Modeling Sea Ice Thickness using Machine Learning and Remote Sensing Modalities

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Modeling Sea Ice Thickness using Machine Learning and Remote Sensing Modalities

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Acknowledgement

I hereby declare that I can carry out the present work independently without outside help. and used only the sources and aids indicated. I assure Furthermore, that I have not yet submitted this thesis to any other examination board.

Abstract

Little is known about the state of Arctic sea ice at any given instance in time. The harshness of the Arctic naturally limits the amount of in-situ data that can be collected, resulting in gathered data being limited in both location and time. Remote sensing modalities such as Synthetic Aperture Radar (SAR) imaging and laser altimetry help compensate for the lack of data, but suffer from uncertainty because of its inherent indirectness. Furthermore, precise remote sensing modalities tend to be severely limited in spatial and temporal availability, while broad methods are more accessible at the expense of precision. This thesis focuses on the intersection of these two problems and explores the possibility of corroborating remote sensing methods to create a precise, accessible source of data that can be used to examine sea ice at a local scale.

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Introduction

In recent decades, understanding the state of sea ice has grown increasingly important. Sea ice analysis at large scales can provide valuable insight into the trajectory of climate change and at local scale has implications in fields like arctic navigation. Understanding sea-ice thickness in particular, is important for both of these applications. For example, the thickness of the ice can be analyzed over time to track ice mass in relation to global warning or interpreted locally to predict shipping speed through ice-covered water [1].

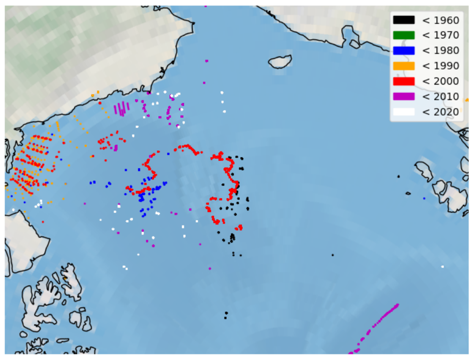


Figure 1.1: Historic In-Situ Data Availability in the Beaufort Sea Region

Due to the harsh nature of the arctic, in-situ studies of arctic ice are infrequent both in time and space. Thus, most analyses depend heavily on remote sensing methods. These methods cumulatively provide magnitudes more data than in-situ measurements can achieve, but differ in modality, methodology and resolution. Synthetic Aperture Radar (SAR) and light detection and ranging (LiDAR) are some such modalities that survey the arctic region. Furthermore, organizations like the the National Aeronautics and Space Administration (NASA) and European Space Agency (ESA) freely provide this information through their constellation of satellites.

Each of these remote sensing methods have their individual strengths and limitations. ICESat-2 (IS-2), a NASA LiDAR satellite, works by emitting individual photons and timing their returns. Praised for its precision, its readings are statistically corrected to adjust for ambient light, cloud occlusion (atmospheric scattering), snow and ice scattering, and the physical problem of first-photon bias [2]. IS-2's statistical robustness offers valuable local observation with less than 5 meters of total geolocation error (mean $+1\sigma$) [3].

In contrast to IS-2's highly accurate and local measurements, SAR imaging offers significantly more expansive data with a loss in local precision. SAR images Earth's surface by emitting radio waves and then reconstructing the surface composition based upon the return signal. The physical difference between photons and radio waves means that LiDAR's limitations with occlusion are actually imperceptible to SAR satellites. Radio waves permeate clouds and snow, and the reconstructed image is independent of light [4]. These weather independent properties make SAR an excellent modality to monitor sea ice especially during winter seasons, with satellites like Sentinel-2 (SN-2) from NASA offering 290 kilometer swaths of imaging, at resolutions ranging between 10 and 60 meters [5]. It's important to note that despite its extensiveness, SAR is more sensitive to physical factors like surface roughness, slant, and type, and also suffers from speckle noise [4].

Given the availability of remote sensed data and their different observed properties, there is much to be learned about the state of the sea ice by corroborating these data sources with each other. Uniquely, the corroboration of a SAR image with precise LiDAR measurements suggests the possibility of developing a convolutional neural network (CNN) to accurately predict sea ice thickness using expansive SAR imaging. Doing so successfully would

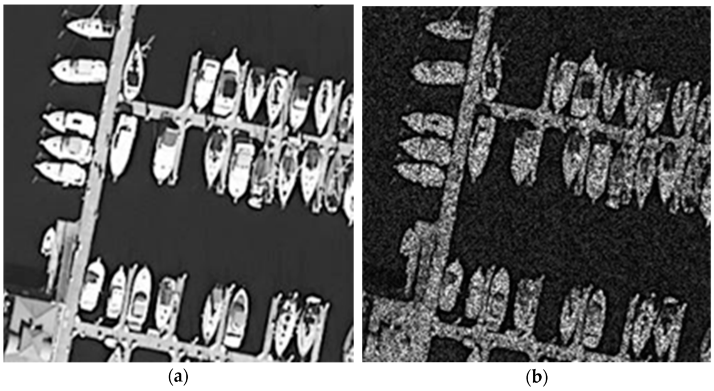


Figure 1.2: a. Optical Image; b. SAR Image with speckle noise

effectively map IS-2's precision onto the weather agnostic, extensive imaging gathered by SAR satellites, thus allowing for local scale analysis of sea ice across large regions.

Given that ice thickness is not a property directly measured by LiDAR nor captured in SAR imagery, sets of assumptions need to be made to deduce the property through related measurements. A leading paradigm in modeling ice thickness is through the assumption of hydrostatic equilibrium [6] [7] [8], in which the properties of the ice sheet are deduced based upon the fact that the ice is buoyant in sea water (Figure 1.3). In this assumption, LiDAR measurements retrieve the elevations of the snow covered ice-surface in relation to the sea surface, and statistically infer the sea ice surface height. It's possible to relate the ice's total thickness to these elevation measurements by combining these relative heights with their associated substance densities (Equation 1.1). NASA's IS-2 L4 Along-Track Sea Ice Thickness product is a closely related example of this topic, and produced arctic ice thickness results between October 2018 and May 2022 [6].

There are critiques with the established hydrostatic model. Ice density at a local scale is a variable property - it's dependent on factors like salinity,

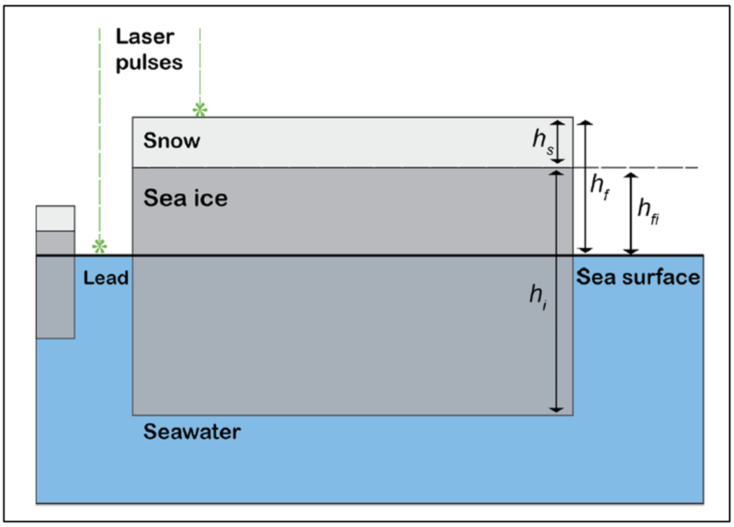


Figure 1.3: Ice Thickness Isostatic Assumption
[6]

temperature, air volume and exposure [1], and has a large enough observable difference that ice can be reliably classified into first and multi-year ice by SAR imaging alone [9]. Some studies delineate ice density by whether it's above or below the waterline, but find that air-rich above water ice only contributes to 10% of the total density of the ice sheet. Given the variability, the exact local density of sea ice in the remote arctic is ephemeral, but generally agreed upon to be between 900-940 $\frac{kg}{m^3}$, with some studies proposing a slightly wider range of 892-945 [1]. As a concrete example though, IS-2's L4 product settled to use a value of 916 $\frac{kg}{m^3}$ for ice above and below the waterline.

$$h_i = \frac{h_f \rho_w}{(\rho_w - \rho_i)} + \frac{h_s(\rho_s - \rho_w)}{(\rho_w - \rho_i)} \tag{1.1}$$

where:

h_i = Sea ice thickness (m) ρ_i = Density of sea ice $(900 - 940\frac{kg}{m^3})$

ρ_w = Density of water ρ_s = Density of snow

h_f = Freeboard height (m) h_s = Snow depth (m)

Even with the established hydrostatic model in place to infer sea ice thickness from remote sensing methods, there is an innate problem with the corroboration of SAR and LiDAR. IS-2 has an orbit cycle of 91 days, meaning each location is surveyed only once nearly every 3 months [2], while SN-2 orbits nearly once every 5 days [10]. It may appear that there should be plenty of data available given the semi-frequent opportunity for coincidence, but given SN-2's best resolution of 10m, any correlation with IS-2's 17m footprint leads to single pixels of information.

The remainder of the thesis will be split between discussing the data collection and machine learning model experimentation. The data collection section will discuss the procedure for obtaining datasets of interest, as well as some intermediate efforts done to promote accuracy. The experimentation will use the collected data to develop a convolutional neural network to explore the feasibility of using such a source of data for deep learning models.

Data Collection

The data collection portion of this project is immediately tasked with the following set of problems: spatial coincidence, temporal coincidence, and resolution. Given the asynchronous orbits of each satellite and the incompatible resolutions of NASA's SN-2 with its own IS-2, other avenues were explored to obtain precise SAR imaging. Particularly, the European Space Agency (ESA) offered the

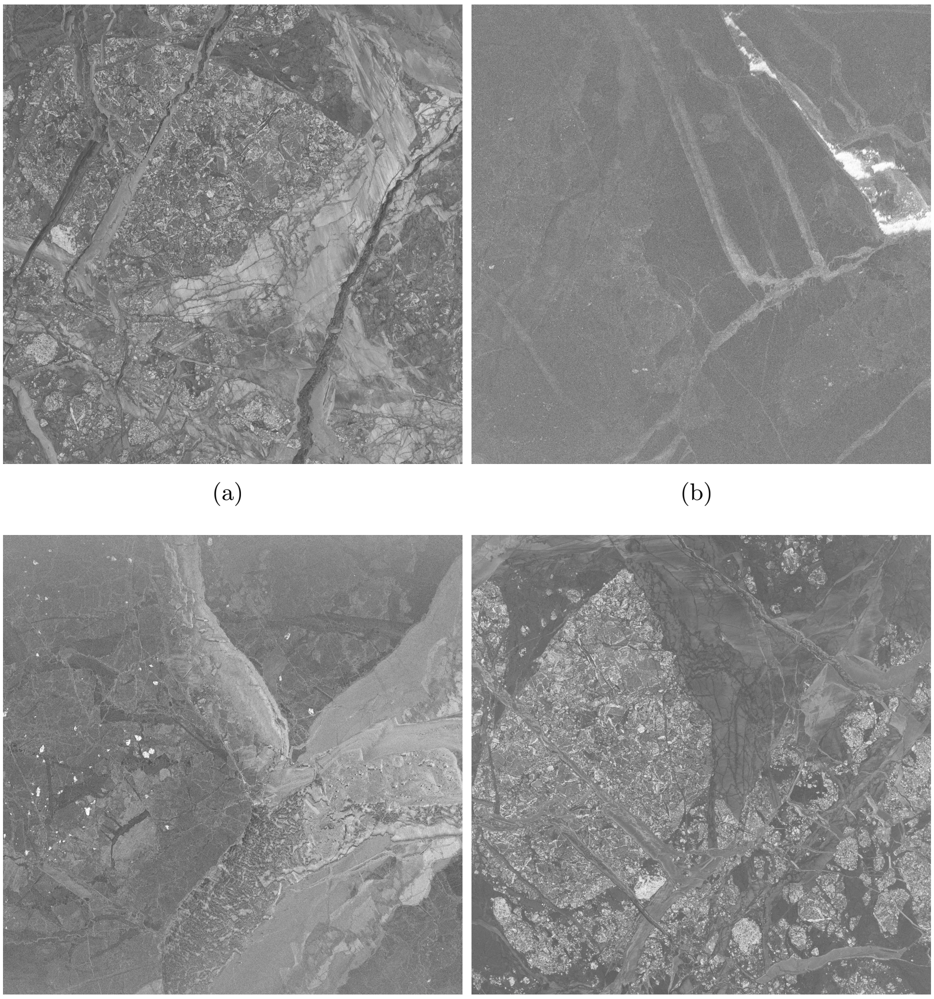
2.1 SAR Imaging

2.2 Laser Altimetry (IceSat-2)

——Default Text ———-

Provide in brief the background information for your work/field keeping in mind that maybe your readers do not have experience with topics your reference or address in your thesis.

In the second part, provide a review of the state of the art relevant to your thesis. Here you present relevant research that relates to your work.



(a) (b) (c) (d)

Figure 2.1: (a), (b), (c), (d)

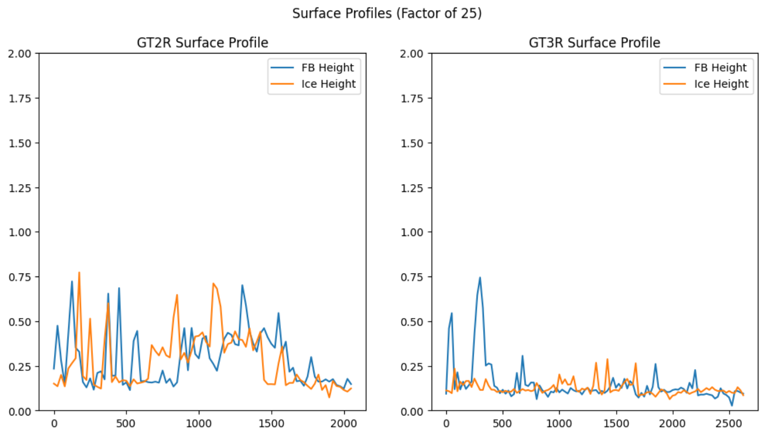


Figure 2.2: Ice Thicknesses

Experimentation

Here you should present how you aimed to answering your question or solving the problem you identified in the introduction. You should present the methods and the instrument you use, the structure of your study or workplan and how you achieved the desirable outcome. The order is indicative, please feel free to rearrange as you see fit.

3.1 Methods

[11] [12]

3.2 Study setup

3.3 Data collection

3.4 Data analysis

Results

Here you present the results of your study (if you carried out one), and any data analysis you may have performed to answer your question. You should consider splitting the results per research question, as these are presented in the introduction

Discussion

In the Discussion section you should elaborate on the following points:

5.1 Research Questions

Here you will answer your research questions, as they appear in the introduction. Answer each question in a different section. Relate your answer to your results. Discuss if your findings support and align with related work or not. Explain why do you think this happens, especially if your findings contradict existing work. Discuss alternative interpretations of your findings.

5.2 Theoretical and Practical Implications

Here you should explain what is your contribution and how it promotes knowledge in the field both in terms of theory and practice. How do you envision your work to change or promote research in the area. How could it be used? How do you envision it to be used?

Conclusion

The result of this thesis is a rough pipeline that links elusive data to a intuitive method of better modeling sea ice. IceSat-2's semi-frequent orbit provides data that can, with planning, be corroborated with other data sources to bridge the gap between different remote sensing methods. The results of the experimentation do not suggest the model is capable of deducing sea-ice thickness from mere SAR imaging.

6.1 Limitations

While intuitive, the fundamental approach to this problem lies on a set of assumptions that may not always be true. At the root of the deduction of sea-ice thickness using IceSat-2 freeboard measurement is the assumption of hydro-static equilibrium at the measured footprint. The equation relies on the densities of snow, ice, and sea water, which are constants that may vary seasonally and geographically. Furthermore, each footprint in this equation is assuming the absence of any other forces acting on the body. This thesis neither considered nor explored the dynamics of sea-ice floes, meaning that the calculated thickness at any given location may differ not only from error, but from a faulty equation derived from an incomplete physical understanding of the observed body.

6.2 Future Work

In the future, this topic can be further explored by examining different machine learning models and architectures that may be better suited on 2-channel, low-resolution imaging. To aid this, more data should be collected from both IceSat-2 and ICEYE.

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