Modeling Sea Ice Thickness using Machine Learning and Remote Sensing Modalities

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Honors Thesis

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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.

//////////////////////////

English Abstract here. The abstract should provide a complete but concise description of your work. In brief, you should address the following: motivation, problem statement, approach, results, and conclusions.

Contents

Introduction

-Why is sea ice important, and what are the applications of understanding it at a closer scale?-

In recent decades, understanding the state of sea ice has grown increasingly more 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].

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

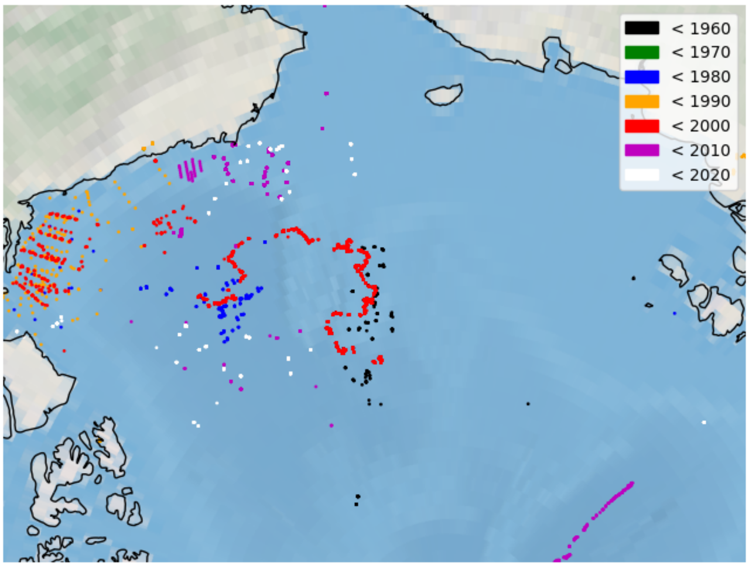

Figure 1.1: Historic In-Situ Data Availability in the Beaufort Sea Region

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 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 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

(**a**)

(**b**)

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

results between October 2018 and May 2022 [6].

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

where:

h_i = Sea ice thickness

h_f = Freeboard height

h_s = Snow depth (m)

ρ_w = Density of water

ρ_i = Density of sea ice

ρ_s = Density of snow

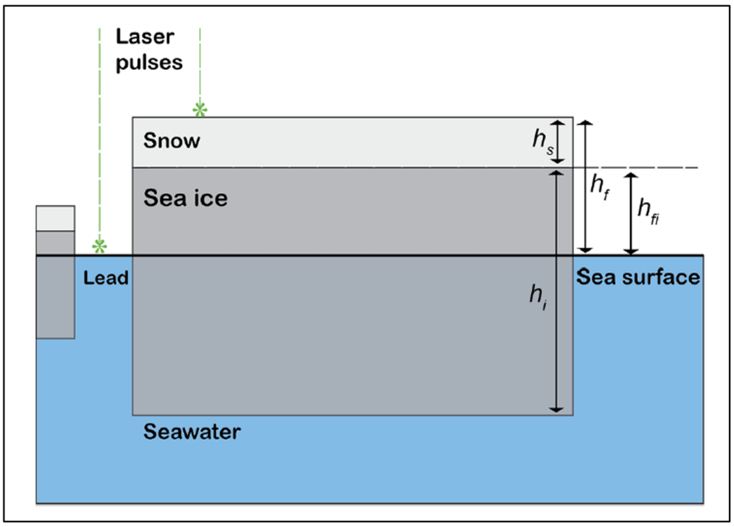

Figure 1.3: Ice Thickness Isostatic Assumption
[6]

Discuss the prevalent sources of data as it stands - NSIDC as a data repository, NASA's Sentinel(1/2), IceSat-2, CryoSat satellites as periodic sources of data. Also give an overview as to how each medium works. This might need to span multiple paragraphs.

Importantly, it's important to recognize that laser altimetry is purely restricted to measuring Earth's surface - meaning the returned measurements are innately incapable of measuring sea-ice thickness, especially in the presence of snow on the surface. (Add source and put it in bibliography)

-Acknowledge that even with the best of the remote sensing methods, many extrapolations of ice-thickness rely on the same fundamental assumption (cite the source that mentioned this)- Discuss isostatic equilibrium and how the physics of it requires density constants which aren't known or measured, and that density itself is dependent on factors like salinity, temperature, and age, all of which are unknown at local temporal and geographic scale. Current research attempts to quantify density have yielded a somewhat consistent range of values between **foo** and **bar**, but even this range has been disputed to be inaccurate [citing the IceSat-2 & CryoSat study, the In-Situ analysis]. (Consider attaching the limitation of distance to the reference surface here, or include it in the limitations).

-Given the limitations, transition into the main idea of the thesis. Mapping LiDAR onto SAR?-

Transition into how SAR imaging can capture a return that indicates sea ice thickness, but it's low resolution from Sentinel-2 prevents it from being local in context. The intuition behind the remainder of the thesis is to coincide precise IceSat-2 LiDAR and data derivatives with widespread SAR imaging, to determine whether sea-ice thickness can be a learnable property from SAR image returns.

The problems with this include the availability of applicable data (such as high-resolution SAR, as the precision of IceSat-2 is immediately lost with low-resolution imagery) and also the coincidence of these two modalities, both spatially and temporally.

-Remove everything from preliminary research - it's not important to the paper. Include the figures of all In-Situ measurements in the Beaufort Sea Region for demonstration of its unavailability especially in relation to the time horizon. Also include the buoyancy chart when discussing the limitations.-

NASA's ICESat-2 L4 Along-Track Sea Ice Thickness highlights this problem, and addresses it using the assumption of hydro-static equilibrium. This equation, expressed as follows, uses the densities of water, sea-ice and snow, alongside the height of the snow to calculate the correlated thickness of the sea ice.

The "On-Ice Arctic Sea Ice Thickness Measurements by Auger, Core, and Electromagnetic Induction, from the Late 1800s Onward, Version 2" contains 69,750 rows of data, spanning 5 categorized regions; the Arctic Ocean, the Beaufort Sea, Greenland Coast, Prudhoe Bay, and Russian Coast. Filtering down to the Beaufort Sea region, a region of interest, yields 23 separate studies ranging between 1958 and 2016.

A single delivery of IceSat-2's ATL10 data product yields a '.h5' file, incompatible with traditional spreadsheets. To access IceSat-2 data in a meaningful way involved developing a script to extract relevant information according to the types enumerated in the data product specification. Columns of interest include the latitude, longitude, time, and calculated freeboard height for each of the three beam pairs. // Consider adding perl and dynamically adding sample rows from the extracted .h5 file. This will give the reader context as to what's being gathered /

Data Collection

In this section, include research relevant to the gathering of data. Include the different metrics that may be captured and the different options presented from different avenues. Much research was done earlier based on the opportunities and limitations of NASA satellites. Include documentation you captured about CryoSat if pertinent to this section.

It may be necessary to include information on SAR imaging in the introduction, so even the non-expert reader can get a functional understanding of the topic.

It may be possible to include figures and other data from the NSIDC In-Situ data repository and discuss the viability of that data as a 'ground-truth' and demonstrate that according to those studies, sea ice was non-normal in distribution. Acknowledge that the data from those studies spanned many miles, and the distribution may sheerly be by variance of ice thickness across the collection area.

Here is where we'll discuss the selection of ICEYE's Data for it's high resolution imaging, and IceSat-2 for it's high-accuracy laser altimetry. It may be possible to include figures to demonstrate how these satellites work, but it may not be pertinent to the thesis (although it would help with understanding).

2.1 Laser Altimetry (IceSat-2)

2.2 SAR Imaging (ICEYE)

——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.

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

[9] [10]

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.

List of Figures

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Insert Appendix Name

A.1 Insert subtitle