Satellite Remote Sensing & Model Reanalysis Estimates of Upper-Ocean Heat Content in the Canada Basin

Amanda Camarato

Follow this and additional works at: https://digitalcommons.csumb.edu/caps_thes_all

This Master's Thesis (Open Access) is brought to you for free and open access by Digital Commons @ CSUMB. It has been accepted for inclusion in Capstone Projects and Master's Theses by an authorized administrator of Digital Commons @ CSUMB. For more information, please contact digitalcommons@csumb.edu.
SATELLITE REMOTE SENSING & MODEL REANALYSIS ESTIMATES
OF UPPER-OCEAN HEAT CONTENT IN THE CANADA BASIN

A Thesis
Presented to the
Faculty of
Moss Landing Marine Laboratories
California State University Monterey Bay

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
in
Marine Science

by
Amanda Camarato
Fall 2021
The Undersigned Faculty Committee Approves the

Thesis of Amanda Camarato:

SATELLITE REMOTE SENSING & MODEL REANALYSIS ESTIMATES OF
UPPER-OCEAN HEAT CONTENT IN THE CANADA BASIN

Thomas Connolly, Chair
Moss Landing Marine Laboratories

Ivano Aiello
Moss Landing Marine Laboratories

Tim Stanton
Naval Postgraduate School, Monterey

Doug Smith
CSUMB Interim Dean of Graduate Studies & Research

12/22/21
Approval Date
DEDICATION

For Bruce, I know you cannot read, but you have been with me since we started this and have shown me true companionship; trust, I am grateful to you.
ABSTRACT

Satellite Remote Sensing & Model Reanalysis Estimates of Upper-Ocean Heat Content in the Canada Basin
by
Amanda Camarato
Master of Science in Marine Science
California State University Monterey Bay, 2021

The partitioning of solar radiation entering the upper ocean in the presence of sea ice during the Arctic summer is essential to predicting future ice retreat. This study compares predicted incoming heat with upper ocean density and thermal structure by constructing a simple, one-dimensional vertical heat budget around drifting buoy clusters deployed as part of the Stratified Ocean Dynamics of the Arctic experiment. Model reanalysis surface heat flux estimates were used with Synthetic Aperture Radar (SAR) and satellite radiometer derived open water fraction (OWF) estimates to construct an incoming surface heat flux budget. The incoming solar radiation forced upper-ocean heat gains, either stored locally or contributing to ice melt, through open water and the thinning ice cover. The estimated seasonal heat input directly through SAR-determined open water is roughly 44 MJ m\(^{-2}\), and the measured heat sinks total 104 MJ m\(^{-2}\) for mixed layer heat gain, basal melting, and basal conductance. Given the lack of sizeable advective heat sources, these results suggest that the residual heat source is through-ice transmittance. A transmission parameter was estimated from the residual heat flux and comparable to previous \textit{in situ} observations of ice transmittance. These results suggest that through-ice transmittance is the dominating heat source around the observation site during the summer 2019 melt season.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABSTRACT</td>
<td>v</td>
</tr>
<tr>
<td>LIST OF TABLES</td>
<td>viii</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>ix</td>
</tr>
<tr>
<td>ACKNOWLEDGEMENTS</td>
<td>x</td>
</tr>
<tr>
<td>INTRODUCTION</td>
<td>11</td>
</tr>
<tr>
<td>DATA SOURCES</td>
<td>17</td>
</tr>
<tr>
<td>Sea Ice Data</td>
<td>18</td>
</tr>
<tr>
<td>Atmospheric Data</td>
<td>21</td>
</tr>
<tr>
<td>Oceanic Data (Temperature, Conductivity, and Pressure)</td>
<td>21</td>
</tr>
<tr>
<td>METHODS</td>
<td>23</td>
</tr>
<tr>
<td>Construct a Simple 1D Heat Budget</td>
<td>23</td>
</tr>
<tr>
<td>Open Water Fraction – SSMI</td>
<td>24</td>
</tr>
<tr>
<td>Open Water Fraction – SAR</td>
<td>24</td>
</tr>
<tr>
<td>Cumulative Radiation Through Open Water</td>
<td>27</td>
</tr>
<tr>
<td>ITP Upper Ocean Heat Integration</td>
<td>27</td>
</tr>
<tr>
<td>Basal Ablation</td>
<td>29</td>
</tr>
<tr>
<td>Ocean-Ice Thermal Conductance</td>
<td>29</td>
</tr>
<tr>
<td>RESULTS</td>
<td>33</td>
</tr>
<tr>
<td>Evolution of the Pycnocline at the Base of the Mixed Layer</td>
<td>33</td>
</tr>
<tr>
<td>Water Mass Encounters</td>
<td>34</td>
</tr>
<tr>
<td>Heat in the Mixed Layer</td>
<td>35</td>
</tr>
<tr>
<td>Basal Melting</td>
<td>38</td>
</tr>
<tr>
<td>Open Water Partitioning of Solar Radiation</td>
<td>40</td>
</tr>
<tr>
<td>Seasonal Heat Budget</td>
<td>44</td>
</tr>
<tr>
<td>DISCUSSION</td>
<td>47</td>
</tr>
<tr>
<td>CONCLUSIONS</td>
<td>53</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>54</td>
</tr>
</tbody>
</table>
A MATCHING SAR IMAGERY TO ITP LOCATION AND TIME ............................59
B ITP PREPROCESSING......................................................................................59
LIST OF TABLES

PAGE

Table 1. ITP Deployment Details. .................................................................17
Table 2. Ice Mask Counts per Cluster & Close-to-Edge Exclusions. ..............24
Table 3. Density thresholds used to track the winter pycnocline. ..................29
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1</td>
<td>Topo-bathymetric chart of the Canada Basin showing ITP location time series.</td>
<td>13</td>
</tr>
<tr>
<td>Figure 2</td>
<td>Aerial image of Cluster 2 instruments being deployed October 2018.</td>
<td>18</td>
</tr>
<tr>
<td>Figure 3</td>
<td>One-day smoothed basal depth time series.</td>
<td>19</td>
</tr>
<tr>
<td>Figure 4</td>
<td>Raw GeoTIFF image (left) and the corresponding ice mask (right) over Cluster 2 on 25 August 2019.</td>
<td>20</td>
</tr>
<tr>
<td>Figure 5</td>
<td>Ice-Tethered Profiler Schematic (Toole et al., 2011)</td>
<td>22</td>
</tr>
<tr>
<td>Figure 6</td>
<td>Example of the SAR image center and zoom method.</td>
<td>26</td>
</tr>
<tr>
<td>Figure 7</td>
<td>Ice temperature profiles at Cluster 2 averaged weekly</td>
<td>31</td>
</tr>
<tr>
<td>Figure 8</td>
<td>The temperature gradient from the ice base to 20cm up from the ice base at Cluster 2 for the 2019 solar season.</td>
<td>32</td>
</tr>
<tr>
<td>Figure 9</td>
<td>Temperature (a) and Potential Density (σθ) (b) profiles for Cluster 2.</td>
<td>34</td>
</tr>
<tr>
<td>Figure 10</td>
<td>Cluster 2 T-S Diagram of the ocean mixed layer.</td>
<td>35</td>
</tr>
<tr>
<td>Figure 11</td>
<td>Timeseries of the cumulative heat sink due to storage and vertical T profiles at Cluster 2.</td>
<td>37</td>
</tr>
<tr>
<td>Figure 12</td>
<td>T and S profiles before, during, and after a dip in QML.</td>
<td>38</td>
</tr>
<tr>
<td>Figure 13</td>
<td>Cluster 2 Ice Basal Depth and Melt Timeseries.</td>
<td>39</td>
</tr>
<tr>
<td>Figure 14</td>
<td>Reanalysis (ECMWF) and observed (WIMBO) wind speed at Cluster 2.</td>
<td>40</td>
</tr>
<tr>
<td>Figure 15</td>
<td>Seasonal ECMWF incoming surface shortwave estimates.</td>
<td>41</td>
</tr>
<tr>
<td>Figure 16</td>
<td>Estimated open-water fraction and open-water modulated incoming shortwave down flux and cumulative shortwave down.</td>
<td>42</td>
</tr>
<tr>
<td>Figure 17</td>
<td>Original SAR images and the matching binary ice-water image.</td>
<td>43</td>
</tr>
<tr>
<td>Figure 18</td>
<td>Original SAR images and the matching binary ice-water image.</td>
<td>44</td>
</tr>
<tr>
<td>Figure 19</td>
<td>Sources and sinks to the overall budget for summer 2019 using SSMI-estimated OWF shortwave down input</td>
<td>45</td>
</tr>
<tr>
<td>Figure 20</td>
<td>Sources and sinks to the overall budget for summer 2019 using SAR-estimated OWF shortwave down input</td>
<td>46</td>
</tr>
<tr>
<td>Figure 21</td>
<td>(a) Residual heat flux from the 1D budget using SAR-derived OWF</td>
<td>49</td>
</tr>
<tr>
<td>Figure 22</td>
<td>Cluster 2 vertical T and S representative profiles during the early, mid, and late-season.</td>
<td>51</td>
</tr>
</tbody>
</table>
ACKNOWLEDGEMENTS

I would like to express my gratitude to my primary advisor, Dr. Tom Connolly, who welcomed me into the Physical Oceanography lab, guided me throughout this project and provided numerous helpful discussions and constructive suggestions. I also thank Dr. Tim Stanton, my research supervisor, for offering the golden opportunity to travel to the Arctic and conduct this wonderful project. Dr. Ivano Aiello gave new insight and warm encouragement. The meticulous technical help provided by Dr. William Shaw was greatly appreciated. I wish to extend special thanks to Dr. John Hargrove for providing the valuable synthetic aperture radar data crucial to this study and technical support to use it. I appreciate the ice data support from Dr. Jeremy Wilkinson. Data visualization was facilitated by the efforts of the developers of MATLAB tools for CMOcean Colormaps (https://matplotlib.org/cmocean/). This project was supported by National Science Foundation Office of Polar Programs grant 1723400 and the Office of Naval Research High Latitude program under grants N00014-19-1-2205 and N00014-20-1-2633.
INTRODUCTION

Arctic sea ice is sensitive to summer solar radiation entering the ocean. This sensitivity makes it an indicator of changes to the global climate, and such changes impact the earth-energy balance. Sea ice greatly affects the Arctic energy budget (Frey et al., 2011; Perovich et al., 2007), which influences mid-latitude weather (Semmler et al., 2012) and sea-ice ecosystems (Arndt & Nicolaus, 2014; Barber et al., 2015). In the last two decades, the Arctic ice pack has been reducing in extent by nearly 13% per decade (Gautier, 2019), and perennial sea ice is being replaced by thin and more fragile seasonal ice (Döscher et al., 2014; Jeffries et al., 2013). The decrease in extent and thickness of sea ice impacts the radiative partitioning between the ice and ocean, and the thermodynamics and physical processes of such ice decay are not well understood (Meredith & Sommerkorn, 2019). Sea ice cover provides thermal insulation between the ocean and the atmosphere, and its properties determine the solar partitioning (Frey et al., 2011). Perennial ice characteristics differ significantly from seasonal ice in that seasonal ice transmits more light, drifts more quickly, is weaker to deformation, and potentially floods given a thick snow cover. This shift in Arctic ice cover from predominantly perennial to seasonal ice cover is a considerable change that requires further research to understand the solar radiative impacts on the existing system.

Sea ice melts primarily during the summer when the constant sun presence allows solar radiation to melt snow cover, form melt ponds, and increase open water areas, providing pathways to melt the ice and heat the upper ocean. The amount of solar radiation transmitted to the ocean through ice or directly to the ocean depends on the surface albedo, defined as the proportion of incident light backscattered off the surface and back into the atmosphere. Snow-covered perennial and seasonal ice has the highest albedo, with typical values around 0.85 (Perovich & Polashenski, 2012). The albedo lowers to 0.8-0.6 when snow begins to melt. When meltwater pools atop the ice, melt ponds form and significantly lower the albedo to 0.5-0.3. Ice-free areas directly absorb solar radiation and have the lowest albedo of 0.05. Seasonal ice-albedo feedback loops are initiated after the snow is warmed by
solar radiation. As ice conditions deteriorate, the albedo decreases, which increases the amount of solar radiation transmitted and absorbed (Gallaher et al., 2016; Light et al., 2008; Perovich et al., 2002). Much of the solar radiation that enters the upper ocean is stored as heat in the mixed layer and melts ice from the underside during wind-driven mixing events (Stanton et al., 2012). The more ice melts, the more solar radiation enters the system, causing strong positive feedback. Details of surface heat flux processes in sea ice-covered oceans are needed to increase confidence about radiative distribution in the ocean and ice and enhance future system predictability.

The progression of ice melt and the evolution of the upper ocean heat content in the Canada Basin (Figure 1) is described as a four-stage process (Gallaher et al., 2016). These four stages, observed in the Beaufort Sea, illustrate how changes in the mixed-layer heat play an essential role in sea ice cover. Stage I is the initial snow-covered condition of the upper ocean during spring. The transition to Stage II is marked by increased heat and freshwater storage and a shallowing of the surface mixed layer. The transition to Stage III is determined by a shallow summer mixed layer and the formation of a near-surface temperature maximum (NSTM). An NSTM is a shallow, relatively fresh layer where heat is stored. This NSTM feature exists seasonally in the upper ocean, primarily in the Pacific sector (Jackson et al., 2010). When present, the NSTM layer is decoupled from the mixed layer and sits beneath a thin fresher surface layer near the seawater melting point. The summer halocline and the mixed layer are shallow enough to absorb incoming radiation and persist long enough to accumulate heat for extended periods during the summer (Jackson et al., 2010). Stage IV occurs after the formation of the NSTM and describes a transition to a marginal ice zone where there is more than 30% open water.
Disposition of upper-ocean heat is important for understanding the key aspects of the Arctic climate and its short- and long-term variability (Steele et al., 2010). This is especially true for the Beaufort Gyre, within the Canadian Basin, as it is a large region of ice recirculation and retention and freshwater storage in the Arctic (Proshutinsky et al., 2009; Thomas, 2017). The Beaufort Gyre circulation patterns are tied to water and ice properties, which greatly influence the Arctic climate variability (Proshutinsky et al., 2002). A vertically-integrated, one-dimensional (1D, no horizontal gradients) upper ocean heat budget provides a thermodynamic framework to evaluate processes that set ocean temperatures and drive heat fluxes (Gallaher et al., 2016; Krikken & Hazeleger, 2015). This framework is expressed as the ocean heat content responding to the integrals of fluxes that act as heat sources or heat sinks:

\[ Q_{ML} = \int (heat \ flux \ sources - heat \ flux \ sinks) \ dt \quad Eq. 1 \]

where \( Q_{ML} \), the vertical integration of heat in the mixed layer, is an intermediary between heat flux sources and sinks. In the spring and summer analysis, heat flux sources consist of the latent and sensible heat fluxes from the atmosphere, downwelling long and shortwave radiative fluxes incident on the ice and ocean surface, and vertical diffusive heat fluxes from the pycnocline at the base mixed layer. Heat flux sinks consist of the latent heat flux of
melting ice, outgoing longwave radiative flux, and ocean to ice conductive fluxes (Gallaher et al., 2016). During the Arctic summer in the southwest Beaufort Sea, the dominant heat source in the surface mixed layers is from solar radiation, with smaller heat contributions from the pycnocline through turbulent diffusion and entrainment (Shaw et al., 2009). Other work has found that local radiative forcing through open water accounts for most of the heat storage gains and basal melting in the seasonal ice zone of the Canada Basin (Gallaher et al., 2016; Steele et al., 2010). However, annual and spatial differences in ice-modulated radiative partitioning entering the upper ocean are not well understood, specifically how changes in seasonal ice concentration relate to sea ice melt and upper ocean heat storage.

Data is needed from the atmosphere, sea ice, and ocean to quantify heat content and fluxes with a 1D heat budget. The most difficult data to access is sea ice data and ocean observations in these regions. Using clusters of buoys on multiyear ice floes that collect air-ice-ocean observations, data from these buoys can be incorporated into a 1D heat budget (Gallaher et al., 2016). Additional data needed to evaluate the budget can be gathered from model reanalysis estimates and remote sensing.

A crucial component of the heat budget is the partitioning of solar radiation between the open and ice-covered ocean because the ice cover directly modulates solar radiation by obstructing direct absorption into the upper ocean (Frey et al., 2011; Thomas, 2017). This analysis uses two types of satellite-based ice concentration estimates to establish the time evolution of the open water area as the summer progresses. Satellite passive microwave sensors measure the brightness temperature of the Earth’s surface (which includes the ocean and ice) and that of the atmosphere in multiple far-infrared bands to infer ice coverage over large areas. Brightness temperature is a function of naturally emitted, longwave blackbody radiation and is used to calculate ice concentration. The atmospheric portion of the detected blackbody emissions and the different emissive ice properties, like snow cover, salinity, and crystal structure, result in uncertainties in ice concentration estimates (Meier et al., 2017; Stanton et al., 2012). Satellite passive microwave sensors are the standard data source for the percentage of ice cover and changes in ice extent; however, limitations include coarse resolution of 25-70km and sensitivity to atmospheric perturbations (Kwok, 2002). Additionally, there are summer melt-seasonal limitations to the accuracy of sea ice
concentration because conditions over the footprint of the radiometers are dominated by variability in phase changes and increasing salinity (Arkus & Cavalieri, 2009).

Synthetic Aperture Radar (SAR) is a less-used, alternative data source for surface conditions and ice cover which relies on active microwave sensors. Backscatter signals from transmitted microwave pulses generated by SAR sensors on satellites can create high resolution (5 – 100m pixel size) sea ice images. Such images can provide reasonable temporal resolution and high spatial resolution coverage of ice surface structure in most atmospheric conditions, including dark or cloudy conditions (Comiso & Kwok, 1996; Pichierri & Rabus, 2018). SAR sensors send dual-polarized microwave signals to the Earth’s surface and measure the polarized-complex signal return. Unlike longwave radiation, SAR microwave signals have a wavelength much longer than particles in clouds and are therefore not impacted by cloud cover. SAR return signals are used to create backscatter images over wide (100km) swaths as the satellites transit overhead. In these images, smooth, calm water appears black because less of the signal is back-reflected to the satellite. Rough topography, like ice, appears gray or white because these surfaces reflect more of the signal to the satellite receiving antenna—objects with wavelengths close to the transmitter signal (10cm wavelength) backscatter brightly. For example, wind-roughened water backscatters enough of the signal back to appear as ice, and frost flowers on thin, new ice also backscatter brightly to appear as if it is thick multiyear ice. Because of this, SAR image interpretation is not directly comparable to visible imagery interpretation, making it challenging to determine ephemeral features, like melt ponds and frost flowers, from open water and ice.

While there are other more deterministic sources of sea ice conditions, like satellite and airborne visible imagery, SAR data is far more systematically available for analysis, works in low light and dark conditions, is unaffected by cloud cover, has a high spatial resolution, and does not have the same summer limitations as passive microwave data (Kwok, 2002). Combining these remote sensing data with ocean measurements and atmospheric model reanalysis estimates makes it possible to assess the solar radiative heat partitioning in the upper ocean. A deep basin, without coastal influences, is an ideal location for assessing the temporal and spatial variability in how ice cover affects solar radiation adsorption. This study aims to compare predicted incoming heat with upper ocean structure by constructing a simple, 1D heat budget using drifting buoy instruments in the Canada
Basin, model reanalysis surface heat flux estimates, and satellite-derived open water fraction (OWF) estimates. How heat budgets differ between active and passive microwave-derived OWF are used to assess the practicality of SAR as a source for OWF data in the summer.
DATA SOURCES

A range of satellite, model, and in situ observations were combined to construct a vertical 1D heat budget during the summer melt season. Satellite observations consisted of active and passive microwave data to estimate the percentage of ice cover in the study region. Model observations consisted of European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis data over the study region, including surface solar radiation, air temperature, and wind information. In situ observations were made from a cluster of autonomous platforms embedded in ice floes that encompassed GPS location, atmospheric measurements, ice temperature measurements, and ocean hydrographic profiles.

As part of a multi-faceted Office of Naval Research (ONR) sponsored Stratified Ocean Dynamics in the Arctic (SODA) experiment, ice-based autonomous instrument platforms were deployed in the Fall of 2018 in the Beaufort Sea (Lee et al., 2016). Three clusters of instruments were deployed on ice floes (see Table 1 for the deployment details of each cluster). In each cluster, two platforms collected data used in this study, the Ice Tethered Profilers (ITP) and the Weather, Wave, Ice Mass Balance, and Ocean (WIMBO) drifters. The ITPs, designed and deployed by the Woods Hole Oceanographic Institution, collected oceanographic profile observations. The WIMBOs, deployed by the British Antarctic Survey, collected atmospheric and ice observations. Each platform was installed approximately 100m from the other in the same ice floe (Figure 2). Each reported their data remotely using a satellite link and included GPS location.

Table 1. ITP Deployment Details.

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Buoy</th>
<th>Deployment Date</th>
<th>Deployment Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ITP 105</td>
<td>6 October 2018</td>
<td>80° 8.2 N, 141° 43.9 W</td>
</tr>
<tr>
<td>2</td>
<td>ITP 104</td>
<td>3 October 2018</td>
<td>80° 31.9 N, 136° 39.0 W</td>
</tr>
<tr>
<td>3</td>
<td>ITP 103</td>
<td>1 October 2018</td>
<td>78° 53.3 N, 134° 52.4 W</td>
</tr>
</tbody>
</table>
Figure 2. Aerial image of Cluster 2 instruments being deployed October 2018. The ITP (circle) and the WIMBO (square) are at least 100m apart (not measured). USCG Cutter Healy is on the edge of the floe. Image is for conceptualizing and not scaled—photo credit: Martin Doble.

**SEA ICE DATA**

There are two categories of sea ice properties used in this study. One is the basal ice depth and total thickness, measured adjacent to each WIMBO buoy, and the second is the ice concentration over a large area surrounding each buoy cluster, which is derived from remote sensing. An Ice-Mass-Balance (IMB) sensor near each WIMBO used a vertical string of temperature sensors with 2cm spacing. From this sensor, ice base depth and ice thickness time series were calculated (J. Wilkinson, personal communication, 2019). These measurements were smoothed over one day to reduce discretization noise from the hourly-sampled data (Figure 3).
Figure 3. One-day smoothed basal depth time series, measured by WIMBOs, where the y-axis represents the distance below the ice surface for each cluster. Cluster 1 (blue) data ends before the melt season begins. Cluster 2 (orange) and Cluster 3 (green) show when ice growth ends, and melt begins seen around DOY 150 when ice depth is at a maximum.

This study uses two independent sources for ice concentration estimates of the icepack around each buoy cluster. The first sea ice concentration estimate is derived from SAR overpass data. Following the buoy clusters’ deployment in 2018, the Center for Southeastern Tropical Advanced Remote Sensing (CSTARS) facility arranged high-resolution Cosmo-SkyMed and TerraSAR/TanDEM-X targeted SAR GeoTIFF captures around the clusters. SAR GeoTIFF capture properties are variable and dependent on the satellite’s look angle and orientation during the image swath capture. Ice mask GeoTIFFs were hand-developed from these targeted captures by the CSTARS facility (J. Hargrove, personal communication, 2020). An ice mask is a binary representation of a GeoTIFF image.
where each pixel has been categorized as ice or open water (Figure 4). Each GeoTIFF ice mask’s coverage area was varied between two sizes, covering roughly 40x40km or 150x150km. Each pixel covers approximately a 20m square. These data were calculated from the geo-referenced brightness data for each pixel. Since there is no robust method to determine the presence of melt ponds or their properties, melt ponds large enough to be detected (at least greater than 20x20m) are considered open water in the SAR images.

![Figure 4. Raw GeoTIFF image (left) and the corresponding ice mask (right) over Cluster 2 on 25 August 2019. The raw image in the left panel shows gray textures on the ice floes, and the ice mask on the right panel shows a binary representation without the grayscale texture.](image)

The second source for ice concentration estimates was from the Special Sensor Microwave Imager (SSMI) radiometer and sea ice concentration products from the NASA National Snow and Ice Data Center (NSIDC) Distributed Active Archive Center (Cavalieri et al., 1996). This data product used passive microwaves to provide daily-averaged sea ice concentration in 25x25km grid resolution in the form of an ice concentration (Ivanova et al., 2015). The closest proximity 25x25km grid square to each ITP location daily was extracted from the gridded SSMI data fields using a MATLAB routine (W. Shaw, personal communication, 2019) to estimate the buoy clusters local ice concentration.
ATMOSPHERIC DATA

Shortwave downwelling solar radiation estimates from the ECMWF Reanalysis Atmospheric Model (ERA5) (Hersbach et al., 2018) were used as the primary observations of shortwave downwelling radiation incident on the surface of the ice from 70-90 degrees North for all longitudes, in half-hourly averages, for 2019. ECMWF reanalysis estimates of 10m wind speed and direction were used to infer local wind conditions and verify the WIMBO wind measurement at 2m above the ice.

OCEANIC DATA (TEMPERATURE, CONDUCTIVITY, AND PRESSURE)

ITPs sampled temperature (T), conductivity (C), and pressure (P) from approximately 7m to 760m depth (Krishfield et al., 2008; Toole et al., 2011) (Figure 5). The raw data for ITP 103, ITP 104, and ITP 105 was retrieved from the Woods Hole Oceanographic Institution (2019, 2020a, 2020b). This data included one-way profile data of T (°C) and C reported at 2dbar pressure increments at approximately three-hour intervals and SBE-37 microcat surface measurements of temperature and salinity at a fixed depth of 5m or 6m.
Figure 5. Ice-Tethered Profiler Schematic (Toole et al., 2011) shows the surface buoy positioned on top of an ice floe and the crawling profiler, which measures temperature, pressure, and conductivity installed at each cluster. The profiler takes measurements every 2dbar as it crawls up and down the mooring wire from ~8m deep to 800m deep every six hours.
METHODS

CONSTRUCT A SIMPLE 1D HEAT BUDGET

These data can be used together to form a heat budget of the upper ocean by expanding Eq. 1 with the heat flux source and sink terms into:

\[ R_{\text{residual}} = Q_{\text{rad-ow}} + Q_{\text{ml}} + Q_{\text{th-ice}} + Q_{\text{cond}} \quad (J \ m^{-2}) \quad \text{Eq. 2} \]

where the Residual is informative of one or more unknown terms by subtraction, \( Q_{\text{rad-ow}} \) is the time integral shortwave flux input through open water, \( Q_{\text{ml}} \) is ocean heat content, \( Q_{\text{th-ice}} \) is the time integral of latent heat flux loss of basal ice melt, and \( Q_{\text{cond}} \) is the time integral of the ocean to ice conductive heat flux. The sign convention is that incoming shortwave radiation is positive, and the heat content and the latent heat flux loss are negative. Ice conductance is negative when the ice surface is cooler than the bottom and positive when it is warmer than the bottom.

The known source term included is the cumulative shortwave radiation through open water (\( Q_{\text{rad-ow}} \)), and the following not-included terms are the latent and sensible heat from the atmosphere, downwelling longwave radiation incident on the ice and ocean surface, and vertical diffusive heat from the pycnocline at the base mixed layer. Heat exchanges from longwave radiation balance are assumed to be small and sensible, and latent heat changes between air and water are assumed to be small due to the high ice concentration. Vertical diffusive heat fluxes during the solar season are also assumed small (~0.1–1.5 W m\(^{-2}\), Perovich et al., 2003; Perovich & Elder, 2002; Shaw et al., 2009) and not included following Gallaher et al., 2016. The known sink terms are ocean heat content (\( Q_{\text{ml}} \)), latent heat losses (\( Q_{\text{th-ice}} \)), and ocean to ice conductance (\( Q_{\text{cond}} \)) and are included in the budget. The temporal frame for this heat budget extends from early summer just before the upper ocean begins to accumulate heat on 10 May 2019 (year day 130), well before basal ice melts, and ends when the ITP profile data stops reporting on 29 August 2019 (year day 241) for Cluster 1 and 2, and 27 July 2019 (year day 208) for Cluster 3.
OPEN WATER FRACTION – SSMI

Open water fraction from the satellite radiometer SSMI was calculated by subtracting the ice concentration from one:

\[
OWF_{ssmi} = 1 - \text{concentration (fractional percent)} \tag{Eq. 3}
\]

Since the SSMI 25x25km grid is larger than the SAR radius used (15km), the daily SSMI-derived concentration used to represent the clusters’ ice conditions is the closest grid point to the ITP position (i.e., there is no spatial averaging). The daily averaged SSMI ice concentration values were linearly interpolated using the MATLAB interp1 function to the half-hourly ECMWF reporting times.

OPEN WATER FRACTION – SAR

The closest TerraSAR/TanDEM-X SAR gridded-field data was matched with ITP locations over each cluster for the time series. Twelve ice masks from Cluster 1, five ice masks from Cluster 2, and three ice masks from Cluster 3 were excluded for having a low-pixel count from the ITP location being close to the image edge. Often not centered in an image, the geographic position of each pixel was used to identify the location of the ITP in each GeoTIFF (red asterisk in Figure 6), and the pixels within a 15km radii circle were identified. When the ITP location was not centered, some of the 15km-radii circle extended beyond the data (shown in the Masked Image in Figure 6) because most ice masks covered a 40x40km area. To capture local conditions as best as possible, ice masks where more than 80% of the circle extended beyond the data were excluded (Table 2).

Table 2. Ice Mask Counts per Cluster & Close-to-Edge Exclusions.

<table>
<thead>
<tr>
<th>Tiff Image/Ice Mask File Counts</th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Useable within seasonal timespan (DOY 130-241)</td>
<td>27</td>
<td>30</td>
<td>18</td>
</tr>
<tr>
<td># Images with 80% of zoomed circle inside</td>
<td>15</td>
<td>25</td>
<td>15</td>
</tr>
</tbody>
</table>

OWF was calculated by adding up the number of ice-designated and water-designated pixels of each ice mask radially masked around a buoy, visualized in Figure 6, using:

\[
OWF_{SAR} = \frac{\text{water}}{\text{water} + \text{ice}} (\text{fractional percent}) \tag{Eq. 4}
\]
where water is the sum of water-designated pixels within a 15 km radius, and ice is the sum of the ice-designated pixels within the same radius, centered on the closest ITP position and time match. Unless the ITP location matched a pixel location near the center of an image, the 15km radii were likely to extend outside the image.
Figure 6. Example of the SAR image center and zoom method on DOY 234 at Cluster 2. (a) The full ice mask rotated into North-East space. A red asterisk marks the ITP location, and a red circle marks the 15km radius. Note that part of the circle is outside the image. The masked version (b) shows the pixels used to determine OWF within the 15 km radius. In this example, note that the pixels used are not a full circle since the radius fell outside the image.
Cluster 1 had OWF available approximately every seven days, and Clusters 2-3 yields SAR OWF estimates approximately every four days during the melt season. To align the calculated OWF with the ECMWF incoming shortwave solar fluxes, the OWF estimates were linearly interpolated using the MATLAB interp1 function to the half-hourly ECMWF data. Detailed steps of this analysis process are described in Appendix A.

**Cumulative Radiation Through Open Water**

The cumulative shortwave radiation, source term, through open water was calculated using the time integral of a flux:

\[
Q_{rad-ow} = \int F_{rad-ow} \, dt \quad (J \, m^{-2})
\]

Eq. 5

where \( dt \) is the difference between ECMWF time samples \([s]\) (~30 minutes) and \( F_{rad-ow} \) is the amount of incident shortwave flux entering the ocean through open water modulated by the albedo of open water and the local fraction of open water, calculated using SAR and SSMI estimates of OWF following Gallaher et al., 2016:

\[
F_{rad-ow} = F_{rad} A_{ow} [1 - \alpha_{ow}] \quad (W \, m^{-2})
\]

Eq. 6

where \( F_{rad} \) is ECMWF SWD irradiance at the surface \([W \, m^{-2}]\), \( A_{ow} \) is the area of open water around a buoy cluster (derived from SAR or SSMI), and \( \alpha_{ow} \) is the albedo of open water (0.05).

**ITP Upper Ocean Heat Integration**

The mixed-layer heat content (first sink term) relative to the freezing temperature was calculated using ITP data by integrating the in situ temperature from the base of the mixed layer to the surface (Gallaher et al., 2016; Timmermans et al., 2018) using:

\[
Q_{ml} = c_{p,w} \rho_0 \int_{z_2}^{z_1} T_{ml}(S, P) \, dz \quad (J \, m^{-2})
\]

Eq. 7

where \( c_{p,w} \) is the specific heat capacity of seawater (~3986 \( J \, kg^{-1}C^{-1} \)), \( \rho_0 \) is the reference (surface) density of seawater (~1023 \( kg \, m^{-3} \)), \( z_2 \) is the lower limit (isopycnal at the base of the mixed layer, m), \( z_1 \) is the upper limit (shallowest temperature and salinity observation, m), and \( T_{ml} \) is the temperature of the mixed layer (°C) calculated using:
\[ T_{ml} = T - T_f \quad (°C) \]  
Eq. 8

where \( T_f \) [°C.] is the freezing point of seawater (Fofonoff & Millard, 1983) calculated by:

\[ T_f = a_0 + a_1 S^{3/2} + a_2 S^2 + bP \]  
Eq. 9

where \( a_0 \) is -0.0575, \( a_1 \) is 1.710523, \( a_2 \) is -2.154996, \( b \) is -7.53, \( S \) is the measured salinity in the pressure bin above the pycnocline (\( z_2 \)), and \( P \) is the measured pressure at the pycnocline (dbars).

The 2m binned ITP data was edited to exclude null values and add single point T/S data from the Microcat measurement made above the upper profiling limit. Profile data up to the ice was extrapolated from the shallowest observation to the surface (2dbar depth bin). For details, see Appendix B. The methodology for determining the depth of the pycnocline (lower limit of integration, \( z_2 \)) follows Albee (2019) and Gallaher et al. (2016). This depth of the mixed layer base is identified using a density offset from the mean surface density. At the beginning of the time series (winter conditions), the threshold for the change in density (\( \sigma \)) used is 0.3. Different \( \sigma \) thresholds were selected as the melt season progressed to identify the depth of the mixed layer. As the melt season evolves, heat and meltwater input alters the density properties near the surface. The density difference between the surface and the pycnocline at the base of the mixed layer differ in time, even though the depth of the mixed layer remains relatively consistent, which drives different \( \sigma \) offset selections. The day of the year (DOY), change in \( \sigma \) threshold, and the time frames for using each threshold are summarized in Table 3. While the pycnocline depth remained relatively constant, there were slight changes throughout the season as the buoys drifted over different water masses.
Table 3. Density thresholds used to track the winter pycnocline.

<table>
<thead>
<tr>
<th>Day and Threshold</th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOY</td>
<td>175</td>
<td>166</td>
<td>152</td>
</tr>
<tr>
<td>Δ σ threshold</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>DOY</td>
<td>191.5</td>
<td>195</td>
<td>180</td>
</tr>
<tr>
<td>Δ σ threshold</td>
<td>0.4</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>DOY</td>
<td>211.5</td>
<td>216</td>
<td>184.5</td>
</tr>
<tr>
<td>Δ σ threshold</td>
<td>0.8</td>
<td>0.8</td>
<td>1.0</td>
</tr>
<tr>
<td>DOY</td>
<td>218</td>
<td>223</td>
<td>201.5</td>
</tr>
<tr>
<td>Δ σ threshold</td>
<td>1.0</td>
<td>1.1</td>
<td>1.2</td>
</tr>
</tbody>
</table>

**Basal Ablation**

Basal ablation ($Q_{th_{ice}}$) quantifies the transfer of heat from the ocean to the latent heat of fusion melting the ice and assumes that the change in ice thickness is spatially uniform around each ITP. To determine the heat contribution to melting the bottom of the ice floe, the latent heat of ice, the second sink term, was calculated using:

$$Q_{th_{ice}} = q_{th} \rho_{ice} \Delta z_{ice} \ (J \ m^{-2})$$  \hspace{1cm} Eq. 10

where $q_{th}$ is the latent heat of fusion for sea ice ($3 \times 10^5 \ J \ kg^{-1}$), $\rho_{ice}$ is the density of sea ice ($910 \ kg \ m^{-3}$) (Perovich 2005, Shaw et al. 2009), and $\Delta z_{ice}$ is the change in ice thickness [m]. Both $q_{th}$ and $\rho_{ice}$ are constants for ice that is at least second-year and uniform density. The change in ice thickness was determined using:

$$\Delta z_{ice} = \text{diff[mean ice depth]} \ (m)$$  \hspace{1cm} Eq. 11

and a starting value for basal ice depth was chosen by looking at the ice depth maximum for each cluster (Figure 3) to capture summer basal ablation only (not winter growth). The depth was relatively flat (no ice growth or melt apparent) for Cluster 2 and 3 around 30 May 2019, and subsequently, the starting melt date of DOY 150 was chosen.

**Ocean-Ice Thermal Conductance**

The cumulative ocean-ice thermal conductive flux is a sink term when the ice is cooler than the ocean and can be a source term if the upper portion of the ice is warmer than the bottom portion. Conductance was calculated using the time integral of the conductive flux:

$$Q_{cond} = \int (\kappa_{ice} \ \frac{\partial T}{\partial n}) \ ds \ (W/m^2)$$  \hspace{1cm} Eq. 12

where $\kappa_{ice}$ is the thermal conductivity of ice, $T$ is ice temperature, and $n$ is the normal vector to the ice surface. The surface temperature was obtained from SAR data analysis.
\[ Q_{\text{cond}} = \int F_{\text{cond}} \, dt \quad (J \, m^{-2}) \quad \text{Eq. 12} \]

where \( dt \) is the difference between ice temperature time samples [s], and \( F_{\text{cond}} \) is the conductive flux, calculated using Fourier’s law of thermal conduction following (Pringle et al., 2006):

\[ F_{\text{cond}} = k_{\text{ice}} \times \frac{dT}{dz} \quad (W \, m^{-2}) \quad \text{Eq. 13} \]

where \( k_{\text{ice}} \) is experimentally measured thermal conductivity of multiyear ice (1.88 \( W \, m^{-1} K^{-1} \)) and \( \frac{dT}{dz} \) is the temperature gradient over 20cm from the base of the ice calculated using the ice temperature string from the WIMBO buoy. To exclude sensor measurements at the surface, in the air, or the ocean, top and bottom averages were compared to form a criterion to locate the temperature sensors at the bottom of the ice. The average ocean temperature was calculated by taking the average of the last meter of measurements, seen at depths below 3m (Figure 7), where the temperature is nearly constant. The average surface temperature was taken from 0.8-1.2m from the surface sensor, avoiding possible air temperature or snow measurements. If the average surface temperature was less than the ocean temperature, the profile was considered a winter case; otherwise, it was considered a summer case. Basal depth location was identified based on this criterion and by locating the sensor where the temperature measurement was cooler than ocean temperature for the winter case and warmer than the ocean temperature for the summer case. Ten consecutive temperature measurements starting 10cm above the basal depth were used to calculate the near-ocean ice temperature gradient (Figure 7, Figure 8). The gradient was calculated using the MATLAB polyfit function that calculates the slope or gradient using a least-squares fit method. A despike function was used to remove outliers (Figure 8).
Figure 7. (a) Ice temperature profiles at Cluster 2 averaged weekly for the study period (DOY 130-240), where lighter colors represent earlier in the season and the darker colors represent the end of the season. Temperature measurements are seen from ~0-2.8m, where 0 denotes the top of the thermistor, measuring air temperature. The temperature string measured ocean temperatures approximately 2.8m below the surface and deeper, seen as straight-line profiles. (b) The IMB temperature profile on DOY 207 shows a basal temperature gradient of -0.5 °Cm⁻¹. The green asterisk represents the algorithm-located basal depth, and the blue asterisks represent the data used to determine the temperature gradient.
Figure 8. The temperature gradient from the ice base to 20cm up from the ice base at Cluster 2 for the 2019 solar season. Short-term fluctuations represent noise in measurements combined with sampling method limitations.
RESULTS

The buoy clusters deployed in the Fall of 2018 remained in the northeastern Canada Basin through the summer of 2019. During this time, Clusters 1 and 2 drift trajectories did not follow the Beaufort Gyre circulation pattern and remained in a region of known near-permanent pack ice. The drift trajectory for Cluster 3 followed the circulation pattern of the Beaufort Gyre over the Canadian shelf, causing the ITP to capture a range of mesoscale shelf structures. The trajectories seen for Cluster 1 and 2 show them in the deep basin during the analysis period (Figure 1), indicating that the measurements are geographically isolated from regions where the heat content of the mixed layer can be dominated by advective heat sources from shelf interaction or water masses. Cluster 3 did not have measurements over a deep basin, so it was not used in this 1D heat budget study. The vertical 1D heat budget results are based on Cluster 2 due to data availability. Cluster 1 lacks data to compute basal melting, a large sink term in the budget; however, some data from Cluster 1 was used as validation for similarity to understand the results seen around Cluster 2 due to the geographic similarities between the two throughout the summer.

EVOLUTION OF THE PYCNOCLINE AT THE BASE OF THE MIXED LAYER

ITP profiles from Cluster 2 of temperature, salinity, and depth show a strong salinity-dominated stratification throughout the study period (Figure 9), resulting in a dynamically isolated surface mixed layer. The pycnocline location, marked by black dots in Figure 9, is at depths around 55m early and mid-way through the melt season and remains intact but with increasing depth variations of +/- 10m later in the time series. The change in surface conditions becomes apparent around DOY 170 when the summer halocline decouples the surface from the remaining mixed layer around 20m depth as expressed in the formation of a near-surface warm layer. The winter structure of the mixed layer can be seen earlier in the profiles in Figure 9 around DOY 140.
Figure 9. Temperature (a) and Potential Density ($\sigma_\theta$) (b) profiles for Cluster 2 during the 2019 solar season with depth on the y-axis. Black dots denote the integration depth used to calculate $Q_{ML}$. (a) Color scaling is zoomed in to highlight the separation of the cooler mixed layer (0-55m) and the warmer layer below the pycnocline (55-100m). (b) The density anomaly shows stratification is driven by salinity.

**WATER MASS ENCOUNTERS**

Cluster 2 T/S properties (Figure 10) retain a similar shape throughout the melt season but shift vertically as the season progresses in response to warming and the fresh layer formation. Overall, the T/S plots indicate that Cluster 2 buoys encountered similar water masses during the analysis period, supporting a 1D budget in this region and study period. Near-vertical density contours (Figure 10, black dotted lines) indicate that the salinity dominates stratification. Water masses present at the beginning of the study (i.e., DOY 130 – 140) are like the masses at the end of the study (i.e., DOY 220 –250), differing primarily in
temperature. Near freezing conditions are briefly present at the beginning of the time series in early May.

Figure 10. Cluster 2 T-S Diagram of the ocean mixed layer down to the integration depth used in the heat content calculation. Contour lines represent the density anomaly $\sigma$ (kg m$^{-3}$) at pressure $P$ (dbar). The color axis is time for the 2019 solar season, and the dashed blue line indicates the freezing point. Early in the season, the temperature is near freezing, and seasonal warmer temperatures reside below the cooler, fresher layer at the surface.

**HEAT IN THE MIXED LAYER**

Evolving heat storage in the mixed layer (sink #1) is shown as $Q_{ML}$ (Figure 11a), which is the heat content between the base of the mixed layer (located by black dots in Figure 11b) to the surface. Within the summer analysis period, $Q_{ML}$ increases to 39 MJ m$^{-2}$ by early August. By late August (after DOY 235), there is a cooling and melting event where $\approx$9 MJ m$^{-2}$ is lost from the summer halocline layer (Figure 11a). This cooling and
melting are seen after a mild two-day wind event followed by eroding of the surface stratification, a surge in basal melting, and a drop in the near-surface temperature. Short-term heat content changes seen in $Q_{\text{ML}}$ (Figure 11a) are reflected as noise in flux estimates in the 1D model, driven by a combination of instrumentation noise, the method used to determine the mixed-layer base, and changes in the mixed layer depth as the ITP drifts over slightly different water masses. The seasonal increase of $Q_{\text{ML}}$ is a more accurate representation of the heat distribution during the summer cycle. An example drift through a different water mass is shown in Figure 12 by vertical profiles of $T$ and $S$ where the pycnocline depth changed (asterisks), and the upper ocean structure (15-25m) shows an NSTM.
Figure 11. Timeseries of the (a) Cumulative heat sink due to storage in the ocean mixed layer where gray dots represent the unfiltered values, and the blue line represents a 10-day mean and (b) vertical temperature profiles at Cluster 2 show increased temperatures as it accumulates heat throughout the solar season. Black dots represent the QML integration depth. The zoomed-in temperature color scale highlights the heat trapped below the winter pycnocline throughout the melt season. The last five days (DOY 235-240) show a cooling in the upper 20m (b) seen by a darker temperature color and an increase in QML (a) from -36 MJm$^{-2}$ to -30 MJm$^{-2}$.
Figure 12. T and S profiles before, during, and after a dip in $Q_{ML}$ around DOY 210. Note the DOY 209.5 profile between 15-25dbar that there is a temporary increase in T and S, seen in the cross-hatched area. Above the winter pycnocline, the profiles are similar before and after the dip in $Q_{ML}$.

**BASAL MELTING**

At the beginning of this analysis period, basal ice depth remains relatively constant; no ice growth or melting is indicated. As the ice begins to melt (~DOY 150 or 30 May), the basal ice depth decreases (Figure 13a). The seasonal heat attributed to melting ($Q_{LH}$ in Figure 13b) is -59.0 MJ m$^{-2}$, with -15 MJ m$^{-2}$ contributed during the last five days. The last five days of the time series coincide with a mild wind event in Figure 14. Ice base depths (Figure 13a) show short-term changes that, when translated to the basal melt term, $Q_{LH}$, appear as bursts of ice growth or melt. This noise is a symptom of the sampling method and
measurement limitations and does not represent actual conditions because basal temperatures remain above freezing for this study period.

Figure 13. Cluster 2 ice basal depth and melt time series. (a) Depth of the ice floe in the ocean, determined by through-ice temperature measurements from WIMBO 4. Maximum thickness was 1.35m with a seasonal loss of 0.20m (b) Cumulated latent heat of fusion contribution to basal melting. In both panels, gray dots represent raw values, and the blue and yellow lines represent 5-day smoothed values.
Figure 14. Reanalysis (ECMWF) and observed (WIMBO) wind speed at Cluster 2 during August 2019. ECMWF (blue) 10m wind speed compared to WIMBO (orange) 2m measured wind speed both indicate mild wind events in August around year day 225 and 235. Note the good agreement between the WIMBO point measurements and the 28km grid-averaged wind estimate.

**OPEN WATER PARTITIONING OF SOLAR RADIATION**

Over the study period, 5000 MJ m$^{-2}$ of shortwave radiation accumulated at Cluster 2 (Figure 15). Satellite radiometer estimates of open water generally detect a higher OWF percentage than SAR-derived estimates (Figure 16a). OWF is zero for both SAR and SSMI until after DOY 140 (20 May 2019), followed by a considerable disagreement between SSMI and SAR OWF estimates during year days 180-210 (29 June-29 July 2019). SSMI estimated that 140 MJ m$^{-2}$ of heat is input through open water, while SAR estimated a total of 43.7 MJ m$^{-2}$ (Figure 16c). Shortwave-down estimates are reasonably close to incident measurements taken at the WIMBO (not shown) and are considered a valid representation of local values.
During year days 180-210, when the differences were most notable, original SAR images and their matching ice mask were visually inspected along with the derived OWF and compared to the SSMI-derived OWF. The SAR-determined OWF is supported by inspecting the raw images as shown in Figure 17 and Figure 18, and it is reasonable to conclude that the areas that appear to be open water more closely match the OWF calculated by SAR than with SSMI (Figure 16, DOY 143, 187, 207, 235).

Figure 15. Seasonal ECMWF incoming surface shortwave estimates. (a) Cumulative incident shortwave on the surface, (b) incident shortwave surface flux, raw (showing diurnal variation), and filtered (showing seasonal variation).
Figure 16. SAR (orange) and SSMI (blue) (a) Estimated open-water in a 15km radius around the ITP. Considerable disagreement between SAR and SSMI appears during year days 180-205. (b) The open-water modulated incoming shortwave down flux determined by SAR and SSMI, and the (c) Cumulative incoming shortwave down modulated by open water fraction. The differences in open water fraction seen in (a) are amplified, showing the seasonal impact to heat that directly entered the upper ocean.
Figure 17. Original SAR images (a and c) and the matching binary ice-water image (b and d) used to calculate OWF for Cluster 2. A red asterisk marks the ITP location at capture time with the 15km radius around the ITP shown in the red circle. Examples here are of early season (a) and (b) and mid-season (c) and (d) SAR captures where an increase of open water can be seen primarily in the ice masks.
Figure 18. Original SAR images (a and c) and the matching binary ice-water image (b and d) used to calculate OWF for Cluster 2. A red asterisk marks the ITP location at capture time with the 15km radius around the ITP shown in the red circle. Examples here are a wide-coverage capture in late July (a) and (b) and a higher-resolution capture at the end of August (c) and (d). Note the difference in resolution between a SAR capture covering a larger area in (a) and (b) versus the smaller area seen in (c) and (d).

**SEASONAL HEAT BUDGET**

This local budget shows that heat input was partitioned evenly between basal melting ($Q_{LH}$) and ocean heat storage ($Q_{ML}$) until the mild mixing event in late August when basal melting accounted for roughly 2/3rds of the seasonal heat sink (Figure 19, Figure 20). The
seasonal total solar input through SSMI-determined OWF (138.6 MJ m\(^{-2}\)) accounted for the combination of basal melting (-59.0 MJ m\(^{-2}\)), upper ocean heat storage (-32.3 MJ m\(^{-2}\)), and ice conductance (-14.5 MJ m\(^{-2}\)) measured at Cluster 2 by the end of the summer melt season, with a residual surplus of 33.3 MJ m\(^{-2}\) (Figure 19).

Figure 19. Sources and sinks to the overall budget for summer 2019 using SSMI-estimated OWF shortwave down input. Blue is direct open water short wave down cumulated heat input (source #1), orange is cumulated heat storage in the mixed layer (sink #1), yellow is basal melting (sink #2), and purple is ocean-ice conductance (sink #3 and source #2). The black line represents the sum of the terms (residual). Lines for sink terms represent filtered values, and gray dots represent their unfiltered values.

Comparing the SAR heat prediction of incoming shortwave down solar radiation (source #1) to the ocean mixed-layer heat storage (sink #1) and basal melting (sink #2), and conductance (sink #3 and source #2), there is a negative residual using SAR-determined open water fraction (Figure 20) with the solar input accounting for 42% of the sink terms. Early in
the season, the conductive sink largely contributed to the negative residual before the detected onset of basal melt and heat storage after DOY 160. This simple budget is designed to be a lower bound estimate of the incoming heat and, as such, the heat sink terms would be greater than the heat source; however, the magnitude of the residual (-62 MJ m$^{-2}$) indicates the presence of another heat source.

Figure 20. Sources and sinks to the overall budget for summer 2019 using SAR-estimated OWF shortwave down input. Blue is direct open water short wave down cumulated heat input (source #1), orange is cumulated heat storage in the mixed layer (sink #1), yellow is basal melting (sink #2), and purple is ocean-ice conductance (sink #3 and source #2). The black line represents the sum of the terms (residual). Lines for sink terms represent filtered values, and gray dots represent their unfiltered values.
DISCUSSION

This study has provided an opportunity to compare two methods of estimating ice coverage in the Beaufort Sea. OWF estimates differ notably between SAR and SSMI mid-to-late melt season (Figure 16a), in the likely absence of snow cover when satellite radiometers are expected to have difficulty in detecting sea ice. Due to the brightness temperature dependency on salinity and ice surface temperature during phase changes (ice/water), the radiometric signature is sensitive to errors during seasonal variability (Ivanova et al., 2015; Kern et al., 2016). The known limitations with using SAR to derive ice concentration are spatial resolution and possible misclassification while generating binary ice masks that identify open water pixels. SAR image pixel resolution can cause errors if ice floes are smaller than the resolution (~20x20m). However, classification confidence is high for the binary ice masks used in this study because they are generated by inspection of pixel intensity probability distributions for each image (J. Hargrove, personal communication, August 2020). While there are sources of bias in both, SAR is believed to be more accurate than SSMI based on visual inspections of the raw images and the binary ice masks (Figure 17, Figure 18), the known limitations of SSMI, and importantly in this study, the sign of the residual from the seasonal heat budget (Figure 19, Figure 20).

Using SSMI estimated OWF in the 1D budget (Figure 19) suggests SSMI significantly over-estimated OWF and, therefore, the solar radiation entering the ocean mixed layer. Since this heat budget is intended to represent the lower bound of the solar radiation entering the system, as it does not account for through-ice or melt pond transmitted radiation, it is reasonable to argue that SSMI consistently overestimated ice concentration for the mid to late 2019 melt season. In contrast, when using SAR-estimated OWF in the 1D budget, the result is a negative residual (Figure 20), indicating the presence of additional heating sources. The seasonal total solar input through SAR-determined OWF (43.7 MJ m\(^{-2}\)) accounted for 42% of the combination of basal melting (-59.0 MJ m\(^{-2}\)), upper ocean heat storage (-32.3 MJ m\(^{-2}\)), and ice conductance (-14.5 MJ m\(^{-2}\)) measured at Cluster 2 by the end of the melt season, with 58% (-62.0 MJ m\(^{-2}\)) remaining to an additional source term (Figure 21). Additional sources of heat that could be responsible for this residual are lateral flux
gradients not included in the 1D budget and through ice and melt pond solar contributions. However, given that the region in this study is generally isolated from mesoscale structures and is in a region of near-permanent pack ice, the residual heat is likely local through-ice transmittance.

To investigate transmission as another source, the seasonal residual was first converted to a seasonal flux [W m\(^{-2}\)] at the 6-hour ITP time sample interval and averaged into 15-day block means (Figure 21a). Contributions to the variability seen in the raw residual flux (Figure 21a) include noise from measured data and the time-varied ocean integration volume. From the residual flux 15-day block mean, the transmission was calculated using:

\[
Transmission = \frac{F_{rad}}{F_{res}}
\]

where \(F_{rad}\) is the ECMWF SWD irradiance at the surface [W m\(^{-2}\)] and \(F_{res}\) is the residual flux [W m\(^{-2}\)]. The transmission encompasses the combined contributions of bare or melting ice and ponded ice. When translating the budget residual to a transmission time series, the seasonal values range from 0.018-0.05 (Figure 21b). When comparing to \textit{in situ} transmittances, Light et al. (2015) observed 0.04-0.25 for bare ice measured in 2010 and 2011 in the Southern Beaufort Sea. The inferred transmittance values are on the low end of Light’s observations, but this could be attributed to the Cluster 2 higher latitude where the angle of solar radiation is lower, and the shortwave down is spread over a larger area as well as the local ice having different optical properties affecting scattering and transmission. Additionally, transmittance was low at the beginning of the season and increased throughout, with two distinct dips (Figure 22b). These dips may be associated with melt pond drainage events like those observed by Gallaher et al. (2016); however, there is no data to confirm this. As melt ponds are known to transmit more solar radiation than bare ice, the increase in transmission could indicate pond formation, and the dip in transmittance around DOY 200 could indicate a pond drainage event. While timing is not exact each year, as soon as the surface air temperatures cool from summer high values and wind is present in late summer, sensible heat loss from the ocean to the atmosphere increases and becomes an additional sink term. The air surface temperature cooled (Figure 11b), and the wind increased (Figure 14) on DOY 235, indicating that at the end of the data series, sensible heat loss likely contributed to the budget and related to a decline in transmittance at the end of the season (Figure 21b).
Since sensible heat loss is not a factor until the last few days of the season, including it in the budget would likely obscure the seasonal transmittance result. Given that the hypothetical ice radiation transmission is within a range of measured values with similar ice thickness, it is plausible that the SAR residual budget represents reasonable transmission values for this solar season in the Northern Beaufort Sea.

Figure 21. (a) Residual heat flux from the 1D budget using SAR-derived OWF. The blue dotted line represents the calculated residual flux, and the black line with circles represents the 15-day mean of those values. (b) Cluster 2 15-day running mean inferred transmittance calculated from the 1D budget residual flux using SAR-derived OWF.

A weakness of the 1D approach is the time-varied integration depth used to determine ocean heat content, which may influence the magnitude of the residual heating source. As the instruments drift over different ocean structures, the upper ocean control volume expands and contracts, appearing as short-term heat gains and losses in the budget. Low pass filtering over ten days better represents the heat storage in the mixed layer. Ocean heating from the
net surface longwave radiation balance and the sensible and latent heat changes between air and water are assumed to be minor due to the small OWF seen in the SAR data, except sensible heat loss during the last five days mentioned earlier. Turbulent heat fluxes from the strong permanent pycnocline into the mixed-layer are also assumed to be minor (~0.1–1.5 W m\(^{-2}\)), as previously determined in other studies (Perovich & Elder, 2002; Shaw et al., 2009). When comparing the magnitude of the 15-day residual flux in Figure 21a (3.8-8.2 W m\(^{-2}\)) to the estimated pycnocline fluxes, it is reasonable to suppose the magnitude of the pycnocline fluxes are minor and not contributing to the overall seasonal trend. The method of choosing the integration depth (i.e., based on a difference from the surface density) is vulnerable to density anomalies encountered when the instruments drift through ocean eddies. However, vertical profiles of the upper 100m show that in the early, mid, and late-season that the pycnocline was consistently identified by this method and suggests that these events do not significantly alter the season-integrated budget (Figure 22). By accurately identifying the pycnocline depth, it is not likely that heat from below the pycnocline was mistakenly included in the budget. Minor pycnocline fluxes and effective determination of time-varied integration depth support the 1D model’s output of an additional heating source and the inferred transmittance.
Figure 22. Cluster 2 vertical T and S representative profiles during the early, mid, and late season. The asterisk represents the identified integration depth to calculate heat content. The early-season (blue dots) and late-season (black circles) profiles show intended pycnocline depth as seen in both profiles, where the asterisk location is at a corner of the profiles. The mid-season (red line) profile shows the pycnocline integration depth in a stratified layer just below the upper layer.

The 1D local budget residual of -62 MJ m\(^{-2}\) further indicates that incoming solar radiation through open water contributed less to observed heat storage and basal melting than determined by previous studies in other, more southerly Beaufort Sea locations (Gallaher et al., 2016; Perovich et al., 2008). Gallaher et al. (2016) found that transmission through ice and melt ponds accounted for 36% of basal melting and upper ocean heat storage in the Canada Basin during the 2014 solar season. Dissimilarities between the budgets that likely impact the difference in partitioning are the ice concentration data source and the magnitude of open water. Gallaher et al. (2016) used 8.3m pixel size TerraSAR-X images to estimate
open water, allowing detection of smaller ice floes than possible in this study. The magnitude of open water was also considerably higher at 30-50% from DOY 190-230 (Figure 6b, Gallaher et al., 2016) compared to this study, where the SAR-estimated OWF was 4-14% (Figure 16a) for the same time frame, resulting in a large difference in cumulated heat. The difference in seasonal ice concentration patterns between the southwest Canadian Basin and the northeastern Canadian Basin likely indicates that transmission and conductive heat flux have a more significant impact on the overall summer ocean heat budgets in regions with higher ice concentration.
CONCLUSIONS

This 1D heat budget is a framework for understanding the partitioning of solar radiation entering the ocean in the Arctic and how the upper-ocean heat gains, either stored locally or contributed to ice melt, are supported for the 2019 solar season in the Northern Beaufort Sea. In the Northwest Canadian Basin during the 2019 summer, the sign of the residual term at the end of the season (Figure 19 and Figure 20) indicates that SAR-derived OWF better represents sea ice concentration than the SSMI-derived OWF. SSMI-derived OWF is insufficient to support the sinks determined in the mixed layer heat budget, suggesting that previous budgets using satellite radiometer OWF estimates to consider the plausibility of basal melting via direct absorption of solar radiation through open water missed other important processes, like through-ice transmission. The budget shows that solar-radiation-influenced ocean heat and basal melting are present in an area with relatively high ice concentrations, but direct absorption through open water is insufficient to account for the seasonal heat storage and basal melt. SAR-derived OWF accounts for 42% heat sinks, and the residual of the 1D local budget supports reasonable estimates of local through-ice transmittance. Between the heat budget in this study and those observed in the seasonal ice zone of the Canada Basin, the local radiative partitioning indicates regional differences between solar season melt processes and suggests that the dominating incoming summer heat source is dependent on the relationship between incident solar radiation and ice concentration. These results highlight the importance of in situ and remote observations across the Arctic to connect ice surface conditions and properties in this region and the need for improved estimates of ice and melt-pond radiation transmittance in regional atmosphere-ice-ocean coupled numerical models in the Arctic.
REFERENCES


Döscher, R., Vihma, T., & Maksimovich, E. (2014). Recent advances in understanding the Arctic climate system state and change from a sea ice perspective: A review. *Atmospheric Chemistry and Physics, 14*(24), 13571–13600. https://doi.org/10.5194/acp-14-13571-2014


APPENDIX A

MATCHING SAR IMAGERY TO ITP LOCATION AND TIME

Position information was extracted from the GeoTIFF and the timestamp from the GeoTIFF filename to match SAR GeoTIFFs to an ITP location and time. The GeoTIFF timestamp was then matched to the closest ITP time and verified that the time difference was less than 0.5 days. From the GeoTIFF pixel information matrix, the latitude and longitude coordinates were extracted from each pixel and converted\(^1\) to polar stereographic position (distance along +90 from the North Pole in meters) for each pixel, and each buoy reported position. The pixel with the closest proximity (and within 500m) to the ITP position nearest to image time was identified and marked as the ITP location in each GeoTIFF. From this location, pixels within a 15 km radius were added into a sum of either water or ice, and from these two, the open water fraction was calculated using Eq. 4. Following this, the final calculation was to linearly interpolate the OWF estimates to ECMWF sample time (~half an hour).

APPENDIX B

ITP PREPROCESSING

The raw ITP data was reduced to exclude null values, exclude data below the mixed later (excluding extra microcat data), and data was added by extrapolating the shallowest observation as a constant from the shallowest observation to the surface (two decibar). To do this, first, NaNs were filtered out of the time vector. Then, microcat measurements that did not match the profiled sample time (~three hours) were filtered out of temperature (T), salinity (S), and pressure (P). Microcat surface measurements were sampled more frequently than the profiler measurements, making it necessary to remove the extra samples that did not coincide with profiler samples. Following this, profiles that were all NaN values were removed. T, S, and P

\(^1\) Conversion was done using geo2ps_ibcao.m from Bill Shaw. The error introduced with this conversion is roughly 3 to 4 m (T. Stanton, personal communication, 31 October 2020).
were re-binned according to depth (vs. sample index). Before this step, the shallowest measurement was in the first bin. This made room to add extrapolated data to represent the surface and made it easier to associate the change in depth (2 dbar or ~2 m) with the bin or row index. Profile data was then isolated to only include measurements from the surface to 100 dbar; since the winter pycnocline (isolated around 55 dbar) was well above 100 dbar, the data at depth was not needed. Following this step, profiles of all NaN existed again and were removed. The next step adjusted the start and stop time for the series to match all other data. T and S profiles were plotted against P, and each profile was manually inspected to determine if there was data that appeared incorrect, like obvious salinity spikes. There were a few profiles removed that appeared to be salinity spikes. Since the shallowest measurement was variable, the first 20 dbars of T and S data were inspected for gaps in time between samples. Samples with three or fewer missing were linearly interpolated to correct for small gaps in SBE-37 microcat measurements. To capture surface conditions, the shallowest T & S observations were filled in 2 m bins from the shallowest observation up to two dbar. This was necessary because the cumulative heat input to the upper ocean would miss considering surface measurements and underestimate the amount of heat in the upper ocean. This was the last step before using the T, S, and P profiles from the ITP to calculate ocean parameters, like pycnocline depth and departure from freezing.