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Machine Learning Algorithms for Automated Satellite Snow and Sea Ice Detection

George Bonev
The Graduate Center, City University of New York

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MACHINE LEARNING ALGORITHMS FOR AUTOMATED SATELLITE SNOW AND SEA ICE DETECTION

by

GEORGE Bonev

A dissertation submitted to the Graduate Faculty in Computer Science in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2017
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This manuscript has been read and accepted by the Graduate Faculty in Computer Science in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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THE CITY UNIVERSITY OF NEW YORK
Abstract

Machine learning algorithms for automated satellite snow and sea ice detection

by

George Bonev

Adviser: Professor Irina Gladkova

The continuous mapping of snow and ice cover, particularly in the arctic and poles, are critical to understanding the earth and atmospheric science. Much of the world’s sea ice and snow covers the most inhospitable places, making measurements from satellite-based remote sensors essential. Despite the wealth of data from these instruments many challenges remain. For instance, remote sensing instruments reside on-board different satellites and observe the earth at different portions of the electromagnetic spectrum with different spatial footprints. Integrating and fusing this information to make estimates of the surface is a subject of active research.

In response to these challenges, this dissertation will present two algorithms that utilize methods from statistics and machine learning, with the goal of improving on the quality and accuracy of current snow and sea ice detection products. The first algorithm aims at implementing snow detection using optical/infrared instrument data. The novelty in this approach is that the classifier is trained using ground station measurements of snow depth that are collocated with the reflectance observed at the satellite. Several classification methods are compared using this training data to identify the one yielding the highest accuracy and optimal space/time complexity. The algorithm is then evaluated against the current operational NASA snow product and it is found that it produces comparable and in some cases
superior accuracy results. The second algorithm presents a fully automated approach to sea ice detection that integrates data obtained from passive microwave and optical/infrared satellite instruments. For a particular region of interest the algorithm generates sea ice maps of each individual satellite overpass and then aggregates them to a daily composite level, maximizing the amount of high resolution information available. The algorithm is evaluated at both, the individual satellite overpass level, and at the daily composite level. Results show that at the single overpass level for clear-sky regions, the developed multi-sensor algorithm performs with accuracy similar to that of the optical/infrared products, with the advantage of being able to also classify partially cloud-obscured regions with the help of passive microwave data. At the daily composite level, results show that the algorithm’s performance with respect to total ice extent is in line with other daily products, with the novelty of being fully automated and having higher resolution.
Acknowledgments

First and foremost, I would like to thank my dissertation adviser Irina Gladkova, who has been an inspiration and from whom I have learned so much. I would also like to thank the other members of my Ph.D. committee, Michael Grossberg, Peter Romanov, Robert M. Haralick, and Alexey Kaplan, for all of their valuable input, and for agreeing to serve. While working in Irina’s lab, it was also a real pleasure being colleagues with Fazlul Shahriar, Hannah Aizenman and Andrew Fitzgerald.

Finally I would like to thank my mother Mariana Boneva, without whom none of this would be possible.
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Chapter 1

Introduction

The overall distributions of snow and sea ice over the Arctic and Antarctic regions have received substantial attention in recent years. An alarming decreasing trend in the Arctic sea ice extent of more than 4% per decade over the period from 1979 to 2010 has been observed Cavalieri and Parkinson (2012). The greatest losses occur during the month of September which is at the end of the Arctic summer season. The eight lowest sea ice extents recorded to date have all happened in the past 8 years Stroeve et al. (2015). Recent reports on changes in the Arctic environment cite snow and sea ice as the two most critical variables Monitoring et al. (2012) for understanding climate change. It is expected that in the 21st century changes will become increasingly dramatic Frei and Gong (2005); Barbante et al. (2017) and spatially and temporally complex Brown and Mote (2009).

Although the global scale changes in snow and sea ice cover are important indicators of climactic variations, they also affect other components of the Earth’s ecosystems on a variety of levels. Through their thermal and radiative properties which modulate transfers of energy and mass at the surface-atmosphere interface Zhang (2005), they affect the overlaying atmosphere and thereby play an important role in the complex web of feedbacks that control
local to global climate Barry (2002). Scientists have concluded that to reduce uncertainties about the causal links and validity of current weather model results, we need a better understanding and modeling capabilities related to the Arctic sea ice cover and terrestrial snow cover Vihma (2014); Barbante et al. (2017). Accurate snow/sea ice detection is therefore critical for obtaining improved predictive model simulations.

Because of the large extent of polar snow/sea ice cover and the difficulties associated with in situ observations in those regions, remote sensing is the only practical way to estimate these important climactic variables on the space and time scales required. Advances in satellite capabilities, as well as in algorithm development, have led to improved monitoring on a regional and global basis. Currently some aspects of snow/sea ice extent can be derived from a large array of instruments that provide earth observations by sampling different portions of the electromagnetic spectrum. These instruments vary from high frequency radars to passive microwave radiometers and include:

- Moderate-Resolution Imaging Spectroradiometer (MODIS),
- Visible Infrared Imaging Radiometer Suite (VIIRS),
- Advanced Microwave Scanning Radiometer-2 (AMSR-2),
- Special Sensor Microwave Imager (SSMI/S),
- Advanced Scatterometer (ASCAT),
- Advanced Very High Resolution Radiometer (AVHRR),
- Advanced Baseline Imager (ABI),
- Spinning Enhanced Visible and Infrared Imager (SEVIRI),
- RadarSat radar,
CHAPTER 1. INTRODUCTION

- Sentinel-1 Synthetics Aperture Radar.

Despite the wealth of data provided by these instruments it is important to be cognizant of their strengths and limitations summarized in table 1.1.

<table>
<thead>
<tr>
<th>Instrument type</th>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
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<td>Optical (Visible and Infrared)</td>
<td>High Spatial Resolution, necessary for determining coastal ice, ice leads, and polynyas.</td>
<td>Data has large gaps due to clouds and limited lighting conditions (ex. night).</td>
</tr>
<tr>
<td>Passive Microwave</td>
<td>Not affected by clouds or lighting conditions.</td>
<td>Coarse spatial resolution and problems with water attenuation causing misclassification under melting conditions.</td>
</tr>
<tr>
<td>Active Microwave (Scatterometer)</td>
<td>Primary source of ice detection under clouds.</td>
<td>Coarse spatial resolution and misclassification caused by windy surface conditions.</td>
</tr>
<tr>
<td>High Frequency Active (SAR)</td>
<td>High spatial resolution with cloud-free, all illumination observational capacities for detection.</td>
<td>Sporadic coverage and difficulty with the presence of high winds.</td>
</tr>
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Table 1.1: Summary of remote sensing instruments’ types and their strengths and weaknesses.

Currently the only way to effectively aggregate all remote sensing data into one product that utilizes the strengths of each instrument and mitigates its weaknesses, is through human involvement. This is the approach currently taken by the National Ice Center (NIC) in their Interactive Multisensor Snow and Ice Mapping System (IMS) Ramsay (1998, 2000); Helfrich et al. (2007). Trained snow and sea ice analysts evaluate all available remote sensing data on a spatial and temporal scale and derive daily and weekly global snow and sea ice maps.

Although, this product has gone through significant improvements since its inception in the late 1990s, there is still more to be desired. One major drawback alluded to in a recent satellite snow product inter comparison and evaluation experiment Nagler et al. (2014) is the lack of a standardized file format between various snow and sea ice products of the same type. Other drawbacks include the speed with which products are developed and the subjectivity
in analysts’ judgment.

One promising avenue, and an area where great efforts are currently being made, is to de-
velop an automated classifier that utilizes remote sensing data from all available instruments
to accurately detect the presence of snow/sea ice on the Earth’s surface. The algorithms
presented in this dissertation are designed with this goal.
Chapter 2

Background

In this chapter brief descriptions of the remote sensing instruments utilized by the algorithms introduced in this dissertation are given. Summaries of some existing operational and experimental algorithms that are based on these instruments are also provided.

2.1 Remote Sensing Instruments

Given the nature of interaction between sea ice/snow cover and electromagnetic radiation of different frequencies, satellite observations based on a variety of passive and active sensors can be used for detection. As mentioned earlier, there are many types of instruments that provide the measurements necessary for monitoring global scale snow and sea ice variations. The two most popular, and used in the algorithms this dissertation presents, rely on either (1) the visible and infrared, or (2) microwave, portions of the electromagnetic spectrum. Although there are other instruments such as active microwave scatterometers or synthetic aperture radars that provide observations suitable for snow/sea ice detection, they suffer from either temporal, spatial, or signal quality limitations and are thus omitted from further consideration.
2.1.1 Visible and near-infrared

Due to their high albedo, or amount of solar energy reflected from the Earth’s surface back into space (approximately 80% or more in the visible part of the electromagnetic spectrum), compared to other surfaces, snow and sea ice extent detection via visible and infrared observations has been relatively effective in most circumstances.

Moderate-Resolution Imaging Spectroradiometer (MODIS)

The Moderate Resolution Imaging Spectroradiometer was launched as a research/experimental instrument on board two of the National Aeronautics and Space Administration (NASA) Earth Observation System’s (EOS) polar-orbiting satellites Aqua and Terra. It uses cross-track scan mirrors, collecting optics, and a set of individual detector elements to provide imagery of Earth’s surface and clouds in 36 discrete spectral bands. Its primary objectives are to study global vegetation and land cover, global land-surface change, vegetation properties, surface albedo, surface temperature and snow and ice cover on a daily or near-daily basis. MODIS’s spectral bands cover parts of the electromagnetic spectrum ranging from approximately 0.4\(\mu\)m to 14.0\(\mu\)m. The instrument’s spatial resolution at nadir varies based on the spectral band from 250m to 1km Barnes et al. (1998).

Visible Infrared Imaging Radiometer Suite (VIIRS)

The Visible Infrared Imaging Radiometer Suite was launched as an operational monitoring instrument currently flying on board the National Polar-Orbiting Operational Environmental Satellite System’s (NPOESS) Preparatory Project (NPP) polar-orbiting satellite. It uses 4 Focal Plane Assemblies to hold 21 spectral bands and a “Day-Night Band” (DNB). Its main purpose is to obtain measurements of the Earth’s oceans, land surface, and atmosphere which will be utilized in the creation of a wide range of Environmental Data Records. It provides
global coverage on a daily basis. VIIRS spectral bands range from 0.4µm to 12.0µm and come in either 340m or 740m spatial resolution at nadir Murphy et al. (2006).

**Limitations**

First, since visible imagery is limited to the portion of the surface illuminated by sunlight, darkness and low illumination scenes are problematic. Second, clouds interfere with visible measurements in two ways. All but the thinnest clouds reflect a significant portion of visible radiation, thus preventing any visible radiative information about the surface from reaching the satellite. Also, because the albedos of clouds and snow/sea ice are often similar, discriminating between cloud-obscured and snow/sea ice surfaces can be often difficult. However, near-infrared bands can be used to distinguish between snow/sea ice and most clouds because the near-infrared reflectance of most clouds is high while the near infrared reflectance of snow is low (see figure 2.1).

![Figure 2.1: Spectral reflectance of natural surfaces and clouds Romanov (2014).](image)
Vegetation can also obstruct visible and infrared information about snow from reaching the satellite sensor. Forrest canopies protrude above the snow pack, lowering the surface albedo and partially or completely obscuring the underlying surface, making it difficult to determine snow extent or amount Frei et al. (2012).

2.1.2 Passive Microwave

Because snow grain dimensions can be similar to microwave wavelengths, snow is efficient at scattering microwave radiation naturally emitted from the Earth’s surface. Thus, microwave emission from a snow covered surface is diminished relative to a snow-free surface, and the presence of snow can frequently be identified Hall et al. (2005). Equivalently, the dialectic permittivity of seawater at microwave frequencies is many times larger than that of sea ice. This results in distinct polarization, intensity and directional scattering properties that allow their effective separation Rivas (2007). In contrast to visible and infrared, passive microwave does not depend on the presence of sunlight and thus provides an alternative at high latitude regions. Also, passive microwave is almost completely transmitted through non-precipitating clouds, offering the potential to estimate snow cover under many cloudy conditions that obstruct visible and infrared observations.

Special Sensor Microwave Imager (SSM/I)

The Special Sensor Microwave Imager is an imaging microwave radiometer. It was launched as part of the Defense Meteorological Satellite Program (DMSP) on the series of DMSP F-x satellites. It measures dual-polarized microwave radiance at 19, 37 and 85GHz, and vertically polarized radiances at 22 GHz. The SSM/I scans the Earth’s surface conically with a swath of 1400 km width. Thus operating from a near-polar orbit, it provides an almost global daily coverage. The sampling distance is 12.5 km at the 85GHz channel and 25 km at the other channels. Due to the fact that SSM/I utilizes only one broadband antenna, the per pixel
spatial resolution of each frequency band is determined through diffraction. This results in varying spatial resolutions depending on frequency Kaleschke et al. (2001).

**Advanced Microwave Scanning Radiometer-2 (AMSR2)**

The *Advanced Microwave Scanning Radiometer-2* is a multi-frequency, total-power microwave radiometer system that was launched on the first satellite of the Japanese Water Series of Global Change Observation Mission (GCOM-W1). The instrument measures dual-polarized microwave radiance at 6.925, 7.3, 10.65, 18.87, 23.8, 36.5, and 89.0 GHz. The instrument employs a conical scanning mechanism at a rotation speed of 40 rpm to observe the Earth’s surface with a constant incidence angle of 55 degrees. Multiple feed horns are clustered to realize multi-frequency simultaneous observation. Per pixel spatial resolution varies with the frequency of the band Oki et al. (2010).

**Limitations**

There are a variety of factors that limit the monitoring of snow/sea ice using passive microwave sensors. For snow, one major limitation is the presence of liquid water in the snow pack. The microwave emission from which masks the snow signal and inhibits the ability of microwave sensors to detect wet snow. Similarly, water from precipitating clouds can also obstruct microwave emissions. Also, because of the relatively weak microwave signal emitted from terrestrial surfaces, microwave sensor footprints are necessarily large (≈ 10 to 25 km). Finally, vegetation in and above snow emits microwave radiation, and can confuse detection algorithms. Frei et al. (2012)

Grasping the physical meaning and limitations of the remote sensing data measured by the instruments presented in this chapter is key to understanding the theoretical underpinnings of the algorithms that utilize them presented in the next chapter.
2.2 Snow and Sea Ice Detection Products and Algorithms

There are many digital snow/sea ice extent products based on satellite observations from the instruments presented in Section 2.1 available. The two most widely used visible and infrared based products are the suite derived from the Moderate-Resolution Imaging Spectroradiometer (MODIS) (section 2.2.1) Hall et al. (1995, 2001, 2002); Hall and Riggs (2007) and the Interactive Multisensor Snow and Ice mapping system (IMS) (section 2.2.2) Ramsay (1998); Helfrich et al. (2007). Both of these products produce snow and sea ice extent maps on a global scale daily.

There are many other approaches that can be used to estimate either snow or sea ice extent individually. The MODIS Snow-Covered Area and Grain size (MODSCAG) model based algorithm Painter et al. (2009), attempts to address certain limitations of standard MODIS snow products over complex terrain, by using a library of reflectance characteristics for different surface types. Two passive microwave based algorithms that use input data from the SSM/I Grumbine (1996) and AMSR-2 Comiso and Cho (2013) instruments, provide an automated approach to determining Sea Ice Concentration. An Artificial Neural Network algorithm that also estimates Fractional Snow Cover (FSC) Dobreva and Klein (2011) provides a comparable alternative to the operational MODIS product. Another Neural Network based algorithm that classifies Arctic sea ice, cloud, water and leads based on visible and infrared measurements is also presented McIntire and Simpson (2002). Finally, a couple of automated multi-sensor blended approaches, one for snow cover Foster et al. (2011) and one for sea ice extent Eastwood et al. (2014), are also reviewed for comparative analysis.


2.2.1 MODIS Snowmap and Icemap algorithms

SnowMap

The National Aeronautics and Space Administration (NASA) has developed a threshold based automated MODIS snow-mapping algorithm Hall et al. (1995), that uses at-satellite reflectances in MODIS bands 4 (0.545-0.565 µm) and 6 (1.628-1.652 µm) to calculate a normalized difference snow index (NDSI) based on the following formula:

\[
NDSI = \frac{\text{band4} - \text{band6}}{\text{band4} + \text{band6}}
\]  

(2.1)

In non-densely forested regions pixels are mapped as snow if the NDSI is \(\geq 0.4\) and reflectances in MODIS band 2 (0.841-0.876 µm) are \(> 11\%\) and in band 4 (0.545-0.565 µm) are \(\geq 10\%). In densely forested regions snow will cause an increase in the visible wavelengths with respect to the near-infrared. This behavior is captured in a normalized difference vegetation index (NDVI) as snow will tend to lower NDVI. MODIS bands 1 (0.620-0.670 µm) and 2 (0.841-0.876 µm) are used to calculate NDVI and the formula is as follows:

\[
NDVI = \frac{\text{band2} - \text{band1}}{\text{band2} + \text{band1}}
\]  

(2.2)

Figure 2.2 shows the algorithm’s decision boundary in NDSI, NDVI space.

In addition to the metrics above a “thermal mask” is used Romanov et al. (2000) to eliminate confusion with cloud cover, aerosol effects, and snow/sand on coastlines. Using MODIS infrared bands 31 (10.78-11.28 µm) and 32 (11.77-12.27 µm), a split window technique Key et al. (1997) is used to estimate ground temperature. If the temperature of a pixel is \(> 283^\circ K\), then the pixel is not mapped as snow.
The snow-mapping algorithm also utilizes a MODIS cloud-mask product (MOD35, MYD35) Hall et al. (2001). This product provides an “unobstructed-field-of-view” flag. Pixels for which that flag is set to ‘certain-cloud’, are not analyzed for the presence of snow. Another circumstance in which the snow-mapping algorithm is not applied is if the surface viewed is in darkness. This is also determined using the cloud-product and is defined as pixels for which the solar zenith angle is $\geq 85^\circ$.

Oceans and inland waters are also ‘masked’ using the 1km resolution land/water mask contained in the MODIS geo-location product. The 1km land/water mask is applied to the four corresponding 500m resolution pixels in the snow-mapping algorithm.

**IceMap**

The MODIS sea ice algorithm Hall et al. (2001) utilizes sea ice’s reflectance characteristics in the visible and near infrared and its sharp contrast to open water for identification. The algorithm also utilizes an Ice Surface Temperature metric, which is used as an additional
CHAPTER 2. BACKGROUND

discriminatory variable.

Just as in the snow algorithm, the first step in the NASA sea ice algorithm is to identify sea ice pixels where NDSI is $\geq 0.4$ and reflectances in MODIS band 2 (0.841-0.876 $\mu$m) are $> 11\%$ and in band 4 (0.545-0.565 $\mu$m) are $\geq 10\%$.

The second step initially computes the Ice Surface Temperature using the following formula Key et al. (1997):

$$IST = a + bT_{11.03\mu m} + c(T_{11.03\mu m} - T_{12.02\mu m}) + d[(T_{11.03\mu m} - T_{12.02\mu m})(\sec(q) - 1)]$$  \hfill (2.3)

where,

$T_{11.03\mu m}$ is the brightness temperature at 11.03$\mu$m (MODIS Band 31)
$T_{11.03\mu m}$ is the brightness temperature at 12.02$\mu$m (MODIS Band 32)
$q$ is the sensor zenith angle

$a, b, c, d$ are regression coefficients specified by table 2.1 from Key et al. (1997).

<table>
<thead>
<tr>
<th>Northern Hemisphere</th>
<th>$a$</th>
<th>$b$</th>
<th>$c$</th>
<th>$d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$&lt; 240^\circ K$</td>
<td>-1.5711228087</td>
<td>1.0054774067</td>
<td>1.8532794923</td>
<td>-0.7905176303</td>
</tr>
<tr>
<td>$240 - 260^\circ K$</td>
<td>-2.3726968515</td>
<td>1.0086040702</td>
<td>1.6948238801</td>
<td>-0.2052523236</td>
</tr>
<tr>
<td>$&gt; 260^\circ K$</td>
<td>-4.2953046345</td>
<td>1.0150179031</td>
<td>1.9495254583</td>
<td>0.1971325790</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Southern Hemisphere</th>
<th>$a$</th>
<th>$b$</th>
<th>$c$</th>
<th>$d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$&lt; 240^\circ K$</td>
<td>-0.1594802497</td>
<td>0.9999256454</td>
<td>1.3903881106</td>
<td>-0.4135749071</td>
</tr>
<tr>
<td>$240 - 260^\circ K$</td>
<td>-3.3294560023</td>
<td>1.0129459037</td>
<td>1.2145725777</td>
<td>0.1310171301</td>
</tr>
<tr>
<td>$&gt; 260^\circ K$</td>
<td>-5.2073604160</td>
<td>1.0194285947</td>
<td>1.5102495616</td>
<td>0.2603553496</td>
</tr>
</tbody>
</table>

Table 2.1: Coefficients used in the calculation of IST.

Once the Ice Surface Temperature is computed, sea ice is identified using a $271.4^\circ K$ freezing point threshold, where a pixel with a value less than the threshold is classified as ice, and above it as water. Finally the results of the two steps are combined and the outputted ice
cover mask is the result of their agreement.

\subsection{Interactive Multisensor Snow and Ice Mapping System (IMS)}

The \textit{Interactive Multisensor Snow and Ice Mapping System} (IMS) is the most recent version of a product that dates back to the 1960s. IMS mapping of snow and sea ice extent has primarily relied on visible and near infrared imagery, but also includes data and information from a number of different sources. The key feature that sets IMS apart from other products is human involvement in the analysis, which is required for operational purposes Ramsay (1998).

Despite there being a number of improvements and corrections in the production of the NOAA product that occurred in the earlier years, the biggest change in methodology was implemented in the late 1990s. Until then, NOAA snow/sea ice maps were produced on a weekly basis by trained meteorologists who would visually interpret photographic copies of visible band imagery, and manually produce maps that would subsequently be digitized with spatial resolution between 150 km and 200 km. In 1997 NOAA began producing snow maps using the IMS, with improved spatial (24 km) and temporal (daily) resolutions. IMS is operated by trained analysts who produce a daily digital product utilizing Geographic Information System technology and incorporating a variety of, and an ongoing expansion of, technological capabilities as well as sources of information. Since 1999, when weekly manual mapping was discontinued, daily IMS maps have been produced Ramsay (1998). Technological advancements since 1999 have led to even higher resolution (4 km) snow mapping Helfrich et al. (2007).

IMS produces estimates of snow and sea ice extent across the globe every day, regardless of the presence of clouds. This is possible primarily for two reasons. First, analysts use
sources of information other than visible and near infrared imagery. Second, because IMS analysts can loop through sequential images, their ability to evaluate scenes is based on an integration of information from both spatial and temporal perspectives. Thus, a key feature of the IMS product is that human judgment as to which data sources are most reliable in different conditions and regions, and as to the final evaluation of where the snow and sea ice are, remains an integral part of the process, and one of the strengths of the IMS product.

2.2.3 The MODIS Snow-Covered Area and Grain size (MOD-SCAG) model and algorithm

Some of the difficulties inherent in the interpretation of remotely sensed images are exacerbated in regions with complex terrain. Due to variability of slope, aspect, and land cover, the local solar illumination angle varies within one satellite footprint. In fact, due to co-registration differences between an image and a digital elevation model, illumination angles, and therefore reflectance characteristics, are often unknown. To address such issues, Painter et al. (2009) developed the MODSCAG model, which estimates mean grain size and fractional snow cover from MODIS data using linear spectral mixture analysis and a library of reflectance characteristics of different surface types. This model has relatively small errors, and could potentially be applied globally, but so far has been validated mostly in regions of complex terrain.

2.2.4 Passive Microwave Sea Ice Concentration Algorithms

Satellite passive microwave data provides some of the most comprehensive large-scale characterizations of global sea ice cover. Two algorithms that have been used to derive sea ice concentrations from multichannel data are presented. One is the NASA Team algorithm that is used operationally with the SSM/I instrument Grumbine (1996) and the other is the
Bootstrap algorithm that is used operationally with the AMSR-2 instrument Comiso and Cho (2013).

**NASA Team Algorithm**

In the NASA Team algorithm described in Grumbine (1996) total sea ice concentration ($C_T$) is given by the sum of two types of ice concentrations: first-year ice ($C_{FY}$) and multi-year ice ($C_{MY}$). It is defined as:

\[ C_T = C_{FY} + C_{MY} \]  

(2.4)

where

\[ C_{FY} = \frac{a_0 + a_1 PR + a_2 GR + a_3 PR \cdot GR}{D}, \]  

(2.5)

\[ C_{MY} = \frac{b_0 + b_1 PR + b_2 GR + b_3 PR \cdot GR}{D}, \]  

(2.6)

and

\[ D = c_0 + c_1 PR + c_2 GR + c_3 PR \cdot GR \]  

(2.7)

The polarization ratio ($PR$), defined as:

\[ PR = \frac{T_B(19V) - T_B(19H)}{T_B(19V) + T_B(19H)}, \]  

(2.8)

is based on the fact that the difference between the vertically and horizontally polarized radiances at 19 GHz is small for ice in comparison with that for ocean.
The spectral gradient ($GR$), defined as:

$$GR = \frac{T_B(37V) - T_B(19V)}{T_B(37V) + T_B(19V)},$$

(2.9)

is based on the fact that the discrimination between the two ice types is greater at 37 GHz than at 19 GHz.

The coefficients $a_i$, $b_i$, and $c_i$ (i=0:3) are functions of a set of nine $T_B$'s (brightness temperatures), referred to as the algorithm’s tie points, and are observed SSM/I radiances for ice-free ocean, and the two sea ice types during winter for each of the three SSM/I channels used. The algorithm tie points as well as the coefficients used in Eq. 2.5-2.7 are given in Table 2.2 from Comiso et al. (1997). The two sets of SSM/I tie points (one for the Northern and Southern Hemispheres) represent a “global” set that is designed for mapping global sea ice concentration on a large scale.
### Northern Hemisphere

<table>
<thead>
<tr>
<th>Channel</th>
<th>OW</th>
<th>FY Ice</th>
<th>MY Ice</th>
</tr>
</thead>
<tbody>
<tr>
<td>19.4H</td>
<td>100.8</td>
<td>242.8</td>
<td>203.9</td>
</tr>
<tr>
<td>19.4V</td>
<td>177.1</td>
<td>258.2</td>
<td>223.2</td>
</tr>
<tr>
<td>37.0V</td>
<td>201.7</td>
<td>252.8</td>
<td>186.3</td>
</tr>
</tbody>
</table>

\[ a_0 = 3286.56 \quad b_0 = -790.321 \quad c_0 = 2032.20 \]
\[ a_1 = -20764.9 \quad b_1 = 12825.8 \quad c_1 = 9241.50 \]
\[ a_2 = 23893.1 \quad b_2 = -33104.7 \quad c_2 = -5655.62 \]
\[ a_3 = 47944.5 \quad b_3 = -47720.8 \quad c_3 = -12864.9 \]

### Southern Hemisphere

<table>
<thead>
<tr>
<th>Channel</th>
<th>OW</th>
<th>FY Ice</th>
<th>MY Ice</th>
</tr>
</thead>
<tbody>
<tr>
<td>19.4H</td>
<td>100.3</td>
<td>237.8</td>
<td>193.7</td>
</tr>
<tr>
<td>19.4V</td>
<td>176.6</td>
<td>249.8</td>
<td>221.6</td>
</tr>
<tr>
<td>37.0V</td>
<td>200.5</td>
<td>243.3</td>
<td>190.3</td>
</tr>
</tbody>
</table>

\[ a_0 = 3055.00 \quad b_0 = -782.750 \quad c_0 = 2078.00 \]
\[ a_1 = -18592.6 \quad b_1 = 13453.5 \quad c_1 = 7423.28 \]
\[ a_2 = 20906.9 \quad b_2 = -33098.3 \quad c_2 = -3376.76 \]
\[ a_3 = 42554.5 \quad b_3 = -47334.6 \quad c_3 = -8722.03 \]

Table 2.2: NASA Team Sea Ice algorithm tie points and the coefficients used in the calculation of SSMI Sea Ice Concentration Comiso et al. (1997).

**Comiso Bootstrap Algorithm**

Unlike the NASA Team algorithm, the Comiso Bootstrap algorithm described in Comiso and Cho (2013), assumes that to obtain ice concentration it is not necessary to identify the ice type. It states that the ice concentration \( C_i \), corresponding to an observed brightness
temperature $T_B$, is given by:

$$C_i = \frac{T_B - T_o}{T_i - T_o}$$  \hspace{1cm} (2.10)

where $T_o$ and $T_i$ are reference brightness temperatures of open water and sea ice, respectively. Sea ice in this case can be any or a combination of the various ice types. $T_B$, $T_o$ and $T_i$ all include contributions from the intervening atmosphere. Appropriate values of $T_o$ and $T_i$ should be used in equation 2.10 and are determined from a set of two channels 1 and 2, which are either 37GHz H and V, or 19GHz V and 37GHz V. A general equation for ice concentration ($C$) for any data point $B$, using this 2 channel scheme is defined as:

$$C = \sqrt{\frac{(T_{1B} - T_{1o})^2 + (T_{2B} - T_{2o})^2}{(T_{2i} - T_{2o})^2 + (T_{1i} - T_{1o})^2}}$$  \hspace{1cm} (2.11)

where $T_{1i}$ and $T_{2i}$ are reference temperatures for ice, and $T_{1o}$ and $T_{2o}$ are reference temperatures for water. More details on how these temperatures are computed and on the physics of the technique can be found in Comiso and Cho (2013).

### 2.2.5 Machine Learning Based Algorithms

Machine learning presents an alternative to the statistical and physical methods for estimating snow and sea ice extent. Artificial Neural Networks (ANNs) are a machine learning technique often used for learning relationships between input and output variables. ANNs define an information processing model that stores empirical knowledge through a learning process and subsequently makes it available for future use. ANNs have been utilized in various remote sensing applications. Their main advantage is the fact that they don’t require the assumption of a pixel being a linear mixture of signals.
There are only a few studies that utilize machine learning, and more specifically ANNs, for satellite snow and sea ice detection. Two algorithms from this space are reviewed in this section. One implements a fractional snow cover mapping approach via feed forward artificial neural network analysis of MODIS surface reflectance data Dobreva and Klein (2011). The other uses a combination of feed-forward neural networks and data from the 1.6 $\mu$m middle infrared channel to classify satellite data into sea ice, cloud, water and leads McIntire and Simpson (2002).

**Fractional snow cover via ANN and MODIS reflectance**

In Dobreva and Klein (2011) a multilayer feed-forward Artificial Neural Network with one hidden layer is used. Since the network is feed-forward and not recurrent, it does not include any feedback loops, so inputs to a neuron are not influenced by its output. In this multi-layer feed-forward configuration the input layer of source neurons (surface reflectance, NDSI, NDVI, and land cover of a pixel) project to a hidden layer of neurons that project directly to the output layer, which corresponds to the snow fraction of the pixel. The network utilizes the hyperbolic tangent function as its transfer function. The network is trained using the back-propagation algorithm. The training data is derived from higher resolution imager data obtained from the Landsat instrument. Snow fractions from the higher resolution images were aggregated to compute the expected snow fraction values at MODIS resolution.

The algorithm performed well with accuracy around 90%. This level of accuracy was in most cases equal or better than that of the operational MODIS snow fraction product.

**Arctic sea ice, cloud, water and lead classification FFNN algorithm**

For the method described in McIntire and Simpson (2002) a combination of reflectance data obtained from the Chinese Fengyun-1C satellite (with a special emphasis on the daytime
1.6-µm middle infrared data that is extremely useful for discriminating between ice and clouds) and a multistage feed-forward Neural Network are used to achieve improved daytime classification of clouds, sea ice, leads, and open water that is needed for polar studies.

The algorithm uses three stages to separate Arctic sea ice from cloud, water, and leads. Each neural network stage, computes an image-specific normalized \([0, 1]\) dynamic threshold for a specific wavelength band. Each normalized dynamic threshold is then compared with also normalized image data for classification at that stage.

Preprocessed (i.e. noise removal, navigation, subsection) input data enters stage 1 of the algorithm, whose goal is to associate the majority of illuminated water cloud with high values of 1.6-µm observations. Stage 2 detects residual clouds using a low 11-µm signature in the unclassified data pass to it from stage 1, based on the assumption that the detected residual cloud is an ice cloud. Stage 3 examines the remaining unclassified data: water/leads have low values of albedo at visible wavelengths, while sea ice has high values. Cloud shadow in the scene can potentially compromise stage 3, thus a post processing cloud shadow removal method is utilized to mitigate this issue.

Each stage of the algorithm contains an Artificial Neural Network with one hidden layer. These networks are trained individually using the back-propagation algorithm. The training data used consists of the layer inputs, i.e. sensor image statics for each of the three sensor frequencies used (0.63µm, 1.6µm, and 11µm), and predetermined optimal thresholds, obtained from a human expert with several years of experience.

The algorithm performance was validated against Independent Sea Ice Analysis McIntire and Simpson (2002) of the National Weather service for random periods between April and
August 2001. The overall accuracy of classification was found to be 98% for the 218,700 testing data points.

### 2.2.6 Multi-Instrument Integrated Algorithms

Given the limitations of instrument types, presented in Section 2.1, algorithms that attempt to mitigate these limitations by utilizing data from different sensors provide a promising avenue for improving our satellite snow and sea ice detection abilities. Two methods for combining data from different instruments are reviewed.

The first method described in Foster et al. (2011) derives a global snow extent map using data from MODIS (visible and infrared), AMSR-E (passive microwave) and QSCAT (active microwave). Since snow cover extent is identified better at the visible and infrared wavelengths, MODIS observations are used as the default. The passive and active microwave derived snow cover is used only in areas where MODIS observations are limited by clouds or darkness. The “blending” is done at the binary mask level therefore the output based on simple boolean logic between the maps generated by the three types of instruments and external masks that specify cloud, night, and weather affected pixels.

More recently Liang et al. (2015) developed a snow depth retrieval algorithm that integrates microwave brightness temperatures from the SSM/I family of instruments and visible and infrared reflectance from MODIS. In this study, the snow depth retrieval is regarded as a regression problem that is solved by a Support Vector Machine (SVM). In this formulation, the independent variables are the microwave brightness temperature and the visible/infrared surface reflectance. The dependent variable is the snow depth to be retrieved. Initially, a set of sample data points are used to train the SVM and generate a regression function that maps the remotely sensed data to snow depth. This set of sample data points was derived
by collocating satellite visible and infrared observations with ground station measurements of snow depth in the regions covered by the satellite pixels. Once the regression function is computed, snow depth can be easily retrieved by applying it on new testing data.

This algorithm was validated against a number of different operational snow depth retrieval products Liang et al. (2015). It was shown to be significantly more accurate than all existing approaches at the time of publication.
2.3 Summary

This chapter summarizes a number of different existing approaches to satellite snow and sea ice detection. With the exception of the human curated IMS product, the operational algorithms based on both the visible and infrared, and the passive microwave portions of the electromagnetic spectrum suffer from the limitations of the nature of instruments they were designed for. The suite of MODIS products does not work under cloudy and dark conditions and the suite of passive microwave products suffer from a coarse spatial resolution and artifacts due to weather effects. Although, the IMS product seems to provide a reasonable alternative to these limitations, it has some of its own. Manual snow and sea ice mapping drawn by humans, is a subjective, labor intensive and time consuming procedure. Thus, automated snow and sea ice detection algorithms that utilize all available sources of information and generate output at the highest spatial resolution are to be desired.

From the small number of attempts at applying machine learning techniques to this task, the results seem encouraging. Moreover, coupling these techniques with a multi-sensor integrated approach seems to be the most promising path to more accurate high quality snow and sea ice detection.
Chapter 3

Algorithms

3.1 Snow Detection

This section explores and evaluates the performance of a number of statistical classification algorithms against the currently operational NASA snow detection algorithm for MODIS (SnowMap). To fit the statistical models training data is obtained from Snow Telemetry (SNOTEL) sites operated by the Natural Resources Conservation Service (NRCS)(https://www.wcc.nrcs.usda.gov/snow/snotel-wedata.html). The sites measure snow depth on a daily basis across 798 locations in the western United States. Due to the fact that SnowMap only utilizes four of the 7 optical bands available at 500m resolution on MODIS, the intuition is that statistical classifiers that employ all 7 bands may be able to capture some non-linear relationships in the data, which maybe missed by the physical model.

3.1.1 Training Data

The training data set consists of MODIS optical reflectance measurements of the 7 bands available at 500m resolution with bandwidths centered around 0.47µm (Band 3), 0.55µm (Band 4), 0.64µm (Band 1), 0.86µm (Band 2), 1.24µm (Band 5), 1.64µm (Band 6), and
2.13µm (Band 7). In addition to the reflectance bands two emissive bands are used to compute surface temperature, namely bands 31 and 32 with bandwidths centered around 11µm and 12µm, respectively. Snow depth measurements in inches obtained from the ground snow telemetry stations are also used.

The training set is build by co-locating the satellite reflectance and brightness temperature observations with the snow telemetry site depth measurements using time and geo-spatial metadata. The registration is achieved via a Nearest Neighbor search. The resulting database contains rows for each MODIS overpass of the snow telemetry station. Figure 3.1 shows the geographic layout of the 798 NRCS SNOTEL sites and a sample of the spatial coverage of MODIS overpasses from the Aqua and Terra satellites.

![Figure 3.1: (a) A map of the 798 NRCS SNOTEL sites used. (b) Spatial Coverage of a sample set of MODIS granules from each satellite (blue: Aqua, green: Terra)](image)

Initially, to visualize the training data in the database described above, Principle Component Analysis (PCA) is used to project the seven reflectance inputs to a three dimensional space. Figure 3.2 shows the resulting projection, in which the class labels are computed by assigning snow to all observations with snow depth measurements greater than 0.
Figure 3.2: The PCA projected training data from \( \mathbb{R}^7 \) to \( \mathbb{R}^3 \), to make 3D visualization possible. It is apparent from this figure that the two classes snow (red) and land (blue) are separable.

From Figure 3.2 there appears to be a potential linear boundary separating the two classes: snow-free land (blue) and snow (red). This suggests that a linear classifier can be effective in delimiting these classes.
3.1.2 Classifier Descriptions

In this section four standard classification methods are considered. The choice of classifiers is based on a few factors. Since the classes in the data set appear linearly separable, some linear classifiers are chosen. Optimized implementations for all methods used are provided by the Python ‘Scikit-learn’ library Pedregosa et al. (2011). The methods chosen, their classification criteria, assumptions and parameters are shown in Table 3.1.
### Classifier Classification Criteria Assumptions and Parameters

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Classification Criteria</th>
<th>Assumptions and Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic Regression</td>
<td>negative log likelihood of conditional probability of a class given the features</td>
<td>- coordinate descent</td>
</tr>
<tr>
<td>K-Nearest Neighbor</td>
<td>distance to neighboring members of a class</td>
<td>- non-parametric</td>
</tr>
<tr>
<td>Linear Discriminant</td>
<td>maximum likelihood of the class conditional probability of the features give a specific class</td>
<td>- k=5</td>
</tr>
<tr>
<td>Analysis</td>
<td>conditional distribution of data for each class is Gaussian</td>
<td>- Euclidean Distance</td>
</tr>
<tr>
<td>Gaussian Naive Bayes</td>
<td>maximum likelihood of the conditional probability of the features given a class</td>
<td>- likelihood of features is Gaussian</td>
</tr>
<tr>
<td></td>
<td>- features are conditionally independent</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.1: List of classifiers considered, with their criteria, assumptions and parameters.

In the method descriptions the following notations are used:

- $X$ is a feature vector consisting of reflectance values from the 7 500m resolution MODIS bands i.e. $X = [R_{0.47\mu m}, R_{0.55\mu m}, R_{0.64\mu m}, R_{0.86\mu m}, R_{1.24\mu m}, R_{1.64\mu m}, R_{2.13\mu m}]$.

- $y$ is a class label derived from snow-depth measurements. $y \in \{y_s, y_l\}$ where $y_s$ is the class label for snow (i.e. snow-depth greater than 0) and $y_l$ is the class label for land.

### Logistic Regression

Logistic regression, also known as logit regression, maximum-entropy (MaxEnt), or the log-linear classifier, is a linear model for classification. It models the conditional probability as

$$P(y_i \mid X_i) = \frac{1}{1 + e^{-y_i w^t X_i}}, \quad (3.1)$$
where $y_i$ is the class label for observation $X_i$, and $w$ is the weight vector or the regression coefficients. Since this is a logistic function, it takes on values between zero and one. Given the two-class training data of $n$ observations $\{X_i, y_i\}_{i=1}^n$, logistic regression minimizes the following regularized negative log-likelihood $L(w \mid X)$:

$$\log(L(w \mid X)) = C \sum_{i=1}^n \log(P(y_i \mid X_i, w)) \quad (3.2)$$

where $C > 0$ is a penalty parameter, which controls the amount of regularization. There are numerous optimization methods that can be applied to train logistic regression, including iterative scaling, coordinate descent, quasi-Newton, and truncated Newton. The ‘Scikit-learn’ implementation of logistic regression used in this comparison employs coordinate descent methods to solve the dual form of logistic regression.

**K-nearest neighbors**

K-nearest neighbors classifier is a non-parametric method which can be often successful in situations where the decision boundary is very irregular. It is a type of instance-based learning which classifies based on a simple majority vote of the nearest neighbors of each point: a query point is assigned the class which the majority of its neighbors belong to.

Euclidean distance is used as the distance metric, and $k = 5$ for the number of nearest neighbors. This value for the $k$ hyper-parameter is chosen empirically.

**Linear discriminant analysis**

Linear discriminant analysis (LDA) is a classifier that uses a linear decision surface. It has a closed-form solution that can be easily computed, and it has no hyper-parameters that require tuning.
LDA works by modeling the class conditional distribution of the data $P(X \mid y)$ for each class as a Gaussian distribution. The prediction is obtained by using the Bayes’ rule:

$$P(y \mid X) = \frac{P(X \mid y) \cdot P(y)}{P(X)} = \sum_{z \in \{y_s, y_l\}} \frac{P(X \mid z) \cdot p(z)}{P(y)}$$  \hspace{1cm} (3.3)$$

The Gaussians for each class are assumed to share the same covariance matrix. From the log-probability ratio $\log[P(y = y_s \mid X)/P(y = y_l \mid X)]$ it can be seen that this leads to a linear decision surface.

**Gaussian Naive Bayes**

A naive Bayes classifier is based on applying Bayes’ theorem with the assumption of independence between every pair of features. That is, given a class variable $y$ and feature vectors $X_1, \ldots X_n$, it is assumed:

$$P(X_i \mid y, X_1, \ldots, X_{i-1}, X_{i+1}, \ldots, X_n) = P(X_i \mid y)$$  \hspace{1cm} (3.4)$$

for all $i$. Using this assumption, Bayes’ theorem simplifies to

$$P(y \mid X_1, \ldots, X_n) = \frac{P(y)P(X_1, \ldots, X_n \mid y)}{P(X_1, \ldots, X_n)} = \frac{P(y) \prod_{i=1}^{n} P(X_i \mid y)}{P(X_1, \ldots, X_n)}$$  \hspace{1cm} (3.5)$$

Since $P(X_1, \ldots, X_n)$ is constant given the inputs, following classification rule is used:

$$\hat{y} = \arg \max_y P(y) \prod_{i=1}^{n} P(X_i \mid y)$$  \hspace{1cm} (3.6)$$

and Maximum A Posteriori (MAP) estimation is used to estimate $P(y)$ and $P(X_i \mid y)$.
A Gaussian Naive Bayes Chan et al. (1979) classifier assumes the likelihood of features is Gaussian:

\[ P(X_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp \left( -\frac{(X_i - \mu_y)^2}{2\pi\sigma_y^2} \right) \]  

(3.7)

The parameters \( \sigma_y \) and \( \mu_y \) are computed for each class \( y \).

### 3.1.3 Classifier Comparison

In this section, the four classification methods are tested on the training data set. For this, a 10-fold cross validation on the whole training set is performed. The original set of observations are randomly partitioned into 10 equal size subsamples. Of the 10 subsamples, a single subsample is retained as the validation data for testing the classifier, and the remaining 9 subsamples are used as training data. The cross-validation process is then repeated 10 times (the folds), with each of the 10 subsamples used exactly once as the validation data.

Tables 3.2 show the results. The following four metrics are computed for each of the ten folds:

- The accuracy (ACC) is the ratio of correct predictions of land and snow over the total number of observations.

- The true positive rate (TPR) is the ratio \( TP/P \), where \( TP \) is the number of observations in the positive class \( y_s \) (snow) predicted as belonging to class \( y_s \) by the classifier and \( P \) is the total number of observations in class \( y_s \).

- The false positive rate (FPR) is the ratio \( FP/N \), where \( FP \) is the number of observations in the negative class \( y_l \) (land) predicted as belonging to class \( y_s \) by the classifier and \( N \) is the total number of observations in class \( y_l \).
CHAPTER 3. ALGORITHMS

- Intuitively in a perfect scenario, $FPR = 0$ and $TPR = 1$. Therefore another meaningful metric shown is the Euclidian distance (Dist) between the (FPR, TPR) for the classifier evaluated and the optimal point (0,1).

From the tables, it can be observed that logistic regression, LDA, and KNN perform very well, with about 93% accuracy. Logistic regression however, has a significantly lower FPR than both LDA and KNN, meaning it misclassifies land as snow at a significantly lower rate. All other metrics between the three classifiers are comparable. Gaussian NB performs poorly compared to the other classifiers with a 85% accuracy. This is probably caused by the bold assumption of conditional independence between features.

Figure 3.3 shows the receiver operating characteristic (ROC) for all the classifiers. The curves and the area under them mostly agree with the observations from Table 3.2. As mentioned earlier, an optimal classifier would maximize the area under its ROC curve and minimize its distance to the point (FPR=0, TPR=1). Given these criteria Logistic regression’s ROC curve is superior to others. It is also important to note that all classifiers are much closer to the TPR-axis than the line TPR=1, which means that the class $y_s$ (snow) is favored over $y_l$ (land).
Table 3.2: The tables show the result of a 10-fold cross validation on the four classifiers. TPR is the true positive rate, FPR is false positive rate, and Dist is the Euclidean distance from (FPR, TPR) to (0, 1).
Algorithm computation time is also an important factor to consider, given the fact that snow maps need to be computed in real time as satellite data becomes available. The time needed to train and test each of the four classifiers considered is shown in table 3.3. Although the Logistic Regression classifier has the longest training time, i.e. the pre-processing time needed to compute model parameters, that is done once, it has the shortest prediction (testing) time, which is needed to compute a snow map for each satellite granule.
### Table 3.3: The time (in seconds) taken to train and test using each classifier. Training is done on the whole training set, and testing is done on a per granule basis. The values are the minimum timing out of 5 trials.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Training time (s)</th>
<th>Testing time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic Regression</td>
<td>1.5524</td>
<td>0.7690</td>
</tr>
<tr>
<td>LDA</td>
<td>0.0811</td>
<td>1.0719</td>
</tr>
<tr>
<td>Gaussian NB</td>
<td>0.0407</td>
<td>2.8592</td>
</tr>
<tr>
<td>KNN</td>
<td>0.1256</td>
<td>373.96</td>
</tr>
</tbody>
</table>

Since the logistic regression classifier proved optimal with highest accuracy, and shortest prediction time, its snow maps are computed for two test granules, shown in Figure 3.4, for visual comparison. For each granule the following images are shown, RGB (true color image), NASA snow mask (SnowMap), and the snow mask produced by the logistic regression classifier. The white areas in the color image can be either cloud or snow, but since cloud pixels are masked out using the cloud mask provided in the SnowMap algorithm, clouds should not be misclassified as snow. Upon visual comparison of the logistic regression snow masks with the other images, it is apparent that its output is very similar to that of NASA’s SnowMap algorithm.
Figure 3.4: Snow classification of three different locations at: a-c) December 25th, 2010, 6:30PM; d-f) April 27th, 2011, 6:10PM; g-i) Jan 20th, 2011, 5:25PM. Left column contain RGB true color images. Snow (black) and no-snow (white) for two different algorithms is shown in the middle and right columns.
3.1.4 Evaluation and Results

In this section the performance of the Logistic Regression classifier is evaluated against that of the NASA SnowMap algorithm using the snow depth measurement database as ground truth. Since the SnowMap algorithm is slightly different due to detector damage on Aqua, each satellite is evaluated separately. The evaluation is performed on clear sky only pixels, as determined by the NASA cloud mask used in the SnowMap algorithm.

Initially SnowMap is compared to all classifiers in the ROC - (FPR,TPR) space, shown in Figure 3.5. Since the parameters of SnowMap are fixed, a ‘curve’ cannot be computed for it, but just a point in the space. As can be seen from the plots, for Terra (Figure 3.5(a)), SnowMap’s point is located almost directly on top of Logistic Regression, KNN and LDA’s curves, meaning that all 4 algorithms perform with relatively similar accuracy. In the plot for Aqua (Figure 3.5(b)) however, SnowMap’s point is located further from the optimal (0,1) corner, than Logistic Regression, KNN and LDA, meaning that it has subpotimal values for FPR and TPR. As observed in the previous section Logistic Regression is superior to the other classifiers.
Expanding on the result from Figure 3.5, scatter plots of per snow depth measurement stations’ (FPR, TPR) points for each Logistic Regression and SnowMap on Aqua and Terra are shown in Figure 3.6. Again the point (0,1) is optimal in these plots, thus minimizing the distance to it is desired. As can be seen from both plots Logistic Regression performs similarly to SnowMap on Terra and is slightly superior on Aqua.
Figure 3.6: ROC Scatter Plots of Logistic Regression and NASA SnowMap for (a) Terra; (b) Aqua.

Figure 3.7 shows the confusion scatter plots of NASA SnowMap and Logistic Regression in the (NDSI, NDVI) space. Each cloud free satellite observation is plotted with the following color scheme: blue - true positive (correctly classified snow); green - true negative (correctly classified land); red - false negative (misclassified snow); magenta - false positive (misclassified land). As can be seen in Figure 3.7(a) SnowMap has a significant number of misclassifications around its static decision boundry (Figure 2.2), while Logistic Regression has a lot less misclassifications in that region. Another important observation is the substantial difference in the number of false positive (magenta) misclassifications. Logistic Regression has a much lower number of them as compared to SnowMap, which is to be expected given its low FPR from the previous evaluation.
Figure 3.7: NASA SnowMap (a) vs Logistic Regression (b) confusion scatter plots in NDSI, NDVI space. Blue corresponds to True Positives, Green corresponds to True Negatives, Red corresponds to False Negatives, and Magenta to False Positives.

Based on the above, it is expected that Logistic Regression is slightly superior at identifying snow on the snow/land boundary, and is also less likely to misclassify land pixels as snow. This is visually confirmed in Figure 3.8. In the upper left quadrant of the image, it is apparent that the Logistic Regression snow mask has more pixels identified as snow, as opposed to the SnowMap snow mask.
Figure 3.8: (a) RGB (true color); (b) Logistic Regression Mask; (c) NASA SnowMap Mask;
3.2 Sea Ice Detection

The ultimate objective of the algorithm presented in this section is to improve the mapping and characterization of the sea ice distribution in polar regions. Despite a large number of automated satellite-based sea ice extent datasets currently available, sea ice analysts still rely mostly on original satellite imagery (provided by satellite optical, passive microwave and active microwave instruments). The automated products derived from satellite optical data have gaps in the area of coverage due to clouds and darkness. Passive microwave products have poor spatial resolution. Automated ice identification based on radar data are not quite reliable due to a considerable difficulty in discriminating between sea ice and other rough ice-free ocean surfaces caused by winds.

In this section we present a novel multi-sensor algorithm that first extracts maximum information on sea ice distribution from the optical/infrared instruments VIIRS and MODIS, including regions covered by thin semitransparent clouds, then supplements the output with microwave measurements, and finally aggregates the results into a cloud gap free daily product. This ability to identify ice cover through thin clouds, that are usually masked out by traditional cloud detection algorithms, allows for expansion of the effective coverage of the sea ice distribution and thus more accurate and detailed delineation of the ice edge.

3.2.1 Training Data

Representative cases annotated by analysts at the National Ice Center are used as training data for this chapter. The representative images over regions of interest were subjectively chosen and annotated by different analysts. Figure 3.9 shows the six examples used to develop the algorithm. As can be seen, the image enhancements used by human operators vary from case to case. The annotations indicate where open water is visible both with and
without thin clouds. Other annotations also indicate ice with and without thin cloud, as well as thick cloud regions where determination of the surface from reflected light imagery is likely impossible. From examination of the annotated images, small representative areas have been manually marked up near the points annotated with similar visual properties.

Figure 3.9: Six representative examples of NIC special support and manual mark-up.

Since the goal of the algorithm is to identify the surface as ice or water wherever that determination is possible, we have defined the following 5 classes: 1) confident open water which
may be covered by a thin cloud (rendered in blue); 2) water under clouds which is visually identifiable from the natural color imagery (rendered in green); 3) confident sea ice which may have thin cloud (rendered in red); 4) thick cloud (rendered in yellow); and 5) uncertain regions which may include cloud shadows (magenta), mixed or broken ice, leads and polynyas (cyan). This labeled data set was used in our algorithm development for feature selection, ice/water classification development, ice/water daily composite maps and case-by-case validation.

Traditional automated sea ice extent algorithms usually rely on an external cloud mask, which in general is more conservative in identifying clouds than a human ice analyst. When clouds are thin and ice or water are clearly visible, human sea ice analysts use that information in their classification of ice extent. In human analysis, a particularly useful false color composition that partially enables such classification can be built from the MODIS instrument using derived reflectance from $R_{0.47\,\mu m}$ (MODIS band 3), $R_{1.6\,\mu m}$ (MODIS band 6), $R_{2.1\,\mu m}$ (MODIS band 7) which are usually visualized as RGB respectively. For this 3-6-7 false color RGB, the displayed red channel, corresponding to measurements in visible spectra (band 3), provide a clear distinction between water versus cloud and ice, whereas the infrared bands 6 and 7 (green and blue) facilitate ice versus cloud discrimination. In the visible spectral bands cloud and ice appear much brighter then water, while in the infrared spectra, ice appears darker than clouds. As a result the 3-6-7 false color image shows ice in bright red (high value only in $R_{0.47\,\mu m}$), cloud in white (high values in all three bands) and water will appear dark (low values in all three bands). MODIS band 3-6-7 false color images corresponding to the selected marked-up examples are shown in Figure 3.10. The main challenge in visual identification of sea ice is discriminating water from shadowed regions. The cloud shadow over either the ice surface or other cloud appears dark and can easily be confused with water.
Figure 3.10: MODIS band 3-6-7 false color images, corresponding to selected examples shown in Figure 3.9.

Figure 3.11 shows 2D scatter plots of band 3 and 6 reflectance values, for all of the manually marked up classes, using the same coloring scheme as in Figure 3.9. As can be seen in these plots, water, ice and cloud clusters appear to be separable for each individual example. The relative positions of the classes with respect to each other are preserved, with ice (red) on the right, water (blue) in the lower left, and clouds (yellow) at the top. Clouds over water
(green) fall between the water and cloud clusters and clouds over ice (orange) are similarly located on the path from ice to cloud. This suggests using visible bands as the “R” direction of the false color space and bands 6 and 7 as “G” direction. Shadows (magenta) are appearing in the middle, sometimes overlapping with ice pixels and sometimes spreading towards the “water domain”.

It should be noted that although the relative position of the classes within single case study is the same, there is a significant variation with respect to the position of each class across the different images (cf. Figure 3.11). This makes it difficult to separate the classes using distance measures from pixels with known classes such as universal thresholds, nearest neighbor methods or queries to Look Up Tables (LUT). These variations are attributed to satellite viewing angle, solar zenith angle, atmospheric conditions, and seasonal cycles. Therefore, the selected features should be at least partially invariant.
Figure 3.11: Scatter plots of marked up class labels from NIC annotated examples.
This work introduces a novel 3D false color feature space which shares the property of the 3-6-7 false color composition that ice is displayed in red. This was achieved utilizing manually labeled satellite imagery (including examples shown in Figures 3.9-3.11), by expert analysts from the National Ice Center (NIC). The spectral signatures of each target class are extracted and used to compute coefficients to a logistic function that maps the input albedo into a feature whose value is high for the class it was derived for.

![Image](image_url)

Figure 3.12: a) False color cube with colors corresponding to selected classes: shadows (black), water (blue), thin cloud over water (cyan), ice (red), thin cloud over ice (yellow), cloud (green), thin ice or cold, nearly freezing point water (magenta); b) Spectral curves corresponding to selected representative water pixels (blue), shadows (black), ice-covered pixels (red), cloudy pixels (green).

The purpose of this novel feature space is to emphasize the two main classes: the ice class and the water class even if they are partially obscured by clouds. Since the cloud class was of no interest for this study, the desired 3D feature space and the corresponding false color composition are called Ice-Water (I-W) space and I-W false color image. With “white” allocated for geographically determined land, the color choice for clouds and water classes are considered to be yellow and blue respectively. That choice calls for a space with the (0,0,1) corner reserved for water (high in blue and low in the other two components), the (1,0,0) corner allocated for ice (high in red and low in other components) and the (1,1,0) corner reserved for clouds (high in both, red and green; low in blue) as shown in Figure 3.12a. The
9D space containing reflective, shortwave IR and thermal bands centered around 0.46nm, 0.56nm, 0.65nm, 0.86nm, 1.24nm, 1.6nm, 2.2nm, 11nm and 12nm is projected to 3D color cube, mapping seven types of spectral curves into seven (color-coded) corners of the RGB cube, shown in Figure 3.12a. Spectral curves over reflective bands corresponding to selected representative water pixels (blue), shadows (black), ice-covered pixels (red), cloudy pixels (green) are shown in Figure 3.12b.

The I-W false color images, corresponding to the same six selected cases as in Figures 3.9-3.11, are shown in Figure 3.13. The ice is more pronounced then in 3-6-7 False Color images (cf. Figure 3.10), especially under thin clouds. The shadowed regions (appearing dark) are also much more separable from open water (blue).
3.2.2 Algorithm Description

The overall multi-sensor algorithm to generate cloud-free region based gridded daily ice maps has two parts:

A) Generate an ice map on a per satellite overpass basis, for the region in question, by

Figure 3.13: I-W False color for annotated examples shown in Figure 3.9. The ice is more pronounced then in 3-6-7 False Color images (cf. Figure 3.10), especially under thin clouds. The shadowed regions (appearing dark) are also much more separable from open water (blue).
supplementing imager reflectance data with microwave observations closest in time.

B) Combine ice maps from individual satellite overpass ice maps in an optimal way, resulting in an enhanced, high resolution, cloud gap free daily ice extent product.

It is important to note that part A results in a per satellite overpass product which is valuable in its own right. When visibility allows for it, multiple passes can reveal ice movement and rapidly changing conditions. The detailed procedure of per satellite overpass labelling is described in section 3.1. Part B (combining individual imager overpass labels into a daily product) is described in section 3.2.

**Single Overpass Ice Map Classification**

In what follows, we will first outline the main steps in part A of the algorithm and then discuss the rationale and implementation of each step in greater detail. The algorithm relies on re-gridded imager and microwave overpasses for a predetermined geographic region and consists of 3 main steps:

Step A1. Extracts maximum information on the sea ice cover from a single pass of one of the imaging instruments VIIRS and MODIS, including regions covered by thin, semitransparent clouds;

Step A2. Supplements classification by the microwave measurements, resulting in 5 intermediate classes:

(a) ice-free water,

(b) sea ice,

(c) water under thick clouds,

(d) ice under thick clouds,
(e) undetermined class (insufficient information);

Step A3. Generates a (per satellite overpass) supervised classifier, using labels from Step A2 as a training set in an ice-water feature space constructed from reflective, shortwave IR and thermal bands centered around 0.46nm, 0.64nm, 0.86nm, 1.24nm, 1.6nm, 11nm and 12nm from the optical/infrared instrument as well as polarization and gradient ratios of 18 and 36 GHz radiometer channels of the passive microwave instrument with the goal to eliminate the ‘undetermined’ class;

Figure 3.14: Block diagram describing the structure and data flow of the individual satellite overpass classification algorithm.

The block diagram in Figure 3.14, shows the main components of the satellite overpass labeling procedure. Steps A1-A3 are shaded in light gray as they consist of multiple block elements. The data flow is outlined by the input/output arrows.

Step A1 takes, as input, the imager data alone. Using a specially designed 3 dimensional feature space that suppresses thin clouds and amplifies the discrimination between open water and ice, three feature images are produced which summarize the imager input. In step A2 the data from the imager and microwave inputs is combined to confidently identify the five sets of class labels ice, ice-free water, ice under cloud, ice-free water under cloud, and
leads and shadows. These class labels are then used in step A3 as training data masks to fit a scene specific linear classification model that is based on features from both imager and passive microwave data. In the same step this classification model is then used to classify any pixels that remain unlabeled. The output of Step A3 is an array of labels classifying each pixel in the scene.
Figure 3.15: All images obtained for January 16, 2016 over the western coast of the Ross Sea region. (a) VIIRS RGB at 11:37UTC; (b) Feature Space of Step A1 represented as a false color; (c) AMSR-2 L2 Sea Ice Concentration product at 09:35UTC; (d) VIIRS L2 Cloud Mask at 11:37UTC used in the Ice Concentration intermediate product (IVIIC) with green: cloud, gray: clear-sky and white: land; (e) Training Labels (output of Step A2) and (f) Satellite overpass ice map (output of Step A3) with red: ice, blue: water, orange: ice under cloud, green: water under cloud, gray: unclassified, and white: land.

Steps A1-A3 are performed for every optical/infrared and closest in time passive microwave overpass set for a given day and gridded region. Figure 3.15 shows the described steps for one particular MODIS/AMSR-2 set. A true color RGB composite is depicted in Figure 3.15(a)
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for visual reference with the coast represented as a red line. Figure 3.15(b), shows a false color representation of the feature space mapping performed in Step A1. Note in this representation ice is red and is clearly distinguished from the cyan and green cloud, despite looking similar in the RGB reference. In addition to the features from Figure 3.15(b), the level 2 microwave sea ice concentration, displayed in Figure 3.15(c), is passed in as input to Step A2. Note that the microwave information in 3.15(c) is lower resolution as seen in the ice (red) but does identify the ice free open water through the clouds (blue). In contrast to our algorithm Figure 3.15(d) shows the cloud mask used to eliminate cloud covered pixels (green) in the VIIRS level 2 sea ice concentration algorithm to demonstrate the large area identified as cloud, and thus not classified. Figure 3.15(e) depicts the training labels output by Step A2. The red regions have been confidently identified as ice, with orange representing ice under cloud. Blue is open water, green indicates clouds over water, while gray region was not confidently classified. Note the gray region is largely on boundaries between classes or on the coast. Figure 3.15(f) displays the final classification output by Step A3 in which most of the gray regions have been resolved. Areas near the coast occluded by cloud often remain a problem since microwave is not reliable there. In the following subsections a description of the detailed implementation of each step of part A is provided.

Non-linear Feature Mapping (Step A1) (Ice-Water feature space)

As described in Section 3.2.1, a non-linear mapping function that projects imager albedo from visible, near infrared and shortwave infrared bands, to a 3D feature space has been developed. This novel mapping function provides better separation of our main target classes i.e. ice and water. This was achieved utilizing manually labelled satellite imagery. The spectral signatures of each target class were extracted and used to compute coefficients to a logistic function that maps the input albedo into a feature whose value is high for the class
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it was derived for.

The feature mapping function \( F \) is a 3D vector valued function on the optical/infrared bands Blue \((R_{0.47\mu m})\), Green \((R_{0.55\mu m})\), Red \((R_{0.64\mu m})\), Near Infrared \((R_{0.86\mu m})\), Shortwave Infrared 1 \((R_{1.24\mu m})\) and Shortwave Infrared 2 \((R_{1.64\mu m})\) that we write as:

\[
V_R = [R_{0.47\mu m}, R_{0.55\mu m}, R_{0.64\mu m}, R_{0.86\mu m}, R_{1.24\mu m}, R_{1.64\mu m}], \quad (3.8)
\]

a reflectance vector for each pixel in the scene. The feature function \( F(V_R) \) is then defined as

\[
F(V_R) = \begin{cases} 
[F_r, F_g, F_b], & (R_{0.47\mu m} - R_{0.64\mu m}) > 0.25 \text{ and } F_r > 0.5 \\
[0, 0, 0], & \text{otherwise}
\end{cases} \quad (3.9)
\]

where \( F_r, F_g, F_b \) are three functions of \( V_R \) defined below and the condition \((R_{0.47\mu m} - R_{0.64\mu m}) > 0.25 \) and \( F_r > 0.5 \) is imposed so that \( F \) does not produce a false value when lighting conditions are very poor.

The component functions were carefully and empirically constructed through a painstaking examination of the surface under many lighting, viewing angle, water and sea ice conditions to disambiguate sea ice and open sea in the presence of clouds, shadows, and leads. To define \( F_r(V_R) \), first \( F_{r_{\text{init}}}(V_R) \) is defined as:

\[
F_{r_{\text{init}}}(V_R) = \lambda[(V_R - M_S) \cdot A_r], \quad (3.10)
\]

where \( A_r = [0, 0, 0, 1, -1], \lambda = 10, \text{ and } M_S = [0.502, 0.308, 0.235, 0.166, 0.067, 0.0250] \) is the mean vector of the shadow class that will be used to additively normalize the data so that
$V_R$’s corresponding to shadow pixels are projected to 0 ($F_r = F_g = F_b = 0$). Using $F_{r_{init}}(V_R)$, $F_r(V_R)$ is defined as:

$$F_r(V_R) = \sigma(\alpha_r[(F_{r_{init}}(V_R) + 100y) - \beta_r]),$$  

(3.11)

using sigmoid function $\sigma(u) = (1 + e^{-u})^{-1}$, with $\alpha_r = 4$, $\beta_r = -0.1$ and $y = R_{0.64\mu m} - 0.71(R_{0.55\mu m}) - 0.29(R_{0.86\mu m}) + 0.01$. The definition of $F_r(V_R)$ was crafted as to specifically respond to ice, and agree with current products such as the MODIS derived NASA sea ice mask.

The second feature $F_g$ is defined as:

$$F_g(V_R) = \lambda[(V_R - M_S) \cdot A_g],$$  

(3.12)

with weights vector $A_g = [0.1716, 0.9686, 1.3454, 0.3948, 0.2857, 0.0265]$. This feature is designed to respond to clouds, with a low value for thin transparent clouds and a high value for thick opaque clouds.

For the third feature $F_b$ the following is initialized:

$$F_{b_{init}}(V_R) = \lambda[(V_R - M_S) \cdot A_b],$$  

(3.13)

with weights vector $A_b = [0.5, 1, 1, 0.3, 0, 0]$. The sigmoid function is then applied to generate:

$$F_{b_0}(V_R) = \sigma(\alpha_b(F_{b_{init}}(V_R) - \beta_b)),$$  

(3.14)
with constants $\alpha_b = 10$ and $\beta_b = 0.4$. Then a water indicator is defined as:

$$w(V_R) = F_r(V_R) + 0.38F_\kappa(V_R)^2 - 0.78F_\kappa(V_R) - 0.1$$  \hspace{1cm} (3.15)

Finally, $F_b(V_R)$ is defined as:

$$F_b(V_R) = \begin{cases} 
1, & w(V_R) < 0 \\
0, & w(V_R) \geq 0 
\end{cases}$$ \hspace{1cm} (3.16)

This feature is designed to respond to water, with the value 1 where the imager data suggests water is present and 0 otherwise.

**Optical/Infrared/Microwave Confident Class Labeling (Step A2)**

An automated logic based procedure is designed, which combines information about the surface conditions from the passive microwave and optical/infrared observations, to label a subset of pixels in the scene into the five confident classes: ice, ice-free water, ice under cloud, ice-free water under cloud, and leads and shadows. This confident labeling will later be used to fit an automatic classifier to label any remaining unlabeled pixels in the scene. A geographic reference grid is defined for the scene at the approximate resolution of the optical/infrared instrument, to make it possible to fuse its data with the passive microwave data. The procedure begins by first examining the passive microwave L2 Sea Ice Concentration Product:

- *Training regions from microwave L2 Sea Ice Concentration Product*

In this step the procedure takes advantage of the passive microwaves ability to provide
cloud-free surface information in the scene by extracting regions classified as “microwave ice” or “microwave water”. Since passive microwave data is known to have issues due to its coarse resolution, only pixels away from the ice edge and land border are considered. Figure 3.16(a) shows an example of the regions identified in this step with water (blue), ice (red), unused (gray) and land (white).

To initialize the algorithm, locations \( p = (lon, lat) \), that fall into “microwave ice” and “microwave water” training regions, denoted by \( Z_{MI} \) and \( Z_{MW} \) respectively, based on the L2 passive microwave sea ice concentration product are identified. To define these regions, first a geographic reference to partition the grid cells in the scene into land and ocean sets, denoted by \( Z_L \) and \( Z_O \) respectively, are used. The goal is to exclude pixels, which may be near land or the boundary between ice and water. In both these cases the microwave ice concentration product is less accurate. So first an exclusion region \( Z_E \) is defined as:

\[
Z_E = \{ q \in Z_O | f(q) \geq \mu_l \} \cup Z_L
\]  

(3.17)

with \( f(q) \) being the microwave sea ice concentration value at location \( q \) and \( \mu_l = 0.1 \), representing ice concentration of 10\%, is determined empirically. The region of microwave confident water (\( Z_{MW} \)) is then defined as points far from \( Z_E \) that have a low concentration value:

\[
Z_{MW} = \{ p \in Z_O | d(p, q) > \delta, q \in Z_E, f(p) < \mu_l \},
\]  

(3.18)

where \( d(p, q) \) is the distance measure between the locations \( p \) and \( q \), and \( \delta \) is the minimum allowable distance to the exclusion region \( Z_E \) that is empirically determined. In
practice $Z_E$ defines a binary exclusion image mask (binary image) that is 1 for grid cells in the region and 0 outside. Similarly, the $Z_{MW}$ mask is the result of the binary “AND” operation between the inequality defining low sea ice concentration and the negation mask of a dilation of the binary exclusion image mask using a 61x61 window (which is essentially $\delta$).

Using the same methodology, the microwave confident ice mask is defined as:

$$Z_{MI} = \{ p \in Z_O | d(p, q) > \delta, q \in Z_E, f(p) > \mu_h \},$$

(3.19)

where $\mu_h = 0.8$, representing ice concentration of 80%, is determined empirically. Here the $Z_{MI}$ mask is the result of an erosion of the binary mask that results from the inequality defining high sea ice concentration using a 61x61 window.

- Merging confident optical/infrared features and microwave labeling

In this step the microwave derived training regions are utilized in conjunction with the optical/infrared derived features and reflectance, to identify confident class labels for a subset of locations in the scene. The five target classes for which confident labels are assigned are: ice, water, ice under cloud, water under cloud and leads/shadows. Letting $V_R(p)$ be the optical/infrared reflectance vector above at a grid cell $p$, and using the imager feature mapping function $F$, then the features of a false color composition image for the scene are defined as $r(p) = F_r(V_R(p))$, $g(p) = F_g(V_R(p))$, and $b(p) = F_b(V_R(p))$. With this notation, confident labels for the ice class, as determined by the optical/infrared instrument, are identified using a box in the feature space as:

$$r(p) \geq \theta_{I,R}, g(p) \leq \theta_{I,G}, b(p) < \theta_{I,B}$$

(3.20)
with ice thresholds \((\theta_{I,R}, \theta_{I,G}, \theta_{I,B}) = (0.7, 0.5, 0.5)\), again, determined empirically. As previously mentioned, the intuition is that the feature space has been chosen so that pixels with a strong \(r\) response are ice.

While there is some variability in the feature space, these thresholds are reliably associated with ice across overpasses, particularly when considered together with the microwave data. Those grid cells that are in the optical/infrared feature space box defined by these thresholds and which reside in the microwave confident ice region \((Z_{MI})\) are considered confident ice \(Z_{I_0}\):

\[
Z_{I_0} = \{p \in Z_O | p \in Z_{MI}, r(p) \geq \theta_{I,R}, g(p) \leq \theta_{I,G}, b(p) < \theta_{I,B}\}.
\]  

These pixels have a high \(r\) response in the feature space and relatively low \(g\) and \(b\) response by design to give the known classes the appropriate visual identification. For locations with relatively high \(r\) and \(g\) response, due to the presence of thick clouds, that also fall into the microwave confident ice region, an ice under cloud class \(Z_{I_1}\) is defined:

\[
Z_{I_1} = \{p \in Z_O | p \in Z_{MI}, r(p) \geq \theta_{I,R}, g(p) > \theta_{I,G}, b(p) < \theta_{I,B}\}.
\]  

Similarly, we segment points with a high \(b\) response and low \(r\) response that reside inside the microwave confident water region \((Z_{MW})\) to form a general water class \(Z_W\):

\[
Z_W = \{p \in Z_O | p \in Z_{MW}, r(p) < \theta_{W,R}, b(p) > \theta_{W,B}\},
\]  

where the set of water thresholds \((\theta_{W,R}, \theta_{W,B}) = (0.1, 0.5)\) are empirically determined. Here the feature space is engineered so that water is both dark in \(r\) and 1 in the binary
We further break $Z_W$ into two regions: one for which the reflectance measured at the 0.64$\mu$m (visible red) band of the optical instrument indicates this region of confident water is clear (or under thin cloud), namely $Z_{W_0}$ when $(R_{0.64\mu m}(p) \leq 0.3)$; and one for which the indication is a thicker cloud over water, namely $Z_{W_1}$ when $(R_{0.64\mu m}(p) > 0.3)$. The reason why the optical reflectance value is used as opposed to the $g$ feature, is because the feature space is designed to suppress clouds.

Lastly, a fifth class is defined to account for the presence of leads and shadows over ice which are visually dark, thus having a low value in all three features and residing in the microwave confident ice region $Z_{I_2}$:

$$Z_{I_2} = \{ p \in Z_O | p \in Z_{MI}, r(p) < \theta_{S,R}, g(p) < \theta_{S,G}, b(p) < \theta_{S,B} \},$$

with feature thresholds $(\theta_{S,R}, \theta_{S,G}, \theta_{S,B}) = (0.1, 0.1, 0.1)$, determined empirically.

Using the five confident sets defined above we define an uncertain region set $Z_U$:

$$Z_U = Z_0 \setminus (Z_{W_0} \cup Z_{W_1} \cup Z_{I_0} \cup Z_{I_1} \cup Z_{I_2})$$

An example of the resulting regions achieved in this step is shown in Figure 3.16(b). As can be seen, the uncertain regions (gray) tend to be on the boundaries of clouds, water and ice, and on the coast.
Figure 3.16: (a) Passive-microwave derived training regions (red: microwave ice, blue: microwave water, gray: excluded, white: land); (b) Blended confident labels and (c) LDA labeling without nearest neighbor expansion with red: ice, blue: water, orange: ice under cloud, green: water under cloud, gray: unclassified, and white: land.

• Nearest-Neighbor Search

The purpose of this procedure is to maximize the utility of the high resolution information available from the optical/infrared instrument by performing a nearest neighbor search with a conservative distance threshold, using a pixels feature vector and spatial location. This procedure is only performed on pixels belonging to the $Z_{W_0}$ (confident water) and $Z_{I_0}$ (confident ice) regions. It results in the expansion of those regions to pixels that are spatially close and have similar feature vectors. Figure 3.16(b) shows the training classes before the nearest neighbor expansion is applied, and Figure 3.15(e) shows them after. It is evident that there is a significant increase in the amount of “confident ice” (red) pixels in the latter image. To underline the importance of this procedure we show the resulting maps of the individual overpass algorithm continuing the process with and without it, in Figures 3.15(f) and 3.16(c) respectively. Note the
misclassified pixels on the ice edge in Figure 3.16(c), and their correct classification in Figure 3.15(f).

**Single Overpass Ice Map Classification with Linear Discriminant Analysis (Step A3)**

In order to resolve areas that have not been identified by step A2 using the conservative threshold procedure, an automatic statistical linear classifier is fitted and then applied to the remaining pixels i.e. members of the set $Z_U$. The intuition is that the previous step outputs examples of grid cells for all classes present in the scene which allows for the fitting of a statistical model using Linear Discriminant Analysis (LDA). The inputs to the classifier are the features derived in Step A1, as well as the two normalized difference ratios used in producing the standard level 2 passive microwave ice fraction product (i.e. Polarization Ratio (PR) and Gradient Ratio (GR) as defined in the Comiso Bootstrap Algorithm). This results in a 5-dimensional feature space. Once the model is fit to the training data, it is then applied to assign one of the five target classes across the remaining unknown grid cells in $Z_U$. The passive microwave inputs are directly used, rather than their derived ice concentration, to preserve as much information as possible for the classification. The final resulting ice map of this classification is shown in Figure 3.15(e).

**Daily Compositing**

This procedure merges the pre-labeled gridded scene overpasses, using logic that assigns higher weights to optical-based classification from Step A1 and lower weights to classification involving microwave observations obtained in Steps A2 and A3, to create a high resolution daily ice extent product.

Each day there are multiple passes over polar regions from polar orbiting satellites, such
as Aqua, Terra and Suomi-NPP, yielding multiple overpassed overlapping the same region. Having multiple overpasses over the same region is important because cloud cover is a significant problem. Figure 3.17(c), exhibits the fraction of cloud obscured overpasses per pixel, derived from the L2 imager cloud mask for one day. Due to the conservative nature of the imager cloud detection algorithm, a large percentage of the scene is not classified, due to 100% cloud obstruction for the day in question. As clouds move between passes, as can be seen in Figures 3.17(a), 3.17(b), 3.17(d), and 3.17(e), there are more observations of the surface with clear sky or at least through thin cloud. We now present a method to aggregate these individual ice masks and provide a daily product that combines all the available information to achieve the most accurate cloud free ice/water mask possible shown in Figure 3.17(f).
Figure 3.17: All images obtained from December 2\textsuperscript{nd}, 2015 in the Ross Sea. (a) VIIRS at 00:41 UTC; (b) VIIRS at 02:19 UTC; (c) Imager overpass L2 cloud cover fraction; (d) VIIRS at 04:02 UTC; (e) MODIS (Terra) at 18:45 UTC; (f) MISIC daily sea ice map (red: ice, blue: water).

Let $L = \{aI, aW, aCI, aCW, \text{Null}\}$ be a set of labels that indicate, respectively: $aI$-confident ice (clear sky), $aW$-confident water (clear sky), $aCI$-classified ice (ice under cloud), $aCW$-classified water (water under cloud) and $\text{Null}$-undecided. If $p$ is some location, then a mask is a function so that $M(p)$ has a value in $L$. Let $\{M_1, M_2, ..., M_J\}$ be the set of masks for individual overpasses for a given day. The approach for computing the Multi-Instrument Sea Ice Composite (MISIC) product $D$ is to first consider the confident (clear sky) observations. The majority rule only amongst these observations is used to determine ice or water. If it is
a tie, and there is at least one observation, it is resolved with a determination of water. If there aren’t any clear sky observations then the majority of the classified ice/water pixels is used, and again water is assigned if there is a tie (assuming at least one observation). More formally for each grid cell $p$ 4 non-negative counts are computed:

$$AI(p) = |\{j | M_j(p) = aI\}|,$$

$$AW(p) = |\{j | M_j(p) = aW\}|,$$  \hfill (3.26)

$$ACI(p) = |\{j | M_j(p) = aCI\}|,$$

$$ACW(p) = |\{j | M_j(p) = aCW\}|$$ \hfill (3.29)

and $|\ast|$ is the cardinality of the set.

For each location, if there are any confident observations, $AI(p) + AW(p) > 0$, and if there are more confident water observations at the grid cell $AI(p) \leq AW(p)$, then it is classified as water $D(p) = bW$, where $bW$ is the label for water in the daily product. It is classified as ice, $D(p) = bI$ if $AW(p) < AI(p)$ where $bI$ is the label for ice. If $AI(p) + AW(p) = 0$ but $ACI(p) + ACW(p) > 0$ then $D(p) = bW$ if $ACI(p) \leq ACW(p)$, and $D(p) = bI$ if $ACW(p) < ACI(p)$. Finally, if there are no observations $D(p)$ is unassigned.

Figure 3.18(a) shows the percentage of confident ice observations i.e. $\frac{AI(p)}{AI(p)+AW(p)}$. Similarly Figure 3.18(b) shows the percentage of cloudy ice observations i.e. $\frac{AI(p)}{AI(p)+AW(p)}$. Intuitively pixels in $D$ classified as ice have a value greater 0.5 in both images and all other ocean pixels are classified as water.
3.2.3 Evaluation and Results

The previous section describes both an algorithm for producing a sea ice map for each optical/imager instrument overpass, and an aggregated MISIC daily product. Daily ice products can take advantage of cloud movement and multiple overpasses provide more opportunities for un-occluded visible observations of the earth’s surface. When multiple visible observations of the same portions of the surface are available, individual overpass maps provide an opportunity to study ice changes or motion within a day. A comparison between these two types of ice maps and current operational products follows.

Single Overpass Ice Map Evaluation

Evaluation of MISIC’s single overpass ice maps is done through comparison with NASA’s MODIS IceMap product, using higher resolution Landsat 8 data as ground truth. A repre-
sentative case is shown in Figure 3.19 depicting a scene from August 6th, 2015 off the east coast of Greenland. In Figure 3.19(a) the MISIC three-value feature space is shown in false color created from MODIS (Terra) at 13:40 UTC. In this image, ice (appearing in red in the false color composition) is dominating the scene. A thicker patch of cloud, shown in green, is visible in the center left with thin cloud over ice in yellow, and over water in cyan. The corresponding MODIS RGB-color image is shown in Figure 3.19(b), and from a Landsat 8 image from the same day at 14:13 UTC in Figure 3.19(c). In the RGB images (both Landsat and MODIS) clouds are present but the details of the surface ice and water are readily apparent. The MISIC single overpass ice map, shown in Figure 3.19(d), captures these high resolution features through the thin clouds, resolving the thicker part of the cloud with the help of supplementary microwave data. In contrast, both the MODIS IceMap (MOD29) product, and the higher resolution Landsat product, shown in Figure 3.19(b,c) respectively, are largely obscured by aggressive cloud masks. Where those products indicate ice or water, it is apparent that the MODIS product lacks much of the detail visible in both the MISIC product and the Landsat image, particularly in the center bottom where MODIS misclassifies mixed water and ice as cloud. This exemplifies the increase in coverage achieved through MISIC’s ability to classify surface conditions under thin clouds.
Table 3.4 shows the statistics of the August 6th, 2015 scene classification, along with 5 other cases. For all examples the classification of the IceMap and MISIC MODIS-based products are up-sampled to the Landsat 8 reference scene and resolution, and the Landsat quality band (which contains ice/water classification) is used as ground truth for cloud-clear pixels in all products. In all cases shown, the True Positive Rate (TPR) is superior for the IceMap product while the False Positive Rate (FPR) is superior in 5/6 cases for MISIC. This is mostly indicative of the IceMap product being more aggressive in the classification of ice.

Figure 3.19: All images obtained from August 6th, 2015 in the Greenland Sea. (a) MODIS(Terra) based Features at 13:40 UTC; (b) MODIS RGB; (c) Landsat 8 RGB at 14:13 UTC; (d) MISIC overpass labels; (e) MODIS IceMap (MOD29) labels; (f) Landsat 8 Quality Assessment Band labels.
### Table 3.4: Evaluation parameters and their values for the 6 representative examples.

<table>
<thead>
<tr>
<th>Date</th>
<th>Product</th>
<th>TPR</th>
<th>FPR</th>
<th>ACC</th>
<th>Cov. Inc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>05/25</td>
<td>MISIC</td>
<td>0.945</td>
<td>0.026</td>
<td>0.961</td>
<td>67.380%</td>
</tr>
<tr>
<td></td>
<td>IceMap</td>
<td>0.957</td>
<td>0.019</td>
<td>0.970</td>
<td>N/A</td>
</tr>
<tr>
<td>08/06</td>
<td>MISIC</td>
<td>0.896</td>
<td>0.353</td>
<td>0.828</td>
<td>86.725%</td>
</tr>
<tr>
<td></td>
<td>IceMap</td>
<td>0.971</td>
<td>0.579</td>
<td>0.821</td>
<td>N/A</td>
</tr>
<tr>
<td>08/17</td>
<td>MISIC</td>
<td>0.899</td>
<td>0.197</td>
<td>0.871</td>
<td>75.484%</td>
</tr>
<tr>
<td></td>
<td>IceMap</td>
<td>0.966</td>
<td>0.488</td>
<td>0.836</td>
<td>N/A</td>
</tr>
<tr>
<td>09/11</td>
<td>MISIC</td>
<td>0.822</td>
<td>0.121</td>
<td>0.834</td>
<td>56.937%</td>
</tr>
<tr>
<td></td>
<td>IceMap</td>
<td>0.975</td>
<td>0.352</td>
<td>0.906</td>
<td>N/A</td>
</tr>
<tr>
<td>09/15</td>
<td>MISIC</td>
<td>0.886</td>
<td>0.011</td>
<td>0.962</td>
<td>90.954%</td>
</tr>
<tr>
<td></td>
<td>IceMap</td>
<td>0.925</td>
<td>0.016</td>
<td>0.968</td>
<td>N/A</td>
</tr>
<tr>
<td>12/02</td>
<td>MISIC</td>
<td>0.987</td>
<td>0.351</td>
<td>0.955</td>
<td>89.481%</td>
</tr>
<tr>
<td></td>
<td>IceMap</td>
<td>0.998</td>
<td>0.517</td>
<td>0.950</td>
<td>N/A</td>
</tr>
</tbody>
</table>

The overall accuracy is approximately equal. The important thing to note here is the percent of pixels IceMap declares as cloud, which are now classified by the MISIC single overpass product, shown in the last column. Thus the MISIC product provides a high resolution accurate classification comparable to the IceMap product, but is able to classify ice and water through thin cloud at high resolution, and thicker cloud with the aid of supplemental passive microwave.

The last example of Table 3.4, based on MODIS (Terra) acquired on December 2nd, 2015 at 18:45 UTC, and Landsat 8 at 19:18 UTC, near the Ross Sea, is shown in Figure 3.20. Again Figure 3.20(a) shows the MISIC three value false color, clearly showing thin cloud running from the bottom to top through the left center of the image. The numerous ice floes are clearly identifiable, which can be seen from the corresponding MODIS and Landsat 8 RGB images shown in Figure 3.20(b,c). As in Figure 3.19, the MISIC single overpass product indicates the ice floes as well as the thin cloud, while the IceMap and Landsat 8 products block much of the central image with a cloud mask. A coded comparison of Landsat 8 with IceMap (Figure 3.21(a)), and MISIC granule product (Figure 3.21(b)) shows agreement on ice in red, water in blue and disagreement in green. While both pick up the floe details,
again, the IceMap is much more aggressive in declaring ice as well as leaving thin cloud masked.

Figure 3.20: Images in a,c,d, and f obtained from MODIS (Terra) on December 2nd, 2015 at 18:45 UTC. Images in b and e obtained from Landsat 8 at 19:18 UTC. (a) MODIS based Features; (b) Landsat 8 RGB; (c) MODIS RGB; (d) MISIC granule labels; (e) Landsat 8 Quality Assessment Band labels; (f) MODIS IceMap (MOD29) labels.
Chapter 3. Algorithms

Figure 3.21: Coded comparison between Landsat 8 quality band and (a) IceMap and (b) MISIC. Input data same as Figure 3.20.

Mis-identifying clouds is a well-known and frequent problem in the IceMap product as can be seen in Figure 3.22 from derived stitched MODIS (Aqua) granules on September 15th, 2015 at 13:10 UTC and 13:15 UTC. From the RGB shown in Figure 3.22(a) it is clear that the swirl in the center is mixed ice, yet the IceMap declares it cloud while MISIC correctly identifies it.

Figure 3.22: Images derived from MODIS (Aqua) on September 15th, 2015 at 13:10 UTC and 13:15 UTC. (a) MODIS RGB; (b) MODIS IceMap labels; (c) MISIC overpass labels.
Daily Composite Evaluation

Overall validation of the daily composite over a large region is challenging. There are very limited and sparse in-situ measurements. Even the notion of daily ground truth is difficult. In particular, it is possible for ice to move several kilometers over the course of a day, making clear-cut delineation of ice and water ill defined. The claim is that this fully automated algorithm’s product is consistent with the best semi-automated products available. These products include: the Interactive Multisensor Snow and Ice Mapping System (IMS) (National Ice Center, 2017) produced and hosted by the National Ice Center; the Daily Sea Ice Concentration Analyses product produced and hosted by the Marine Modeling & Analysis Branch (MMAB) (Grumbine, 2014) of the National Centers for Environmental Protection (NCEP); the Global Sea Ice Concentration product produced and hosted by the Ocean and Sea Ice Centre at the EUMETSAT Network of Satellite Application Facilities (OSI SAF) (Eastwood, 2017); and the Global Daily Ice Edge product produced by the Canadian Meteorological Center (CMC) (Meteorological Center, 2012).

The consistency of MISIC’s daily ice extent for the time series October 1st-15th, 2015 corresponding to sea ice freeze-up time in the Beaufort Sea is evaluated. The product comparison results are shown in Figure 3.23. The light gray solid line represents ice extent according to NCEP microwave ice concentration thresholded at 0.5 with the grey shading band showing ice extent corresponding to thresholds between 0.25 and 0.75. It is apparent that most daily ice products including IMS, OSI SAF, CMC and the MISIC presented here, stay within this band. The NIC product follows the same shape but is much more aggressive in indicated ice due to its mission requirements to protect shipping. There is a consistent increase in the ice extent over time, as the sea freezes throughout October. The figure also shows the products converging with the freeze up as the ice becomes less variable. Whereas, some of the other
products tend to be more aggressive at indicating ice, MISIC has been developed to reveal high resolution ice features which may account for its generally consistent lower estimate of ice extent. Still the MISIC daily surface classification is able to automatically achieve an ice extent, consistent with microwave-based products, while maintaining the higher resolution, outperforming optical/infrared-based semi-manually created products.

Figure 3.23: Daily product ice fraction comparison of different ice coverage products in the Beaufort Sea region from 10/1/2015-10/15/2015. MISIC aggregate ice fraction consistent with current operational products.

Optical/infrared based products such as IceMap have similar resolution to the MISIC product. Yet because IceMap uses an aggressive cloud mask, coverage is often limited by the frequent presence of clouds. For thin and even moderate clouds, the MISIC algorithm does not mask, but instead attempts to classify the surface through the clouds. This should be contrasted with methods that simply use microwave whenever any amount of cloud is present. By using any surface optical/infrared data available, MISIC is able to achieve higher resolu-
tion over partly cloud occluded areas than achievable with microwave.

Figure 3.24 shows the same period in the Beaufort Sea region used in Figure 3.23. The area where a determination of ice vs water, using all the IceMap observation is indicated in Figure 3.24 as the blue bar. MISIC is able to also determine ice vs. water in those regions, while in addition MISIC classification using visible is able to discriminate ice and water though thin cloud at least once during the day shown in gray. Finally, the red portion shows the area where MISIC falls back to microwave to complete the classification. Note that over this period between 60% and 25% of the region was cloud obscured according to the MODIS cloud mask, but could still be identified using MISIC.

Figure 3.24: Daily product ice fraction comparison in the Beaufort Sea region from 10/1/2015-10/15/2015.

It has been observed that the most challenging case for the MISIC product is a water-ice
mixture during the freezing of new ice and re-melting. One such case is shown in Figure 3.25 where (a) is an RGB Landsat image of a location in the Greenland Sea on September 11th, 2015 where new ice is being formed. The Landsat mask is shown in (b) with the MISIC granule mask shown in (c).

Two crop regions where details are evaluated are shown in (a). In one crop, indicated by the green box at the bottom, not only is there new ice but the surface is occluded by small intermittent clouds as is clear from the crop’s RGB(d). These clouds are also evident from the MISIC preliminary sure classes shown in (e). In (f) it can be seen that the MISIC daily product algorithm is effective at combining the available information to make a determination of the ice water boundary that is consistent with the IceMap product (g) but at higher resolution and over more of the region. If we consider the top crop in (a), whose RGB is show in (h), it is apparent that the single overpass MISIC is able to correctly identify ice. However, when combining several passes the MISIC daily composite product is unable to make a correct determination (j) and classifies large areas as open water which are clearly ice even in the low resolution IceMap (k). In addition, much of the detail of leads and small ice flows are lost in the daily product (j). Part of this is unavoidably due to ice motion and changes in the ice state over the day. Nevertheless, in future work we will refine the algorithm to preserve as much of the detail as possible and eliminate some of the confusion from multiple passes resulting in misclassification.
Figure 3.25: All images pertain to Greenland Sea on September 11th, 2015. (a) Landsat 8 RGB at 13:49UTC; (b) Landsat 8 Quality Assessment Band labels; (c) MISIC single overpass labels; (d) Crop 1 Landsat 8 RGB; (e) Crop 1 Landsat 8 Quality Assessment Band labels; (f) Crop 1 MISIC single overpass labels; (g) Crop 1 MODIS IceMap (MOD29) labels; (h) Crop 2 Landsat 8 RGB; (i) Crop 2 Landsat 8 Quality Assessment Band labels; (j) Crop 2 MISIC single overpass labels; (k) Crop 2 MODIS IceMap (MOD29) labels.
Chapter 4

Summary

This dissertation discussed machine learning approaches for the automated detection of snow and sea ice using satellite instrument data. We first analyzed if using machine learning methods can improve NASA’s current operational snow detection algorithm. Four machine learning classification methods were considered and evaluated using optical/infrared data from the MODIS instrument onboard the Aqua and Terra satellites and snow depth measurements from ground stations, to identify snow pixels on the earth’s surface under clear sky conditions. The Logistic Regression algorithm, which proved most suitable, was then evaluated against the currently operational NASA SnowMap product and yielded comparable results in terms of accuracy. Results also showed slight potential for better identification of snow pixels on the snow/land boundary and superior classification of snow-free land.

We then presented a novel automated algorithm, the Multi-Instrument Sea Ice Classifier (MISIC), that uses optical/infrared and microwave data from multiple instruments (MODIS, VIIRs, and AMSR-2) to create sea ice maps. The algorithm produces a single overpass sea ice map by utilizing optical/infrared instrument data with spatially and temporally correlated passive microwave data. An approach to combining these single overpass maps and
generating a daily composite map is also presented. Evaluation of the single overpass product showed that it dramatically increases surface coverage through its ability to merge high resolution features that are only partially obscured by clouds with most recent passive microwave data to produce an optimal current estimate of the sea ice on the surface. Evaluation of the daily composite maps, showed an increase in resolution over other daily products, by taking advantage of the multiple high resolution single overpass maps and merging clear sky regions. It was also shown that the total sea ice cover identified by the daily composite maps were consistent with current state of the art expert driven approaches.

Beyond its direct application, this algorithms can, at a minimum, provide an important guide for analysts, through their ability to quickly summarize data from multiple sources, thus helping accelerate the creation of expert derived interactive products.
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