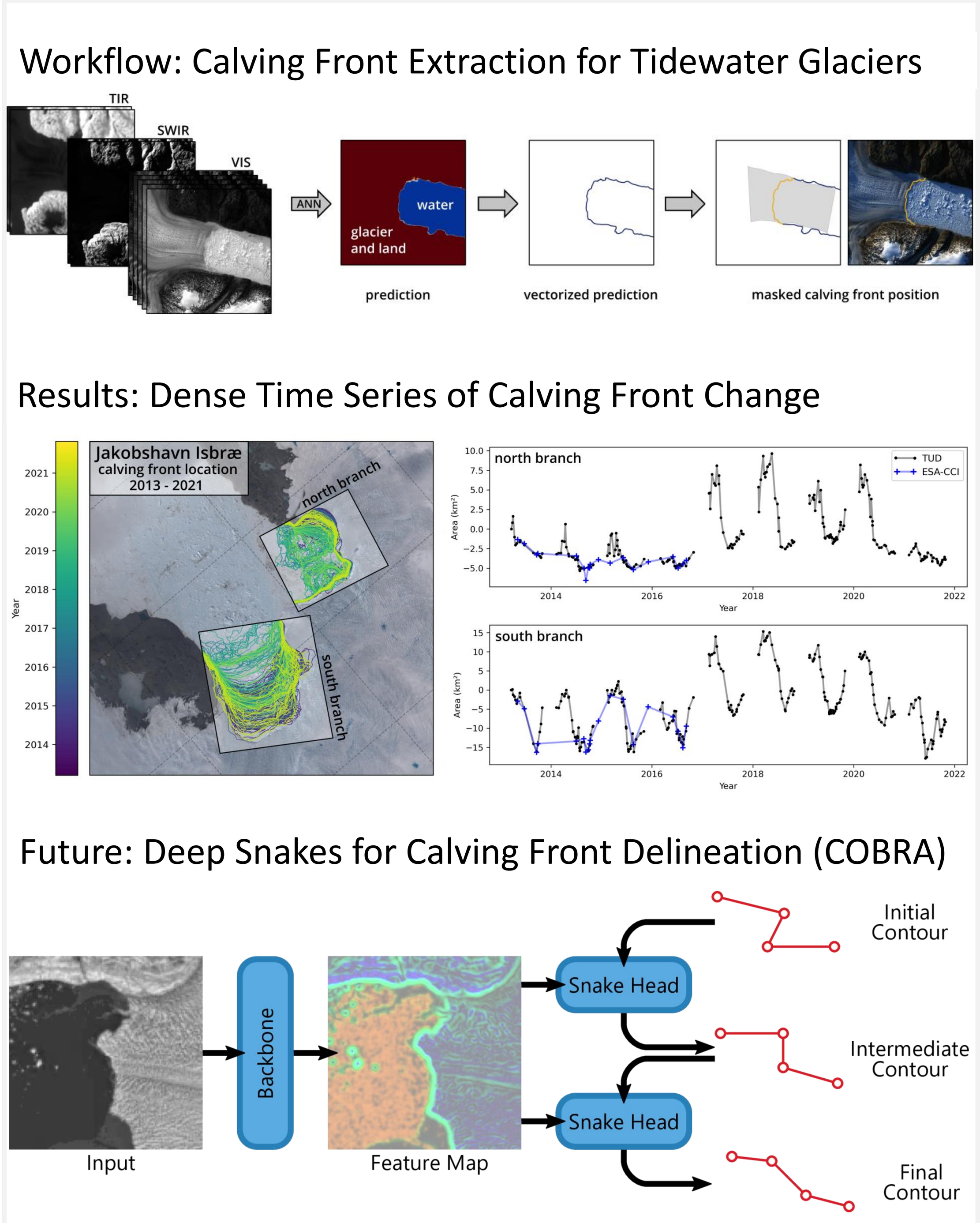

Abb. 4 Workflow for calving front extraction based on multi-spectral input data from Landsat-8 (upper). Exemplary calving front time series for Jakobshavn Isbrae glacier 2013-2021 with seasonal dynamics (middle) and deep snakes algorithm COBRA for gapless calving front extraction (lower). [Loebel, Heidler]

IV. Mapping Supraglacial Lakes

The influence of supraglacial meltwater accumulation on the stability of ice shelves remains poorly constrained. Hence, the monitoring of supraglacial lake formation and lake dynamics is of high importance. The automated classification of supraglacial lakes in optical imagery is performed with a Random Forest classifier whereas the more challenging SAR data required an DL-based approach with a ResUnet. The combined machine learning approach achieved classification accuracies (F1-score) of approx. 93% for SAR and 95% for optical imagery. Based on this, bi-weekly maximum lake extents for six Antarctic ice shelves were mapped between 2015 and 2022. The high transferable and scalable implementation will allow regular monitoring of supraglacial lakes in Antarctica in the future [5].

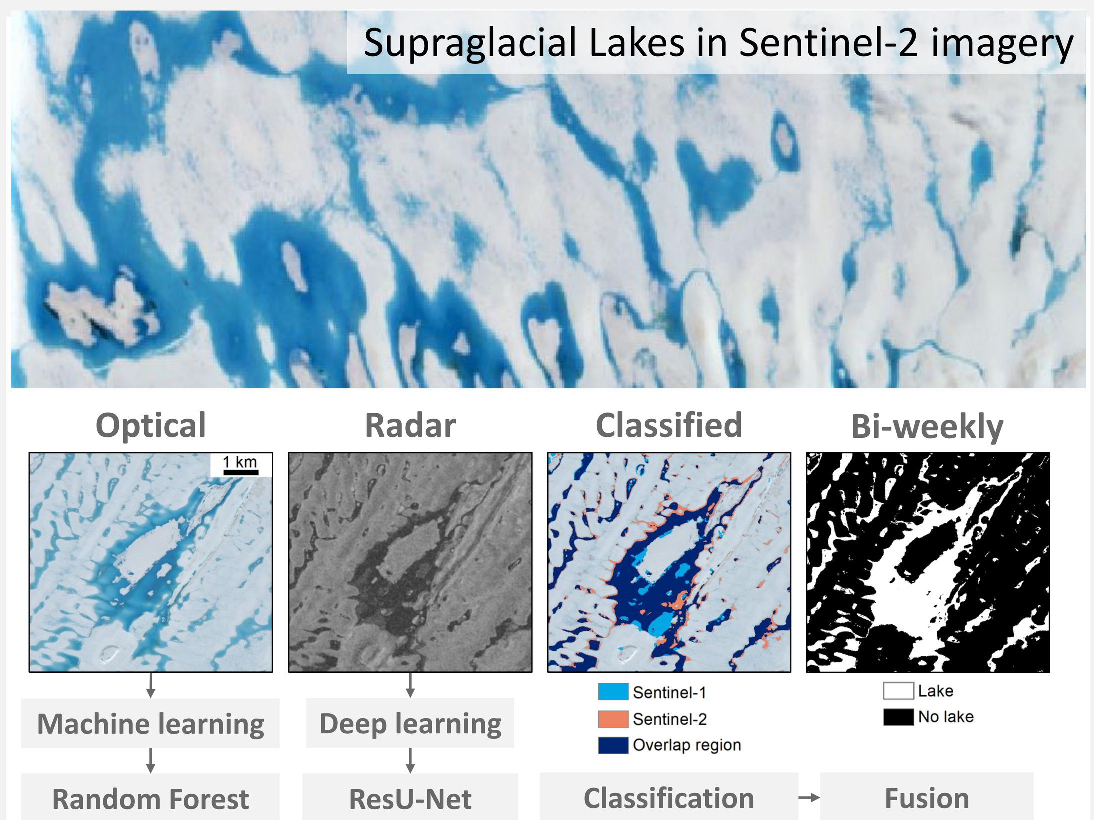

Abb. 5 Automated classification of supraglacial lakes in multi-sensor remote sensing data based on Random Forest and ResUNet and final fusion of the classification results. [Dirscherl]

V. Monitoring Antarctic Ice Shelf Fronts

Antarctica's coastline is fringed with floating ice shelves restraining the discharge of upstream grounded ice. The buttressing effect decreases when certain ice shelf areas are lost or ice shelves disintegrate completely with important implications for ice sheet dynamics and sea level rise. Therefore, it is important to continuously monitor ice shelf front positions which is only possible with Sentinel-1 SAR data being independent from polar night and clouds. The challenging task of front extraction is performed with a HED-Unet [6]. This DL-model architecture combines segmentation and edge detection in one. The accuracy compared to manual front delineation is 209±12 m (5.2 pixel) for dual polarized imagery and 432±21 m (8.8 pixel) for single polarized imagery. Frontal movement can be determined with higher accuracies of 63±68 m (1.6 pixel) for dual and 107±126 m (2.7 pixel) for single polarized imagery. The automatically extracted fronts (>19.000) are available at the EOC Geoservice and are updated on a monthly basis to provide a continuous and ongoing time series of Antarctic ice shelf front change [7,8].

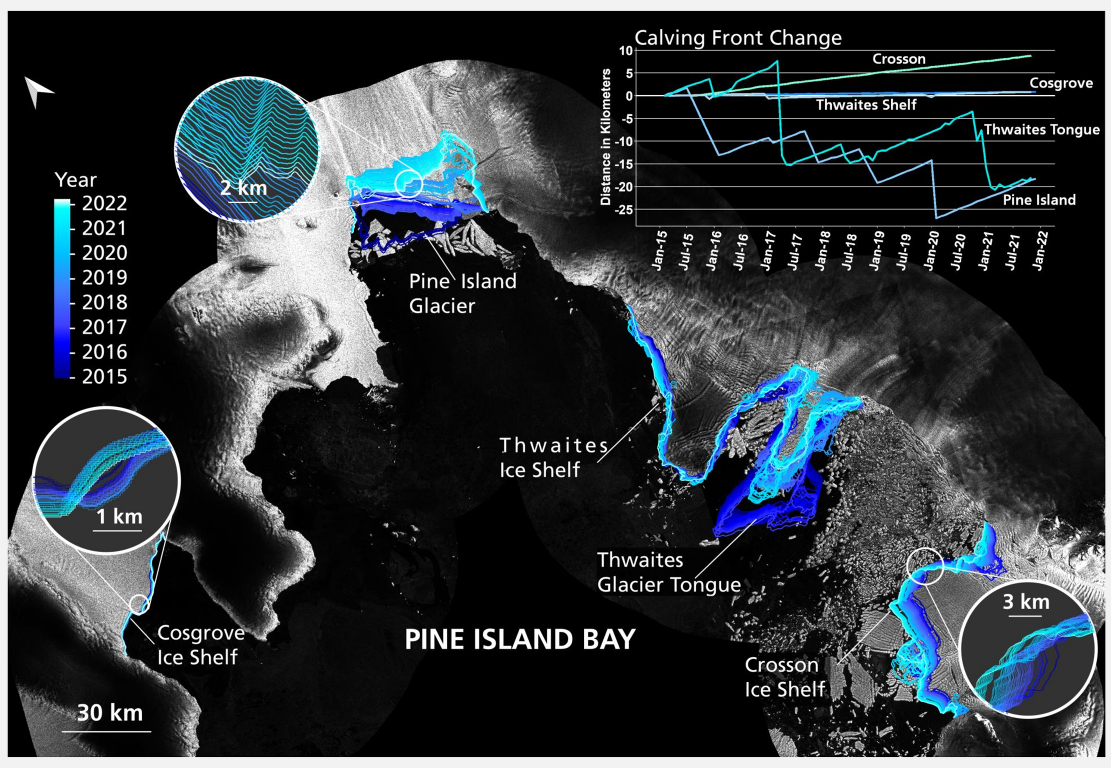

Abb. 6 Calving front change in Pine Island Bay since 2015 automatically extracted from Sentinel-1 SAR data with the HED-Unet. The circles highlight the very detailed front positions and different calving front dynamics are shown in the upper right plot [7].

Conclusion

The presented examples highlight the benefit of DL-based feature extraction from remote sensing data for cryospheric research. The results outperformed approaches with traditional image processing techniques or made the detection of certain features possible at all, even though, mostly segmentation tasks were addressed and solved with improved or modified versions of a common Unet . In return, this means that many more advances from artificial intelligence research have to be explored and transferred to cryospheric research questions including time series analysis, DL-based change detection techniques or future predictions of cryospheric change.

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