A New Algorithm (ECICE) to Estimate Ice Concentration from Remote Sensing Observations: an Application to 85 GHz Passive Microwave Data

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ABSTRACT

A new algorithm, called Environment Canada’s Ice Concentration Extractor (ECICE), has been developed to calculate total ice concentration and partial concentration of each ice type from remote sensing observations. It employs two new concepts. First, it obtains a best estimate of ice concentrations by minimizing the sum of squared difference between observed and estimated radiometric values based on a linear radiometric model for each ice type. Second, instead of employing a single radiometric value (tie point) for each ice type, it utilizes the probability density distribution of the radiometric values for each ice type. Then in a Monte Carlo simulation, 1000 radiometric values are randomly selected, total and ice-type concentrations are calculated by solving the minimization problem and finally median values from the 1000 simulations are chosen. The algorithm was applied to the winter sea ice in the Gulf of St. Lawrence, Canada using observations from SSM/I 85GHz channel. Results were evaluated against ice concentration estimates from the operational analysis of Radarsat images at the Canadian Ice Service (CIS). Statistics of the differences between the output concentration and CIS estimates show that ECICE can successfully identify open water and consolidated pack ice pixels better than the Enhanced NASA Team (NT2) algorithm. However, in areas of ice concentrations between 20% and 70%, the algorithm’s performance could not be precisely evaluated because the typical size of the CIS’s analysis polygon is much larger than the footprint of the 85GHz SSM/I channel. Hence, the algorithm captures information at a finer spatial scale. Examples of using one, two and three radiometric parameters to calculate the concentrations are presented.

1. INTRODUCTION

Ice type and concentration are important input for operational sea ice monitoring products, numerical weather prediction models and regional climate models. An equally important bi-product is ice edge delineation, which is derived from ice concentration. Passive microwave observations are commonly used to estimate total ice concentration and, to a limited extent, ice types and their partial concentrations. The sensors that have been widely used for this purpose are the Special Sensor Microwave Imager (SSM/I) onboard the Defense Meteorological Satellite Program (DMSP) platform since 1987 [1]; and the Advanced Microwave Scanning Radiometer (AMSR-E) onboard the NASA EOS Aqua satellite since 2002 [2].
A few algorithms have been developed to retrieve ice concentration from passive microwave data. Among them are: NORSEX [3], NASA Team (NT) [4], Bootstrap [5], AES-York [6], NASA Thin Ice [7], the Enhanced NASA Team (NT2) [8], Svendsen's [9] SEALION [10 and 11], and ASI [12]. The last three algorithms use observation from the fine resolution channels, 85GHz on SSM/I (15X13 km² resolution), or 89 GHz on AMSR-E (4X6 km² resolution). The other algorithms use observations from the 19GHz data (69X43 km² resolution from SSM/I and 16X17 km² resolution from AMSR-E) in combination with the 37GHz data (28X37 km² resolution from SSM/I). Typical application of any algorithm involves using observation from the fine resolution channels. The study recommended combining more than one algorithm so that the virtue of each one will be retained. In another study [14] it was concluded that total ice concentration can be estimated from NORSEX, NT, Bootstrap, and AES-York with an accuracy of 5% to 10% during the dry period (winter and spring), and 10% to 20% during the wet period (summer). A recent study [15] concluded that AES-York and NT2 algorithms underestimate total ice concentration by 9% and 13%; respectively, while NT2 is successful in discriminating between thin and thick ice if they coexist in equal percentage in the footprint. Other evaluation/validation studies are presented in [16, 17, 18, 19]. A most recent study [20] includes evaluation of ASI algorithm using AMSR-E data over the Arctic ice.

With the many options of sea ice concentration retrieval algorithms, the sea ice remote sensing community has been occupied with the question of which algorithm works better and under which ice and atmospheric conditions. A more compelling question would be: what are the common factors that lead to general failure of algorithms especially in seasonal ice regimes? The following paragraphs identify those factors and show how ECICE addresses them.

Perhaps the most common cause of the algorithms' failure in seasonal ice regimes is their use of a single tie point (a typical radiometric value) to represent a given ice type [21]. Even under stable winter conditions the surface emission from any ice type (especially thin ice) occupies a range of values. Using one value of tie point may contribute to calculation of ice concentration above 100%. This has been pointed out in [22], where the authors enabled the solution to be found in the range between 0 and 120% in order to allow the variability of the algorithm to be directly comparable to other algorithms. Some algorithms allow for adaptive tie points to account for regional and seasonal dependence [7], [10]. However, the use of probability distribution of the input
radiometric parameter(s) for each ice type seems to be a more realistic option than using a single tie point. Hence, this concept is introduced in ECICE instead of using a single tie point for each surface.

Existing algorithms are usually successful in estimating total ice concentration under stable winter conditions (with limitations established based on surface conditions), but they generally fail to estimate concentration of ice types [15], [23]. Concentration of thickness-based ice types is an important operational requirement because it is connected to the mechanical strength of ice. It is also significant for weather and climate studies because the radiative and thermal properties of thin and thick ice vary considerably [24]. However, the challenge of identifying thickness-based ice types using passive microwave data is the overlap of their brightness temperature distributions. The ECICE employs a mathematical optimization technique to overcome the issue of overlapping distributions. This is another concept, which has replaced the traditional approach of determining ice concentration by solving a unique set of linear algebraic equations that relates a given radiometric observation to tie points and concentrations of ice types that comprises its footprint.

Microwave emission, and hence ice concentration algorithms, are affected by ice surface composition rather than bulk ice properties. This is particularly true for thin ice (thickness < 15 cm) whose surface features spatial and temporal variability at scales much finer than the sensor’s resolution. Due to the steep temperature gradient within thin ice, combined with variation in atmospheric conditions, snow on the surface undergoes rapid and complex processes including melting and re-freezing, metamorphosis, formation of a hoar layer at its base, changing to slush, drawing brine liquid from the underlying highly saline ice surface, etc. [25], [26], [27]. These processes create radiometrically different surfaces of the same ice category. A few studies attempted to address this surface complexity. For example, NT2 accounts for surface glaze and layering [17] by using a threshold of a gradient ratio [8]. ECICE is generic enough in that it accommodates any surface as long as it is defined by a reasonable probability distribution of each observation.

Finally, a common disadvantage of using satellite passive microwave data in ice parameter retrieval is their large footprints, which usually contain highly heterogeneous range of ice types. This renders the parameter retrieval not robust enough for operational use, especially in seasonal ice regimes or ice margin zones. Hence, an important criterion in developing ECICE was its ability to use the fine-resolution, high-frequency channels of passive microwave data for ice concentration retrieval. These data, however, suffer from two difficulties. First, observations are usually affected by meteorological conditions. Correction for meteorological influences is included in ECICE. Secondly, distribution of brightness temperature values from ice types and open water overlap heavily [28]. The optimization technique in ECICE is particularly useful in resolving this difficulty. It should be mentioned, however, that although the optimization technique is applied to 85GHz data, the 36GHz observations were used to identify open water pixel and hence skip ice concentration calculations (Sec. 2.1).
2. DESCRIPTION OF THE ALGORITHM

Figure 1 is a flowchart of the algorithm. The core component is an optimization technique that searches for the ice type concentration vector which minimizes the sums of the square of difference between the radiometric observation (after accounting for meteorological effects if necessary) and an expected value generated from a linear model. The model comprises a set of familiar equations in which each equation decomposes a single observation, integrated over the sensor’s footprint, into components produced by the ice types that comprise the footprint, weighted by the concentration of each type. For example, if three observations from the 85GHz radiometer onboard the SSM/I are selected to calculate concentrations of three ice types plus open water, the equations will take the form:

\[ \sum_{i=1}^{4} c_i \varepsilon_{85,i} T_b \]

The solution is subject to the following constraint:

\[ \sum_{i=1}^{4} c_i = 1 \]  

Here, \( T_{b85,O} \) and \( T_{b85,H,O} \) are the weather-corrected brightness temperature in the vertical and horizontal polarization observation respectively, \( PR_{85,O} \) is the weather-corrected polarization ratio, \( T_s \) is the surface temperature, \( c_i \) is the concentration of surface type \( i \), and \( PR_{85,i}, \varepsilon_{85,i} \) are typical values (traditionally called tie points) of polarization ratio and emissivity in V and H polarizations, respectively. In the rest of this paper those values are called characteristic radiometric parameter values (CRPV) and are selected from the probability distributions of the parameters (Sec. 2.4). In this application the four surface types are New ice (NI) of thickness < 10 cm, Young ice (YI) of thickness between 10 cm and 30 cm, First-Year ice (FY) of thickness > 30 cm and open water (OW). However, results are also presented from using two parameters (brightness temperature and polarization ratio) to solve for three surfaces: combined NI and YI, FYI and OW. The polarization ratio is defined as

\[ PR_{85,O} = (T_{b85,O} - T_{b85,H,O}) / (T_{b85,O} + T_{b85,H,O}) \]

It should be noted that similar equations that represent any type and number of observations (infrared, optical or radar) may be used. Although the above four equations can be solved to determine concentration of the four surface types, the algorithm does not use this approach. Instead, it uses an optimization technique, which
accommodates inequality constraints to keep the solution for the concentration within the range 0 to 100% (Sec. 2.3). Other modules are introduced to accommodate specifics of the given observations. In this application two modules are included to suite SSM/I 85GHz observations; a filter to flag out open water pixels, and a scheme to account for meteorological influences on the observations.

It is worth noting that the equations in the linear model (1) must be independent and should represent as much as possible uncorrelated measurements. The polarization ratio at the L.H.S. of the third equation in (1) is derived from the observations according to (3), but the CRPVs at the R.H.S. are derived independently using (3) from the distributions of the brightness temperatures. This is what makes the third equation independent of the first two in (1).

2.1 The open water filter

To identify open water pixels, a filter was developed using the physical surface temperature and an inequality condition on the \( T_{b_{85V}} \) based on the ratio \( GR_{85V37V} \), which is defined as:

\[
GR_{85V37V} = \frac{T_{b_{85V}} - T_{b_{37V}}}{T_{b_{85V}} + T_{b_{37V}}} \quad (4)
\]

Where \( T_{b_{37V}} \) is the brightness temperature from 37GHz vertical polarization channel. The condition on the \( T_{b_{85V}} \) is:

\[
T_{b_{85V}} \leq 1000 \times GR_{85V37V} + 192.5 \quad (5)
\]

\( T_{b_{85V}} \) is in °K. If the pixel satisfies (5) and its surface temperature is higher than -3 °C, then it is considered open water and hence the solution using the optimization technique should be skipped. The rationale behind the condition in (5) is explained in Fig. 2, which shows the distribution of output from ECICE without using the above filter. Data were obtained from the 3 images where OW misidentification was particularly bad. The categories of the points (as shown in the legend) are based on comparing the algorithm’s output against CIS estimates. For example, the solid diamond “open water – correct” category represents footprints which are identified as open water by both the ECICE output and CIS estimate, while “open water – incorrect” category represents open water footprints as estimated by CIS but where ECICE outputs non-zero concentration. The figure shows that most of open water pixels (according to CIS estimates) are located at the right side of the threshold line while ice pixels (with any concentration) are located at the left side. Equation (5) fixes 90.4% of the OW points incorrectly identified as ice-mixed points. Conversely, it erroneously identifies 4.6 16.2% of ice-mixed points as OW. This should cause displacement of the ice edge more towards the pack ice. For this reason the condition of surface temperature was introduced to complement the gradient condition (5). It improves OW identification to a level of 94.51%.
Most of the OW points that are wrongly identified by ECICE without the above filter have Tb values much higher than the typical values for OW (i.e. they approach the range of ice values). This anomaly could not be explained in terms of the meteorological parameters (Sec. 2.2). However, it might be caused by a rain or freezing rain event. In a recent study on microwave radiation from artificial sea ice [29] higher Tb$_{85}$ values were observed (particularly from the vertical polarization) from water surface during rainfall.

### 2.2 Correction of 85GHz brightness temperature for the meteorological influences

Observations from the 85GHz channel are corrected to remove the contribution of three meteorological influences: integrated water vapor (W), cloud liquid water content (L), and wind speed over sea water (V). Scattering by precipitation particles (in liquid or solid form) decreases Tb$_{85}$, while absorption and emission increase it [30]. The net effect is an increase of Tb$_{85}$ with W or L. Likewise, an increase in V causes roughening of the water surface, and hence an increase of Tb$_{85V}$ and Tb$_{85H}$. The increase in Tb$_{85H}$ occurs at a higher rate, which makes the polarization difference decreases significantly with increasing wind speed [31]. This causes overestimation of ice concentration over rough open water.

Correction of Tb$_{85p}$ (where p stands for the polarization; H or V) for the above-mentioned parameters follows the procedures in [11]. The influence of W and L is subtracted from the original brightness temperature using the following equation (all radiometric parameters denote 85GHz observations):

$$Tb_{p-corr-WL} = Tb_p - \sum_{k=1}^{n} C_k \left( \sum_{i,j=0}^{4} a_{ji}(\varepsilon_p(V))W^iL^j \right)$$

where Tb$_{p-corr-WL}$ is the brightness temperature corrected for W and L, and a$_{ji}$ are coefficients that depend on the surface emissivity, which in turn is a function of wind speed when the correction is made over open water. A lookup-table of the coefficients, along with the open water emissivity variation with wind speed $\varepsilon_p(V)$, are provided in [11]. The term between the brackets in the R.H.S. of the above equation is a fourth-order polynomial. The subscript k refers to the surface type, while n denotes the number of surface types. Different sets of coefficients a$_{ji}$ are obtained for different surfaces because emissivity varies between surfaces. The correction is conducted for the contribution of each surface type. Total correction for W and L is the sum of those contributions weighed by estimates of concentration of each surface type, C$_k$. Correction for the influence of wind speed over ocean surface is carried out using the following equation:

$$Tb_{p-corr-WLV} = Tp_{p-corr-WL} - C_{OW} \sum_{i=0}^{4} b_i V^i$$

Where Tb$_{p-corr-WLV}$ is the observation corrected for the three parameters W, L, and V, and C$_{OW}$ is the OW concentration. Once again, the coefficients b$_i$ are provided in [11]. They
were obtained using regression of results from the microwave radiative transfer model MWMOD [31] obtained at fixed values of W, L and V. All concentrations in the above equations are obtained from using the optimization technique against non-corrected observations (Fig. 1). In previous algorithms (e.g. [11]), correction for meteorological parameters is implemented simultaneously with solving the equations for ice concentration because the correction needs concentration values. In testing those algorithms, it was found that this interactive mode of solution could be problematic because the solution often diverges. So, in ECICE, the correction was implemented in one step followed by the application of the optimization technique. Correction for wind speed over OW is applied only when OW concentration is ≥80%. At less concentration, OW becomes enclosed within sea ice floes, which makes it less responsive to the wind effect.

The meteorological parameters were obtained from the Global Environmental Multiscale (GEM) model (the operational weather model used in the Canadian Meteorological Centre (CMC)) at same locations as of the SSM/I footprints and at a time usually within a few minutes from the SSM/I acquisition. GEM was run in hindcast mode starting from the closest synoptic time (i.e. 00, 06, 12, and 18) that preceded the SSMI acquisition time. GEM “analysis” results are archived at those times. The time step of GEM is 7.5 minutes. The run ends at the time closest to SSM/I acquisition. This method is better than using climatic average data. The bias of the ocean surface wind speed from the regional GEM over the northwest Atlantic with respect to buoy observation is 0.42 m/sec [32]. It should be recalled that correction for meteorological parameters was performed on the 85GHz but not on the 37GHz observations.

2.3 The optimization technique

Solution of the linear system presented in (1) and (2) is likely to produce resolutions with negative values of concentration $c_i$. For this reason the following set of constraints was introduced:

$$ c_i \geq 0 \quad i = 1,2,3,4 $$ (8)

The problem is then treated as an optimization problem because the search space is now restricted according to (8). The terms on the LHS of (1) are now viewed as observations containing an error and they deviate from the expected values obtained from the RHS. Mathematically, the problem is to find the solution for $c_i$ that minimizes that difference, which is represented by the following objective function:

$$ f(c) = \left( \sum_{i=1}^{i=4} (c_i (e_{85V,i} - Th_{85V,O}) / Th_{85V,O})^2 \right) + \left( \sum_{i=1}^{i=4} (c_i (e_{85H,i} - Th_{85H,O}) / Th_{85H,O})^2 \right) + \left( \sum_{i=1}^{i=4} (c_i PR_{85,i} - PR_{85,O}) / PR_{85,O})^2 \right) + \left( \sum_{i=1}^{i=4} c_i - 1 \right)^2 $$ (9)
Subject to the equality constraint (2) and the inequality constraints (8). Each term in the above equation is normalized by dividing by the observation value; hence each term has an equal weight in the function. All possible values of $c_i$ that satisfy the above constraints are called feasible solutions. Equation (2) is both an equality constraint and part of the objective function. Since the method takes advantage of the quadratic objective function, the exclusion of (2) from (9) would cause the matrix of second derivatives of the function to be ill-conditioned or singular; making the problem difficult to solve.

To account for the constraints, the notion of Lagrange function $L$ [33] is introduced:

$$L(c, \lambda) = f(c) - \sum_{k=1}^{k=j} \lambda_k (A_k c - b_k)$$  \hspace{1cm} (10)

Here, $A_k c - b_k$ is an active constraint, re-written in vector form, which originates from the inequality constraint $k$, $\lambda_k$ is the corresponding Lagrange multiplier, and $j$ is the total number of active constraints, which is determined during the optimization process. Constraints are said to be active at a feasible point if that point lies on a boundary formed by the constraint. An equality constraint, therefore, is always active, while an inequality constraint is active only if a feasible solution lies on its boundary. If that happen the inequality constraint will take the form of an equality constraint

$$c_k = 0 \quad k = 1, 2, 3, \text{ or } 4$$  \hspace{1cm} (11)

Hence, the coefficients in (10) for the equality constraint (2), are $A_k$=[1,1,1,1] and $b_k$=1. If an inequality constraint $k$ has become active (e.g. $c_k$=0), then all components $A_k$=0 except for the component $k$, while $b_k$=0. For example if $c_2$ becomes active ($c_2$=0), then $A_k$=[0,1,0,0] and $b_k$=0. Minimizing the Lagrange function (10) is equivalent to minimizing (9) subject to constraints (2) and (8), provided the correct set of active constraints is found.

Note that not all inequality constraints will be active at the same time. The algorithm uses the primal active set method to select the correct active set and Newton’s Method to minimize the Lagrange function; both are outlined in [33].

With the formulation in (10), the problem can now be considered as unconstrained optimization of multivariable equation. The necessary and sufficient conditions for a minimum are defined by setting the gradient vector to zero and the eigenvalues of the matrix of second derivatives must all be greater than zero. This is the essence of the solution by Newton’s Method. The solution is obtained by taking a second-order Taylor expansion of the Lagrange function (10) around an initial point that satisfies all constraints and setting the following:

$$\nabla L(c, \lambda) = 0, \text{ where } \nabla = \begin{bmatrix} \nabla_c L \\ \nabla_\lambda L \end{bmatrix}$$  \hspace{1cm} (12)
The parameter $\lambda$ is the Lagrange multiplier vector that satisfies the solution. The result is the following system of linear equations:

$$\begin{bmatrix} \nabla^2 f & -A^T \\ -A & 0 \end{bmatrix} \begin{bmatrix} \Delta c \\ \lambda_{\text{new}} \end{bmatrix} = \begin{bmatrix} -\nabla f \\ 0 \end{bmatrix}$$  \hspace{1cm} (13)$$

In this system, $A$ is the matrix formed by taking each $A_i$ as a row. Solving this system yields a step, $\Delta c$, towards the solution, and a new estimate of the Lagrange multipliers, $\lambda_{\text{new}}$. As mentioned previously, the matrix of second derivatives in this system cannot be ill-conditioned, otherwise this system becomes numerically difficult to solve.

The updated estimate of the solution at each iteration of Newton’s Method proceeds as follows.

$$c^{(k+1)} = c^{(k)} + \Delta c^{(k)}$$

$$\lambda^{(k+1)} = \lambda^{(k)}_{\text{new}}$$  \hspace{1cm} (14)$$

Because the objective function (9) is quadratic and all of the constraint functions are linear, the matrix in the LHS of equation (13) is constant. This means that the solution, given the current active set, can be found in the first iteration by solving the linear system (13). The primal active set method is now used to check if the solution is feasible and if the active set is correct.

In most cases, computing the new estimate of $c$ in (14) will result in violation of one or more of the inactive inequality constraints (8), causing the solution to become infeasible. To prevent this, a line search technique is applied to the Newton step, so that (14) becomes:

$$c^{(k+1)} = c^{(k)} + \alpha^{(k)} \cdot \Delta c^{(k)}$$  \hspace{1cm} (15)$$

where $\alpha$ is the step length and $\Delta c^{(k)}$ now defines the search direction. The step length is calculated for each ice type “i” as follows:

$$\alpha^{(k)}_i = \begin{cases} 
\frac{c_i^{(k)}}{-\Delta c_i^{(k)}} & \text{if } c_i^{(k+1)} < 0 \\
1 & \text{if } 0 \leq c_i^{(k+1)} \leq 1
\end{cases}$$  \hspace{1cm} (16)$$

The largest absolute value of $\alpha_i$ is then chosen in order to ensure that no inequality constraints are violated, and $\alpha^{(k)}$ is chosen such that:

$$\alpha^{(k)} = \min_{i=1,2,3,4} |\alpha_i^{(k)}|$$  \hspace{1cm} (17)$$
If $\alpha$ is less than 1, the increment vector $\Delta c$ is then divided multiplied by that value. This is equivalent to shifting the solution to have it located on the boundary of the inequality constraint “$i$” that corresponds to the minimum of $|\alpha_i|$. The constraint is then added to the active set. A new linear system (13) is constructed and Newton’s method is applied for a next iteration. This process is repeated until no new constraints are activated. Once this is done, the Lagrange multipliers are examined to see if the active set is correct. If the current point is indeed the optimal solution, all Lagrange multipliers of the active inequality constraints will be positive. If any is negative, the constraint associated with the smallest (i.e. most negative) Lagrange multiplier is removed from the active set, and the iterative process continues until all Lagrange multipliers are positive.

The optimization method is summarized in the following steps:

1) Choose an initial feasible solution, $c^{(0)}$ to satisfy the equality constraint $\sum_{i=1}^{N} c_i = 1$ and all inequality constraints. A choice of $c^{(0)}=0.25$ is appropriate.

2) Construct the objective function (9) and the linear system (13) to include the initial active set. With the above choice, the initial active set encompasses only the equality constraint (2) for the first iteration.

3) Use Newton’s method to find the interval from the initial solution that minimizes the objective function; that is to compute $\Delta c^{(k)}$ and $\lambda^{(k)}$ from equation (14).

4) If $c^{(k+1)} = c^{(k)} + \Delta c^{(k)}$ violates one or more of the inactive inequality constraints, compute $\alpha^{(k)}$ from (17). In this case $\alpha^{(k)}$ should be less than one. Otherwise set $\alpha^{(k)}=1$, then go to step 6.

5) Update the solution using (15), then add the inequality constraint that has just been violated to the active set by modifying the linear system (13). Then go to step 3.

6) If no more inequality constraints have been violated (or none at all), check $\lambda^{(k)}$. If any multiplier associated with any inequality constraint is negative, remove the constraint. If more than one multiplier is negative, remove the constraint corresponding to the most negative $\lambda^{(k)}$ from the active set and go to step 3.

7) The iterative process ends when no more constraints are violated and all multipliers are positive. At this point the solution is found.

2.4 Generation of the characteristic radiometric parameters values for each surface type

The CRPV included in (1) and (9) are randomly selected from the probability distribution of each radiometric parameter (the emissivity and polarization ratio as specified in (1)) for each surface (Fig. 1). The algorithm randomly selects 1000 sets of values using a Monte Carlo simulation technique and use each set to solve for a possible concentration vector.

To obtain probability distribution of any radiometric parameter included in (1), the parameter has to be sampled over homogeneous areas of the relevant ice type or open water. Those areas were identified in the CIS Radarsat image analysis output (Sec.
3.1). Only polygons (or equivalently SSM/I footprints) associated with an arbitrarily-set thresholds of low values of meteorological parameters L, V and W were considered. This allows the calculation of the emissivity as the ratio between the observed brightness temperature and surface temperature. The latter was obtained from GEM at the center of each SSM/I footprint. Surface temperature is assumed to be equal to the average temperature from the radiating layer. The number of footprints that were available to compile the probability distributions for OW, NI, YI, and FYI were 24, 21, 344, and 199; respectively. Only a few footprints of homogeneous NI were available, and for OW there were many homogenous footprints in the data set, but only a few with near-zero surface wind velocity.

Figure 2 shows the probability distribution of emissivity and polarization ratio for open water and the three ice types. Open water exhibits a narrow distribution, which is relatively well separated from all ice types. The distributions from YI and FYI data overlap heavily, while the distribution from NI features a long and discontinuous tail. This can be attributed to the limited number of points but it is also a manifestation of its complex surface that generates significantly broad radiometric range.

The generation of CRPV proceeds as follows: a random number generator is used to generate a set of numbers, one for each surface type, based on the standard uniform distribution. Each number, u, is then transformed into CRPV of each parameter ($\varepsilon_{85V,i}$, $\varepsilon_{85H,i}$ and $PR_{85,i}$). The inversion method [34] is performed by using “u” as an index to the cumulative probability distribution “F(t)” of each radiometric parameter and the CRPV is determined as $t = F^{-1}(u)$. Hence, the probability distribution of those 1000 generated CRPVs will follow the input probability distribution of the relevant parameter for the given surface. Note that the input distribution does not have to be a standard function (e.g. Guassian). Figure 3 is a graphical illustration of this process. It should be mentioned that PR is determined as $t = F^{-1}(1-u)$ in this application because as the open water fraction increases surface emissivity decreases but PR increases.

2.5 Deriving the final solution of the concentration vector

The final concentration vector is obtained by taking the median of the concentration vector solutions from the 1000 trials using different CRPV sets (Fig. 1). The median for each ice type or water surface is then normalized such that the summation of concentration of all types (i.e. total concentration is 100%). If $c_k^*$ represents the final concentration of surface type $k$ and $c_k$ is the median from the optimal solutions using the 1000 CRPVs, then:

$$c_k^* = \frac{c_k}{\sum_{j=1}^{4} c_j} \quad k = 1,2,3,4 \quad (18)$$

3. AN APPLICATION TO THE GULF OF ST. LAWRENCE 2003 WINTER DATA
3.1 Data Set

The algorithm was applied to a set of SSM/I data acquired over the Gulf of St. Lawrence, in the winter of 2003 (January to the end of March). This period features initial ice growth, followed by peak ice conditions, then the beginning of spring degraded ice. Detailed ice conditions and the atmospheric deriving parameters in this area are introduced in [35]. A total of 21 SSM/I orbits were selected to coincide with the Radarsat images acquired and analyzed by CIS during their operational ice monitoring program. The time difference between SSM/I and Radarsat acquisitions was typically 30 minutes.

All Radarsat images were from the ScanSAR mode [36], which features 100m pixel spacing. Each image was visually analyzed in near-real time by a trained analyst. The analysis consists of drawing contours around selected areas that, in the analyst’s view, contain uniform ice type distribution and concentrations. These areas are called Ice Analysis Polygons (IAPs). For each IAP, the analyst encodes the total ice concentration, predominant ice types, and their partial concentrations. This information was used to evaluate the algorithm’s performance. The algorithm was applied to SSM/I orbit data, rather than gridded data, in order to avoid errors caused by spatial and temporal averaging associated with the gridded data. Hence, SSM/I observations and the derived ice concentration can be compared against results from any coincident and co-located remote sensing data set.

3.2 Evaluation Approach

A data fusion technique [21], [37] was used to map the IAPs and the elliptical SSM/I footprints on the coincident Radarsat image using the latitude/longitude coordinates of IAPs contours and the viewing geometry of the radiometer onboard SSM/I. ECICE output can then be compared quantitatively and qualitatively with CIS analysis results and related to the SSM/I sub-pixel information as obtained from Radarsat images. The spatial accuracy of the data fusion technique hinges upon the geolocation accuracy of pixels from each data set. Typically, the accuracy is 2-5 pixel spacing for Radarsat data and one pixel spacing for SSM/I data. Hence, error in the SSM/I pixel location has a more severe impact on the sub-pixel contents as revealed in Radarsat images. In the following discussions application of ECICE using 85GHz observations (\(T_{b85V}, T_{b85H},\) and \(PR_{85}\)) are denoted ECICE-85, whereas application using 37GHz observations is denoted ECICE-37.

3.3 Results and Discussions

3.3.1 Qualitative evaluation:

The examples shown in this subsection were obtained using the three radiometric observations included in (1). They provide visual evidence of the conclusions from the qualitative analysis in Sec. 3.3.2. The examples show where the algorithm succeeds or fails and how smooth the transition of the output concentration between OW and pack
ice is. This latter aspect is an important criterion in evaluating the algorithm’s performance.

Figure 5 shows five pairs of images acquired on different days. Each pair comprises the Radarsat image with the IAPs overlaid in yellow lines (on the left), and the same image with the total ice concentration from the CIS analysis and the ECICE output (on the right). Ice concentration from the CIS analysis is represented by the color of each polygon, while concentration from ECICE is represented by the color of the elliptic footprints of SSM/I 85 GHz observations. The same color code is used for both data sets (as shown in the color bar) so that when ECICE results agree with CIS estimates, the elliptic footprint contours disappear. The first bin in the color code represents concentrations from zero to 4%.

The image of 030122 (Fig. 5a) shows ice in the early formation stage. Although the ice edge is very loosely defined, the figure shows that ECICE is fairly successful in discriminating ice from OW. Note the gradual progress of ice concentration from ECICE in polygon 3. CIS estimate calls for 30% of YI type in this polygon. Discrepancy between ECICE and CIS estimates is observed in polygons 1 and 4, but this can be partly attributed to the 47 minutes time difference between Radarsat and SSM/I data acquisitions. In highly mobile young ice regimes ice distribution may change rapidly. It is also interesting to note the discrepancy in the lower part polygon 2, which according to Radarsat image, seem to be of different attributes than the rest of the polygon. Using the fine resolution 85GHz observations, ECICE can capture such spatial variations of concentration within a given IAP. The ocean surface wind which causes the brighter band in the middle of the Radarsat image does not leave similar effect on the SSM/I observations, and hence does not affect the algorithm’s results.

As the ice continued to grow, the ice edge drifted away from the coastline and the pack ice became better defined. This is the condition of the data acquired on 030202 (Fig. 5b). Radarsat and SSM/I acquisitions were 11 minutes apart. Differences between ECICE and CIS estimates (30% and 50%, respectively) exist at ice edge (polygons 1, 3, 4 and the area indicated by the arrow in Fig. 5b-1). This can be attributed either to the non-uniform ice distribution within CIS polygons or the spatial variability of the thin ice surface, which dominates the region. Polygon 2 was assigned 20% NI in CIS estimate but ECICE produced zero almost everywhere. In polygons 5, 6 and 7 full agreement between ECICE and CIS results is observed.

The best agreement between ECICE and CIS estimates is observed in areas of consolidated thick ice (> 15 cm). This is the condition of the data acquired on 030212 (Fig. 5-c), with 65 minutes difference between Radarsat and SSM/I acquisitions. The scene features 70%-100% Gray and Gray-White ice (which constitute the YI category of thickness between 15 cm and 30 cm). Consolidated ice scenes should be viewed as “calibrating” data against which the algorithms’ performance in estimating total ice concentration can be assessed. That is because the CIS estimates are reliable in this case, and both the IAP and the footprints will feature homogeneous distribution of ice. This also implies the homogeneity of the footprints that are fully located within an IAP.
ECICE produced less than 10% ice concentration in polygon 1, where the estimate from CIS was 50% total concentration distributed among Gray White, Gray and New ice types with concentrations 10%, 30%, and 10% respectively. This is another evidence of discrepancy between the algorithm and CIS estimates in areas of lower ice concentration. The open water in polygon 2 is correctly identified by ECICE.

Figure 5d shows a Radarsat image acquired on 030225, 23 minutes before the SSM/I data acquisition. Once again, note the gradual, and hence more realistic, transition of ice concentration by ECICE from OW to 100% ice in polygons 1, 2 and the location marked by the arrow. Polygons 3 and 5 feature sea ice drift in response to westerly wind. ECICE reproduced almost the exact values as CIS analysis. CIS analysis assigns combination of FY and Gray ice to polygons 4 and 6, NI to polygon 7, YI to polygon 8 and FY ice to polygon 9. ECICE produces less than 100% in parts of those polygons although visual analysis of the Radarsat confirms the 100% concentration. Ancillary data are required to explain the underestimated values from ECICE or perhaps using other radiometric observations in ECICE may produce better results. It is known, for example, that when slush constitutes part of the radiating layer of microwave emission, $T_b^h$ decreases significantly while $T_b^v$ remains almost constant from all channels [38] [29]. This causes the polarization ratio to increase and hence the ice concentration estimate to decrease.

The time difference between Radarsat and SSM/I acquisitions for day 030318 (Fig. 5e) was only 5 minutes, which excludes any possibility of scene change at the ice edge due to acquisition times from the two sensors. Discrepancy between ECICE and CIS estimates of ice concentration is visible in all labeled polygons in the ice edge regime. The abrupt transition of CIS estimates between polygons 4, 5 and 6 is manifested as smooth transition in the ECICE results. ECICE, however, shows much less concentration than CIS estimates in polygons 3, which is assigned 70% concentration of FY ice. Upon examining the Radarsat image, this lower concentration seem to more realistic. Open water areas are well identified by ECICE and so are their boundaries with the ice field.

An example of partial concentration of ice types NI, YI and FY is shown in Figure 6 using the same parameters $T_b^{85V}$, $T_b^{85H}$, and $PR_{85}$. The data were acquired on February 15, 2003 with 26 minutes time difference between the two sensors’ overpasses. In general, ECICE is fairly successful in estimating the NI concentration in this scene but less so in reproducing the CIS estimates of YI and FYI. This can be attributed to the fact that the probability distributions for YI and FY ice types overlap significantly while the distribution for NI is relatively distinct especially in the $T_b^{85H}$ and $PR_{85}$ domains (Fig. 3). This example is qualitative evidence that the quality of surface type concentration output depends on the quality of the given radiometric parameter distributions for those surfaces. ECICE produced an uneven distribution of YI type within polygon 2, and overestimates its concentration in polygon 5. The worst output from ECICE is the significantly high concentration of FY ice in polygon 1 and at the bottom part of polygon 7, where CIS analysis assigns zero concentration for this type. ECICE, however, is fairly successful in reproducing the dominant FY ice in polygon 6, and to a lesser extent the
dominant YI type in polygons 3 and 4. This example is representative of ECICE output of ice type concentrations.

Comparison with NT2

Figures 7a and 7b are a comparison of total ice concentration obtained from NT2 and ECICE using 37GHz observations. Satellite data were acquired on March 18, 2003. ECICE-37 produces more accurate results in the consolidated ice zone (100% concentration) and to some extent in the ice edge zone (the yellow polygons). No weather or OW correction was used in this case. These two images should also be compared to the ECICE-85 results in Fig. 5e-2 for the same date. The comparison reveals the improved performance of the 37GHz data (with respect to CIS estimates). Comparison between the areas indicated by arrows in Fig. 7b against the corresponding area in Fig. 5e-2, indicates that the larger deviation of ECICE-85 from CIS estimates is not as much attributed to the ability of 85GHz to capture variation of ice concentration at finer scale, as it is due to the better separation between OW and sea ice in the 37GHz data.

3.3.2 Quantitative evaluation

3.3.2.1 Evaluation of total ice concentration output

The evaluation is based on statistics of difference between ECICE-85 ice concentration output and the corresponding estimates from CIS. Only SSM/I pixels, which are fully located inside an IAP were used. Statistics of total ice concentration from NT2 (which operates on 19GHz and 37GHz but uses 85GHz only to account for surface layering) are included in order to allow comparison against ECICE output. For that reason, results from using ECICE-37 are also included. Comparison against SeaLion (which operates solely on 85GHz) is not included because the performance of this algorithm was found to be erratic [40]. Conditions under which CIS analysis may or may not be used as truth are pointed out in the following discussions. Only 2062 footprints were available for calculations from NT2 and ECICE-37, whereas 12950 footprints were available for calculations from ECICE-85.

Table 1 includes the mean of the absolute values of the difference between estimates of total ice concentration from the algorithm and CIS analysis. Same values are plotted in Fig. 8. For open water identification, ECICE-85 is more successful than NT2. Based on CIS estimate, out of the 6297 OW pixels available for ECICE-85, 5.49% were incorrectly identified to contain ice. On the other hand, out of the 1107 OW pixels available for NT2, 15.71% were incorrectly identified to contain ice. For those wrongly identified pixels, the mean values of the overestimated ice concentration are 2.86% and 7.66% from ECICE-85 and NT2 respectively. It should be noted that out of the 5.49% of misidentified water pixels in ECICE-85 there were 2.24% pixels with temperature colder than -3°C. Those pixels were not filtered as OW and hence assigned a non-zero ice concentration by the optimization technique. This might be attributed to wrong estimates of surface temperature from GEM. No assessment of this parameter was
available. Using ECICE-37, OW pixels were identified at less accuracy (7.30%) than using 85GHz, and at same accuracy as produced by NT2. This relatively poor accuracy, given the better separateness of 37GHz observations of OW from ice types, is perhaps due to absence of OW filter in ECICE-37. Recall that under rainfall, OW surface becomes as radiometrically warm as ice surface (Sec. 2.1).

In the mid range of ice concentration (20% to 80%), ECICE-85 shows more discrepancy (up to 35.341%) with CIS estimates (Table 1 and Fig. 8). On the other hand, NT2 and ECICE-37 demonstrate less discrepancy (around 20%) for concentrations 40%, 50%, and 60%. In this range, three problems with CIS analysis should be considered as limitations to its use as "truth" data. First, estimated ice concentrations are more likely to be conservative (i.e. overestimated [21]). Secondly, concentrations from CIS are always provided in tenth, which is too coarse a step to be used against output of calculated concentration. Obviously, this effect becomes more pronounced at concentration values other than the 0% and 100%. Thirdly and most importantly, in areas of mixed sea ice and water, it is difficult to delineate sub-areas of homogeneous distribution of the estimated ice concentration. So, in an IAP which is assigned 70% total ice concentration it is much more likely that this concentration is distributed non-uniformly over the polygon area. If the passive microwave observations have footprint size much smaller than the typical size of the IAP (typically, an IAP is 10 times larger than the 85GHz footprint area), then they should be able to resolve spatial variations of ice concentration within the IAP. This should lead to larger differences between ECICE-85 and CIS estimates in the 20%-80% concentration range, but those differences should not necessarily be interpreted as errors.

Figure 9 illustrates this point. It shows two Radarsat image segments acquired on January 22, 2003 (a), and January 29, 2003 (b), with one dominant IAP at the ice edge in each image. According to CIS analysis, the polygon in (a) has 30% YI concentration, while the polygon in (b) has 80% concentration divided into 50% and 30% among YI and NI types. While Radarsat image (a) is featureless, image (b) shows progressive concentration towards the pack ice. Results from ECICE-85 are more consistent with this progression, hence considered to be more reliable than CIS analysis in this case. Statistics of differences between ECICE-85 and CIS ice concentration estimates should be interpreted against this background information.

As mentioned before, the situation of pack ice (≥90% concentration) is best suited to assess the performance of ECICE. In this range, ECICE-85 outperforms NT2 in estimating total ice concentration. At 100% total ice concentration, deviation of ECICE-85 and NT2 from CIS estimates are 7.56% and 18.75%, respectively. ECICE-37 produces 5.72%, which an even smaller deviation. In fact, the deviation of ECICE-37 is less at every concentration levels (Table 1). This is a manifestation of the better separability between OW and sea ice in the 37GHz observations.

Probability distributions of total ice concentration output from ECICE-85 and NT2 at each concentration level as defined by CIS analysis are shown in Fig. 10. For areas of 30% ice concentration, both ECICE-85 and NT2 return a high frequency of occurrence
of the 0-5% concentration values. As ice concentration increases, a wider distribution of total ice concentration from ECICE-85 is observed with a smaller likelihood of occurrence of the 0-5% concentration. At 80% and 90% concentration estimates from CIS, the peak of the ECICE-85 output distributions are found at 100%, with long tails that extend to 0%. The tails reflect the spatial variation of ice concentration as identified by ECICE-85 in what is assumed to be a uniform IAP. The peak at 100% concentration is an indication that the analysis polygons of 80% or 90% total ice concentration have in fact 100% dominant concentrations. These results highlight the advantage of both ECICE and the data fusion technique to evaluate the algorithm’s performance. NT2 algorithm, on the other hand, tends to have narrower distribution around the given value from the CIS analysis when the latter is in the range 20% to 50%. After that the distribution becomes broader and peaks at less estimates of ice concentration than those given by CIS analysis (for example, it peaks at 70% concentration when CIS analysis estimates 90% concentration).

3.3.2.2. Evaluation of ice type concentration

Table 2 includes the mean and standard deviation of the absolute values of difference between ECICE-85 estimate of each ice type (NI, YI, and FY) and the corresponding estimate from CIS analysis. Data for total ice concentration (copied from table 1) are included for completeness. Out of the 5.49% of OW pixels which are wrongly identified as OW-ice mixture, the ice type that is most likely be assigned by ECICE-85 is FY (it has maximum deviation of 2.52% concentration from the correct zero concentration). This can be explained in view of the fact that Tb from such erroneously-identified pixels is much higher than typical Tb from OW (Sec. 2.1). The deviation for the NI type is generally smaller than that for YI and FY ice. This is a manifestation of the highly overlapping distributions of the radiometric parameters for YI and FY ice types, along with the fairly well separated distribution of NI from these two types (see Fig. 3). So, misidentifying YI as FY ice or vice versa is expected. This observation explains the relatively successful identification of ice types when the total ice concentration is low, which usually implies prevalence of NI type.

In case of 100% ice concentration, the deviation of the total concentration is small as mentioned before (7.56%) but the deviation of YI and FY ice concentrations are considerably higher 30.45% and 26.58%, respectively. Deviation of NI is relatively small (11.73%) but since NI usually does not exist at this high concentration value, the small deviation means success of ECICE in predicting the zero values of the NI in this case. The relatively low deviation obtained from using data from all concentration (last row in table 2) is attributed to relative success in determining ice type concentration at low concentration values. In general, for most ice type concentrations, the mean and standard deviation of the differences are large. Hence, it can be concluded that retrieval of ice type concentration using ECICE is not as successful as it is for total ice concentration. Other radiometric observations with more separated distributions for the given ice types should be examined in the future.

3.3.3 Error sources and Algorithm’s sensitivity to noise in input data
The algorithm’s errors relative to CIS analysis have been discussed in previous sections. In this section, the sensitivity of the algorithm to the input radiometric parameters (Tb\textsubscript{85V} and Tb\textsubscript{85h}) is discussed. A numerical experiment by applying ECICE using Tb\textsubscript{85V} in the range 230°K -250°K, and Tb\textsubscript{85h} 180°K -220°K. All meteorological parameters are assigned values below the threshold that triggers corrections of the radiometric parameters.

Results of total ice concentration are shown in Fig. 11. The main observation is that total ice concentration varies linearly with Tb\textsubscript{85h} but non-linearly with Tb\textsubscript{85V}. For any value of Tb\textsubscript{85V}, the concentration increases by an average of 1.5% per one degree increase in Tb\textsubscript{85h}. The non-linear variation of total concentration with Tb\textsubscript{85V} is further demonstrated in Fig. 12. At low values of Tb\textsubscript{85h}, typical of the radiometrically cold OW, ice concentration decreases slightly then increases at a rate of 0.67% per one degree increase in Tb\textsubscript{85v}. This pattern is reversed at the higher end of Tb\textsubscript{85h}, typical of radiation from surface layering and glaze [17], where a negligible increase in concentration with Tb\textsubscript{85V} is observed up to approximately 245°K, followed by a decrease of 5% concentration per one degree increase in Tb\textsubscript{85v}. It should be emphasized that any results from ECICE is a manifestation of the input probability distributions of the radiometric parameters for each ice type. This is where physics of radiation from the surface is manifested.

The accuracy of the results depends on the quality of the input distributions, not strictly on the number of the input radiometric parameters. The former determines the best number of the latter that is required for maximum accuracy. Limited experimentation with radiometric parameters was conducted in this study to find the best set. Figure 13 includes output from using single and combinations of radiometric parameters, all from the SSM/I 85GHz observations. It shows that Tb\textsubscript{85h} is sufficient to reproduce fairly accurate estimates of total ice concentration, while PR\textsubscript{85} results in differences with CIS estimates in the west region of the Gulf (left of the image). The use of both parameters does not improve the situation but adding Tb\textsubscript{85v} produces the best results (slightly better than using Tb\textsubscript{85h} alone).

4. CONCLUSIONS

A new algorithm has been developed to determine total ice concentration along with concentration of selected ice types, using any set of remote sensing observations. It is based on optimizing an objective function that represents the error between observations and expected values, subject to equality and inequality constraints. Modules can be added to make it suitable to a specific remotely-sensed data set. The algorithm replaces the concept of using a single “tie point” representative of an ice type with the distribution of the given radiometric parameter from that type. An application to determine ice concentration in the Gulf of St. Lawrence, Canada, during the winter of 2003 is presented. The algorithm was run using 85GHz, then 37GHz observations from the passive microwave sensor SSM/I. Results are compared to ice concentration
estimates from the Radarsat image analysis, which is routinely conducted in the Canadian Ice Service (CIS) within their national operational ice monitoring program.

Qualitative and quantitative assessments of the algorithm show its general success in determining total ice concentration in open water and consolidated pack ice areas. In case of OW, ECICE using 85GHz data incorrectly identified 5.49% of the total pixels to have ice concentration of 2.86% on average. An OW filter is activated in this case. Using the 37GHz SSM/I data, ECICE and NT2 misidentified 9.52% and 15.71% of the total OW pixels with an average ice concentration of 7.3% and 7.66%, respectively. No OW filter was activated in ECICE in this case.

For 100% total ice concentration cases, as defined by CIS analysis, deviation from CIS estimates were 7.58% and 5.72% on the average when using SSM/I 85GHz and 37 GHz data, respectively. The same deviation of NT2 output was 18.75% (all underestimation). This is the most important result from this study. It points to the potential of using ECICE against fine-resolution data from passive microwave (e.g. 89GHz from AMSR-E) to study spatial and seasonal variability of small-scale dynamic features of Arctic ice. As total ice concentration decreases, estimates from ECICE using 85GHz observations deviate more from CIS estimates than the corresponding deviation when 37GHz data were used in ECICE or NT2. This is partly due to the finer scale of the 85GHz footprints which can capture spatial variation of ice concentration within what is assumed to be areas of uniform concentration in CIS analysis. Hence, the higher deviation from using the 85GHz observations may not be viewed as an error in this case. Visual examples are presented to prove this argument. But the significantly less deviation from using the 37GHz compared to 85GHz observations in ECICE algorithm is a reflection of the better separability of OW from ice types on the radiometric parameter scale.

ECICE is successful in reproducing the gradual increase in ice concentration from OW to the pack ice through the ice edge. However, assessment of the algorithm in this regime requires more accurate validation data with finer resolution comparable to the footprint. ECICE is less accurate in estimating concentration of ice types, compared to total ice concentration. At 100% total ice concentration from CIS data, ECICE estimates deviate from CIS by an average of 11.73%, 30.45% and 26.68% for NI, YI, and FY ice types, respectively. This reflects the degree of the separability of distribution of radiometric parameters for those ice types. The accuracy depends on the degree of separability of the distributions of ice types in the domains of the used radiometric parameters (NI type is relatively well-separated from the other two types). The success of ECICE in determining the ice type concentration hinges upon providing separated distribution for each ice type.

This paper has focused on the algorithm’s description and preliminary results from the first application in an operational ice regime. Further work is needed to assess its performance in other ice regions in different seasons and using different radiometric parameters so that a best set of parameters can be identified against regions and seasons.
ACKNOWLEDGMENT

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REFERENCES


Figure captions:

Fig. 1 Flowchart of the ECICE algorithm

Fig. 2 Distribution of data points from SSM/I pixels in the GR85V37V, Tb85V space showing the threshold line that was used to filter out open water footprints. Labels in the legend are based on CIS ice concentration estimates in relation to the ECICE output.

Fig. 3 Probability density function of emissivity and polarization ratio for open water and the three sea ice types. Data obtained from polygons of homogeneous cover available from CIS Radarsat image analysis

Fig. 4 A graphical illustration of the process to generate a set of characteristic radiometric values for each surface from the distribution of the radiometric parameter.

Fig. 5 Radarsat images (left) with outlines of the CIS IAPs and the corresponding results of total ice concentration from the CIS image analysis and ECICE algorithm (right). The concentrations are color coded. ECICE results are from using 85GHz observations (Tb85h, Tb85v, and PR85).

Fig. 6 Radarsat image acquired on Feb. 15, 2003 (a), with total ice concentration from SSM/I 85GHz data (b), and partial ice concentration of New ice (c), Young ice (d), and FY ice types (e), all calculated using the 3 equations for Tb85h, Tb85v, and PR85.

Fig. 7 Total ice concentration from NT2 (a) and ECICE-37 (b), for data acquired on March 18, 2003. Ellipses represent the 37GHz footprints. These images should be compared to the results in Fig. 5e-2 from using ECICE-85.

Fig. 8 Mean value and standard deviation (error bars) of the difference between CIS estimates of total ice concentration and the corresponding estimates from NT2 and ECICE (using 85GHz observations) for each ice concentration value provided by CIS.

Fig. 9 Two examples showing spatial variation of total ice concentration from ECICE using 85GHz observations. The CIS analysis assigns uniform distribution of ice concentration of 30% and 80% in the marked polygons in (a) and (b), respectively.

Fig. 10 Distributions of ice concentrations from ECICE and NT2 for sets of polygons of constant ice concentration defined by CIS analysis (these concentrations are in ascending order from top to bottom and from left to right).

Fig. 11 Variation of total ice concentration using ECICE-85 with two input parameters Tb85V and Tb85h against range of values of these parameters.

Fig. 12 Sensitivity of ECICE using Tb85V and Tb85h to variation in Tb85V for given values of Tb85h.
Fig. 13 Total ice concentration from ECICE using different combinations of radiometric parameters from 85GHz observations. The Radarsat image was acquired on Feb. 19, 2003. Combination of the three parameters produced the best results although using $Tb_{85h}$ alone is almost as accurate.
Generate a random number for each surface. From this point on, there is one trial out of 1000. Calculate a set of characteristic radiometric parameter values (CRPV) for each surface. Have 1000 trials been run? Determine median concentration of each surface. Normalize concentration estimates. End.
Fig. 2 Distribution of data points from SSM/I pixels in the $G_{R85V37V}$, $T_{b85V}$ space showing the threshold line that was used to filter out open water footprints. Labels in the legend are based on CIS ice concentration estimates in relation to the ECICE output.
Fig. 3 Probability density function of emissivity and polarization ratio for open water and the three sea ice types. Data obtained from polygons of homogeneous cover available from CIS Radarsat image analysis.
Fig. 4 A graphical illustration of the process to generate a set of characteristic radiometric values for each surface from the distribution of the radiometric parameter.
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Fig. 6 Radarsat image acquired on Feb. 15, 2003 (a), with total ice concentration from SSM/I 85GHz data (b), and partial ice concentration of New ice (c), Young ice (d), and FY ice types (e), all calculated using the 3 equations for $T_{b85h}$, $T_{b85v}$, and $PR_{85}$. 

Nova Scotia

Atlantic ocean
Fig. 7 Total ice concentration from NT2 (a) and ECICE-37 (b), for data acquired on March 18, 2003. Ellipses represent the 37GHz footprints. These images should be compared to the results in Fig. 5e-2 from using ECICE-85.
Table 1 Mean of the absolute difference in total ice concentration between the algorithm output and CIS estimates, along with the total number of SSM/I pixels used to generate those values. ECICE results are presented from using 85GHz or 37GHz observations.

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<th>85 GHz observations</th>
<th>37 GHz observations</th>
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<td></td>
<td>ECICE</td>
<td>NT2</td>
<td></td>
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<tr>
<td></td>
<td>No. of footprints</td>
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<tr>
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<tr>
<td></td>
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Fig. 8 Mean value and standard deviation (error bars) of the difference between CIS estimates of total ice concentration and the corresponding estimates from NT2 and ECICE (using 85GHz observations) for each ice concentration value provided by CIS.
Fig. 9 Two examples showing spatial variation of total ice concentration from ECICE using 85GHz observations. The CIS analysis assigns uniform distribution of ice concentration of 30% and 80% in the marked polygons in (a) and (b), respectively.
Fig. 10 Distributions of ice concentrations from ECICE and NT2 for sets of polygons of constant ice concentration defined by CIS analysis (these concentrations are in ascending order from top to bottom and from left to right).
Table 2 Mean and standard deviation of the absolute value of difference between ECICE-85 and CIS ice concentration estimates for each ice type and each concentration value as provided by CIS analysis. Data are presented as %.

<table>
<thead>
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<th>YI</th>
<th>FY</th>
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<td>mean</td>
<td>std. dev.</td>
<td>mean</td>
<td>std. dev.</td>
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Fig. 11 Variation of total ice concentration using ECICE-85 with two input parameters $T_b^{85V}$ and $T_b^{85h}$ against range of values of these parameters.
Fig. 12 Sensitivity of ECICE using $T_b^{85V}$ and $T_b^{85h}$ to variation in $T_b^{85V}$ for given values of $T_b^{85h}$. 
Fig. 13 Total ice concentration from ECICE using different combinations of radiometric parameters from 85GHz observations. The Radarsat image was acquired on Feb. 19, 2003. Combination of the three parameters produced the best results although using $T_b_{85h}$ alone is almost as accurate.