Improved sea ice concentration estimation through fusing classified SAR imagery and AMSR-E data

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Abstract

A method to automatically combine binary ice/water information from synthetic aperture radar (SAR) sea ice images with the AMSR-E (Advanced Microwave Scanning Radiometer-EOS) daily ice concentration product is proposed for the purpose of generating sea ice concentration estimates with improved detail and accuracy. First, each pixel in the SAR image is labeled as ice or water using the MAGIC (MAp-Guided Ice Classification) SAR image classification system. Second, the labeled pixels are modeled as a Bernoulli process and combined with the AMSR-E ice concentration data in a Bayesian framework to generate improved ice concentration estimation. Visually interpreted ice/water extent and sea ice image analyses from the Canadian Ice Service (CIS) are used as comparison data. The combination of SAR ice/water labeled pixels with the AMSR-E ice concentration is shown to improve the ice concentration estimates, especially at the ice edge where substantial improvements are observed. While the present study uses ice/water information from SAR, the method is general and could be used with other sources of ice/water remote sensed data.

Index Terms

Sea ice concentration, data fusion, SAR, passive microwave

I. INTRODUCTION

Sea ice concentration is the percentage of sea ice coverage in a specified area. The openings in the ice cover have an important impact on the heat flux between the ocean and atmosphere [1]. Accurate knowledge of the sea ice state is critical for weather forecasting, climate research and Arctic operations, such as drilling and navigation in ice-infested waters [2]. Passive microwave radiometers and synthetic aperture radars (SARs) are the most commonly used sensors for large scale sea ice monitoring purposes, due to their ability to image earth surface under almost all weather and sun illumination conditions.
Passive microwave sensors operate at multiple frequencies. Different frequencies feature different spatial resolutions and sensitivity to atmospheric conditions. For the low-frequency channels (e.g., 6.9GHz) on a passive microwave sensor there is no atmospheric influence on the observed brightness temperature. However, at these frequencies the spatial footprint of the measurement is large ($\approx 50\text{km}$). As the frequency increases, the size of the spatial footprint decreases, at the expense of increased atmospheric contamination of the surface signal. The finest resolution at which information is available on current passive microwave sensors is approximately $5\text{km} \times 3\text{km}$, which is provided by the 89GHz channel of the AMSR2 sensor [3]. Passive microwave sensors are often used to produce operational ice concentration products [4]–[7], the resolution of which depends on the channels used in the retrieval algorithm.

SARs are also largely insensitive to atmospheric conditions and solar illumination. As active microwave sensors, these can achieve finer spatial resolution compared to passive microwave sensors, even when taking measurements at a low frequency (1.4GHz). The spatial resolution of SAR sensors ranges from a few meters to several hundred meters [8]. However, due to the complex relationship between the SAR backscatter and sea surface conditions, automated interpretation of SAR imagery for ice concentration estimation is challenging. A robust ice concentration estimation algorithm has not yet been developed. For operational sea ice mapping, SAR images are manually interpreted to create ice concentration maps by expert ice analysts [5]. This is time consuming and subjective, and the resulting analysis may not capture the abundant detail in SAR images. The development of a computer based method to automatically estimate ice concentration from SAR images is of significant interest to ice services worldwide.

Ice concentration estimation and ice-water classification from SAR images are closely related topics. Recent advances in the ice-water classification of SAR images [9]–[11] have made it possible to label SAR image pixels as ice or water efficiently. This paper represents a method to fuse passive microwave sea ice concentration data and ice/water labels from an automated SAR image classification system. By using both sources of information, the complexity of directly estimating ice concentration from SAR images is reduced. The proposed method is computationally efficient and is shown to be able to generate ice concentration estimates with improved detail and accuracy compared to that from using passive microwave or SAR data only.
II. BACKGROUND

Sea ice concentration can be retrieved from passive microwave radiometers due to the strong delineation between brightness temperatures over water and those over sea ice. Similarly, in the absence of clouds, there is a strong contrast between the albedo of ice and that of water, which enables an estimate of ice concentration from the AVHRR sensor [12]. In contrast, there is no robust, direct, relationship between ice concentration and SAR image backscatter available at the present time.

SAR backscatter over sea ice is highly sensitive to surface conditions, such as surface roughness, moisture, snow cover, as well as imaging geometry. Methods to estimate ice concentration from SAR images generally use image features in algorithms from the machine intelligence community. Berg and Eriksson [13] used the estimated probability of a pixel being ice or water, together with the weighted autocorrelation of the backscatter, as inputs for a feed forward back propagation neural network, which was used to label SAR image pixels as ice or water. Ice concentration was retrieved from these labels by averaging classified pixels over local geographic regions. Due to the impact of inhomogeneous surface conditions on the SAR signal, surface condition changes were interpreted in their algorithm as changes of ice concentration, which lead to discrepancies between their ice concentration and that from the verification data. Karvonen [14] used a GMM (Gaussian mixture model) of SAR HH band backscatter autocorrelation calculated for homogeneous segments in an algorithm to estimate ice concentration for each segment. The sea ice concentration was one minus the mixture fraction of the open water class in the GMM. Errors occurred due to the overestimation of ice concentration in areas of very low concentration and strong underestimation of ice concentration caused by very wet snow. A recent study by Karvonen [15] used dual-polarized SAR data within a neural network framework to estimate sea ice concentration, an overall mean absolute error of 13%, and bias of 3.5% were made when compared against ice charts. In a study by Kasapoglu [16], SAR image features are selected for each incidence angle range and fused with ice concentration by passive microwave imagery using a linear mixture model. The results showed an improvement from incorporating the SAR imagery, still the results were largely affected by surface condition variations which are possibly not captured due to the linear model used.

In addition to ice concentration estimation from SAR images, automatic classification and segmentation of SAR images has seen considerable progress in recent years [10], [11].
Yu proposed a SAR image segmentation method that uses a Markov random field (MRF) and edge penalty. This method takes the spatial information in the image into account and optimizes the segmentation of the entire image in an MRF model. This method is being used in the MAGIC (MAp Guided Ice Classification) system. In particular, the extension of this system is able to classify SAR images into ice and water regions robustly.

The availability of stable interpretation algorithms for both types of data has motivated the present study, which aims to combine low resolution ice concentration data from passive microwave images and high resolution ice/water labels that are generated from SAR image to produce ice concentration estimate with improved resolution and accuracy. More specifically, ice water labels that are provided by the MAGIC system are combined with ice concentration from AMSR-E using a Bayesian framework to generate improved ice concentration estimates. The probability of an the ice/water labels given the state is modeled using a Bernoulli distribution. The AMSR-E ice concentration is modeled using a Gaussian distribution.

The data fusion method used here is closely related with data assimilation. Data assimilation is the process to incorporate observations into a prognostic forecast model, such as a coupled ice-ocean model, for improved forecasting. This prognostic model is then evolved forward in time, and the model state from this forecast provides the initial state (which is called background state in data assimilation) for the next assimilation cycle. Both the method used in the present study and data assimilation are combining information from different sources to generate a optimal state estimate, except that the current method does this for each image separately without a forecasting model. Data assimilation has been demonstrated to improve sea ice states in a number of studies. Different from this work, the majority of these studies assimilate sea ice concentration from passive microwave radiometers. In the future, the proposed approach could be directly incorporated into a sea ice data assimilation system, for example, as an additional term in the cost function of a variational data assimilation system.

This paper is organized as follows: the study area and data are described in Section III, Section IV discusses the details of the data fusion method and the model between ice concentration and ice-water classification results from SAR images, analysis of the approach is carried out in Section V, followed by experimental results, analysis and conclusions in Section VI and VII respectively.
III. Study area and datasets used

The study area is located in the Beaufort Sea, north of Alaska (Fig. 1). This region is almost fully ice-covered in the winter and contains a mixture of ice and open water regions from July to September. The data acquisition time ranges from April 2010 to August 2011. Both melt and freezing period are present in the dataset used. Multiple data sources are used in this study. RADARSAT-2 images and AMSR-E ice concentration maps are used by the proposed algorithm to generate refined ice concentration estimations. IMS (Interactive Multi-sensor Snow and Ice Mapping System) ice extent [25], image analysis chart and manual ice/water classification of SAR images guided by ice charts are used for verification purposes.

A. RADARSAT-2 images

RADARSAT-2 HH and HV polarized ScanSAR wide beam images are used in this study. Each image has a swath width of 500 km, with nominal pixel spacing of 50 m x 50 m [26]. Fifty-one scenes covering the period from April 18, 2010 to August 18, 2011 over the study area were acquired and used.

B. AMSR-E daily sea ice concentration

AMSR-E sea ice concentration data generated by the ASI algorithm [4] was used due to its relatively fine spatial resolution among all available sea ice concentration products.
The data were generated by the Integrated Climate Data Center of University Hamburg\(^1\). This dataset was generated from the AMSR-E 89GHz channel data, and gridded to a pixel spacing of 6.25 km before distribution (the spatial resolution of AMSR-E 89 GHz band is 6 km \(\times\) 4 km). ASI is based on the difference between vertically and horizontally polarized brightness temperatures at 89GHz. The errors are normally below 10% for mid and high ice concentration areas (above 65%). The errors for low ice concentration areas depend on the weather conditions \(^4\), which are generally larger than that of middle or high ice concentration areas. Note that the AMSR2 ice concentration produced by a new version \(^27\) of the ASI algorithm features finer spatial resolution than the AMSR-E ice concentration maps. AMSR2 is not used in the present study as the set of SAR images used were acquired in 2009-2010, whereas data from AMSR2 only became available in 2012.

C. IMS 4 km sea ice extent

Data from IMS (Interactive Multi-sensor Snow and Ice Mapping System) are used as one of the data sources for comparison with the analyses from data fusion. The IMS product is a sea ice extent with 4 km spatial resolution \(^25\). This data set is produced and distributed by the National Snow and Ice Data Center (NSIDC). The data are produced by expert interpretation based on ice climatology and a variety of data sources including geostationary, AVHRR, MODIS and passive or active microwave based observations. Due to the fact that the IMS product relies heavily on AVHRR and MODIS data, it can be considered relatively independent of the inputs to the data fusion. IMS identifies locations with over 50% of ice cover as ice \(^28\).

D. Image analysis charts from CIS

Of the image set used here, 15 images have corresponding image analysis charts, which were obtained from the Canadian Ice Service (CIS). These image analysis charts are used as an auxiliary comparison dataset. The image analysis charts are produced manually by expert analysts at CIS and represent an manual interpretation of the SAR imagery. Hence, they are not independent of the ice/water labels used in the data fusion. The image analyses provide eleven levels of ice concentration from 0 to 1 with an interval of 0.1. An ice concentration level is assigned to a region considered by the analyst as having relatively homogeneous

\(^1\)http://icdc.zmaw.de/seaiceconcentration_asi_amsre.html
conditions. The size and shape of these homogeneous regions, which are called polygons, vary within each image analysis chart as well as between various ice charts. The image analysis charts acquired from CIS are sampled points of the original image analysis charts with a sampling interval of 8 km by 5 km. Example of an sampled image analysis chart used is shown in Figure 2.

E. Visual interpretation of sea ice extent

Image analysis charts lack small scale details of the ice cover. For the purpose of being able to confirm these details, ice/water labels are assigned to SAR image regions manually [11] under the guidance of ice charts. Both the manually generated labels and automatically generated labels of the SAR images are labeled based on the same segmentation results generated by the MAGIC system (pixels belonging to the same polygon have the same ice/water labels). The interpreted ice extent from SAR images is therefore not independent on the ice/water labels used in the data fusion.

IV. CLASSIFICATION OF DUAL-POLARIZED RADARSAT-2 IMAGES

The SAR images are first down-sampled by averaging pixels over 8 by 8 blocks to reduce the noise and data volume, which results in nominal pixel spacing of 400 meters.
Homogeneous regions in the images are then identified, classified, and labeled as belonging to either ice or water using the IRGS (Iterative Region Growing Semantics) segmentation based method [18] within the MAGIC (MAp-Guided Ice Classification) system [9], [11]. The reported overall accuracy of the classification system is 96% when verification is carried out with expert visual interpretation of the images [11]. The minimum classification accuracy was 90% for one scene in August, possibly due to the presence of wet snow on the ice surface.

V. METHODOLOGY

The proposed algorithm takes AMSR-E ice concentration and ice/water labels from dual-polarized SAR images as input to generate refined ice concentration estimates at the resolution of down-sampled SAR images. The AMSR-E ice concentration images are distributed in polar stereographic projection. Re-projection and interpolation using a nearest-neighbor interpolation method was performed using GDAL (Geospatial Data Abstraction Library) to bring the AMSR-E ice concentration to the same projection and pixel spacing as the RADARSAT-2 images before the fusion process. A Bayesian model is used to combine the re-projected AMSR-E ice concentration and the ice/water labels from MAGIC. In this model, the AMSR-E ice concentration at a given pixel location is the background denoted by $x^b$, and the ice or water label of the SAR image pixel is the observation denoted by $y$. Pixels with $y = 1$ and $y = 0$ correspond to the pixel being labeled as ice or water respectively. The ice concentration estimate from the data fusion method is denoted by $x^a$, and will be referred to as the analysis. The difference between the analysis and the background state $x^a - x^b$ is referred to as the analysis increment.

In the Bayesian approach, the posterior probability distribution function (pdf) of the state, $x$ (ice concentration at a given location in this case), given the observations $y$, is represented by [29]

$$p(x|y) \propto p(y|x)p(x),$$

where $p(y|x)$ is the pdf of the observations given $x$, and $p(x)$ is the pdf describing the distribution of the state, $x$. The most likely state estimate is expressed as the MAP (maximum a posteriori) estimate,

$$x^a = \arg \max_x p(x|y) = \arg \max_x [p(y|x)p(x)].$$

For the present study, the observations are discrete. In this case, \( y \) only takes value 0 or 1. Instead of using (1) which describes the posterior pdf, the following expression (3) is used to describe the posterior probability

\[
p(x|y) \propto P(y|x)p(x).
\]

where, \( P(y|x) \) is the probability of the location been labeled as ice or water for a given ice concentration. The MAP estimate (3) of the ice concentration is then given by

\[
x^a = \arg \max_x p(x|y) = \arg \max_x [P(y|x)p(x)].
\]

A. Specification of \( p(x) \)

The prior distribution of ice concentration \( p(x) \) is specified using a Gaussian distribution centered at \( x^b \). For simplicity, the errors between different ice concentration locations are considered independent, which leads to

\[
p(x) \propto \exp \left[ -\frac{(x - x^b)^2}{2\sigma^2_b} \right],
\]

where \( \sigma_b \) is the background error standard deviation.

B. Specification of \( P(y|x) \)

To represent the probability of an ice or water observation given the state, \( P(y|x) \), an empirical model has been developed because no physical model is available. In the model development, the observations are assumed to be independent, identically distributed (i.i.d.) random variables that follow a Bernoulli distribution, which means that \( P(y=0|x) = 1 - P(y=1|x) \). The empirical observation model was developed based on the following observations and constraints:

1) When \( x \) is 0 or 1, the probability of a pixel being labeled as ice given \( x \) should be close to 0 and 1 respectively. That is,

\[
P(y = 1|x = 0) \approx 0
\]

\[
P(y = 1|x = 1) \approx 1.
\]

2) When the ice concentration increases, a pixel is more likely to be labeled as ice. This implies \( P(y = 1|x) \) should be a monotonically increasing curve with increasing \( x \). That is,

\[
\frac{dP(y = 1|x)}{x} >= 0.
\]
3) When the ice concentration is close to 0 or 1, the probability of a pixel being classified as ice or water should not change significantly with \( x \). That is, the curve describing \( P(y|x) \) should have a small slope when \( x \) is close to 0 or 1.

Those constraints are satisfied by an S-shaped curve, which can be represented by a function of the following form (Fig. 3),

\[
P(y = 1|x) = \frac{1}{1 + e^{-rx+q}}, \quad r, q \in \mathbb{R} \quad r > 0, q > 0
\]

which is referred to as the observation model. The selection of the two parameters in this model, \( r \) and \( q \), will be discussed in Section VI-A.

C. Construction of the cost function

After the substitution of (8) and (5) into (4) and application of the \(-\log\) operator, the problem of maximizing \( p(x|y) \) becomes one of minimizing \(-\ln(p(x|y))\). The function that is minimized, which will be called the cost function, is given by (9a) for the case when the observation is ice, and is given by (9b) for the case when the observation is water:

\[
x^a = \arg \min_x \left[ \frac{1}{2}(x - x^b)^2/\sigma_b^2 + \ln(1 + e^{-rx+q}) \right] \quad \text{if } y=1 \quad (9a)
\]

\[
x^a = \arg \min_x \left[ \frac{1}{2}(x - x^b)^2/\sigma_b^2 - \ln\left(1 - \frac{1}{1 + e^{-rx+q}}\right) \right] \quad \text{if } y=0. \quad (9b)
\]

VI. EXAMINATION OF THE OBSERVATION MODEL

The observation model, given by (8), describes the probability of a pixel been labeled as ice or water by the classification algorithm given the state, as shown in Fig. 3 for various values of the parameters \( r \) and \( q \). A larger \( r \) corresponds to a steeper slope of the observation function, while the parameter \( q \) shifts the shape of the observation function along the \( x \) axis.

These observation models are also examined by looking at the relationship between \( x^a \) and \( x^b \) for two cases where the SAR image labels \( y \) are ice \((y = 1)\) or water \((y = 0)\) for \( x^b \) from 0 to 1. The background error standard deviation \( \sigma_b \) is set to 0.1 to be consistent with the ice chart error [4]. The analysis term \( x^a \) are obtained by optimizing (9) using Matlab \( \circ \) function \texttt{fminbnd} which finds the minimum of a given function on a fixed interval. The results are illustrated in Fig. 4.

Fig. 4(a) demonstrates that when the observation is ice (solid lines), the analysis approaches the background state gradually with increasing ice concentration, and the analysis increment
Fig. 3: The proposed model describing the probability of a pixel being classified as ice given the ice concentration, $P(y = 1|x)$, based on \( \mathcal{N} \) at different parameter settings \((r,q)\). The solid lines correspond to when different values of \( r \) are used, while the dotted lines correspond to when different values of \( q \) are used.

decreases. This agrees with the intuition that the pixels with higher ice concentration are more likely to be labeled as ice, and that the ice labels do not contain much additional information when the background ice concentration is high. In a similar manner, when the observation is water, the analysis is very close to the background state at low ice concentration, but their difference increases as the ice concentration increases. An ice observation \( y = 1 \) can only lead to a positive ice increment and the value of this increment approaches zero as ice concentration approaches 1. Similarly, an open water observation \( y = 0 \) can only lead to a negative ice increment, and the value of this increment approaches zero as the ice concentration approaches zero. Together, these imply that for the current method the ice concentration in the analysis will always be between zero and one.

Larger \( r \) means larger impact of the observation on the analysis increases, e.g., the magnitude of the analysis increment increases with increasing \( r \) (Fig. 4(a,c)). A similar pattern applies to parameter \( q \).

For the present study, values of \( q = 0.3 \) and \( r = 15 \) were chosen to enable a reasonable impact of the ice (water) observation when background ice concentration is very low or very high and to limit the impact of the ice observation to ice concentration values below 0.5. In other words, when the ice concentration in the state is greater than 0.5 an ice observation will not be able to generate an ice increment. This reflects a belief that when ice concentration
is greater than 0.5 it will be observed as ice (e.g., $x = 0.5$ may correspond to $y = 1$), hence in this situation, an ice observation cannot provide any additional information to the state estimate. Similarly, for a water observation, this means the water observation has no impact when the ice concentration is less than approximately 0.1 as shown in Fig. 4(d).

Another method to obtain a fusion model is to fit a regression model between the fraction of ice pixels and the ASI ice concentration. In our experiment, the data fusion results using the fitted curve were worse than those using the proposed model (8). The fitted model is, therefore, not used in this study.

Fig. 4: The effect of model parameters on the relationship between $x^a$ and $x^b$. Solid lines are for cases when the observation is ice; dashed lines are for the cases when the observation is water. Different parameter settings are represented by different colors.
VII. EXPERIMENT USING REAL DATA

A. Experimental set-up

In this experiment, ice water labels from classified SAR images (\(y\)) are fused with an ice concentration state (\(x^b\)) which is the ASI ice concentration generated from passive microwave data. The error variance \(\sigma_b^2\) is set to 0.1\(^2\) based on error estimate given in [4]. For the ice/water labels, no error estimate is required. The parameters \(q\) and \(r\) indicate the relative impact of the observation on the state, as discussed in Section VI. In the experiment, for each day during the period of April 18, 2010 to August 18, 2011 that a classified image is available, the ice/water labels are fused with the ASI ice concentration state from the given day. Each day is processed independently of previous or subsequent days. The output from the data fusion is an ice concentration analysis.

To compare against the ice/water states (IMS analyses and visual analyses of MAGIC labels), the ice concentration analyses from the data fusion need to be converted to binary values. The ice concentration from the data fusion is, therefore, downscaled to the resolution of IMS using local averaging. A threshold of 30\% is then applied to the downscaled ice concentration to be consistent with the classification scheme [11], i.e., a point with ice concentration greater than 30\% is considered to be ice, and a point with ice concentration less than 30\% is considered to be water. The error of \(x^a\) (noted by \(e_a\)) is calculated as the proportion of misclassified pixels in the binary ice concentration analysis with respect to IMS ice extent. The background error \(e_b\) is calculated in a similar manner. Note that when both \(x^a\) and \(x^b\) are below or above the threshold, they are not distinguishable after converted to binary values, so the calculated error difference between the analysis and background is smaller than the actual error difference.

B. Results

1) Results for October 6\(^{th}\), 2010: This is the scene with the largest improvement by fusion of SAR information. As shown in Fig. [5], the analysis increment is larger at the ice edge than in the middle of the ice pack, and that some of the small openings in the ice pack seen in the observations are carried forward to the analysis. This is partly due to the nature of binary data fusion, which can only generate an analysis increment when the background differs significantly from the observations, and partly due to the high resolution of SAR images, which provide much more information of the ice edge as compared to passive microwave data.
Fig. 5: Results for the scene acquired in October 6th, 2010, which shows the enhanced details due to data fusion. (a) HH band SAR image; (b) HV band SAR image (scaled); (c) ice-water classification results (yellow is ice, blue is water); (d), AMSR-E ice concentration; (e) analysis from the data fusion; (f) analysis increment which is the element-wise difference between panels (d) and (e).
2) Results for October 25\textsuperscript{th}, 2010: While the data fusion led to an improvement in the sea ice concentration for most days, it led to a degradation on October 25th, 2010. This may be caused by the large classification errors in this scene as shown in Fig. \ref{fig:classification_errors}. Therefore, an operational implementation of the data fusion method would require the development of observation quality control criteria to ensure minimal misclassification in the observation set.

3) Comparison of analyses with ice extent from IMS and manual interpretation: Error statistics of the data fusion results for the days with classified SAR images are shown in Fig. \ref{fig:error_statistics}. The sub-plots in the left column use manual interpretation of ice extent as ground truth and the right column uses IMS. The vertical dashed line is the separation between year 2010 and 2011. The difference of the proportion of incorrectly classified pixels between the AMSR-E ice concentration and the analysis is shown in panels (a) and (b) of Fig. \ref{fig:inc_correct}. In general, the error of the analysis is smaller than the error of the AMSR-E ice concentration in almost all 51 scenes. The errors can also be expressed as the proportion of ice pixels that are incorrectly classified as water and the proportion of water pixels being incorrectly classified as ice, which are shown in panels (c) and (d) of Fig. \ref{fig:inc_correct}. A positive number denotes an improvement due to the data fusion. The data fusion leads to a net reduction of the number of ice pixels that were misclassified as water. This implies that there is an underestimation of ice concentration in the AMSR-E ice concentration compared to the IMS ice extent and manual interpretation of the ice extent.

4) Comparison of analyses with image analysis charts: The analyses of the proposed algorithm are compared with scenes that have image analysis charts. The image analysis charts are reprojected to the projection of the SAR images. Each sample point of the image analysis chart is compared with the averaged analysis from data fusion, which is carried out within its neighborhood of size $8km \times 5km$ to match the sampling interval of the image analysis charts. The AMSR-E ice concentration is also compared with the image analysis chart using the same scheme. The resulting mean and standard deviation of the ice concentration difference are shown in Fig. \ref{fig:image_analysis_chart}. The data fusion results underestimate the ice concentration, but show consistent improvements against the background state in both mean error and standard deviation. The underestimation could be caused by the fact that image analysis charts are known to over predict the ice concentration (because they are generated in the interest of marine safety), or it could be caused by the underestimation of the ice concentration in low ice concentration regions for the AMSR-E data \cite{4}. An absolute improvement of 1.1\% in mean
Fig. 6: Result from October 25, 2010, which show a decrease in performance due to a possible classification error. SAR classification result (c) is showing large areas of misclassification of ice (white) into water (black) in the upper right of the image and water into ice outside the ice edges, which leads to incorrect decreasing ice concentration in ice pack (blue in (f)) and increasing ice concentration in water regions (red in (f)).
Fig. 7: Results compared to ice/water extent data (manual interpreted ice extent for the left column and the IMS ice extent for the right column). The vertical dashed line is the separation of year 2010 and 2011. Panel (a) and (b) are the differences between the analysis and AMSR-E ice concentration; Panel (c) and (d) both are the differences of errors in panel (a) and (b) separated for ice and water.

error against the AMSR-E daily sea ice concentration is observed. The relative improvement in mean error (mean error difference between the background state and analyses divided by the mean error of the background state) is about 5.6%. For the standard deviation, the absolute improvement is 1.3%, and the relative improvement is 4.9%.

VIII. Summary

Binary ice/water labels are fused with the AMSR-E ice concentration has been carried out using three different data sets. All evaluation results indicate that the data fusion has a positive impact on ice concentration estimation. Accurate information of the ice edges is particularly important for navigation in ice infested waters. It was found that substantial analysis increments are typically located at the ice edges.
Fig. 8: Result compared to image analysis chart. Panel (a) and (b) are the error bias and standard deviation of the AMSR-E ice concentration and data fusion results when verified against image analysis chart.

The algorithm used in the classification of SAR images is very complex and it would be difficult to model the classification process accurately. Instead, an empirical model is used here to describe the relationship between the classification results and ice concentration. The parameters of the empirical model have been set in a heuristic way in this study. In the simulations carried out, when \( r \) is set between 7 and 15, the assimilation results show negligible differences. Therefore, no further model tuning was carried out.

The proposed method depends on the classification results of SAR images. The SAR image classification method adopted here is a segmentation based method. Observations from neighboring pixels are not independent in nature. The spatial context information could be taken into account by adding a homogeneity constraint to the cost function, or by modeling the spatial correlations between observations. These will be investigated in a forthcoming study.

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REFERENCES


