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Sea Ice and Atmospheric Parameter Retrieval From Satellite Microwave Radiometers: Synergy of AMSR2 and SMOS Compared With the CIMR Candidate Mission

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Abstract Research on improving the prediction skill of climate models requires refining the quality of observational data used for initializing and tuning the models. This is especially true in the polar regions where uncertainties about the interactions between sea ice, ocean, and atmosphere are driving ongoing monitoring efforts. The Copernicus Imaging Microwave Radiometer (CIMR) is an European Space Agency (ESA) candidate mission which promises to offer high resolution, low uncertainty observation capabilities at the 1.4, 6.9, 10.65, 18.7, and 36.5 GHz frequencies. To assess the potential impact of CIMR for sea ice parameter retrieval, a comparison is made between retrievals based on present AMSR2 observations and a retrieval using future CIMR equivalent observations over a data set of validated sea ice concentration (SIC) values. An optimal estimation retrieval method (OEM) is used which can use input from different channel combinations to retrieve seven geophysical parameters (sea ice concentration, multi-year ice fraction, ice surface temperature, columnar water vapor, liquid water path, over ocean wind speed, and sea surface temperature). An advantage of CIMR over existing radiometers is that it would provide higher spatial resolution observations at the lower frequency channels (6.9, 10.65, and 18.7 GHz) which are less sensitive to atmospheric influence. This enables the passive microwave based retrieval of SIC and other surface parameters with higher resolution and lower uncertainty than is currently possible. An information content analysis expands the comparison between AMSR2 and CIMR to all retrievable surface and atmospheric parameters. This analysis quantifies the contributions to the observed signal and highlights the differences between different input channel combinations. The higher resolution of the low frequency CIMR channels allow for unprecedented detail to be achieved in Arctic passive microwave sea ice retrievals. The presence of 1.4 GHz channels on board CIMR opens up the possibility for thin sea ice thickness (SIT) retrieval. A combination of collocated AMSR2 and SMOS observations is used to simulate a full CIMR suite of measurements, and the OEM is modified to include SIT as a retrieval parameter. The output from different retrieval configurations is compared with an operational SIT product. The CIMR instrument can provide increased accuracy for SIC retrieval at very high resolutions with a combination of the 18.7 and 36.5 GHz channels while also maintaining sensitivity for atmospheric water vapor retrieval. In combination with the 1.4 GHz channels, SIT can be added as an eighth retrieval parameter with performance on par with existing operational products.

Plain Language Summary In order to improve exiting climate models a number of challenges have to be overcome which have to do with interactions between sea ice, the open ocean, and the atmosphere. One way to address these challenges is to use higher quality satellite observations of these variables for tuning and running these models. The Copernicus Imaging Microwave Radiometer is an European Space Agency Candidate mission which promises to offer high resolution and accurate observations at the 1.4, 6.9, 10.65, 18.7, and 36.5 GHz frequencies. At present one of the highest resolution sea ice concentration products is based on the 89 GHz channels of the AMSR2 satellite instrument. This frequency however is not ideal for observing surface parameters as it is sensitive to the presence of clouds. The lower frequency channels of the CIMR instrument are less influenced by the atmosphere. As such these frequencies would be much better suited for observing multiple sea ice parameters like concentration, different ice types, the sea ice thickness, and surface temperature as well as ocean parameters such as sea surface temperature, sea surface salinity, and ocean wind speed. Based on this we
perform a performance comparison between the existing AMSR2 89 GHz and different CIMR channel combinations. The analysis is done using a common retrieval method for up to seven different parameters (sea ice concentration, ice types, ice surface temperature, sea surface temperature, ocean wind speed, total water vapor, and cloud liquid water) and which allows for using single or multifrequency channels as input. The focus is on the retrieval of sea ice concentration, but the other atmospheric and surface parameters are discussed as well. The CIMR 6.9 GHz channel offers the best sea ice concentration performance with a resolution of 15 km and an accuracy around 2%. The CIMR channel combination of 18.7 and 36.5 GHz offers good sea ice concentration accuracy at 4% but at a much higher resolution of 5 km, which is comparable with the present day AMSR2 89 GHz high resolution product. Using the CIMR channel combination also provides good sensitivity for retrieving the atmospheric parameters cloud liquid water and water vapor content. By using the full set of CIMR channels, including the two 1.4 GHz ones, sea ice thickness values below 30 cm can be retrieved alongside the other seven parameters.

1. Introduction

The Arctic sea ice and its seasonal variability heavily influence the heat balance between the atmosphere and the ocean. The Arctic is affected more than any other region by global warming, and its evolution is a sensitive indicator for global climate change. Therefore, the increased activity in an ice diminished Arctic calls for regular higher resolution and reliable observations.

Satellite monitoring efforts have shown that sea ice extent has been in decline throughout all months of the year since 1979. This trend has been accelerating since the early 1990s (Comiso et al., 2017). A recent study combining submarine sonars, satellite altimeters, and satellite scatterometers concludes that Arctic sea ice thickness has declined by 66% over the last six decades while the fraction of old sea ice that has survived multiple melt seasons has decreased by 50% between 1999 and 2017 (Kwok, 2018).

Single parameter retrieval methods based on passive microwave satellite measurements have been developed for sea ice concentration (SIC) retrieval, for example, Comiso et al. (1997), Svendsen et al. (1987), Spreen et al. (2008), Shokr et al. (2008), and Markus and Cavalieri (2000), as well as for integrated water vapor content (Melsheimer & Heygster, 2008; Scarlat et al., 2018). In such algorithms the contribution of the retrieved parameter is the signal of interest while the contributions from all the other geophysical parameters that also influence the microwave emission are seen as noise that needs to be filtered out or compensated for by using other channels of the radiometer or through a priori data.

The basic idea of multiparameter retrieval is to find a set of geophysical parameters which, if applied to a forward model, simultaneously yield a best possible approximation of the observed brightness temperatures for all radiometer channels. Over open ocean, such a retrieval exists and has been applied for more than a decade, for example, Wentz and Meissner (2000). However, over sea ice, an integrated retrieval is much more difficult. The main challenge is the high and highly variable surface emissivity which dominates the microwave signal. Although sea ice forward models exist (e.g., Tonboe, 2005), their use in integrated retrieval has been limited because the number of required geophysical parameters is high and their values are generally unknown, so that until now only little effort has been undertaken for integrated retrieval of surface and atmospheric parameters over sea ice (Kongoli et al., 2011; Pedersen, 2019; Scarlat et al., 2017) compared to the established retrieval methods over open ocean. In order to take advantage of the multispectral capabilities of imaging radiometers, in Melsheimer et al. (2008) an integrated retrieval method is proposed that can retrieve the seven geophysical parameters: wind speed over ocean (WSP), integrated total water vapor (TWW), liquid water path (LWP), sea surface temperature (SST), ice surface temperature (IST), sea ice concentration (SIC), and multi-year ice fraction (MYIF).

An optimal estimation method (OEM) is used to invert the forward model and extract the ensemble of seven parameters that optimally match the observed brightness temperatures. A priori information from climatological and meteorological sources is used to constrain the method to the natural variability of each parameter.

This approach was further developed in Scarlat et al. (2017) by establishing the method sensitivity to the chosen constraints and potential sources of bias. Initial tests indicated deficiencies in the forward model
stemming from the implementation of the empirical sea ice emissivities and the treatment of the ice surface temperature. A number of corrections were subsequently developed in Scarlat (2018), and the resulting OEM configuration was tested against other retrieval products over all parameters. The OEM has been developed for the AMSR series of instruments in order to take advantage of the different parameter sensitivities offered by the full instrument channel suite. While AMSR-E instrument has been in operation for 9 years between 2002 and 2011 and its successor, AMSR2, is operational since April 2012, the highest resolution SIC products have depended on the two 89 GHz channels present on these instruments. A capability gap has been identified for such high accuracy, high resolution SIC products in case AMSR2 fails before its successor becomes operational. The upcoming Copernicus Imaging Microwave Radiometer (CIMR) mission aims to address this capability gap by providing a high accuracy low frequency channel selection at much higher resolutions. Besides including the 6.9, 10.8, 18.7, and 36.5 GHz channels common with the AMSR series, albeit at a higher resolution, CIMR would also have two 1.4 GHz channels which provide continuity to the current SMOS and SMAP missions at a similar resolution to existing instruments.

By taking advantage of the multichannel input characteristic of the OEM, this study aims to investigate the performance profile of a retrieval application tailored to the CIMR instrument characteristics. By design there are many similarities between CIMR and the AMSR series of instruments; however, a CIMR adapted OEM requires different constraints as well as an expanded forward model that can handle the 1.4 GHz channel simulations for atmosphere as well as open ocean and sea ice surfaces.

As the main advantage of CIMR is projected to be high accuracy and high resolution SIC retrieval, the comparison correspondent is the AMSR2 ASI SIC retrieval based on the high resolution 89 GHz channels.

The data used for building and testing the CIMR equivalent channel combination to be used as OEM input is described in section 2.

The optimal estimation method is described in more detail in Scarlat et al. (2017). This method together with the improvements discussed in Scarlat (2018) represent the retrieval scheme that is used throughout the present study. The necessary adaptations to the CIMR scheme as well as information content theory are described in section 3.

Section 4 describes the results with several subsections dedicated to the different aspects of implementing an OEM retrieval scheme for a future CIMR architecture and comparing it with existing capabilities. Several metrics are used to compare a number of SIC retrievals based on CIMR channel combinations and a benchmark AMSR2 89 GHz based SIC retrieval. A sensitivity study of CIMR and AMSR2 channels for the different retrieval parameters of the OEM is discussed in section 4.1.1. The comparison of SIC retrieval performance is presented in section 4.1.2. As a performance prediction metric the estimated retrieval precision for different retrieval schemes is discussed in section 4.1.3. The atmospheric influence on different CIMR and AMSR2 based retrievals is quantified using information content analysis in section 4.1.4.

As a complementary capability to SIC retrieval performance, the CIMR L-band channels can provide sensitivity to thin sea ice thickness. SIC retrieval accuracy can be improved in scenes with very thin ice if the thickness influence is accounted for. The advantages of including these channels in a OEM retrieval are explored in section 4.2. A summary and the conclusions are presented in section 5.

2. Data
2.1. CIMR Equivalent Input

Copernicus (http://www.copernicus.eu/) is an European system for monitoring the Earth. It includes earth observation satellites (notably the Sentinel series developed by ESA), ground-based measurements, and services to process data providing users with reliable and up-to-date information through a set of services related to environmental and security issues. The CIMR candidate mission (http://www.cimr.eu/) considers includes a global multifrequency imaging microwave radiometer, with a focus on high-latitude regions in support of European Union (EU) Arctic Policy (see https://eeas.europa.eu/arctic-policy/eu-arctic-policy_en). It is part of the expansion of the current Copernicus Space Component (CSC) capabilities described in the CSC long-term scenario to address the user requirements compiled by the European Commission. The proposed channel structure of the CIMR instrument and a comparison with other passive microwave radiometers are shown in Figure 1.
The aim of the Copernicus Imaging Microwave Radiometer Mission is to provide high spatial resolution microwave imaging radiometry measurements and derived products with global coverage and sub-daily revisit in the polar regions to address Copernicus user needs. The primary objectives of the CIMR mission are to

1. measure all-weather sea ice concentration (SIC) and sea ice extent at a spatial resolution of ≤5km, with a standard uncertainty of ≤5%, and sub-daily coverage of the polar regions and daily coverage of adjacent seas;
2. measure all-weather sea surface temperature (SST) at an effective spatial resolution of ≤15 km, with a standard uncertainty of ≤0.2 K and focusing on sub-daily coverage of polar regions and daily coverage of adjacent seas; and
3. ensure improved continuity of AMSR-type observing capability in synergy with other missions (e.g., MetOp SG(B)).

This study is focused primarily on the first and last of these three points. Using AMSR-E/2 and SMOS observations as CIMR equivalent brightness temperatures allows assessing the capabilities of this instrument to retrieve sea ice concentration at the target resolution and uncertainty thresholds stated in the primary objectives. Furthermore, a comparison with AMSR-type 89 GHz based high resolution SIC retrievals is presented in order to emphasize both the capability continuity which CIMR would provide as well as the synergy options given by the multichannel input nature of the OEM-based retrieval.

2.2. AMSR-E/2 Input

The Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) was a passive microwave radiometer on board the National Aeronautics and Space Administration (NASA) Aqua spacecraft. It has a conical scan geometry with an incidence angle of 55°. The instrument measures microwave emissions from the Earth's surface and atmosphere in 12 channels at six different frequencies between 6.9 and 89 GHz in vertical and horizontal polarizations (Imaoka et al., 2002). The AMSR-E covers the years 2002 to 2011, while AMSR2, the successor of AMSR-E, provides observations since 2012 to the present.

The channels of both AMSR-E and AMSR2 are described in Table 1. Because the footprint of the 89 GHz channels is so small (3.5 × 5.9 km²) in order to sample the Earth's surface without gaps there are two scans for these channels, Scan A and Scan B, that are interweaved to cover the gap between the scan lines.
Table 1

| Band (GHz) | AMSR-E spatial resolution (km × km) | AMSR2 spatial resolution (km × km) |
|-----------|-----------------------------------|-----------------------------------|
| 6.93      | 75 × 43                           | 62 × 35                           |
| 7.3       | —                                 | 62 × 35                           |
| 10.65     | 51 × 29                           | 42 × 24                           |
| 18.7      | 27 × 16                           | 22 × 14                           |
| 23.8      | 32 × 18                           | 19 × 11                           |
| 36.5      | 14 × 8                            | 12 × 7                            |
| 89.0      | 6 × 4                             | 5 × 3                             |

The AMSR-E Level 2A (L2A) data set (Ashcroft & Wentz, 2013) contains several spatially consistent subsets of brightness temperature observations resampled to the footprint sizes of the 6.9, 10.7, 18.7, 36.5, and 89 GHz channels. The different subsets are produced by resampling the higher resolution channels to match the larger footprint size of the lower resolution channels. Every Level 2A observation in a scan line is calculated using the coefficients that correspond to the relative weights of all neighboring Level 1A observations. These coefficients are unique for every position within one scan line, but they do not vary between different scan lines. The weighting coefficients for the Level 1A observations are produced using the Backus-Gilbert method (Stogryn, 1978).

2.3. SMOS L-Band Input

ESA’s Soil Moisture Ocean Salinity (SMOS) mission launched in November 2009 carries an L-band synthetic aperture microwave radiometer which takes measurements at a large range of incidence angles. While the initial purpose of SMOS was to retrieve soil moisture (Kerr et al., 2012) and sea surface salinity (Zine et al., 2008; Font et al., 2010), it has been shown (Kaleschke et al., 2010, 2012) that L-band measurements also offer sensitivity to thin sea ice thickness (SIT) up to 50 cm. As the CIMR instrument is projected to include two L-band channels (H and V polarizations) with a large scanning antenna setup at a fixed incidence angle of 55°, selected measurements from SMOS at the same incidence angle are used as equivalent data for the CIMR 1.4 GHz channels.

2.4. The Round Robin Data Package

In order to test the sea ice concentration retrieval of our method we used the round robin data set (Pedersen et al., 2019). It comprises two subsets (SIC1 and SICO) which contain cases of validated 100% sea ice concentration (SIC1) and cases of open water near, but at a safe distance from the ice edge (SICO). The data set originates from the sea ice project of the ESA Climate Change Initiative and it provides a source for validating sea ice concentration retrieval (Ivanova et al., 2015; Pedersen & Saldo, 2012) and for testing atmospheric parameter retrieval over pure surface types. The data package includes collocated ERA-Interim values for WSP, integrated columnar water vapor, liquid water path, sea surface temperature, ice surface temperature, and scatterometer backscatter data from ASCAT. The temporal coverage for the RRDP version used in this work spans from 2007 to 2011. The 100% SIC RRDP is not recommended for use during the Arctic summer when the SIC1 data points cannot be validated and so the analysis performed with this data package is limited to data points from January to April and November to December of every year. In general the summer season poses significant challenges to all retrieval methods based on satellite passive microwave remote sensing. The surface melt characteristic for Arctic sea ice can drastically alter the radiometric signature of the surface in a short time frame. As a consequence of this both obtaining a reliable validation data set and comparing different retrieval methods during the Arctic summer season is especially difficult.

3. Methods

3.1. Optimal Estimation Method

The basic idea of the optimal estimation retrieval is to find the set of seven geophysical parameters for which a forward model can best approximate the observed brightness temperatures. The sensitivity to the forward model input and the methodology to construct the covariance matrices that act as constraints on the retrieval have been explored in Scarlat et al. (2017). The first constraint is on the parameter space, and it represents...
the variability limits for the geophysical parameters. As the present study aims to simulate a CIMR like configuration, the geophysical constraints include the sea ice thickness parameter. The background covariance matrix, expressed through equivalent standard deviation values, is shown in Table 2.

A similar constraint is used for the observation space. This is the covariance matrix for the brightness temperatures $S_e$. It constrains the forward model simulated brightness temperatures to a reasonable accuracy. This level of accuracy for the simulated brightness temperatures is chosen based on the combined measurement, forward modeling, and geophysical parameter errors. Together they influence how far the simulated values can deviate from the observed brightness temperatures. The matrix is developed to match the CIMR channel structure with the equivalent standard deviation values for the brightness temperature covariance matrix diagonal elements shown in Table 3.

### 3.2. The Forward Model

The forward model is needed in order to translate the seven geophysical parameters into the 12 brightness temperatures of the AMSR-E radiometer channels.

The original implementation of the forward model (Wentz & Meissner, 2000) was designed to work over open ocean surfaces. In order to also use it over the ice covered areas, the calculation of the surface emission was modified in order to account for the different microwave emissivity of sea ice (Melsheimer et al., 2008). Each pixel is considered as being formed of a mixture of open water, first year and multi-year ice. The division is necessary because of the different radiometric signatures of these two ice types. First year ice is formed during one cold season with a thickness above 30 cm and large variability in surface types which can be level, rough, or with ridges (WMO, 2014). Multi-year ice is sea ice that has survived at least one melt season and on average has more ridges but with smoother topography than for first year ice. The forward model upwelling brightness temperature of the surface is

$$T_{\text{B,surface}} = C_{\text{ow}} \cdot \epsilon_{\text{ow}} \cdot T_{\text{ow}} + C_{\text{fyi}} \cdot \epsilon_{\text{fyi}} \cdot T_{\text{fyi}} + C_{\text{myi}} \cdot \epsilon_{\text{myi}} \cdot T_{\text{myi}},$$

where $C_{\text{ow}}$, $C_{\text{fyi}}$, and $C_{\text{myi}}$ represent the concentration of each surface type in the current pixel. The sum of these three contributing factors must be 1. Corresponding to each surface type $\epsilon_{\text{ow}}$, $\epsilon_{\text{fyi}}$, and $\epsilon_{\text{myi}}$ are the microwave channel specific emissivities for open water, first year ice, and multi-year ice, respectively. Likewise $T_{\text{ow}}$, $T_{\text{fyi}}$, and $T_{\text{myi}}$ are the physical temperatures of each surface type. These correspond to the retrieval parameters of SST for $T_{\text{ow}}$ while IST represents the linear mix of $T_{\text{fyi}}$ and $T_{\text{myi}}$ in the satellite scene.

### Table 3

| Channel | $S_e$ |
|---------|-------|
| 1.4V    | 2.56  |
| 1.4H    | 3.99  |
| 6.9V    | 1.54  |
| 6.9H    | 2.20  |
| 10.7V   | 1.27  |
| 10.7H   | 2.34  |
| 18.7V   | 0.99  |
| 18.7H   | 2.22  |
| 36.5V   | 1.59  |
| 36.5H   | 1.63  |

*Note.* Shown here are the standard deviations (K).
In turn, the reflectivity of a pixel will be calculated from individual reflectivities of each surface type.

\[ R_{\text{eff}} = 1 - \varepsilon_{\text{eff}} \]

\[ R_{\text{eff}} = 1 - (C_{\text{ow}} \varepsilon_{\text{ow}} + C_{\text{fyi}} \varepsilon_{\text{fyi}} + C_{\text{myi}} \varepsilon_{\text{myi}}). \]

(1)

The required frequency dependent emissivities (\( \varepsilon_{\text{ow}}, \varepsilon_{\text{fyi}}, \) and \( \varepsilon_{\text{myi}} \)) are based on the empirically retrieved values from Mathews (2007).

Two important corrections connected to the forward model implementation over sea ice are added in Scarlat (2018). First the sea ice surface temperature treatment is modified to take into account the frequency specific penetration depth based on the methodology described in Mathews (2007). A set of regression coefficients were used in order to relate the reanalysis 2 m air temperature to the emission layer temperature. This correction offers a better representation of the emission layer temperature which contributes to the microwave signal instead of basing the forward model calculations on the reanalysis supplied skin surface temperature and is implemented for all AMSR-E and CIMR common channels.

The second correction modifies the empirical emissivities toward minimizing the difference between simulated and observed brightness temperatures.

3.3. Extending the Forward Model to Include L-Band Brightness Temperatures

As the original forward model was designed to work for the AMSR-E channels, the forward model needs additional data to be extended to the L-band channels. Over open ocean the existing dielectric model is used to calculate the frequency dependent emissivity of a calm ocean. The semi-empirical wind dependence parametrization from Ruf (2003) is used to construct the total upward component. This dependence is given by

\[ \varepsilon_h = \varepsilon_{h,0} + u(0.0007 + 0.000015\theta_{\text{inc}}) \]

\[ \varepsilon_v = \varepsilon_{v,0} + 0.0007u. \]

(2)

where \( \varepsilon_v, \varepsilon_h \) represent the total vertical and respectively horizontally polarized emissivities, \( \varepsilon_{v,0}, \varepsilon_{h,0} \) are the polarized emissivities of a calm ocean derived from the ocean dielectric model, and \( u \) is the neutral stability near-surface wind speed. For this study the incidence angle \( \theta_{\text{inc}} \) used is 55°.

For the total atmospheric opacity a dependence on surface temperature and atmospheric water vapor from the same Ruf (2003) is used:

\[ \tau = (0.009364 + 0.000024127V) \sec(\theta_{\text{inc}}). \]

(3)

The total opacity \( \tau \) is in nepers, and \( V \) represents the total height integrated columnar water vapor load of the atmosphere in centimeters. The original formulation of this equation from the referenced work is used, using nepers as a dimensionless measurement unit for the atmospheric attenuation. The neper is an accepted SI logarithmic unit which uses the natural base logarithm as opposed to the decibel which uses the base-10 logarithm. Equation (3) shows the weak dependence of microwave radiation at the 1.4 GHz frequency on atmospheric constituents and it has been derived by performing a regression fit between L-band opacities and integrated water vapor values from a large ensemble of globally distributed radiosonde profiles over the ocean.

The final relevant dependence for the brightness temperature at L-band on the sea surface temperature (SST) is included in the expressions for the upwelling and downwelling brightness temperatures:

\[ T_{B,\text{up}} = (1 - e^{-\tau})(\text{SST} + 258.15) \]

\[ T_{B,\text{down}} = (1 - e^{-\tau})(\text{SST} + 263.15). \]

(4)

The total \( v/h \) polarized brightness temperature observable by an instrument in orbit is then according to Ulaby et al. (2014)

\[ T_{b,p} = T_{B,\text{up}} + [(T_e e^{-\tau} + T_{B,\text{down}})(1 - \varepsilon_{v/h}) + \varepsilon_{v/h}\text{SST}] e^{-\tau}, \]

(5)

with \( p \) the polarization vertical (v) or horizontal (h), SST the sea surface temperature in Kelvin, and, specific to L-band radiation, \( T_e \) is the background cosmic radiation which is given in Ruf (2003) as 6 K.
Table 4
Empirical Sea Ice Surface Emissivities Differentiated by Ice Type

| Channel | Multi-year ice pixels | First year ice pixels |
|---------|-----------------------|-----------------------|
| 1.4V    | 0.842                 | 0.899                 |
| 1.4H    | 0.799                 | 0.863                 |
| 6.7V    | 0.958                 | 0.972                 |
| 6.7H    | 0.868                 | 0.866                 |
| 10.7V   | 0.960                 | 0.948                 |
| 10.7H   | 0.879                 | 0.845                 |
| 18.7V   | 0.965                 | 0.885                 |
| 18.7H   | 0.887                 | 0.799                 |
| 23.8V   | 0.960                 | 0.839                 |
| 23.8H   | 0.882                 | 0.763                 |
| 36.5V   | 0.946                 | 0.731                 |
| 36.5H   | 0.864                 | 0.675                 |

For simulating L-band measurements over sea ice covered areas the same implementation of mixed surface types as for the AMSR-E implementation of the forward model is used. Thus, any pixel is considered to contain three different surface types, open water for which the upward contribution is calculated as detailed above, and first year and multi-year ice respectively for the sea ice cover. A simplified implementation is used for the sea ice surface emissivity where an empirical value is used to calculate the sea ice emitted upwelling radiation. The empirical sea ice emissivities have been derived from 2 years of RRDP data using collocated ECMWF skin temperature values and SMOS L-band observations. Any errors or biases inherent in the ECMWF product are propagated to the simulated brightness temperatures; however, this is considered an acceptable trade-off for the convenience and availability of ECMWF data for the times and locations of the RRDP data points. In order to avoid a biased retrieval and to compensate for this increased uncertainty in the forward model input, the affected channels have a decreased weight in the brightness temperature covariance matrix.

Only winter months are selected from the 2 years of data, then only pixels with low water vapor content were used (TWV < 2 kg m$^{-2}$) and the remaining pixels were divided by ice type into >95% FYI and a >95% MYI sets using the NASA Team algorithm. In these conditions we can approximate the observed brightness temperature at L-band as coming only from the upwelling sea ice signal. The empirical sea ice type specific emissivities will then be derived from

$$e_{FYI/MYI} = \frac{T_b}{T_{skin}}.$$  \hspace{1cm} (6)

$T_b$ is the observed brightness temperature, and $T_{skin}$ is the collocated ECMWF skin temperature. This is a significant source of bias as, especially at this frequency, the layer of sea ice that contributes to the upward emission is thicker than just the skin layer (considered to be the snow/sea ice interface layer). The temperature of this bulk emitting layer can vary significantly depending on the ice type, thickness, and brine content. As mentioned in section 3.2, a set of empirical regression coefficients have been derived in Mathews (2007) for all channels of AMSR-E which relate the two meter air temperature from a reanalysis data set with the ice type bulk emitting layer temperature. These coefficients are implemented for the CIMR equivalent channels at 6.9, 10.65, 18.7, and 36.5 GHz so that a realistic emission layer temperature is used for the surface emission calculation. As there are no reliable sources for such a mechanism at the 1.4 GHz frequency and considering the limited scope of demonstrating the potential capabilities of L-band remote sensing over a restricted winter test data set where we can reasonably assume that the sea ice is thicker than 50 cm, we believe this implementation can work. The thick sea ice condition is necessary only for the data set used to extract L-band emissivities without a sensitivity to sea ice thickness. The main benefit from using the L-band channels is the sensitivity to sea ice thickness, and we do not expect to include them in any retrieval scheme where the first guess data shows sea ice thicker than 0.5 m is present. For thin sea ice scenes the emissivity...
Table 5
Fit Parameters for All CIMR Equivalent Channels Used to Model the TB Dependence on SIT in the Forward Model

| Channel frequency | Polarization | a    | b    | c  |
|-------------------|--------------|------|------|----|
| 1.4 V-pol         | 246.48       | 147.36 | 10.23 |
| H-pol             | 212.33       | 72.13  | 18.30 |
| 6.9 V-pol         | 250.17       | 121.78 | 6.67  |
| H-pol             | 220.71       | −16.12 | 7.18  |
| 10.65 V-pol       | 250.99       | 127.95 | 6.39  |
| H-pol             | 228.62       | −0.40  | 7.40  |
| 18.7 V-pol        | 255.07       | 151.90 | 6.30  |
| H-pol             | 238.25       | 29.60  | 7.22  |
| 36.5 V-pol        | 254.80       | 188.71 | 6.01  |
| H-pol             | 242.62       | 83.87  | 6.71  |

dependence on sea ice thickness is used instead of the empirical emissivities. This L-band emissivity implementation serves as a placeholder for simulating a full CIMR suite test run over the RRDP set. The full set of channel wise emissivities used for all tests presented in section 4 are shown in Table 4.

3.3.1. Including the Sea Ice Thickness Dependence
Two of the main advantages of the L-band channels are their sensitivity to thin sea ice thicknesses and lack of sensitivity to atmospheric influence. This means that for an OEM application using the CIMR channel configuration the SIT parameter can be included into the state vector. A simple brightness temperature to sea ice thickness \((x)\) dependence is implemented in the forward model following

\[
TB(x) = a(a - b) * \exp\left(-\frac{x}{c}\right).
\]  

(7)

The function is fitted to the measured v and h polarization brightness temperatures for the SIT values resulting from the cumulative freezing degree days method over the training data set described in Huntemann et al. (2014). This empirical method relates SIT to air temperature available from numerical weather prediction data.

\[
SIT[cm] = 1.33(CFDD[^{°C}])^{0.58}.
\]  

(8)

The CFDD parameter is the daily average temperature (below the sea ice freezing point), in Celsius integrated in time since the point of sea ice formation.

The fit parameters relating brightness temperature to sea ice thickness \(a, b,\) and \(c\) are given in Table 5.

3.4. Information Content Theory
The information content of a measurement as described by Rodgers (2000) represents the change in the logarithm of the number of distinct states of the system that is being measured, based on the original definition by Shannon and Weaver (1949). The number of distinct states that the measured system can take is called the system entropy. The base 2 logarithm of this change in entropy gives the information content in bits.

For a given probability distribution function \(P\) which characterizes the possible states of the system, the information content of a measurement depends on the system entropy \(S(P)\). The change in entropy as a result of the measurement is

\[
H = S(P_{o}) - S(P_{p}).
\]  

(9)

the information content of the measurement. \(P_{o}\) represents our knowledge of the state of the system before the measurement is performed, and \(P_{p}\) represents the state after. The decrease in entropy is equivalent to a decrease in the uncertainty of our knowledge about the state of the system, and it represents the new information that the measurement brings.

If we assume Gaussian distribution the entropy of the system is then
with \(|S_a|\) being the determinant of the background covariance matrix which describes our knowledge about the system before the measurements are made (a priori). The change in entropy following the measurement or the information content of the measurement will then be

\[
H = -\frac{1}{2} \ln |S_p S_a^{-1}|,
\]

\(S_p\) being the covariance matrix of the system after the measurement and \(S_a\) the system covariance matrix before the measurement.

This method was used for analyzing the OEM output in Scarlat (2018) where different channel combinations of AMSR-E were compared in order to find the best compromise between atmospheric and surface retrieval performance. In the present study we are interested in the performance of the CIMR adapted OEM, in particular for high resolution SIC retrieval. Information content analysis can provide a good way to rank different CIMR channel combinations and to compare the influence of atmospheric parameters on the total retrieval output quantified in bits of information. This is especially relevant when comparing any CIMR equivalent configuration with the benchmark AMSR2 89 GHz based retrieval.

### 4. Results and Discussion

#### 4.1. Evaluating SIC Retrievals from CIMR and AMSR2 89 GHz

##### 4.1.1. Sensitivity Study for CIMR Equivalent Channels

One way to predict the potential impact of each CIMR channel on the sea ice retrieval is to check the forward model Jacobian matrix for the full set of retrieved parameters. This matrix is calculated for each retrieval pixel and all seven parameters associated with the basic OEM configuration. It indicates the change in the individual channel brightness temperature (Tb) for a small perturbation in an individual state vector parameter. In order to compare the relative influence of the state vector parameters with each other and across different channels, the elements of the forward model Jacobian have been averaged over the whole data set and normalized by the a priori parameter uncertainty (standard deviation) derived from the \(S_a\) matrix variances. For a better insight into how these parameter sensitivities vary depending on the surface conditions, the Jacobian elements are averaged separately for all RRDP compact ice (SIC1) and open water (SIC0) scenes, respectively.

To continue the parallel with existing AMSR2 capabilities, for both SIC1 and SIC0 cases all CIMR channels as well as the 89 GHz channels have been included in the analysis.

Figure 2 shows the normalized parameter sensitivities for all CIMR channels plus the two AMSR2 89 GHz channels. The rows represent the radiometer channels, and the columns are the seven retrieval parameters.
of the OEM. The brightness temperature data comes from the RRDP collocated AMSR2 measurements for the channels between 6.9 and 89 GHz and from SMOS for the 1.4 GHz L-band observations. The temporal coverage is for winter months (November–April) of the years 2013–2015. The color of each cell represents the magnitude of the TB change in for a mean change in the retrieval parameter.

On the left side of Figure 2 the Jacobian for the SIC0 tests is shown. SIC is the most influential parameter followed by LWP, TWV, and WSP with SST being the least important for the forward model calculations. Over SIC0 the atmospheric parameters determine TB responses over all channels. This means that different retrieval channel combinations are possible as all channels provide some measure of sensitivity for these parameters. The 89 GHz channels provide the best sensitivity for LWP while the 6.9 GHz channels are most sensitive to SIC but in both cases there are adjacent frequency channels which provide similar sensitivities.

On the right side of Figure 2 the corresponding Jacobian values are plotted for the SIC1 test scenario. Out of the seven state vector parameters some are not represented over SIC1 such as SST and WSP as they do not impact the surface emitted brightness temperatures. Out of the remaining five parameters that can influence the Tbs, SIC shows the strongest impact. It determines large TB responses across all channels with the relative channel sensitivity decreasing with frequency. The other parameter that triggers a response in all channels is the MYIF where the TB change increases with frequency from 6.9 to 36.5 GHz. The 6.9 GHz channels show the highest sensitivity to SIC changes in both polarizations. They are closely followed by the 10.6 GHz channels. For the atmospheric parameters, the 89 GHz channels stand out as the most sensitive to both LWP and TWV. This is particularly important as these atmospheric parameters have low responses in the lower frequency channels.

Based only on the Jacobians we can say that the CIMR channels are oriented toward surface parameter sensitivity, both over SIC1 and SIC0 scenarios while the AMSR2 specific 89 GHz channels offer the highest atmospheric sensitivity of this set. These channel sensitivities offer up good synergy possibilities between CIMR and other instruments using the 89 GHz channels such as the future AMSR3 mission or the MWI (Microwave Imaging Radiometer) on board MetOp SG.

4.1.2. Comparing Retrievals Over 100% and 0% SIC Surfaces

The bar plot in Figure 3 shows the ranking of different OEM retrieval schemes for SIC1 and SIC0 output, respectively. The different products are arranged by increasing mean SIC standard deviation over SIC1 and over SIC0. This type of analysis is similar to that made in Ivanova et al. (2015) but only applied to the OEM retrieval using different input combinations. For ease of reading the plot, the channel frequencies have been rounded (1.4 → 1; 6.9 → 7; 10.7 → 11; 18.7 → 19; 36.5 → 37).

The capability of using different combinations of input channels is one of the features of the OEM retrieval and so that all possible combinations of CIMR channels could be tested over the same RRDP data set. The main criterion for pairing different channels together is to maximize sensitivity to certain retrieval parameters and to preserve a desired output resolution. In order to avoid inconsistencies between channels, the OEM uses a resampled product where any combination of input channel Tbs is down-sampled to the resolution and footprint center coordinates of the lowest resolution channels. As such the resolution of the retrieval product will always be that of the lowest frequency channels used as input to the OEM. As a consequence, the benefits of channel specific sensitivities need to be weighed against the resulting retrieval resolution for any combination. The 6.9 GHz channels offer the lowest retrieval standard deviation over both SIC1 and SIC0 but also have a low spatial resolution (from CIMR channels only the 1.4 GHz ones have a lower resolution). A number of retrieval schemes score below the 5% threshold for mean accuracy defined for the CIMR mission requirement. Out of these the 19–37 combination achieves about 4% mean SIC standard deviation and would offer a resolution similar to that of the AMSR2 89 GHz channels which on their own score a mean SIC standard deviation of 12%, that is, three times worse. It also can be seen that the 19–37 combination is needed for low SIC uncertainties as the standard deviation of the single frequency retrievals (only 19 and only 37) are significantly higher than for the combined frequency retrieval.

4.1.3. OEM Multiparameter Retrieval Precision Estimation for Different Channel Combinations

While the primary CIMR parameter is SIC, as the OEM retrieves a full suite of seven geophysical parameters it is interesting to analyze the performance profile over all retrievable parameters in order to fully compare the different input channel combinations. A feature of the OEM approach is that each optimisation result is associated with an estimation covariance matrix $\hat{\Sigma}_e$ (Scarlat et al., 2017). This matrix contains the variances of each state vector parameter on the principal diagonal. These variances are a measure of how much the
uncertainty space has been reduced for each parameter under the constraints of the a priori covariance matrix ($S_a$) and the measurement covariance matrix ($S_y$). These variances can be understood as retrieval precision, completely determined by the natural variability of each geophysical parameter and the accuracy of the simulated brightness temperatures. This estimated parameter precision is not the same as the retrieval accuracy. Rather it should be considered a diagnostic metric which allows for comparing the performance of different input combinations while using a common retrieval method. This analysis is similar to that performed in Kilic et al. (2012) but including the full brightness temperature forward model error included in the brightness temperature matrix $S_T$. In addition to instrumental error, this also includes the simulation and forward model parameter error (Rodgers, 2000; Scarlat et al., 2017).

As we do not have any true CIMR measurements at present, the brightness temperature constraints (TB covariance matrix $S_T$, see section 3.1) used for this study are based on conservative estimates of AMSR-E/2 measurement and forward model errors (Scarlat, 2018). As such the nominal values of estimated parameter precision are less important for the purpose of this study than the relative ranking of different OEM input channel combinations. The plots in Figure 4 show the estimated precision levels (parameter standard deviation) for four different OEM schemes over the SIC0 data set. While the estimated uncertainty values can only be positive, because of the graphical symmetry of the plot these whiskers can stretch below 0 when the mean is very low and the standard deviation is sufficiently large. The estimated precision is constrained by the a priori knowledge of parameter uncertainty, that is, a retrieval uncertainty which is higher than the a priori uncertainty is penalized by a cost increase as the aim of the retrieval is to improve on the a priori.

For comparing the four OEM schemes both the mean, median, and length of the standard deviation error bar are taken into consideration. A smaller mean value represents better precision for a given parameter, while the position of the median gives an idea about the distribution of values inside one standard deviation. How close the mean and median are to the a priori standard deviation is also a good way to judge if a particular OEM setup can indeed improve on the a priori knowledge.

This comparison between the different OEM retrieval schemes is meant to show the strong points of using CIMR equivalent channels for multiple parameter retrievals.

Figure 3. Standard deviation for SIC retrieval using different channel combinations for the 100% (SIC1) and 0% (SIC0) test data sets.
Figure 4. Point plots of four different OEM input schemes using only the 6.9 GHz, only the 89 GHz, a combination of 18.7 and 36.5 GHz, and the full set of CIMR channels, respectively. The position of the dot and associated error bar represent the mean ± one standard deviation value for each OEM scheme. The “X” symbols indicates the position of the median value. The a priori uncertainty levels are indicated by the black horizontal lines. The values displayed next to the plot elements represent the mean (black), median (orange), and a priori standard deviation (red). Retrievals are run over all scenes of the RRDP SIC0 data set.

As this test compares single and multichannel OEM schemes, it is expected for the former to achieve little improvement for parameters where there is little sensitivity. Such examples are for TWV and LWP parameters when using only the 6.9 GHz channels or WSP and SST parameters in the case of the 89 GHz channels. This can be seen in the plots of Figure 4 where the median is close to the a priori limit.

In section 4.1.2 the behavior of the OEM SIC retrieval is analyzed and the 89 GHz only setup is shown to have very high variability. Here we look in more detail at how the other retrieval parameters behave for this retrieval scheme. The high variability is present for all parameters over SIC0 with the best precision shown for LWP retrieval where the 89 GHz frequency has the best sensitivity of all (as seen in Figure 2). For TWV
retrieval the mean precision value is the second best (at 2.47 mm), but
the median value (3.22 mm) is close to the a priori limit (3.32 mm). SIC
retrieval in the context of the SIC0 data set represents how stable each
channel combination is for scenes with little ice cover. Here the 89 GHz
channel SIC retrieval is associated with the worst precision performance
with both median (14.1%) and mean values (15.25%) far higher than all
other OEM schemes. An OEM retrieval based on combining the CIMR
channel at 18.7 and 36.5 GHz can offer resolutions similar to using the
AMSR2 89 GHz channels but with reduced variability over all parameters
and especially better performance for SIC retrieval. Out of the three OEM
schemes based on CIMR channels, both the mean (3.88%) and median
(3.4%) indicate much better precision than the 89 GHz channels. Besides
SIC, this channel combination improves the precision levels below the
a priori uncertainty for LWP and WSP as well. The 6.9 GHz channels
alone stand out for the SIC and SST retrieval precision. The lack of sen-
sitivity to atmospheric parameters makes this OEM a good option for
surface parameter retrieval. Lastly the full set of CIMR channels used for
the 1.4 → 36.5 GHz OEM version benefits from the combined sensitivi-
ties at these frequencies. Over all parameters it has the lowest precision
variability, indicating a stable retrieval. This stands out especially for SIC
retrieval where the lowest mean (1.76%) and lowest median (1.62%) are achieved. This performance how-
ever is achieved at the cost of the spatial resolution which is equal to the resolution of the lowest frequency
channels used as OEM input (around 36 km for 1.4 GHz).

The main conclusion from Figure 4 is that the lower frequency combinations based on CIMR channels can
offer superior precision not only for SIC retrieval but also for most atmospheric and surface parameters over
open water scenes. Additionally, the 18.7–36.5 GHz combination of CIMR would offer comparable levels
of precision with the 89 GHz channels for atmospheric parameters and superior precision for SIC while
maintaining a high output resolution.

The plot shown in Figure 5 is the same type of graphic as in Figure 4. It shows the estimated precision level
of SST retrieval for the same four OEM schemes over SIC0 scenes when no forward model error is included
and the method is constrained to 0.1% SIC. This would be the minimum theoretical precision level estimated
for SST retrieval in cases where there is high certainty for an open water surface. Ignoring the model error
means that the input channels can be weighted only by their projected Noise Equivalent Delta Temperature
(NEΔT) values for the CIMR instrument and as a result the estimated retrieval precision is increased. For
such a testing scenario the SST precision estimate for the 1.4–36.5 GHz setup has a mean value of only 0.3
K with an even smaller median value at 0.2 K. These values are significantly lower than those shown in
Figure 4 and demonstrate the importance of accounting for realistic model error in the precision estimation.
If the previous estimated errors (shown in Figure 4) are a measure of the method precision levels in a realistic
retrieval environment, this plot (Figure 5) shows the instrument accuracy level of CIMR independent of the
retrieval method and forward model used.

In Figure 6 the same type of analysis is performed for the RRDP SIC1 data set for all relevant parameters.
Similar to the results over SIC0, for 100% SIC the 89 GHz channels based retrieval is more precise than all
the other schemes for the atmospheric parameters of TWV (but with very high variability) and LWP. Com-
pared to the results over open ocean however, the precision variability is increased. This can be explained by
the typically lower values encountered over 100% SIC scenes which become challenging even for the high
atmospheric sensitivity of the 89 GHz channels. While all retrievals are close to the a priori uncertainty for
TWV, for LWP even the scheme including all CIMR channels together cannot match the precision of the
AMSR2 89 GHz channels used alone as the high frequency channels reach precision levels around 0.05 mm
compared to 0.09 mm for the full CIMR channel suite.

The high spatial resolution CIMR channel combination of 18.7 + 36.5 GHz deliver high and stable SIC
retrieval precision (mean and median both at 1.8%). This channel combination delivers the most infor-
mation about LWP as the mean and median precision levels around 0.1 mm are stable even after adding
the other four low frequency CIMR channels (1.4 and 6.9 GHz, H and V) to the OEM input. A similar
Figure 6. Point plots of four different OEM input schemes using only the 6.9 GHz, only the 89 GHz, a combination of 18.7 and 36.5 GHz, and the full set of CIMR channels, respectively. These plots are similar to those shown in Figure 4 but using all scenes of the RRDP SIC1 data set.

Situation is seen for ice types retrieval where the MYIF precision performance is comparable between the $1.4 \rightarrow 36.5$ GHz and the $18.7 + 36.5$ GHz OEM schemes.

In full sea ice cover conditions, the 6.9 GHz channels alone offer good precision (around 2%) for SIC retrieval. For all other parameters this single frequency setup cannot improve much on the background uncertainty levels as the presence of sea ice dominates the measured signal. The 6.9 GHz channels lack sensitivity for atmospheric, ice types, and the ice surface temperature parameters as first shown in Figure 2. This low sensitivity means no cost incentive for the OEM to modify the a priori model input. The a priori uncertainty is repeated in the retrieval for all parameters except for SIC.
The full CIMR channel suite offers lower variability, as over SIC0, with most of the sensitivity for LWP and MYIF provided by the two higher frequency 18.7 and 36.5 GHz channels. Using all channels however allows for improving the precision performance for SIC even more (below 1% uncertainty) and for IST where the variability is greatly reduced.

This comparison over SIC 1 showcases again the contrast between using the atmospherically sensitive 89 GHz and the surface sensitive lower frequency channels in the retrieval. In conclusion, the retrievals based on CIMR equivalent channels show better precision than the 89 GHz retrieval for all surface parameters. The 18.7–36.5 GHz retrieval with the highest spatial resolution for CIMR shows reasonable precision for both SIC and MYIF parameters while still providing some sensitivity for LWP (on the order of 0.1 mm).

### 4.1.4. Estimating the Atmospheric Influence on Different Retrieval Schemes

Atmospheric influence is the main error source for SIC retrieval using the 89 GHz channels (Spreen et al., 2008) which makes it important to investigate the strength of the atmospheric contribution to the observed brightness temperatures for different channel combinations. This is done using information content analysis to quantify the individual parameter contributions. The bar plots in Figure 7 show the information content analysis for four different OEM retrieval schemes. These are the 6.9 \rightarrow 36.5 combination which uses all CIMR channels except the 1.4 GHz ones, the high spatial resolution 18.7 + 36.5 GHz combination, the 6.9 GHz channels alone, and the two AMSR2 89 GHz channels. The top plot represents the tests run over SIC0 while the bottom plot shows the SIC1 tests.
The color of each bar segment represents the independent information content (in bits) retrieved for each individual parameter. As the signal is made up of contributions from all of these parameters, the total information content of the retrieval is the sum over all parameters. A next to each version description is the maximum resolution achievable by resampling the channels to the footprint of the lowest frequency channel in the combination.

The plots in Figure 7 give the information content analysis for four possible OEM configurations, three of these are based on CIMR frequencies and one on the 89 GHz channels. This type of analysis allows us to quantify the atmospheric and surface contributions to each retrieval scheme. This is a useful metric for comparing the retrieval performance of different channel combinations and for different retrieval parameters. Maximum information content is retrieved from the CIMR 6.9 → 36.5 channel combination at around 7.5 bits for both SIC0 and SIC1 scenes. This version offers sensitivity to all surface as well as all atmospheric parameters over SIC0 with the highest information content about SST out of all four tested versions. While over SIC1 the retrieval is dominated by the contribution from SIC and ice types, there is still information available about the atmospheric parameters as well as IST. The retrieval resolution from this CIMR channel setup would be 15 km as all high frequency channels are resampled to match the footprint of the 6.9 GHz channels. Compared to the previous scheme, the combination of 18.7 and 36.5 GHz channels would offer only slightly degraded total information content (6.9 vs. 7.4 bits) while offering a much finer resolution of 5 km. Using only the 6.9 GHz channels the retrieved information is dominated by the SIC signal with some sensitivity left for SST and WSP over SIC0 and conversely ice types and IST over SIC1. As surface parameters determine most of the retrieved information with this channel combination this makes it a benchmark for SIC retrieval with minimum atmospheric interference. The 89 GHz retrieval shows the largest information content for both SIC1 and SIC0 scenes related to atmospheric parameters (LWP and TWV), which have higher contributions to the signal than the surface parameters. This is why weather filters are necessary for single parameter sea ice concentration retrievals which use the 89 GHz frequency (Spreen et al., 2008).

This analysis shows that the 18.7 + 36.5 combination is largely complementary with the 89 GHz scheme. The 89 GHz version offers significant information content on LWP, which is especially important over sea ice covered areas where atmospheric measurements are difficult. However, the CIMR equivalent combination of 18.7 and 36.5 GHz offers higher surface parameter retrieval performance with lower atmospheric interference at the same high spatial resolution as the 89 GHz scheme. For a more complete retrieval with the maximum information content on both SIC, ice types, surface temperature, and the relevant atmospheric parameters, a combination of the CIMR 18.7 and 36.5 GHz channels as well as a prospective AMSR3 (for the same resolution) or MetOp SG Microwave Imager instrument (at a lower resolution but nearly simultaneous observations) 89 GHz pair of channels will work. Any such multi-instrument synergy would however face the challenges of overflight time and footprint discrepancies. Such differences can become significant in the context of sea ice drift and fast moving atmospheric patterns.

4.2. Advantages of Including the L-Band Channels in the CIMR OEM Retrieval

An important feature of CIMR is the inclusion of the two channels at 1.4 GHz. This frequency offers additional sensitivity for thin (≤50 cm) sea ice thickness (SIT) retrieval. In order to be added to the state vector, the dependency of brightness temperatures on this parameter has to be included in the surface emission calculations of the forward model. For this purpose, a special thin sea ice data set (Heygster et al., 2014) was processed using collocated CIMR equivalent Tbs from AMSR-E as well as SMOS L-band measurements at a 55° incidence angle. This data set was randomly divided into two subsets to be used as training and testing, respectively. The two subsets are considered to be adequately large (n = 9,993 for each set) that they can be seen as independent for this proof of concept testing. In order to maintain consistency, for each channel a function of the same shape as that shown in equation (7) is used to fit the channel TB to the learning data set SIT. The SIT versus TB dependency curves for each CIMR equivalent channel are shown in Figure 8, and the a, b, and c parameters are given in Table 5. Because of the varying penetration depth of radiation at the different frequencies, the retrievable range of SIT values decreases with frequency. While the L-band channels maintain sensitivity throughout the whole range of values covered by this thin sea ice data set, for the higher frequencies there is a drop in sensitivity from a maximum retrievable value of 30 cm at 6.9 GHz to 15 cm at 36.5 GHz. In this context, the maximum retrieval value represents the SIT value at which the slope of the fit curve is lower than 0.1. Past these maximum values, there is almost no change in the brightness temperatures. A practical retrieval limit from the brightness temperature to SIT fit in Arctic conditions is 50 cm for first year ice (see Kaleschke et al., 2010, Section 5.1.4). Above this value the uncertainty is on
Figure 8. SIT fit functions for all CIMR channels.
the order of the retrieved value. While the testing scenario is done for thin sea ice scenes (<30 cm), for an operational retrieval any values above 50 cm would be flagged as thick sea ice.

Pairing channels with significantly different parameter sensitivities is a feature of the OEM. While it is not expected that the high frequency channels can contribute much information to the SIT parameter, we demonstrate that a retrieval for eight parameters (including SIT) is possible using CIMR like input observations. A priori knowledge is necessary for this new state vector parameter and as such the SMOS retrieved SIT (Huntemann et al., 2014) was used. This is a straightforward empirical method that could also be adapted to work for the future CIMR L-band channels at the fixed incidence angle of 55° as has been done for the SMAP instrument (Patilea et al., 2019).

The testing involved different OEM configurations in order to determine which factors influence most the SIT retrieval as well as the consistency of the other state vector parameters. As the SIT parameter is included as an extra step in the forward model calculation it is expected that the other sea ice parameters (SIC and MYIF) are affected as well. The retrieved SIT is compared with the a priori SMOS data which is an appropriate sanity test according to Rodgers (2000) as the retrieval is naturally expected to be close to the background levels, while any strong deviation would signal a problem with the method. The empirical SMOS retrieval uses L-band brightness temperatures measured at an incidence angle interval between 40 and 50° while the OEM input Tbs are sampled for the CIMR incidence angle of 55°.

In Figure 9 SIT retrievals from four different OEM configurations are compared to the SMOS 40–50° incidence angle SIT retrieval. These plots need to be interpreted together with the statistical values given in Table 6 for the retrieved SIC and MYIF parameters. All the sea ice parameters have to be viewed in context as the method is not completely calibrated for an eight parameter retrieval including the L-band channels, and the method can be biased toward one parameter or the other depending on the tested configuration. The scenes of this data set comprise validated thin sea ice which means that the expected values for SIC and MYIF are around 100% and 0%, respectively, as thin sea ice is associated with young ice types.

Figure 9. SIT retrieved using different OEM configurations compared with the SMOS retrieval for the test data subset. The color of the data points represents the OEM retrieved SIC. OEM configurations: (a) using only the L-band TB dependence on SIT; (b) the OEM uses all channels; (c) L-band channels are given more weight in calculating the cost function; (d) a priori SIC is set to be 100% and corresponding weight for this parameter background value increased.
Table 6
Comparison Statistics Between OEM Retrieval and SMOS SIT Retrieval

| OEM configuration | SIT [cm] | SIC [%] | MYIF [%] |
|-------------------|---------|---------|----------|
|                   | Bias    | RMSD    | R        | Mean   | STD  | Mean   | STD  |
| A - L-band only   | -7.99   | 8.93    | 0.69     | 85.43  | 9.52 | -0.62  | 2.46 |
| B - all channels  | -0.28   | 3.50    | 0.79     | 101.23 | 7.42 | 1.70   | 7.30 |
| C - high weight L-band | -1.68 | 5.10    | 0.79     | 101.70 | 10.04 | 0.08   | 8.59 |
| D - fixed 100% SIC | -1.26   | 3.11    | 0.89     | 99.79  | 2.43 | 1.35   | 5.11 |

Note. SIC and MYIF retrieval statistics are also shown.

Initially we test the modified forward model in the OEM with only the L-band Tbs connected to the SIT parameter. In effect this allows for TB changes only in these channels to affect the retrieval. In the result shown in subplot (a) there is an obvious relationship between the lower thickness data points (as retrieved with the SMOS method) and the OEM retrieved lower SIC. As all data points are considered to be 100% SIC in this data set that the radiometric signature at the higher frequency channels for a 100% SIC scene with low SIT can be confused with that of a scene with lower SIC. These are the low (cyan) SIC pixels which register as 5–10 cm SIT on the SMOS axis but are retrieved as 50% SIC with 15–30 cm SIT by the OEM. The statistics (Table 6) show that this configuration agrees the least with the SMOS SIT retrieval, with a moderately high correlation of 0.69 while having a relatively large bias (8 cm) and high RMSD at around 8.9 cm. From all tested configurations, this OEM scheme also has the lowest mean retrieved SIC at 85% while the MYIF seems to stay within reasonable limits for this test data set with a mean value close to 0% and a standard deviation of 2.5%. This shows that the ice type retrieval is not biased in this retrieval while SIC is. This happens because low thickness sea ice has lower emissivity than the typical value used in the forward model parameterizations. In this case the method can only compensate for this lower emissivity in the higher frequency channels by allowing for an increased ice free water area fraction.

In order to correct for this behavior, in subplot (b) the forward model includes the SIT influence on FYI emission for all channels. This means that the high frequency sensitivity to very low SIT values can now be leveraged, and the resulting retrieval shows this. Most of the low SIC outliers from subplot (a) are now gone, and the range of OEM retrieved SIT between 5 and 15 cm is better populated while the average SIC value also increased. This is a good example of how the different sensitivities of the input channels help provide a consistent retrieval of multiple surface parameters. While the low SIT pixels are now correctly identified there are still a few pixels retrieved as having high SIT (30–50 cm) and low SIC (50%) at the same time. These pixels correspond to higher thicknesses in the SMOS retrieval as well so they could only depend on the L-band channel brightness temperature variability. The much better agreement with the SMOS SIT retrieval is mirrored in the statistics as the bias between the two retrievals is now close to zero while the RMSD decreased by more than half to 3.5 cm and the correlation increased to 0.79. The biggest change that can be seen in the plot is for SIC retrieval where the mean value has increased closer to 100% while the standard deviation decreased to 7.4%. This behavior is in line with what is expected from allowing all channels to constrain the SIT parameter thus benefiting from the different sensitivities to different value ranges of ice thickness as well as improving the consistency of the SIC retrieval. While there is an increase in the MYIF parameter variability (7.3% standard deviation up form 2.5%) the mean value remains close to zero (1.7%).

To test the effect of L-band TB variability on the outliers, in subplot (c) a version of the OEM retrieval is shown in which the weight of the L-band channels is increased by reducing the standard error from 3.8 to 1 K. This amounts to increasing the penalty on the cost function if the simulated brightness temperatures deviate from the measurements. This constrains the method to change the sea ice parameters in a way that matches closer with the L-band measurements. The result is that the outliers with very low SIC values present in plot (B) are now gone while the overall distribution of data points shows a larger number of high (>35 cm) SIT pixels. This behavior showcases the need for properly balancing the channel weights to ensure an unbiased retrieval while maximizing the channel specific sensitivities. For the (C) configuration in Table 6 the impact of increased L-band weights can mainly be seen in the increased SIT bias and RMSD when compared to the SMOS retrieval. A slight increase in SIC standard deviation (10% vs. 7.4%) around a similar mean as in case B) (101.7% vs. 101.2%) can be associated with the increased variability of the SIT retrieval. In accord with the other two sea ice parameters also MYIF shows the highest variability (8.6%) around a similar mean (0.1%)
as in the previously tested OEM schemes. In conclusion, this type of configuration where one channel is weighted above the precision capabilities of the forward model can lead to instability in the retrieval. This test aims to show that increasing the weights for the SIT sensitive L-band channels will help in avoiding local minima of lower SIC and higher SIT. In an operational setup the weights need to be adjusted to reflect realistically on the forward model accuracy as over-tuning TB constraints can lead to instability in other parameters. For the setup of this study the higher permitted initial deviation of 3.86 K is partially justifiable by the unavoidable mismatch between the SMOS footprints and the collocated AMSR2 footprints. Such a mismatch can be avoided when all channel measurements originate from a single instrument, and we believe that 1 K is not an unreasonable goal for a future model accuracy level.

In conclusion, this type of configuration where one channel is weighted above the precision capabilities of the forward model can lead to instability in the retrieval. This test aims to show that increasing the weights for the SIT sensitive L-band channels will help in avoiding local minima of lower SIC and higher SIT. In an operational setup the weights need to be adjusted to reflect realistically on the forward model accuracy as over-tuning TB constraints can lead to instability in other parameters. For the setup of this study the higher permitted initial deviation of 3.86 K is partially justifiable by the unavoidable mismatch between the SMOS footprints and the collocated AMSR2 footprints. Such a mismatch can be avoided when all channel measurements originate from a single instrument, and we believe that 1 K is not an unreasonable goal for a future model accuracy level.

In this case only the SIT and MYIF parameters can be modified in order to match the TB measurements and as such, the SIT retrieval case matches best with the SMOS retrieval. The full 100% cover assumption is also consistent with the SMOS SIT algorithm result. For the SIT comparison, this OEM configuration scores the second lowest bias (1.3 cm), the lowest RMSD (3 cm), and the highest correlation (0.89) with the SMOS SIT product. Because of the way the SIC a priori data is constrained, the corresponding retrieval is unsurprisingly stable with a standard deviation of only 2.4% around the mean value of 99.8%. The MYIF mean value is still low (1.4%) with decreased variability (5.11%) that can be associated with the low SIC variability. While this configuration cannot be used for an Arctic wide retrieval, it shows what possible localized configurations of the method could achieve when the a priori state of one or more of the retrieval parameters can be estimated with high confidence.

In Figure 9 the OEM SIT retrieval is compared to the SMOS SIT product as a sanity test to show that a CIMR equivalent 10 channel input and eight parameter output OEM configuration is feasible. A more complete evaluation of the OEM retrieval can only be made with in situ observations of SIT. Thin sea ice is a temporary phase during the freeze-up period and as such lasts for a relatively short window of time where ground data can be collected.

One such evaluation has been attempted using the data set of sea ice thickness from ship observations taken during the R/V Sikuliaq Arctic cruise from 5 October to 4 November 2015. A significant difference in coverage is to be expected between ship observations which are estimated to cover an area of 1 km radius around the ship during daytime, while during night time the observations can be considered relevant only for the area in the immediate vicinity of the ship. This footprint has to be compared with the much larger satellite footprint (both the SMOS and AMSR2 6.9 GHz equivalent footprints are 50–60 km in diameter). Such discrepancies are difficult to avoid when comparing satellite and in situ observations, especially for parameters such as SIT where there is little validation grade data available. As such, the results of comparing the satellite-based SIT retrieval with ship observation data proved to be inconclusive with little insight on the retrieval performance.

5. Conclusions

In order to estimate the potential performance of the CIMR instrument compared to existing capabilities, an optimal estimation approach has been adapted to CIMR equivalent brightness temperatures based on collocated observations from the AMSR-E/2 and SMOS instruments.

The procedure presented here retrieves seven surface and atmospheric parameters and allows for comparing the performance of different input channel combinations for different retrieval parameters. Through information content analysis, the surface and atmospheric contributions to each retrieval setup can be quantified, and the best channel combination can be matched to the sensitivity and resolution requirements. The best overall SIC retrieval setup uses only the 6.9 GHz channels (Figure 3). This OEM implementation consistently show the best agreement with a validated set of 0% and 100% SIC cases, as well as the best estimated precision out of all versions tested. In order to achieve resolutions comparable to the best current passive microwave products, a combination of the 18.7 and 36.5 GHz channels would offer SIC retrieval.
performance only slightly less accurate than the 6.9 GHz channels alone but much better than the 89 GHz channels can achieve.

An added benefit of the high resolution channel combination is that at the same time they offer reasonable sensitivity to ice types as well as to atmospheric water vapor (Figures 4 and 6). While at present there are other satellite passive microwave-based SIC products available that can achieve high accuracies (≤5%), the primary objective of CIMR is to combine such accuracy levels with the high resolution (5 km) currently available only by using the 89 GHz channels alone. The main conclusion of this study is that the combination of CIMR 18.7 + 36.5 GHz channels has the potential to meet both the accuracy of ≤5% and the resolution goal of ≤5 km.

A new feature of the presented OEM is the inclusion of the L-band channels which have been incorporated in the forward model, including open ocean, sea ice, and atmospheric components in order to simulate how CIMR-based OEM runs would function. While the contribution of these channels to the initial seven parameters is marginal, the real benefit comes from the ability to include the SIT parameter to the state vector. A sanity test comparison using different OEM configurations against an operational SIT retrieval using L-band observations has been performed. Using all CIMR equivalent channels in the OEM setup shows better agreement with the comparison retrieval while providing reasonable sea ice parameter retrieval including consistent values for both SIC and MYIF (Figures 9b and 9c). The most precise SIT results can be obtained when there is high trust in the a priori knowledge about the sea ice cover which is similar to how the current SMOS based SIT retrieval is applied (Figure 9d).

A second comparison using a set of ship observations of SIT has proven to be inconclusive because of atmospheric influence, high wind speed action over open water patches as well as the emission of nonhomogeneous young ice types which affect predominantly the higher frequency channels.

As a conclusion to this attempt to simulate a CIMR like OEM setup, the eight parameter retrieval (including SIT) is feasible and can deliver performance on par with existing operational products as long as the channel weights are balanced within the capabilities of the forward model. A more complex L-band forward model based on validated sea ice thickness data would help with setting realistic OEM constraints for this parameter. Having large data sets with validated thin sea ice cover can help to establish these weights; however, such data sets can only be obtained from future field campaigns.

At present a synergistic combination of AMSR2 and SMOS observations can be used as input for the OEM. The most challenging aspect of this approach is the influence of temporal and spatial discrepancy between instrument footprints. As sea ice drifts and weather patterns move, combining data from instruments which observe slightly different scenes would result in a biased OEM output. While this study supports the concept of using multichannel retrievals to take advantage of the complementary geophysical sensitivities they provide, more dedicated work is needed to address the footprint matching discrepancies and develop a process to combine the input from different passive microwave instruments into an operational implementation of the OEM.

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References
Ashcroft, P., & Wentz, F. (2013). AMSR-E/Aqua L2A global swath spatially-resampled brightness temperatures version 3. Journal of Geophysical Research: Oceans, 118, 6883–6900. https://doi.org/10.1002/2013JC018268.
Font, J., Boutin, J., Reul, N., Spurgeon, P., Ballabera, J., Chuprin, A., et al. (2010). Overview of SMOS level 2 ocean salinity processing and first results. In 2010 IEEE International Geoscience and Remote Sensing Symposium (pp. 3146–3149). IEEE.
Heygster, G., Huntemann, M., Ivanova, N., Saldo, R., & Pedersen, L. T. (2014). Response of passive microwave sea ice concentration algorithms to thin ice. In 2014 IEEE geoscience and remote sensing symposium (pp. 3618–3621).
Huntemann, M., Heygster, G., Kaleschke, L., Krumpen, T., Mäkynen, M., & Drusch, M. (2014). Empirical sea ice thickness retrieval during the freeze up period from SMOS high incident angle observations. The Cryosphere, 8, 439–451.
Imaoka, K., Seto, T., Takehina, T., Kawanishi, T., & Shibata, A. (2002). Instrument characteristics and calibration of AMSR and AMSR-E. In Geoscience and Remote Sensing Symposium, 2002. IGARSS’02. 2002 IEEE International (Vol. 1, pp. 18–20).
Ivanova, N., Pedersen, L., Tonboe, R., Kern, S., Heygster, G., Lavergne, T., et al. (2015). Inter-comparison and evaluation of sea ice algorithms: Towards further identification of challenges and optimal approach using passive microwave observations. The Cryosphere, 9(5), 1797–1817.
Kaleschke, L., Maab, N., Haas, C., Hendricks, S., Heygster, G., & Tonboe, R. (2010). A sea-ice thickness retrieval model for 1.4 GHz radiometry and application to airborne measurements over low salinity sea-ice. The Cryosphere, 4(4), 583–592.
Kaleschke, L., Tian-Kunze, X., Maas, N., Mäkynen, M., & Drusch, M. (2012). Seaice thickness retrieval from SMOS brightness temperatures during the Arctic freeze-up period. Geophysical Research Letters, 39, L05501. https://doi.org/10.1029/2012GL050916

Kerr, Y. H., Waldteufel, P., Richaume, P., Wigneron, J. P., Ferrazzoli, P., Mahmoody, A., et al. (2012). The SMOS soil moisture retrieval algorithm. IEEE Transactions on Geoscience and Remote Sensing, 50(5), 1384–1403.

Kilic, L., Prigent, C., Aires, F., Boutin, J., Heygster, G., Tonboe, R. T., et al. (2018). Expected performances of the Copernicus Imaging Microwave Radiometer (CIMR) for an all-weather and high spatial resolution estimation of ocean and sea ice parameters. Journal of Geophysical Research: Oceans, 123, 7564–7580.

Kongoli, C., Boukabara, S. A., Yan, B., Weng, F., & Ferraro, R. (2011). A new sea-ice concentration algorithm based on microwave surface emissivities—Application to AMSU measurements. IEEE Transactions on Geoscience and Remote Sensing, 49(1), 175–189.

Kwok, R. (2018). Arctic sea ice thickness, volume, and multi-year ice coverage: Losses and coupled variability (1958–2018). Environmental Research Letters, 13(10), 105005.

Lavergne, T. (2018). CIMR compared to other PMRs: Channels and spatial resolution. https://figshare.com/articles/CIMR_compared_to_other_PMRs_Channels_and_Spatial_resolution/7177730, https://doi.org/10.6084/m9.figshare.7177730.v1

Markus, T., & Cavalieri, D. J. (2000). An enhancement of the NASA Team sea ice algorithm. IEEE Transactions on Geoscience and Remote Sensing, 38(3), 1387–1398.

Matthews, N. (2007). Retrieval of surface emissivity of sea ice and temperature profiles over sea ice from passive microwave radiometers, University of Bremen. http://nbn-resolving.de/urn:nbn:de:gbv:46-diss000108511

Melsheimer, C., & Heygster, G. (2008). Improved retrieval of total water vapor over polar regions from AMSU-B microwave radiometer data. IEEE Transactions on Geoscience and Remote Sensing, 46(8), 2307–2322.

Melsheimer, C., Heygster, G., & Pedersen, L. T. (2008). Integrated retrieval of surface and atmospheric parameters over the Arctic from AMSR-E satellite microwave radiometer data using inverse methods. In IGARSS 2008-2008 IEEE International Geoscience and Remote Sensing Symposium, 4, pp. IV–96.

Patilea, C., Heygster, G., Huntermann, M., & Spreen, G. (2019). Combined SMAP–SMOSIIthin sea ice thickness retrieval. Cryosphere, 13, 675–691.

Pedersen, L. T. (1994). Merging microwave radiometer data and meteorological data for improved sea ice concentrations. EARSeL Advances in Remote Sensing, 2(2-XII), 81–89.

Pedersen, L. T., & Saldo, R. (2012). Sea ice concentration (sic) round robin data package. Pedersen, L. T., Saldo, R., Ivanova, N., Kern, S., Heygster, G., & Tonboe, R. (2019). Reference dataset for sea ice concentration. https://doi.org/10.6084/m9.figshare.6626549.v6

Rodgers, C. D. (2000). Inverse methods for atmospheric sounding: Theory and practice. World scientific.

Ruf, C. S. (2003). Vicarious calibration of an ocean salinity radiometer from low earth orbit. Journal of Atmospheric and Oceanic Technology, 20(11), 1656–1670.

Scarlat, R. C. (2018). Improving an optimal estimation algorithm for surface and atmospheric parameter retrieval using passive microwave data in the Arctic, Universität Bremen. http://nbn-resolving.de/urn:nbn:de:gbv:46-00106738-16

Scarlat, R. C., Heygster, G., & Pedersen, L. T. (2017). Experiences with an optimal estimation algorithm for surface and atmospheric parameter retrieval from passive microwave data in the Arctic. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10(9), 3934–3947.

Scarlat, R. C., Melsheimer, C., & Heygster, G. (2018). Retrieval of total water vapour in the Arctic using microwave humidity sounders. Atmospheric Measurement Techniques, 11(4), 2067.

Shannon, C., & Weaver, W. (1949). The Mathematical theory of information. Urbana: University of Illinois Press.

Shokr, M., Lambe, A., & Agnew, T. (2008). A new algorithm (ECICE) to estimate ice concentration from remote sensing observations: An application to 85 GHz passive microwave data. IEEE Transactions on Geoscience and Remote Sensing, 46(12), 4104–4121.

Stogryn, A. (1978). Estimates of brightness temperatures from scanning radiometer data. IEEE Transactions on Antennas and Propagation, 26(5), 720–726.

Svendsen, E., Matzler, C., & Grenfell, T. C. (1987). A model for retrieving total sea ice concentration from a spaceborne dual-polarized passive microwave instrument operating near 90 GHz. International Journal of Remote Sensing, 8(10), 1479–1487.

Tonboe, R. (2005). A mass and thermodynamic model for sea ice. Danish Meteorological Institute Scientific Report 05-10, Copenhagen.

Ulaby, F. T., Long, D. G., Blackwell, W. J., Elachi, C., Fung, A. K., Ruf, C., et al. (2014). Microwave radar and radiometric remote sensing (Vol. 4). Ann Arbor: University of Michigan Press Ann Arbor.

WMO (2014). Sea ice nomenclature. World Meteorological Organization.

Wentz, F. J., & Meisner, T. (2000). AMSR ocean algorithm. Algorithm Theoretical Basis Document (ATBD). version 2.

Zine, S., Boutin, J., Font, J., Reul, N., Waldteufel, P., Gabarró, C., et al. (2008). Overview of the SMOS sea surface salinity prototype processor. IEEE Transactions on Geoscience and Remote Sensing, 46(3), 621–645.