Understanding the Arctic will help us understanding climate change.

Accurate estimates of melt pond fraction are required for models that simulate and predict the Arctic climate system which collectively contribute to our understanding of long-term trends and climate change impacts.

Simple methods that rely on single features are not applicable and more complex methods that rely on multiple features are needed. This work implements a Deep Learning architecture U-Net.

**Changing Arctic, Melt Ponds and Heat Budget**

Recent studies show that the Arctic is warming up to four times faster than the rest of the world. Sea ice extent has been shown to reduce steadily in recent years and will further increase in future, causing predictions of a seasonal ice-free Arctic by 2050. Effects on our global climate system are possible while effects on local people and shipping routes are already tremendous.

Strong seasonal changes of Arctic surface properties occur in summer, when temperatures rise close to or above zero degrees. The melting of sea ice and snow leads to the formation of melt ponds, pools of water that collect on areas of lower topography. They start to appear around mid-May, cover up to about 60-80% in June and July (Eicken et al., 2004; Maykut et al., 1992) and finally refreeze in August and Septmeber. (typical values in central Arctic range from 15% to 40% (Istomina, Heygster, Huntemann 2015). Melt ponds have a strong effect on the Arctic energy budget. Due to their darker appearance, they absorb significantly more sunlight than reflecting sea ice and snow. This causes surrounding areas to warm up, leading to further melt and increased interactions between sea ice, atmosphere and ocean / rapid changes of surface properties.

The impact of melt ponds on the Arctic climate system is dependent on their spatial extent. Melt pond fraction, here referred to as the proportion of sea ice surface covered by ponds, has been shown to be a crucial parameter for models that simulate and predict Arctic climate evolution. “Predicting the future Arctic climate has relevance for stakeholders and is a key aspect of policies for the Arctic regions (Pörtner 2022)”. However, this is not sufficiently integrated in recent models (Dorn 2018; Hunke 2013; Zhang 2018). This is partly due to missing methodology and rapid changes. Developing accurate methods to retrieve and analyse melt pond fraction is an ongoing research area.

To investigate melt pond fraction, methods are needed that separate imagery into melt pond, sea ice and ocean classes. Ideally, this method can be applied to different seasons, regions and platforms.

* MPF is object to strong seasonal changes and long-term changes (MYI)

**Spatial Possibilities to observe Melt Ponds**

Assessing melt pond fraction is hampered by the remoteness of the Arctic Ocean. What is desired is an accurate Artic-wide estimation on a regular basis, to retrieve melt ponds at various stages. However, existing methods are a trade-off of spatial coverage and resolution.

Ground-based measurements are

Remote Sensing (for a general introduction to Remote Sensing, see …)

* Satellites were unsuccessful to derive mpf – stroeve et al
* Istomina 2015 – airborne is still very important

The focus on this work is on airborne imagery, that can fully resolve melt ponds and provide the potential to validate satellite imagery, as in Niehaus et al. Spatial coverage is limited.

**Spectral Possibilities to observe Melt Ponds**

Depending on the sensor used, remote sensing techniques record radiation of different wavelengths. Often used for melt pond fraction are visual (VIS) imagery. This is affected by clouds and cannot operate in the absence of sunlight, as in polar night.

Measurement in the microwave range are unaffected by these conditions. However, existing methods lack of resolution.

Thermal infrared imagery (TIR) measures the emissivity of thermal radiation with wavelengths around 10ym. TIR imagery can operate in the absence of sunlight, however, is affected by clouds. Thielke et al observed that surface temperature can depict winter sea ice surface structures, opening the potential of melt pond retrieval in summer (Figure 1). TIR imagery provides the additional potential to investigate thermal properties of melt ponds (specific application might be to extent temperature mapping of summer – winter).

To derive these parameters, surface structures need to be segmented into different types. The aim of this work is to develop a method to segment summer helicopter-borne TIR imagery, as retrieved by Thielke et al., into melt ponds, sea ice and ocean. This method would provide the potential for incorporating an additional spectrum and dataset into melt pond studies and study of thermal properties of surface structures, relevant to better understand the Arctic heat budget. Spatially and temporally varying surface temperatures “impose unique requirements” on the algorithm used (Subsection below). So far, existing methods are not applicable.

**Previous Studies of Melt Pond Segmentation**

Semantic segmentation is the task of assigning a class value to each pixel of an image. This can be done based on image features such as…

In VIS imagery, melt ponds can be detected relatively easily due to their distinct blueish to dark grey colour appearance (Perovich 1996) in contrast to white ice and snow, and dark blue ocean (Figure 2).

* Thresholding
* Supervised learning methods
* Edge-based detection

**Requirements for IR Image Segmentation**

Simple color-based methods are not applicable to IR images which are challenged by spatially and temporally changing surface temperatures. Lindas work required manual feature setting, in winter data easier. In summer, rising temperatures mix relative temperature values. Due to its salt content, the freezing point of ocean water gets reduced and it can be relatively warmer or colder compared to sea ice (Figure 3). Also, different melt ponds seem to have different temperatures, as shown in Figure 4.

Likewise, simple edge-based methods fail due to blurring effects and unclear borders (Figure 5).

Required is a method that takes shapes and context into account. Melt ponds can appear in various sizes and shapes, depending on their evolutionary stage. Sizes range from cm2 to km2 (Perovich et al., 2002). Melt ponds can have simple, circular shapes to complex, interconnected structures (Hohenegger 2012; Polashenski 2012). They are embedded on sea ice surface, with possibly occurring at the edges.

Collectively, temperature, size, shape and context could account for an accurate detection of melt ponds from IR images.

**Convolutional Neural Networks**

In recent years, major improvement in image classification and segmentation could be achieved with Convolutional Neural Networks (CNN). CNNs are supervised deep learning methods, that learn features at different image scales. They could capture local features like shape, and context on a global scale. Do not need handcrafted features. Robustness to variations in position and scale, applicable for various pond sizes.

CNNs consist of the following layers:

* Convolutional Blocks
* Pooling Layers

iteratively learn features from images. Their main advantages is automated feature learning that do not require manual feature design and expertise, improving with experience. CNN consist of the following layers:

* Learn representations of data with multiple level of abstraction
* Need no manual feature design

By stacking a decoder / reversing convolutions, spatial information can be restored and CNNs used for segmentation task.

**U-Net**

U-Net is a CNN-based architecture serving the encoder-decoder paradigm. It was originally introduced by Ronneberger et al. for biomedical image segmentation. In addition to CNN layers, U-Net uses

* Upsampling Blocks
* Skip Connections

U-Net is a relatively simple architecture that has been proven successful in remote sensing applications. U-Net is commonly used with many design variations, providing potential for future adjustments.

* DL for RS paper

**Overfitting**

CNN-based architectures contain millions to billions of parameters that get trained on labelled data. To sufficiently learn features and generalize well to unseen samples, they usually need thousands of images to get trained on. Otherwise, they show the behaviour of overfitting: Adjust too well to training data, such that generalization is not possible.

For the task at hand, this means huge amount of labelled masks required, which was not possible for the scope of this work.

Regularization techniques have been developed that make training with small data possible. Successful examples

Regularization techniques investigated in this study include:

* Augmentation
* Patch Extraction
* Transfer Learning
* Dropout

**Augmentation**

**Patch Extraction**

**Transfer Learning**

**Dropout**

Overfitting. Especially in remote sensing tasks were (a) data availability is hampered and (b) manual annotation is necessary.

(Basic idea: with increasing model complexity 🡪 overfitting)

Different regularization methods have been developed to tackle this problem.

* Augmentation
* (Patch Extraction)
* Transfer Learning
* Dropout

The objective of this thesis is to build a segmentation method that segments helicopter-borne TIR images to melt ponds, sea ice and ocean. This task is especially challenged by (a) complex methods needed to solve changing surface structures and (b) small data available due to challenging annotation process. A U-Net is trained with different configurations and overfitting methods.

The contributions are summarized in the following:

* Annotated IR dataset
* Model experiments on different configurations, with special focus on overfitting techniques
* Pipeline providence

The reminder of this thesis is structured in the following: In section Methodology, we present our dataset, annotation process and training pipeline. In results we discuss the performance of various model configurations. In discussion, we discuss our results. We conclude our findings in conclusion.

This work builds a U-Net. To better access the applicability of results given by the method in a more general and inter-spectral context, it is compared to optical MPF.

Microwave measurements such as SAR, AMSR, … are not affected by both of these conditions. However, … Thermal Infrared Imagery (TIR) measures the emissivity of thermal radiation as defined in … of surface structures. TIR are affected by clouds. Figure 2 underlines this potential for melt ponds. Additionally, thermal properties of melt ponds can be investigated (why is this important). A specific application is the prediction of melt ponds from temperature anomalies, as done in… So far, no high-resolution TIR satellite is operating. We use airborne imagery. This data can be used to later improve satellite retrievals and serve as a bridge between high resolution ground based and spatially covering satellite.

* Thinning and shrinking of Arctic sea ice extent has changed faster in recent decades (Meredith et al 2019)
* Changing Arctic: Perovich
* and Richter-Menge, 2009; Haas et al., 2008; Kwok and Rothrock, 2009; Serreze et al., 2007
* Arctic Amplification: Rantanen et al
* Seasonally ice-free Arctic around mid-century (Notz 2020)
* Near-surface air temperature in the Arctic is increasing up to four times faster than the rest of the Earth (Rantanen et al 2022)
* Arctic amplification (Serreze et al 2009)
* Jet stream could weaken (Cohen et al 2020)
* Decline of sea ice and cold winters in mid-latitudes (Vihma 2014). (but still only weak relations – Cohen 2020, Blackport 2019)

With increasing temperatures, sea ice dynamics change. During the summer months, melt ponds form. Ice-albedo feedback. Melt ponds are significant features that form as pools of water in lower topography areas. They impact the Arctic heat budget by being darker and absorbing significantly more sunlight than sea ice and snow. have significant on the overall Arctic heat budge, significantly contributing to the positive melting amplification, known as ice-albedo feedback. They also contribute to ecosystem impacts, providing habitat for algae and changing light transmission.

* “sea ice has manifold interactions with ocean beneath and atmosphere above”
* Ice-albedo feedback Perovich 2011, Serreze 2009
* In summer, larger open water area allows more heat absorption during summer through solar radiation (Stroeve 2014)
* Ice thickness can be strongly altered by small changes in the heat content (Kwok and Untersteiner 2011), effected by atmospheric warming (caused by anthropogenic emissions) and changed heat input from the ocean due to Atlantification and more wind or more freshwater ability
* Shrinking sea ice / more melt ponds lead to more heat absorption 🡪 thinner ice and smaller sea ice area 🡪 reduced sea ice role as a blanket for the ocean / less insulation 🡪 stronger interaction between ocean, ice and snow and atmosphere (Hansen 2005) and increase of heat fluxes.
* Landrum and Holland 2022: model shows future increasing ocean heat flux towards atmosphere caused by reduced ice thickness and snow depth 🡪 more unstable atmospheric boundary layer in fall and early winter (MORE HEAT FLUXES)
* Heat budget is essential for modelling purposes (Uttal 2002), sensitive to changes in various parameters such as sea ice extent (Cao 2019), climate and weather prediction models rely on a good representation of the heat budget of sea ice (Lüpkes 2008)
* Melt ponds strongly influence heat fluxes
* “to investigate the detailed processes of Arctic sea ice, observations are crucial”

Observations of melt ponds are important to better understand heat budget and sea ice dynamics.

* Ground-based measurements are rare and only local scale; might not be representative for the large extent of the Arctic sea ice (Maykut 1982; Zakhvatkina 2019)
* Satellite imagery: Low-resolution and high-resolution
  + Daily pan-Arctic TIR satellites spatial resolution of 1km
  + More detailed measurements are essential for a better process understanding and validation of satellite products, which then can be used to investigate the Arctic-wide scale on a daily basis
  + Satellite based observations are often used as model input as they provide near-real-time observations and cover the evolution over a longer period (Kwok and Untersteiner 2011)
  + On the intermediate scale, airborne measurements can bridge between in situ and satellite based
* Airborne images (Hannah) can fully resolve melt ponds with their spatial resolution

To address scientific questions from imagery collected and derive parameters like melt pond fraction, imagery needs to be segmented into different surface types.

This work aims to develop a method for surface segmentation on helicopter-borne TIR imagery as originally introduced in Linda, to address scientific questions. Examples are (a) deriving melt pond fraction, (b) thermal properties of melt ponds. Spatially and temporally varying surface temperatures “impose unique requirements” on the algorithm used (Subsection below). So far, no such tool is available.

**Melt Ponds in Thermal Infrared Imagery**

Measures the thermal radiation emitted by surface structures (sensitive to TIR spectrum with wavelength around 10mym)

Main advantage of IR imagery is no dependency on sunlight

* Valuable in polar night, not dependent on light
* Affected by clouds (Microwave not; but have comparable low spatial resolution except for SAR)
* Lindas dissertation: “surface temperature seems to reflect the surface topography”

Melt ponds in IR, describe some of flight 9

Figure – blue describes relatively low temperatures and yellow relatively warm ones

**Melt Pond Fraction**

Melt pond fraction is the proportion of sea ice surface covered by ponds. This fraction can be derived from remote sensing image data. Fraction is required for climate models

* Help for a better understanding of the Arctic heat budget
* Preconditioning of melt ponds
* Validation of satellite imagery (Hannah)

Quantifying the distribution of melt ponds is crucial for studying the Arctic sea ice dynamics (and ecosystem impacts). Accurate estimates of melt pond fraction are required for models that simulate and predict the Arctic climate system which collectively contribute to our understanding of long-term trends and climate change impacts. Melt pond fraction, the proportion of sea ice surface covered by ponds, can be derived from image data. Methods are needed that separate images into melt pond, sea ice and ocean classes.

“helps for understanding sea ice characteristics during summer and might extend to climate models and future predictions.”

* Predicting the future Arctic climate has relevance for stakeholders and is a key aspect of policies for the Arctic regions (Pörtner 2022)
* Analyze the variability and evolution of surface properties like melt pond and sea ice fraction, floe size distribution, ocean and ice surface temperature
* Improve satellite imagery

**Melt Pond Segmentation**

Segmenting melt ponds is important for climate evaluation and sea ice dynamics. Recent work has focused on optical imagery.

Semantic segmentation is the task of assigning a class value to each pixel of an image.

Recent work has mainly focussed on retrieving melt ponds from optical imagery.

Collectively, temperature, size, shape and context could account for an accurate detection of melt ponds from IR images.

* Surface temperatures of different types change spatially and temporally

For the task of segmentation, this is especially challenging. Segmentation can not be done on color only, therefore simple methods introduced in Section Related Work do not work or require manual feature setting, as been done in Lindas work. To develop a condition independent method, what is required is a method that can:

* Take the shape of features into account
* Regards context
* Is not based on a single feature – color, texture, edges – only.
* Minimal manual intervention

Melt pond shape:

* “in the course of the melting season, small ponds start to coalesce and form complex clusters on the ice surface”
* **Hohenegger 2012**: new ponds have simple, circular shape. When grow bigger, connect to each other, reach 10m2, complexity of shape increases
* Popovic 2018: void pond coverage model
* Lateral transport between ponds (Polashenski 2012)