

Article

A Passive Microwave/Imager integrated approach to generating high resolution automated daily sea-ice maps

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Abstract: With the ever increasing importance of understanding climate change and the limitations associated with collecting data in the polar regions, it is critical to maximize the utility of satellite observations of critical structures such as sea ice. Accurate sea ice maps play a significant role in climate models for the region and provide initial conditions for weather models. An increase in their accuracy and spatial resolution would therefore have a broad impact. In addition, many of the current sea ice products interactively integrate observations from multiple instruments and platforms through the extensive time and effort of human operators. To facilitate that effort, this work presents a fully automated Microwave/Imager Sea Ice Classifier (MISIC) algorithm that integrates imagery obtained from optical instruments onboard polar orbiting platforms, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) from the Aqua and Terra satellites, the Visible Infrared Imaging Radiometer Suite (VIIRS) from the Suomi National Polar-orbiting Partnership (S-NPP), with data from passive microwave sensors such as the Advanced Microwave Scanning Radiometer 2 (AMSR-2) from the Japanese GCOM-W1, to produce cloud-free daily sea ice maps at the maximum available spatial resolution. Our evaluation shows that the algorithm performs with high accuracy on a single imager observation level and is consistent with current state of the art products on a daily map level. The algorithm may be used directly as a high quality fused imager/microwave product at the daily or per overpass level or as an input to interactive algorithms, dramatically reducing the imagery operators need to review.

Keywords: sea-ice extent; multi-sensor fusion; visible, infrared, passive microwave instruments; Arctic; Antarctic; MODIS; VIIRS; AMSR-2;

1. Introduction

Sea ice cover is both an important indicator and a critical factor in Earth's climate and weather system. The overall distribution of sea ice in the Arctic and Antarctic regions has a significant impact on water management, transportation, weather forecasting, and climate change studies. It affects atmosphere-ocean energy exchange by modulating the physical and optical properties of the ocean surface [1]. The character and distribution of sea ice affects the thermohaline structure and the fresh water balance of the ocean. Thus in understanding both ocean and atmosphere it is critical to monitor ice cover distribution, seasonal variability and long-term trends. These trends in the polar region may be studied through parameters such as the position of the sea ice front, total ice extent, ice concentration and thickness [2-7]. These parameters are widely viewed as major indicators of climate variability and change. In addition to their use for understanding and monitoring the climate, sea ice

extent and concentration are key inputs to numerical weather prediction (NWP) models operated by National Centers for Environmental Prediction (NCEP) of NOAA National Weather Service (NWS).

Despite several currently available automated satellite-based ice cover datasets, analysts at National Ice Center (NIC) tend to rely on original satellite imagery from optical, passive microwave and active microwave sensors in their daily interactive analysis. This is primarily due to the fact that different instruments have different strengths and weaknesses with respect to ice retrievals and there is no automated algorithm compatible with interactive sea ice analysis that integrates the observations from instruments of various types which fully preserves the complementary information available from each instrument type. Such algorithm would unequivocally facilitate the work of human ice analysts and would result in more accurate ice products including ice extent, edge and type. In this paper we present an algorithm that, first, extracts maximum information on the sea ice cover (including observations made over semitransparent clouds) from matching the classification results obtained from optical and microwave observations independently and then fuses these results in an optimal way. Heterogeneous observations from optical and microwave sensors are combined to produce an enhanced high resolution, gap free daily ice extent product. Unlike approaches which simply use coarser resolution microwave when clouds are present, our algorithm extracts surface information through thin and moderate clouds preserving information available in high resolution optical imagers whenever possible.

2. Background

To facilitate the description of the algorithm and provide some background for its motivation we will first summarize the current sea ice datasets and approaches for the passive microwave and imager instruments.

Passive Microwave: Sea ice can be studied using satellite observations in the microwave portions of the electromagnetic spectrum [8]. This is because at these frequencies, the dielectric permittivity of seawater is many times larger than that of ice, resulting in distinct polarizations, as well as intensity and directional scattering properties that allow the effective separation of sea surface types [9]. As a result, a large array of passive microwave instruments aboard various polar-orbiting satellites have been used to generate sea ice products for decades. For instance, products have been based on the two most commonly used algorithms to compute sea ice concentration using passive microwave data, the NASA Team (NT) algorithm [10] and the Bootstrap (BS) algorithm [11, 12]. Both of these algorithms utilize a brightness temperature difference (TBD) at varying polarizations and frequencies to define a linear function that retrieves the sea ice concentration value. More details on these algorithms and their comparison can be found in [13] and the references therein.

Passive microwave products provide some of the most comprehensive large scale characterizations of global ice cover due to their all-weather capability and high temporal coverage. The main drawback of these products, however, is their relatively low spatial resolution. For example, products derived from the Special Sensor Microwave/Imager (SSM/I) onboard the Defense Meteorological Satellite Program (DMSP) F8, F11 and F13 satellites have a spatial grid cell size of 25 km × 25 km [14]. Products derived from the Advanced Microwave Scanning Radiometer 2 (AMSR2) onboard the Japanese Global Change Observation Mission 1st (GCOM-W1) satellite have a spatial grid cell size of 12.5 km × 12.5 km [12]. In contrast to the low resolution passive microwave instruments, active microwave instruments such as the space borne synthetic aperture radar (SAR) can provide high resolution, all-weather observations [15], however they lack in spatial coverage and temporal frequency.

Imager: Remote sensing data from the visible and infrared wavelengths are also commonly used for sea ice detection [16]. A specific spectral feature of ice, namely a sharp drop of the ice reflectance from high values in the visible spectral bands to very low values in the shortwave and in the middle infrared distinguishes ice from ice free water and most types of clouds and thus allows for automated identification of snow and ice in the satellite imagery and for generation of snow and ice maps. A number of automated algorithms to identify and map ice cover have been developed for observations made with optical sensors onboard both polar orbiting and geostationary satellites (e.g. [17] and [18]).

The algorithm to identify ice is similar to the one for snow [19] and uses MODIS observations in the visible, near infrared, shortwave infrared and infrared spectral bands. Due to clouds occluding the surface and the inability to properly identify ice at night, daily ice products have gaps in the area coverage.

Although the baseline MODIS sea ice identification algorithm (hereafter “IceMap”) [20] utilizes observations in several spectral bands ranging from visible to far infrared, the primary feature used to distinguish between ice and open water is the Normalized Difference Snow Index (NDSI). The NDSI is defined as the normalized ratio of reflectance observed in MODIS band 4 (centered at about $0.55\mu\text{m}$, R_4) and in band 6 ($1.6\mu\text{m}$, R_6), $\text{NDSI} = (R_4 - R_6) / (R_4 + R_6)$ [20]. Sea ice detection is achieved through a two-step sequential procedure. The first step is a set of grouped criteria tests for sea ice reflectance characteristics in the visible and near-infrared regions. Criteria for sea ice are: 1) NDSI greater than 0.4; 2) visible reflectance band 2 ($0.86\mu\text{m}$) greater than 0.11 and band 1 ($0.65\mu\text{m}$) greater than 0.10. A pixel that passes this group of criteria tests is identified as sea ice in this step. The second step utilizes brightness temperatures from emissive bands 31 ($11.03\mu\text{m}$) and 32 ($12.02\mu\text{m}$) to compute Ice Surface Temperature (IST) [21] values. If a pixel was identified as ice in the first step and its IST is less than 271.4°K , it is classified as ice, otherwise it is classified as water.

Accurate identification of cloud-contaminated pixels in the satellite imagery is a critical step in the automated ice cover mapping as well as in all satellite-based land surface and ocean applications. The existing NASA MODIS data processing system incorporates a global cloud identification algorithm, which may not perform in an optimal way over polar regions. Often, clouds will be falsely interpreted as ice by imager cloud classification algorithms. In other cases, the erroneous interpretation of the cloud clear scenes as cloudy results in reduced ice product coverage and limits the ability to track temporal changes in the ice cover distribution. Estimates reported in [22] show that the current MODIS cloud mask overestimates the cloud amount over polar areas. This assessment generally agrees with the results of our qualitative analysis of the cloud mask incorporated in the MODIS ice product. Besides the fact that the existing cloud-screening needs improvement, the semitransparent clouds very often allow for discriminating between ice and water. Thus, developing of an algorithm to identify ice cover underneath thin clouds would allow for expanding the effective area coverage of the ice cover maps and hence for a more accurate and detailed delineation of the of the ice edge.

Cloud-caused gaps in the area coverage are not the only issue inherent to MODIS cryosphere products. The extent of ice in the areas of broken ice is typically overestimated. The ice identification algorithm often fails to properly discriminate ice from ice-free water, especially where poor solar illumination conditions dramatically reduce the accuracy of the optical imager product.

Given the limitations of optical and microwave instruments, developing ice products that integrate sensors is an important area of open research [23]. Currently the most widely used multisensor ice product is produced by the Interactive Multisensor Snow and Ice Mapping System (IMS) operated by the National Ice Center (NIC) [24, 25, 26]. 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. 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 supplement visible and near infrared imagery with many other sources of information such as passive microwave and active radar data. Second, because IMS analysts use a temporal sequence of images over recent days, they can integrate 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 sea ice is, remains an integral part of the process, and one of the strengths of the IMS product. However, manual sea ice mapping drawn by humans, is a subjective, labor intensive and time consuming procedure, that is not easily scalable as satellite resolution increases.

Another example of an integrated product is the Multisensor Analyzed Sea Ice Extent – AMSR2 (MASAM2) product. This product uses the microwave sea ice concentration product derived from

AMSR2 at concentration greater than or equal to 70% as a basis, and then integrates the sea ice edge from the IMS daily product to construct a high concentration ice product with a more accurate ice edge [27]. Although this product does improve on some of the drawbacks, it is still lacking in resolution and the manual labor associated with the IMS product. Thus the need for an automated product with the coverage of passive microwave but preserving the high resolution of optical data, in the presence of thin clouds, remains.

3. Algorithm

The algorithm we propose to generate cloud-free region based gridded daily ice maps has two parts:

- A. Generate an ice map on a per imager overpass basis, for the region in question, by supplementing imager reflectance data with microwave observations closest in time.
- B. Combine ice maps from individual imager overpasses in an optimal way, resulting in an enhanced, high resolution, cloud gap free daily ice extent product.

We note that part A results in a per imager 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 imager 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.

3.1. Imager overpass 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:
 - 1) ice-free water,
 - 2) sea ice,
 - 3) water under thick clouds,
 - 4) ice under thick clouds,
 - 5) undetermined class (insufficient information);
- **Step A3.** Generates (per imager overpass) a supervised classifier, using labels from Step A2 as a training set in an experimentally derived 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 imager instrument as well as polarization and gradient ratios of 18 and 36 GHz radiometer channels of the microwave instrument;

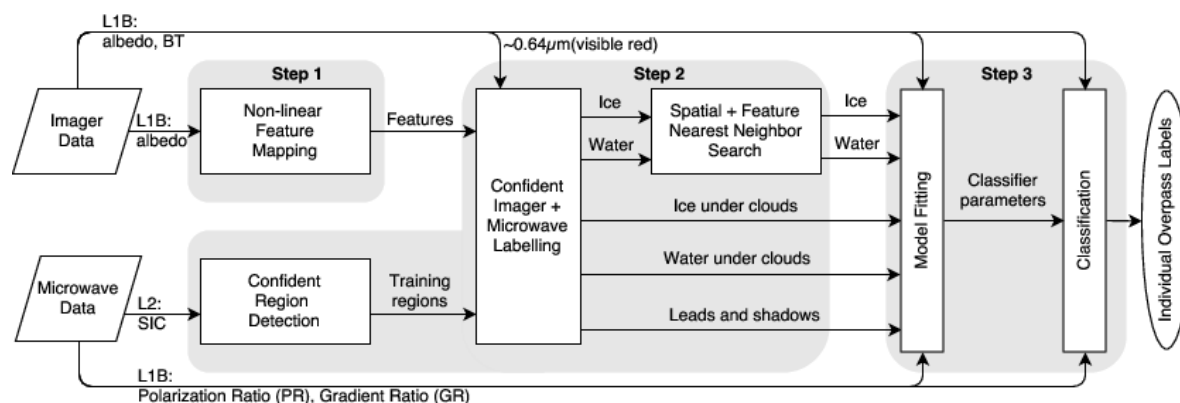


Figure 1. Block diagram of imager overpass classification.

The block diagram in Figure 1, shows the main components of the imager overpass labelling procedure. Steps A1-A3 are shaded in light grey 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.

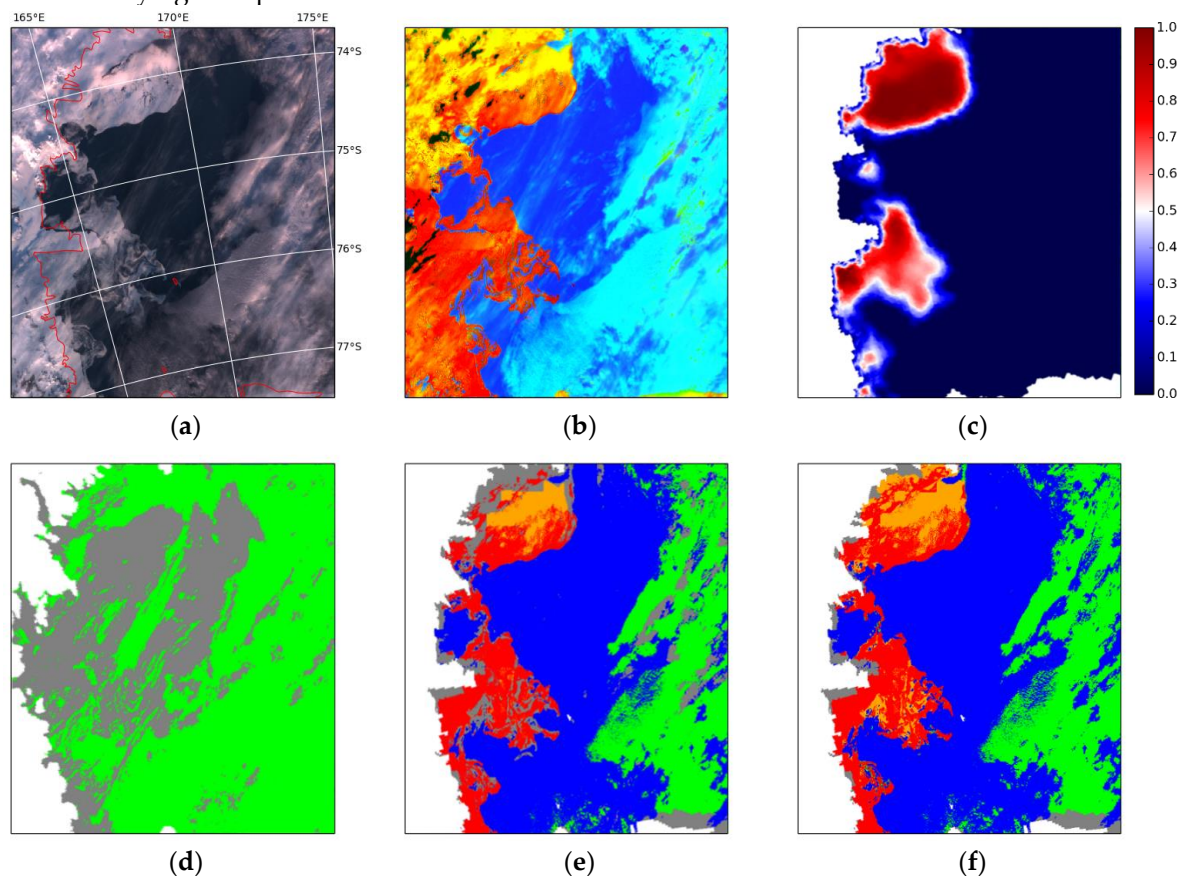


Figure 2. All images obtained for January 16, 2016 over the western coast of the Ross Sea region. (a) VIIRS RGB at 11:37UTC; (b) Feature Space of Step A1 represented as a false color; (c) AMSR-2 L2 Sea

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) Imager overpass labels (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 imager and closest in time complete microwave overpass set for a given day and gridded region. Figure 2 shows the described Steps for one particular MODIS/AMSR-2 set. A true color RGB composite is depicted in Figure 2(a) for visual reference with the coast represented as a red line. Figure 2(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 2(b), the level 2 microwave sea ice concentration, displayed in Figure 2(c), is passed in as input to Step A2. Note that the microwave information in 2(c) is lower resolution as seen in the ice (red) but does identify the ice free open water through the clouds (blue). In Figure 2(d) the cloud mask used to eliminate cloud covered pixels (green) in the VIIRS level 2 sea ice concentration algorithm is shown to demonstrate the large area identified as cloud, and thus not classified by the conservative VIIRS algorithm. Figure 2(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 2(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 we describe the detailed implementation of each step of part A in the algorithm.

3.1.1 Non-linear Feature Mapping (Step A1)

We have developed a non-linear mapping function that projects imager albedo from visible, near infrared and shortwave infrared bands, to a 3D feature space that provides better separation of our main target classes i.e. ice and water. This is achieved utilizing manually labelled satellite imagery, by expert analysts from the National Ice Center (NIC). 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 it was derived for.

The feature mapping function F is a 3D vector valued function on the imager 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:

$$V_R = [R_{0.47\mu m}, R_{0.55\mu m}, R_{0.64\mu m}, R_{0.86\mu m}, R_{1.24\mu m}, R_{1.64\mu m}],$$

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

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

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 $F_r(V_R)$, we first define $F_{r_{init}}(V_R)$ as

$$F_{r_{init}} = \lambda[(V_R - M_S) \cdot A_r]$$

where $A_r = [0, 0, 0, 1, -1, 0]$, $\lambda = 10$, 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 shadows are at the origin. Using $F_{r_{init}}(V_R)$ we define $F_r(V_R)$ as

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

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:

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

with weights vector $A_r = [-0.1716, 0.9686, -1.3454, 0.3948, 0.2857, 0.0265]$. 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 we initialize the following:

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

with weights vector $A_b = [-0.5, 1, -1, 0.3, 0, 0]$. We then apply the sigmoid function,

$$F_{b_0} = \sigma(\alpha_b(F_{b_{init}} - \beta_r))$$

with constants $\alpha_b = 10$ and $\beta_b = 0.4$. We then define,

$$w = F_r + 0.38F_{b_0}^2 - 0.78F_{b_0} - 0.1$$

Finally, we define F_b as:

$$F_b = \begin{cases} 1, & w < 0 \\ 0, & w \geq 0 \end{cases}$$

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

3.1.2 Imager/Microwave Confident Labelling (Step A2)

We have designed an automated logic based procedure, which combines information about the surface conditions from the passive microwave and imager observations, to label a subset of pixels in the scene into 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 imager, to make it possible to fuse imager 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 we take advantage of passive microwave's 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, we only consider pixels away from the ice edge and land border. Figure 3(a) shows an example of the regions identified in this step with water(blue), ice(red), unused(gray) and land(white).

To initialize our algorithm, we identify 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. To define these regions, we first use a geographic reference to partition the grid cells in the scene into land and ocean sets, denoted by Z_L and Z_O respectively. We want 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 we can first define an exclusion region Z_E as

$$Z_E = \{q \in Z_O \mid f(q) \geq \mu_l\} \cup Z_L$$

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 low concentration value:

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

where $d(p, q)$ is the distance measure between the locations p and q , and δ 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 δ).

Using the same methodology, the microwave confident ice mask can be defined as

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

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 imager and microwave labelling

In this step we utilize the microwave derived training regions, in conjunction with our imager derived features and reflectance, to identify confident class labels for a subset of locations in the scene. The five target classes we for which will assign confident labels are: ice, water, ice under cloud, water under cloud and leads/shadows. If $V_R(p)$ is the imager reflectance vector above at a grid cell p , and using our imager feature map F , then define from our image $r(p) = F_r(V_R(p))$, $g(p) = F_g(V_R(p))$, $b(p) = F_b(V_R(p))$. With this notation, we identify confident labels for the ice class, as determined by the imager, using a box in our feature space as:

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

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 was chosen so that pixels with a strong r response are ice, as described above.

While there is some variability in the feature space, these thresholds are reliably associated with ice across granules, particularly when considered together with the microwave data. Those grid cells that are in the imager 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} :

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

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, we define an ice under cloud class Z_{I_1} :

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

with feature thresholds $(\theta_{I,R}, \theta_{I,G}, \theta_{I,B}) = (0.7, 0.5, 0.5)$, determined empirically.

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 likely water class Z_W :

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

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, and b which is the high value of $\theta_{W,B}$.

We further break Z_W into two regions: one for which the reflectance measured at the $\sim 0.64\mu\text{m}$ (visible red) band of the imager indicates this region of confident water is clear (or under thin cloud) Z_{W_0} ($R_{0.64\mu\text{m}}(p) \leq 0.3$) and one for which the indication is a thicker cloud over water Z_{W_1} ($R_{0.64\mu\text{m}}(p) > 0.3$). The reason why we use the imager reflectance value as opposed to the g feature, is because our feature space is designed to suppress clouds.

Lastly, we define a fifth class 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 reside in the microwave confident ice region Z_{I_2} :

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

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

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

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

An example of some of the resulting regions is shown in Figure 3(b). As can be seen, the uncertain regions (gray) tend to be on the boundaries of clouds, water and ice, and on the coast.

• Nearest neighbor search

In this procedure we maximize the high resolution information available from the imager by performing a nearest neighbor search with a conservative distance threshold, using a pixel's 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(b) shows the training classes before the nearest neighbor expansion is applied, and Figure 2(e) shows them after. As you can see 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 output of continuing the process with and without it, in Figures 2(f) and 3(c) respectively. Note the misclassified pixels on the ice edge in Figure 3(c), and their correct classification in Figure 2(f).

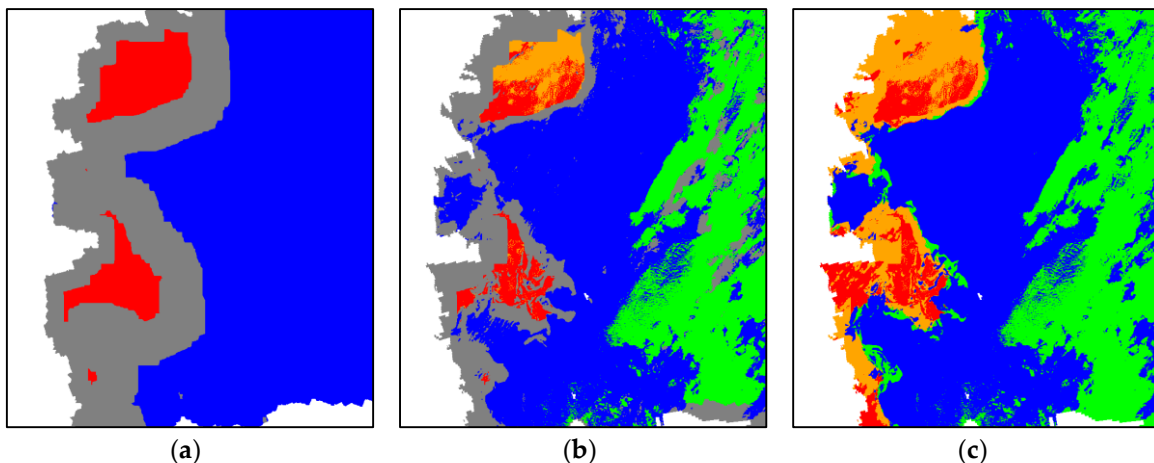


Figure 3. (a) Passive-microwave derived training regions (red: microwave ice, blue: microwave water, gray: excluded, white: land); (b) Blended confident labels and (c) LDA labeling without nearest neighbor expansion with red: ice, blue: water, orange: ice under cloud, green: water under cloud, gray: unclassified, and white: land.

3.1.3 Per Granule Classification with Linear Discriminant Analysis (Step A3)

In order to resolve areas that have not been identified by step A2 using our conservative threshold procedure, we fit and then apply an automatic statistical linear classifier 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 us to fit a statistical model using Linear Discriminant Analysis (LDA)[28]. 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 Bootstrap Algorithm). This results in a 5-dimensional feature space. Once the model is fit to the training data, it is 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 result of this classification is shown in Figure 2(e).

3.2. Daily Compositing

This procedure merges the pre-labeled gridded scene overpasses, using logic that assigns higher weights to imager-based classification from Step A1 and lower weights to classification involving microwave observations obtained in the Steps A2 & A3, to obtain 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 granules overlapping the same region. Having multiple granules over the same region is important because cloud cover is a significant problem. Figure 4(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 4(a), 4(b), 4(d), and 4(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 ice/water mask possible.

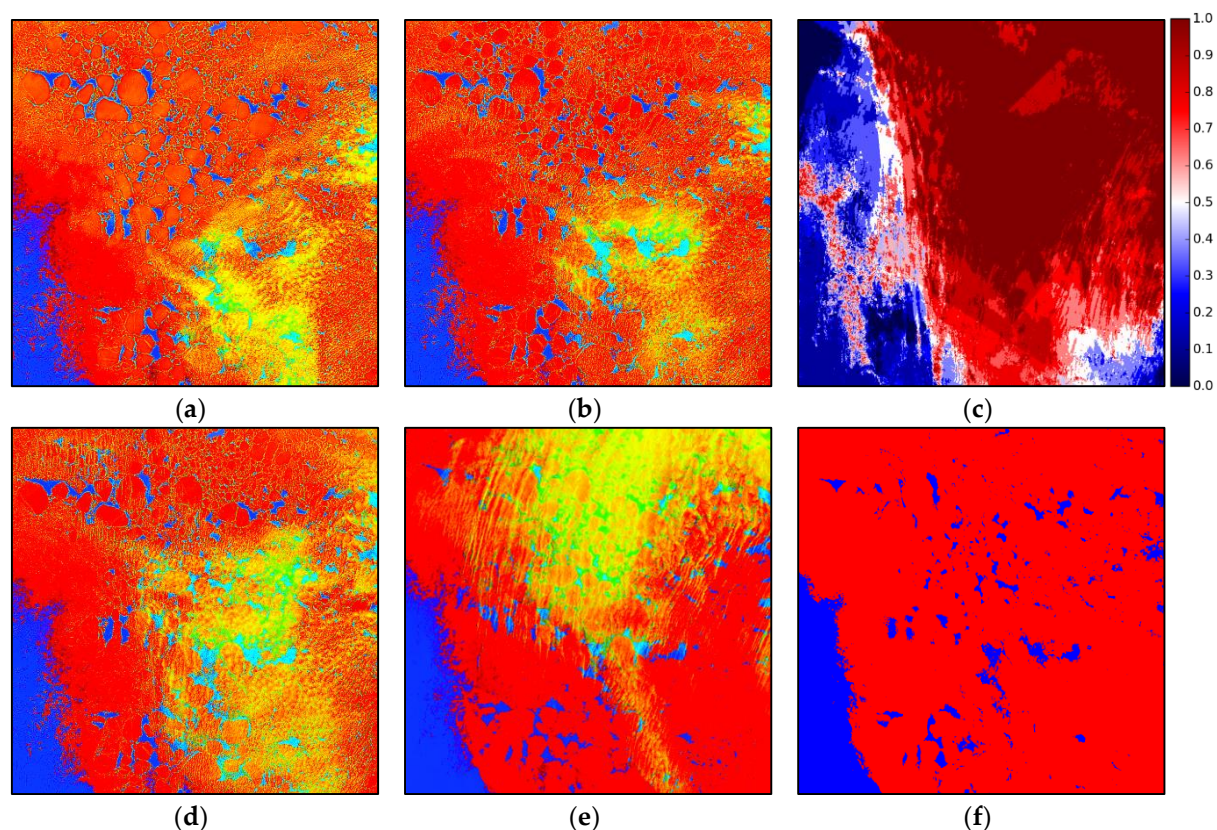


Figure 4. All images obtained from December 2nd, 2015 in the Ross Sea. (a) VIIRS at 00:41UTC; (b) VIIRS at 02:19UTC; (c) Imager overpass L2 cloud cover fraction; (d) VIIRS at 04:02UTC; (e) MODIS (Terra) at 18:45UTC; (f) MISIC daily sea ice map (**red**: ice, **blue**: water).

Let $L = \{aI, aW, aCI, aCW, Null\}$ 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 *Null*-undecided. If p is some location, then a mask is a function so that $M(p)$ has a value in L . Let $\{M_1, M_2, \dots, M_j\}$ 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 that we will first consider the confident (clear sky) observations. We will use the majority rule only amongst these observations to determine ice or water. If it is a tie, and there is at least one observation, we resolve the tie with a determination of water. If we do not have any clear sky observations then we will take the majority of the classified ice/water and again use water if it is a tie (assuming at least one observation). More formally for each grid cell p we compute 4 non-negative counts

$$AI(p) = |\{j | M_j(p) = aI1\}|,$$

$$AW(p) = |\{j | M_j(p) = aW1\}|,$$

$$ACI(p) = |\{j | M_j(p) = aCI1\}|,$$

$$ACW(p) = |\{j | M_j(p) = aCW1\}|,$$

and $|\cdot|$ 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 5(a) shows the percentage of confident ice observations i.e. $\frac{AI(p)}{AI(p) + AW(p)}$. Similarly figure 5(b) shows the percentage of cloudy ice observations i.e. $\frac{ACI(p)}{ACI(p) + ACW(p)}$. 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.

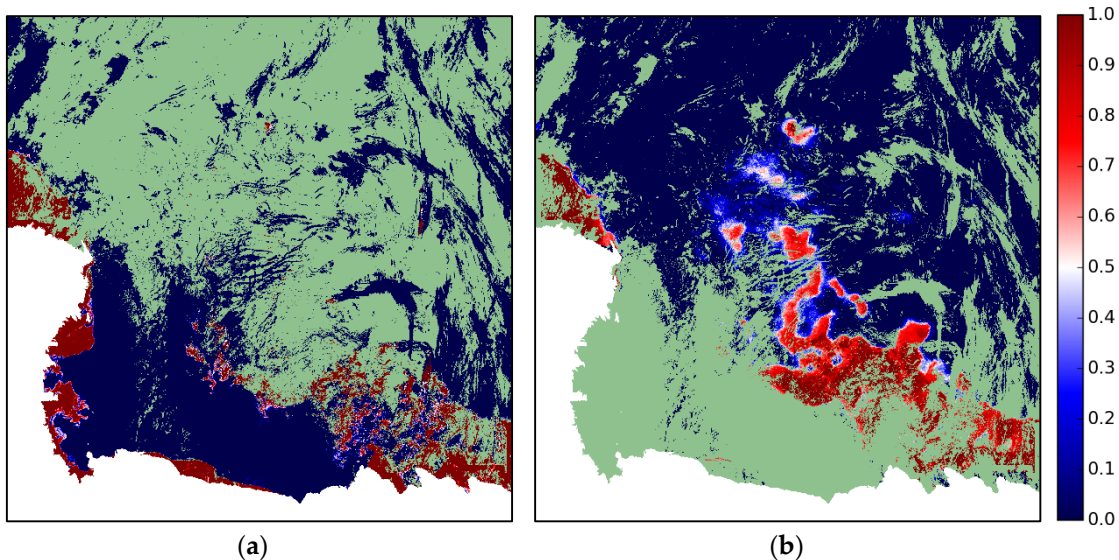


Figure 5. MISIC daily product construction steps. **green** corresponds to pixels not being processed. (a) Step 1: Percentage of pixels observed as confident ice. (b) Step 2: Percentage of pixels observed as ice under cloud.

4. Evaluation and Results

In the previous section we have described both an algorithm for producing a sea ice product for each visible input granule, and an aggregated MISIC daily product. Daily ice products can take

advantage of cloud movement and multiple granules to provide more opportunities for un-occluded visible observations of the earth surface. When multiple visible observations of the same portions of the surface are available, individual granule products provide an opportunity to study ice changes or motion within a day. We compare both daily and granule based products with those currently available.

4.1. Granule based Evaluation

We have been evaluating the MISIC product since the summer of 2015. A representative case is shown in Figure 6 depicting a scene from August 6th, 2015 off the east coast of Greenland. In Figure 6(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 6(b), and from a Landsat 8 image from the same day at 14:13 UTC in Figure 6(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 granule product, shown in Figure 6(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 (MOD26) product, and even the Landsat product, shown in Figure 6(b,c) respectively, are largely obscured by aggressive cloud masks. Where those products indicate ice or water, we see that the MODIS product lacks much of the detail visible in both the MISIC product and the Landsat image, particularly center bottom where MODIS misclassifies mixed water and ice as cloud.

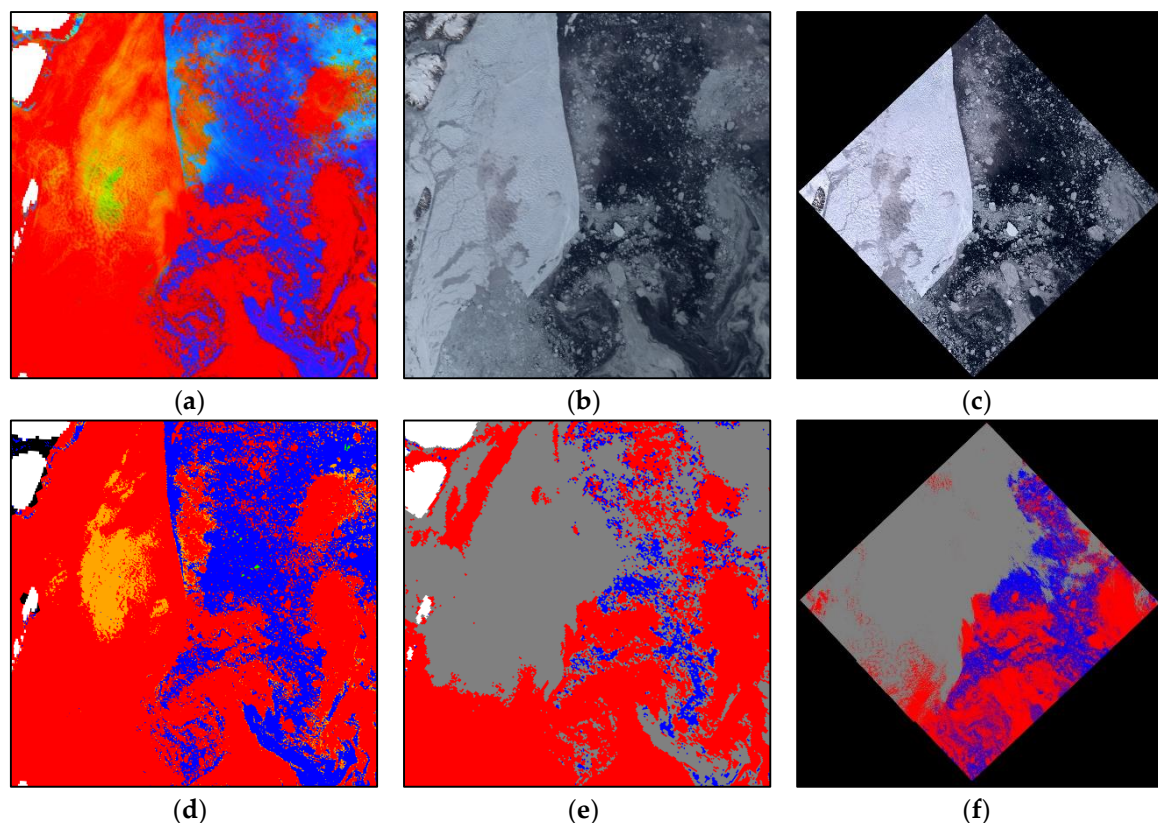


Figure 6. All images obtained from August 6th, 2015 in the Greenland Sea. (a) MODIS (Terra) based Features at 13:40 UTC; (b) MODIS RGB; (c) Landsat 8 RGB at 14:13 UTC; (d) MISIC overpass labels; (e) MODIS IceMap (MOD29) labels; (f) Landsat 8 Quality Assessment Band labels.

Table 1 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. The over-all 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 granule product, shown in the last column. Thus the MISIC product provides a high resolution accurate classification comparable to the MODIS 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.

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

Table 1. Evaluation parameters and their values for 6 examples.

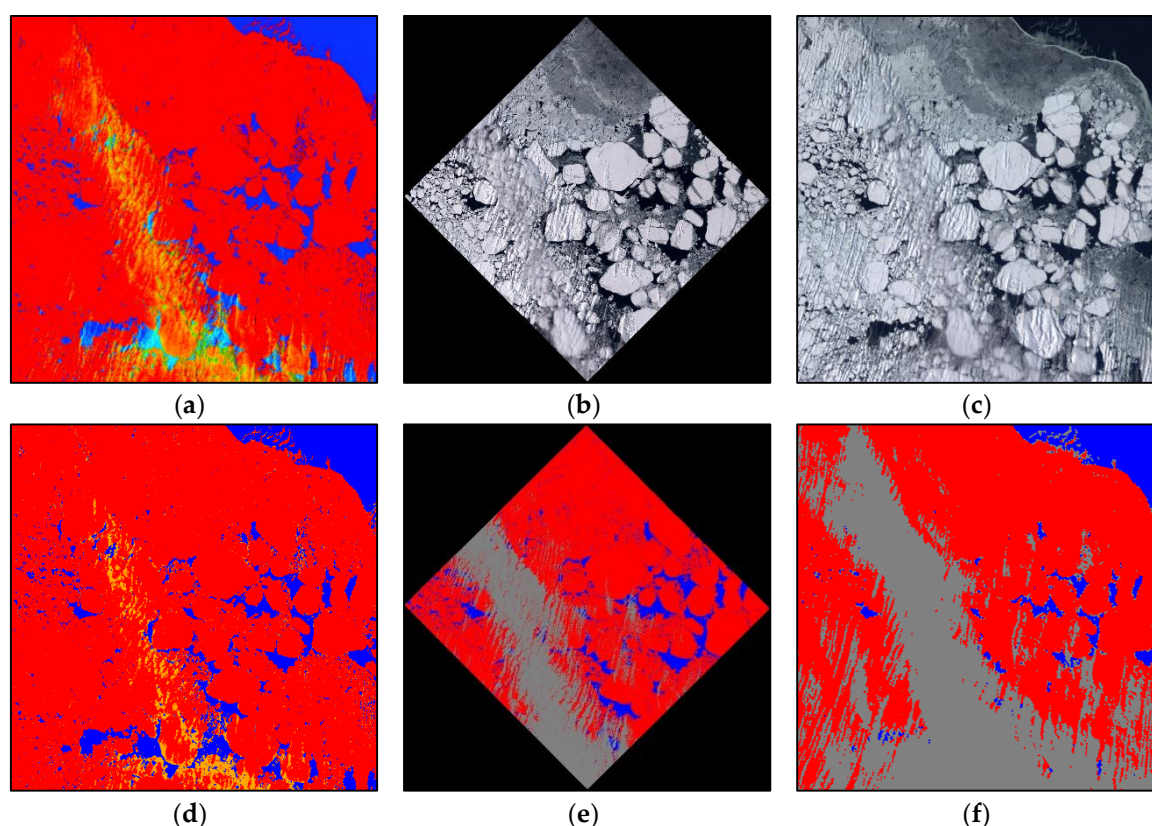


Figure 7. Images in a,c,d, and f obtained from MODIS (Terra) on December 2nd, 2015 @ 18:45UTC. Images in b and e obtained from Landsat 8 at 19:18UTC. (a) MODIS based Features; (b) Landsat 8 RGB; (c) MODIS RGB; (d) MISIC granule labels; (e) Landsat 8 Quality Assessment Band labels; (f) MODIS IceMap (MOD29) labels.

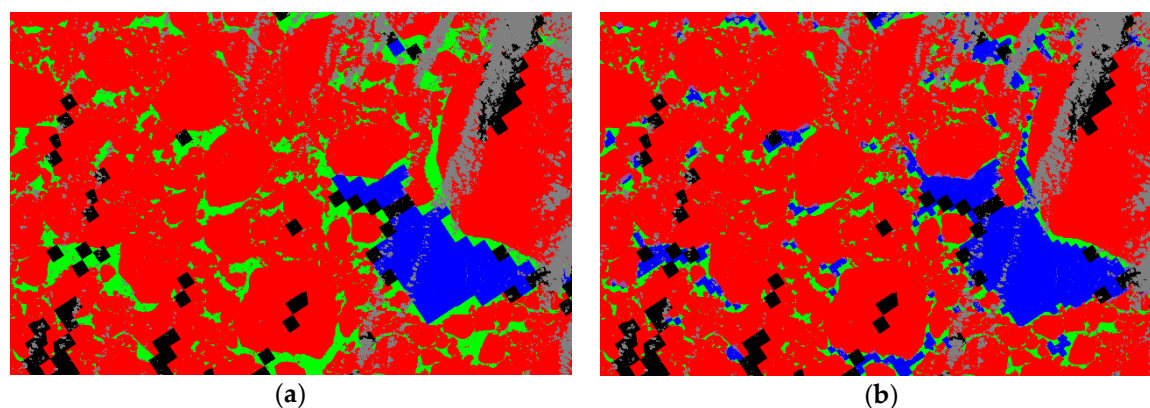


Figure 8. Coded comparison between Landsat 8 quality band and (a) IceMap and (b) MISIC. Input data same as Figure 7.

The last example of Table 1, based on a 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 7. Again Figure 7a 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 as is obvious from the corresponding MODIS and Landsat 8 RGB images shown in Figure 7b, c. As in Figure 6 the MISIC granule 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 8a), and MISIC granule product (Figure 8b) 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.

Mis-identified clouds are a well-known and frequent problem in the IceMap product as can be seen in Figure 8 from derived stitched MODIS (Aqua) granules on September 15th, 2015 at 13:10 UTC and 13:15 UTC. From the RGB shown in Figure 8a it is clear that the swirl in the center is mixed ice, yet the IceMap declares it cloud while MISIC correctly identifies it.

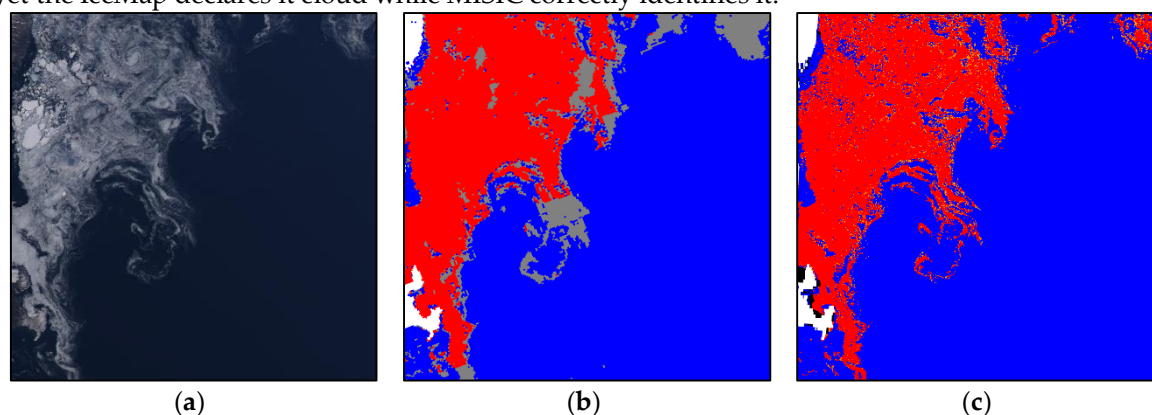


Figure 9. Images derived from MODIS (Aqua) on September 15th, 2015 at 13:10UTC and 13:15UTC. (a) MODIS RGB; (b) MODIS IceMap labels; (c) MISIC granule labels.

4.2. Daily Product Evaluation

Overall validation of the daily product 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. Our claim is that our fully automated product is consistent with the best semi-automated products available. These products include: the Interactive Multisensor Snow and Ice Mapping System (IMS) 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) 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); and the Global Daily Ice Edge product produced by the Canadian Meteorological Center (CMC) and distributed by the NASA Jet Propulsion Laboratory through the Physical Oceanography Distributed Active Archive Center (PODAAC).

We present the consistency of ice extent for the time series Oct. 1st–15th, 2015 corresponding to sea ice freeze-up time in the Beaufort Sea. The product comparison results are shown in Figure 10. The light gray line without dots represents ice extent according to NCEP microwave thresholded at .5 with the grey shading band showing ice extent corresponding to thresholds between .25 and .75. We see 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. There is a consistent increase in the ice extent over time, as the sea freezes throughout October. We also see 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 prediction is able to automatically achieve an ice extent, consistent with microwave-based products, while maintaining the higher resolution, outperforming imager-based semi-manually created products.

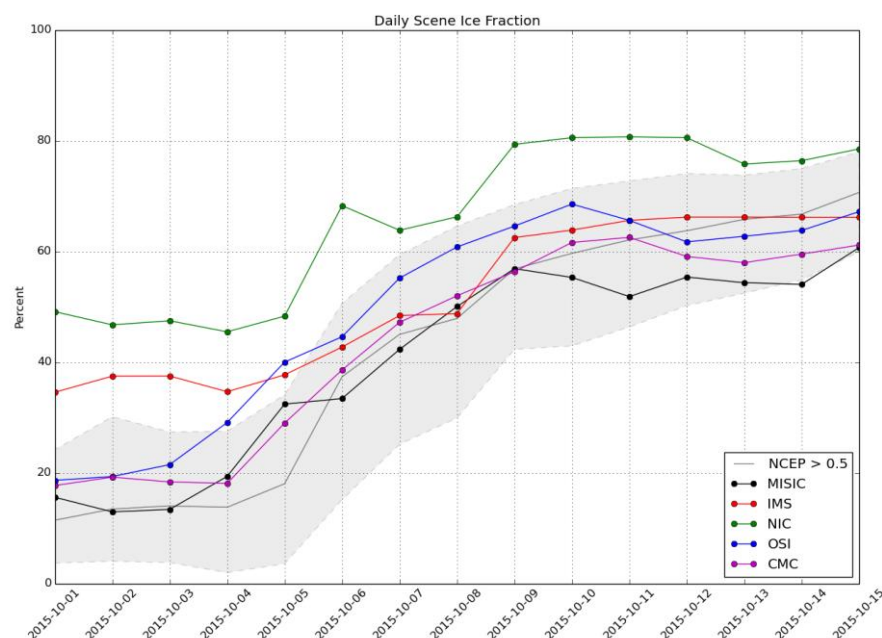


Figure 10. Daily product ice fraction comparison of different ice coverage products in the Beaufort Sea region from 10/1/2015–10/15/2015. MISIC aggregate ice fraction consistent with current operational products.

Imager 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 visible/infrared data available, MISIC is able to achieve higher resolution over partly cloud occluded areas than achievable with microwave.

Figure 11 shows the same period in the Beaufort Sea region used in Figure 10. The area where a determination of ice vs water, using all the IceMap observation is indicated in Figure 10 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.

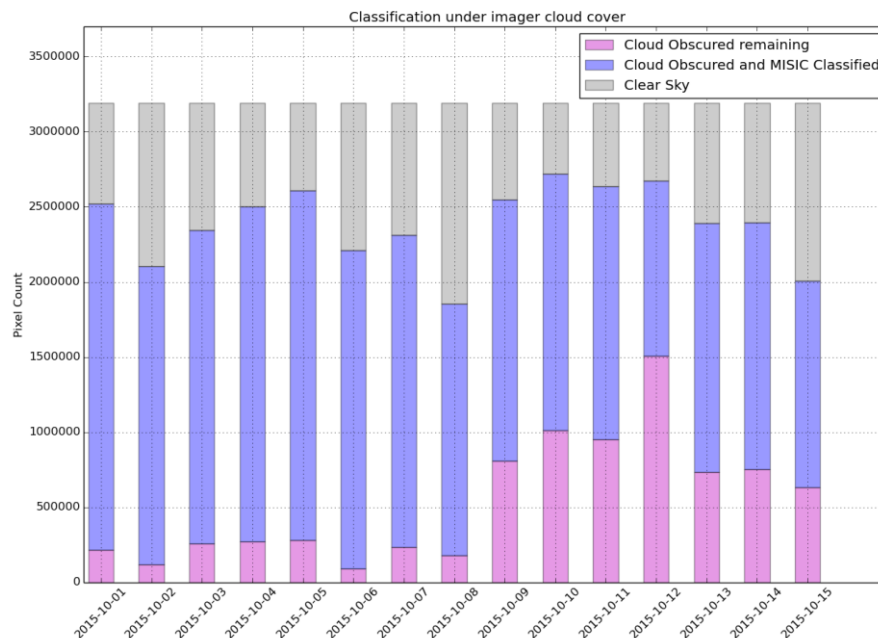


Figure 11. Daily product ice fraction comparison in the Beaufort Sea region from 10/1/2015-10/15/2015.

5. Discussion

We have 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 a case is shown in Figure 12 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 details are shown in (a). In one detail, indicated by the red box at the top, not only is there new ice but the surface is occluded by small intermittent clouds as is clear from the RGB detail (d). These clouds are also evident from the MISIC preliminary sure classes shown in (e). In (f) we see 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 bottom detail in (a), whose RGB is shown in (h) we see that the per granule MISIC is able to correctly identify ICE. However, when combining several passes the MISIC daily 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.

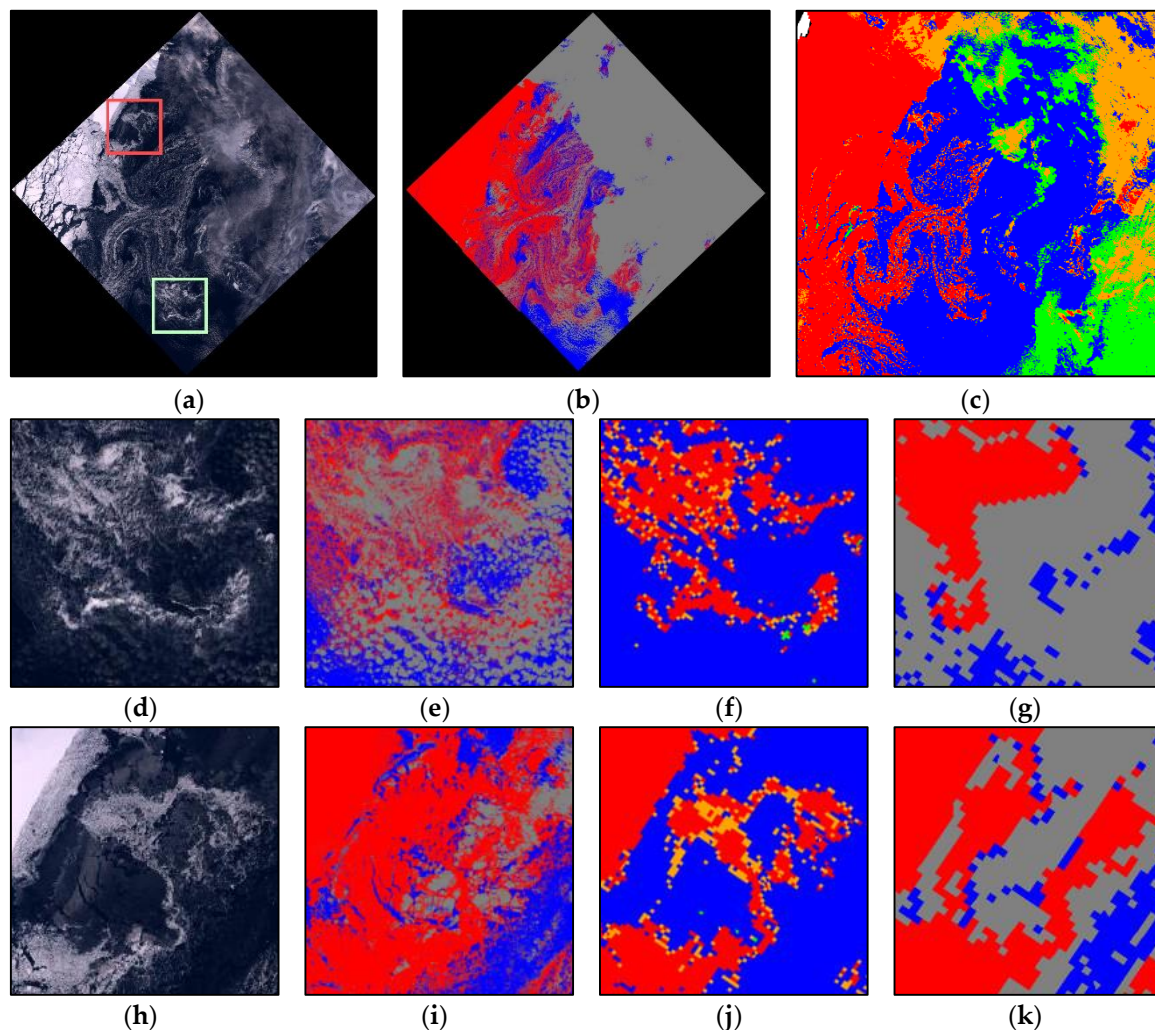


Figure 12. All images pertain to Greenland Sea on September 11th, 2015. (a) Landsat 8 RGB at 13:49UTC; (b) Landsat 8 Quality Assessment Band labels; (c) MISIC granule labels; (d) Crop 1 Landsat 8 RGB; (e) Crop 1 Landsat 8 Quality Assessment Band labels; (f) Crop 1 MISIC Granule labels; (g) Crop 1 MODIS IceMap (MOD29) labels; (h) Crop 2 Landsat 8 RGB; (i) Crop 2 Landsat 8 Quality Assessment Band labels; (j) Crop 2 MISIC Granule labels; (k) Crop 2 MODIS IceMap (MOD29) labels.

6. Conclusions

In this work we have presented an automated algorithm, MISIC capable of using imager and microwave data from multiple instruments (MODIS, VIIRS, and AMSER-2) to estimate sea ice cover. The algorithm produces a single-pass enhanced version which combines the data from an imager single-pass with microwave data. We also show how to use multiple passes to create daily product consistent with state of the art interactive products produced through expert guidance. In addition to providing automation, the single pass enhanced algorithm dramatically increases surface coverage over products like the MODIS based IceMap. When thin clouds are present the MISIC single-pass enhanced product can combine the high resolution surface features only partially obscured by clouds, with the most recent microwave data, to produce the best current estimate the sea ice on the surface. When the surface is covered by thick clouds the algorithm fills the missing data using cloud penetrating microwave data, at the cost of lower resolution. We have also shown that by combining the single-pass enhanced automated ice mask into a daily product increase the resolution over microwave where surface features were visible, potentially through then clouds, at some point during the day. Beyond direct use of the automated product these products can provide important guides since they quickly summarize many information sources and can thus to accelerate the

creation of expert derived interactive products. Our work product, algorithm and code is currently being evaluated by the Navy/NOAA National Ice Center (NIC) to assist in NIC products.

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Conflicts of Interest: The authors declare no conflict of interest.

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