Arctic-Kara and Barents Sea Ice Thickness Estimation Based on CryoSat-2 Radar Altimeter and Sentinel-1 Dual-Polarized SAR

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Abstract. We present a method to combine CryoSat-2 (CS-2-CS2) radar altimeter and Sentinel-1 synthetic aperture radar (SAR) data to obtain sea ice thickness (SIT) estimates for the Barents and Kara Seas. Our approach yields larger spatial coverage and better accuracy compared to estimates based on either CS-2 or SAR alone. From the viewpoint of tactical navigation along-track altimeter SIT estimates are sparse, and the goal of our study is to develop a method to interpolate altimeter SIT measurements between CS-2 ground tracks. The SIT estimation method developed here is based on interpolation and extrapolation of CS-2 sea ice thickness (SIT) data to obtain sea ice thickness (SIT) estimates for the Barents and Kara Seas. We studied two approaches: CS2 directly interpolated to SAR segments, and CS2 SIT interpolated to SAR segments with mapping the CS2 SIT distributions to correspond SIT distribution of the PIOMAS ice model. Our approaches yield larger spatial coverage and better accuracy compared to SIT estimates based on either CS2 or SAR data alone. The agreement with modeled SIT is better than with the CS2SMOS SIT. The average differences when compared to ice models and the AARI ice chart SIT were typically tens of centimeters and there was a significant positive bias when compared to the AARI SIT (on average 27 cm) and a similar bias (24 cm) when compared to the CS2SMOS SIT. Our results are directly applicable to the future CRISTAL mission and Copernicus programme SAR missions.

1 Introduction

The goal of this study is to use Sentinel-1 (S-1) C-band SAR data to inter- and extrapolate Cryosat-2 interpolate CryoSat-2 (CS2) sea ice thickness (SIT) estimates to spatially cover the whole Barents and Kara Sea (BKS) area (see Fig. 1). Sea-ice thickness (SIT) is an essential sea ice parameter. We have chosen this study area because we have collected S-1 data over BKS since 2015 and also generated daily S-1 mosaics covering the area. Using combination of the CS2 and S-1 data it is possible to estimate SIT with much finer resolution and much larger spatial coverage than using only the CS2, or an other altimeter data. The interpolated CS2 SIT is assigned for classified SAR segments, i.e. locally uniform sea ice areas in the SAR imagery.
In this way we are able to provide accurate boundaries of different ice areas and provide a typical SIT for each of these areas based on the CS2 SIT data conducted within the areas themselves or nearby similar areas.

SIT is one of the essential climate variables. It is a key parameter, together with sea ice concentration (SIC), for estimating total ice volume over any given area of interest. Accurate estimates of SIT are important for ice navigation, off-shore engineering and construction [IMarEST (2015)], climate studies as well as sea ice and weather forecasting [Jung et al. (2014)]. The ocean–atmosphere heat, mass, momentum, and gas exchanges are controlled by the sea-ice thickness SIT distribution in the polar oceans. Thin ice with a thickness of less than half a meter produces strong heat and salt fluxes and affects the weather and deep water circulation in the polar oceans [McPhee (2008)]. Thick ice insulates the relatively warm ocean from the cold atmosphere maintaining the polar conditions, and is mainly responsible for the proportion of ice that persists through the summer melt period, which is particularly important for the summer radiation budget. For ship navigation in sea-ice-covered waters, the estimation of ice thickness is essential.

Estimation of ice thickness from radar and laser altimeter data has been studied extensively in recent years. Altimeters onboard several satellites have provided estimates of sea ice thickness and volume time series and trends for the Arctic and Antarctic Oceans for recent decades. Such methods have been applied and evaluated e.g. in Laxon et al. (2003); Giles et al. (2008); Kwok and Comiso (2002); Petty et al. (2020). In this study we use the CryoSat-2 (CS-2) radar altimeter data Wingham et al. (2006).

Due to the nature of altimeter measurements and the orbit pattern of the platform, CS-2 gives spatially and temporally sparse SIT information in temporal scales from one day to few weeks. Examples of all available CS-2 ice thickness estimates during the period of one day and one week over our Barents and Kara Seas study area are shown in Figure 1. From the viewpoint of tactical navigation these estimates are sparse, and the goal of our study is to develop a method to extrapolate altimeter SIT estimates between CS-2 ground tracks.

SIT algorithms combining CS-2 and other sources of information, e.g. SMOS (Soil Moisture and Ocean Salinity) mission with the the MIRAS (Microwave Imaging Radiometer using Aperture Synthesis) instrument exist Ricker et al. (2017). However, these algorithms still have relatively poor spatial and temporal resolution (25 km, weekly estimates updated daily). Thus more algorithms fusing CS-2 data with data from instruments with higher spatial and temporal resolution are needed for timely high resolution SIT estimates. Such ice thickness estimates can then be used e.g. in navigation and data assimilation to high resolution ocean sea ice forecast models.

Traditionally satellite altimeters, including CS-2, cannot estimate thickness of thin ice (<0.5 m) with reasonable uncertainty. Although recently launched ICESat-2 improves thin ice estimation, giving reasonable uncertainties down to SIT approximately 0.2 m Petty et al. (2020). Detection of thin ice and its thickness estimation can be done using satellite TIR imagery, e.g., from Moderate Resolution Imaging Spectroradiometer (MODIS), based ice surface temperature ($T_s$) together with atmospheric forcing data through ice surface heat balance equation Yu and Rothrock (2016). Unfortunately, this method is restricted by cloud cover and quality of cloud masking in polar conditions Frey et al. (2008). A daily MODIS SIT chart combined from swath SIT charts, which mitigates the cloud problem, has been developed in Makynen and Karvonen (2017). In addition, daily cloud-cover corrected MODIS SIT composites for polynya monitoring have been produced utilizing several days of swath data Paul et al. (2015). Thin ice detection and its SIT estimation in winter conditions are also possible with microwave radiometer
data. Thin ice thickness retrieval algorithms have been developed for low-frequency L-band brightness temperature (TB) data from SMOS and Soil Moisture Active Passive (SMAP) missions Kaleschke et al. (2012); Tian-Kunze et al. (2014); Huntemann et al. (2014); Kaleschke et al. (2016); Schmitt and Kaleschke (2018).

With the SMOS data SIT can be estimated up to 0.5–1.5 m thick ice Kaleschke et al. (2016). The drawback of the SMOS data is its poor spatial resolution, 35–50 km, which does not allow to detect leads and smaller polynyas. For high-frequency radiometer data (36 and 90 GHz), thin ice SIT retrieval algorithms have also been developed, e.g. Martin et al. (2004); Iwamoto et al. (2014).

The thin ice SIT can be typically estimated up to 20 cm, and the SIT data are used for polynya monitoring, e.g. Onshima et al. (2016).

Estimation of SIT with synthetic aperture radar (SAR) data has been studied before. In the Baltic Sea, SIT estimation of deformed ice under dry snow conditions is possible through a statistical relationship between the ice freeboard and the radar backscatter Similä et al. (2010)(Similä et al., 2010). The standard deviation of the average large-scale surface roughness \( F \) increases with increasing average \( F_{\text{surface roughness}} \), and, as the average surface roughness increases, the backscatter also increases. An exponential empirical model was derived for estimating \( F_{\text{average surface roughness}} \) from the backscattering coefficient (\( \sigma^0 \)) and dominant thickness of level ice. A good correlation between the L- and C-band co-polarization ratio and SIT of undeformed ice in the Sea of Okhotsk have been found Nakamura et al. (2006). The co-polarization ratio has little sensitivity to ice surface roughness and is related to variations in salinity, i.e. ice surface dielectric constant, that can be caused by changes in SIT (Wakabayashi et al., 2004). Toyota et al. (2011) found good correlation between ALOS/PALSAR L-band HH-polarization \( \sigma^0 \) and SIT (R = 0.86) and surface roughness (R = 0.70) in the seasonal ice zone (SIZ), and derived linear relation between \( \sigma^0 \) and SIT (SIT from 0.2 to 0.6 m). They suggested that satellite L-band \( \sigma^0 \) data allows to estimate SIT distribution in the SIZ, where surface roughness is closely related with the SIT distribution through deformation processes. Airborne C-band polarimetric SAR (POLSAR) data together with a theoretical backscattering model have been used to estimate SIT in the 0–10 cm range (Kwok et al., 1995). Zhang et al. (2016) derived SIT estimation method for undeformed first-year ice under dry snow conditions based on sea ice thermodynamic model and forward scattering model for C-band compact polarimetric (CP) SAR images. Using simulated CP imagery from RADARSAT-2 POLSAR SIT estimation was possible up to 80 cm thickness. SAR data have also been used to estimate SIT of pancake ice from the way in which the pancake ice changes the dispersion relation of the waves, dampens the wave amplitude and causes dissipation of the energy of the waves, i.e., it changes the wavelength of ocean waves as they enter the ice (Wadhams et al. 2018). SIT retrieval methods based only on the SAR data are still experimental, and no operational solutions are yet available.

As indicated by these earlier studies SAR, especially C-band SAR (S-1), alone is not capable of estimating accurately Arctic SIT. Thus, complementary data is required for reasonable Arctic SIT estimation. In this paper we try to overcome this deficiency by proposing a method to utilize CS2 SIT as complementary data to SAR data to estimate Arctic SIT.

Detection of thin ice and its thickness estimation can be done using satellite thermal infrared (TIR) imagery, e.g., from Moderate Resolution Imaging Spectroradiometer (MODIS). Satellite based ice surface temperature (\( T_s \)) is combined with atmospheric forcing data through ice surface heat balance equation for the SIT estimation Yu and Rothrock (2016). Unfortunately, this method is restricted by cloud cover and quality of cloud masking in polar conditions Frey et al. (2008). A daily MODIS
SIT chart combined from swath SIT charts, which mitigates the cloud problem, has been developed in Makynen and Karvonen (2017). In addition, daily cloud-cover corrected MODIS SIT composites for polynya monitoring in the Arctic and Antarctic have been produced utilizing several days of swath data Paul et al. (2015); Preusser et al. (2016).

Thin ice detection and its SIT estimation in winter conditions are also possible with microwave radiometer data. Thin ice thickness retrieval algorithms have been developed for low-frequency L-band brightness temperature (TB) data from SMOS and Soil Moisture Active Passive (SMAP) missions Kaleschke et al. (2012); Tian-Kunze et al. (2014); Huntemann et al. (2014); Kaleschke (2015). With the SMOS data SIT can be estimated up to 0.5–1.5 m thick ice Kaleschke et al. (2016). The drawback of the SMOS data is its poor spatial resolution, 35–50 km, which does not allow to detect leads and smaller polynyas. For high-frequency radiometer data (36 and 90 GHz), thin ice SIT retrieval algorithms have also been developed, e.g. Martin et al. (2004); Iwamoto et al. (2014); Smith et al. (2018). The thin ice SIT can be typically estimated up to 20 cm, and the SIT data are used for polynya monitoring, e.g. Onshima et al. (2016).

Estimation of ice thickness from radar and laser altimeter data has been studied extensively in recent years. Altimeters onboard several satellites have provided estimates of sea ice thickness and volume time series and trends for the Arctic and Antarctic Oceans for recent decades. Such methods have been applied and evaluated e.g. in Laxon et al. (2003); Giles et al. (2008); Kwok and Zhang (2015). Traditionally satellite altimeters, including CS2, cannot estimate thickness of thin ice (<0.5 m) with reasonable certainty. Wingham et al. (2006). However, the recently launched ICESat-2 improves thin ice estimation, giving reasonable uncertainties down to SIT of approximately 0.2 m Petty et al. (2020).

In this study we use the CS2 radar altimeter SIT data Wingham et al. (2006). Due to the nature of altimeter measurements and the orbit pattern of the platform, CS2 gives spatially and temporally sparse SIT information in temporal scales from one day to few weeks. Examples of all available CS2 ice thickness estimates during the period of one day and one week over our Barents and Kara Seas study area are shown in Figure 1. Especially for tactical navigation these estimates are sparse. Thus, our goal is to develop a method to interpolate altimeter SIT estimates between CS2 ground tracks.

SIT estimation algorithms combining CS2 and other sources of information, e.g. SMOS (Soil Moisture and Ocean Salinity) mission with the MIRAS (Microwave Imaging Radiometer using Aperture Synthesis) instrument exist Ricker et al. (2017). However, these algorithms still have relatively poor spatial and temporal resolution (25 km, weekly estimates updated daily). Therefore, algorithms fusing CS2 data with data from instruments with higher spatial and temporal resolution are needed for timely high-resolution SIT estimates. Such SIT estimates can then be used e.g. in navigation and data assimilation to high-resolution ocean-sea ice forecast models.

The structure of this paper is as follows: the study area, time period and weather conditions are described in Section 2, then the data sets used in the study are described in Section 3, followed by the description of the data preprocessing, and the proposed SIT estimation method combining CS2 SIT and SAR data in Section 4. The proposed SIT interpolation is based on pairwise similarity of segments and their pairwise distance and time difference. The texture similarity is measured by similarity of several segment-wise SAR texture features. The texture features and the similarity criteria are described in detail in Section 4. The estimation results and their evaluation are presented in Section 5. For evaluation we have used sea ice model data, ice chart
data and also included comparisons to the SIT charts based on CS2 and the ESA SMOS radiometer data Ricker et al. (2017), and to the MODS SIT charts Makinen and Karyonen (2017). Finally, discussion and conclusions are provided in Section 6.

2 Study Area, Sea Ice and Weather Conditions and Time Period

Our study covers Kara and Barents Seas, see Fig. 2. Seasonal sea ice is found over most of our study area. In the far north, however, multi-year ice (MYI) is present year-round Johannessen et al. (2007). The average dates for the ice formation over the area varies from September 40th-10th in the north to mid-November in the southern Kara Sea and south-eastern Barents Sea (Pechora Sea), and March-April in the central Barents Sea (west of Novaya Zemlya) Johannessen et al. (2007). Melting season begins in late April in the marginal ice zone of the Barents Sea. By the end of June the central Barents Sea and the Pechora Sea are usually ice-free. In August the ice edge reaches Svalbard and Franz Josef Land. In the Kara Sea, melting gradually begins in May and continues through July and August. Most of the Kara Sea is ice-free between mid-July and mid-August. In Kara Sea, the ice season lasts for 6–9 months depending on the location and seasonal conditions. We have only used wintertime data (January-April, October-December) for two calendar years, 2016 and 2017. Currently, radar altimeter SIT retrieval is only possible in dry snow winter conditions Kern et al. (2020). During the melt season the radar wave penetration in snow pack is ambiguous and surface type classification often fails due to melt ponds which give similar radar waveforms as the leads.

Throughout our study we use the following coordinate system (CS) based on polar stereographic projection with a center longitude of 55°E, reference latitude (latitude of the correct scale) of 70°N and the WGS84 datum. The upper left (UL) and lower right (LR) coordinates, i.e. the polar stereographic CS northing and easting in meters are: UL=(-700000,-1100000) and LR=(-2550000,1100000). The size of the study area is 2200 km (easting) by 1850 km (northing).

2.1 Weather Conditions

Air Average daily air temperature data \( T_a \) from four coastal weather stations (Kongsøya, Vize, Im. M.V. Popova, and Varandey) shown in Fig. 2 are used to evaluate the weather conditions, periods of cold and warm weather, during our study period: January-April and October-December in 2016 and 2017. The daily average air temperature \( T_{am} \) \( (T_a) \) data from the four stations are shown in Fig. 3. We set here \( T_{am} T_a <-5 \degree C \) to represent dry snow cold conditions, and \( T_{am} T_a >0 \degree C \) to moist/wet snow conditions where when the snow pack, if exists, prevents or significantly attenuates radar returns from sea ice. Between these \( T_{am} T_a \) limits the state of the ice snow pack is ambiguous as it depends on \( T_a \) history and time of the CS-2 CS2 and S-1 data acquisition, e.g. early morning vs. late afternoon. The \( T_{am} T_a \) data will not be used classify the CS-2 to classify the CS2 and S-1 into different weather condition classes, but to support analysis on the accuracy of SIT from the combined CS-2 CS2 and S-1 data. It is noted that the \( T_{am} T_a \) limits above are only approximations.

At the Vize station, representing the northern part of the Kara Sea, \( T_{am} \) during January-April 2016 is mostly below –5 °C, there is only few instances of one to three day long periods of \( T_{am} \) above –5 °C, and – \( T_{am} \) is all the time below 0 °C. \( T_{am} \) at the Popova station, which is located at the central Kara Sea, has similar behaviour, but from around 21 Apr onwards \( T_{am} \) is over –5 °C. At the Kongsøya station located on the Barents Sea, east of Svalbard, \( T_{am} \) is much warmer and is below –5 °C only.
During half of the days in January-April, but still \( T_{\text{air}} \) is over 0 °C only in the beginning of Jan. At the Varandey station in the Pechora Sea \( T_{\text{air}} \) shows very cold weather in Jan, short periods of \( T_{\text{air}} > 5 \) °C in Feb and Mar, and then rather warm weather after first week of Apr. We estimate that the period Jan-Apr during first part of our two year study period, from January to April 2016 represent our analysis of the \( (T_a) \) data from the four weather stations, suggests that this time period represents typically cold dry snow conditions in our study area.

During October 2016 to Apr 2017 \( T_{\text{air}} \) from the Vize station is over 0 °C during the first week of October and mostly over -5 °C up to end of third week of November. After that there is only few cases of 1-3 day long periods of \( T_{\text{air}} \) above -5 °C. At the Popova station \( T_{\text{air}} \) is over 0 °C during first two weeks of October, and mostly below -5 °C after beginning of November. The Kongsøya \( T_{\text{air}} \) is all the time over -5 °C up to 24 November, and afterwards there are variable periods of \( T_{\text{air}} \) above and below -5 °C with an average decreasing \( T_{\text{air}} \) trend. \( T_{\text{air}} \) is all the time below -5 °C in Apr. At the Varandey station \( T_{\text{air}} \) is above 0 °C up to end of October. After beginning of November \( T_{\text{air}} \) is mostly below -5 °C. There is a period of warm weather in 15-26 Mar with \( T_{\text{air}} \) sometimes being slightly over 0 °C. We conclude that CS-1: The second part of the study period, from October 2016 to April 2017, covers one winter sea ice season. Our analysis shows the CS2 and S-1 data from the beginning of October to roughly mid-November is typically affected by wet or moist snow conditions, depending on the diurnal acquisition time and location in our study area (more probable in the Barents and Pechora Seas). Data acquired from mid-November 2016 to Apr 2017 mostly represent cold winter conditions.

In October - December 2017 the Vize \( T_{\text{air}} \) is continously below -5 °C after 5 November. It is never above 0 °C. At the Popova station \( T_{\text{air}} \) very close to or above 0 °C during first two weeks of October. It is mostly below -5 °C after 7 November. In the Barents Sea at the Kongsøya stations \( T_{\text{air}} \) is longer periods below -5 °C only in 20-30 November, and 25 Dec onwards. At the Varandey station \( T_{\text{air}} \) is above 0 °C in 1-10 October, and continously above -5 °C up to 7 November. Afterwards there are periods up to 10 days with \( T_{\text{air}} \) either above or below -5 °C. The third, and the last, part of the study period is from October to December 2017, and represents sea ice freeze-up and early winter conditions. It seems that in the Kara Sea the time period after first week of November 2017 can be assumed to represent mostly cold winter conditions. In the Barents and Pechora Seas in November and December there are also periods of cold winter conditions, but sometimes \( T_{\text{air}} - T_a \) is between -5 and 0 °C, when there could have been moist snow effects on the radar signatures.

3 Data

In this section we present the data sets used in our study.

3.1 CryoSat-2 Data

CS2’s primary payload is the Synthetic Aperture Interferometric Radar Altimeter operating in the Ku-Band (13.6 GHz) which allows a much smaller sampling footprint (about 250-300 m in the satellite track direction) than earlier satellite radar along track direction Scagliola (2013)) than traditional pulse-limited altimeters. Over sea ice, CS2 echoes are assumed to scatter from the interface between the ice surface and the layer of overlying snow Laxon et al. (2013), thus enabling freeboard,
denoted by $F$ here, estimation, and further, sea ice thickness calculation by SIT calculation assuming known snow depth and density, and sea ice density (e.g. climatologically derived).

The quantity altimeters measure is surface elevation, from which freeboard ($F$) can be derived from. Assuming hydrostatic equilibrium and known sea ice density ($\rho_i$), snow density ($\rho_s$) and thickness ($h_s$), and water density ($\rho_w$) the following equation can be formed for the SIT ($h_i$) estimation.

$$h_i = \frac{\rho_w}{\rho_w - \rho_i} F - \frac{\rho_w - \rho_s}{\rho_w - \rho_i} h_s.$$  \hspace{1cm} (1)

In dry snow conditions, the radar scattering and backscattering penetrate the snow cover and the backscattering comes from the ice surface, i.e. the ice freeboard is measured by a radar altimeter. In dry snow conditions $h_i$ can be estimated from the ice freeboard $F_i$:

$$h_i = \frac{\rho_w}{\rho_w - \rho_i} F_i + \frac{\rho_s}{\rho_w - \rho_i} h_s.$$  \hspace{1cm} (2)

As can be seen from equation above, snow equations above, $h_s$ estimate has a large effect on retrieved SIT. In the case of radar altimeters, such as CS-2 CS2 used here, $h_s$ is also required for signal wave propagation speed correction in deriving $F$.

A more detailed analysis on the effect of snow can be found in Kern et al. (2015). In this study, like in many other CS-2-based CS2-based sea ice thickness products, climatological snow depth and density based on the Warren climatology Warren et al. (1999) are used.

In this study we have computed sea ice thickness SIT with FMI implementation of the python sea-ice radar altimetry tool-box (PySiral, available in: https://github.com/shendric/pysiral). The primary input has been the European Space Agency’s CS-2 Baseline-C CS2 Baseline-D Level-1B product. Our processing follows the algorithm of Ricker et al. (2014); Hendricks et al. (2016) and for auxiliary Ricker et al. (2014); Hendricks et al. (2021). For auxiliary data we have used the DTU15 mean sea surface height product, EUMETSAT OSISAF sea ice concentration and sea ice type, as well as Warren 1999 snow depth and density data with the 50 percent reduction over first-year ice first proposed by Kurtz and Farrell (2011).

3.2 Sentinel-1 SAR

All the available Copernicus Sentinel-1 (S-1 C-band dual-polarized Extra Wide (EW) swath mode level 1 Ground Range Detected Medium resolution (GRDM) SAR data with the HH/HV polarization channels over the BKS study area and period (January-April and October-December 2016, and January-April and October-December 2017) were used in this study. The SENTINEL-1 SAR data are publicly available through the European Space Agency (ESA) Copernicus Science Hub (https://scihub.copernicus.eu/). The S-1 EW SAR images cover a region of 410 by 400 km in size, with a pixel size of 40 m and a spatial resolution of 95–91 by 90 m (range by azimuth), and have $\theta_0$ variation from 19$^\circ$ to 47$^\circ$.

3.3 Reference Datadata

In our study we use the Russian AARI Arctic-Antarctic Research Institute (AARI) ice charts, Ocean Reanalysis System 5 (ORAS5 PIOMAS), Pan-Arctic Ice-Ocean Modeling and Assimilation System (PIOMAS), and TOPAZ4 ice model ocean-sea
ice reanalyses SIT data, CS2SMOS SIT data Ricker et al. (2017) and MODIS daily SIT charts Makynen and Karvonen (2017) as reference data. They are used to evaluate the performance of our CS2-SAR SIT estimation method. The TOPAZ4 SIT model data are also used to remap the CryoSat-2 training data set based on cumulative SIT distributions.

### 3.3.1 AARI ice charts

Arctic and Antarctic Research Institute (AARI) produces weekly ice charts for many Arctic regions, including the Barents and Kara Seas Bushuev et al. (2007). The ice charts are based on the available visible AARI (2018); Afanasyeva et al. (2019) . These charts are currently widely used for a variety of scientific and practical tasks. The main input data for the ice chart generation is remote sensing data from various optical, thermal infrared and SAR imagery and reports from coastal stations and ships. The polygonalization of images and subsequent interpretation and mapping of ice conditions are carried out microwave satellite sensors, including MODIS, AVHRR (Advanced Very-High-Resolution Radiometer), S-1 SAR, Sentinel-3 OLCI (Ocean and Land Colour Instrument). The regional ice charts are based on satellite imagery collected over a period of 2-3 days. The more recent information is in priority. In case of absence of up-to-date information, the data for previous day is used. The ice charts are generated by skilled ice analysts experts using an ArcGIS workstation. The ice analyst defines homogeneous sea ice zones, polygons, on georeferenced satellite imagery, and assigns various sea ice attributes, e.g. sea ice concentration, to the polygons. In this process also auxiliary data, e.g. operational monitoring of sea ice drift using satellite data, and Observations from hydrometeorological stations of Roshydromet, are utilized. The main purpose of the a regional weekly ice chart is to show the spatial distribution and characteristics of sea ice. Many sea ice details within polygons are ignored. The AARI The AARI weekly ice charts are in the digital SIGRID-3 vector file format JCOMM (2014b). We have not found any publication that discusses the uncertainty of the AARI weekly ice chart. The AARI ice charts are available at: http://wdc.aari.ru/datasets/d0004/.

The ice charts convey their information in codes that are explained in JCOMM (2014a). The charts show total concentration (code CT) and partial concentrations of the first, second, and third thickest ice (codes CA, CB, and CC) along with their respective stages of development (SA, SB, and SC) and form of ice (FA, FB, FC) for polygonal areas of variable sizes. The concentrations are shown with intervals of either one or two tenths wide. The stage of development is defined as ice thickness intervals. Following thickness ranges are used: nilas (<10 cm), young ice (10–30 cm), grey ice (10-15 cm), grey-white ice (15-30 cm), thin FYI first-year ice (FYI) (30–70 cm), medium FYI (70–120 cm), thick FYI (>=120 cm), FYI in general (>=30 cm), and old ice (>=120 cm). The form of ice carries information on e.g. ice floe size or occurrence of landfast ice. Some polygons only have one or two stage of development classes assigned to them (i.e. polygons are more homogeneous homogeneous).

In the ice charting community, the definition of ice thickness that the ice charts reports is somewhat ambiguous. For the AARI charts, Afanasyeva et al. (2019) states that: “Fast stage of development, i.e. SIT range, estimation fast ice thickness measured at a hydrometeorological station serves as a reference Afanasyeva et al. (2019). Looking at a satellite image, ice expert matches brightness of drifting ice outside the shore to brightness of land-fast ice with known thickness. Thus, Further, monitoring SIT at a seashore stations allows to estimate the rate of ice growth in remote areas. Here we interpret the AARI ice thickness SIT as the thickness of level ice in the area - analogous to the thermodynamic grown fast ice.
For validation, polygons from AARI charts were gridded to the AARI ice charts were interpolated to an 1 km km grid covering our study area. Then for each AARI ice chart polygon a mid-range SIC and mid-range SIT or upper or lower SIT values of the first, second, and third thickest ice types were assigned. However, for FYI general type (SIT>=30 cm) a SIT value of 95 cm is used (same as for thick FYI). An average SIT for each chart polygon was calculated as a sum of the SIT values for the three ice types weighted with their concentrations. Finally, the gridded charts for the Barents and Kara Seas were combined together, see an example in Fig. 8(c). This processing of the AARI charts has been used previously by Makynen and Karvonen (2017). The total number of the AARI weekly charts used in the validation was 37 (time span from 4 Jan until 26 Dec, excluding the summer period) for both the Barents and Kara Seas.

3.4 Model Reanalysis Data CS2SMOS weekly SIT chart

The SMOS L-band brightness temperature data are currently used estimate SIT for thin ice areas (<1 m) Kaleschke et al. (2012), while CS2 data allows to estimate SIT for thicker ice (>1 m) Ricker et al. (2017). The CS2SMOS SIT product merges the SMOS and CS2 SIT data which are complementary to each other. The CS2 SIT used in the merging is a weekly averaged product, and the daily SMOS SIT product is likewise averaged to weekly temporal scale. Optimal interpolation similar to Böhme and Send (2005); McIntosh (1990) are used to merge the data sets into the regular product grid.

3.5 Model reanalysis data

3.5.1 TOPAZ4

TOPAZ4 is a coupled ocean-sea ice model with advanced data assimilation system for the North Atlantic Ocean and Arctic Sakov et al. (2012). The data assimilation is based on the use of ensemble Kalman filter Evensen (1994). The resolution of the TOPAZ4 model grid is 12–16 km. TOPAZ4 is operationally available in CMEMS (Copernicus Marine Environment Monitoring Service) funded by European Commission. In this study we have used the TOPAZ4 daily reanalysis ice thickness values (CMEMS product ARCTIC_REANALYSIS_PHY_002_003) Copernicum PUM (2020). The CS2SMOS thickness Ricker et al. (2017), based on fusion of Cryosat-2 CS2 and SMOS SIT is assimilated to the TOPAZ4 reanalysis SIT product. The modelled during wintertime, from end of October to early April. The modeled sea-ice thickness provided by the TOPAZ4 CMEMS product is a diagnostic variable based on prognostically calculated sea-ice volume divided by sea-ice concentration for each model grid cell. Accordingly, it provides the mean sea-ice thickness for the portion of grid cell that is covered by sea ice.

3.5.2 ORAS5

Because As TOPAZ4 seems to underestimate the Arctic ice thickness (Xie et al., 2018), we also used the ORAS5 (Ocean Reanalysis System 5) reanalysis SIT data Zuo et al. (2017, 2019),(Zuo et al. (2017), Zuo et al. (2019)). Tietsche et al. (2017) calculated the root-mean-square-difference between ORAP5ORAS5, the prototype of ORAS5, and ICESat sea-ice thicknesses to be of 1.0 m, comparable to the PIOMAS product (Schweiger et al. , 2011), see also section 3.5.3. The ORAS5 data are
produced by the European Centre of Medium-Range Weather Forecasts (ECMWF) in 0.25 degree nominal resolution in a stretched global tri-polar grid with the poles in northern Canada, Eurasia and the South Pole. This grid has a resolution of about 5–15 km in the Arctic. A feature of ORAS5 is that in the open-water part of a grid cell sea ice forms at a certain initial thickness of the order of $H_0 = 0.5$ m Tietsche et al. (2017). Such a treatment of initial sea ice is common in geophysical sea-ice models (Lemieux et al., 2018). The initial thickness $H_0$ is, coincidentally, close to the thinnest ice CS2 is able to reliably measure. As TOPAZ4, the ORAS5 product provides the diagnostic sea-ice thickness for each grid cell that has been calculated by dividing the modeled sea-ice volume by concentration.

### 3.5.3 PIOMAS

Additionally we utilized the PIOMAS model (Pan-Arctic Ice Ocean Modeling and Assimilation System) Zhang and Rothrock (2003) SIT data which have a coarser resolution than TOPAZ4 and ORAS5. Despite the coarse resolution, PIOMAS sea-ice volume agrees well with the ICESat estimates (Schweiger et al., 2011). The PIOMAS model grid is a stretched generalized orthogonal curvilinear coordinate (GOCC) system. A GOCC system allows a coordinate transformation that displaces the pole of the model grid. The PIOMAS model data are in the GOCC grid with the northern grid pole displaced into Greenland. The PIOMAS resolution in our study area is around 40 km. Unlike TOPAZ4 and ORAS5, PIOMAS provides sea-ice volume per unit area, which was divided by the PIOMAS sea-ice concentration to obtain sea-ice thickness per grid cell. Because of the coarse resolution of the PIOMAS data we did not use it in direct comparisons, but we utilize it in defining the mapping of CS2 thicknesses to model compliant thicknesses in Section 3.

### 3.6 MODIS Daily SIT Chart

Daily MODIS ice thickness ($h_{iM}$) charts for our study area have been processed for two winters, from November 2015 to April 2017. All the details on the daily chart processing can be found in Makynen and Karvonen (2017). The daily charts are based on all available Aqua and Terra MODIS $h_{iM}$ swath charts. Charts for very cloudy days were manually excluded. The total number of the daily charts is 317.

The MODIS based SIT charts have pixel size of 1 km, but the cloud mask has 10 km pixel size. The daily $h_{iM}$ chart shows daily median $h_{iM} (h_{iM}^d)$ for pixels which had at least two $h_{iM}$ samples from the swath charts. The requirement for having at least two valid $h_{iM}$ samples decreases the errors due to the misdetected clouds in the swath charts. $h_{iM}^d$ has following values:

- **Thickness categories**
  - (1) 0-0.3 m
  - (2) 0.31-0.5 m
  - (3) $h_{iM}^d$ > 0.5 m

*The first category is given as cm in the MODIS SIT chart*, for the second category the value 40 cm is given in the SIT maps, and for the third category the value 50 cm is given in the SIT chart.

The MODIS $h_{iM}$ swath charts are based on ice surface temperature from the MODIS/Terra or Aqua Sea Ice Extent 5-Min L2 Swath 1km product (MOD29/MYD29) and ERA-Interim atmospheric forcing data. The processing method of the $h_{iM}$ swath chart is described in detail in Makynen et al. (2013). Cloud masking for the swath $h_{iM}$ charts was conducted using fully automatic methods Makynen and Karvonen (2017). As the uncertainty of the retrieved $h_{iM}$ increases with increasing
air temperature $T_a$, the $h_{i,M}$ retrieval with the MODIS swath data was not conducted when $T_a > -5 \, ^\circ C$. The typical maximum reliable $h_{i,M}$ (max 50% uncertainty) is 0.35-0.50 m Makynen et al. (2013).

4 Methodology

3.1 S-1 preprocessing

We georectified and sampled the S-1 SAR data into a 100-m pixel size. Absolute calibration was applied to get the backscattering coefficient value at each pixel in logarithmic scale (unit dB). The calibration to provide the backscattering coefficients ($\sigma_{HH}^0$ and $\sigma_{HV}^0$ for HH- and HV-channel) at image location (pixel $i$) was performed according to the following equation Bourbigot et al. (2016):

$$\sigma_i^0 = \frac{(DN_i^2 - n_i)}{A_i^2}$$

(DN$_i$ is the original image pixel value at location $i$, $n_i$ is the provided noise data at location $i$, and $A_i$ the provided calibration coefficient at location $i$.)

The S1 data was preprocessed by applying a linear incidence angle correction Makynen and Karvonen (2017) to the HH channel and a combined incidence angle and noise floor correction to the HV channel, for details, see Karvonen (2017). The HH channel incidence angle correction has been tuned for sea ice. This leads to reduced performance on open water because of the varying contribution of the water surface due to waves (Bragg scattering) to the backscattering measured by SAR backscatter by ocean waves. After incidence angle and noise floor corrections the image data were geo-rectified into the polar stereographic projection specified in Section 2. After geo-rectification the imagery were down-sampled to 500 m resolution, and finally the daily mosaics were constructed by overlaying the newer images over the older ones such that at each mosaic grid cell (pixel) the newest SAR data prior to the mosaic time label, which was defined to be 12:00 UTC daily here, was available.

The mosaic was initialized only in the beginning of the mosaicking (in this case in the beginning January 2016). In practice the data at a given grid cell location were never older than three days from the mosaic time label. Separate mosaics for the HH and HV channels were constructed. Finally, a land mask based on the GSHHG coastline (Wessel and Smith , 1996) was applied to the mosaic to exclude land areas. The SAR mosaics of 21 February 2017 for the HH and HV channels are shown in Fig. 4 and a detail of the channel images small parts of the mosaics (more details visible) in Fig. 5.

SAR images were processed to 8 bits-per-pixel images by scaling the $\sigma^0$ between 1 and 255 (0 representing background). The scaling for the HH channel is such that -30 dB corresponds to the pixel value of one and 0 dB corresponds to the pixel value of 255. For HV channel the decibel values are -40 and 0, respectively. For segmentation the meanshift (MS) algorithm Fukunaga and Hostetler (1975) was first applied to locate the modes of the two-dimensional (HH and HV) SAR data. The meanshift algorithm has been empirically adjusted so that about 10-15 modes will be produced after convergence. The initial 10-15 categories based on MS were then used as a starting point for iterated conditional modes (ICM) segmentation Besag (1986).
3.2 Interpolation of CS2 using S-1 SAR

We also identify the low SIC areas (SAR segments with SIC < 50%) and exclude them from the SIT estimation procedure. The algorithm utilizing both SAR and AMSR2 microwave radiometer data of Karvonen (2017) is used to locate the low SIC areas.

First, the SAR mosaics are segmented. Next, the CS-2 SIT values are mapped to SAR segments where enough CS-2 SIT measurements are available. Then the SIT is estimated for the rest of the segments by using a difference function describing the similarity of the segments and pairwise distance of each pair of segments in time and space. The difference function includes several SAR features in addition to the temporal and spatial distance of the segments. The data of January-April and October-December 2016 were used for training the algorithm and January-April and October-December 2017 data were used for evaluating the algorithm performance.

4 Methodology

In the first sub-section we describe the SAR processing including calibration, resampling to the desired projection and cropping to the study area as well as building daily SAR mosaics. Interpolation of the CS2 SIT is then described in the following subsection. This interpolation consist of several steps, including SAR segmentation, computing segment-wise SAR texture features used in the matching of the SAR segments used to define the SIT value to be assigned to each SAR segment. In the third subsection we describe the remapping of the SIT applied here to better correspondence between the estimated SIT and modeled SIT.

A block diagram of the SIT estimation algorithm is presented in Fig. 6. In the first phase the CS2–CS2 SIT values are assigned to SAR–segments of the segmented SAR mosaic. Only the segments with a large enough number of CS2 SIT measurements (>N) within them get a SIT directly assigned. The SIT value assigned to the segments is the median of the CS2 SIT values within the segment. In the next phase the difference function a difference function to other segments with CS2 SIT measurements and withing a predefined distance and time range is computed for all the segments without an assigned SIT value yet between all the segments with an already assigned SIT value within range. The difference function describes the pairwise segment similarity, being small for similar segments and larger for different segments. In the following phase a SIT is assigned—interpolated to the segments without a SIT value using a median-based on the CS2 SIT values within the similar segments. For one segment the of SIT values of M segments with the smallest difference function values. As a last step, a remapping the segments ordered by ascending similarity (difference function) with respect to the segment are used to interpolate the SIT for the segment. The CS2 SIT values of the most similar segments are included until the number of SIT values exceeds the threshold value N, The average of these included CS2 SIT values weighted by the inverse of the segment difference is then assigned to the segment. For the remapped estimates a mapping based on histograms of the estimated SIT and PIOMAS, ORAS5 and TOPAZ4 model reanalyses SITs for the training data are ice model SIT for a training data is performed to get bias corrected SIT estimate for each segment. reduced bias with respect to the reference data. These steps are describe in more detail in the following subsections.
4.1 Interpolation of CS2 SIT using S-1 SAR

In this subsection we describe the mapping and interpolation of the CS2 SIT to SAR segments. SAR segments represent uniform areas in the SAR image and each SAR segment is here assumed to have a uniform SIT value derived from the CS2 SIT values within the segment or interpolated from the CS2 SIT values of other SAR segments with CS2 SIT values in the case there are not enough CS2 SIT values within a SAR segment.

As we want to provide SIT estimates for uniform areas of the SAR mosaics, i.e., SAR segments, the mosaics first need to be segmented. After segmentation the CS2 SIT values are mapped to SAR segments where enough single CS2 SIT measurements are available. The SIT value assigned to these segments is the median value of the CS2 SIT values within the segment. Then the SIT is estimated (interpolated) for the rest of the segments by utilizing a difference function describing the similarity of the segments and pairwise distance of each pair of segments in time and space. The difference function includes difference of several SAR texture features in addition to the temporal and spatial pairwise distance of the segments. The data of January-April and October-December 2016 were used for training the algorithm and January-April and October-December 2017 data were used for evaluating the algorithm performance.

The SAR features were computed within a round-shaped window with a radius R. In this study we have used R=5 pixels. Median of the feature values within each segment were then assigned to the segments as segment-wise texture features. The features used in this study are:

- HH backscattering coefficient ($\sigma_{HH}^0$ in dB)
- HV backscattering coefficient ($\sigma_{HV}^0$ in dB)
- HH coefficient of variations ($E_{HH}$)
- HV coefficient of variations ($E_{HV}$)
- HH local autocorrelations ($C_{HH}$)
- HV local autocorrelations ($C_{HV}$)
- HHentropies ($E$)
- HV entropies ($E_{HV}$ channel cross-correlation ($C_{HV}$)
- HH local variogram slopes ($V_{HH}$)
- HV local variogram slopes ($V_{HV}$)
- HH coefficient of variations ($C_{HH}$)
- HV coefficient of variations ($C_{HV}$)
- HH edge point densities ($D_{HH}$ and $D_{EE}$)
• HV edge point densities ($D_E^{HV}$)

• HH corner point densities ($D_C^{HH}$)

• HV corner point densities ($D_C^{E}$)

• HH/HV channel cross-correlation ($C_c^{DHV}$)

The feature computation windows were overlapping by half of the window size (i.e. window radius) in the both coordinate directions.

Entropy $E$ Shannon (1948) was computed as

$$E = -\sum_{k=0}^{255} p_k \log_2 p_k,$$

where $p_k$’s are the proportions of each gray tone $k$ within each computation window. Auto-correlation $C_A$ Box and Jenkins (1976) was computed as

$$C_A(k, l) = \frac{\sum_{i,j \in W} (I(i-k,j-l) - \mu_W) (I(i,j) - \mu_W)}{|B| \sigma_W^2},$$

where $I(k,l)$ is the pixel value at image location $(k,l)$. Mean over the horizontal, vertical and diagonal directions i.e. $(k,l) = (0,1), (k,l) = (1,0), (k,l) = (1,1)$ and $(k,l) = (1,-1)$ was used to accomplish directional independence. The computation window is here denoted by $W$. $\sigma_W$ and $\mu_W$ are the mean and standard deviation within the window, respectively.

The cross-correlation $C_c$ Knapp and Carter (1976) between the SAR polarization channels (HH and HV,) here denoted by $X$ (HH) and $Y$ (HV), is

$$C_c(k, l) = \frac{1}{N_p \sigma_x \sigma_y} \times \sum_{i,j \in W} (X(k+i,l+j) - \mu_x) (Y(k+i,l+j) - \mu_y),$$

where $k$ and $l$ refer to the row and column coordinates of the window center image pixel, respectively, $\sigma_x$ and $\mu_x$ are the mean and standard deviation, respectively, of the window in $X$ and $\sigma_y$ and $\mu_y$ are the mean and standard deviation, respectively, of the window in $Y$. $N_p$ is the number of pixels within the window denoted by $W$.

We also computed texture features based on local variograms. The variograms were locally estimated in a window with a radius of five pixels. Assuming a stationary and isotropic process, the variogram $\gamma$ is (locally) dependent on the inter-distance, here denoted by $h$, only Cressie (1993), and can be estimated as

$$\gamma(h) = \frac{1}{2|H_{h,N_d}|} \sum_{i,j \in N_h \cap N_d} |z_i - z_j|^2,$$
where $z_i$ and $z_j$ are the pixel values at locations $i$ and $j$, whose distance is $d$, $N_d$ is the set of pixels with the mutual distance $d$ and $|N_d|$ is the number of these pixels within the window. We have computed the length of approximately linear part of the variogram as a function of $h$, and the slope of a linear fit of this linear part of the variogram. These are referred here as features $V_1^{ch}$ and $V_2^{ch}$, where $ch$ (channel) is either HH or HV.

The coefficient of variation is computed as

$$C_v = \frac{\sigma_w}{\mu_w},$$

(8)

where $\sigma$ and $\mu$ are the standard deviation and mean within the window $w$. $C_v$ is computed separately for the HH and HV channels, respectively, i.e. we have $C_v^{HH}$ and $C_v^{HV}$.

Edge and corner points represent the locations with large sudden change in $\sigma^0$, i.e. where high local gradients appear. Corner points are the points where the edge direction abruptly changes. The edge and corner points counts ($N_e$ and $N_c$) were extracted for each segment using local binary patterns Ojala et al. (1996) in a similar way as presented in Karvonen (2016). The proportion of the number of edge and corner points with respect to each segment area (in pixels) was computed for both polarization channels and they were used as texture features. These features are denoted here by $N_e^{HH}$, $N_e^{HV}$, $N_c^{HH}$ and $N_c^{HV}$.

Based on the segmentation result and the SAR texture features complemented by $\sigma_0^{HH}$ and $\sigma_0^{HV}$, the segment-wise median values of each texture feature and channel-wise SAR backscattering coefficients were calculated, resulting to a total of 15 SAR features (13 texture features and two backscattering coefficients) for each segment. As an example of the segmentation the segmentation result of the SAR mosaic of 21 February 2017, segmented SAR mosaics with $\sigma_0^{HH}$ and $\sigma_0^{HV}$ medians assigned to SAR segments on 21 Feb 2017 is shown in Fig. 3, and a detail of these HH and HV channel figures mosaics in Fig. 4. We use the SIT estimation and reference SIT data of this day as an example in the following sections.

According to our analysis the SIT difference between two segments was mainly explained by L1 difference of a few features ($\sigma_0^{HV}$, HV entropy and HH edge density) and the spatial distance between segment means, based on a least squares fit of the training data (Jan-Apr and Oct-Dec 2016), but other features also had minor effect. For this reason we have used all the above-mentioned features in our difference function because the number of features did not produce any computational problems with respect to execution time or hardware resources on a common desktop personal computer.

The 2016 (January-April, October-December) CS-2 and SAR data were used for training and 2017 (January-April, October-December) data for testing the method. The segment difference function $T$ was defined as linear combination of the SAR feature differences and temporal and spatial distance between as a segment pair:

$$T = c_t \Delta t + c_d \Delta D + \sum_{k=1}^{N_t} c_k |\Delta f_k|$$

(9)

$\Delta t$ is the (absolute) time difference in days, $\Delta D$ is the distance difference between the centres of the segments, $\Delta f_k$ is the difference between the SAR feature $f_k$ ($k = 1, \ldots, 15$) of the two segments in comparison. The 2016 CS-2-CS2 thickness and SAR mosaics (training data) were used in defining the coefficients $c_t$, $c_d$, $c_k$, using a non-negative least squares (LS) fit. Non-negative LS was used because all the absolute differences should have an increasing effect on $T$. 

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According to our analysis the SIT difference between two segments was mainly explained by the absolute difference, i.e. L1 difference, of a few features, $\sigma^2_{H/V}$, HV entropy and HH edge density and the spatial distance between segment means were the most significant features based on a least squares fit of the training data. However, other features also had minor effect (small but non-zero coefficients based on the LS). For this reason we have used all the above-mentioned features in our difference function because the number of features did not produce any computational problems with respect to execution time or hardware resources on a common desktop personal computer. Because the training data set consisted of data of a whole year with CS2 SIT data (Jan-Apr, Oct-Dec) we consider this as a representative training data set and assume there is no significant overfitting.

As training data we used the CS2-CS2 SIT values assigned to the segments. Each 2016 training data SAR segment with an assigned SIT were included and the neighboring assigned SIT values and the corresponding segment pair-wise feature differences were used in the LS fit, i.e. each segment pair with an assigned CS2-CS2 SIT were utilized.

SIT for a segment (S) without a SIT value were obtained as follows: T between S and all the other segments within a predefined time and distance range was computed and the median of the SIT values corresponding to the $M$ segments with the smallest values of T within a predefined spatio temporal search range was assigned to segment S SIT. The spatio temporal search range was 10 days in time (for natural reasons only backwards) and 1000 km (2000 pixels) in range. segments were ordered by ascending T. Then the CS2 SIT values of the other segments, in addition to possible CS2 SIT values with segment S (less than N values), were included in a set of SIT values, until the number of the values in the list exceeds the threshold value N (strictly is equal to N or more than N). The SIT assigned to S was the weighted average of the SIT values of the collected SIT value set. The weights used in the averaging are relative to the inverse values of T corresponding to the segment from which the SIT values are. The possible (less than N) CS2 SIT values of the segment itself are included with the same weight as the CS2 SIT values within the segment with the smallest non-zero value of T. We have used parameter values of N=9 and M=5-7 in this study.

In Fig. 7 the dependence of the SIT difference on the SAR feature linear combination, pairwise segment distance and pairwise segment time difference is shown for the 2016 data. Here the time difference is restricted to be less than one day (i.e. using only the same day data) and distance less than 500 pixels (250 km) for the Fig. 7a, describing the dependence on the pairwise segment texture difference. For the Fig. 7b, describing the dependence of the SIT difference on the pairwise segment distance, and 7c, describing the dependence of the SIT difference on the segment time difference, the normalized pairwise texture difference is restricted to be under 0.1, and for Fig. 7b the time difference less than one day, and for Fig. 7c the distance difference is restricted to be less than 250 km. It can be seen that there is a clear correlation between the linear combination of the texture feature differences and the SIT difference. There is quite large deviation, however, the correlation is around 0.5. For the pairwise segment distance and the pairwise segment time difference, correlations are smaller (0.28 and 0.22, respectively) but there is still a visible trend. Based on the slopes of the linear fits, the average increase of SIT difference is 2.9 cm/100 km and 2.1 cm/day.

4.2 Ice chart and model compliant CS2 product
Because SIT was significantly overestimated for SIT was significantly overestimated for After defining the coefficients \( c_1, c_2 \) and \( c_3 \) in (9) using the training data we tested the SIT estimation for the 2016 training data. It was observed that SIT is significantly overestimated in the 2016 training data when compared to the modeled and AARI SIT. Therefore, we introduce a mapping based on ORAS5 and the PIOMAS model reanalysis SIT data to reduce this SIT overestimation. The CS–2 SIT measurements were further mapped CS–2 SIT measurements are now further mapped based on the training data of 2016 and the corresponding PIOMAS reanalysis SIT in the range 0–200 cm of CS–2. The coarser resolution PIOMAS data were selected for this purpose because ORAS5 does not give reasonable SIT values for SIT less than 50 cm Tietsche et al. (2017). Above 200 cm a linear fit to the linear part (up to 350 cm) of the ORAS5 SIT histogram correspondence was used because from about 200 cm ORAS5 indicates thicker ice and the problem with ice model reanalysis data has been underestimated. Also ORAS5 SIT starts to saturate above 350 cm and this part of the matching was not used in the mapping and the mapping above 350 cm uses the same linear slope defined for the interval 200–350 cm. The adapted SIT histogram mapping is based on the normalized histograms and minimizing the Kolmogorov-Smirnov distance (i.e. mapping the cumulative histograms) of the CS–2 SIT and the TOPAZ4 reanalysis SIT. The Kolmogorov-Smirnov distance, \( D_m \), for a variable \( x \) is also defined as

\[
D_m = \sup_x |F_i(x) - F_c(x)|, \quad (10)
\]

where \( \sup_x \) is the supremum within the range of \( x \) (SIT in our case) and \( F_i(x) \) and \( F_c(x) \) are the cumulative probability density functions (CDF’s) of the ORAS5 or PIOMAS SIT, and CS–2 CS–2 SIT computed for the 2016 training data set. In our case we have quantized the SIT into integer centimeters with 16 bits, and the SIT histograms are used as approximations of probability density functions (PDF’s). The SIT values were quantized to 1 cm accuracy and 16 bits.

This mapping based on the 2016 training data CS–2 SIT and 2016 CS–2 SIT and PIOMAS model SIT is shown in Fig. 7 as a red curve, until 200 cm it follows the PIOMAS mapping and above 200 cm a linear fit to ORAS5. As a green curve. For reference also the Topaz4 matching result is shown in the Figure as a green curve AARI ice chart SIT, ORAS5 model SIT, and TOPAZ4 model SIT (blue curve) matching results are shown in 8. It can be seen that Topaz4-TOPAZ4 reanalysis SIT mapping is at significantly lower level than the mapping for the other two models.

5 Results

5.1 Measures used in evaluation of the results

We have compared the SIT values produced by the CS2–S–1 algorithm to the SIT based on the AARI ice charts, ORAS5, PIOMAS and TOPAZ4 reanalysis SITs to evaluate the performance of the SIT estimation algorithm performance. In the comparisons we have used the following measures of difference between the CS2–S–1 SIT estimates and the reference SIT:

\[
C = \frac{1}{N_v N_s \sigma_{\text{ref}}} \sum_{i=1}^{N_v} \left( (X_i - \mu)(X_i^{\text{ref}} - \mu_{\text{ref}}) \right), \quad (11)
\]
\[ D_{L1} = \frac{1}{N_s} \sum_{i=1}^{N_s} |X_i - X_i^{\text{ref}}|, \]  
(12)

\[ D_{\text{sgn}} = \frac{1}{N_s} \sum_{i=1}^{N_s} (X_i - X_i^{\text{ref}}), \]  
(13)

\[ D_{\text{RMS}} = \sqrt{\frac{1}{N_s} \sum_{i=1}^{N_s} (X_i^{\text{est}} - X_i^{\text{ref}})^2}. \]  
(14)

\( N_s \) refers to the number of samples (number of grid points involved) used in the comparison and \( X_i \) \((i = 1 \ldots N_s)\) are the estimated values of SIT and \( X_i^{\text{ref}} \) are the values of the reference SIT data at the same location as \( X_i \). \( C \) is the correlation, \( D_{L1} \) is the L1 difference and \( D_{\text{sgn}} \) is the signed L1 difference giving the estimation bias, positive bias indicating overestimation and negative bias indicating underestimation. \( D_{\text{RMS}} \) is the root-mean-square difference. \( \mu \) and \( \mu_{\text{ref}} \) are the means of the estimated SIT and reference SIT, and \( \sigma \), \( \sigma_{\text{ref}} \) are the standard deviations of the estimated SIT and reference SIT, respectively. All the difference measures were computed in the resolution of each reference data set, i.e. the CS2 SIT assigned to SAR segments and interpolated, given in a high-resolution grid, were down-sampled to each reference data set resolution. This approach was not applicable to the single CS2 SIT measurements and for them the difference measures were computed directly, using the nearest reference data set grid point SIT for each measurement as the reference SIT.

On average the correlation between the non-interpolated CS2 SIT estimates and AARI SIT was 0.22. Correlation between CS-2 SIT and the two model SIT (TOPAZ4 and ORAS5) were 0.18 and 0.12 respectively. The L1 difference and bias of the CS-2 SIT w.r.t. AARI SIT were 50 cm and 35 cm, CS-2 showing thicker ice. The L1 difference and bias of the CS-2 SIT w.r.t. TOPAZ4 reanalysis SIT were 52 cm and 31 cm, again CS-2 being thicker. The corresponding numbers w.r.t. ORAS5 SIT were 49 cm and 0 cm. Interestingly, for the ORAS5 which initiates its ice thickness at 50 cm has zero bias against the CS-2 estimates. As the CS2 SIT data covers only the time period from October to April the weather conditions were mostly with dry snow conditions, i.e. \( T_a \) was mainly below zero degrees for the time range studied. Only in the early winter (October-November) there were some periods with \( T_a \) above zero and potential to have wet snow on sea ice. In this study we do evaluate the effect of wet snow on the SIT estimation. For reliable estimation of the effect of wet snow conditions on estimation more data acquired during the melting period would be required.

The correlation for the CS-2 SIT assigned to SAR segments was somewhat higher, around 0.35

### 5.2 Difference statistics between the estimates and reference data

The statistics from the comparisons between the CS2/S1 SIT, without and with the proposed histogram mapping, and the different reference SIT data sets are shown in Tables 1-4. The correlations w.r.t. the two reference between different SIT data sets for each 2017 winter month and their averages and standard deviations are presented shown in Table 1, the corresponding L1 differences biases in Table II, the biases L1 differences in Table III and the RMSD’s in Table IV. Also the differences for reference, the average difference measures and correlations between the three different reference SIT data sets are shown in Table V. CS-2 in the tables refers to the CS-2 data mapped to the segments with more than N CS-2 measurements available.
The monthly cross-correlations between the estimated SIT and the AARI ice chart SIT were very small, only 0.15. There was a significant bias, CS2 SIT being on average 83 cm larger than the AARI chart SIT. This also reflects to the high L1 differences and RMS differences between the CS2 and AARI SITs. The statistics of the CS2 SIT with respect to the AARI SIT are given in the first columns of Tables 1-4. The numbers were similar with respect to the estimated remapped SIT w.r.t. AARI SIT were quite similar with values around 0.3-0.4 during the winter months (January-April, December). For the freeze-up months (October-November) the cross-correlation w.r.t. AARI SIT were higher, up to about 0.7 in October and about 0.45 in November. This is explained by the thinner ice and smaller deviation in ice thickness. The same phenomena can be seen in the cross-correlations w.r.t. TOPAZ4 and ORAS5-SIT. Also warm weather and thin moist snow cover may have an effect on the results in October and November.

The cross-correlation of the estimated SIT and remapped estimated SIT w.r.t. AARI SIT and TOPAZ4 reanalysis SIT were similar both monthly and on average. The average cross-correlations w.r.t. AARI SIT were 0.37 for the estimated SIT and 0.39 for the remapped estimated SIT. The corresponding values w.r.t. TOPAZ4 reanalysis SIT were 0.39 and 0.42, and w.r.t. ORAS5 SIT 0.35 and 0.39. The minimum cross-correlation values were reached in March, except w.r.t. TOPAZ4 reanalysis SIT in January three ice models, showing small correlations and large positive bias (overestimation by CS2). Because of their similarity these values were not included to the tables.

The monthly L1 differences were smaller for the freeze-up period and increasing as the average ice thickness increased in the course of the winter as the average ice thickness increased. The L1 difference of the estimated SIT and remapped estimated SIT w.r.t. AARI SIT, and TOPAZ4 correlations for the interpolated CS2 SIT assigned to the SAR segments was significantly higher, around 0.64. The monthly correlations between the interpolated CS2/S-1 SIT and ORAS5 reanalysis SIT were smaller for the remapped estimated SIT which was expected as the target of the remapping was to reduce the large positive bias. The average and maximum L1 difference w.r.t. the remapped interpolated CS2/S-1 SIT with respect to the AARI SIT were 48/78 cm for the estimated SIT and 36 cm/48 cm for the remapped estimated SIT. The maximum similar, and in the range 0.52-0.76. The highest values were reached in March and April. The corresponding values w.r.t. Topaz reanalysis were 48/77 cm and 38/52 cm and w.r.t ORAS5 SIT 46/63 cm and 37 April and October. The CS2/S-1 SIT correlations were quite similar with respect to the model data for all the studied models.

The biases (i.e.-)

The monthly signed L1 differences in Table III have been computed such that positive values indicate overestimation w.r.t. the reference value and negative values underestimation. The monthly bias (signed L1 differences)-difference in Table II also increases for the estimated SIT w.r.t. both with respect to both the AARI SIT and TOPAZ4 reanalysis-model reanalysis SIT as the ice gets thicker, indicating significant overestimation. For the remapped estimated SIT bias remains interpolated SIT bias remains at a lower level for all the studied months, w.r.t. with respect to ORAS5 there was even small underestimation on average, but w.r.t. with respect to TOPAZ4 reanalysis SIT some overestimation. The averages and maximum biases for the estimated SIT w.r.t. interpolated SIT with respect to the AARI SIT were 327/67-46 cm (maximum reached in March). The corresponding values w.r.t. with respect to the AARI SIT for the remapped estimated SIT were 21 interpolated SIT were 6/41 14 cm (maximum underestimation in April). The corresponding values w.r.t. with respect to the TOPAZ4 reanalysis-SIT were
The CS-2 SAR segments, CS2 SIT, the reanalysis SIT were 29/72 cm and 2649 cm and 8/45-16 cm, respectively. The corresponding values w.r.t. with respect to the ORAS5 SIT were 36/22-20 cm and -15/-22-20 cm, i.e. slight underestimation. The biases of the remapped SIT w.r.t. ORAS5 SIT were slightly negative for all the months but still L1D and RMSD w.r.t., for the PIOMAS model data the corresponding figures were 14/31 cm and -7/-13 cm.

The monthly L1 differences in Table III were smaller for the freeze-up period and higher for the winter months, starting to decrease in April. The L1 difference with respect to the AARI SIT, and TOPAZ4, ORAS5 and PIOMAS reanalysis SIT were smaller for the remapped estimated SIT which was expected as the target of the remapping was to reduce the relatively large positive bias. The average and maximum L1 difference with respect to AARI SIT were 32/51 cm for the interpolated SIT and 14/21 cm for the remapped interpolated SIT. The maximum values were reached in January and March. The corresponding values with respect to TOPAZ reanalysis were 32/52 cm and 17/26 cm, with respect to ORAS5 SIT than for the unmapped SIT 29/41 cm and 24/31 cm and with respect to PIOMAS SIT 29/42 cm and 21/30 cm. The difference maxima were reached in February-April for all the cases.

The RMS difference has a similar behaviour as differences in Table IV, have a similar behavior as the L1 differences. It RMSD also increases as the average ice thickness increases in the course of the winter and smallest RMSD values were reached during the freeze-up months (October-November, October-December). The average and monthly maximum RMSD values for the estimated SIT w.r.t. with respect to the AARI SIT were 6456/94-81 cm, and the corresponding values for the remapped estimated SIT were 4525/57-34 cm. The corresponding values w.r.t. with respect to the TOPAZ4 reanalysis SIT were 6958/98-84 cm for the estimated SIT and 54 interpolated SIT and 29/64-41 cm for the remapped estimated SIT, and interpolated SIT, the corresponding values w.r.t. with respect to the ORAS5 SIT were 6049/80-65 cm for the estimated SIT and 4838/59-50 cm for the remapped interpolated SIT, and the corresponding values with respect to PIOMAS SIT were the 52/73 cm for the estimated remapped SIT, SIT and 35/46 cm for the remapped interpolated SIT. The average maxima were again reached during the winter months (January-April).

For the CS-2 SIT mapped to SAR segments, CS2 SIT the difference measures shown in Tables I-IV, indicate large positive bias (overestimation) and other difference measures w.r.t. large L1D and RMSD with respect to the AARI SIT, TOPAZ4 and ORAS5 and PIOMAS reanalysis SIT. These values are highest for the winter months with thickest ice, and smaller for the freeze-up (October-November/early winter (October-December). The cross-correlations w.r.t. with respect to all reference data sets were low, significantly lower than for the estimated-interpolated CS2/S-1 SIT.

It should be noted that also the reference SIT data sets differ from each other. These differences are shown in see Table V. The average cross-correlations between the reference data sets were in the range 0.54-0.60. The TOPAZ4 and AARI SIT values were on average quite close to each other, having only low bias, but the ORAS5 SIT was then on average 35-40 cm above them.

Furthermore, the reader should note Furthermore, it is noted that in our evaluation the compared randomly sampled points were located in highly dissimilar regions, characteristic for the different data sets, with different sizes and shapes (such as ice model grid points, SAR segments, ice chart polygons).
In order to assess how far from the assigned CS2 measurement the SIT can be interpolated and still give usable estimates, we studied the effect of distance and time on the SIT difference (or in other words, estimation error) using our training data set of 2016. We used the assigned CS-2-CS2 SIT values as reference and searched for sets of segments with either constant time difference or constant distance and defined the increase of ice-thickness-SIT difference as a function of the difference in the other.

The average increase in estimation error for the 2016 training data training data set as a function of time was 1.6 km/day and of space was 1.3 distance was 2.9 km/100 km. This indicates that the contribution of distance difference to the total difference is in maximum (corresponding to the search range boundaries) around 4.4 cm for the 1000 pixel (500 km) spatial search range and 16-21 cm for the 10 day temporal search range.

An example of the SIT estimation of 21 February 2017 without and with the histogram remapping can be seen in Fig. 89. For reference also the AARI SIT and the TOPAZ and ORAS5 reanalysis SIT and CS2SMOS SIT have been included in Fig. 89. This figure represents a typical case with a general agreement of the thinner and thicker ice fields generally in agreement compared to with the reference data but still indicating quite much difference differences due to the details of the local SIT distribution, given in higher level of detail in the estimated CS2/SAR S-1 SIT.

We also included a comparison of the proposed SIT estimates (interpolated and remapped versions) to the CS2SMOS SIT data Ricker et al. (2017) for our 2017 test data set. These comparison results are shown in Tables 6 and 7. The results are discussed more in the following subsection.

5.3 Difference maps and estimation uncertainty

We also provide difference maps of the unmapped and remapped SIT with respect to the AARI ice chart SIT in Fig. 6 for the 21 Feb 2021 case and for the 2017 test data set on the average. It can be seen that the unmapped interpolated SIT overestimates SIT with respect to the AARI ice chart SIT, both for the 21 Feb 2017 case and on the average in many areas. For the remapped interpolated SIT estimates the overestimation is significantly smaller with respect to the AARI ice chart SIT for both the case of 21 Feb 2017 and on average.

SIT difference charts with respect to the CsSMOS SIT on 21 Feb 2017 and the average difference charts for 2017 are shown in Fig. 11. It can be seen that the SIT differences are are quite similar to the differences with respect to the AARI ice charts.

There is some more underestimation in the northeastern part of the study area compared to the difference maps with the AARI SIT. Also this comparison indicates that the interpolated SIT estimates deem to overestimate SIT and the remapped interpolated SIT values are less biased.

As we are using a (segment) difference function, we compute its median value for each segment mapped. This value corresponds to the mapping and the larger it is the larger the uncertainty of the SIT estimation can be considered. We have scaled the difference T values to the range 0-100 (based on the training data difference function values) and in Fig. 6-12 the scaled difference function for the estimation of 21 February 2017 is shown. The highest uncertainty is found at the ice edge and in the Ob delta area. The uncertainty could probably also be used for iteratively re-estimating the SIT of segments with the highest uncertainties.
5.4 Comparison to MODIS SIT

We also performed some comparisons of the **CS-2 interpolated CS2/S-1 SIT estimates** against the daily MODIS SIT charts. The MODIS product only gives thin ice thicknesses and the thicker ice thicknesses are very roughly categorized, i.e. **only roughly categorized: SIT in 1-30 cm range, and then one category for SIT of 31-50 cm and another for SIT over 50 cm.** There were **MODIS SIT charts for the winter 2017 (January-April).** The monthly correlations between the thin MODIS SIT (1-30 cm) and the SIT estimated by the proposed method varied between 0.15 to 0.25. We also computed the averages of the estimated SIT for the three MODIS SIT categories, i.e. 1-30 cm, 31-50 cm and over 50 cm for each month and for the estimated SIT and estimated remapped SIT. These are presented in Table 58. It can be seen that the averages increase towards a thicker MODIS thickness category for both the estimates, but the increases are quite small and the averages are too high for both the methods, some less for the remapped estimate. It can also be seen that the averages increase as a function of time, i.e. as ice gets thicker in the course of time. Based on this experiment we can conclude that the SIT estimates, even with the proposed remapping, tends to overestimate specifically thin ice thickness, SIT, specifically for thin ice.

For visual evaluation and comparison to the SIT estimates of Fig. 9 we also show the MODIS SIT collage for February 21 2017 in Fig. 6. For better visual appearance the color scale is the same as in different from that of Fig. 9, except that the thickest MODIS SIT category (SIT>50 cm) is cyan in the figure. Because in a daily MODIS SIT chart SIT can typically be computed only for small areas due to cloud cover, the collage is composed of two weeks of MODIS SIT charts with the most recent available MODIS SIT value at each grid point. The areas with no data during the 2-week period are indicated by the black color in the figure.

When comparing the MODIS SIT collage of Fig. 6 with the daily **CS-2 CS2/S-1 SIT estimate** in Fig. 8b we notice that most of the ice-covered areas of the study area belong to the thickest MODIS SIT category (SIT>50 cm). The thin ice areas according to the MODIS SIT are located near the Kara gate (southern Kara Sea) and near the ice edge in the northwestern part of the study area. These are in general in agreement with the **CS-2 CS2/S-1 SIT.** Also some thicker ice patches within or in the vicinity of the MODIS SIT thin ice areas can be identified in the **CS-2 CS2/S-1 SIT.** The general pattern detecting thinner ice in the south and near ice edge is present in both **CS-2 CS2/S-1** and MODIS SIT. This general large scale pattern can be seen throughout the winter. However, the SIT estimates include many anomalous local details due to the dynamic nature of the ice field and the fact that the data are not exactly simultaneous.

### 6 Discussion and Conclusions

In this study an algorithm for inter/extrapolating of the **CS-2 interpolating of the CS2 SIT data** over the S-1 daily Kara and Barents Sea S-1 SAR mosaic was developed and evaluated by comparisons to SIT derived from Russian Arctic the AARI ice charts and two three ice model reanalysis data sets. **Baseline-D CS2 data Meloni et al. (2020)** were used in this study. Baseline-D data were was the most recent version when our data analysis were made. We wanted to demonstrate the potential of our method, as well as to evaluate its performance. **Our method is capable of interpolating CS2 SIT values to areas between orbit ground tracks where SIT measurements are not available.** We found significant differences (both low correlation and
high low correlation, large bias) between non-interpolated CS-2-CS2 SIT and the reference data. Given the different nature of our reference data, this was not surprising. The match between CS2 and reference data improved with the introduction of segmentwise medians. However, there was still a significant difference were still significant differences, especially a high positive bias due to different nature of CS-2-CS2 SIT estimates and the reference SIT data sets. To reduce this bias, we performed a mapping based on the PDF’s (histograms) of the CS-2-CS2 SIT and PIOMAS ORAS5 ice model reanalysis SIT of the for our training data set. This mapping reduced the positive bias which also reflected to reduced LID and RMSD. However, the remapped CS-2-CS2 data should not be understood as more correct, but as one more akin to the model SIT.

We used the 2016 data (January-April, October-December) as training data set and 2017 data (January-April, October-December) as a test data set in this study. There would have been different ways of dividing the data into the training and test data sets, e.g. randomly selected days or one whole season for training instead of using calendar year data from two seasons. However, with some preliminary tests this did not have any significant effect on the results and we selected this chronological order (training data earlier than test data) for this study. The training and evaluation of this study was also performed for January-April and November-December. This was because both the CS2 SIT and AARI ice chart ice stage of development were not available outside of this period, i.e. under wet surface conditions. For such conditions reliable estimation of SIT is difficult or even impossible with the current data and algorithms. This is due to the deviating behavior of radar signal at the wet air/snow-ice boundary, compared to a frozen surface.

An alternative to directly using CS2 SIT would have been to utilize CS2 ice freeboard. Then ice freeboard could have been computed from modeled ice and snow data using Eq. (1). Freeboard could be more suitable quantity for comparisons because radar backscatter and ice freeboard are statistically related as reported in Similä et al. (2010) and the radar penetrates the snow layer and radar backscattering is from the ice surface layer in dry snow conditions. Using ice freeboard can also reduce the effect of incorrect snow depth.

An interesting result was that the inter/extrapolation interpolation does not decrease the correlation with respect to the reference data compared to (incomplete) SIT resulting from CS-2-CS2 data assigned to SAR segments, or CS-2-CS2 data as individual measurements. In many cases correlations were even slightly higher for the results with For example, the correlation for the CS2 SIT assigned to segments with respect to the AARI ice chart SIT were on average around 0.64. This is a similar value as for the interpolated segment-wise CS2 SIT. For the individual point-wise CS2 SIT values the correlations were significantly lower.

In parts of the SAR data and inter/extrapolation included. Here the mapping was based on PIOMAS/ORAS5 model reanalysis data of the training data of 2016. TOPAZ4 reanalysis still seems to underestimate the high SIT values, this is suggested e.g. by the comparison results between TOPAZ4 and ORAS5-SIT in Table V study area there may exists areas with wet snow on sea ice Rösel et al. (2016). Wet snow will have an effect on the SIT estimate accuracy in the late winter. Because the CS2 SIT is produced for the winter months only, i.e. stopped at the end of April, indicating that most of the melt-down period, most likely to have wet snow on ice, is excluded. In this study the uncertainty due to wet snow was not studied but this will be an interesting topic for further studies.
In general, evaluation of ice thickness over Arctic is difficult because of lack of reliable reference data. Another problem is the scale are the different scales of the SIT measurements, estimates and models. SIT measurements, if available, are typically point measurements or measurements with a footprint of a few meters to a few tens of meters (e.g. SIT measurements by drilling or Electromagnetic induction based EM measurements), and the model grid cells, EO satellite measurements or segment-wise SAR estimates represent averages over several square kilometers ($\text{km}^2$). Also ice charts give averages of typically quite large polygons of several tens or even hundreds of $\text{km}^2$.

According to the results the monthly biases without any remapping the interpolated CS2 SIT are positive with respect to the AARI SIT and smaller but still positive with respect to the ice model data sets. For the remapped interpolated SIT all the biases are smaller. Comparison to the CS2SMOS SIT product with the 2017 test data indicate large overestimation for the interpolated CS2 SIT estimates. This large positive bias was decreased significantly for the remapped estimates and was on average only a few centimeters.

We selected parameters, such as N, empirically. The sensitivity of SIT to parameters chosen was not studied thoroughly yet. It will be a topic for future research. For example the value of N was selected such that we had enough segments with CS-2 CS2 SIT assigned to them to get inter/extrapolated interpolated SIT for all the segments of a daily SAR mosaic. Currently the value of N is relatively small for a typical SAR segment. A higher value of N would be preferable. However, a higher value of N in turn would reduce the number of segments included in the estimation and also increase the possibility of too few assigned SIT values for the inter/extrapolation interpolation step. For this reason we used a moderate moderately small value of N.

The relatively larger differences w.r.t. the reference—large differences with respect to the reference SIT data sets can at least partly be explained by the different resolutions and level of detail of the SIT estimates. The CS-2CS2/S-1 SIT has a resolution of 500 m (the SAR mosaic resolution) which is significantly higher than the resolution of the ORAS5, PIOMAS and TOPAZ4 reanalyses (over 10 km) and also the AARI ice chart level of detail. Furthermore the original CS-2 CS2 measurements stem from individual footprints that are approximately 300 m x 1600 m. Even though the ice charts have a nominal resolution up to about 1 km, in practice it is impossible for the ice analysts to include all the ice field details in this scale within the limited time available for making the ice charts. Instead, the ice analysts tend to draw larger polygons, representing rather homogeneous sea ice, neglecting the details, and assigning areal average values to the polygons. However, the polygon boundaries typically have the precision of the nominal ice chart resolution. For this reason of varying scales we have used the reference data resolution in the comparisons and downsampled the interpolated CS2 SIT accordingly. For the individual CS2 SIT measurements we used the nearest reference grid point data.

We also studied use of regularized linear regression (LASSO) Tibshirani (1996) for reducing the number of texture features needed in the SIT estimation. According to our first tests the performance was nearly similar with less texture parameters involved, but on the other hand the need for computational resources with the amount of LS fit parameters used now were not significantly larger than with a reduced number of parameters, and thus we here used all the studied parameters in the LS fit in this study. In the future, reduction of LS fit parameters could be studied more, if seen necessary, e.g. for more efficient computing to cover larger sea areas in a reasonable time. This may be required to meet near-real-time processing conditions for operational SIT estimation, e.g. for a pan-Arctic high-resolution SIT product.
Snow depth in winter conditions can be estimated based on microwave radiometer data, e.g. see Rostosky et al. (2018). More precise snow density estimation can then be utilized to yield more precise SIT estimates. Microwave radiometer data can be utilized to locate the thin ice regions, e.g. AMSR2 based thin ice (SIT>20 cm) detection has been recently developed for the Barents and Kara Seas. One future goal will be integration of microwave radiometer data in the algorithm to get better estimates of snow cover on sea ice and thin ice presence.

In some areas near the ice edge there still seems to exist local SIT overestimation with respect to the reference data. One possible way to reduce this overestimation would be to adjust the algorithm parameters such that the spatial search radius would be more restricted near the ice edge, i.e. dependent on the geographical location. This could also be adjusted by varying the weight assigned to pairwise segment distance in the difference function T. However, this alternative will require a significant amount of additional research.

As the proposed method uses several CS2 SIT values to assign a SIT value to a SAR segment, it is also possible to give estimates of the SIT range or SIT distribution of the segments. This does not even require development of new algorithm, only selecting a suitable value of parameter N (number of CS2 SIT values required for a segment) and extracting the SIT range or distribution from the CS2 SIT measurements.

In the future we also plan to study segment clustering and then assigning CS2-CS2 SIT value median or mode of each segment cluster to all segments of a segment cluster instead of single segment medians. An easy solution would be to merge small segments into their neighboring larger segments to remove all the segments smaller than a given area. This would give more CS2-CS2 measurements within the segments but on the other hand also giving then give SIT estimates representing averages of larger areas. Despite of this it should be noted that the segment boundaries, representing different ice fields, are still represented in the resolution of the segmentation. With these approaches we aim to overcome the problem of either having too few CS2-CS2 SIT values assigned to segments or too few segments with an assigned SIT. Also more detailed utilization of SIT distributions of segment clusters with a large enough number of SIT samples for forming statistically reliable SIT distributions should be studied. Including thin ice detection (thickness <20 cm) from microwave radiometer using a method in Makynen and Simila (2019) could also improve the SIT estimation results. In some cases also large SAR segments could be split into smaller ones to get more detailed and more accurate local SIT estimates.

To match segments we compute the value of the segment-wise difference function T for the matched segments. The value of T could possibly be used to implement an iterative SIT assigning scheme. In this scheme only SIT values with T less than a selected threshold value would be assigned to segments and the process iterated using all the SIT values assigned during the previous iterations in assigning SIT values to the segments still without an assigned SIT at each iteration. The threshold to be applied could also be varying as a function of the iteration.

The evaluation of this study was performed for January-April and November-December. This was because both the CS-2 SIT and AARI ice chart ice stage of development were not available for wet surface conditions. For such conditions reliable estimation of SIT is difficult or even impossible with the current data and algorithms. This is due to the deviating behaviour of radar signal at the wet air/snow-ice boundary, compared to a frozen surface.
It may be possible to use the dependence of the biases on the phase of the winter (related to average SIT), such as early freeze-up, freeze-up, melt-down, mid-winter, early spring phase, to reduce the bias by applying a bias-reducing mapping dependent on the phase of the winter instead on a common mapping for the whole winter. The phase of the winter could roughly be estimated based on the estimated average ice thickness.

We also studied use of regularized linear regression (LASSO) Tibshiran (1996) for reducing the number of texture features needed in the SIT estimation. According to our first tests the performance was nearly similar with less texture parameters involved, but on the other hand the need for computational resources with the amount of LS fit parameters used now were not significantly larger than with a reduced number of parameters, and thus we here used all the studied parameters in the LS fit in this study. In the future reduction of LS fit parameters could be studied more if necessary e.g. for more efficient computing to cover larger sea areas in a reasonable time. This may be required to meet conditions for operational production, e.g. for a pan-Arctic high resolution SIT product. Also different algorithm parameters (weights used in the difference function $T$) could be tested for different phases of winter. This would require a larger multi-year training data set and a significant amount of additional work but could be one way to improve the SIT estimation accuracy.

Our algorithm can be easily adapted to any satellite altimeter SIT product. This study is especially relevant for the future CRISTAL mission Kern et al. (2020). After its expected launch in late 2027, CRISTAL shall provide a time-critical SIT product, which can be merged with SAR data to interpolate SIT between the CRISTAL ground tracks. Thus our study is one of the necessary steps in introducing satellite altimeter data into the realm of operational ice charting. Before CRISTAL, our algorithm can be applied to ICESat-2 as well as to Sentinel-3 SRAL based SIT estimates.
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Table 1. Monthly average cross-correlations between the SIT estimates studied \textit{w.r.t.} to the reference data set SIT. SIT refers to the proposed algorithm SIT, RSIT refers to the proposed algorithm SIT with remapping based on the histogram mapping with model data, CS2 refers to the values assigned to the SAR segments (without inter- or extrapolation), A refers to the SIT derived from the AARI ice charts, T refers to the Topaz4 model reanalysis SIT, and O refers to the ORAS5 model SIT.

| Month | CS2/A | SIT/A | RSIT/A | CS2/T-SIT/T | RSIT/T | CS2SIT/O | SITRSIT/O | SIT/PM | RSIT/OPM |
|-------|-------|-------|--------|-------------|--------|-----------|-----------|--------|----------|
| 01/17 | 0.05  | 0.20  | 0.26   | 0.52        | 0.05   | 0.43      | 0.19      | 0.49   | 0.25     | -0.03    |
| 02/17 | 0.43  | 0.13  | 0.29   | 0.61        | 0.34   | 0.51      | 0.27      | 0.57   | 0.30     | 0.26     |
| 03/17 | 0.24  | 0.24  | 0.25   | 0.69        | 0.34   | 0.64      | 0.38      | 0.68   | 0.07     | 0.23     |
| 04/17 | 0.24  | 0.13  | 0.38   | 0.71        | 0.41   | 0.76      | 0.41      | 0.65   | 0.40     | 0.09     |
| 10/17 | 0.34  | 0.12  | 0.73   | 0.75        | 0.29   | 0.76      | 0.74      | 0.77   | 0.73     | 0.25     |
| 11/17 | 0.37  | 0.08  | 0.44   | 0.65        | 0.27   | 0.60      | 0.45      | 0.63   | 0.51     | 0.25     |
| 12/17 | -0.07 | 0.14  | 0.28   | 0.54        | -0.06  | 0.51      | 0.34      | 0.56   | 0.40     | -0.05    |
| Ave.  | 0.22  | 0.15  | 0.37   | 0.64        | 0.29   | 0.58      | 0.39      | 0.62   | 0.42     | 0.12     |
| Std.  | 0.18  | 0.05  | 0.17   | 0.09        | 0.16   | 0.07      | 0.15      | 0.11   | 0.16     | 0.14     |

Table 2. Monthly average bias \textit{in cm} between the different SIT estimates \textit{w.r.t.} to the reference SIT data sets. The symbols are the same as in Table 1.

| Month | CS2/A | SIT/A | RSIT/A | CS2/T-SIT/T | RSIT/T | CS2SIT/O | SITRSIT/O | SIT/PM | RSIT/OPM |
|-------|-------|-------|--------|-------------|--------|-----------|-----------|--------|----------|
| 01/17 | 41.5  | 118   | 26.5   | 29.2        | 36.0   | 31        | 30.7      | 11     | 29.3     | -9.6     |
| 02/17 | 43.4  | 105   | 57.5   | 46.1        | 35.4   | 48        | 61.2      | 16     | 45.0     | -1.4     |
| 03/17 | 54.1  | 104   | 66.8   | 45          | 35.4   | 10        | 72.4      | 12     | 41.0     | 14.5     |
| 04/17 | 47.4  | 82    | 58.0   | 42.3        | 42.2   | 49        | 66.5      | 12     | 32.8     | 5.7      |
| 10/17 | -1.4  | 43    | 5.0    | 0           | -5.3   | 4         | 8.7       | -5     | 3.2      | -18.2    |
| 11/17 | 13.3  | 48    | 15.4   | 17.3        | 8.2    | 10        | 17.6      | -2     | 19.5     | -20.5    |
| 12/17 | 19.8  | 45    | 17.2   | 22.0        | 11.9   | 14        | 17.0      | -8     | 21.8     | -21.6    |
| Ave.  | 34.6  | 83    | 32.5   | 27          | 20.2   | 6         | 37.6      | 8      | 25.8     | -0.1     |
| Std.  | 20.6  | 28.7  | 24.9   | 17.9        | 13.4   | 5.27      | 20.1      | 19.7   | 26.7     | -0.4     |
Table 3. Monthly average L1 difference in cm between the different SIT estimates \textit{w.r.t.} the reference-reference SIT data sets SIT. The symbols are the same as in Table 1.

| Month | CS2/A | SIT/A | RSIT/A | CS2/T-SIT/T | RSIT/T | CS2SIT/O | SSRSIT/O | SIT/PM | RSIT/OPM |
|-------|-------|-------|--------|-------------|--------|----------|----------|--------|-----------|
| 01/17 | 52.0 | 40.8 | 38.3 | 52.5 | 42.2 | 41.0 | 49.2 | 43.2 | 38.8 |
| 02/17 | 52.2 | 41.1 | 48.1 | 49.8 | 66.9 | 52.4 | 43.2 | 47.1 | 38.3 |
| 03/17 | 68.5 | 78.4 | 47.6 | 67.2 | 77.2 | 49.4 | 60.7 | 62.8 | 44.8 |
| 04/17 | 62.0 | 69.7 | 38.0 | 62.8 | 75.8 | 50.6 | 56.3 | 57.9 | 48.3 |
| 10/17 | 38.5 | 28.1 | 22.5 | 40.8 | 26.1 | 22.4 | 36.7 | 38.7 | 33.8 |
| 11/17 | 24.8 | 29.3 | 30.4 | 27.7 | 27.5 | 27.9 | 30.5 | 35.3 | 30.4 |
| 12/17 | 30.5 | 28.2 | 32.0 | 29.5 | 26.7 | 29.0 | 35.6 | 32.5 | 27.6 |
| Ave. | 50.2 | 48.0 | 36.3 | 53.1 | 48.1 | 37.9 | 48.6 | 45.6 | 37.0 |
| Std. | 16.7 | 27.3 | 21.8 | 15.6 | 45.5 | 19.2 | 23.6 | 11.9 | 6.8 |

Table 4. Monthly average RMS difference in cm between the different SIT estimates \textit{w.r.t.} the reference-reference SIT data sets SIT. The symbols are the same as in Table 4.

| Month | CS2/A | SIT/A | RSIT/A | CS2/T-SIT/T | RSIT/T | CS2SIT/O | SSRSIT/O | SIT/PM | RSIT/OPM |
|-------|-------|-------|--------|-------------|--------|----------|----------|--------|-----------|
| 01/17 | 69.7 | 54.3 | 46.3 | 70.8 | 59.5 | 51.6 | 66.1 | 55.6 | 48.8 |
| 02/17 | 67.6 | 79.2 | 56.2 | 67.4 | 84.4 | 62.9 | 61.9 | 62.3 | 49.5 |
| 03/17 | 82.9 | 93.9 | 57.1 | 87.1 | 98.0 | 63.0 | 79.1 | 80.4 | 58.7 |
| 04/17 | 72.6 | 84.6 | 48.2 | 78.7 | 94.2 | 63.6 | 72.5 | 73.5 | 58.5 |
| 10/17 | 42.1 | 39.5 | 31.5 | 50.0 | 41.3 | 33.6 | 45.8 | 47.2 | 41.0 |
| 11/17 | 33.2 | 40.4 | 32.2 | 36.4 | 41.6 | 37.9 | 37.6 | 43.6 | 38.3 |
| 12/17 | 47.2 | 35.6 | 36.8 | 47.3 | 37.2 | 37.8 | 48.6 | 44.4 | 37.0 |
| Ave. | 65.3 | 64.3 | 45.5 | 71.3 | 68.7 | 50.7 | 64.7 | 59.5 | 48.2 |
| Std. | 18.6 | 36.2 | 24.2 | 24.0 | 18.4 | 26.1 | 26.6 | 17.1 | 9.4 |

Table 5. Monthly average \textit{Average} difference measures between the reference data sets. The symbols are AARI ice chart SIT (A), CS2SMOS SIT (CS2SM) and SIT of the same as in Table 43 three ice models. O refers to ORAS5, T refers to TOPAZ4, PM refers to PIOMAS.

| Measure | O/A/T-ACS2SM | O/A/TO | A/T/A | O/A/TPM | TACS2SM/O | QCS2SM/A-T | QCS2SM/OPM |
|---------|-------------|------|-------|--------|----------|-----------|------------|
| 01/17 CC | 0.32 | 0.47 | 0.48 | 4.2 | 45.9 | 50.4 | 20.2 |
| Bias | 0.49 | 51.7 | 32.2 | 57.4 | 61.4 | 6 | - |
| 02/17 L1D | 0.42 | 0.54 | 0.51 | -2.6 | 45.2 | 48.9 | 22 |
| RMSD | 49.8 | 36.0 | 60.9 | 65.6 | 22 | 29 | |

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Table 6. Comparison between the CS2 SIT assigned to SAR mosaic segments and CS2SMOS SIT.

| Month       | 01/17       | 02/17       | 03/17       | 04/17-04/17 | 04/17-10/17 | 04/17-11/17 | 04/17-12/17 | 04/17-12/17 | 04/17-12/17 |
|-------------|--------------|--------------|--------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Corr.       | 29.1±0.55    | 46.2±0.62    | 48.8±0.72    | 42.6±0.67   | 60.7±0.75   | 67.3±0.74   | 67.3±0.74   | 67.3±0.74   | 67.3±0.74   |
| Bias (cm)   | -8.5±31     | 39.4±38     | 47.9±34     | 33.1±34     | 48.9±41     | 57.4±9      | 48.5±13     | 63.7±24     | 75.2±14     |
| L1D (cm)    | 0.86±33     | 0.71±42     | 0.78±41     | -3.7±43     | 21.8±8      | 25.5±12     | 17.2±17     | 30.5±28     | 32.7±15     |
| RMSD (cm)   | 34.3±67     | 35.3±73     | 38.7±67     | 68          | 22          | 31          | 40          | 53          | 21          |

Table 7. Comparison between the CS2 assigned to SAR mosaic segments with the mapping and CS2SMOS SIT.

| Month       | 01/17       | 02/17       | 03/17       | 04/17       | 04/17-10/17 | 04/17-11/17 | 04/17-12/17 | 04/17-12/17 | 04/17-12/17 |
|-------------|--------------|--------------|--------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Corr.       | -2.3±0.62    | 33.9±0.67    | 36.1±0.74    | 13.1±0.70   | 37.4±0.77   | 37.3±0.70   | 18.8±0.62   | 39.9±0.69   | 41.7±0.66   |
| Bias (cm)   | 0.48±10      | 0.40±8       | 0.51±2       | 0.2±3       | 40.4±0      | 39.8±1      | 46.4±0      | 43.7±2      | 40.8±5      |
| L1D (cm)    | 23.4±15      | 46.8±21      | 47.4±15      | 60.6±25     | 0.5±6       | 0.5±6       | -5.1±11     | 35.7±16     | 40.9±7      |
| RMSD (cm)   | 22.3±29      | 43.0±34      | 44.9±37      | 34.4±40     | 52.4±14     | 57.5±16     | 21          | 27          | 11          |

Table 8. Monthly averages of estimated SIT (SIT) and remapped SIT (Rem. SIT) for the MODIS daily SIT chart categories. All values are in cm. The MODIS SIT categories are 1-30 cm (Cat1), 31-50 cm (Cat2) and over 50 cm (Cat3).

| Month       | SIT ave. Cat1 | SIT ave. Cat2 | SIT ave. Cat3 | Rem. SIT ave. Cat1 | Rem. SIT ave. Cat2 | Rem. SIT Cat3 |
|-------------|---------------|---------------|---------------|--------------------|--------------------|---------------|
| 01/2017     | 61±92         | 71±98         | 73±103        | 50±50              | 69±53              | 70±56         |
| 02/2017     | 97±99         | 112±108       | 116±119       | 80±54              | 94±66              | 94±68         |
| 03/2017     | 135±122       | 142±129       | 145±139       | 100±67             | 106±73             | 106±77        |
| 04/2017     | 140±120       | 146±131       | 151±139       | 102±67             | 106±73             | 109±78        |
Figure 1. CS-2 SIT CryoSat-2 sea ice thickness measurements of (A) one day and (B) one week before 21 February 2017. The colormap ends up to 250 cm; ice thicker than 250 cm appears as red.
Figure 2. The Barents and Kara Seas study area in the used polar stereographic projection. Air temperature data from four coastal weather stations shown with black dots are used in this study. ©FMI.
Figure 3. NCEP/NCAR reanalysis average daily air temperature during the period 2016-2017 -from four coastal weather stations shown in Figure 1.
Figure 4. Sentinel-1 HH (A) and HV (B) mosaic $\sigma^0$ segment median on 21 Feb 2017.
Figure 5. Cropped area of the HH (A) and HV (B) segment median images of Fig. 4.
Figure 6. Algorithm block diagram for the sea ice thickness estimation using combination of the CryoSat-2 sea ice thickness data and Sentinel-1 SAR imagery. We have used N=9 and M=5-7 in this study.

Figure 7. The CS-2/PIOMAS/ORASS A: Dependence of the SIT mapping based difference on histogram matching (red), the pairwise SAR segment texture difference, B: Dependence of the SIT difference on the pairwise SAR segment distance, C: Dependence of the SIT difference on the pairwise SAR segment time difference. Also, the cyan lines in the mappings corresponding figures represent the linear least squares regression.
Figure 8. The correspondence of the CryoSat-2 SIT to three AARI ice chart SIT and modeled SIT from the three models are shown studied based on histogram matching.
Figure 9. A: CS-2/CS2/S-1 SIT, B: remapped CS-2/CS2/S-1 SIT, C: AARI ice chart SIT, D: TOPAZ4 ice model reanalysis SIT, and E: ORAS5 model ice model SIT and F: CS2/SMOS SIT of 21 February 2021-2017.
MODIS–proposed remapped SIT collage based on two weeks MODIS and AARI ice chart SIT before for 21 Feb 2017. The areas without data are indicated by black color 2017. C: Average difference of the proposed (unmapped) SIT and all the AARI ice thicker than 50 cm is indicated by cyan color chart SIT for the 2017 data, corresponding to 100 cm in D: Average difference of the colormap proposed remapped SIT and the AARI ice chart SIT for the 2017 data.

Figure 10. Median segment difference ($T$) as a measure of uncertainty: A: Difference of the proposed (unmapped) SIT estimates for 21 Feb 2017. The values of $T$ have been scaled to the range 0-100 cm and AARI ice chart SIT, based on the variation in the training data. B: Difference of $T$ in the training data.
Figure 11. A: Difference of the proposed (unmapped) SIT and CS2SMOS SIT for the 21 Feb 2021 case, B: Difference of the proposed remapped SIT and CS2SMOS SIT for the 21 Feb 2017 case, C: Average difference of the proposed (unmapped) SIT and the CS2SMOS SIT for the 2017 data, D: Average difference of the proposed remapped SIT and the CS2SMOS SIT for the 2017 data.
Figure 12. Segment difference ($T$) as a measure of uncertainty of the SIT estimates. This is the segment difference for the 21 Feb 2017 case. The values of $T$ have been scaled to the range 0-100, based on the variation of $T$ in the training data. The black area is open water.
Figure 13. MODIS SIT collage based on two weeks of MODIS daily SIT charts before 21 Feb 2017. The areas without data are indicated by gray color and all the ice thicker than 50 cm is indicated by green color, corresponding to 60 cm in the colormap.