Climate Data Record (CDR) Program

# Climate Algorithm Theoretical Basis Document (C-ATBD)

## Sea Ice Concentration

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# REVISION HISTORY

| Rev. | Author | DSR No. | Description | Date |
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| 1 | Walt Meier, Research Scientist, NSIDC | DSR-112 | Initial release. | 09/20/2011 |
| 2 | Walt Meier, Research Scientist, NSIDC | DSR-204 | Added description of monthly files and memory allocations for processing. Sections 3.2, 3.4.4, and 5.6. | 05/29/2012 |
| 3 | Walt Meier, Research Scientist, NSIDC | DSR-411 | Changes made to describe Version 2 Revision 0 of the CDR. Sections 3.2, 3.3.1, 3.4.1.4, 3.4.4.1, 3.4.4.2, and 5.6. 6.1.4 (deleted) | 03/26/2013 |
| 4 | Ann Windnagel, Professional Research Assistant, NSIDC | DSR-920 | Changes made to describe Version 2 Revision 1 of the CDR. Updated Figures 2 and 5 in Section 3.2, Sections 1.3 and 5.6, and Table 12. | 09/19/2015 |
| 5 | Ann Windnagel, Professional Research Assistant, NSIDC | DSR-1148 | Changes made to describe Version 3 and the near-real-time portion of the time series: Updated sections 1.1, 2.1, 2.2, 3, 4, 5.6, 6, and 8. | 09/14/2017 |
| 6 | Ann Windnagel, Professional Research Assistant, NSIDC | DSR-1216 | Changes made to describe Version 3 Revision 1. Updated sections 3.2, 3.3, and 3.4. Changes made to address Version 3.1: Updated section 3.3.1. | 12/20/2017 |
| 7 | Ann Windnagel, Professional Research Assistant, NSIDC | DSR-1240 | Changes made to tables 3, 4, and 5: instruments for the input data were changed from SMMIS and SMM/I to SSMIS and SSM/I. | 03/06/2018 |
| 8 | Ann Windnagel, Professional Research Assistant, NSIDC | DSR-1525 | Made major updates to the entire document to reflect the new Version 4 TCDR and Version 2 ICDR release. | 04/19/2021 |
| 9 | Ann Windnagel, Professional Research Assistant, NSIDC | DSR-1527 | Minor revision due to typographical errors | 06/03/2021 |
| | | | | |

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# 1. Introduction

## 1.1 Purpose

The purpose of this document is to describe the sea ice climate data record (CDR) algorithm (Meier et al. 2014; Peng et al. 2013). Beginning in 2015, updates are submitted to the National Centers for Environmental Information (NCEI) by Florence Fetterer at the National Snow and Ice Data Center (NSIDC).

The CDR algorithm is used to create the Sea Ice Concentration CDR from passive microwave data from the Scanning Multichannel Microwave Radiometer (SMMR) on the Nimbus 7 satellite and the Special Sensor Microwave/Imager (SSM/I) and the Special Sensor Microwave Imager and Sounder (SSMIS) sensors on U.S. Department of Defense Meteorological Satellite Program (DMSP) platforms. The goal of the Sea Ice Concentration CDR is to provide a consistent, reliable, and well-documented product that meets CDR guidelines as defined in *Climate Data Records from Environmental Satellites* (NAS, 2004). This product is supplied in two parts. A final product that is created from quality controlled input data available from NSIDC as the *NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration* (https://nsidc.org/data/g02202), and a near-real-time provisional product that is created from provisional input data available from NSIDC as the *Near-Real-Time NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration* (https://nsidc.org/data/g10016). The near-real-time provisional product is provided to users until the release of the finalized Sea Ice Concentration CDR (NOAA data set ID 01B-11, NSIDC data set ID G02202), which is available with an approximate three to six month latency.

The algorithm is defined in the computer program (code) that accompanies this document; and thus, the intent here is to provide a guide to understanding that algorithm, from both a scientific perspective and a software engineering perspective in order to assist in evaluation of the code.

## 1.2 Definitions

Following is a summary of the symbols used to define the algorithm.

$$T_B = brightness\ temperature = \varepsilon * T \tag{1}$$

$$\varepsilon = emissivity \tag{2}$$

$$T = physical\ temperature \tag{3}$$

$$PR = polarization\ ratio \tag{4}$$

$$GR = gradient\ ratio \tag{5}$$

## 1.3 Referencing this Document

This document should be referenced as follows:

Sea Ice Concentration - Climate Algorithm Theoretical Basis Document, NOAA Climate Data Record Program CDRP-ATBD-0107 Rev. 8 (2021). Available at https://www.ncdc.noaa.gov/cdr/oceanic/sea-ice-concentration.

## 1.4 Document Maintenance

This is the ATBD for the Sea Ice Concentration Climate Data Record, Version 4, Revision 0 and the Near-Real-Time Sea Ice Concentration Climate Data Record, Version 2, Revision 0. The source code is used to create both products.

# 2. Observing Systems Overview

## 2.1 Products Generated

The primary generated product is the Sea Ice Concentration climate data record based on gridded brightness temperatures ($T_B$s) from the Nimbsu-7 SMMR and the DMSP series of SSM/I and SSMIS passive microwave radiometers. These data are an estimate of sea ice concentration that are produced by combining concentration estimates from two algorithms developed at the NASA Goddard Space Flight Center (GSFC): the NASA Team algorithm (Cavalieri et al., 1984) and the Bootstrap algorithm (Comiso, 1986). These algorithms are described in more detail in section 3 Algorithm Description. For the finalized portion of this product, called the Thematic CDR (TCDR, NSIDC data set ID G02202), NSIDC uses each individual algorithm to process and combine gridded brightness temperatures from SMMR data acquired from NASA Goddard Space Flight Center (GSFC) and swath brightness temperature data from SSM/I and SSMIS acquired from Remote Sensing Systems, Inc. (RSS). For the near-real-time provisional portion of this product, called the Interim CDR (ICDR, NSIDC data set ID G10016), NSIDC uses each individual algorithm to process and combine swath brightness temperature data from the NOAA Comprehensive Large Array-Data Stewardship System (CLASS). See section 3.3 Algorithm Input for more information on the input brightness temperatures.

Accompanying the concentration estimates are data quality information fields. One field is a concentration standard deviation that indicates spatial variability and the variability between the NASA Team and Bootstrap algorithm estimates. Grid cells with high standard deviations indicate values with lower confidence levels. Another field includes quality information such as melt state and proximity to the coast, regimes that tend to have higher errors.

## 2.2 Instrument Characteristics

The SMMR passive microwave sensor was launch aboard the Nimbus-7 satellite in October 1978. The SMMR sensor was a ten-channel sensor that measured orthogonally polarized (horizontal and vertical) antenna temperature data in five microwave frequencies: 6.6, 10.7, 18.0, 21.0, and 37.0 GHz (Gloersen and Hardis, 1978). NASA Nimbus-7 SMMR sensor, which predates DMSP and extends the total time series to late 1978 with every-other-day concentration estimates.

The first SSM/I sensor was launched aboard the DMSP-F8 mission in 1987 (Hollinger et al., 1990). A series of SSM/I conically-scanning sensors on subsequent DMSP satellites has provided a continuous data stream since then. However, only sensors on the DMSP-F8, -F11, -F13, -F17, and -F18 platforms are used in the generation of the CDR. The SSM/I sensor has seven channels at four frequencies. The 19.4, 37.0, and 85.5 GHz frequencies are dual polarized, horizontal (H) and vertical (V); the 22.2 GHz frequency has only a single vertically polarized channel. The 85.5 GHz frequencies are not used in the sea ice concentration algorithms.

Beginning with the launch of F16 in 2003, the SSM/I sensor was replaced by the SSMIS sensor. The SSMIS sensor has the same 19.4, 22.2, and 37.0 GHz channels; however, the 85.5 GHz channels on SSM/I are replaced with 91.0 GHz channels on SSMIS (Kunkee et al., 2008), which is not used in the algorithms. The SSMIS sensor also includes several higher frequency sounding channels that are not used for the sea ice products and are not archived at NSIDC.

For simplicity, the channels are sometimes denoted as simply 18H, 18V, 19H, 19V, 22V, 37H, and 37V. Depending on the platform, the satellite altitudes are 830 to 955 km and sensor (earth incidence) angles are 50.2 to 53.4 degrees. See Table 1 for details of each platform.

| **Parameter** | **Nimbus-7** | **DMSP-F8** | **DMSP-F11** | **DMSP-F13** | **DMSP-F17** | **DMSP-F18** |
|---|---|---|---|---|---|---|
| Nominal Altitude (km)* | 955 | 860 | 830 | 850 | 855 | 833 |
| Inclination Angle (degrees) | 99.1 | 98.8 | 98.8 | 98.8 | 98.8 | 98.6 |
| Orbital Period (minutes) | 104 | 102 | 101 | 102 | 102 | 102 |
| Ascending Node Equatorial Crossing (approximate local time) | 12:00 P.M. | 6:00 A.M. | 5:00 P.M. | 5:43 P.M. | 5:31 P.M. | 8:00 P.M. |
| Algorithm Frequencies (GHz)* | 18.0, 37.0 | 19.4, 37.0 | 19.4, 37.0 | 19.4, 37.0 | 19.4, 37.0 | 19.4, 37.0 |
| Earth Incidence Angle (degrees)* | 50.2 | 53.1 | 52.8 | 53.4 | 53.1 | 53.1 |

Table 1: Comparison of Nimbus and DMSP orbital parameters

*Indicates sensor and spacecraft orbital characteristics of the three sensors used in generating the sea ice concentrations.

A polar orbit and wide swath provides near-complete coverage at least once per day in the polar regions except for a small region around the North Pole called the pole hole. The SSMIS sensor has a wider swath width (1700 km) compared to the SSM/I sensor (1400 km), which reduces the size of the pole hole. The footprint or instantaneous field of view (IFOV) of the sensor varies with frequency (Table 2).

| **Frequency (GHz)** | **SMMR (km)** | **SSM/I (km)** | **SSMIS (km)** |
|---|---|---|---|
| 18.0/19.35 | 55 x 41 | 69 x 43 | 72 x 44 |
| 21.0/22.235 | 46 x 30 | 60 x 40 | 72 x 44 |
| 37.0 | 27 x 18 | 37 x 28 | 44 x 26 |

Table 2: IFOV of SMMR, SSM/I, and SSMIS frequencies used in the sea ice concentration CDR algorithm (Gloersen and Barath, 1977; Hollinger et al., 1990; Kunkee et al., 2008)

Regardless of footprint size, the low frequency channels (19.4 – 37.0 GHz) are gridded to a 25 km polar stereographic grid.

# 3. Algorithm Description

## 3.1 Algorithm Overview

The Sea Ice Concentration CDR algorithm uses concentration estimates derived at NSIDC from the NASA Team (Cavalieri et al., 1984) and Bootstrap (Comiso, 1986) algorithms as input data and merges them into a combined single concentration estimate based on the known characteristics of the two algorithms. First, the Bootstrap 10% concentration threshold is used as a cutoff to define the limit of the ice edge. Second, within the ice edge, the higher of the two concentration estimates from the NASA Team and Bootstrap algorithms is used for the CDR input value. The reason for these two approaches is discussed further in section Sea Ice Concentration Climate Data Record Algorithm. Automated quality control measures are implemented independently on the NASA Team and Bootstrap outputs. Two weather filters (one for each algorithm), based on ratios of channels sensitive to enhanced emission over open water, are used to filter weather effects. Separate land-spillover corrections are used for each of the algorithms to filter out much of the error due to mixed land/ocean grid cells. Finally, valid ice masks are applied to screen out errant retrievals of ice in regions where sea ice never occurs.

## 3.2 Processing Outline

The following flow diagram (Figure 1) describe the general processing for the finalized daily and monthly TCDR sea ice concentrations and the near-real-time provisional daily and monthly ICDR sea ice concentrations.

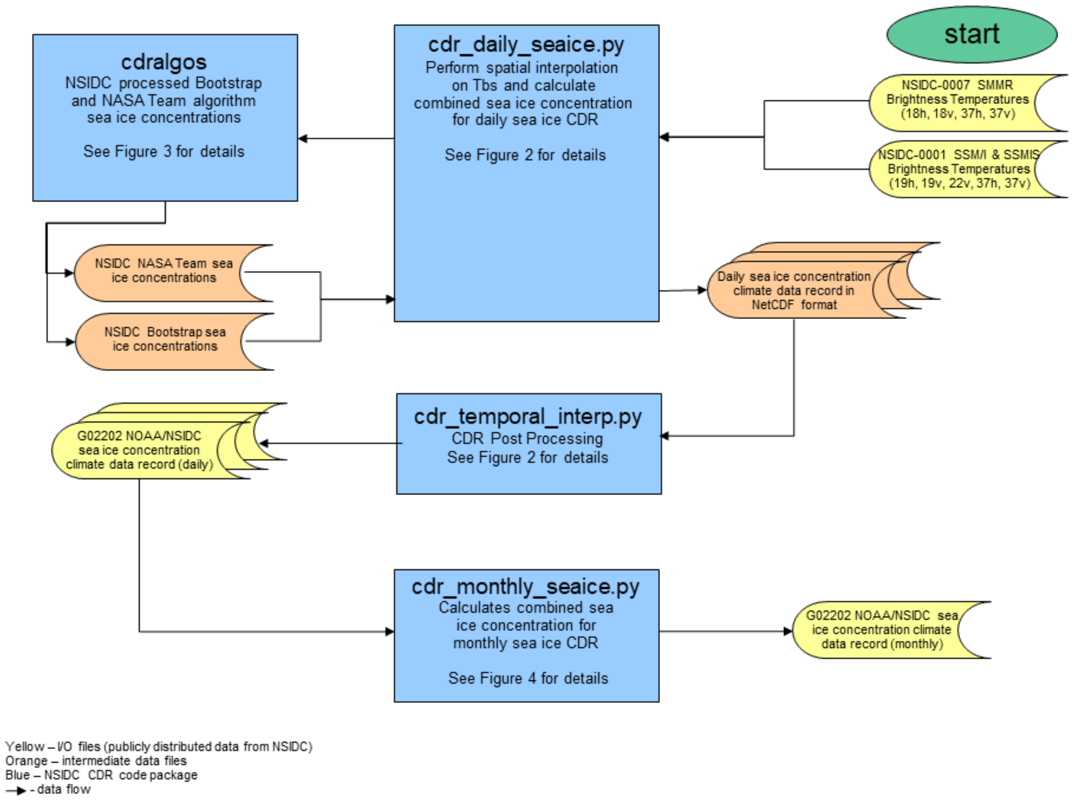


Figure 1: Flowchart showing the overview of sea ice concentration TCDR processing. Note that the ICDR processing is identical except that the input data is NSIDC-0080 SSMIS brightness temperatures and the output is G10016.

### 3.2.1 Daily Processing

The following flow diagrams (Figure 2 and Figure 3) describe the processing of the daily CDR sea ice concentration in detail.

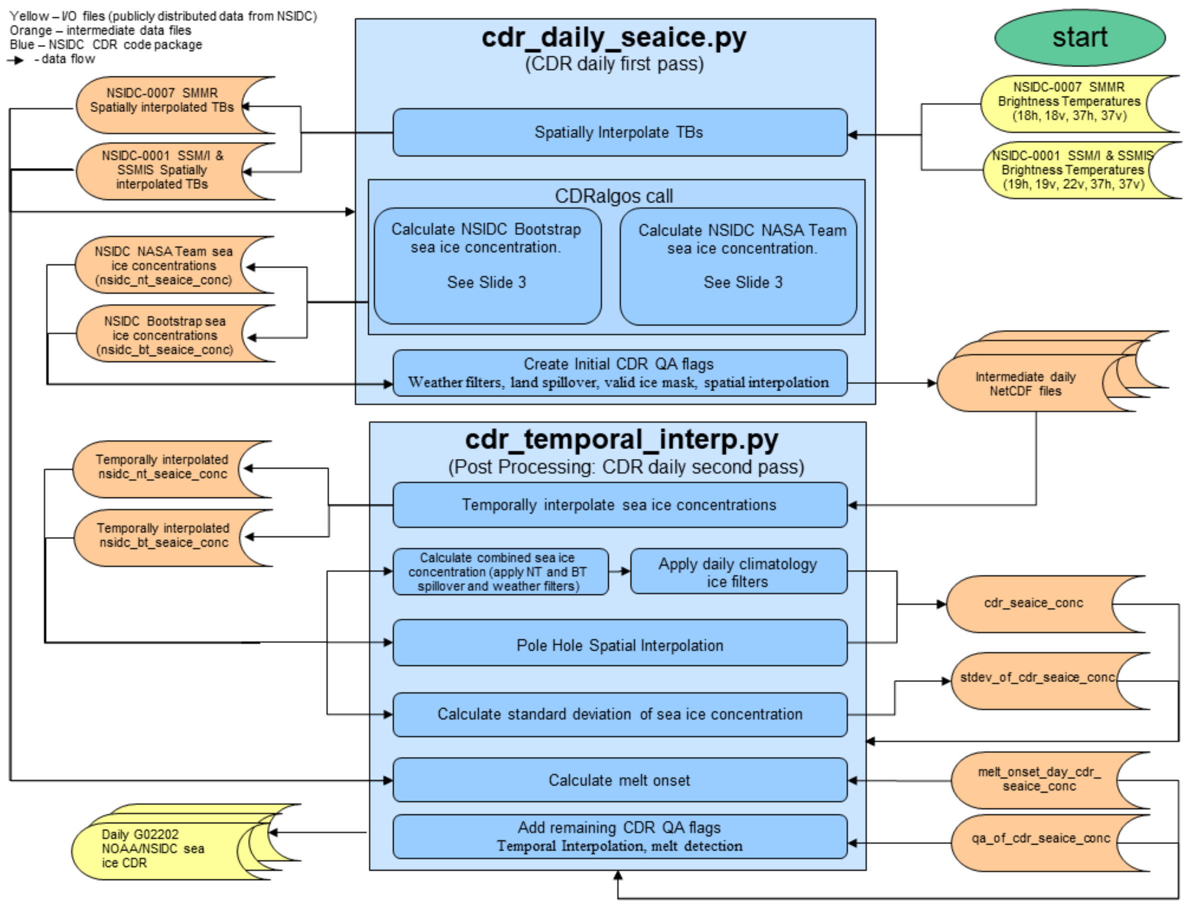


Figure 2: Overview of main python code for the daily sea ice concentration TCDR processing. Note that the ICDR processing is identical except that the input data is NSIDC-0080 SSMIS brightness temperatures and the output is the daily G10016.

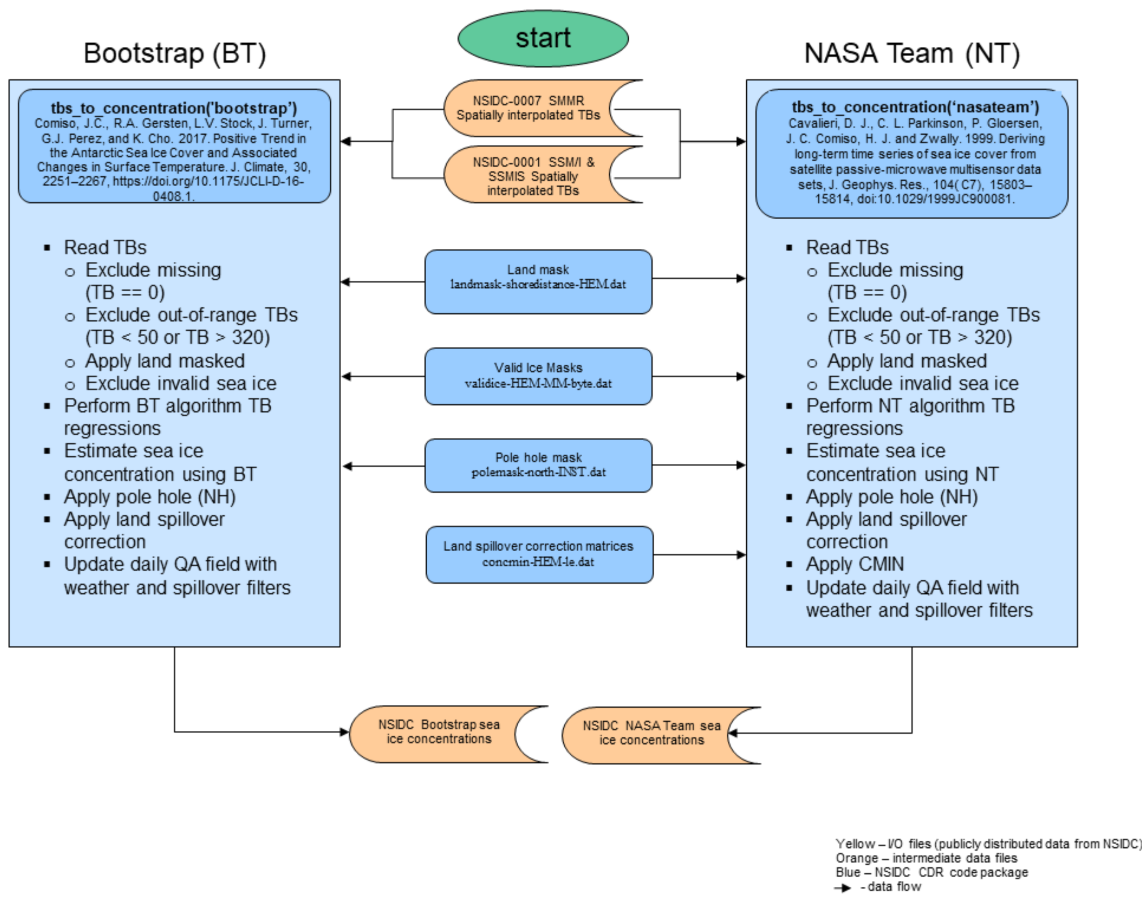


Figure 3: Overview of the TCDR CDRAlgos Bootstrap and NASA Team processing code. Note that the ICDR processing is identical except that the input data is NSIDC-0080 SSMIS spatially interpolated brightness temperatures.

### 3.2.2 Monthly Processing

The following flow diagram (Figure 4) describes the processing of the monthly CDR sea ice concentration for the finalized TCDR data and the near-real-time ICDR data.

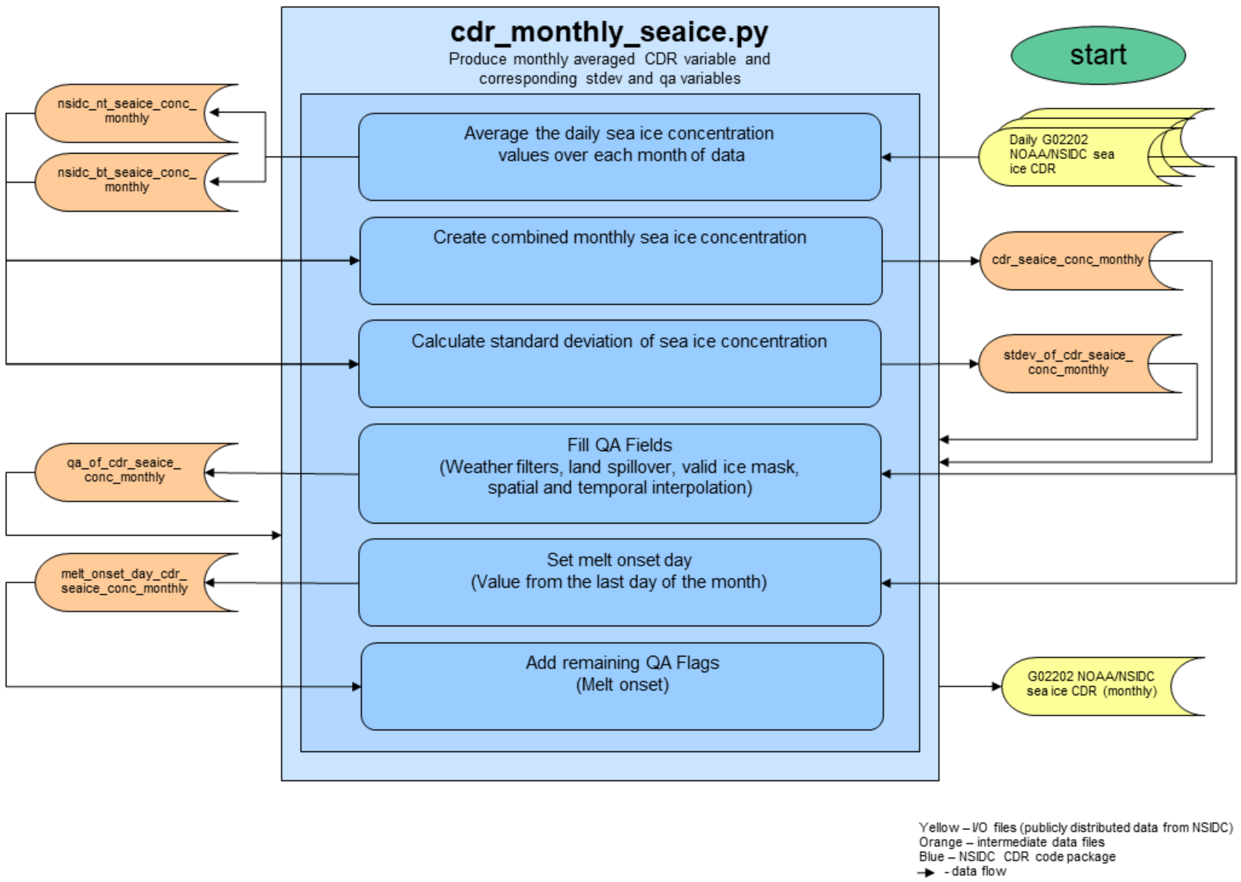


Figure 4: Monthly TCDR processing. Note that the ICDR processing is identical except that the input data is the daily G10016 data and the output is G10016 monthly data.

## 3.3 Algorithm Input

### 3.3.1 Primary Sensor Data

Calibrated and gridded brightness temperatures from Nimbus-7 SMMR, DMSP SSM/I, and DMSP SSMIS passive microwave sensors are used as the primary input data for this sea ice concentration CDR. The brightness temperature data for the finalized TCDR and near-real-time ICDR portions of the product are obtained from two different data storage facilities: RSS and CLASS, respectively. Both the RSS and CLASS use enhanced processing methods to correct errors and improve calibration and geolocation of the swath brightness temperatures. Specific processing information on the input swath data is available from RSS (http://www.remss.com/missions/ssmi/) and CLASS (https://www.avl.class.noaa.gov/saa/products/search?datatype_family=DMSP).

NSIDC obtains the input swath data from RSS and CLASS and then grids them onto a 25 km polar stereographic grid for both Arctic and Antarctic regions. These data sets are publicly available through NSIDC's web site. See Table 3 for a list of these data sets, the temporal range, and the product they apply to.

For current processing of the TCDR, NSIDC is using Version 7 RSS DMSP SSMIS brightness temperatures. Earlier periods use different versions (see Table 3). Because the sea ice algorithms are intercalibrated at the product (concentration) level, the brightness temperature version is less important because the intercalibration adjustment includes any necessary changes due to differences in brightness temperature versions. However, when Version 7 is available for the entire DMSP record and resources allow, a full reprocessing will be considered.

For the processing of the ICDR, NSIDC uses DMSP SSMIS brightness temperatures obtained from CLASS that do not have a version number associated with them. These NRT data may contain errors and are not suitable for time series, anomalies, or trends analyses. Near-real-time products do not undergo quality assessment and are therefore not optimal for use in long-term climate studies. The near-real-time portion of this product are available from NSIDC as the Near-Real-Time NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration (https://nsidc.org/data/g10016). This NRT sea ice concentration ICDR is meant as a provisional interim estimate to span the gap before the availability of the finalized sea ice concentration TCDR, which have an approximate three to six month latency before they are available from NSDIC as the NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration (https://nsidc.org/data/g02202). However, once the RSS brightness temperatures become available, the finalized portion of the CDR is processed, which replaces the near-real-time portion. Table 3 shows the instruments used for the input data for the CDR.

| **Sensor** | **Temporal Range** | **Source/Data Version** | **Product it Applies to** | **NSIDC Data Product** |
|---|---|---|---|---|
| DMSP-F18 SSMIS | Near-real-time | CLASS (no version given) | ICDR | https://nsidc.org/data/nsidc-0080 |
| DMSP-F17 SSMIS | 01 Jan 2008 – most current processing date | RSS V7 | TCDR | https://nsidc.org/data/nsidc-0001 |
| DMSP-F13 SSM/I | 01 Oct 1995 – 31 Dec 2007 | RSS V4 | TCDR | https://nsidc.org/data/nsidc-0001 |

| | | | | |
|---|---|---|---|---|
| DMSP-F11 SMM/I | 03 Dec 1991 – 30 Sep 1995 | RSS V3 | TCDR | https://nsidc.org/data/nsidc-0001 |
| DMSP-F8 SSM/I | 10 Jul 1987 – 02 Dec 1991<br>Note: There are no data from 3 December 1987 through 12 January 1988 due to satellite problems. | RSS V3 | TCDR | https://nsidc.org/data/nsidc-0001 |
| Nimbus-7 SMMR | 25 October 1978 – 09 Jul 1987 | NSIDC V1 | TCDR | https://nsidc.org/data/nsidc-0007 |

Table 3: Version history and dates of the instruments used for the input brightness temperatures for the sea ice CDR variable.

The swath data are gridded onto a daily composite 25 km polar stereographic grid using a drop-in-the-bucket method. For each grid cell, all footprints from all passes each day whose centers fall within the grid cell are averaged together. Thus, some grid cells may be an average of several (4 or 5) passes during a given day and some may be from only one pass; some grid cells are typically not filled due to sensor characteristics, such as the large footprint. Note that the polar stereographic grid is not equal area; the latitude of the true scale (tangent of the planar grid) is 70 degrees. The Northern Hemisphere grid is 304 columns by 448 rows, and the Southern Hemisphere grid is 316 columns by 332 rows. Further information on the polar stereographic grid used at NSIDC can be found on the NSIDC web site on the Polar Stereographic Projection and Grid web page (https://nsidc.org/data/polar-stereo/ps_grids.html).

The brightness temperatures are from the SMMR sensor on Nimbus-7, the SSM/I sensors on the DMSP-F8, -F11, and -F13 platforms, and the SSMIS sensors from the DMSP-F17 and -F18 platforms (Table 4). The rationale for using only these satellites was made to keep the equatorial crossing times as consistent as possible to minimize potential diurnal effects from data on sun-synchronous orbits of the DMSP satellites.

The passive microwave channels employed for the sea ice concentration product are the 19.4, 22.2, and 37.0 GHz frequencies. The NASA Team algorithm uses the 19.35 GHz horizontal (H) and vertical (V) polarization channels and the 37.0 GHz vertical channel. The 22.2 GHz V channel is used with the 19.4 GHz V for one of the weather filters. The Bootstrap algorithm uses 37 GHz H and V channels and the 19.35 GHz V channel; it also uses the 22.2 GHz V channel for a weather filter.

| Passive Microwave Sensor Sources for Sea Ice CDR | | | | | | |
|---|---|---|---|---|---|---|
| **Satellite** | **Sensor** | **Frequencies (GHz)** | **Launch Date (Data Available) [Data at NSIDC]** | **Ascending Equatorial Crossing Time At Launch (Most Recent, Date)** | **Swath Width (km)** | **Mean Altitude (km)** |
| NIMBUS-7 | SMMR | 18, 37 | 10/24/78<br>[10/25/78-8/20/87] | 12:00 | 783 | 955 |
| DMSP-F8 | SSM/I | 19, 22, 37 | 6/18/87<br>[7/9/87-12/30/91] | 06:15<br>(06:17, 9/2/95) | 1400 | 840 |
| DMSP-F11 | SSM/I | 19, 22, 37 | 11/28/91<br>(12/6/91-5/16/00)<br>[12/3/91-9/30/95] | 18:11<br>(18:25, 9/2/95) | 1400 | 859 |
| DMSP-F13 | SSM/I | 19, 22, 37 | 3/24/95<br>(3/25/95-11/19/09)<br>[5/3/95-12/31/08] | 17:42<br>(18:33, 11/28/07) | 1400 | 850 |
| DMSP-F17 | SSMIS | 19, 22, 37 | 11/4/06<br>(12/14/06-present)<br>[1/1/07-3/31/16]] | (17:31, 11/28/07) | 1700 | 850 |
| DMSP-F18 | SSMIS | 19, 22, 37 | 10/18/09<br>(3/8/10-present)<br>[4/1/16-present) | 20:00 | 1700 | 833 |

Table 4: Brightness temperature sources and channel frequencies used for the sea ice CDR.

### 3.3.2 Ancillary Data

Ancillary data required to run the NASA team and Bootstrap algorithms: (A) land masks imbedded within each field, based on masks developed by GSFC, (B) valid sea ice masks to define the limits of possible sea ice, (C) a climatological minimum sea ice mask (CMIN) (for the NASA Team only used in the land-spillover correction), and (D) a melt onset estimate for the Northern Hemisphere to be used in the quality field. Each of these is discussed further below.

A. Each sea ice concentration and associated fields include an embedded land mask. See Table 7 for a description of the mask fields. Both the NASA Team and Bootstrap algorithms use the same mask.

B. Ocean climatology masks are used to remove any remaining spurious ice not filtered by automated corrections in regions where sea ice is not possible. There are monthly masks for each hemisphere. For the Northern Hemisphere, remaining spurious ice is removed using the Polar Stereographic Valid Ice Masks Derived from National Ice Center Monthly Sea Ice Climatologies. There are 12 masks, one for each month. They are available from NSIDC (https://nsidc.org/data/nsidc-0622). The Southern Hemisphere masks, produced from information from Goddard, are found in the ancillary directory in the code base that is available for download from the NOAA NCEI CDR program. In addition, there are also daily climatology ice masks derived from Bootstrap Sea Ice Concentrations for both the Northern and Southern hemispheres. The masks are discussed further in section 3.4.1.3 Quality Control Procedures.

C. Because of the large instantaneous field of view of the SMMR, SSM/I, and SSMIS sensors, mixed land-ocean grid cells occur. These present a problem for the automated concentration algorithm because the emission from the combined land-ocean region has a signature similar to sea ice and is interpreted as such by the algorithms. For the NASA Team algorithm, a filtering mechanism has been implemented to automatically remove much of these false coastal ice grid cells by using a weighting based on the proximity of the grid cell to the coast and a minimum concentration matrix, CMIN. There is one CMIN field for each hemisphere. The CMIN matrix is described below in Section Quality Control Procedures.

D. A near-real-time version of a snow melt onset over sea ice field algorithm by Drobot and Anderson (2001) is used as an input for the Northern Hemisphere quality indicator. Liquid water over the ice changes the surface emission resulting in errors in the algorithms, typically an underestimation of concentration. Thus, occurrence of melt in a grid cell is an indication of lower quality.

### 3.3.3 Derived Data

Not applicable.

### 3.3.4 Forward Models

Not applicable.

## 3.4 Theoretical Description

Passive microwave radiation is naturally emitted by the Earth's surface and overlying atmosphere. This emission is a complex function of the microwave radiative properties of the emitting body (Hallikainen and Winebrenner, 1992). However, for the purposes of microwave remote sensing, the relationship can be described as a simple function of the physical temperature (T) of the emitting body and the emissivity (ε) of the body.

$$T_B = \varepsilon * T \tag{6}$$

$T_B$ is the brightness temperature and is the parameter (after calibrations) retrieved by satellite sensors and is the input parameter to passive microwave sea ice concentration algorithms.

### 3.4.1 Physical and Mathematical Description

The microwave electromagnetic properties of sea ice are a function of the physical properties of the ice, such as crystal structure, salinity, temperature, or snow cover. In addition, open water typically has an electromagnetic emission signature that is distinct from sea ice emission (Eppler et al., 1992). These properties form the basis for passive microwave retrieval of sea ice concentrations.

Specifically, the unfrozen water surface is highly reflective in much of the microwave regime, resulting in low emission. In addition, emission from liquid water is highly polarized. When salt water initially freezes into first-year (FY) ice (ice that has formed since the end of the previous melt season), the microwave emission changes substantially; the surface emission increases and is only weakly polarized. Over time as freezing continues, brine pockets within the sea ice drain, particularly if the sea ice survives a summer melt season when much of the brine is flushed by melt water. This multi-year (MY) ice has a more complex signature with characteristics generally between water and FY ice. Other surface features can modify the microwave emission, particularly snow cover, which can scatter the ice surface emission and/or emit radiation from within the snow pack. Atmospheric emission also contributes to any signal received by a satellite sensor. These issues result in uncertainties in the retrieved concentrations, which are discussed further below.

Because of the complexities of the sea ice surface as well as surface and atmospheric emission and scattering, direct physical relationships between the microwave emission and the physical sea ice concentration are not feasible. Thus, the standard approach is to derive concentration through empirical relationships. These empirically-derived algorithms take advantage of the fact that brightness temperature in microwave frequencies tend to cluster around consistent values for pure surface types (100% water or 100% sea ice). Concentration can then be derived using a simple linear mixing equation (Zwally et al., 1983) for any brightness temperature that falls between the two pure surface values:

$$T_B = T_I C_I + T_O(1-C_I) \tag{7}$$

Where $T_B$ is the observed brightness temperature, $T_I$ is the brightness temperature for 100% sea ice, $T_O$ is the brightness temperature for open water, and $C_I$ is the sea ice concentration.

In reality, such an approach is limited by the surface ambiguities and atmospheric emission. Using combinations of more than one frequency and polarization limits these effects, resulting in better discrimination between water and different ice types and a more accurate concentration estimate.

There have been numerous algorithms derived using various combinations of the frequencies and polarizations on the SMMR and SSM/I sensors. Two commonly used algorithms are the NASA Team (Cavalieri et al., 1984) and Bootstrap (Comiso, 1986), both developed at NASA GSFC. The sea ice concentration CDR described here is produced via a combination of estimates from the NASA Team algorithm and the Bootstrap algorithm. Below, each algorithm is described in more detail followed by a description of quality control (QC) procedures and the procedure to merge the two algorithm estimates into the final CDR product with the sea ice concentration CDR algorithm.

#### 3.4.1.1 NASA Team Algorithm

The NASA Team algorithm uses brightness temperatures from the 19V, 19H, and 37V channels (Cavalieri et al., 1984). The methodology is based on two brightness temperature ratios, the polarization ratio (PR) and spectral gradient ratio (GR), as defined below:

$$PR(19) = [T_B(19V) - T_B(19H))]/[T_B(19V) + T_B(19H)] \tag{8}$$

$$GR(37V/19V) = [T_B(37V) - T_B(19V)]/[T_B(37V) + T_B(19V)] \tag{9}$$

When PR and GR are plotted against each other, brightness temperature values tend to cluster in two locations, an open water (0% ice) point and a line representing 100% ice concentration, roughly forming a triangle. The concentration of a grid cell with a given GR and PR value is calculated by a linear interpolation between the open water point and the 100% line segment (Figure 5).

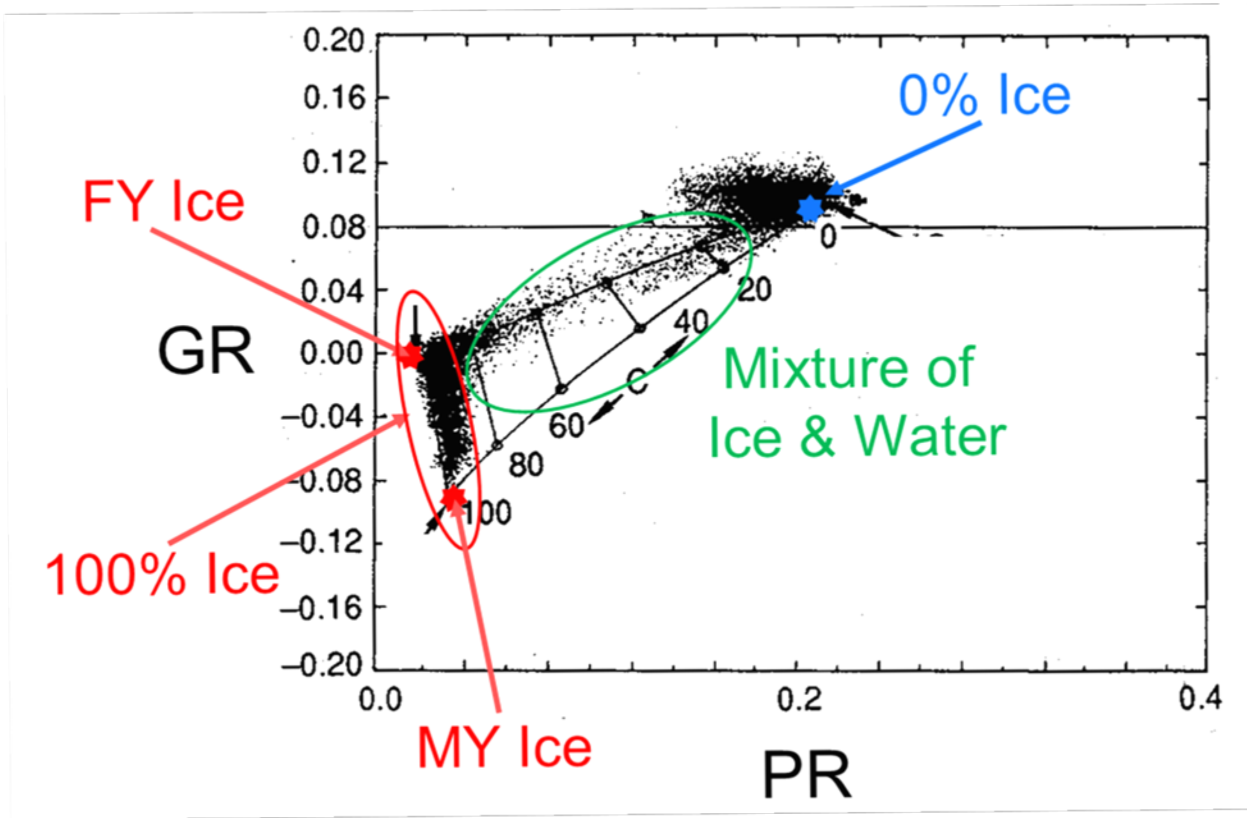


Figure 5: Sample plot of GR vs. PR with typical clustering of grid cell values (small dots) around the 0% ice (open water) point (blue star) and the 100% ice line (circled in red). First year (FY) ice clusters at the top of the 100% ice line, and multi-year (MY) ice clusters at the bottom. Points with a mixture of ice and water (circled in green) fall between these two extremes. Adapted from Figure 10-2 of Steffen et al. (1992).

Mathematically, these two ratios are combined in the following two equations:

$$C_F = (a_0 + a_1PR + a_2GR + a_3PR * GR)/D \quad (10)$$

$$C_M = (b_0 + b_1PR + b_2GR + b_3PR * GR)/D \quad (11)$$

$$\text{where } D = c_0 + c_1PR + c_2GR + c_3PR * GR \quad (12)$$

The $C_F$ and $C_M$ parameters represent ice concentration for two different sea ice types. In the Arctic, these generally correspond to FY ice ($C_F$: ice that has grown since the previous summer) and MY ice ($C_M$: ice that has survived at least one melt season). In the Antarctic, due to its small amount of MY ice and different ice characteristics, $C_M$ and $C_F$ do not necessarily correspond to the age types and are simply denoted as Type A and Type B. Total ice concentration ($C_T$) is the sum of the two partial concentrations.

$$C_T = C_F + C_M \quad (13)$$

The $a_i$, $b_i$, $c_i$ (i=0, 3) coefficients are empirically derived from nine observed $T_B$s at each of the 3 channels for 3 pure surface types (two sea ice and one open water). These $T_B$s, called tie-points, were originally derived for the SMMR sensor (Cavalieri et al., 1984). The tie-points were adjusted for subsequent sensors via intercalibration of the concentration/extent fields during sensor overlap periods to ensure consistency through the time series (Cavalieri et al., 1999). Tie-point adjustments are made via a linear regression analysis along with additional adjustments for open water tie-points. The tie-point adjustment procedure and tie-point values for all sensors through F13 SSM/I are provided in Cavalieri et al. (1999). Tie-points for F17 are described in Cavalieri et al. (2011). See Table 5.

| | | | | |
|---|---|---|---|---|
| **NIMBUS 7 SMMR** | | | | |
| **Arctic** | | **18H** | **18V** | **37V** |
| | OW | 98.5 | 168.7 | 199.4 |
| | FY | 225.2 | 242.2 | 239.8 |
| | MY | 186.8 | 210.2 | 180.8 |
| **Antarctic** | | | | |
| | OW | 98.5 | 168.7 | 199.4 |
| | A | 232.2 | 247.1 | 245.5 |
| | B | 205.2 | 237.0 | 210.0 |
| **DMSP-F8 SSMI** | | | | |
| **Arctic** | | **19H þ** | **19V þ** | **37V þ** |
| | OW | 113.2 +0.2 | 183.4 +0.5 | 204.0 -1.6 |
| | FY | 235.5 | 251.5 | 242.0 |
| | MY | 198.5 | 222.1 | 184.2 |
| **Antarctic** | | | | |
| | OW | 117.0 +7.7 | 185.3 +3.8 | 207.1 +5.3 |
| | A | 242.6 | 256.6 | 248.1 |
| | B | 215.7 | 246.9 | 212.4 |
| **DMSP-F11 SSMI** | | | | |
| **Arctic** | | **19H þ** | **19V þ** | **37V þ** |
| | OW | 113.6 +0.5 | 185.1 +0.5 | 204.8 +0.2 |
| | FY | 235.3 | 251.4 | 242.0 |
| | MY | 198.3 | 222.5 | 185.1 |
| **Antarctic** | | | | |
| | OW | 115.7 +0.1 | 186.2 -0.4 | 207.1 -1.4 |
| | A | 241.2 | 255.5 | 245.6 |
| | B | 214.6 | 246.2 | 211.3 -2.0 |
| **DMSP-F13 SSMI** | | | | |

| Arctic | | 19H | 19V | 37V |
|---|---|---|---|---|
| | OW | 114.4 | 185.2 | 205.2 |
| | FY | 235.4 | 251.2 | 241.1 |
| | MY | 198.6 | 222.4 | 186.2 |
| Antarctic | | | | |
| | OW | 117.0 +0.3 | 186.0 | 206.9 |
| | A | 241.4 | 256.0 | 245.6 |
| | B | 214.9 | 246.6 | 211.1 |
| | | DMSP-F17 SSMIS | | |
| Arctic | | 19H | 19V | 37V |
| | OW | 113.4 | 184.9 | 207.1 |
| | FY | 232.0 | 248.4 | 242.3 |
| | MY | 196.0 | 220.7 | 188.5 |
| Antarctic | | | | |
| | OW | 113.4 | 184.9 | 207.1 |
| | A | 237.8 | 253.1 | 246.6 |
| | B | 211.9 | 244.4 | 212.6 |
| | | DMSP-F18 SSMIS | | |
| Arctic | | 19H | 19V | 37V |
| | OW | 113.4 | 184.9 | 207.1 |
| | FY | 232.0 | 248.4 | 242.3 |
| | MY | 196.0 | 220.7 | 188.5 |
| Antarctic | | | | |
| | OW | 113.4 | 184.9 | 207.1 |
| | A | 237.8 | 253.1 | 246.6 |
| | B | 211.9 | 244.4 | 212.6 |

Table 5: Tie-point values (in Kelvin) for each SSM/I and SSMIS sensor along with original SMMR values. The þ column is the additional adjustment required for open water tie-points (no adjustment was needed for F17 or F18).

The algorithm can sometimes obtain concentration values that are less than 0% or are greater 100%, both of which are clearly unphysical. Such values are set to 0% and 100%, respectively.

#### 3.4.1.2 Bootstrap Algorithm

Like the NASA Team algorithm, the Bootstrap algorithm is empirically derived based on relationships of brightness temperatures at different channels. The current version of the Bootstrap algorithm is 3.1 (Comiso et al., 2017), which is used in the CDR processing. The Bootstrap method uses the fact that scatter plots of different sets of channels show distinct clusters that correspond to pure surface types (100% sea ice or open water) (Comiso, 1986).

Figure 6 shows a schematic of the general relationship between two channels. Points that fall along line segment AD represent 100% ice cover. Points that cluster around point O represent open water (0% ice). Concentration for a point B is determined by a linear interpolation along the distance from O to I where I is the intersection of segment OB and segment AD. This is described by the following equation:

$$C = (T_B - T_O)/(T_I - T_O) \tag{14}$$

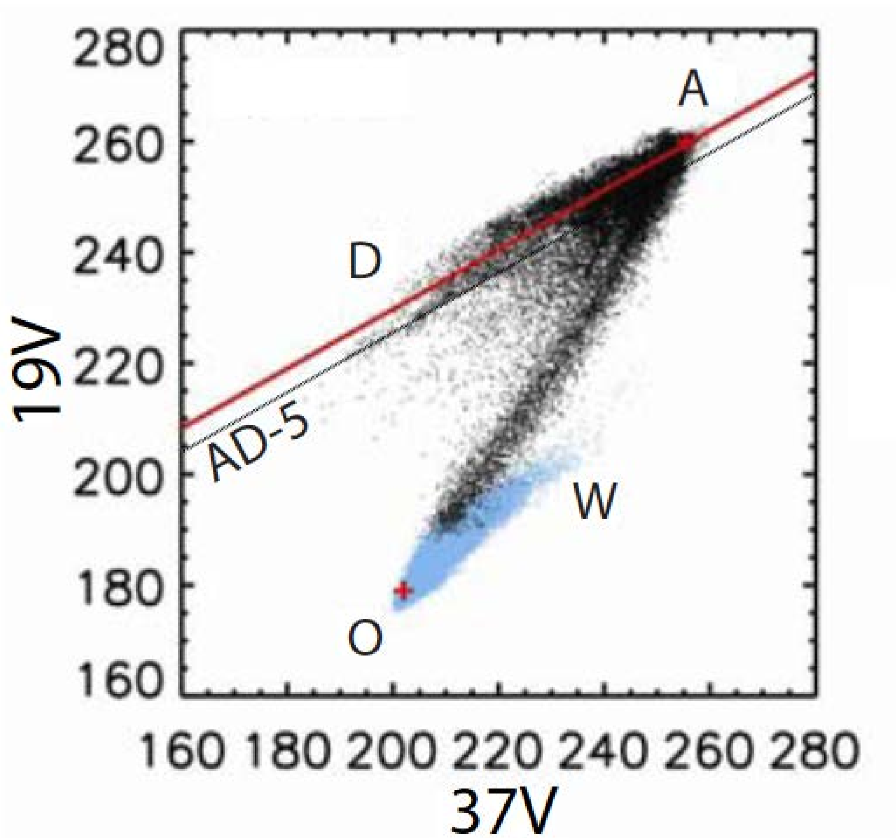


Figure 6: Example of the relationship of the 19V vs. 37V $T_B$ (in Kelvin) used in the Bootstrap algorithm. Brightness temperatures typically cluster around the line segments AD (representing 100% sea ice) and OW (representing 100% open water). For points that fall below the AD-5 line (dotted line), bootstrap uses $T_B$ relationships for 37H vs. 37V. Adapted from Comiso and Nishio (2008).

The Bootstrap algorithm uses two such combinations, 37H versus 37V and 19V versus 37V, denoted as HV37 and V1937, respectively. Points that fall within 5 K of the AD segment in a HV37 plot, corresponding roughly to concentrations > 90%, use this approach. Points that fall below the AD-5 line, use the V1937 relationship to derive the concentration. Slope and offset values for line segment AD were originally derived for each hemisphere for different seasonal conditions (Table 2 in Comiso et al, 1997). However, a newer formulation was developed where slope and offsets are derived for each daily field based on the clustering of sea ice signatures within the daily brightness temperatures (Comiso and Nishio, 2008). This dynamic tie point adjustment allows for day-to-day changes in sea ice microwave characteristics. Further refinements were later done, including adjusting open water tie points (Comiso et al., 2017). It is this latest version of the Bootstrap algorithm (Version 3), with dynamic sea ice and open water tie points, that is used in Version 4 of the CDR.

Intersensor calibration is done similar to the way it is done for the NASA Team algorithm where brightness temperatures from the sensors are regressed against each other. One sensor's brightness temperatures are adjusted based on the regression with the other sensor. However, because the slope and offset values are derived each day based on the brightness temperatures, there are not specific slope/offset (tie-point) adjustments between sensors. Also, while the NASA Team originally derived the tie-points for SMMR and then adjusted future sensors to maintain consistency with SMMR, the newest version of the Bootstrap algorithm used AMSR-E as a baseline and adjusted SSM/I and SMMR brightness temperatures to be consistent with AMSR-E. Because AMSR-E is a newer and more advanced sensor, the intersensor calibration should be more accurate and more consistent overall. This is discussed further in Comiso and Nishio (2008) as well as further minor improvements for the latest version in Comiso et al. (2017).

The algorithm can sometimes obtain concentration values that are less than 0% or are greater 100%, both of which are clearly unphysical. Such values are set to 0% and 100% respectively.

#### 3.4.1.3 Quality Control Procedures

Several automated quality control procedures have been implemented to spatially and temporally fill in missing data and to filter out spurious concentration values.

Small amounts of missing data are common in satellite data, especially over a satellite record spanning more than 40 years. Reasons for missing data are numerous and range from issues with the instrument onboard the satellite, satellite viewing angles, and problems arising at the ground stations when data are downloaded from the satellite. These missing data are handled in two ways in the CDR processing code. First, a spatial interpolation is performed on the input brightness temperature data to fill small gaps (a few pixels). Then, temporal interpolation is performed on the sea ice concentration data to fill larger gaps (full swaths or entire days). These are described further in detail in sections below.

The main sources of the spurious ice grid cells are: ocean surface brightness temperature variation, atmospheric emission, and mixed land-ocean IFOV in a grid cell.

These are first discussed in general and then the specific filters used to remove much of these effects are described for each of the NASA Team and Bootstrap products.

Both algorithms assume that open water can be represented as a single point in the clustering of different channel combinations. However, it is evident in Figure 5 and Figure 6 that there is considerable spread around the open water point. This is primarily due to weather effects, namely: roughening of the ocean surface by winds, which increases the microwave emission of the water; and atmospheric emission, primarily due to water vapor and liquid water (clouds), which will also increase the emission retrieved by the sensor. Atmospheric emission is most pronounced during rain fall over the open ocean. Emission from the atmosphere has the largest effect on the 19.35 GHz channels because they are near to frequencies (22.235 GHz) in which there is strong water vapor emission.

Spurious ice is also common along ice-free coasts. Because of the large IFOV (up to 72 km x 44 km for 19.35 GHz), brightness temperature values from ocean grid cells near the coast often contain microwave emission from both land and ocean. These mixed grid cells of ocean/land have a brightness temperature signature that is often interpreted by the algorithms as sea ice. When sea ice is actually present along the coast, the effect is small, but when there is no ice present, artifacts of false ice appear. This is commonly called the land-spillover effect because emission from the land surface "spills over" into ocean grid cells.

Automated filters used to correct these spurious concentrations are discussed further in sections below. It is possible, however, that the automated filters may also remove real ice in some conditions.

### *Brightness Temperature Spatial Interpolation*

The input brightness temperatures that are used to produce the sea ice CDR sometimes contain small gaps in the data fields. These occur commonly in the fields, especially in the more equator-ward parts of the grids. This is because of the drop-in-the-bucket (DITB) method used for gridding the brightness temperature swath data. The DITB method simply averages all footprints (swaths) into a grid in a given day based on the center location of the footprint. For example, at each grid cell, all footprints whose centers are within that grid cell's boundaries are found. However, because the footprints are larger than grid cell size, some grid cells have no footprint centers. So these are empty grid cells (i.e., have a missing or zero value). These happen more equator-ward because there are fewer overlapping swaths and thus more chance of empty grid cells.

These empty grid cells are generally isolated, that is, 1 or 2 missing grid cells surrounded by cells with valid $T_B$ values. To correct for these missing grid cells, they are filled by bilinear interpolation where by the grid cell is filled with the average of the four grid cells that surround it: one above, one below, one to the left, and one to the right. However, to make the spatial filling algorithm more robust and allow for filling of neighboring missing grid cells, a threshold of at least three out of the four surrounding cells with valid values was set. A flag called spatial_interpolation_flag marks the channels that were interpolated. See section 3.4.4.1 for more information on this flag.

This spatial interpolation is performed on all $T_B$ channels prior to the input data being passed into the sea ice concentration algorithms. Larger gaps in the data are filled by temporal interpolation (see the section below).

***Sea Ice Concentration Temporal Interpolation***

To fill larger gaps in the data such as missing swaths or missing days of data, a temporal interpolation is performed on the sea ice concentration data. Once the $T_B$s are processed through the NASA Team and Bootstrap sea ice algorithms, the temporal interpolation is applied. The method of interpolation is performed by locating a missing sea ice concentration grid cell on a particular date and then using linear interpolation to fill that value from data on either side of that date. Data can be interpolated with values of up to five days on either side of the missing date and those days do not have to be evenly spaced on either side. For example, a missing grid cell can be interpolated from a data point one day in the past and one day in the future or a data point two days in the past and four days in the future up to a data point five days in the past and five days in the future. This linear interpolation method is the preferred technique of temporal interpolation. However, in some cases, gaps still exist after this interpolation scheme is performed because two data points on either side of the missing value are not found with which to linear interpolate. To attempt to further fill these gaps, a single-sided gap filling is performed whereby we check if there is at least one data value up to three days on either side of the date and then simply copy that value into the missing grid cell. A flag called temporal_interpolation_flag marks the data that were interpolated. See section 3.4.4.1 for more information on this flag.

***Pole Hole Spatial Interpolation***

A polar orbit and wide swath provides near-complete coverage at least once per day in the polar regions except for a small region around the North Pole called the pole hole. The size of this hole has changed through time as the instruments have advanced. See Table 8 for a list of the sizes of the holes by instrument. A spatial interpolation has been applied to the pole hole to fill this area. The method involves averaging all sea ice concentration grid cell values that surround the hole and then filling the missing grid cells within the hole with that average. Thus, all grid cells within the pole hole have the same concentration value. This interpolation is done on the NASA Team and Bootstrap sea ice concentrations after they have been temporally interpolated. A value of 32 is set in the spatial_interpolation_flag variable identifying this region as being interpolated. See section 3.4.4.1 for more information on this flag.

Note: The current pole hole is quite small (Table 8); and even though the ice edge has retreated a lot in recent years, the hole is still well within the boundary of where we are confident that ice exists. However, it is important to note that one cannot assume what the concentration is, especially in late Arctic summer and early autumn. Thus, we would advise caution in using the interpolated data in long-term trends or climatology analyses and would generally recommend against it. For time series analysis (trends), users should still apply the pole hole mask (see section 3.4.3.3). We are filling the hole to provide a complete field for users that want/need complete fields without gaps (e.g., modelers).

***NASA Team Weather Filters***

Spurious ice over open water is removed by a threshold of the GR3719 ratio (Equation 9) and an additional GR2219 ratio:

$$GR(22V/19V) = [T_B(22V) - T_B(19V)]/[T_B(22V) + T_B(19V)] \tag{15}$$

Using the following criteria listed in Table 6:

| Instrument | Hemisphere | Criteria |
|---|---|---|
| SMMR | Northern | GR3719 > 0.070 → concentration = 0<br>GR2219 → N/A |
| SMMR | Southern | GR3719 > 0.076 → concentration = 0<br>GR2219 → N/A |
| SSM/I | Northern | GR3719 > 0.050 → concentration = 0<br>GR2219 > 0.045 → concentration = 0 |
| SSM/I | Southern | GR3719 > 0.050 → concentration = 0<br>GR2219 > 0.045 → concentration = 0 |
| SSMIS | Northern | GR3719 > 0.050 → concentration = 0<br>GR2219 > 0.045 → concentration = 0 |
| SSMIS | Southern | GR3719 > 0.057 → concentration = 0<br>GR2219 > 0.045 → concentration = 0 |

Table 6. GR3719 and Gr2219 criteria by instrument and hemisphere

Note that NASA Goddard uses a GR3719 threshold of 0.053 for SSMIS in the Southern Hemisphere, and a GR3719 threshold of 0.076 for SMMR in the Southern Hemisphere. While creating the Version 4 sea ice CDR, it was found that slightly adjusting those thresholds led to better agreement in the satellite transitions for the CDR product.

***Bootstrap Weather Filters***

The Bootstrap algorithm also uses combinations of 19V, 22V, and 37V as a weather filter, but the methodology follows the overall Bootstrap by thresholding above a cluster of points in (1) 19V vs. 37V, and (2) 19V vs. (22V-19V) $T_B$ scatter plots (Figure 7).

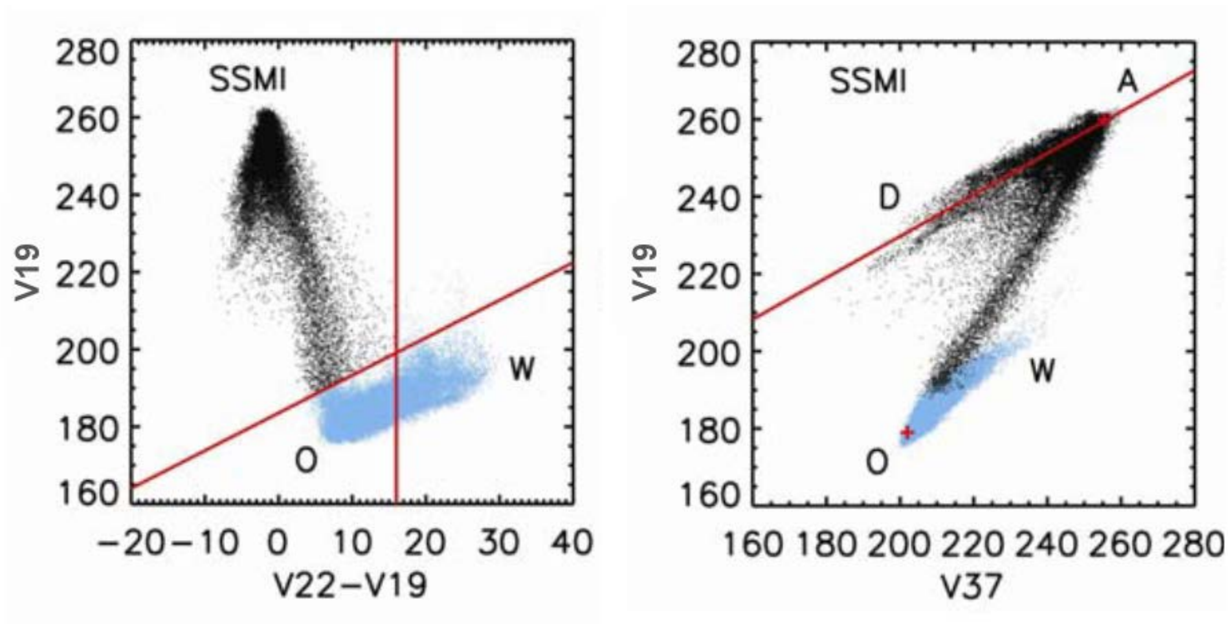


Figure 7: Sample scatter plot of 19V vs. (22V-19V) (left) and 19V vs. 37V (right) $T_B$s. Values shaded in blue around the OW segment are masked to 0% concentration. From Comiso and Nishio (2008).

### *NASA Team Land-Spillover Correction*

For the NASA Team algorithm, a filtering mechanism has been implemented to automatically remove many of the false coastal ice grid cells by using a weighting based on the proximity of the grid cell to the coast and a minimum concentration matrix, CMIN. This method removes many, but not all errors due to land-spillover. The procedure is done in three steps (summarized from Cavalieri et al., 1999):

1. A static matrix, M, was created for each hemisphere's polar stereographic grid. Using the land mask, all grid cells were defined as shore, near-shore, off-shore, or non-coastal ocean. A shore cell is one that is directly adjacent to land. For example, for grid cell (I,J) in Figure 8, at least one A grid cell is land. A near-shore grid cell is one grid cell removed from land; in Figure 8, no A grid cells are land, but at least one B cell is land. An off-shore grid is two grid cells removed from land, that is, no A or B cells are land, but at least one C cell is land. Off-shore grid cells are more than three grid cells from land, so no A, B, or C cells around a point (I,J) are land. The rationale for this is that any influence will decrease farther from shore; and with a maximum footprint scale of approximately 70 km (19.35 GHz SSM/I channels are 69 x 43 km), any land effect should not extend more than three 25 km grid cells from land.

| | | | | | | |
|---|---|---|---|---|---|---|
| | | C | C | C | | |
| | C | B | B | B | C | |
| C | B | A | A | A | B | C |
| C | B | A | I,J | A | B | C |
| C | B | A | A | A | B | C |
| | C | B | B | B | C | |
| | | C | C | C | | |

Figure 8: Example of grid cell neighbor to define coastal proximity classification for a grid cell, (I,J). From Cavalieri et al. (1999).

2. A minimum ice concentration field, CMIN, is created from one year of data: 1992. First, a matrix of minimum monthly average concentrations is created for the year. Then these concentrations are adjusted based on the classifications in the M matrix. At off-shore grid cells, any CMIN values exceeding 20% are reduced to 20%. At near-shore grid cells, any CMIN values exceeding 40% are reduced to 40%. At shore grid cells, any CMIN values exceeding 60% are reduced to 60%.
3. During processing, concentrations in the offshore, near-shore, and shore grid cells are adjusted using the CMIN matrix. For each grid cell class in CMIN, a “neighborhood” is defined. For off-shore cells, the neighborhood is the 3 x 3 box surrounding the cell. A near-shore cell neighborhood is a 5 x 5 box, and a shore neighborhood is a 7 x 7 box. For each neighborhood box, if at least three grid cells contain open water (<15% ice), then the concentration of the center grid cell is adjusted by subtracting the concentration of the coincident grid cell in the CMIN matrix. Wherever the calculation results in negative values, the concentration is set to 0%.

### *Bootstrap Land-Spillover Correction*

The Bootstrap algorithm uses a simpler method developed by Cho et al. (1996). It uses a 3 x 3 filter around each grid cell. If at least one of the 3 x 3 group of grid cells is land, then the center grid value is replaced by the minimum non-land value within the 3 x 3 grid cell group.

### *CDR Sea Ice Filtering*

Weather effects can cause the passive microwave signature of seawater to appear like that of ice (Cavalieri 1995). Atmospheric water vapor is often the reason behind false-ice detection. Most of these false-ice signatures are removed with a standard brightness-temperature filter, but some are too close to those of real ice and require another method to be removed. Unlike the Goddard products, which apply manual corrections, the CDR uses an automated process to filter any lingering false ice. This is accomplished by applying the NASA Team weather and land spill over corrections and the Bootstrap weather and land spillover corrections to the CDR sea ice concentrations. This takes the place of the Goddard manual corrections. Although it may not remove all false ice as well as manual correction can, it is a good approximation and is fully traceable.

***Valid Ice Masks***

**Northern Hemisphere**

The best way to evaluate where ice can be is to look at a climatology of sea ice occurrence, where the climatology is built from Arctic-wide sea ice analyses over as long a period as possible from many different sources. These show where ice detected by the satellite data algorithm is most likely to be valid ice, based on where ice has existed in the past.

For the Northern Hemisphere, these weather effects and land spillovers are corrected with the Polar Stereographic Valid Ice Masks Derived from National Ice Center Monthly Sea Ice Climatologies, available from NSIDC (https://nsidc.org/data/nsidc-0622). The climatology used for these masks is the National Ice Center Arctic Sea Ice Charts and Climatologies in Gridded Format. It includes 12 masks showing the maximum sea ice extent, one for each month of the year, over the period 1972 to 2007. In addition, a day-of-year climatology ice mask is applied to the SMMR era only that is derived from the Goddard Bootstrap algorithm NSIDC-0079 data.

**Southern Hemisphere**

In the Southern Hemisphere, masks based on the monthly sea surface temperature (SST) climatology of Levitus and Boyer (1994) are used. A temperature threshold of 275 K was used to determine the mask boundary for each month. Any sea ice concentrations above 0% calculated by the algorithms in regions where the masks do not allow sea ice are set to zero in the final concentration estimates. In addition, a day-of-year climatology ice mask is applied to the SMMR era only that is derived from the Goddard Bootstrap algorithm NSIDC-0079 data.

#### 3.4.1.4 Sea Ice Concentration Climate Data Record Algorithm

NSIDC processes the input brightness temperatures into two intermediate sea ice concentrations using the two Goddard-developed algorithms: NASA Team (Cavalieri et al., 1984) and Bootstrap (Comiso, 1986). Then, these two intermediate sea ice concentrations are merged together using the sea ice concentration CDR algorithm that is described below.

The NASA Team and Bootstrap algorithms and their associated automated QC procedures are run independently. Then, the algorithm concentration values are combined to create the CDR concentration field by selecting the larger concentration value between the NASA Team and Bootstrap outputs for each grid cell and implementing a 10% concentration threshold based on Bootstrap concentrations. The details and rationale for these two steps are provided below:

1. At each sea ice grid cell, the concentration between the NASA Team and the Bootstrap output are compared, and whichever value is greater is selected as the CDR value. Both algorithms tend to underestimate concentration, as is discussed more in section 5.5 Algorithm Validation and Error Assessment, but the source and the effect on the underestimation differs between algorithms. The NASA Team algorithm, because it uses a ratio of brightness temperatures, tends to cancel out any physical temperature effects. The Bootstrap algorithm uses relationships between two brightness temperatures that are dependent on physical temperature. Thus, physical temperature changes can affect Bootstrap estimates. This occurs primarily in regimes with very low temperatures: winter in the high Arctic and near the Antarctic coast (Comiso et al., 1997). During winter conditions with more moderate temperatures, NASA Team concentrations also tend to have more of a low bias (Kwok, 2002; Meier, 2005). During melt conditions, both algorithms tend to underestimate concentration; but the effect is more pronounced in the NASA Team algorithm. Also, the NASA Team estimates are biased lower than the Bootstrap estimates (Comiso et al., 1997; Meier, 2005; Andersen et. al, 2007).

   While these characteristics of the algorithm are true in an overall general sense, ice conditions and algorithm performance can vary from grid cell to grid cell; and in some cases, this approach will result in an overestimation of concentration (Meier, 2005). However, using the higher concentration between the two algorithms will tend to reduce the overall underestimation of the CDR estimate.

2. A 10% concentration threshold based on the Bootstrap concentration is used to define the ice edge (the boundary between ice and open water). A 15% cutoff is a common standard that has been in use for many years (Zwally et al., 1983) and in comparison studies with other satellite data, has agreed well, on an average basis, with the observed ice edge (Cavalieri et al., 1991; Meier et al., 2003). Also, the applied weather filters typically remove most concentrations below 15% (Cavalier et al., 1999). However, there are indications that the Bootstrap algorithm can potentially detect ice at as low as 8% levels (Comiso and Nishio, 2008). Thus, a 10% cutoff was chosen for the CDR data fields. However, the validity of this assumption depends on the character of the ice edge as well as ocean and atmospheric conditions and for total extent and area calculations a 15% cutoff is still recommended. The 10% cutoff in the CDR field will miss some

real ice, but low concentrations have much higher uncertainties and because of the large footprint of the SSM/I and SSMIS sensors (see Table 2) any ice edge has precision of two or three 25 km x 25 km grid cells. The 10% cutoff removes many potentially high error concentration estimates and provides a standard throughout the time series.

The rationale for only using the Bootstrap estimates to define the edge is two-fold. First, just the maximum value criteria between Bootstrap and NASA Team discussed will yield more low-concentration, high-error grid cells than using only one algorithm. Second, the Bootstrap data were reprocessed (Comiso and Nishio, 2008) to intercalibrate ice extents with AMSR-E Bootstrap products. The AMSR-E sensor has a much smaller footprint and, thus, is able to obtain a more precise ice edge (Comiso and Nishio, 2008). So, the SSM/I-SSMIS Bootstrap algorithm likely yields extent and area fields that better match the real values. Another possible approach is to require that both the NASA Team and Bootstrap estimates must have concentrations greater than 15% to be included, but it is felt that this would be too stringent and miss some legitimate sea ice grid cells. Also, such a combination could possibly introduce small artifacts to trends in long-term sea ice extent time series.

#### 3.4.1.5 Comparison of NSIDC-Processed and Goddard-Processed Brightness Temperatures Using the NASA Team and Bootstrap Algorithms

The process that NSIDC uses to convert brightness temperatures to sea ice concentration using the NASA Team and Bootstrap algorithms is very similar to the way Goddard processes their ice concentrations with a few known differences. NSIDC uses a new brightness temperature version for the F8 period from what Goddard used. In addition, NSIDC uses a corrected version of brightness temperatures for F11 and F13, while Goddard used the uncorrected version for their NASA team product but the corrected version for their Bootstrap V3 product. The two processing streams also use different valid ice masks. Both the NSIDC-processed and Goddard-processed brightness temperatures use a similar automated spatial and temporal interpolation method, however, Goddard also performs an additional manual QC step to remove spurious ice. In comparisons between the two, there are occasional small variances due to the differences noted here. This section describes these differences in more detail.

Goddard processed their sea ice concentrations using the NSIDC gridded brightness temperature version available at the time of processing. For the TCDR, NSIDC is using the currently available version distributed by NSIDC (https://nsidc.org/data/nsidc-0001). See Table 3 for a list of the versions and the time periods these were used.

For F11 and F13, after initial processing of brightness temperatures at NSIDC and NASA Team concentrations at Goddard, small errors were discovered in the brightness temperature processing resulting in the inclusion of some bad scan lines. These bad scan lines resulted in some small artifacts in the gridded Goddard concentration estimates. After discovery of the brightness temperature processing error, NSIDC reprocessed the affected F11 and F13 data. Goddard reprocessed their concentrations from the Bootstrap algorithm for V3, but the NASA team concentrations were not reprocessed. However, Goddard performs a manual QC process that removed these bad data.

For missing grid cells, both NSIDC and Goddard employ a spatial and temporal interpolation to fill in the missing values. For isolated missing grid cells, a spatial average from surrounding non-missing brightness temperature grid cells is used to fill the missing grid cell. For larger areas of missing data, due to missing swaths or days of brightness temperature data, a temporal interpolation is used where sea ice concentration estimates from the day before and the day after are averaged to fill the missing region. For this temporal interpolation, Goddard only uses an average of the day before and the day after. If there are still large missing areas, Goddard fills these manually. NSIDC, on the other hand, uses an average of up to five days before and five days after to fill large gaps. Because no manual filling is done for the NSIDC-processed concentrations, this larger time range was utilized to attempt to fill as much missing data as possible. For a complete description of the spatial and temporal interpolation method utilized by NSIDC, see section 3.4.1.3 Quality Control Procedures.

For both NASA team and Bootstrap products, Goddard uses a different Northern Hemisphere valid ice mask than NSIDC does. Goddard uses the SST-climatology mask (same source as for the SH), while NSIDC uses the NIC chart climatology (nsidc-0622). NSIDC also applies a daily climatology ice mask derived from Bootstrap Sea Ice Concentrations to both hemispheres.

The most significant difference between the processing at NSIDC and at Goddard is Goddard's use of a manual inspection to correct grid cells with erroneous concentration values. Each daily field was examined at Goddard and a hand-cleaning process was used to remove any sea ice grid cells that were deemed to be erroneous. The majority of these erroneous sea ice values were false coastal ice that were not removed by the land-spillover correction, and false ice over the ocean that were not removed by either weather filter or the ocean mask. In these cases, the grid cell is simply replaced with a 0% value. In very rare cases, the manual QC deemed some legitimate sea ice grid cells to have clearly incorrect concentration values. These concentration values were removed and the affected grid cells were considered missing. These missing values were then filled by Goddard via the interpolation discussed above. See section 3.4.1.3 Quality Control Procedures for a description of how the CDR code handles erroneous concentration values.

### 3.4.2 Data Merging Strategy

Both the NASA Team and Bootstrap algorithms employ varying tie-points to account for changes in sensors and spacecraft. These tie-point adjustments are derived from regressions of brightness temperatures during instrument overlap periods. The adjustments are made at the product level by adjusting the algorithm coefficients so that the derived sea ice fields are as consistent as possible. This approach was found to be more successful than intercalibrating the input brightness temperature fields. The reasons for this are due to several factors. First, the products are derived on daily mean gridded brightness temperatures using a simple drop-in-the-bucket average. A new sensor on a new sun-synchronous satellite will have a different equatorial crossing time. This means that the gridded brightness temperature for a given grid cell will be comprised of swath brightness temperature values from different times of day between data from the old sensor versus the new sensor. Because sea ice, as well as the overlying atmosphere, varies over time, this will result in inconsistencies in the brightness temperature signal even when the brightness temperatures themselves are fully intercalibrated. Second, the sea ice varies on scales far smaller than the footprint of the passive microwave sensors. Thus, any retrieved brightness temperature is likely a mixture of several different surfaces (for example, first-year vs. multi-year, smooth vs. rough/ridged, deep snow vs. snow free, etc.). This makes it difficult to directly match up brightness temperatures from different sensors to the same sea ice conditions over which to intercalibrate. Finally, transitions between sensors may result in a change of frequency, notably for SMMR and SSM/I, where the 18.7 GHz frequency on SMMR was replaced by a 19.35 GHz frequency on SSM/I.

The NASA Team approach uses sensor-specific hemispheric tie-points for each transition (Cavalieri et al., 1999; Cavalieri et al., 2011). Tie-points were originally derived for the SMMR sensor and subsequent transitions to SSM/I and SSMIS adjusted the tie-points to be consistent with the original SMMR record. The Bootstrap algorithm uses daily varying hemispheric tie-points, derived via linear regression analysis on clusters of brightness temperature values of the relevant channels, as in Figure 12 of Comiso (2009), and the adjustment involves a linear regression between brightness temperatures (Comiso and Nishio, 2008). Also, in contrast to the NASA Team, Bootstrap tie-points for SMMR and SSM/I are derived from matching fields from the AMSR-E sensor, which is newer and more accurate.

### 3.4.3 Look-Up Table Description

There are a considerable number of external static data grids and masks used to create this product. This section lists and describes these grids and their origins arranged in alphabetical order by directory and then file name.

#### 3.4.3.1 CDR Land/Coast/Shore Masks

These files are the Northern and Southern Hemisphere masks used for the combined layers of the CDR product. We combined the various masks that were provided by Goddard for the NASA Team and Bootstrap algorithms into a single unified land mask for each hemisphere. The values are provided in Table 7.

| Value | Description |
|---|---|
| 0 | Open ocean (not close to shore) |
| 1 | Land |

| | |
|---|---|
| 2 | Coast (land adjacent to ocean) |
| 3 | Shore (ocean adjacent to land, 1 grid cell from land) |
| 4 | Near-shore (ocean adjacent to shore, 2 grid cells from land) |
| 5 | Far-shore (ocean adjacent to near-shore, 3 grid cells from land) |
| 6 | Lake |

Table 7: CDR land/coast/shore mask values.

The files are named the following:

```
cdralgos/ancillary/landmask/
       landmask-shoredistance-north.dat
       landmask-shoredistance-south.dat
```

#### 3.4.3.2 Valid Sea Ice Climatology Masks

In order to reduce the inclusion of clearly false-positive ice concentration values, two valid ice masks are applied to all data. One is a monthly climatology ice mask and the other is a daily climatology ice mask. In the Northern Hemisphere, the monthly ice mask comes from NSIDC-0622. In the Southern Hemisphere, the monthly masks are derived from the Goddard NASA Team algorithm NSIDC-0051. For both hemispheres, the daily mask is derived from the Goddard Bootstrap algorithm NSIDC-0079 data and is only applied to the CDR sea ice concentration. Ocean cells that are not valid sea ice locations are set to 0% concentration and the qa_of_cdr_seaice_conc is set to 16.

These climatology files are named the following:

```
Monthly ice masks:
cdralgos/ancillary/icemask/
       validice-HEM-MM-byte.dat
Daily ice masks:
seaice_cdr/source/ancillary/doy-validice-HEM-SENSOR.nc
```

Where *HEM* is the hemisphere (north or south), *MM* is the two digit month (01 - 12), and SENSOR is smmr.

#### 3.4.3.3 Pole Hole Masks

In the Northern Hemisphere, there are grid cells near the pole where observations are not possible because of the shape of the satellite's orbit. A pole hole mask file has been generated for each sensor – SMMR, SSMI, and SSMIS – so that these unobserved locations can be treated differently than other missing data.

There are three different masks to account for the three different generations of instruments, whose Arctic pole hole sizes change through the time series (see Table 8). They were created from the data within the NSIDC-0051 data set (https://nsidc.org/data/nsidc-0051) provided to NSIDC by the GSFC.

In this data product, the pole hole is filled where possible. On a first pass, a temporal interpolation is applied. Data from up to five days prior or following are used to fill pole hole locations. If these are not available, the pole hole is filled with the average of the concentration value from all of the grid cells which surround the pole hole.

The approach taken differs from that of some other sea ice concentration products (e.g. NSIDC-0051 and NSIDC-0079) where the pole hole values are left unfilled and observed values are overwritten with the pole hole flag so that the pole hole is the same every day.

Note: The current pole hole is quite small (Table 8); and even though the ice edge has retreated a lot in recent years, the hole is still well within the boundary of where we are confident that ice exists. However, it is important to note that one cannot assume what the concentration is, especially in late Arctic summer and early autumn. Thus, we would advise caution in using the interpolated data in long-term trends or climatology analyses and would generally recommend against it. For time series analysis (trends), users should still apply the pole hole mask. We are filling the hole to provide a complete field for users that want/need complete fields without gaps (e.g., modelers).

The files are named the following:

```
cdralgos/ancillary/polemask/
       polemask-north-INST.dat
```

Where *INST* is the platform identifier (*smmr*, *ssmi*, or *ssmis*).

| Arctic pole hole Mask Name | Arctic pole hole Area (million km$^2$) | Pole Hole Radius (km) | Latitude |
|---|---|---|---|
| polemask-north-ssmis.dat | 0.029 | 94 | 89.18° N |
| polemask-north-ssmi.dat | 0.31 | 311 | 87.2° N |
| polemask-north-smmr.dat | 1.19 | 611 | 84.5° N |

Table 8. Arctic Pole Hole Sizes by Instrument

#### 3.4.3.4 Spillover Correction Matrices

These files represent the input P-matrix data used to compute the weights in the spillover correction and were provided by Nicolo DiGirolamo at GSFC in Greenbelt, MD. They are described in the Cavalieri et. al. (1999). These files were chosen to most accurately reproduce the pre-existing NSIDC sea ice concentration data sets as they are currently in use at GSFC.

The files are named the following:

```
/cdralgos/ancillary/concmin/
```

```
concmin-north-le.dat
concmin-south-le.dat
```

### 3.4.4 Algorithm Output

The sea ice CDR code creates daily and monthly NetCDF data files for each hemisphere. Each daily and monthly CDR file contains four primary CDR fields: a CDR concentration estimate, a standard deviation field, a melt onset flag, and a quality assessment field. Each field is a byte array (except for the standard deviation field that is a float array) on the polar stereographic grid: 304 columns by 448 rows (136,192 bytes) for the Northern Hemisphere and 316 columns by 332 rows (104,912 bytes) for the Southern Hemisphere. In the two sub-sections below, the daily and the monthly fields are described in detail.

**Note:** In addition to the individual daily and monthly NetCDF files, aggregated versions of these files are also produced. For the daily files, there are yearly aggregated files, where a year's worth of daily data is stored in one NetCDF file. For the monthly files, there is one period-of-record file for each hemisphere where all the monthly data are stored in one NetCDF file per hemisphere.

#### 3.4.4.1 Fields in the daily CDR files

The daily TCDR and ICDR files both contain the following variables:

1. cdr_seaice_conc
2. stdev_of_cdr_seaice_conc
3. melt_onset_day_cdr_seaice_conc
4. qa_of_cdr_seaice_conc
5. nsidc_nt_seaice_conc
6. nsidc_bt_seaice_conc
7. spatial_interpolation_flag
8. temporal_interpolation_flag
9. projection
10. time
11. xgrid
12. ygrid
13. latitude
14. longitude

These CDR fields are explained below:

1. Sea Ice Concentration CDR

   This field, named cdr_seaice_conc, contains the sea ice concentration values for the CDR, scaled from 0-100%. This field (and the standard deviation and QA fields discussed below) is processed entirely at NSIDC with all processing steps fully documented (Section 3.4.1.4). For the TCDR, it includes the entire SSM/I-SSMIS time series, 1987-most recent process. For the ICDR, it includes SSMIS for all NRT data. The flag values for the sea ice concentration variables are given in Table 9.

| **Flag Name** | **Value** |
|---|---|
| Missing | 255 |
| Land | 254 |
| Coast/land adjacent to Ocean | 253 |
| Lakes | 252 |
| Northern Hemisphere pole hole (the region around the pole not imaged by the sensor) | 251 |

Table 9: Sea ice concentration variables flag values

2. Spatial Standard Deviation of Sea Ice Concentration

   This field, named stdev_of_cdr_seaice_conc, contains the standard deviation of both the NASA Team and Bootstrap concentration estimate at each ocean/sea ice grid cell for that grid cell and the surrounding 8 grid cells (Figure 9). The standard deviation is calculated from the total of two 3 x 3 arrays of grid cells (one of NASA Team concentrations and one of Bootstrap concentrations), for 18 grid cells in total. Land grid cells within the 3 x 3 array are not included in the calculation; thus, along the coast, fewer than 18 values are used. Any missing grid cells (for example, the pole hole in the Northern Hemisphere) are also not included in the standard deviation. A minimum of 6 valid concentration values out of the 18 total are required to compute a standard deviation. Thus, some grid cells within small bays and inlets may not have a standard deviation value; such cells are likely to be potentially affected by land-spillover and should be considered to have high uncertainties.

   This field is meant to give an indication of the uncertainties in the daily CDR concentration estimate. It is not a quantitative error estimate and should not be used as such. However, it does provide a useful guide to users as to the relative accuracy of concentration estimates relative to surrounding grid cells and can be used to derive relative weights for comparisons, interpolations, or assimilation studies. In winter conditions, away from the ice edge or coast where spatial variability occurs, standard deviations are typically a few percent (Cavalieri et al., 1984) and can potentially serve as a quantitative upper limit of the concentration error (Gloersen et al., 1993).

The error sources for sea ice concentration are described in detail below, but high standard-deviation values will generally correspond to regions where concentration errors are likely higher.

First, isolated sea ice grid cells along the coastline that result from the land-spillover issue discussed above will have higher standard deviations compared to ice-free ocean or high concentration ice cover along the coast because of the mixture of ice and open water (0% ice) in the calculation.

Another region of higher errors occurs along the ice-water boundary (the ice edge) due to limitations in the sensor resolution, to motion of the ice during the 24-hour average period, and to melt/growth of ice. These high gradient regions will have high standard deviation values.

Finally, during melt, the surface and atmospheric effects become relatively larger, leading to more spatial variability and higher standard deviation values. The melt also tends to cause the algorithms to underestimate concentration because they incorrectly interpret the surface melt on top of the ice as increased open water. The NASA Team concentrations generally have a large low bias compared to the Bootstrap concentrations. This is the rationale for computing the standard deviation from both of the algorithms instead of the combined CDR estimate or just one of the algorithms. The lower relative bias in the NASA Team during melt compared to Bootstrap will yield increased standard deviation values, better indicating the presence of melt than using only the CDR concentration standard deviation.

Standard deviation values range from 0-1, and the fill value is -1.

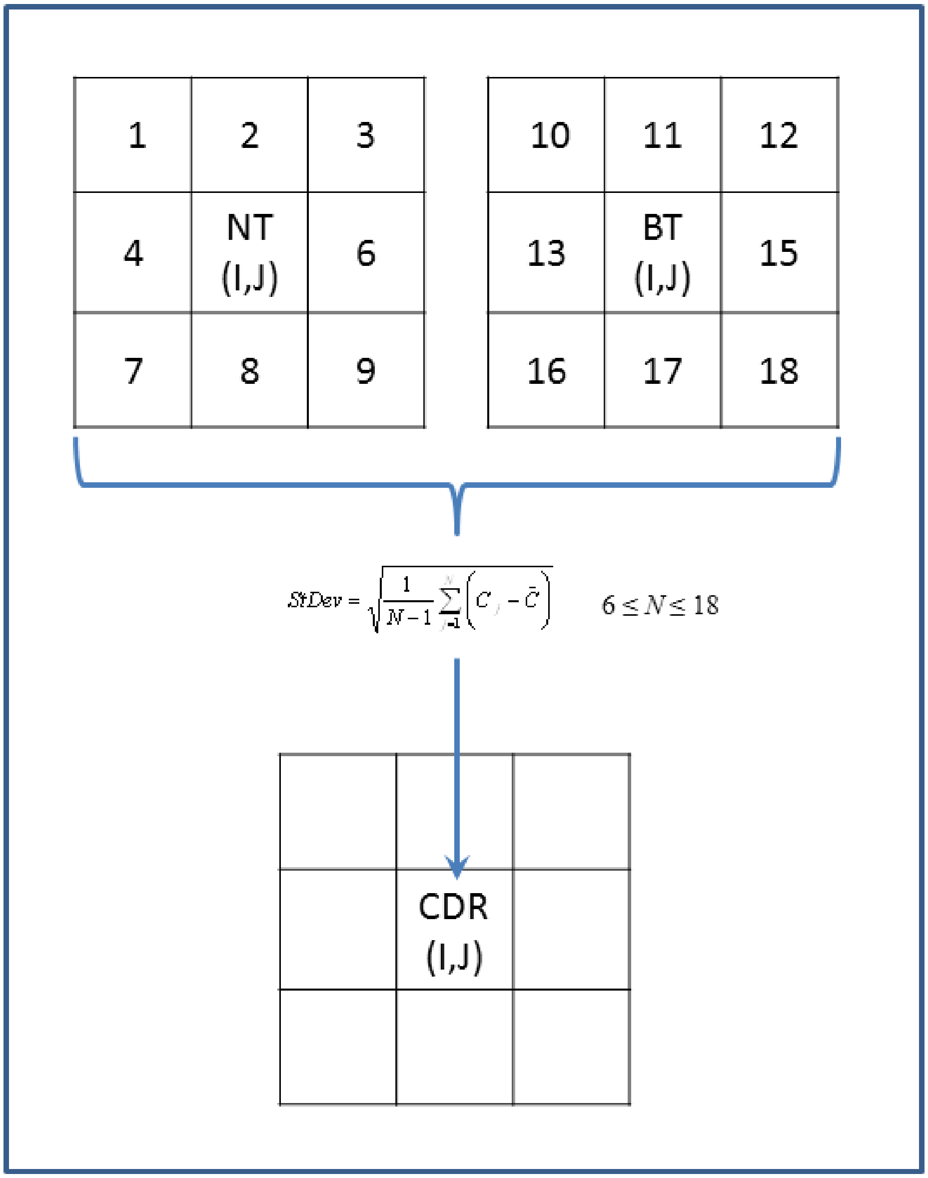


Figure 9: Schematic of grid cell values used in calculation of the CDR standard deviation field. All non-missing ocean/sea ice concentration values (C), from both the NASA Team and Bootstrap algorithm, of the 3 x 3 box surrounding each (I,J) grid cell (up to 18 total values) are used to calculate the standard deviation. A minimum of six grid cells with valid values is used as a threshold for a valid standard deviation.

3. Day of Melt Onset

This field, named melt_onset_day_cdr_seaice_conc, contains the day of year on which melting sea ice was first detected in each grid cell. Once detected, the value is retained for the rest of the year. For example, if a grid cell started melting on day 73, the variable for the grid cell on that day will be 73, as will all subsequent days until the end of the year. The melt onset day is only calculated for the melt season: days 60 through 244, inclusive. Before melting is detected or if no melt is ever detected for that grid cell, the value will be -1 (missing / fill value).

The conditions for melt onset at a particular grid cell are the following:

- Melt detected:
    - Concentration >= 50% at the beginning of the season
    - Grid cell is not land, coast, shore (1 grid cell from coast), near-shore (2 grid cells from coast), or lake
- Current sea ice concentration >= 50%
- Brightness temperature delta (19H - 37H) < 2K
- Presence of brightness temperatures for both channels (19H, 37H)

**Note**: To calculate the melt onset for F17 and F18 data, the input brightness temperatures are first scaled as follows:

$$19H\_scaled = 1.021 * 19H - 1.681 \tag{19}$$

$$37H\_scaled = 1.001 * 37H - 0.650 \tag{20}$$

These equations were derived by a regression between F17 and F13 brightness temperatures during March through September 2007 when there was an overlap period between the two satellites. Regressions were run for each daily average brightness temperature field and slope and intercept values were calculated. These daily slope and intercept values were then averaged over the entire March through September period to derive the equations above.

The reason for applying this adjustment is to account for differences between the F17 and F13 sensors, including sensor characteristics (sensor footprint, geometry), differences in orbit (time of equatorial crossing), etc. For the NASA Team sea ice concentration algorithm, the differences between the two sensors are accounted for by adjusting the algorithm tie-points (Cavalieri et al., 2011). For the Bootstrap sea ice concentration algorithm, only a regression is needed because tie-points are derived daily from the brightness temperature fields. For the melt onset, Equations 19 and 20 are used to make this adjustment.

4. Quality Assessment (QA) Flags

This field, named qa_of_cdr_seaice_conc, provides additional assessment to complement the standard deviation field. This field includes flags for whether the

BT and NT weather and land-spillover filters were applied, if the valid ice mask was applied, if spatial or temporal interpolation was applied, and the melt state. See Table 10.

One of the largest contributors to errors in concentration estimates occurs when surface melt begins (see section 5.5.2). Thus, a melt flag (melt_start_detected) is implemented in the Northern Hemisphere to indicate where melt may be occurring. The melt onset test is performed only in the Northern Hemisphere because the character of the ice cover in the Southern Hemisphere, typified by strong melt-refreeze cycles, does not yield a reliable melt threshold in passive microwave brightness temperature data (Willmes et al., 2009).

The melt flag is a near-real-time version of the Drobot and Anderson (2001) algorithm, which uses a brightness temperature difference threshold to determine whether melt has begun for the overlying snow cover at each sea ice grid cell. The algorithm is implemented as follows:

$$T_B(19H) - T_B(37H) > 2K \rightarrow \textit{no melt} \tag{21}$$

$$T_B(19H) - T_B(37H) \leq 2K \rightarrow \textit{melt has begun} \tag{22}$$

A long-term melt onset climate dataset, NSIDC-0105, is distributed by NSIDC (https://nsidc.org/data/nsidc-0105). That dataset includes a 20-day temporal filter to screen out possible false melt signatures. For simplicity, the temporal filter is not employed in this product. This means that some grid cells flagged as melt may not actually be melting, and thus, the flag is more conservative than the climate dataset. Note that the melt test does not consider any effects of sea ice motion.

The melt onset test is used starting on March 1 (DOY=60), around the time when the maximum sea ice extent is reached each year. Once a grid cell is flagged as melting, it remains so through the rest of the summer until September 1 (DOY=244), roughly the time when extent reaches its minimum value. When the sea ice concentration is zero, the flag will be turned off. In other words, the flag will only be on if melt conditions are met and there is sea ice. Note this is different from the melt_onset_day_cdr_seaice_conc variable which, once set, shows the day of melt onset through the rest of the year. Also note that melt may be intermittent initially in the spring (melt, then refreeze, and melt again) and freeze-up begins near the pole well before September 1. Thus, grid cells that are flagged as melt may not actually have melt occurring and the flag should be used only as a guide for the data quality of the CDR concentration estimates and should not be used specifically for studies on melt. Like the melt_onset_day_cdr_seaice_conc, the input F17 brightness temperatures are scaled. See the note in number 3, Day of Melt Onset, above for more details.

The melt algorithm is not run within two grid cells of the coast due to possible effects of mixed land-ice grid cells. The melt algorithm is also valid only for grid cells with concentrations of at least 50%. These are separately flagged as both situations (coast, low concentration) reflect regimes with likely higher errors.

Table 10 lists the flag values in the QA field, with an explanation for each parameter. Grid cells with more than one flag property contain the sum of both flags. In general, higher values are more likely to have high errors. Note that 0 is the fill value for this variable.

| Condition | Flag Value | Label in NetCDF Variable |
|---|---|---|
| **BT weather filter applied** | 1 | BT_weather_filter_applied |
| **NT weather filter applied** | 2 | NT_weather_filter_applied |
| **BT land spillover applied** | 4 | BT_land_spillover_filter_applied |
| **NT land spillover applied** | 8 | NT_land_spillover_filter_applied |
| **Valid ice mask applied** | 16 | valid_ice_mask_applied |
| **Spatially interpolation applied** | 32 | spatial_interpolation_applied |
| **Temporal interpolation applied** | 64 | temporal_interpolation_applied |
| **Start of Melt Detected (Arctic only)** | 128 | melt_start_detected |

Table 10: List of flag values used in the daily CDR QA field. A grid cell that satisfies more than one criteria will contain the sum of all applicable flag values. For example, where the Bootstrap weather filter and land spillover are applied, the flag value will be 5 (1 for BT weather plus 4 for BT land spillover).

5. NSIDC NASA Team Sea Ice Concentrations

NSIDC includes the intermediate NSIDC processed daily NASA Team sea ice concentration, named nsidc_nt_seaice_conc, in the product suite to provide transparency in the creation of the sea ice CDR product.

These data are similar to the Goddard produced NASA team sea ice concentrations available from NSIDC as the Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS Passive Microwave Data (https://nsidc.org/data/nsidc-0051).

6. NSIDC Bootstrap Sea Ice Concentrations

NSIDC includes the intermediate NSIDC processed Bootstrap sea ice concentration, named nsidc_bt_seaice_conc, in the product suite to provide transparency in the creation of the sea ice CDR product.

These data are similar to the Goddard produced NASA team sea ice concentrations available from NSIDC as the Bootstrap Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS (https://nsidc.org/data/nsidc-0079).

Note that Goddard has released Version 3.1 of their Bootstrap product. They have made minor adjustments to the Bootstrap algorithm that are described in Comiso et al. (2017). With the release of TCDR V4 and ICDR V2, NSIDC has made these adjustments to our processing of the bootstrap algorithm.

7. Spatial Interpolation QC Flag

This field, spatial_interpolation_flag, is set for spatially interpolated grid cells.

| **Condition** | **Flag Value** | **Label in NetCDF Variable** |
|---|---|---|
| 19 GHz vertical brightness temperature spatially interpolated | 1 | 19v_tb_value_interpolated |
| 19 GHz horizontal brightness temperature spatially interpolated | 2 | 19h_tb_value_interpolated |
| 22 GHz vertical brightness temperature spatially interpolated | 4 | 22v_tb_value_interpolated |
| 37 GHz vertical brightness temperature spatially interpolated | 8 | 37v_tb_value_interpolated |
| 37 GHz horizontal brightness temperature spatially interpolated | 16 | 37h_tb_value_interpolated |
| Pole hole spatially interpolated | 32 | pole_hole_value_interpolated |

Table 11. Spatial interpolation flag values. A grid cell that satisfies more than one criteria will contain the sum of all applicable flag values.

8. Temporal Interpolation QC Flag

This field, named temporal_interpolation_flag, provides details on the grid cells that were temporally interpolated. The value for each flag is a 1- or 2-digit number indicating the pair of known data points used in the interpolation. The first number indicates how many days in the past the data point came from and the second number indicates how many days in the future the data point came from, with a max of 5 days in either direction. For example, if the flag value is 24, then the missing grid cell was interpolated from sea ice concentration data from a grid cell from two days prior and four days in the future. For the linear interpolated values, the smallest flag value is 11 where the missing grid cell was interpolated from a grid cell from one day prior and one day in the future. The largest flag value is 55 where the missing grid cell was interpolated from a grid cell from five days prior and five days in the future. For the secondary interpolation schema, where only one day is used, the lowest value is 1, where the missing grid cell is filled by copying the value from one day in the future. The largest value is 30 where the missing grid cell is filled by copying the value from three days prior.

9. Projection

   Describes the projection information for these data.

10. Time

    The date of these data.

11. Xgrid

    The projection grid x centers in meters.

12. Ygrid

    The projection grid y centers in meters.

13. Latitude

    Latitude in degrees north. Note this is found in the aggregated NetCDF files only and not in the individual daily NetCDF files.

14. Longitude

    Longitude in degrees east. Note this is found in the aggregated NetCDF files only and not in the individual daily NetCDF files.

#### 3.4.4.2 Fields in the monthly CDR files

The monthly fields are created from all daily files in the given month. The TCDR and ICDR both contain the following variables:

1. cdr_seaice_conc_monthly
2. stdev_of_cdr_seaice_conc_monthly
3. melt_onset_day_cdr_seaice_conc_monthly
4. qa_of_cdr_seaice_conc_monthly
5. nsidc_nt_seaice_conc_monthly

6. nsidc_bt_seaice_conc_monthly
7. projection
8. time
9. xgrid
10. ygrid
11. latitude
12. longitude

These CDR fields are explained below:

1. Sea Ice Concentration CDR

   This field, named cdr_seaice_conc_monthly, contains the monthly average sea ice concentration values for the CDR, scaled from 0-100%. This field (and the standard deviation and QA fields discussed below) is processed entirely at NSIDC with all processing steps fully documented. For the TCDR, it includes the entire SSM/I-SSMIS time series, 1987-present. For the ICDR, it includes SSMIS for the NRT data. The flag values for the sea ice concentration variables are the same as for the daily fields given in Table 12.

   The monthly average is computed at each grid cell by averaging all available daily values in the month for that grid cell. A minimum of 20 days is required for a valid monthly value. If a grid cell has fewer than 20 days with non-missing data, that grid cell is assigned the missing flag in the monthly field. No concentration threshold is used in the monthly fields – i.e., unlike the daily fields, monthly concentration values of less than 10% may occur.

2. Standard Deviation of Concentration

   This field, named stdev_of_cdr_seaice_conc_monthly, contains the standard deviation (with one degree of freedom) of the daily concentrations in the month. As in the monthly concentration, a minimum of 20 days is required for a valid monthly value. Note that while the daily concentration standard deviation field is based on the variability of the NT and BT concentrations over a 3 x 3 grid cell spatial region, this monthly field is simply the standard deviation of the daily CDR concentrations – i.e., a temporal standard deviation for each grid cell.

3. Day of Melt Onset

   This field, named melt_onset_day_cdr_seaice_conc_monthly, contains the day of year on which melting sea ice was first detected in each grid cell. Once detected, the value is retained for the rest of the year. For example, if a grid cell started melting on day 73, the variable for the grid cell on that day will be 73, as will all subsequent days until the end of the year. The melt onset day is only calculated for the melt season: days 60 through 244, inclusive. Before melting is detected or if no melt is ever detected for that grid cell, the value will be -1 (missing / fill value).

The conditions for melt onset at a particular grid cell are the following:

- Melt detected:
    - Concentration >= 50% at the beginning of the season
    - Grid cell is not land, coast, shore (1 grid cell from coast), near-shore (2 grid cells from coast), or lake
- Current sea ice concentration >= 50%
- Brightness temperature delta (19H - 37H) < 2K
- Presence of brightness temperatures for both channels (19H, 37H)

**Note**: To calculate the melt onset for F17 data (2008 – present), the input brightness temperatures are first scaled as follows:

$$19H\_scaled = 1.021 * 19H - 1.681 \qquad (19, \text{previously listed})$$

$$37H\_scaled = 1.001 * 37H - 0.650 \qquad (20, \text{previously listed})$$

These equations were derived by a regression between F17 and F13 brightness temperatures during March through September 2007 when there was an overlap period between the two satellites. Regressions were run for each daily average brightness temperature field and slope and intercept values were calculated. These daily slope and intercept values were then averaged over the entire March through September period to derive the equations above.

The reason for applying this adjustment is to account for differences between the F17 and F13 sensors, including sensor characteristics (sensor footprint, geometry), differences in orbit (time of equatorial crossing), etc. For the NASA Team sea ice concentration algorithm, the differences between the two sensors are accounted for by adjusting the algorithm tie-points (Cavalieri et al., 2011). For the Bootstrap sea ice concentration algorithm, only a regression is needed because tie-points are derived daily from the brightness temperature fields. For the melt onset, Equations 19 and 20 are used to make this adjustment.

4. Quality Assessment Bit Mask

This field, named qa_of_cdr_seaice_conc_monthly, contains flags indicating the potential quality of monthly averages. The flags are listed in Table 12. They include whether the average concentration exceeds 15%, which is commonly used to define the ice edge and can be used to easily quantify the total extent.

Another flag indicates when average concentration exceeds 30%, which is a commonly used alternate ice edge definition. It may be desired to remove lower concentration ice that tends to have higher errors. Another flag indicates whether at least half the days have a concentration greater than 15%. This provides a monthly median extent, which may be a better representation of the monthly ice presence because an average conflates the spatial and temporal variation through the month. Additionally, there is a flag that indicates whether at least half the days have a concentration greater than 30%. This also provides a monthly median extent, but this higher percentage may leave out questionable or erroneous ice. There are flags to show if a cell was masked by the valid ice mask and whether spatial or temporal interpolation was performed. Finally, there is a flag to note whether melt was detected during the month. Since melt tends to bias concentrations lower, this flag gives a sense of whether melt is having a dominating effect.

| **Condition** | **Flag Value** | **Label in NetCDF File** |
|---|---|---|
| Average concentration exceeds 15% | 1 | Average_concentration_exceeds_0.15 |
| Average concentration exceeds 30% | 2 | Average_concentration_exceeds_0.30 |
| At least half the days have sea ice conc > 15% | 4 | At_least_half_the_days_have_sea_ice_conc_exceeds_0.15 |
| At least half the days have sea ice conc > 30% | 8 | At_least_half_the_days_have_sea_ice_conc_exceeds_0.30 |
| Valid ice mask applied | 16 | Region_masked_by_ocean_climatology |
| At least one day during month has spatial interpolation | 32 | At_least_one_day_during_month_has_spatial_interpolation |
| At least one day during month has temporal interpolation | 64 | At_least_one_day_during_month_has_temporal_interpolation |
| Melt detected (at least one day of melt occurred during the month >= 1) | 128 | At_least_one_day_during_month_has_melt_detected |

Table 12: List of flag values used in the monthly CDR QA bit mask. A grid cell that satisfies more than one criteria will contain the sum of all applicable flag values. For example, if spatial interpolation was performed and melt detected then the value will be 160 (32 + 128).

5. NSIDC NASA Team Monthly Concentrations

   NSIDC includes the intermediate NSIDC processed monthly NASA Team sea ice concentration, named nsidc_nt_seaice_conc_monthly, in the product suite to provide transparency in the creation of the sea ice CDR product.

   These data are similar to the Goddard produced NASA team sea ice concentrations available from NSIDC as the Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS Passive Microwave Data (https://nsidc.org/data/nsidc-0051).

6. NSIDC Bootstrap Monthly Concentrations

   NSIDC includes the intermediate NSIDC processed Bootstrap sea ice concentration, named nsidc_bt_seaice_conc_monthly, in the product suite to provide transparency in the creation of the sea ice CDR product.

   These data are similar to the Goddard produced NASA team sea ice concentrations available from NSIDC as the Bootstrap Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS (https://nsidc.org/data/nsidc-0079).

   Note that Goddard has released Version 3.1 of their Bootstrap product. They have made minor adjustments to the Bootstrap algorithm that are described in Comiso et al. (2017). With the release of TCDR V4 and ICDR V2, NSIDC has made these adjustments to our processing of the bootstrap algorithm.

7. Projection

   Describes the projection information for these data.

8. Time

   The date of these data.

9. Xgrid

   The projection grid x centers in meters.

10. Ygrid

    The projection grid y centers in meters.

11. Latitude

Latitude in degrees north. Note this is found in the aggregated NetCDF files only and not in the individual monthly NetCDF files.

12. Longitude

Longitude in degrees east. Note this is found in the aggregated NetCDF files only and not in the individual monthly NetCDF files.

# 4. Test Datasets and Outputs

## 4.1 Test Input Datasets

The TCDR is tested against two existing, widely available data sets. These are *NSIDC-0051: Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I Passive Microwave Data* (https://nsidc.org/data/nsidc-0051) and *NSIDC-0079: Bootstrap Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I* (https://nsidc.org/data/nsidc-0079).

We worked directly with GSFC and have incorporated some of their code and data into the CDR production. Within the confines of producing a CDR, we have attempted to implement the algorithms and incorporate similar automatic filtering and quality control features to be as consistent as possible with the heritage data products from GSFC.

The near-real-time ICDR product follows the same methodology as the standard TCDR, only run with near-real-time input brightness temperatures. Comparisons between NRT and final sea ice concentration algorithms indicates good agreement between the two, with daily extent and area differences generally below 50,000 square kilometers and overall average differences of 20,000 – 30,000 square kilometers. These are generally <1% of the overall extent and average. Nonetheless, the NRT data should be considered provisional, and it is recommended that only final data be used for climate monitoring.

## 4.2 Test Output Analysis

### 4.2.1 Reproducibility

The test results can be verified by running the algorithm with the same input TBs and the same ancillary fields and then checking to ensure the results are the consistent. For Version 3, Peng et al. (2013) and Meier et al. (2014) verified that the CDR algorithm reasonably reproduce the original concentration fields from SSMI and SSMIS provided by NASA Goddard except for the manual corrections and gap-filling interpolations applied by Goddard. In Version 4, we have confirmed that the consistency with Goddard extends into the SMMR sensor period, and the added spatial and temporal interpolation address data gaps achieves consistent results with the Goddard products.

### 4.2.2 Precision and Accuracy

The precision and accuracy of the algorithms have been evaluated in numerous studies over the years (for example, Cavalieri et al., 1991; Comiso et al., 1997; Kwok, 2002; Meier, 2005; Andersen et al., 2006, 2007; Ivanova et al., 2014). Overall, the algorithm has a precision of ~5% with an accuracy of ~10%. However, uncertainties are higher under some conditions – most notably near the ice edge and when the surface is undergoing melt. In addition, while filters remove many artifacts (see above), some erroneous ice can still occur over the open ocean due to weather effects and along the coast due to land spillover effects (i.e., mixed ocean and land grid cells).

### 4.2.3 Error Budget

Much of the error is largely attributable to the limitations of the source data. First, the spatial resolution of the input sensor data is limiting. Some input brightness temperature sensor footprints have an effective resolution of ~70 km x ~45 km. This means that any variability below this resolution (for example, the location of the ice edge) may be missed. The sensor resolution is also the cause of the land spillover issue, where a sensor footprint incorporates a mixture of land and open water, which in some conditions has a signature that is interpreted by the algorithm as sea ice.

There are more modern sensors, such as the Advanced Microwave Scanning Radiometer (AMSR). However, these records only go back to 2002, so they are not suitable for a long-term CDR. A recently-developed, gridded brightness-temperature product includes a resolution enhancement technique using multiple satellite overpasses to improve gridded resolution from 25 km to 6.25 km (Brodzik et al., 2016). This may reduce the land-spillover effect and improve ice edge detection.

Another limitation is surface melt. Passive microwave sensors are sensitive to the phase state of water (liquid or solid), which allows the algorithms to distinguish between sea ice and ocean. However, because the microwave emission comes from at or near the surface, water on the surface of the ice is interpreted as liquid. This causes the algorithms to underestimate concentration when ice is melting. The algorithms can be potentially adjusted to reduce this, but then they tend to overestimate concentration during non-melt conditions. Dynamic (automatically varying) daily tie-points alleviate this effect some by allowing the algorithm to adjust to different surface conditions, as is now done within the Bootstrap component of the CDR. See Table 13 for an overview of each of these errors.

| Error | Magnitude | Description |
|---|---|---|
| Inter-satellite bias | <0.5% of total sea ice extent and area | Inter-calibration has been done to minimize differences in algorithm outputs. Analysis of inter-calibrated retrievals show small differences (Cavalieri et al., 1999; 2012). However, some overlap periods were short and during periods (summer) of high variability. Thus, quantitative values may underestimate the true bias. |
| Diurnal correction | Undetermined/ minimal | Daily average $T_B$ fields are used, which removes most diurnal effects. Different sensors have different orbits that result in some diurnal impacts, but these are implicitly addressed in the satellite intercalibration, which reduces such effects to near zero over most of the ice pack, though larger effects can occur in narrow band near the ice edge. More recent data (since the mid-1990s) have had longer overlaps and |

| | | |
|---|---|---|
| | | thus greater confidence in the consistency between sensors (Meier and Stewart, 2019). |
| Unknown calibration drifts | Undetermined/ minimal | This has not been investigated in detail for the CDR. However, other studies (e.g., Meier and Stewart, 2020) have shown no evidence of significant effects of drift on the sea ice fields. |
| Effect of changes in surface properties | Undetermined/ minimal | The sea ice algorithms are sensitive to surface conditions and tend to underestimate concentration during melt and for new ice. As melt is occurring earlier and is more widespread, errors in concentration and area trends may result. However, the implementation of dynamic algorithm coefficients (dynamic tie points) within the Bootstrap component of the CDR product can account for seasonal and interannual shifts in surface conditions. |

Table 13: Possible error sources and magnitudes for the sea ice CDR

# 5. Practical Considerations

## 5.1 Numerical Computation Considerations

No parallelization or difficulties in matrix inversions are expected. Round-off errors exist in conversions between data types (floating point to byte and the reverse), but these are expected and well within the tolerance of the current algorithm and instrument accuracy.

## 5.2 Programming and Procedural Considerations

Daily processing is independent and can be run in parallel, except for the melt algorithm information, which must be run as a post processing step.

Numerical Python (NumPy) is required for CDR processing. Python library, *nose*, is used in testing.

## 5.3 Quality Assessment and Diagnostics

Researchers can assess and improve a CDR by comparing it with operational products. Absolute error can be approximated via comparison to operational sea ice products, such as those produced by the U.S. National Ice Center or the Canadian Ice Service; but it is important to keep in mind that such products have an operational focus different from the climate focus of the CDR, and the two are not expected to be consistent with each other. The documentation for the daily Multi-sensor Analyzed Sea Ice Extent (MASIE) (https://nsidc.org/data/masie), distributed by NSIDC in cooperation with NIC, gives a summary of how satellite passive microwave CDRs differ from operational products.

## 5.4 Exception Handling

Error cases in the code are caught and informative error messages are printed on exit.

## 5.5 Algorithm Validation and Error Assessment

Several studies over the years have assessed ice concentration estimates from the NASA Team and Bootstrap algorithms. These assessments have typically used coincident airborne or satellite remote sensing data from optical, thermal, or radar sensors, generally at a higher spatial resolution than the SSM/I and SSMIS instruments but with only local or regional coverage. Several assessments indicate an accuracy of approximately 5% during mid-winter conditions away from the coast and the ice edge (Steffen et al., 1992; Gloersen et al., 1993; Comiso et al., 1997; Meier et al., 2005; Andersen et al., 2007, Belchansky and Douglas, 2002). Other assessments suggest concentration estimates are less accurate. Kwok (2002) found that passive microwave overestimates open water by three to five times in winter. Partington et al. (2003) found a difference with operational charts that was relatively low in the winter but rose to more than 20% in summer. Errors can come from problems with the sensor, from weather effects, and from inadequacies in the algorithm. For example, a satellite's orbit may drift over time, which may degrade an instrument's data quality. Most SSM/I instruments were in use long past their designed lifetime expectancy. Atmospheric water vapor is a weather effect that can modulate the passive microwave signature of the surface, particularly at the 19 GHz frequency, causing ice concentration to be overestimated. Finally, while the emissivity of seawater is quite constant, that of sea ice varies considerably depending on many factors including age, thickness, and surface roughness. When one considers that algorithms must arrive at a single number for ice concentration taking into account the varying brightness temperatures of all the different surface types that may fill the footprints of the 19 GHz and 37 GHz channels and that those footprints differ in size and shape across the instrument swath, one can appreciate the difficulty of the problem. *Microwave Remote Sensing of Sea Ice*, F. Carsey, editor, is a comprehensive overview of the subject (Carsey, 1992).When melt ponds form on the surface of ice floes in the summer, the ice concentration appears to decline when in fact the true concentration may not have changed (Fetterer and Untersteiner, 1998). Melt state is a surface effect that may in itself contain a climate trend, which could influence sea ice concentration trend estimates. This and other concentration error sources have been examined to some extent in Andersen et al. (2007), and their influence appears to be small compared to the estimated sea ice trends, but such effects should be kept in mind when using these data.

### 5.5.1 Errors from sensor characteristics and gridding scheme

There are four errors that come from the sensor characteristics: (A) sensor noise, (B) the transition between sensors, (C) the large IFOV of the sensors, and (D) the 24-hour composite.

A. One source of error is simply from sensor noise. The SSM/I and SSMIS sensors have been found to have an RMS error of 0.5 K to 1.0 K (Wentz, 1997). A sensitivity study of NASA Team algorithm concentration (https://nsidc.org/data/pm/nasateam-index) found that the concentration sensitivity is about 1-2% per 1 K (Gloersen et al., 1993). Thus, the algorithm precision is about 1%.

B. Another potential sensor error results from the transition between sensors on different platforms. The brightness temperature regression and tie-point adjustment corrects for this, though small artifacts remain (Cavalieri et al., 1999; Comiso and Nishio, 2008). Comparison of ice extent estimates from sensor overlap periods indicate that the adjustments yield agreements that are on the order of 0.05% or less and about 0.5% for sea ice area (Cavalieri et al., 1999; Cavalieri et al., 2011). Short overlap periods of early sensor transitions (SMMR to F8 and F8 to F11) may not account for the full seasonal variability (Meier et al., 2011; Cavalieri et al., 2011) and differences may be higher in some cases. However, differences appear to be well below the sensitivity of the instrument, thus, providing confidence in the robustness of the intercalibrated algorithms through the time series.

C. A more significant limitation of the sensors are the large sensor footprint (IFOV) of the SSM/I and SSMIS channels. Though all input brightness temperatures are gridded to the 25 km polar stereographic grid, the IFOV of the sensor is coarser than this (Table 2), as low as 70 x 45 km for the 19.35 GHz channel. This means that the sensor is obtaining information from up to a 3 x 2 grid cell (75 km x 50 km) region, but because a simple drop-in-the-bucket gridding method is used, that signature is placed in a single grid cell. This results in a spatial "smearing" across several grid cells. Also, some grid cells do not coincide with the center of the sensor footprint and are, thus, left as missing even though there is brightness temperature information available at that region. This effect also causes the land-spillover issue of grid cells with a mixture of land and water brightness temperatures that can be interpreted by the algorithms as sea ice.

D. Another issue is the use of 24-hour composite average brightness temperatures as input for the concentration algorithms. Sea ice can drift with the winds and ocean currents over a 24-hour period, and the surface properties of the sea ice can also change considerably. Thus, the daily brightness temperature fields of the surface properties at a given grid cell are an amalgamation of conditions over 24 hours.

   Some of the effect caused by this spatial and temporal compositing of the brightness temperatures is ameliorated because these data have been used consistently for algorithm development, tie-point derivation, intersensor adjustment, and all processing. Thus, these effects, while limiting accuracy on a grid cell level, still yield consistent large-scale trends and variability in the sea ice cover. Regions with sharp gradients in brightness temperature, such as the ice edge and the land/water boundary, are most affected by these characteristics.

   Of particular note is the compositing effect on the precision of the ice edge. First, the ice edge is a region of sharp brightness temperature gradients and rapid (less than 24 hour) variability. Second, there is necessarily ambiguity in the ice edge location due to the limited spatial resolution. For example, an ice edge grid cell (that is, the adjoining grid cells are ice-free) with a 50% concentration could mean that the entire cell has a uniformly distributed 50% ice concentration, that half of the grid is covered by 100% ice and the other half is ice free, or something in between. Because the true spatial resolution is limited by the sensor IFOV and not the grid cell area, even with perfect data and a perfect algorithm, the ice edge can in principle only be discerned to within ~50 km. However, the distance between the passive microwave observed (15% concentration) edge and the true ice edge, as determined in ship observations (Ozsoy-Cicek et al., 2009; Ozsoy-Cicek et al., 2011), operational sea ice charts (Partington, 2000), or high resolution satellite data (Meier et al., 2003; Meier, 2005), may be much larger than that.

### 5.5.2 Errors due to surface variation and ambiguities

There are four primary error sources from surface variation and ambiguities: (A) ice type, (B) ice surface variation, (C) physical temperature, and (D) surface melt.

A. While five passive microwave channels are potentially available for discriminating sea ice, not all are completely independent and in practice only three surface types are retrievable, one water and two ice (multi-year and first-year). However, two ice types cannot fully describe the complex surface of the sea ice. Tie-points are derived based on “pure surface types” of 100% ice, typically for thick multi-year or first-year ice (for the Arctic). The actual emission from thin ice (as indicated by the brightness temperature) varies with ice thickness up to perhaps 30 cm. Thus, thin ice cover appears in the algorithms as a mixture of water and thick ice. So, thin ice concentration is often underestimated. Algorithms using specific thin ice tie-points have been developed (Cavalieri et al., 1994), but these are not applicable for hemispheric datasets. Because ice quickly grows thicker in winter months, thin ice tends to constitute a small fraction of the overall ice cover, but can result in large error near the ice edge and regions dominated by thin ice (such as the Sea of Okhotsk). Validation studies indicate that the Bootstrap algorithm is more sensitive to thin ice, and thus, more accurate in those regions than the NASA Team algorithm (Partington, 2000).

B. Beyond thin ice, other sea ice surface variability factors impact the brightness temperature signal, including snow cover, frost flowers, and variations in ice salinity. During winter conditions, these effects are generally small, resulting in average concentration errors of a few percent (Gloersen et al., 1993), though higher errors can occur and are most often underestimations. For example, a comparison between passive microwave sea ice concentrations and concentration derived from high-resolution SAR scenes found that SAR showed less than 0.5% open water area in winter mid-pack sea ice while Bootstrap and NASA Team estimates had 1-3% open water.

   Algorithms have been developed to also employ the higher frequency channels (85.5 GHz on SSM/I) to provide additional information (Markus and Cavalieri, 2000; Spreen et al., 2008). However, these algorithms typically require ancillary atmospheric data and/or radiative transfer modeling because the high frequency channels are more sensitive to atmospheric emission. Also, the high frequency data have anomalies in the early part of the time series, limiting the length of the record, and unlike the lower frequency channels, are not available at all for the 1978-1987 SMMR record.

C. Physical temperature can also cause errors in the sea ice retrieval. Brightness temperature is a function of both the surface emissivity and the physical temperature. So, changes in physical temperature change the retrieved brightness temperature and hence the concentration. The algorithm tie-points implicitly account for a physical temperature, but large variations in temperature can cause errors. The Bootstrap algorithm concentrations have a low bias in extremely cold conditions, typically during the mid-winter season in the high Arctic and near the Antarctic coast. Use of daily tie-points limits this effect, but estimates are still biased low. The NASA Team algorithm uses brightness temperature ratios, so the effect of physical temperature largely cancels out within the algorithm equations.

D. The largest surface effect on the retrieved concentration accuracy is surface melt. When the snow cover overlying the sea ice begins to melt, the microwave emission changes significantly because of the different emissive properties of water in the frozen state versus the liquid state (Eppler et al., 1992). The brightness temperature values over melting snow and ice are effectively interpreted by the algorithms as a mixture of sea ice and open water. The effect is further exacerbated when melt ponds form on the surface of the ice. Thus, a substantial low bias in summer concentrations of 20-30% from both NASA Team and Bootstrap algorithms has been found in numerous studies (Agnew and Howell, 2003; Gloersen et al., 1993; Cavalieri, 1994; Comiso et al., 1997; Partington, 2000; Meier, 2005)

### 5.5.3 Errors due to atmospheric effects

A significant advantage of passive microwave data for sea ice concentration retrieval is that atmospheric emission is typically in the SSM/I and SSMIS frequencies used in the algorithms. This provides all-sky capabilities and allows satellite passive microwave sensors to obtain complete, daily sea ice concentration fields.

However, while atmospheric emission or atmosphere-induced surface emission is typically small, it can cause significant errors in some situations. The atmosphere primarily affects the algorithms over open water and thin ice.

The first effect is not direct emission by the atmosphere but an induced effect. Wind blowing over the ocean roughens the surface, which increases the emission. Even a relatively light wind (for example, 5 m/s) can increase emission enough to register several percent concentration of sea ice when no ice is present (Gloersen et al., 1993; Andersen et al., 2006). The use of weather filters and a 15% concentration threshold eliminates most, but not all, wind effects.

The primary atmospheric emission sources are water vapor and liquid water in clouds. These sources also increase the emission retrieved by the sensor and serve to erroneously increase ice concentration. Sensitivity studies indicate that these effects can be up to a 10-20% concentration bias for open water, with decreasing effects as sea ice concentration increases (Maslanik, 1992; Oelke, 1997; Andersen et al., 2006). Thus, such effects are primarily limited to open water and near-edge sea ice grid cells. The weather filters and the 15% threshold remove much of the effect over water, but some artifacts may remain.

### 5.5.4 Summary of error sources and magnitudes

Table 14 summarizes the error sources, expected potential magnitude of the error, the spatial and/or temporal regime, and the relative effect on each algorithm (BT, NT). These are ranges of typical values as reported in the cited validation studies. Errors at any given grid cell may be larger. Note that many errors will be mitigated in the monthly average fields. Thus, monthly averages are generally more accurate and more stable and are better suited for climate analyses.

| **Error Source** | **Typical Magnitude and bias (if any)** | **Spatial/Temporal Regime** | **Relative Effect on Algorithm** |
|---|---|---|---|
| Sensor Noise | +/-1% | All | NT and BT |
| IFOV/Gridding | <5% | Winter, pack ice | NT and BT |
| IFOV/ Gridding | 0-100% | Sharp gradients (e.g., ice edge, coast) | NT and BT |
| Intersensor calibration | ~0.1% | All | NT and BT |
| Physical temperature | <5%, low | Winter, cold | BT more than NT |
| Non-melt surface variation | <5%, low | Winter, central pack ice | NT more than BT |
| Thin ice | ~30-50%, low | Near ice edge, fall freeze-up | NT more than BT |
| Surface melt | ~10-30%, low | Summer | NT more than BT |
| Wind | 5-20%, high | Open water | NT and BT |
| Water Vapor, Liquid Water | 0-20%, high | Open water and ice near edge | NT and BT |

Table 14: List of error sources and typical magnitudes for the NASA Team (NT) and Bootstrap (BT) algorithms with biases and typical regimes.

## 5.6 Processing Environment and Resources

The code is containerized using Docker. The base image uses continuumio/ miniconda3:4.9.2, which uses a Debian 10 OS. Additional packages installed by the Advanced Package Tool (APT) are gfortran and make. The Docker image size is ~1.15GB on disk.

Docker-compose is used to run the CDR code in a docker container which has mounts to networked storage at NSIDC. The entire stack runs on NSIDC virtual machine (VM) infrastructure.

The VM that runs the docker container uses 2 CPUs, which is utilized by the daily first-pass code, however, it can run on one. The VM uses an Ubuntu 16.04 Xenial64 template and has 4 GB of RAM. A day's worth of data can be processed in this environment in approximately 12 seconds.

The size of the input and output files is list in Table 15.

| **File Type** | **Size** |
|---|---|
| Code package | 2.5 MB (zipped), 7.5 MB (unzipped) |
| TCDR/ICDR Input files | Northern hemisphere: 1.5 MB/day<br>Southern hemisphere: 1.0 MB/day |
| TCDR/ICDR Daily output files | Northern hemisphere: ~250 KB/file/day<br>Southern hemisphere: ~190 KB/file/day |
| TCDR/ICDR Monthly output files | Northern hemisphere: ~260 KB/file/month<br>Southern hemisphere: ~280 KB/file/month |
| Ancillary files | ~4 MB |

Table 15: Code package and input/output memory requirements

The following libraries are required to run the cdr_daily_seaice.py and cdr_monthly_seaice.py routines.

**Core/Python Libraries:**

The code is packaged as a Docker image. As such, any system that runs Docker and has the appropriate data on disk can run this code. All third party libraries listed below are installed from the conda-forge (https://conda-forge.github.io/feedstocks) or APT.

- python >=3.8.0,<4.0.0a
- jinja2 >=2.11.2,<3.0.0a
- netcdf4 >=1.5.0,<2.0.0a
- nco
- numpy >=1.19.0,<1.20.0a
- pyyaml >=5.3.1,<6.0.0a
- invoke >=1.4.1,<2.0.0a
- gfortran
- make

# 6. Assumptions and Limitations

As noted elsewhere, a primary limitation is the spatial resolution (sensor footprint) of the input data, which limits the detail that can be retrieved by the algorithm. The product is on a 25 km (nominal) resolution grid, but some input data has a resolution as ~70 km x ~45 km. This means that small-scale features are not explicitly resolved by the algorithm and the precision of the ice edge location is limited to ~25 km at best. This is generally not sufficient for operational support (for example, navigational guidance) and the product should not be used for such purposes. The primary application of the product is for long-term climate monitoring and general guidance on overall regional and global sea ice concentrations, not operational and/or local applications.

## 6.1 Algorithm Performance

The algorithm is empirically derived based on the microwave emission of pure surface types. Because of the number of sensor frequency and polarization combinations that are completely independent, only three surface types can be discriminated by the algorithm – two for sea ice and one for open water. However, the sea ice surface in particular, is highly heterogeneous. The microwave signature of ice varies based on ice thickness (up to ~50 cm), snow cover, and melt state. For a global, long-term algorithm, the algorithm is tuned to thick, cold sea ice conditions. This means that the algorithm tends to underperform in regions of thin ice and during melt conditions. Heavy snow cover can also impact the algorithm retrieval, especially if the snow grain size changes significantly and/or there are melt/re-freeze events. Over open water, ocean waves and/or atmospheric emission (especially by liquid water clouds) can increase the surface emission signal and result in false ice retrieval. Weather filters (discussed above in the NASA Team Weather Filters and Bootstrap Weather Filters sections) have been included to ameliorate as much of these effects as possible, but occasionally some false ice can still occur.

## 6.2 Sensor Performance

The sensor performance is dependent on operations by the DMSP. Radiometic calibration between sensor transitions is corrected by the sensor-specific tie-point adjustments used by the algorithm, but changes in calibration within a sensor are not addressed. The concentration fields are monitored and sudden changes are an indication of changes in calibration or other sensor malfunction. Generally, these spurious changes have been short-lived, but when they are chronic, the algorithm can be transitioned to use a new sensor. Radiometric noise for the passive microwave sensors has not been an issue.

# 7. Future Enhancements

Other enhancements in the sea ice concentration CDR will be considered for the future, pending available funding. Some of the main potential enhancements are discussed below.

### 7.1.1 Reprocessing of SSM/I using a new version of brightness temperatures

The current CDR product is based on multiple versions of RSS brightness temperatures. See Table 3. The intersensor adjustments between F13 and F17 were made using these versions of brightness temperatures, so any differences in RSS versions should be accounted for within the algorithm intersensor adjustments. However, we aim to do a full reprocessing with a consistent, updated brightness temperature product. One option would be to use RSS Version 7 for all SSM/I and SSMIS data at NSIDC. There are also new brightness temperature products produced by Colorado State University (CSU) for SSMI and SSMIS and distributed as an FCDR through the NOAA CDR program (https://www.ncdc.noaa.gov/cdr/fundamental/ssmis-brightness-temperature-csu). The CSU product may be updated at NASA Goddard to include SMMR as well (W. Berg, CSU, pers. comm.). We will investigate these products for a potential full reprocessing of the sea ice product when resources allow.

### 7.1.2 EASE-Grid 2.0 version of sea ice CDR

Another potential source for gridded brightness temperatures is the NASA MEaSUREs enhanced EASE-Grid 2.0 (EASE2) gridded product (https://nsidc.org/data/nsidc-0630). These use CSU swath brightness temperatures as a source and create twice-daily TB composites on the EASE2 grid, including enhanced resolution fields. These TBs are now being routinely processed by the NASA DAAC at NSIDC and ongoing production, including near-real-time fields is being supported by the DAAC. These would provide a suitable source of already-gridded fields. The EASE2 grid is equal area, which is easier to work with, and it includes standard geographic parameters (ellipsoid, datum, etc.) that make the data more compatible with modern software packages such as Python and GIS.

### 7.1.3 New algorithm coefficients for calibration

While intercalibration has been done on the current input data and algorithm coefficients (tie points) are varying (by satellite for NASA Team, daily for Bootstrap), further enhancement is possible and may be necessary for transition to new brightness temperatures. The approach would follow the Bootstrap methodology to continue to allow daily-varying tie points, with adaptations to the NASA Team, and potential further refinements.

### 7.1.4 Improved pole-hole filling

The current pole-hole fill is a simple average, based on the average concentration of surrounding cells. This provides a reasonable gap-fill, but does not include any spatial variability. We will investigate new methods to add realistic spatial variability to the pole hole.

### 7.1.5 Filling remaining temporal gaps using statistical modeling

While the temporal and spatial interpolation fills most gaps, there are still some periods that do not have data, most notably, Dec 1987 and Jan 1988. This is a large time gap where simple temporal interpolation is not reasonable. However, more advanced methods are possible, including statistical modeling approaches. We will investigate such methods to fill that 1987-1988 and other smaller remaining gaps. Because the gap is so larger and the method will be unique, we may decide to provide this as an ancillary product so that users more clearly understand that that period is missing data and the “data” during that period is actually based on statistical modeling.

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# Appendix A - ACRONYMS AND ABBREVIATIONS

| Acronym or Abbreviation | Meaning |
|---|---|
| BT | Bootstrap |
| CATBD | Climate Algorithm Theoretical Basis Document |
| CDR | Climate Data Record |
| CLASS | Comprehensive Large Array-data Stewardship System |
| DAAC | Distributed Active Archive Center |
| DMSP | Defense Meteorological Satellite Program |
| DOY | Day of Year |
| IFOV | Instantaneous Field of View |
| FY | First Year |
| GSFC | Goddard Space Flight Center |
| H | Horizontal |
| ICDR | Interim Climate Data Record |
| MY | Multi-year |
| NAS | National Academies of Science |
| NASA | National Aeronautics and Space Administration |
| NCEI | National Center for Environmental Information |
| NOAA | National Oceanic and Atmospheres Administration |
| NSIDC | National Snow and Ice Data Center |
| NRT | Near Real Time |
| NT | NASA Team |
| OW | Open Water |
| QC | Quality Control |
| RSS | Remote Sensing Systems, Inc. |
| SMMR | Scanning Multichannel Microwave Radiometer |
| SSM/I | Special Sensor Microwave Imager |
| SSMIS | Special Sensor Microwave Imager/Sounder |
| SST | Sea Surface Temperature |
| TCDR | Thematic Climate Data Record |
| V | Vertical |