Introduction

The Antarctic Ice Sheet (AIS) is experiencing increased surface melt due to anthropogenic increases in atmospheric temperature. Increased ice sheet melt causes sea-level rise, a major consequence of climate change that affects coastal populations globally. Surface meltwater can runoff directly to the ocean, pond on the ice surface, evaporate, percolate down within the firn and ice layers, and refreeze on or in other portions of the ice sheet. Surface melt-induced firn densification and hydrofracture redistribute water and heat within ice sheets which affects large-scale ice dynamics. These processes are thought to be major contributors to the disintegration of the Larsen A, B, and C ice shelves off the eastern slopes of the Antarctic Peninsula (Vaughan and Doake, 1996; Scambos et al., 2003, 2009; McGrath et al., 2012). Ice shelf collapse, while not directly contributing to sea level rise, initiates enhanced glacial calving due to reduced buttressing (Rignot et al., 2004). Melt-induced firn densification and hydrofracture can be caused by foehn and katabatic winds that induce strong sensible heat fluxes on surface snow and ice. These winds are funneled and accelerate through topographic channels into subgrid-scale winds (SGW\textsuperscript{1}) not represented in most global climate models or reanalysis. Resolved-scale and SGW-induced surface melt can be substantial and is often focused at the grounding line of ice shelves which can dramatically increase the likelihood of ice shelf collapse (Scambos et al., 2000, 2003; Lenaerts et al., 2017). Despite advances in model resolution and in-situ observations, we have not constrained surface melt caused by SGW or assessed hydrofracture potential on most AIS ice shelves. Furthermore, we have overlooked wind-induced surface melt as a contributor to hydrofracture potential for the entire AIS. This leads to large uncertainties in surface melt quantity, ice shelf stability, and ultimately sea level rise estimates.

\textsuperscript{1}For purposes of this proposal SGW are smaller than ERA5 grid resolution (31 km globally)
2 Goals and Objectives

The overall goals of this thesis are twofold. First, quantify the spatio-temporal extent of SGW-induced melt and its contribution to the total annual melt experienced on the AIS. Second, rank ice shelf vulnerability for all ice shelves of the AIS by assessing hydrofracture potential including the heretofore neglected SGW contribution. These goals will be accomplished by using in-situ and reanalysis datasets in combination with machine learning techniques to upscale AWS surface conditions into reanalysis data. Specifically, the ice surface energy budget will be used to explicitly quantify the spatial patterns of surface melt in all seasons and assess hydrofracture potential accounting for resolved-scale melt, precipitation, and, for the first time, SGW melt events. Assessments of the AIS ice shelf energy budgets and hydrofracture potential have never before accounted for in-situ observations of the contributions of SGW melt events.

Research objectives

1. **Quantify surface melt caused by SGW**
   1.1. Develop Foehn/katabatic Detection Algorithm (FonDA) to identify melt events in AWS data.
   1.2. Develop Machine Learning FonDA (ML-FonDA) to identify melt events in ERA5 reanalysis data.
   1.3. Estimate the ice surface energy budget to quantify the energy for melt caused by melt events in ERA5 data.
   1.4. Quantify surface melt by combining ML-FonDA and estimated surface energy budget.
   1.5. Estimate the contribution of SGW-induced melt to total melt

2. **Hydrofracture Potential Index**
   2.1. Develop a Hydrofracture Potential Index (HPI) that ranks ice shelf vulnerability including resolved-scale and SGW-induced surface melt.

3 Background

Ice sheet surface melt is traditionally thought to be dominated by a positive net shortwave radiation flux, and to occur only in the summer when solar radiation and air temperatures peak. However, recent work discovered that polar night foehn winds are a large (up to 23%) contributor to surface melt on the Larsen C Ice Shelf (LCIS), while channeled katabatic winds melt ice shelves on East Antarctica, forming large englacial lakes (Lenaerts et al., 2017; Kuipers Munneke et al., 2018). These studies highlight the substantial nature of SGW-induced melt and the importance of constraining surface melt and hydrofracture potential patterns in all seasons. Efforts to quantify SGW-induced surface melt have only focused on specific AWS sites, or used remote sensing to quantify melt days and summer melt spatial patterns but not melt quantity or seasonal spatial patterns. An accurate assessment of spatio-temporal surface melt and subsequent hydrofracture potential on all AIS ice shelves using surface energy budgets to quantify melt has not been attempted.
Current knowledge of SGW-induced surface melt and subsequent hydrofracture is mainly focused on the summer season due to harsh winter conditions. It is also limited to the Larsen ice shelves and a few East Antarctic ice shelves. In-situ observational studies of SGW which quantify surface melt have focused on the Larsen C ice shelf and Roi Baudouin Ice Shelf. Spatial surface melt pattern studies using satellite-borne and aircraft observations, models, and firn air depletion measurements, focus on the summer season due to the difficulty of winter study and again, are limited to the Antarctic Peninsula and few East Antarctic ice shelves (Holland et al., 2011; Kuipers Munneke et al., 2012, 2018; Luckman et al, 2014; Cape et al., 2015; Elvidge et al, 2015, 2016; Bevan et al., 2017; King et al., 2017; Turton et al., 2018; Zou et al., 2018). One study identifies hydrofracture potential (Vulnerability index) using active microwave scatterometry (QuikSCAT), but it does not take into account the surface energy budget or explicitly quantify melt (Alley et al., 2018).

3.1 Subgrid-scale Winds

Foehn winds are warm and dry downslope winds that form on the leeside of mountain ranges. Foehn winds are most common on the Antarctic Peninsula and east of the Ross Ice Shelf. Elvidge et al., (2016) hypothesised 4 main mechanisms for foehn-warming events that produce large sensible heat fluxes that lead to surface melt: 1) isentropic drawdown where cool moist air is trapped allowing for warm dry air to be brought to the surface, 2) latent heating and precipitation where release of latent heat and change in lapse rate leads to warming at the surface, 3) mechanical mixing where the persistent cold boundary layer is mixed through turbulence with warm air aloft, 4) radiative heating on the leeside of mountains which creates clear skies due to descending air. These events are highly variable within and between seasons, with the ultimate effect on surface conditions dependent on the large-scale atmospheric flow and subgrid-scale topography (Elvidge et al. 2015). The topographic configuration of the Antarctic Peninsula makes foehn possible in all seasons especially in winter and fall caused by a shift in the storm track (Cape et., al 2015). Foehns are well documented in summer and understudied in winter because large scale field campaigns are primarily conducted in the less harsh summer months (Elvidge et al., 2015).

Katabatic winds are density driven winds that are continuously cooled by the underlying AIS and travel downslope. These winds are prominent features on the AIS and are consistent in both strength and direction caused by topographic funneling. They vary seasonally with the strongest winds in the cold winter months when radiative cooling is most prominent (Parish and Cassano 2003). Surface warming for katabatic winds is caused by compression as the cold dry air descends the AIS. Additional warming comes from turbulent mixing where the persistent cold inversion layer above the AIS is mixed bringing warm air aloft to the surface (Lenaerts et al., 2017). Despite different formation mechanisms, SGWs have similar meteorological signatures such as increased wind speed and temperature, and low relative humidity. These make strong SGWs easy to identify in AWS data.

3.2 Surface Melt Impact on Ice Shelves

SGWs can induce surface melt directly through sensible heat transfer and indirectly by eroding surface snow. Snow erosion exposes blue ice which has a lower albedo enhancing surface melt. Sunlight directly heats and melts snow and firn and indirectly increases air
temperature which causes melt. The albedo of fresh snow is high at about 0.9. However as snow warms its specific surface area decreases, and liquid water content increases reducing its albedo. As blue ice is exposed and melt ponds form the albedo is further reduced. This snow melt and blue ice mechanism acts as a powerful positive feedback, perpetuating surface melt. Resolved-scale and SGW-induced surface melt is strongest near the grounding line of ice shelves due to changes in topographic angle and turbulent mixing (Lenaerts et al., 2017). The grounding line is the hinge point where terrestrial glaciers begin to float creating an ice shelf. Storms, tidal changes, and sea-ice variability cause flexure stress on ice shelves that leads to outer ice shelf weakening and calving, and possible total collapse to the grounding line (Massom et al., 2018). When melt water is present, water can fill crevasses, increase the likelihood of hydrofracture and perpetuate crevasse expansion. Crevasses and fractures lead to calving and ice shelf disintegration and form on subgrid-scales locally through ice dynamics and hydrofracture (McGrath et al., 2012; Pollard et al., 2015; Banwell et al. 2019).

Surface melt also causes firn densification where meltwater displaces air and increases the density of the shelf. Water refreezing and expansion increases internal stresses. This process can create an impermeable surface that stops the downward flow of water, forming melt ponds on the ice surface. Densification is not uniform throughout ice shelves and depends on local surface melt conditions and runoff distribution (Holland et al., 2011). Dense ice shelves support surface ponding where meltwater can add hydrostatic pressure strong enough to expand existing ice fractures completely through the ice shelf, eventually leading to hydrofracture. Surface melt ponds also increase surface albedo enhancing melt through a powerful positive feedback loop. In summary, hydrofracture and firn densification can both result directly from surface melt on ice shelves.

4 Data and Methods

4.1 Data Sources

This thesis uses four datasets to accomplish the research goals and objectives. First, I use Justified Automatic Weather Station (JAWS) data that encompasses 319 AWSs from 4 networks, and homogenizes them to a simple hourly averaged netCDF format. AWSs provide valuable in-situ data to determine the surface energy balance and meteorology useful for validating satellite observations and model simulations. Second, ERA5 reanalysis which provides globally gridded hourly meteorological and surface energy flux data. AWS data lack spatial representation making extrapolation of AWS data to the entire AIS difficult. ERA5 has global coverage but misses subgrid-scale processes that can be identified by AWS data (Figure 1). In combination, machine learning will be used to train a model to detect SGW in reanalysis data based on patterns exhibited by AWS data. This aids in expanding the spatial representation of AWSs while accurately representing unresolved SGW-induced melt in large scale datasets. Third, Clouds and the Earth's Radiant Energy System (CERES) is used as a benchmark to evaluate estimated surface energy budgets. Fourth, scatterometry data (from QuikSCAT, ESCAT, and/or ASCAT) will be used to derive ice shelf density and to evaluate historical and current spatial melt patterns. CERES and QuikSCAT serve as diagnostic tools to evaluate melt calculations and hydrofracture potential assessment. We know of no published studies that use machine learning in combination with AWS and reanalysis data.
4.2 Quantify surface melt caused by SGW

4.2.1 SGW melt detection algorithm for AWS

We developed a Foehn/katabatic Detection Algorithm (FonDA) which uses variable thresholds to identify SGW conditions in hourly AWS data. FonDA identifies a SGW melt event using binary classification when three measured field variables surpass their empirically derived thresholds (Figure 2). Despite different formation mechanisms, SGWs have similar meteorological signatures including increased temperature and wind speed and low relative humidity. These similarities make SGW melt events easy to identify in AWS data. FonDA's algorithmic threshold for air temperature is 0°C, which ensures surface melt is possible. Thresholds for relative humidity and wind speed are more dynamic because high winds and low relative humidities do not guarantee temperatures above freezing, they only aid in identifying SGW. FonDA uses quantile regression to identify these variable thresholds. To identify significant SGW melt events, FonDA uses two empirically determined thresholds: the 60th percentile wind speed and 30th percentile relative humidity.

FonDA was calibrated against known SGW melt events in all seasons, to ensure it correctly classifies melt events (e.g., Elvidge et al., 2015; Turton et al., 2018; Kuipers Munneke et al., 2018; Lenaerts et al., 2017). The first study area was the LCIS which contains 9 current and past AWSs with varying temporal distribution (2009-2018). This allows for a smaller study area for calibration.

Attempts to replicate the AWS-identified SGWs using a re-tuned FonDA and ERA5 input did not achieve sufficient accuracy, yielding an f1-score less than 0.5. The f1-Score is a statistical analysis tool used to assess the accuracy of a model when using binary classification. It takes into account both false negative classification and false positive classification for a range between 0 and 1. A model with no true positives, and only false negative and/or false positive results yields 0.0. A model that correctly classifies all true positive results with no false negatives and/or false positives yields 1.0. **Machine-learning is necessary to increase f1-scores and**
successfully detect SGW melt events in satellite-based data. The information gained by FonDA will allow for SGW classification in AWS data useful to train a machine learning algorithm. It identifies SGW melt events in ERA5 reanalysis data using Gradient Boosting Classification machine learning, with FonDA results as the ground truth data.

![Figure 2](image_url)  
**Figure 2**: SGW melt event at AWS 18 on the LCIS, identified by FonDA by light grey shading.

### 4.2.2 Machine learning assisted SGW melt detection in ERA5

Gradient Boosting Classification machine learning is used to identify SGW melt events in ERA5 reanalysis data. Gradient Boosting Classification is a machine-learning technique that uses weak learners, which are variables better than random chance, for prediction. It succeeds because a large number of weak learners become a strong classifier. Gradient Boosting Classification uses decision trees for prediction and can be tuned to reduce model error, increase f1-score, and enhance model robustness with the use of hyperparameters. The algorithm named Machine Learning FonDA (ML-FonDA) uses FonDA results as ground truth data or fine-scale data, and ERA5 hourly instantaneous single level reanalysis data as the course-scale data.

Machine learning is indispensable for accurately detecting SGW melt events in satellite data. The research goal is to reach an f1-score of 0.8, a balance between model complexity and accuracy. I ensure accuracy of the model by using 10-fold cross validation and tune the model using Bayesian hyperparameter optimization, a common machine learning hyperparameter optimization technique. The preliminary model results were extrapolated across the LCIS to estimate climatology of SGW-occurrence, surface energy budget, and melt. This thesis aims to improve the machine learning model and expand this workflow methodology to incorporate all weather stations on the AIS.

One criticism for using machine learning is the inability to see inside the “black box” of the algorithm. This limits our ability to understand why SGW melt events are identified. Information inside the black box of the algorithm is not necessary for the success of the project, however it is useful to optimize prediction and create a robust model. This thesis uses a Python
package called ELI5, which works to debug machine learning classifiers and explain their predictions.

ML-FonDA was initially trained to identify SGW melt events on the LCIS using the most recent 10 years of ERA5 data (2007-2017). This provides a case study and smaller scale region to assess how well the model predicts SGW melt events. The use of machine learning has increased the f1-score by 0.219 for the LCIS, vastly improving SGW prediction in ERA5 data compared to human-calibrated detection. ML-FonDA results for the LCIS provide an f1-Score of 0.719 for SGW melt event prediction in ERA5 data. This number is likely to improve with additional AWS training sets, increased ERA5 variables, and hyperparameter optimization.

### 4.2.3 Surface Energy Budget

Surface melt energy is calculated from observed or analyzed fluxes as,

\[ Melt \text{ Energy} = SW_{net} + LW_{net} + SHF + LHF + G \quad (Wm^{-2}) \]

Where \( SW_{net} \) is the \( SW \downarrow \) minus \( SW \uparrow \); \( LW_{net} \) is the \( LW \downarrow \) minus \( LW \uparrow \); Sensible Heat flux (SHF); Latent Heat Flux (LHF); G is the surface value of the subsurface (conductive) heat flux. The estimated energy budgets for AWSs that provide radiation fluxes will be compared to the ERA5 surface energy budget in the corresponding grid cell. This provides a diagnostic evaluation of how well ERA5 data without SGW effects represent the in-situ surface energy budget and melt energy, despite the disparity in measurement footprint. This diagnostic will also help in calibrating the surface energy budget alteration during ML-FonDA detected SGW events. The SGW-adjusted total energy budget will be compared to and constrained by Clouds and the Earth's Radiant Energy System (CERES) data and verified for melt-events against ESCAT (1990-1999), Seawinds QuikSCAT(2000-2009), and ASCAT (2007-present) when available.

Of the 319 AWSs on the AIS only 19 (all the Institute for Marine and Atmospheric Research (IMAU) AWSs) have radiation instruments. These stations will be used to help calibrate ERA5 surface energy budgets to better represent surface conditions. We cannot compute a full energy budget for the other 300 AWSs. For AWSs with radiometric instruments the surface heat fluxes will be calculated using the bulk aerodynamic equations

\[ SHF = \rho C_e C_p (T_s - T_a)(U_{10}) \quad \text{and} \quad LHF = \rho C_L L_v (Q_s - Q_a)(U_{10}) \]

where \( \rho \) is air density; \( C_e \) and \( C_h \) are non-dimensional eddy exchange coefficients of moisture and heat, respectively; \( L_v \) is the latent heat of vaporization; \( C_p \) is the specific heat capacity of air; \( Q_s \) is the saturated specific humidity at temperature \( T_s \); \( Q_a \) is the air specific humidity; \( T_s \) is surface ice temperature; \( T_a \) is air temperature; and \( U_{10} \) is the 10-meter wind speed. \( C_e \) and \( C_h \) depend on the surface roughness length with an assigned value of 0.04 meters for snow and ice (Bryan et al. 1997).

The surface energy budget during SGW melt events on LCIS for the time period 2007-2017 is heavily influenced by strong sensible heat fluxes in polar night (April-September) and polar day (October-March). The highest mean sensible heat flux occurs in polar night reaching 66.4 W/m² (Figure 3). These results highlight the robustness of the model by identifying the strong sensible heat flux associated with SGW, and indicate that ML-FonDA correctly identifies SGW events in ERA5 data. These estimates quantify surface melt using surface energy balance and include SGW melt events.
4.2.4 SGW-induced melt climatology

ML-FoNDa results and the ERA5 surface energy budget are combined to estimate the surface melt, initially on the Antarctic Peninsula later expanding to the AIS. The melt quantity and spatial pattern climatology of these events is calculated for seasonal, annual, and decadal temporal scales. The total SGW-induced melt is compared with published total annual melt quantity and frequency data and to the AWS surface energy budget and height measurements to evaluate melt quantity. This new surface melt information could illuminate an increase in total annual melt that was not previously known because SGW melt is unresolved in GCMs.

The LCIS surface melt spatial pattern in polar night is consistent with strong melt near the grounding line (Figure 4) as observed on other ice shelves and modeling studies (Elvidge et al., 2016; Lenaerts et al., 2017). There is a strong topographic influence caused by funneling of wind through canyons, and high melt values on the northern portion of the ice shelf, consistent with Holland et al., (2011) and Kuipers Munneke et al., (2012). This melt pattern likely contributes to firn densification, melt pond formation, hydrofracture, and the overall instability of the ice shelf.

4.3 Identify vulnerable ice shelves

4.3.1 Hydrofracture Potential Index

A Hydrofracture Potential Index (HPI) will be developed based on the surface energy budget, accounting for resolved scale and SGW-induced melt, firn density characteristics, and estimated precipitation. The SGW-induced surface melt climatology identified by the previous workflow will be combined with liquid precipitation and firn density estimates to assess the
potential for hydrofracture on an ice shelf. Hydrofracture is not represented in models explicitly because it is difficult to estimate where meltwater is transported, how much surface meltwater or ponding exists, and the location and size of crevasses.

Therefore, a simple linear relationship for surface melt will be used to develop the HPI. Regions with the highest liquid (including SGW-induced surface melt) relative to total precipitation inputs, and the greatest firm density (least porous firm) are most likely to hydrofracture. Firn density will be estimated using a method pioneered by Scambos et al., (2003) to identify firm density based on ESCAT (1990-1999), Seawinds QuikSCAT(2000-2009), and ASCAT (2007-present) backscatter. Microwave-backscatter is weak in fresh snow due to penetration and absorption while dense firn and ice have strong backscatter. This relationship can be used to derive firm density. The HPI will range between 0 (not vulnerable to) and 1 (likely experiencing) hydrofracture. HPI will be compared to estimates from Alley et al., (2018) and evaluated against the Larsen B ice shelf collapse in 2002.

5 Expected Results and Timeline

The expected results of this study are:
- A climatology of frequency and severity of SGWs across the AIS
• A climatology of the spatiotemporal distribution of resolved scale and SGW-induced melt.
• A ranking of which ice shelves around Antarctica are likely to be affected by hydrofracture.

<table>
<thead>
<tr>
<th>Period</th>
<th>Year 3</th>
<th>Year 4</th>
<th>Year 5</th>
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</thead>
<tbody>
<tr>
<td>Accomplishments</td>
<td>Research goal 1 for the LCIS</td>
<td>Research goals 1 and 2 for Larsen A and B</td>
<td>Research goals 1 and 2 for the entire AIS</td>
</tr>
<tr>
<td>Publications</td>
<td>Melt climatology for the LCIS comparing wind-induced melt to solar-induced melt (Geophysical Research Letters)</td>
<td>Evaluate the Hydrofracture Potential Index (HPI) against the Larsen A and B ice shelf collapses (Cryosphere)</td>
<td>Melt climatology and vulnerability assessment for all AIS ice shelves (Geophysical Research Letters)</td>
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6 Impacts of Work

The overarching theme of this thesis is to update current surface melt estimates to include SGW-induced surface melt, and assess ice shelf vulnerability to hydrofracture. Ice shelves presently function as ice buttresses, slowing the rate of ice sheet mass loss. Glacial calving and ice sheet mass loss have a direct impact on sea level rise, thermohaline circulation, and global climate. This work will provide insight into the changing frequency of SGW-induced surface melt due to climate change. It will produce the first ranking of AIS ice-shelf vulnerability to hydrofracture, encompassing both resolved and SGW-induced melt. Thus, it will help focus scientific and public attention on areas most likely to rapidly change and lead to sea level rise.

Past studies of sea level rise do not account for subgrid-scale surface melt. Research suggests SGW-induced melt will likely increase in the future due to climate change, causing ice shelf collapse and grounded glaciers to increase velocity. (Scambos et al., 2000; Bevan et al., 2017; Turton et al., 2018). Further, our current estimation of sea level rise is uncertain, partially due to neglect of subgrid-scale processes in climate models. Sea-level rise is a major consequence of climate change that affects substantial coastal populations globally. This work pioneers estimates of the importance of SGW interactions for the AIS and polar climate system. My results will help better assess SGW-induced melt, ice-shelf vulnerability, and sea level rise and thereby research priorities to reduce future sea-level rise uncertainties.

7 Appendix: Acronyms Used

AIS - Antarctic Ice Sheet
AWS - Automatic Weather Station
CERES - Clouds and the Earth's Radiant Energy System
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