International Refereed Journal of Engineering and Science (IRJES)
ISSN (Online) 2319-183X, (Print) 2319-1821
Volume 13, Issue 2 (Mar.-Apr. 2024), PP. 83-94

A review of sea ice concentration inversion based on microwave radiometer

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Abstract: *Sea ice is one of the sensitive indicators of global climate change, and sea ice concentration is an important factor affecting the ocean heat balance, ecosystem and climate change in the polar circle, as well as an important indicator for evaluating the safety and stability of Arctic shipping lanes and assessing the sea ice condition in the Arctic Ocean. Passive microwave remote sensing technology has high spatial and temporal resolution and can monitor sea ice concentration information in real time, which provides a new means for ice monitoring and early warning. In this paper, from the perspective of passive microwave remote sensing, the principle of sea ice concentration inversion using passive microwave is firstly explained. Secondly, this paper provided a detailed discussion on the inversion method of passive microwave sea ice concentration in the chronological order of low frequency, high frequency, and high low frequency. And summarized the advantages and disadvantages of each type of inversion method (such as low-frequency algorithms that are less affected by external factors but have low spatial resolution, high-frequency algorithms that have high spatial resolution but are susceptible to external environmental influences, and the combination of high and low frequencies to some extent improves the inversion accuracy of sea ice density, but the mechanism of the combination needs further research). Finally, the main problems faced in obtaining sea ice density using passive microwave remote sensing were introduced, and future research on optimization algorithms was prospected based on the combination of low frequency, high frequency, and high low frequency.*
Key words*: sea ice concentration; microwave radiometer; inversion; high frequency; low frequency*

Date of Submission: 02-04-2024 Date of acceptance: 13-04-2024

I. Introduction

Sea ice is one of the most dynamic components of the cryosphere and plays a crucial role in the global climate system, serving as a sensitive indicator of climate change. With its high albedo and low thermal conductivity, sea ice reflects more solar radiation, reducing the absorption of solar energy by the ocean and regulating the energy exchange between the atmosphere and the ocean surface. This, in turn, affects the heat balance of the ocean. Additionally, sea ice serves as an effective insulator, inhibiting the transfer of heat between the atmosphere and the ocean [1]. Sea ice has significant impacts on various aspects including the atmosphere, ecology, environment, ocean, and human activities. Covering approximately 7% of the Earth's surface, sea ice accounts for about 12% of the global ocean area. The extent of sea ice coverage varies greatly with the seasons, extending into mid-latitudes during spring in polar regions and significantly impacting human activities [2].

The rise and development of remote sensing technology have provided an effective means for large-scale sea ice monitoring. Compared to visible light remote sensing, microwave remote sensing has many advantages in detecting sea ice concentration, making it an important technique for identifying sea ice [3]. Microwave remote sensing can be divided into active and passive modes based on the different energy sources [4]. Active microwave remote sensing involves emitting energy towards the target and receiving the reflected energy to obtain information about sea ice. Passive microwave remote sensing is an effective method for extracting target signals, monitoring surface temperatures, and obtaining other environmental parameters using microwave radiation transmission theory and algorithms. Passive microwave remote sensing can cover the entire polar region every day, unaffected by clouds, fog, rain, and other factors, and thus has the characteristics of all-day and all-weather monitoring, making it a primary data source for sea ice monitoring. Sea ice concentration, as a primary parameter of passive microwave remote sensing, is an important descriptor of sea ice characteristics and is widely used in the spatial distribution and extent calculation of sea ice. It is of significant importance for navigation, climate research, weather, and sea ice prediction, as well as for tasks such as offshore operations, sea ice model validation, and climate data assimilation [5]. There has been considerable work on using microwave radiometer data to retrieve sea ice concentration, and efforts have been continuously made to improve the accuracy and spatial resolution of sea ice concentration retrieval and expand the application of new satellite data.

This article first introduces the principles of passive microwave remote sensing technology from the perspective of microwave radiation transmission models and the microwave radiation characteristics of sea ice. It then focuses on explaining the algorithms used to retrieve sea ice concentration based on microwave radiometer data, dividing the algorithms into high-frequency and low-frequency algorithms, as well as other improvement methods, and elaborating on their basic principles. Finally, it provides an outlook on the future development directions of sea ice concentration retrieval.

II. Passive microwave remote sensing technology principles.

Due to the significant difference in emissivity between sea ice and open water, microwave remote sensing provides a solid physical basis for retrieving sea ice concentration. Compared to traditional methods of sea ice concentration measurement, as well as visible and thermal infrared remote sensing, passive microwave remote sensing has a wide coverage area, enabling large-scale continuous observations. It also offers advantages such as all-day, all-weather monitoring, strong penetration capability, and being less affected by cloud cover and fog. Therefore, passive microwave remote sensing is considered the most effective means for monitoring sea ice concentration in polar regions and has been widely applied to rapidly obtain information on sea ice concentration in polar regions.

2.1 Microwave radiation transmission model

The microwave radiation transfer equation is often used as a forward model for retrieving surface parameters from microwave radiation data. The satellite receives the brightness temperature (TB) of microwave radiation, which is a composite of various contributions from the Earth, atmosphere, and space [3]. The contributions to TB received by polar satellite sensors mainly come from three parts: (1) Earth radiation, (2) atmospheric radiation, and (3) space radiation. The microwave radiation transfer equation can be expressed as follows:

$$T_B = T_s e^{-\tau} + T_1 + (1-\varepsilon) T_2 e^{-\tau} + (1-\varepsilon) T_{sp} e^{-2\tau} \qquad (1)$$

Where ε represents the surface emissivity, τ denotes the atmospheric optical thickness, T_s stands for the Earth's surface radiative temperature, T_1 represents the upward atmospheric brightness temperature, T_2 represents the downward atmospheric brightness temperature, and T_{sp} denotes the brightness temperature of cosmic background radiation.

Due to the low humidity in polar regions, there are almost no liquid water droplets in the atmosphere, so the atmospheric contribution can usually be ignored. Cloud cover is typically composed of low-level clouds with such small liquid water content that it does not affect the microwave radiation signal from sea ice. Therefore, the optical thickness can be neglected, assuming τ<<1。Additionally, assuming T_1 and $T_2$are the average atmospheric temperature T_a, performing a first-order Taylor expansion for $e^{-\tau}$ and $e^{-2\tau}$ yields $e^{-\tau} \approx 1-\tau$; $e^{-2\tau} \approx 1-2\tau$. Substituting these into the formula and simplifying, we get:

$$T_B = T_s + \tau\left[(2-\varepsilon)T_a - T_s - 2(1-\varepsilon)T_{sp}\right] + (1-\varepsilon)T_{sp} \qquad (2)$$

Where, the first term on the right-hand side represents the surface brightness temperature, the second term, due to the small τ in polar regions, can be neglected, and the third term represents the sky background radiation, typically less than 1K, which can be disregarded. Therefore, the microwave radiation transfer equation in polar regions can be simplified to:

$$T_B = T_s = \varepsilon t_s \qquad (3)$$

From equation (3), it can be seen that the brightness temperature received by the radiometer is approximately equal to the surface brightness temperature of the Earth. The radiation temperature received by the sensor is influenced by two parameters: the surface emissivity ε and the physical temperature t_s of the surface. ε is related to surface roughness, which is affected by wind speed, while t_s is related to the sea surface temperature.

The radiation brightness temperature received by the sensor can be considered as the linearly weighted sum of the brightness temperatures of various surface types within the field of view of the radiometer, with weights given by the proportions of each surface type. Within the field of view of the microwave radiometer, the brightness temperature is influenced by the emissivities of sea ice and open water. Assuming that there are only three types of surface in the polar region: open water, first-year ice, and multi-year ice, the radiation brightness temperature received by the radiometer is contributed by the sea water, first-year ice, and multi-year ice. The formula for calculating T_B can be expressed as:

$$T_B = C_W T_W + C_{FY} T_{FY} + C_{MY} T_{MY} \qquad (4)$$

Where, C_W,C_{FY} and C_{MY} represent the proportions of open water, first-year ice, and multi-year ice, respectively, while T_W, T_{FY} and T_{MY}represent the brightness temperatures of open water, first-year ice, and multi-year ice, respectively.

The establishment steps of the passive microwave sea ice concentration radiative transfer equation have been provided above. Based on the radiative transfer equation, a simplified radiative transfer equation for sea ice concentration is established by assuming different types of sea ice in the polar region and considering the contribution sources of sensor-received brightness temperatures. The sea ice concentration values are then solved using various solution methods and empirical statistical methods, leading to the development of different sea ice concentration retrieval algorithms.

2.2 The microwave radiation characteristics of sea ice

Sea ice is formed when seawater freezes, consisting of a mixture of ice crystals, brine pockets, and air bubbles. Due to the presence of salt in sea ice, its freezing temperature is typically around -1.8°C. Compared to seawater, sea ice has a higher reflectance to solar radiation, with seawater having an average reflectance of only 0.07, while sea ice ranges from 0.5 to 0.7. Sea ice can be classified into two main categories based on location: fixed ice and drift ice; based on age, it can be categorized as first-year ice or multi-year ice. Sea ice that has grown over one winter season is called first-year ice, while sea ice that has experienced at least one melting season is referred to as multi-year ice. Additionally, sea ice can be classified based on surface features, structure, thickness, distribution, and morphological characteristics. However, in the process of passive microwave sea ice concentration retrieval, sea ice types are mostly considered as first-year ice and multi-year ice, mainly because other sea ice types, although they have distinct characteristics, are difficult to differentiate based on microwave emissivity.

2.3 Passive microwave sensor

Currently, commonly used passive microwave sensors for sea ice concentration retrieval include: (1) the Defense Meteorological Satellite Program (DMSP) carrying the Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave/Imager (SSM/I), and Special Sensor Microwave Imager Sounder (SSMIS); (2) the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) onboard the Aqua satellite and its successor, the Advanced Microwave Scanning Radiometer 2 (AMSR2) onboard the Global Change Observation Mission-Water 1 (GCOM-W1) satellite, which provide higher spatial resolution data (12.5 km); (3) the Microwave Radiation Imager (MWRI) onboard the Fengyun-3 (FY-3) series of satellites from China.

With the development of technology, the future passive microwave sensors will have the following four development trends: (1) towards higher and higher frequencies: the advantage of developing towards higher frequency bands is that it can obtain more detection frequency bands, obtain more detection information, and avoid signal interference from ground and space communication with higher frequency bands; (2) Developing towards more refined detection channels: beneficial for a more detailed understanding of the physical characteristics of the detection object, especially for the detection of atmospheric temperature and humidity profiles. Refined detection layers will be beneficial for improving the accuracy of 3D inversion; (3) Developing towards integration: Multi frequency and multi polarization simultaneous ground observation can provide a more comprehensive and detailed understanding of observation targets; (4) Developing towards higher spatial resolution: obtaining more refined ground object information.

III. Microwave radiometer sea ice density inversion algorithm

Passive microwave remote sensing is the main way to obtain sea ice concentration, and many mature commercial algorithms have been developed. At present, algorithms for analyzing sea ice density using satellite microwave radiometer data include NASA Team algorithm [6], NASA Team 2 algorithm [7], Bootstrap algorithm [8,9], ASI (ARTIST Sea Ice) algorithm [10], NORSEX algorithm [11], Bristol algorithm [12], CalVal algorithm [13], ECICE algorithm [14], etc. Multiple hybrid algorithms have also been developed that use several algorithms: OSI SAF uses several different combinations of algorithms (Bristol+Bootstrap, Bristol+Bootstrap+TUD, Bristol+NASA Team); DMI-Hybrid uses a combination of NASA Team algorithm and Bootstrap algorithm; NIC Hybrid uses a combination of CalVal and NASA Team algorithms [15]. All these algorithms are constantly being improved and perfected, and based on the different microwave frequency channel information used in the algorithms, they can be summarized as high-frequency algorithms and low-frequency algorithms [16]. The two types of algorithms exhibit different advantages and limitations [17]. High frequency algorithms can improve the spatial resolution of sea ice density and provide a more detailed description of sea ice in space. However, high-frequency channels are more sensitive to weather conditions, especially environmental parameters such as water vapor in the atmosphere, liquid water in clouds, precipitation particles, and wind, which can have a certain impact on the inversion results of sea ice density. The sensitivity of low-frequency channels to weather parameters is low, but the spatial resolution of radiation brightness temperature in this channel is low, and the inversion effect is not ideal in the presence of melting pools and ice channels in pixels. The following will provide a brief overview of several typical low-frequency and high-frequency algorithms, as well as other improved inversion methods.

3.1 Low-frequency algorithm

（1） NASA Team algorithm

The NASA Team algorithm [6] was developed by the NASA team and uses two relationships: polarization PR (19) (horizontal and vertical polarization at 19GHz) and gradient GR (37V 19V) (vertical polarization at 19GHz
and37GHz).

$$PR(19)=\frac{T_B(19V)-T_B(19H)}{T_B(19V)+T_B(19H)} \tag{5}$$

$$GR(37V19V)=\frac{\mathrm{T_B}(37V)-\mathrm{T_B}(19V)}{\mathrm{T_B}(37V)+\mathrm{T_B}(19V)} \tag{6}$$

Where, $\mathrm{T_B}$ represents the brightness temperature of the microwave radiometer. The algorithm handles radiation from three surface types: multi-year ice, first-year ice, and open water. Based on this assumption, the brightness temperature of the channels can be determined by Equation (7):

$$\mathrm{T_B}=\mathrm{T_w}(1-\mathrm{C_M}-\mathrm{C_F})+\mathrm{T_F}\mathrm{C_F}+\mathrm{T_M}\mathrm{C_M} \tag{7}$$

Where $\mathrm{T_F}$, $\mathrm{T_M}$ and $\mathrm{T_w}$represent the typical brightness temperatures of first-year ice, multi-year ice, and open water, respectively; $\mathrm{C_F}$ and $\mathrm{C_M}$represent the concentrations of first-year ice and multi-year ice, respectively. The concentrations of first-year ice and multi-year ice can be obtained from PR and GR.

$$\mathrm{C_F}=\frac{\mathrm{a_0}+\mathrm{a_1}\mathrm{PR}+\mathrm{a_2}\mathrm{GR}+\mathrm{a_3}\mathrm{PRGR}}{\mathrm{c_0}+\mathrm{c_1}\mathrm{PR}+\mathrm{c_2}\mathrm{GR}+\mathrm{c_3}\mathrm{PRGR}} \tag{8}$$

$$\mathrm{C_M}=\frac{\mathrm{b_0}+\mathrm{b_1}\mathrm{PR}+\mathrm{b_2}\mathrm{GR}+\mathrm{b_3}\mathrm{PRGR}}{\mathrm{c_0}+\mathrm{c_1}\mathrm{PR}+\mathrm{c_2}\mathrm{GR}+\mathrm{c_3}\mathrm{PRGR}} \tag{9}$$

The coefficients a_i、b_i、c_i（i=0，1，2，3）are determined by nine known brightness temperature values of the surfaces of first-year ice, multi-year ice, and open water under vertical and horizontal polarization at 19GHz, as well as vertical polarization at 37GHz. These typical brightness values serve as reference points and are determined by microwave radiometers (SMMR, SSM/I, SSMI/S) in the Arctic and Antarctic regions.

The NASA Team algorithm uses a simplified radiative transfer equation, assuming that there are three surface types within the satellite observation field of view. Compared to most other algorithms, it can reverse the one-year and multi-year ice density. However, the limitation of this algorithm lies in its weak recognition ability for newly formed ice. In newly formed ice areas, the sea ice density is often underestimated, and the underestimated size is positively correlated with the size of the new ice area [3]. The main reason for its underestimation is that low-frequency channels are more sensitive to the liquid water content in clouds, atmospheric water vapor content, and sea ice surface roughness caused by wind [18].

（2） Boostrap algorithm

The Bootstrap algorithm [8,9] was developed based on clustering analysis of the distribution of emission points in three channels. The algorithm is divided into two modes: polarization mode and frequency mode. Polarization mode is mainly used for ice fixation, while frequency mode can distinguish the effects of the atmosphere and ocean on open water areas with low sea ice concentration, as well as the emissivity changes caused by surface effects such as ice and snow cover in actual changes in sea ice concentration. The frequency mode uses vertical polarization at 19GHz and 37GHz to calculate sea ice density, while the polarization mode uses vertical polarization and horizontal polarization brightness temperature at 37GHz to calculate sea ice density.

（3） Bristol algorithm

The Bristol algorithm [12] is conceptually similar to the Bootstrap algorithm, which uses a three-dimensional pattern of satellite surface brightness temperature and has three channels: 37GHz vertical and horizontal polarization, and 19GHz vertical polarization. However, unlike the Bootstrap algorithm, the Bristol algorithm constructs projections perpendicular to the satellite data plane by introducing coordinate transformations.

The Bristol algorithm is mainly aimed at overcoming the limitations of NASA Team algorithm and Bootstrap algorithm, such as the sensitivity of horizontal polarization brightness temperature to lower layer snow and the problem of discontinuous sea ice density obtained by Bootstrap algorithm when switching modes. The principle of Bristol algorithm is the same as that of Boostrap algorithm, which performs spatial transformation on sea ice density in low-frequency channels, improving the inversion accuracy of sea ice density in high density ice regions. The Bristol algorithm uses a three-dimensional scatter plot and incorporates polarization and frequency schemes into the transformation coordinates, namely:

$$x=TB_{37V}+1.045TB_{37H}+0.525TB_{19V} \tag{10}$$

$$y=0.9164TB_{19V}-TB_{37V}+0.4965TB_{37H} \tag{11}$$

where TB_{37V}, TB_{37H}, and TB_{19V} represent the vertical polarization at 37GHz, horizontal polarization at 37GHz, and vertical polarization brightness temperature at 19GHz, respectively. This algorithm maximizes the utilization of satellite data differences across three channels. Compared to the Bootstrap algorithm, the Bristol algorithm has the advantage of smaller noise.

（4） CalVal algorithm

The CalVal algorithm [13] has been developed for studying, calibrating, and inspecting SSM/I instruments. This algorithm is an improvement of the AES/York algorithm, and its sea ice density is determined by a linear combination of brightness temperatures vertically polarized in 19GHz and 37GHz channels:

$$\mathrm{C} = \mathrm{C}_1 \mathrm{T}_\mathrm{B}(37\mathrm{V}) + \mathrm{C}_2 \mathrm{T}_\mathrm{B}(19\mathrm{V}) + \mathrm{C}_3 \quad (12)$$

where, C_i is the coefficient determined for summer and winter respectively, which is a function of the emissivity of ice and water, as well as the Archie effect. This algorithm can effectively identify ice edges and fully calculate the density of thin ice and sparse ice.

（5） OSI SAF algorithm

The OSI SAF algorithm [19] is a hybrid algorithm developed by the European Organization for the Exploration of Meteorological Satellites (EUMETSAT) for ocean and sea ice satellite applications. It is a linear combination of the Bootstrap algorithm (frequency mode) and Bristol algorithm, using radiation transfer models and numerical weather prediction (NWP) data to correct brightness temperature. The two algorithms have two advantages: one algorithm has been adjusted to perform better in open water and low sea ice density conditions, and the other has been adjusted to perform better in dense ice and high sea ice density conditions. The combination equation of the two algorithms is very simple, which is the linear weighted average of the results of B_{OW} and B_{CI} expressed as follows:

$$\begin{cases} w_{ow} = 1, & B_{ow} < 0.7 \\ w_{ow} = 0, & B_{ow} > 0.9 \\ w_{ow} = 1 - \dfrac{B_{ow} - 0.7}{0.2}, & 0.7 \le B_{ow} \le 0.9 \end{cases} \quad (13)$$

$$SIC_{hybird} = w_{ow} \times B_{ow} + (1 - w_{ow}) \times B_{CI} \quad (14)$$

where, w_{ow} refers to the weight of open water, B_{OW} is the algorithm used in low density areas, and B_{CI} is the algorithm used in high density areas. SIC_{hybird} is a fusion algorithm that combines two algorithms, with a range of [0,1]. In the OSISAF algorithm, the frequency mode of Bootstrap is selected as B_{OW}, and the Bristol algorithm is selected asB_{cI} [20].

（6） SICCI algorithm

The SICCI algorithm developed by ESA and the OSISAF algorithm are similar in that they linearly combine sea ice concentration results obtained from the Bootstrap and Bristol algorithms to generate mixed sea ice concentration [21]. The CalVal algorithm exhibits high accuracy in regions with low sea ice concentration and open water areas, while the Bristol algorithm performs well in regions with high sea ice concentration. Combining the CalVal and Bristol algorithms linearly can improve the accuracy of sea ice concentration inversion [22].

For thin ice, the performance of the CalVal algorithm is better, and its weight is defined as follows: When the Sea Ice Concentration (SIC) value is less than 70%, it is obtained by the CalVal algorithm, and the weight of the algorithm is $W_{CV} = 1$. When the SIC value is greater than or equal to 90%, the weight of the algorithm is $W_{CV} = 0$. When the SIC value is between 70% and 90%, the weight of the CalVal algorithm is defined as:

$$W_{CV} = 1 - \frac{SIC_{CV} - 0.7}{0.2} \quad (15)$$

Where SIC_{CV} is the SIC obtained by the CalVal algorithm, and the weight of the Bristol algorithm is $1-W_{CV}$.

The above low-frequency sea ice density inversion algorithms all use low-frequency data with low spatial resolution that is less affected by external factors. The obtained sea ice density results are less affected by external factors but have low spatial resolution.

3.2 High-frequency algorithm

（1） NASA Team2 algorithm

The NASA Team2 algorithm is often considered an improved version of the NASA Team algorithm, which has the same inversion equation as the NASA Team algorithm [23]. The NASA Team2 algorithm defined three new parameters by rotating PR and GR, and established a parameter database for different sea ice densities and atmospheric conditions using a forward microwave radiation model. The observed data was matched with simulated data to obtain the optimal sea ice density result [24]. Therefore, the inversion accuracy caused by the characteristics of the algorithm itself depends on the accuracy of the sample database. With the changes in global climate and environment, the error of sample databases will increase year by year, and the accuracy of inversion will also be affected. Due to the insensitivity of high-frequency channels to the surface state of sea ice, NASA Team2 algorithm added 85GHz channel data on the basis of NASA Team algorithm, which can solve the problem of underestimation of sea ice density caused by surface effects, and obtain high-resolution inversion results of sea ice density. The defined PR and GR are as follows:

$$PR_R(19) = -\mathrm{GR}(37\mathrm{V}19\mathrm{V}) \sin \emptyset_{19} + \mathrm{PR}(19) \cos \emptyset_{19}$$

$$\Delta GR = GR(85H19H) - GR(85V19V)$$

（2） Near 90GHz algorithm

The Near 90GHz algorithm [10] inverts sea ice density from high-frequency channel data based on polarization differences in 85GHz channels. In order to compensate for the impact of different atmospheric conditions and ice radiation characteristics on high-frequency data, the algorithm is self adjusted. Interpolate the sea ice density of 100% sea ice and 0% open water using a smoothing function:

$$C_T = \left(1 + \frac{b}{a}\right)\frac{P}{P_1} - \frac{b}{a}, \quad C_T \to 1 \tag{16}$$

$$C_T = \left(\frac{b}{a}\right)\frac{P}{P_0} - \frac{b}{a}, \quad C_T \to 0 \tag{17}$$

$$P_1 = \left(1 + \frac{a}{b}\right) P_0 \tag{18}$$

where, b and a are constants, depending on the brightness temperature of sea ice and open water. P_0 and P_1 are the polarimetric differences of sea ice and open water, respectively [8], that is:

$$P = T_B^V - T_B^H \tag{19}$$

Assuming that the variation of atmospheric effects is a smooth function of C_T, apply a third-order polynomial to interpolate between the equations:

$$C_T = d_3P^3 + d_2P^2 + d_1P + d_0 \tag{20}$$

The typical values of sea ice characteristics are:

$$\frac{b}{a} = \frac{\Delta\varepsilon_w 272}{\Delta\varepsilon_{ice}T_{ice} - \Delta\varepsilon_w 272} = -1.14 \tag{21}$$

Substituting P_0 and P_1 into a third-order polynomial yields:

$$\begin{matrix} P_1^3 & P_1^2 & P_1 & 1 \\ P_0^3 & P_0^2 & P_0 & 1 \\ 3P_1^2 & 2P_1^2 & P_1 & 1 \\ 3P_0^2 & 2P_0^2 & P_0 & 1 \end{matrix} \begin{bmatrix} d_3 \\ d_2 \\ d_1 \\ d_0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ -0.14 \\ -1.14 \end{bmatrix} \tag{22}$$

Therefore, by using several sets of P_0 and P_1 values, variables d_0, d_1, d_2 and d_3 can be determined. Substituting them into equation (20), the sea ice concentration can be obtained.

（3） ASI algorithm

The ASI algorithm is designed to effectively utilize the advantages of high-resolution data while reducing atmospheric impact [25]. It is an improvement on the Svendsen algorithm [26] (using nearly 90GHz channels to invert sea ice), with the core idea that the horizontal and vertical polarization differences of all sea ice types (including seasonal ice, multi-year ice, etc.) at 89GHz emissivity are much smaller than those of seawater. Therefore, the horizontal and vertical polarization bright temperature difference at this frequency can be used to calculate sea ice density. If ac is the atmospheric influence rate and PS is the surface polarization brightness temperature difference, then the polarization brightness temperature difference based on sea ice density can be expressed as:

$$\mathrm{P(C)} = \mathrm{P_s a_c} = \left(\mathrm{CP_{s,i}} + (1 - \mathrm{C})\mathrm{P_{s,w}}\right)\mathrm{a_c} \tag{23}$$

where $\mathrm{P_{s,i}}$ and $\mathrm{P_{s,w}}$ represent the polarization brightness temperature difference between sea ice and open water, respectively, and C represents the density of sea ice. Therefore, when C=0, the polarization difference $\mathrm{P_0}$ of water and the polarization difference $\mathrm{P_1}$ of sea ice at C=1 can be expressed as:

$$\mathrm{P_0} = \mathrm{a_0 P_{s,w}} \tag{24}$$

$$\mathrm{P_1} = \mathrm{a_1 P_{s,i}} \tag{25}$$

where, $\mathrm{a_0}$ and $\mathrm{a_1}$ are the atmospheric impact rates at C=0 and C=1, respectively, and $\mathrm{P_0}$ and $\mathrm{P_1}$ are the coefficient values of the algorithm. By Taylor expanding equation (23) at C=0 and C=1 respectively, removing higher-order terms, and assuming that the atmospheric influence changes very little in all sea ice covered areas or non ice covered areas, we can obtain:

$$\mathrm{P} = \mathrm{a_0 C}\left(\mathrm{P_{s,i}} - \mathrm{P_{s,w}}\right) + \mathrm{P_0} \text{when } C \to 0 \tag{26}$$

$$\mathrm{P} = \mathrm{a_1}(\mathrm{C} - 1)\left(\mathrm{P_{s,i}} - \mathrm{P_{s,w}}\right) + \mathrm{P_1} \text{when } C \to 1 \tag{27}$$

Next

$$C=\left(\frac{P}{P_0}-1\right)\left(\frac{P_{s,w}}{P_{s,i}-P_{s,w}}\right)\text{when } C\to 0\#(28)$$

$$C=\frac{P}{P_1}+\left(\frac{P}{P_0}-1\right)\left(\frac{P_{s,w}}{P_{s,i}-P_{s,w}}\right)\text{when } C\to 1\#(29)$$

For the Arctic, usually the ratio of $\frac{P_{s,w}}{P_{s,i}-P_{s,w}}$=-1.14. To calculate all sea ice densities between 0 and 100%, sea ice density is a cubic function of polarization difference, in the following form:

$$C=d_3P^3+d_2P^2+d_1P+d_0 \quad (30)$$

The coefficients d_0、d_1、d_2 and d_3 can be obtained by solving a system of quaternion linear equations:

$$\begin{matrix} {P_0}^3 & {P_0}^2 & P_0 & 1 \\ {P_1}^3 & {P_1}^2 & P_1 & 1 \\ 3{P_0}^3 & 2{P_0}^2 & P_0 & 0 \\ 3{P_1}^3 & 2{P_1}^2 & P_1 & 0 \end{matrix}\begin{bmatrix} d_3 \\ d_2 \\ d_1 \\ d_0 \end{bmatrix}=\begin{bmatrix} 0 \\ 1 \\ -1.14 \\ -0.14 \end{bmatrix} \quad (31)$$

The ASI algorithm is designed to address the significant atmospheric impact on high-frequency channels, where cyclone activity may lead to open water being mistakenly identified as sea ice. Three weather filters were set up to eliminate the influence of liquid water in high-altitude clouds using spectral gradient ratios of 36.5GHz and 18.7GHz channels, respectively; Using the spectral gradient ratio of channels 23.8GHz and 18.7GHz to eliminate the influence of water vapor over open water areas; At the same time, referring to the results of the Bootstrap algorithm, set the corresponding point of the point with zero sea ice density in the ASI algorithm to zero [3].

（4） ASI 3 algorithm

Lu et al. [27] improved the ASI algorithm based on 89GHz brightness temperature data in 2019, resulting in the ASI 3 algorithm. The observation data of these weather effects were corrected using radiation transfer models and optimal estimation methods to retrieve geophysical data. ASI3 reduced the weather effects on floating ice and obtained more accurate retrieval results.

ASI3 weather correction is achieved through the use of OEM atmospheric inversion to simulate changes in brightness temperature caused by atmospheric effects and wind induced rough scattering on the ocean surface. Using this process as a model to convert atmospheric brightness temperature values into near surface brightness temperature values also corrects for some of the effects of temperature and wind on the surface. The radiative transfer model simulates brightness temperature values in two scenarios: (1) a clear and dry atmosphere (TB_{M0}), assuming that the reference surface temperature (T_{ref}) is 271.15K for seawater and 250K for sea ice, and all other parameters (TWV, CLW, wind speed) are zero; (2) The actual atmospheric conditions described in the OEM dataset (TB_{MA}). The difference between these two simulated brightness temperature values is considered to be caused by weather effects from the surface and atmosphere. The corrected brightness temperature value (TB_C) is calculated using the following formula:

$$TB_{MA}=F\left(W,V,L,T_s,SIC_{bkg}\right) \quad (32)$$

$$TB_{M0}=F\left(0{,}0{,}0,T_{ref},SIC_{bkg}\right) \quad (33)$$

$$TB_C=TB_{sat}-\left(TB_{MA}-TB_{M0}\right) \quad (34)$$

Where W, V, L, and Ts are wind, TWV, CLW, and surface temperature from OEM data, respectively. F represents the forward model.

The total sea ice density is represented by a third-order polynomial of PD_{89}, with the standard ASI algorithm using observed PD_{89} values as input, and ASI3 using weather corrected values. The polynomial coefficients are determined by the typical values of PD89 on water surface (P0) and frozen ice (P1), known as the junction point. The combination points used in the standard ASI algorithm are P0=47K and P1=11.7K, which also include weather effects. For the ASI3 algorithm, the tie points are adjusted to new values that are not affected by weather, P0=80K and P1=14K. Based on new binding points and boundary conditions, derive a new polynomial for ASI3:

$$C(\text{ASI3})=1.39\times10^{-6}PD_{89}^3-2.28\times10^{-4}PD_{89}^2+0.0044PD_{89}+1.1029 \quad (35)$$

Under ideal weather correction, sea ice concentration should be a linear function of the corrected polarization difference at 89GHz. However, the coefficients of ASI3 corrected for weather conditions differ significantly, resulting in polynomials that are very close to linear functions. In the range of 0% -100%, the average deviation between sea ice density and linearity is 2.3%. Therefore, the nonlinear method is retained, and for all PD89 values greater than P0 or less than P1, the corresponding sea ice density is set to 0% or 100%, respectively.

(5) ECICE algorithm

Shokr et al. [28] proposed the ECICE (Environment Canada's Ice Concentration Extractor) algorithm, which combines observational data from several different satellite sensors to address the issue of mistakenly identifying multi-year ice as one-year ice during seasonal transitions. ECICE is considered the optimal method for minimizing errors between observed values and predicted concentrations.

ECICE can be used for any combination of remote sensing observations to analyze any number of surfaces, provided that the number of observations is at least equal to the number of given ice types. This method uses a radiation mixing model, solves the radiation equation by using constraint optimization techniques, and treats each type of ice as a probability distribution rather than a single value. The addition of information from multiple sensor combinations to ECICE enables the extension of reliable estimates of the number and type of sea ice surfaces. The ECICE algorithm uses brightness temperature data from high-frequency channels, and calculates the density of different types of ice by normalizing the difference between the observed and calculated brightness temperature values.

$$\begin{aligned} \mathrm{f} = & \left(\sum_{i=1}^{i=4}\left(c_i \varepsilon_{85V,i} T_s - T_{B,85V}\right)/T_{B,85V}\right)^2 + \left(\sum_{i=1}^{i=4}\left(c_i \varepsilon_{85H,i} T_s - T_{B,85V}\right)/T_{B,85H}\right)^2 \\ & + \left(\sum_{i=1}^{i=4}\left(c_i PR_{85,i} - PR_{85}\right)/PR_{85}\right)^2 \\ & + \left(\sum_{i=1}^{i=4} c_i - 1\right)^2 \end{aligned} \tag{36}$$

where, i represents three types of ice and open water; c_i represents the density of three types of ice and open water; $\varepsilon_{85V,i}$ and $\varepsilon_{85H,i}$ are the emissivities of three types of ice and water with vertical and horizontal polarization at 85GHz frequency, respectively; T_s is the physical temperature of the surface; $T_{B,85V}$ and $T_{B,85H}$ are the brightness temperatures observed in the vertical and horizontal polarization directions at 85GHz, respectively; $PR_{85,i}$ and PR_{85} are calculated polarization differences and observed polarization differences at 85GHz, respectively. $T_{B,85V}$, $T_{B,85H}$, and PR_{85} require atmospheric correction through the following three parameters: total water vapor, cloud liquid water, and wind speed near open water areas. In addition, the algorithm uses a filter for open water areas: $T_{B,85V} \leq 1000 GR_{85V37V} + 192.5$. If this relationship holds and the surface temperature is higher than -3 ℃, it is assumed that the pixel contains open water areas and is excluded from optimization.

The above high-frequency sea ice density inversion algorithms all use high-frequency data with high spatial resolution that is greatly affected by external factors. It is necessary to reduce the influence of external environment during use to obtain sea ice density results with low external influence but high spatial resolution. But its accuracy still needs further improvement.

3.3 Other

(1) Combination of high and low frequencies

Liang [20] focused on the Arctic and Antarctic regions and proposed a new method for merging passive microwave remote sensing sea ice concentration retrieval methods in response to the error characteristics of current methods. Based on the overall performance of the ASI algorithm and the Bootstrap algorithm, which perform best respectively in the Arctic and Antarctic regions, ASI algorithm and Bootstrap algorithm were selected as benchmark algorithms. Considering their opposite low and high bias characteristics in the marginal areas of sea ice in both polar regions and during the summer period, an effective fusion was conducted to eliminate the bias impact and form a new sea ice concentration fusion algorithm.

The algorithm adopts different fusion strategies in the Arctic and Antarctic regions, considering both spatial (such as large errors in sea ice marginal zones) and temporal (such as large errors in summer) influences. In the Arctic region, in areas of medium to high sea ice concentration (SIC>30%), the ASI algorithm is primarily used, while in low concentration areas (typically considered as sea ice marginal zones, SIC<=30%), the weights of the ASI algorithm and the Bootstrap algorithm are dynamically adjusted to improve the accuracy of SIC estimation in the marginal zones. In the Antarctic region, in areas of medium to high sea ice concentration (SIC>30%), the Bootstrap algorithm is primarily used, while in low sea ice concentration areas (SIC<=30%), the weights of the Bootstrap algorithm and the ASI algorithm are dynamically adjusted to improve the accuracy of SIC estimation in the marginal zones. In addition to focusing on fusion in low sea ice concentration areas (sea ice marginal zones), the new algorithm also focuses on fusion during the summer period. Consistency assessment results reveal that during the summer period (specifically from June to September in the Arctic and from January to April in the Antarctic), the phenomenon of underestimation by the

ASI algorithm and overestimation by the Bootstrap algorithm is most pronounced. Therefore, during the summer period in the Arctic and Antarctic regions, the inversion algorithms of both methods are fused.

According to the spatial characteristic fusion scheme, in the Arctic region:

$$SIC_{Arc} = a \times C_{ASI} + (1-a) \times C_{BT} \begin{cases} a = 1 & C_{ASI} > 30\% \\ a = 1 - \frac{0.3 - C_{ASI}}{0.3} & C_{ASI} \leq 30\% \end{cases} \tag{37}$$

According to the spatial characteristic fusion scheme, in the Antarctic region:

$$SIC_{Ant} = a \times C_{ASI} + (1-a) \times C_{BT} \begin{cases} a = 0 & C_{ASI} > 30\% \\ a = \frac{0.3 - C_{BT}}{0.3} & C_{ASI} \leq 30\% \end{cases} \tag{38}$$

According to the temporal characteristic fusion scheme, in the Arctic region:

$$SIC_{Arc} = a \times C_{ASI} + (1-a) \times C_{BT} \begin{cases} a = \frac{1}{2} & month = 6\sim 9\ months \\ a = 1 & month = others \end{cases} \tag{39}$$

According to the temporal characteristic fusion scheme, in the Antarctic region:

$$SIC_{Ant} = (1-a) \times C_{ASI} + a \times C_{BT} \begin{cases} a = \frac{1}{2} & month = 1\sim 4\ months \\ a = 1 & month = others \end{cases} \tag{40}$$

Where SIC_{Arc} and SIC_{Ant} represent the sea ice concentration results for the Arctic and Antarctic, respectively, C_{ASI} denotes the sea ice concentration inversion results based on the ASI algorithm, C_{BT} represents the sea ice concentration inversion values based on the Bootstrap algorithm, and a signifies the algorithm fusion weight.

Although the above algorithms have improved the accuracy of sea ice concentration inversion to some extent, the mechanism of integration needs further investigation.

（2） Using temperature reanalysis data

Ye et al. [29] improved the retrieval of multi-year ice (MYI) concentration in 2016 using temperature reanalysis data. They corrected the MYI concentration through detection and replacement, effectively replacing anomalous MYI concentration with interpolated values, resulting in better correction. This method avoids data adjustments due to weather or surface influences, addressing the issue of the ECICE algorithm misclassifying MYI as FYI during warm autumn periods.

Weather correction is based on daily variations in air temperature and MYI concentration. Depending on a threshold related to air temperature, when the daily variation in MYI concentration reaches or exceeds another threshold, the correction process is triggered. Additionally, a third threshold for air temperature is needed to signify the end of the correction process. Sudden increases and decreases in MYI concentration mark the beginning and end of misclassification periods, corresponding to sharp increases and decreases in surface ice temperatures, respectively, as shown in Table 1.

Table 1 Examples of corrections in the fall warm period

September	23	24	25	26	27
F_1	0	1	0	0	0
F_2	0	0	0	0	1
N_{Flag}	0	3	0	0	0
C_{MYI}	C_B	C_1	C_2	C_3	C_A
C'_{MYI}	C_B	C'_1	C'_2	C'_3	C_A

In Table 1, two flags, F_1 and F_2, are initially defined. Flag F_1 indicates the decrease of multi-year ice (MYI) due to high temperatures, while flag F_2 denotes the increase of MYI caused by the return to low temperatures. If conditions for F_1 and F_2 are met, they are set to 1.

$$F_1 = 1\ if\text{：}\ T > T_1\text{，}\ and\ \Delta C_{MYI} < -\Delta C_M \tag{41}$$

$$F_2 = 1\ if\text{：}\ T < T_2\text{，}\ and\ \Delta C_{MYI} > \Delta C_M \tag{42}$$

where, T is the surface air temperature, ΔC_{MYI} is the daily variation of MYI intensity. T_1, T_2, and ΔC_M are three thresholds used to determine the flag, and MYI correction begins with the change of F_1 from 0 to 1 and ends with the change of F_2 from 0 to 1. C_B and C_A in Table 1 represent the MYI intensity before and after the misclassification period (i.e. September 23 and September 27). At the beginning of the adjustment (September 24th), the decrease (absolute value) in MYI intensity change ΔC_{MYI} (i.e. C_1-C_B on September 24th) must be greater than the threshold ΔC_M.

Next, let N_{Flag} denote the number of days identifying misclassified categories. During this period, the erroneously estimated concentration of multi-year ice (MYI) is replaced by interpolation based on C_B and C_A。

The formula for calculating the corrected sea ice concentration C_i' for the i -th day is as follows:

$$C_i' = C_B + i * \frac{C_A - C_B}{N_{Flag} + 1}, \quad i \in \{1,2,\ldots,N_{Flag}\} \#(43)$$

（3） Using ice drift recording

Ye et al. [30] used ice drift records to constrain MYI changes in 2016, and used two thresholds of passive microwave radiation parameters to consider the wetting and metamorphism of snow. This correction method can effectively remove high MYI density anomalies.

The wetting and metamorphism of snow can cause significant changes in microwave brightness and backscattering, leading to the misidentification of FYI as MYI. In many cases, an increase in temperature increases the likelihood of abnormal microwave signals. For a given day, pixels with MYI density exceeding 15% are identified. These pixels constitute the MYI domain for a certain day, and by utilizing the daily ice motion vector, the multi-year ice region is correspondingly expanded to generate a new MYI domain. For pixels located outside the new area, the MYI density on the second day is corrected without checking for any radiation indicators such as snow humidity and deterioration. For pixels in the new domain, the indicator should be checked to determine that the initial estimated density is indeed abnormal.

（4） Based on deep learning and neural networks

In recent years, deep learning based on multi-channel, multipolar, and multi-sensor microwave radiometer data has become an important method for sea ice detection. Belchansky et al. used an improved multi-layer perceptron neural network to invert the concentration of Arctic sea ice over the years based on SSM/I brightness temperature data (19H, 19V, and 37V) [31]. Based on techdemosat-1 data, Yan et al. proposed a method for sea ice detection and inversion of sea ice density using Convolutional Neural Networks (CNN) [32]. Wang et al. used CNN to invert sea ice density based on synthetic aperture radar (SAR) data [33]. Karvonen used multi-layer perceptrons to invert sea ice density based on Sentinel-1 SAR data and AMSR2 data [34]. Chi et al. used deep learning to invert Arctic sea ice concentration based on scanning multi-channel microwave radiometer (SMMR) data and SSM/I data [35]. Chi et al. used deep learning methods to invert Arctic sea ice density based on AMSR2 data [36]. Choi et al. used artificial neural networks to predict Arctic sea ice concentration [37].

3.4 Sea ice concentration products

The European Meteorological Satellite Organization, European Space Agency (ESA), University ä t Bremen, National Oceanic and Atmospheric Administration (NOAA) of the United States, National Snow and Ice Data Center (NSIDC) of the United States, University ä t Hamburg of Germany, and China's National Satellite Meteorological Center have released numerous sea ice concentration products based on microwave radiometer data.

Based on the OSISAF hybrid algorithm and using the ECMWF numerical model results for atmospheric correction, three global sea ice concentration products with resolutions of 10 km and 25 km were released. The European Space Agency has developed three resolutions of sea ice density products based on the SICCI hybrid algorithm. The University of Bremen used ASI and BT algorithms to obtain regional and global sea ice concentration products based on AMSR-E/AMSR2 data; By combining high-resolution MODIS thermal infrared data and AMSR2 data, a winter Arctic sea ice concentration product with a resolution of 1 km was obtained. The National Oceanic and Atmospheric Administration of the United States has released a VIIRS sea ice concentration product with a resolution of 750 meters. The US Ice and Snow Data Center has released multiple sea ice density products, and three representative products were obtained through inversion based on the Bootstrap algorithm, NASA Team algorithm, and NASA Team2 algorithm, respectively. The University of Hamburg in Germany has improved the ASI algorithm (using a 5-day median filter to reduce weather effects) and produced a sea ice density product with a resolution of 12.5 km based on SSM/I-SSMIS data. The China National Satellite Meteorological Center provides polar daily and ten-day products with a resolution of 12.5 km based on the MWRI microwave imaging data from the FY-3 satellite.

3.5 Precision evaluation of sea ice concentration

The evaluation of sea ice density commonly uses the following three methods: (1) ship measurement data: through manual visual discrimination; (2) High resolution optical data: obtaining sea ice density results from optical data; (3) Synthetic Aperture Radar (SAR): Obtaining sea ice density from SAR.

IV. Conclusion

This article mainly introduces the basic principle of passive microwave remote sensing inversion of sea ice density, and then elaborates on the passive microwave sea ice density inversion methods, which are divided into low-frequency and high-frequency algorithms. The inversion principles and main derivation formulas are briefly introduced, and the development process of passive microwave remote sensing in sea ice monitoring is summarized. The problems and solutions it faces are analyzed. Passive microwave remote sensing monitoring of sea ice concentration has the disadvantage of being greatly affected by the environment, and in future research, it is necessary to improve accuracy through optimization algorithms.

Future research on optimization algorithms will focus on the following aspects: (1) Combining existing algorithms to improve the accuracy of sea ice concentration inversion, that is, utilizing the advantages of different algorithms to complement each other to improve the inversion accuracy of sea ice concentration, such as combining high and low frequency algorithms, combining low frequency algorithms, and combining high frequency algorithms; (2) For low-frequency algorithms, improvements are made to the inversion method of sea ice density to improve the accuracy of sea ice density inversion. This involves identifying existing problems in the inversion of sea ice density and improving the existing algorithms. For example, multiple sea ice density inversion formulas can be determined based on seasons or regions, more representative coefficient values can be determined to obtain more accurate sea ice density inversion formulas, and better methods can be found to obtain coefficient values to obtain higher accuracy sea ice density results; (3) For high-frequency algorithms, although they have the advantage of high resolution, they are also easily affected by external environmental factors. Therefore, reducing external environmental factors can be used to improve the inversion accuracy of sea ice density. For example, weather filters can be improved, and data that is heavily affected by external environmental interference can be filtered out and corrected through other means and methods.

Acknowledgement

This research was supported by the Open Fund Project of Key Laboratory of Ocean Observation Technology (No. 2021KLOOTA09), and the Key Laboratory of Grain Information Processing and Control (Henan University of Technology), Ministry of Education (No. KFJJ-2020-113)

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