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1	Abstract. An Arctic and Antarctic sea ice area and extent dataset has been generated by
2	EUMETSAT's Ocean and Sea Ice Satellite Application Facility (OSISAF) using the record of
3	American-microwave radiometer data from <u>NASA's</u> Nimbus 7 Scanning Multichannel Microwave
4	radiometer (SMMR) and the Defense Meteorological satellite Program (DMSP) Special Sensor
5	Microwave/ Imager (SSM/I) and Special Sensor Microwave Imager and Sounder (SSMIS) satellite
6	sensors. The dataset covers the period from Oct. 1978 to Apr. 20154 and updates and further
7	developments are planned for the next phase of the project. The methodology <u>for computing the sea ice</u>
8	concentration is using: 1) numerical weather prediction (NWP) data input to a radiative transfer model
9	(RTM) for correction of the brightness temperatures for reduction of atmospheric noise reducing the
20	impact of weather conditions on the measured brightness temperatures (Tb), 2) dynamical algorithm
21	tie-points to mitigate trends in residual atmospheric, sea ice and water emission characteristics and
22	inter-sensor differences/biases, 3) and a hybrid sea ice concentration algorithm using the Bristol
23	algorithm over ice and the Bootstrap algorithm in frequency mode over open water. A new sea ice
24	concentration uncertainty algorithm has been developed to estimate the spatially and temporally
25	varying variabilities in sea ice concentration uncertainties retrieval accuracy. A comparison to <u>U.S.</u>
26	National Ice Center sea ice charts from the Arctic and the Antarctic shows that ice concentrations are
27	higher in the ice charts than estimated from the radiometer data at intermediate sea_ice concentrations
28	in between open water and 100% ice. The sea ice climate dataset is available for download at
29	(www.osisaf.org) including documentation.
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31	1. Introduction
32	The Arctic sea ice covered area and extent has decreased since the 1970s (Cavalieri and Parkinson,

1 2012). In Antarctica there are large regional differences in trends but overall the sea ice extent is 2 increasing because of changing atmospheric circulation patterns and regional cooling (Comiso et al., 3 2011; Holland and Kwok, 2012). The climatic trends in sea ice extent have been documented using 4 models (Zhang and Walsh, 2006; Goosse and Zunz, 2014), ice charts (Rayner et al., 2003) and in 5 particular the passive microwave data record from American U.S. satellite microwave radiometers 6 (Parkinson and Cavalieri, 2012; Cavalieri and Parkinson, 2012). Here Throughout this paper the sea ice 7 extent is defined as ice covered waters with ice concentrations derived from microwave radiometer 8 data greater than 1530% as in Parkinson and Cavalieri (2008) and at a grid resolution of 12.5 x 12.5 9 kilometers. 10 11 The brightness temperatures measured by the satellite radiometers at the atmospheric window channels 12 are dominated by surface emission. However, the measured brightness temperatures are also affected 13 by atmospheric parameters weather conditions such as wind roughening of the ocean surface, water 14 vapor and cloud liquid water (Wentz, 1983 and 1997; Andersen et al., 2006B). These parameters have 15 trends over the observing period (Wentz et al., 2007). Even though the sensitivity to these parameters is 16 minimized in ice concentration algorithms in general, different algorithms still have different 17 sensitivities resulting in structural uncertainties, i.e. different outcome from different algorithms using 18 the same data (Andersen et al., 2006B). Here we define the noise as the ice concentration fluctuations 19 caused by the instrument electronic components, ice and water surface emissivity variability and 20 weather conditions, i.e. estimated ice concentration variability not caused by changes in the actual ice 21 concentration. 22 23 Because of the algorithms different sensitivities to the noise, and that the noise has climatic trends, the 24 differences are also reflected appear as trends in the sea ice extent trends (Andersen et al., 2007). To 25 minimize these artificial trends caused by noise we must: 1) find algorithms with low sensitivities to 26 the atmospheric and surface emissivity variability, 2) correct the brightness temperatures for the properties that we are able to quantify (NWP data: wind, temperature and atmospheric water vapor), 27 28 and in particular when doing this it is important to 3) calibrate the algorithms to the actual ice and 29 water signatures using dynamical tie-points, and finally 4) quantify the residual uncertainties. The 30 EUMETSAT sea ice climate record (ESICR) is generated according to these principles, 1 - 4, and it is

based on the NASA's Nimbus 7 Scanning Multichannel Microwave Radiometer (SMMR) (1978-1987), the DMSP's the Special Sensor Microwave/Imager (SSM/I) (1987-2009) and the DMSP's Special Sensor Microwave Imager and Sounder (SSMIS) (2003-today) radiometer data. It uses a combination of the Bristol (Smith, 1996) and the Bootstrap (Comiso, 1986) algorithms with dynamical tie-points, explicit atmospheric correction using numerical weather prediction NWP data for error reduction and it comes with spatially and temporally varying sea ice concentration uncertainty estimates describing the sea ice concentration accuracy describing the residual uncertainties. Dynamical tie-points are typical signatures of ice and water used in the sea ice concentration algorithms to scale the ice concentration. These are derived on a daily basis for each hemisphere and therefore adjust the algorithms to the current signatures of ice and water (see section 2.1). Uncertainty The sea ice concentration uncertainty estimates are needed when the ice concentration data are compared to other data sets or when the ice concentrations are assimilated into numerical models. The mean accuracy of some of the more common algorithms, used to compute ice concentration from SSM/I data, such as the NASA Team and Bootstrap are reported to be 1-6% in winter (Steffen and Schweiger, 1991; Emery et al., 1994; Belchansky and Douglas, 2002). The overall accuracy of the SMMR total ice concentrations is estimated to be $\pm 7\%$ (Gloersen et al., 1992). During summer the uncertainties are larger than during winter (Ivanova et al., 2015). 1.1 Description of the Nimbus 7 SMMR instrument and data The SMMR instrument on board the Nimbus 7 satellite operated from Oct. ober 1978 to Aug. ust 1987 (Gloersen et al., 1992). The instrument had 10 channels from the six Dicke radiometers at five frequencies (6.6, 10.7, 18.0, 21.0, 37.0 GHz) and vertical (v) and horizontal (h) linear polarization. The across track scanning was accomplished by tilting the reflector from side to side while maintaining a constant incidence angle on the ground of about 50.2°. The scan track on the ground formed a 780 km wide arc in front of the satellite (Gloersen and Barath, 1977). Because of the satellite orbit inclination and swath width there is no coverage pole-wards of 84°. There is SMMR data only SMMR data were acquired every second day because of satellite power limitations. Data were provided by the National Snow and Ice Data Center (NSIDC) as brightness temperatures in swath "projection" (Meier, 2008).

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1	1.2 Description of the SSM/I and SSMIS instruments and data.				
2	The SSM/I instruments onboard the Defense Meteorological Satellite Program (DMSP) are conically				
3	scanning instruments with 7-seven total power radiometers measuring channels at 19.35v, 19.35h,				
4	22.2h, 37.0v, 37.0h, 85.5v, and 85.5hThe incidence angle is 53.1° degrees and the swath width on the				
5	Earth's surface is about 1400 km. There is no coverage pole-wards of 87 ° degrees . The different				
6	satellites and their operation periods are listed in Table 2. The SSM/I data (version 6 and not the newer				
7	version 7) was purchased by EUMETSAT from Remote Sensing Systems (RSS) as antenna				
8	temperatures and converted to brightness temperatures using RSS software. The Remote Sensing				
9	Systems (RSS) SSM/I version 6 post processing includes geo-location correction, sensor calibration				
10	and quality control procedures, and inter calibration between the different satellites from overlapping				
11	periods. These procedures are documented in the RSS SSM/I User's Manuals (Wentz, 1991; Wentz,				
12	1993; Wentz, 2006).				
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14	The SSMIS is a continuation of the SSM/I series of instruments onboard the DMSP satellites but with				
15	an extension in the number of channels. SSMIS has 24 channels between 19 and 183 GHz. The 19 and				
16	37 GHz channels which are used in the ESICR have identical frequencies on SSM/I and SSMIS.				
17	However, SSMIS has a swath width of about 1700km which gives near complete daily coverage of the				
18	Arctic Ocean. The SSMIS data are from the L2B near real time data-stream <u>issued via EUMETCast</u>				
19	and processed at the U.S. National Ocean and Atmospheric Administration (NOAA).				
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21	1.3 Meteorological data				
22	The Numerical Weather Prediction (NWP) model meteorological data are used for reduction of the				
23	brightness temperatures for atmospheric noise with a radiative transfer model. European Centre for				
24	Medium-range Weather Forecast (ECMWF) ERA 40 data are used for the period from 1978 to 2002,				
25	and ECMWF data from the operational models are used from 2002 onwards. A description of the ERA				
26	40 meteorological data archive and the reanalysis can be found in Kålberg et al. (2004). We use 6				
27	hourly data at a resolution of 1.25 degrees.				
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29	1.4 MODIS data				
30	The coarse resolution of the <u>passive microwave</u> brightness temperature measurements gives rise to an				
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additional uncertainty when sea ice concentration is reproduced at finer grid spacing. We call this smearing uncertainty and it is estimated using a smearing model (see section 2.94.2). High resolution ice concentration data are used as input to the smearing model:- Cloud free and non-calibrated MODIS scenes from the NASA image gallery archive (http://rapidfire.sci.gsfc.nasa.gov/cgibin/imagery/gallery.cgi) were selected manually for their different sea ice conditions: low concentration, medium and high concentration. Parts of the image with cloud cover were cut out manually. The band 1 (620 - 670 nm) brightness (given as pixel values between 0 and 255) is high typically greater than 220 for sea ice and less than 60 for open water. These two upper and lower values are used for scaling pixels between 100% and 0% ice concentration respectively. Pixels with intermediate brightness are assigned intermediate concentrations linearly. Brightness above 220 and below 60 is truncated to 100% and 0% respectively. The 250 m spatial resolution is re-sampled to 1 km pixel resolution. 1.5 Ice chart data for comparison The operational sea ice charts from the U.S. National Ice Center (NIC) are a relatively independent source of ice information (not necessarily unbiased) for comparing to the sea ice concentration estimates are used for comparison with the ESICR sea ice concentration. The ice charts, intended for aiding navigation are produced on a regular-weekly basis covering all seasons, both Scouthern and Nnorthern hemispheres and the time series cover the entire climate record period except for the period Dec. 1994 to Jan. 20063 oin the Southern hemisphere where we have been unable to acquire digital iee charts. The ice charts used for comparison are a combination of three datasets: 1) The NIC ice charts for the Nnorthern Hhemisphere 1972-2007 available at National Snow and Ice Data Center (NSIDC) in gridded format (Fetterer and Fowler, 2009), 2) the NIC ice charts for the sssouthern hemisphere 1973-1994 available at the NSIDC (Fetterer, 2006), and 3) the NIC ice charts for both hemispheres from 2006-2015 available from NIC. Ice charts are produced manually on the basis of a multitude of satellite and reconnaissance data for ship navigation support. The ice charts are detailed manual interpretations of primarily satellite imagery and a subsequent mapping procedure is carried out by ice analysts. The ice charts are primarily

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used for strategic and tactical planning within the offshore and shipping community.

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2	The more recent ice charts are based partly on satellite SAR data e.g. RADARSAT 1 since 1995 and
3	ENVISAT since 2002, various scatterometers together with visual/infrared line scanners e.g. AVHRR,
4	MODIS, OLS whenever possible for daylight and cloud cover conditions. Also the passive microwave
5	data from SMMR and SSMM/I used in this re-processing of ice concentrations have been extensively
6	used for making the ice charts in particular before the launch of wide swath SAR instruments in 1995.
7	In addition to the satellite data ice charts are based on information from ships and aircraft
8	reconnaissance. The NIC ice charts are a weekly compilation of the ice conditions. The different sea
9	ice categories are delineated manually by polygons and assigned a range of sea ice concentrations,
10	thicknesses, type etc. found within the polygon in the ice chart by an ice analyst. This information is
11	represented on the satellite pixel grid by averaging the range of ice concentrations and other properties
12	given within the polygon (Dedrick et al., 2001).
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14	2.0 Methodology
15	2.1 Dynamical tie-points
16	<u>Tie-points are typical signatures of ice and open water which are used in the ice concentration</u>
16 17	Tie-points are typical signatures of ice and open water which are used in the ice concentration algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions
17	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions
17 18	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions
17 18 19	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions of known open water and ice.
17 18 19 20	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions of known open water and ice. During winter, in the consolidated pack ice well away from the ice edge, the ice concentration is very
17 18 19 20 21	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions of known open water and ice. During winter, in the consolidated pack ice well away from the ice edge, the ice concentration is very near 100 %. This has been established using high resolution SAR data, ship observations and by
17 18 19 20 21 22	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions of known open water and ice. During winter, in the consolidated pack ice well away from the ice edge, the ice concentration is very near 100 %. This has been established using high resolution SAR data, ship observations and by comparing the estimates from different ice concentration algorithms (Andersen et al., 2007). The
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17 18 19 20 21 22 23 24	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions of known open water and ice. During winter, in the consolidated pack ice well away from the ice edge, the ice concentration is very near 100 %. This has been established using high resolution SAR data, ship observations and by comparing the estimates from different ice concentration algorithms (Andersen et al., 2007). The apparent fluctuations in the derived ice concentration in the near 100 % ice regime are primarily attributed to snow/ice surface emissivity and temperature around the tie-point signature and only
17 18 19 20 21 22 23 24 25	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions of known open water and ice. During winter, in the consolidated pack ice well away from the ice edge, the ice concentration is very near 100 %. This has been established using high resolution SAR data, ship observations and by comparing the estimates from different ice concentration algorithms (Andersen et al., 2007). The apparent fluctuations in the derived ice concentration in the near 100 % ice regime are primarily attributed to snow/ice surface emissivity and temperature around the tie-point signature and only secondarily to actual ice concentration fluctuations. In the marginal ice zone at intermediate ice
17 18 19 20 21 22 23 24 25 26	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions of known open water and ice. During winter, in the consolidated pack ice well away from the ice edge, the ice concentration is very near 100 %. This has been established using high resolution SAR data, ship observations and by comparing the estimates from different ice concentration algorithms (Andersen et al., 2007). The apparent fluctuations in the derived ice concentration in the near 100 % ice regime are primarily attributed to snow/ice surface emissivity and temperature around the tie-point signature and only secondarily to actual ice concentration fluctuations. In the marginal ice zone at intermediate ice concentrations and over open water the atmospheric emission and wind shear and smearing dominates
17 18 19 20 21 22 23 24 25 26 27	algorithms as a reference. The tie-points are derived by selecting brightness temperatures from regions of known open water and ice. During winter, in the consolidated pack ice well away from the ice edge, the ice concentration is very near 100 %. This has been established using high resolution SAR data, ship observations and by comparing the estimates from different ice concentration algorithms (Andersen et al., 2007). The apparent fluctuations in the derived ice concentration in the near 100 % ice regime are primarily attributed to snow/ice surface emissivity and temperature around the tie-point signature and only secondarily to actual ice concentration fluctuations. In the marginal ice zone at intermediate ice concentrations and over open water the atmospheric emission and wind shear and smearing dominates as error sources. There is no explicit correction for cloud liquid water and this is an uncertainty source

(Andersen et al., 2007). This means that not only does the estimated sea ice extent have a climatic 2 trend; also the atmospheric and surface constituents affecting the microwave emission are changing. In 3 an attempt to compensate for the influence of these artificial trends, the tie-points are derived 4 dynamically using a window of width \pm 15 days centered at the day of the actual sea ice concentration 5 retrieval. It is assumed that ice concentrations greater than 95 % from the NASA Team algorithm 6 (Cavalieri et al., 1984) are in fact a representation of near 100 % ice. The NASA Team algorithm has 7 different sensitivities to artificial trends than the two algorithms used in combination here (Andersen et 8 al., 2007). The ice tie-point is the mean value of these selected data points. The static NASA Team tie-9 points for SMMR are found in Gloersen et al. (1992) and for SSM/I the tie-points are found in 10 Andersen (1998). Geographically, the sea ice tie-point is excluding data of both the SMMR and the 11 SSM/I instruments pole-wards of 84° for consistency between the SMMR and SSM/I periods. The 12 open water tie-point data were selected geographically along two belts on the northern and southern 13 hemisphere respectively (between 53°N and 75°N and between 65°S and 80°S). A land mask including 14 the coastal zone and sea ice maximum extent climatology ensures open water data only. 15 16 There is no attempt to compensate explicitly for sensor drift or inter-sensor calibration differences 17 (even though the SSM/I data have been inter-calibrated) or possible biases in the NWP fields used for 18 atmospheric noise reduction of the brightness temperatures. The dynamical tie-point method is in 19 principle compensating for these problems in a consistent manner. 20 21 2.21 Atmospheric noise reduction of the brightness temperatures using NWP data 22 Using an emission model, the brightness temperatures are corrected for the influence of water vapor in 23 the atmosphere and open water surface roughness caused by wind-shear. The emission model used for 24 atmospheric noise reduction of the SMMR brightness temperatures, Tb, with NWP input is (Wentz, 25 1983): 26 Tb = f(Ts, u *, V, L, Ta)(1),27 where Ts is the physical surface temperature, <u>u</u>U* is the sea surface wind friction velocity, V is the 28 integrated atmospheric water vapor column, L is the atmospheric liquid water column, and Ta is the 29 surface (at 2 m) air temperature. A similar model is used for the SSM/I and SSMIS data (Wentz, 1997).

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Over areas with both ice and water the influence of open water roughness on the brightness

temperatures and the ice emissivity is scaled linearly with the ice concentration. The emissivity of ice is given by standard tie-point emissivities and the total ice concentration is solved by iteration with a first guess of the ice concentration from the NASA Team algorithm (Cavalieri et al., 1984) with static tie-points. The correction procedure is described in detail in Andersen et al. (2006B). The NWP model grid points are co-located with the satellite swath data in time and space using linear interpolation and a correction to the brightness temperatures using Eq. 1 is applied. The potential inconsistencies between the ERA40 and the operational ECWMF models are minimized by the dynamical tie-point adjustment later in the processing and eventually the residual error is included in the error estimate.

The representation of atmospheric liquid water column in the NWP data is not suitable to use for brightness temperature correction because of the spatial and temporal variability of clouds which is higher than the model grid cell size and model time step size. The data are therefore not corrected for the influence of atmospheric liquid water. Assuming a neutral atmospheric temperature profile, the wind speed at 10 m, given by the numerical weather prediction model, is converted to the surface friction velocity using the factor 0.047 for use in the SMMR RTM. The other NWP variables are used directly.

2.2 Dynamical tie-points

Tie points are typical signatures of ice and open water which are used in the ice concentration algorithms as a reference. The tie points are derived by selecting brightness temperatures from regions of known open water and ice.

During winter, in the consolidated pack ice well away from the ice edge, the ice concentration is very near 100 %. This has been established using high resolution SAR data, ship observations and by comparing the estimates from different ice concentration algorithms (Andersen et al., 2007). The apparent fluctuations in the derived ice concentration in the near 100 % ice regime are primarily attributed to snow/ice surface emissivity and temperature and atmospheric variability around the tie-point signature and only secondarily to actual ice concentration fluctuations. In the marginal ice zone at intermediate ice concentrations and over open water the atmospheric emission and wind shear and smearing dominates as error sources. There is no explicit correction for cloud liquid water and this is an uncertainty source over both ice and open water. The fluctuations due to atmospheric and surface

emission are systematic. In fact, different algorithms with different sensitivity to atmospheric and surface emission compute very different trends in sea ice extent on seasonal and decadal time seales (Andersen et al., 2007). This means that not only does the estimated sea ice extent have a climatic trend; also the atmospheric and surface constituents affecting the microwave emission are changing. In an attempt to compensate for the influence of these artificial trends the tie-points are derived dynamically using a window of width ± 15 days centered at the day of the actual sea ice concentration retrieval. It is assumed that ice concentrations greater than 95 % from the NASA Team algorithm (Cavalieri et al., 1984) are in fact a representation of near 100 % ice. The NASA Team algorithm has different sensitivities to artificial trends than the two algorithms (see section 2.3 below) used in combination here (Andersen et al., 2007). The ice tie point is the mean value of these selected data points. The static NASA Team tie-points for SMMR are found in Gloersen et al. (1992) and for SSM/I the tie points are found in Andersen (1998). Geographically, the sea ice tie point is excluding data of both the SMMR and the SSM/I instruments pole wards of 84° for consistency between the SMMR and SSM/I periods. The open water tie point data were selected geographically along two belts on the northern and southern hemisphere respectively (between 53°N and 75°N and between 65°S and 80°S). A land mask including the coastal zone and sea ice maximum extent climatology ensures open water data only. There is no attempt to compensate explicitly for sensor drift or inter-sensor calibration differences (even though the SSM/I data have been inter-calibrated) or possible biases in the NWP fields used for atmospheric noise reduction of the brightness temperatures. The dynamical tie-point method is in principle compensating for these problems in a consistent manner. 2.3 The ice concentration algorithm The analysis of atmospheric sensitivity in Andersen et al. (2006B) showed that the Bootstrap frequency

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The analysis of atmospheric sensitivity in Andersen et al. (2006B) showed that the Bootstrap frequency mode algorithm (Comiso, 1986; Comiso et al., 1997) had the lowest sensitivity to atmospheric noise at low ice concentrations. Furthermore, the comparison to high resolution SAR imagery in Andersen et al. (2007) indicated that among the algorithms using 19 and 37 GHz channels available on both SMMR and SSM/I - SSMIS, the Bristol algorithm (Smith, 1996) had the lowest sensitivity to ice surface emissivity variability. In addition the Bristol algorithm had low sensitivity to atmospheric emission in

- 1 particular at high ice concentrations.
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- 3 Consequently, we use a combination of the Bristol algorithm and the Bootstrap frequency mode
- 4 | algorithm <u>– a so-called hybrid algorithm</u>. The Bootstrap algorithm is used over open water and the
- 5 Bristol algorithm is used over ice. At intermediate concentrations up to 40% the ice concentration is an
- 6 average weighted linearly between the two algorithms. This hybrid algorithm is also used as the
- 7 operational OSI SAF sea ice concentration algorithm.
- 8
- 9 2.4 The Bootstrap and Bristol sea ice concentration algorithms
- The original Bootstrap sea ice concentration algorithm is a combination of two algorithms: the
- 11 polarization mode algorithm which is used over ice and the frequency mode algorithm which is used
- 12 over open water (Comiso, 1986). Only tThe Bootstrap frequency mode algorithm uses T_{19v} and T_{37v} in
- 13 | frequency mode, the open water part, is used here. The algorithm assumes only two surface types: ice
- and open water. The linear relationship yields the following formulation for the total sea ice
- 15 concentration, ic:
- $16 \quad ic_{Bootstrap} = (Tb Tb^{W}Tb^{W^{-}})/(Tb^{I} + Tb^{W}), \tag{2}$
- 17 where Tb is the measured brightness temperature, Tb^{W} is the open water tie-point, and Tb^{I} is the ice tie-
- 18 point.
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- 20 The Bristol algorithm (Smith, 1996) is conceptually similar to the Bootstrap algorithm. In a three-
- dimensional scatter plot spanned by T_{19v} , T_{37v} and T_{37h} the ice points tend to fit a plane surface. The
- only difference to the Bootstrap algorithm is that instead of viewing the data in the T_{19v}, T_{37v} space, the
- 23 Bristol algorithm views the data perpendicular to the data plane, i.e. in a transformed coordinate
- 24 system:
- 25 1. axis: $T_{37v} + 1.045T_{37h} + 0.525T_{19v}$, (3a)
- 26 2. axis: $0.9164T_{19v} T_{37v} + 0.4965T_{37h}$. (3b)
- The remaining analysis is identical to the Bootstrap algorithm.
- The Bootstrap algorithm is used over open water and the Bristol algorithm is used over ice. At

- 1 intermediate concentrations up to 40% (from the Bootstrap ice concentration estimate) the ice
- 2 concentration is an average weighted linearly between the two algorithms i.e.
- 3 $ic = (1 wc) * ic_{Bristol} + wc * ic_{Bootstrap}$ (4a),
- 4 where

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- 5 $wc = (|t ic_{Bootstrap}| + t ic_{Bootstrap})/(2 * t)$ (4b),
- 6 where t is the threshold of 40%.

8 2.45 The sea ice concentration uncertainties

- 9 The uncertainties described in the following sections are generally independent and the squared sum of
- 10 the two estimated components of uncertainty is assumed to represent the total uncertainty squared.
- 11 Each of the components is quantified as the standard deviation of sea ice concentration. The tie-point
- uncertainty $\varepsilon_{\text{tie-point}}$, including residual atmospheric noise, sensor noise and ice surface emissivity
- 13 variability, is derived from measurements as the first component of uncertainty. The representativeness
- error, ε_{smear} , is simulated using a model as the second component of uncertainty, i.e.
- 15 $\varepsilon_{total}^2 = \varepsilon_{tie-point}^2 + \varepsilon_{smear}^2$ (5).

16 <u>2.7 The geo-location error</u>

- 17 Geo location error the geo location error occurs when the satellite is not exactly oriented. Simulations
- 18 show that because of the large footprints (see next section for footprint sizes) compared to the typical
- 19 geo location errors (about ±5 km, Hollinger et al., 1990) the ice concentration uncertainty due to geo-
- 20 location errors is small and neglected here. Locally, the geo location errors may be significant but
- 21 <u>difficult to estimate.</u>

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23 2.4.16 First component: instrument noise, algorithm and tie-point uncertainties

- 24 Both the water surface and ice surface emissivity variability and emission and scattering in the
- 25 atmosphere affects the brightness temperatures and the computed ice concentrations. Different
- 26 algorithms have different sensitivities to these surface and atmospheric parameters (Andersen et al.,
- 27 2006B). Further, both the atmospheric and surface parameters affecting the ice concentration estimates
- 28 have climatic trends (Andersen et al., 2007). To reduce the uncertainties due to atmospheric noise, the

1	brightness temperatures are corrected using NWP data for atmospheric water vapor and open water				
2	roughness. The dynamical tie-points reduce the uncertainty due to the climatic trends in the atmosphere				
3	and on the ice surface on a hemispheric scale while regional trends may still exist. The remaining tie-				
4	point uncertainties are given as the spatial tie point ice concentration standard deviation in regions with				
5	open water or 100% ice.				
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7	Random instrument noise also results in ice concentration uncertainties. The SSM/I instrument noise				
8	results in an ice concentration uncertainty of 1.4 % for the Bristol algorithm, and 1.7 % for the				
9	Bootstrap algorithm in frequency mode (Andersen et al., 2006A). Systematic sensor drift is critical				
10	issue for ice concentration algorithms using static tie-points. Here we use dynamical tie-points intended				
11	for alleviating problems with sensor drift, and inter-sensor calibration. and elimatic trends in ice				
12	surface emissivity and atmospheric emission, i.e. this method minimizes the uncertainties caused by				
13	sensor drift.				
14	In addition to these two sea ice concentration uncertainty components there is the geo-location error. It				
15	occurs when the satellite is not exactly oriented (Poe et al., 2008). Simulations show that because of the				
16	large footprints (see next section for footprint sizes) compared to the typical geo-location errors of the				
17	SSM/I (about ±5 km, Hollinger et al., 1990) the ice concentration uncertainty due to geo-location errors				
18	is small and neglected here. There may be regions along the ice edge and along coastlines where the				
19	geo-location errors may be significant. However, we have not been able to include these errors in the				
20	sea ice concentration uncertainty estimate.				
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22	2.7 The geo location error				
23	Geo location error—the geo location error occurs when the satellite is not exactly oriented. Simulations				
24	show that because of the large footprints (see next section for footprint sizes) compared to the typical				
25	geo location errors (about ±5 km, Hollinger et al., 1990) the ice concentration uncertainty due to geo-				
26	location errors is small and neglected here. Locally the geo-location errors may be significant but				
27	difficult to estimate.				
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29	2.4.28 Second component: the representativeness error				
30	Footprint sizes for the channels used for ice concentration mapping are uneven and range from about				

50-70 km for the 19 GHz channels to about 30 km for the 37 GHz channels. Footprints of uneven size are combined in the algorithms when computing the ice concentration. The footprint ice concentration is represented on a predefined sampling grid. The ice concentration data are normally represented on a finer grid (typically 12.5 or 25 km) than the sensor footprint sizes resolution (30 to 70 km). This effect is called smearing. The combination of footprints of uneven size in the ice concentration algorithm results in an additional smearing effect. This we call the footprint mismatch error. The smearing and the footprint mismatch error cannot be estimated separately. However, the combined error can be estimated if all other error sources and the ice cover reference are known a priori. It can also be simulated using high resolution ice concentration reference data and a model for the satellite measurement footprint patterns. Here we use the model described in section 2.9. 2.9 Simulating the smearing uncertainty The smearing simulation model uses high resolution brightness temperature input to compute the brightness temperatures as would be measured by the coarse resolution radiometers on board the satellite. The high resolution input is compared to the coarse resolution output and realizations of ice concentrations in the OSI SAF hybrid sea ice concentration algorithm. Reference SIC is derived from the brightness of cloud-free MODIS scenes re-sampled to 1 km x 1 km pixel size described in section 1.4. The MODIS pixel brightness across the imageintensity may vary

Reference SIC is derived from the brightness of cloud-free MODIS scenes re-sampled to 1 km x 1 km pixel size described in section 1.4. The MODIS pixel brightness across the image intensity may vary slightly as a function of solar angle and albedo (snow type, and sea ice type) leading to uncertainties in the actual derived ice concentration. However, here it is regarded as the reference truth and it does in fact provide a realistic spatial distribution of ice at the right scale for input to the model and as a reference for comparison. Each of these 1 km x 1 km ice concentration pixels is assigned a microwave brightness temperature using standard tie-points (Comiso et al., 1997) and linear mixing between 0 and 100%. For each 1 km x 1 km brightness temperature pixel elliptical Gauss-shaped antenna patterns (Drusch et al., 1999) are used to simulate brightness temperatures at 19v and 19h, 37v and 37h as it would be measured with SMMR and SSM/I - SSMIS on the satellite. The simulations of brightness temperatures are used as input to the Comiso Boostrap frequency mode (CF) and Bristol algorithms using standard tie-points. The resulting ice concentration estimate is then compared to the ice concentration reference from MODIS sampled to different resolutions, i.e. 1, 5, 10, 12, 25 and 50 km (see Tetab le 2). The STD between the truth at a certain pixel resolution and the simulated satellite

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image is the smearing uncertainty. The smearing uncertainty is assumed uniform between 0\% + \epsilon_{tiepoint}
 2
       and 100% - \varepsilon_{tiepoint}. At 0% and at 100% it logically is zero. Table 2 shows the smearing uncertainty for
 3
       the CF, the Bristol and the average OSI-SAF algorithm STD of the difference at different grid
 4
       resolutions. The final grid resolution is 10 or 12 km which means that the and has a smearing
 5
       uncertainty isof-13% or 12% respectively (Tab. 2). The smearing uncertainty is nearly the same for the
 6
       CF and the Bristol algorithms.
 7
 8
       The MODIS image used for estimating the smearing uncertainty is shown in Figure 1. The image has
 9
       regions of open water, intermediate concentrations and of complete 100% ice cover. The simulated
10
       SSM/I sea ice concentration using figure Figure 1 as input to the OSI-SAF algorithm is shown in figure
11
       Figure 2.
12
13
       2.4.310 The sea ice concentration uncertainty algorithm
14
       The representativeness uncertainty is computed as a function of ice concentration using a model. The
15
       other error sources are computed using the hemispheric standard deviation of the measurements over
16
       open water and over near 100% ice respectively. The ice concentration algorithm provides ice
17
       concentrations which are greater than 100% and less than 0% because of the natural variability of the
18
       measured brightness temperatures around the ice and open water tie points. These unphysical
19
       concentrations are truncated in the processing. Therefore, we write the ice concentration, ie:
20
       ic = (1 - \alpha(ic))water + \alpha(ic)ice
                                                      <del>(6),</del>
21
       where ic is the ice concentration calculated by the algorithm and \alpha as a function of ic is the truncated
22
       ice concentration (constrained to the interval 0-100 %):
       \alpha(ic) = \prod_{0}^{1}(ic)\,ic + H(ic - 1)
23
24
       where \prod_{a}^{b}(x) is the Boxcar function and H(x) the Heaviside step function.
25
       if ic\leq 0 then \alpha=0
26
       if 0 < ic < 1 then \alpha = ic
                                                                        (<u>6</u>8)
27
       if ic\geq 1 then \alpha=1
28
29
       Using equation Eq. 2 and assuming the uncertainty for the ice and water part is independent this leads
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1
       to a total tie-point uncertainty of i.e
 2
       \varepsilon_{tie-point}(\alpha(ic)) = \sqrt{(1-\alpha(ic))^2 \varepsilon_{water}^2 + \alpha^2(ic) \varepsilon_{ice}^2}
                                                                                    (<del>79</del>),
 3
 4
       where \varepsilon_{water} = \varepsilon(IC(P_{water}))
                                                                 (810),
 5
 6
       and open water is determined from open water measurements near the ice edgeby a monthly varying
 7
       ocean mask, IC is the functional mapping of the ice concentration algorithm and P<sub>water</sub> denotes the set
 8
       of swath pixels for all swaths (used for calculating the daily product).
 9
10
       \varepsilon_{ice} = \varepsilon(IC(P_{NT>0.95}))
                                              (911),
11
12
       is the STD of the ice concentrations where the NASA team (NT) algorithm finds estimates ice
13
       concentrations greater than 0.95%.
14
15
       Figure 3 shows t The ice concentration uncertainty ins a function of sea ice concentration (Fig. 3) where
16
       t-The total uncertainty squared is the sum of the two uncertainty components different uncertainties
17
       squared (see eqEq. 54). The smearing uncertainty is zero for open water and for 100 % ice and a-At
18
       these two points on the curve the total uncertainty there is only the tie-point uncertainty (including
19
       sensor and residual atmospheric noise) for open water and ice respectively. The smearing uncertainty
20
       reaches a maximum at intermediate concentrations between (0%+\epsilon_{tiepoint}) and (100% - \epsilon_{tiepoint}).
21
       Uncertainty for ice concentrations smaller than 0% and greater than 100% is the tie-point uncertainty.
22
       Because the sea ice concentration is provided on a relatively fine grid of about 10 km and 12.5 km
23
       compared to the actual resolution of the sensor the smearing uncertainty is the component which is
24
       dominating the total uncertainty for most of the sea-ice concentration range (Fig. ure 3). When the grid
25
       resolution is comparable to the footprint size of the sensor, i.e. in our case aboutactual spatial resolution
26
        of the algorithm at 50 km, the smearing uncertainty (see table Tab. 2) becomes comparable in
27
       magnitude to the tie-point uncertainty which is where the total uncertainty is at a minimum.
28
29
       2.511 From level 2 swath projection data to level 3 daily grids to interpolated level 4 maps
30
       The transition from level 2 swath projection data to the final level 3 and 4 daily predefined EASE and
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polar stereographic-grids includes the gridding of the swath data, the filtering of coast line grid cells, the maximum ice extent masking and spatial and temporal interpolation. Whenever a pixel is altered by any of these processing steps it is at the same time indicated with a flag in the file. The time window of 24 hours is centered at 12:00 UTC. The ice concentration swath data is averaged for each grid cell using the simple weighting function: weight = 1 - 0.3 * (dist/inflrad) (102),where dist is the distance between the data point centerre and the grid cell centerre and inflrad is the radius of influence (18 km). All data from overlapping missions are included in the gridding except the overlap between SMMR and SSM/I. Only the SSM/I data are used during the overlap of 1.5 months between SMMR and SSM/I. 2.5.1 Statistical filtering of ice concentration near the coastline Due to the coarse spatial resolution of the radiometers the data may be influenced by land up to 70 km from the coastline. The emissivity of land along the coastline is comparable to sea ice emissivity and much higher than water emissivity. This means that in the coastal zone, if there is open water or intermediate concentrations, the sea ice concentration will be overestimated. The statistical method which is described in Cavalieri et al. (1999) is used for filtering the ice concentration near the coast. 2.12 Statistical filtering of ice concentration near the coastline Due to the coarse resolution of the radiometers the data may be influenced by land up to 50 km from the coastline. The emissivity of land along the coastline is comparable to sea ice emissivity and much higher than water emissivity. This means that in the coastal zone if there is open water or intermediate concentrations the sea ice concentration will be overestimated. The statistical method which is described in Cavalieri et al. (1999) is used for filtering the ice concentration near the coast: For each grid cell along the coast the monthly mean and the minimum ice concentration is estimated using the

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1985 SMMR and the 1992 SSM/I data. The minimum ice concentration is used instead of the estimated

ice concentration if the adjacent non-coastal grid points are ice free.

1 2 2.5.213 Climatological maximum sea ice extent masking 3 Occasionally spurious sea ice is detected in open water regions far from the ice edge due to 4 atmospheric noise affecting the ice concentration estimate. These spurious sea ice detections are 5 masked out using the monthly maximum extent climatology by NSIDC 6 (http://nsidc.org/data/smmr_ssmi_ancillary/ocean_masks.html). A zone of additional 100 km into the 7 open water has been added to the maximum extent to ensure detection of real sea ice outside of the 8 climatology. 9 10 2.5.314 Level 4: Gap filling by spatial and temporal interpolation 11 Only gGrid cells with missing data are filled with interpolated values in the level 4 processing and 12 interpolated the affected values pixels are flagged. Daily data coverage is never complete due to the 13 hole near the North Pole and occasionally there are missing scan lines, and missing orbits and the hole 14 near the North Pole is never covered by the satellite. Spatial Interpolation interpolation is efficient 15 incan filling small gaps e.g. one or two missing scan lines but it is deceiving when large areas are 16 missing and filled with interpolated values. To overcome this issue, yet implementing a general 17 approach for all cases, both temporal and spatial interpolation is used. 18 <u>In Eq. 6, t</u>The weighting parameters are computed as follows: $w_{i,j}^D = 1/(\sigma_{i,j}^D)^2 (2N_{max} + 1)$ (115) 19 $W^{D}(k,l;i,j) = 1/(\sigma_{k,l}^{D})^{2} \times exp(-0.5(\frac{\Delta(k,l;i,j)}{R_{l,j}})^{2})$ (126). 20 21 where σ is the standard deviation associated to each ice concentration estimate, Δ is the distance 22 between a given (k,l) neighbor and cell (i,j) and R is an auto-correlation radius. The spatial 23 interpolation weight is thus based on an isotropic Gaussian distribution, and almost all (>99.9%) of the 24 interpolation weight is concentrated inside a [-3R;+3R] x [-3R;+3R] km² area, which translates into a [-25 $N_{max}+N_{max}$ x $[-N_{max}+N_{max}]$ grid cells squared area. It was found by testing that R is proportional to the 26 absolute latitude in degrees, i.e. R =latitude of (i,j). 27 28 The interpolation on a given date, D, uses data from the day before and after, i.e. D-1, D and D+1.

The interpolated value at grid cell (i,j) for day D is given by:

- $1 X_{i,j}^D = K(w_{i,j}^{D-1} X_{i,j}^{D-1} + w_{i,j}^{D+1} X_{i,j}^{D+1} + \Sigma_{k,l} W^D(k,l;i,j) X_{k,l}^D) (13),$
- where *X* is the sea ice concentration value and *K* is a normalizing factor given by:
- $3 w_{i,j}^{D-1} + w_{i,j}^{D+1} + \Sigma_{k,l} W^D(k,l;i,j) = 1/k (14)$
- 4 The spatial interpolation from neighbors of cell (i,j) in equation Eq. 136 is only using values from date
- 5 D, while the temporal interpolation is only concerned with the value from the exact (i,j) cell but from
- 6 dates D-1 and D+1. This ensures that the interpolation will be -efficient in the two following extreme
- 7 scenarios: 1) In a region where we never have satellite observations e.g. the data coverage gap near the
- 8 North Pole, the spatial interpolation term will be the only contribution. 2) Conversely, in the case of
- 9 several missing swaths on day D only (nominal coverage on D-1 and D+1), the interpolated values will
- 10 be computed from the previous and next days, taking advantage of the persistence of sea ice
- 11 concentration over relatively short periods. The interpolation for intermediate cases (when both spatial
- 12 and temporal neighbors exist) is a compromise of those extreme situations.
- 13 In Eq. 6, the weighting parameters are computed as follows:

14
$$W_{i,j}^D = 1/(\sigma_{i,j}^D)^2 (2N_{max} + 1)$$
 (15)

15
$$W^D(k,l;i,j) = 1/(\sigma_{k,l}^D)^2 \times exp(-0.5(\frac{\Delta(k,l;i,j)}{R_{i,j}})^2)$$
 (16),

- where σ is the standard deviation associated to each ice concentration estimate. Δ is the distance
- 17 between a given (k,l) neighbor and cell (i,j) and R is an auto correlation radius. The spatial
- 18 interpolation weight is thus based on an isotropic Gaussian distribution, and almost all (>99.9%) of the
- interpolation weight is concentrated inside a [3R;+3R] x [3R;+3R] km² area, which translates into a [
- 20 N_{max};+N_{max}] x [N_{max};+N_{max}] grid cells squared area. It was found by testing that R is proportional to the
- 21 absolute latitude in degrees, i.e. R = latitude of (i,j).
- For the SMMR which was operated every second day, the temporal interpolation is D-2 and D+2
- 23 | instead of D-1 and D+1 for SSM/I and SSMIS.
- 24 3. Results and discussion
- We compared the ESICR to sea ice charts for reference during the period from Oct. 1978 to Apr.
- $26 \quad 201509$ on both hemispheres. There is a gap in the comparison on the southern hemisphere because we
- 27 did not have access to ice charts between Dec. 1994 and Jan. 20063 (see Sect. ion 1.5). The overlap

1 period during July and August 1987 between the SMMR and the SSM/I instruments will be analyzed in 2 more detail in section 3.2. The latter period from 2009 to 2014 is not compared to ice charts. 3 4 It is clear that The ice charts are produced to support ship and offshore operations and not to monitor 5 sea ice as a climate parameter. However, theyit is a relatively independent dataset with a long history, 6 produced in a relatively consistent manner therefore we use it for comparison heredoes well in 7 identifying areas of open water and ice and the comparison does in fact reveal trends in the ESICR 8 noise levels. 9 10 3.1 The ice concentration comparison to sea ice charts 11 The entire period from 1987 to 2009 is covered by ice charts from the NIC on the northern hemisphere. 12 For the southern hemisphere there is gap from Dec. 1994 to Jan. 2003. The NIC ice charts and the sea 13 ice climate recordESICR are gridded onto the 12.5 km EASE grid and compared pixel by pixel. The 14 total concentration in the ice chart is given as the average of a the range of sea ice concentrations, e.g. 15 10% to 30%, describing the variability within each ice chart polygon. For each ice chart concentration 16 level (the total concentration) the The deviation bias and STD -between ice chart and the ice 17 concentration is computed for ice (ice chart concentration greater than 0 %) and for open water (ice 18 chart concentration equal to zero). and the bias and standard deviation is calculated for each 19 concentration level. The bias and standard deviation are reported for ice (> 0% ice concentration), for 20 water (0% ice concentration) and for both ice and water as a total. 21 22 The bias in ice concentration between the Northern Hemisphere National Ice Center ice charts and 23 ESICR ice concentration is shown in figure 4. The ESICR ice concentration is higher than the ice chart 24 over open water by 5 to 15% on the northern hemisphere (Fig. 4). This is due to the fact that the 25 radiometer ice concentration is affected by atmospheric noise and smearing near the ice edge which 26 increases the ESICR ice concentration above zero. Twhile the ice charts have a nominal value of zero 27 over open water. Actually the mean open water ESICR ice concentration is zero at swath level (level 28 2). However, all negative ice concentration estimates are truncated to zero which leaves the small 29 positive bias in the final product (level 4). Also tThe uncorrected noise from particularly cloud liquid

water, but also water vapor and wind over open water gives a positive bias in the ESICR ice

concentrations. This positive bias is not present in the ice charts. The SMMR to SSM/I transition in 1987 is <u>hardly</u> seen as a small increase in the open water bias because even though the SSM/I 19.35 GHz is affected more by water vapor than the 18.0 GHz SMMR instrument. Apparently not all the noise due to water vapor in the atmosphere and wind is removed successfully in the atmospheric correction scheme and there is a trend from the beginning to the end of the comparison. This trend is interpreted as a gradual improvement of the NWP data especially since 2002 where the operational model is used instead of ERA 40.-Trends in the amount of cloud liquid water, which is not included in the Tb correction, could also result in the trend which is seen in Figure 4. However, the higher noise level in SSM/I is quantified in the uncertainties. The ice bias has a clear seasonal cycle and a negative winter bias around -5% to -150%. The negative bias is caused by the truncation of the over 100% ice concentrations. The negative summer sea ice bias is sometimes reaching -20%. This is eaused by anomalous sea ice emissivities during melt, the presence of melt ponds, and perhaps an overestimation of the ice concentrations in the ice chart. Figure 5 shows the northern hemisphere standard deviation of the difference between the ESICR and the national ice center ice charts. Both the standard deviation of open water and ice has a clear seasonal cycle with higher standard deviations during summer than during winter (Fig. 5). T and the standard deviation of open water is has a decreasing trend during the latter part of the record. This could be a result of higher quality wind and water vapor data in the recent part of the ERA40 reanalysis and in the

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operational ECWMF model used since 2002.

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Figure 6 shows the ESICR and national ice center difference for ice, water and both ice and water for the southern hemisphere. There were no digital ice charts available between Dec. 1994 and Jan. 2003. There is a small positive bias over open water on the southern hemisphere due to the truncation of spurious sub-zero ice concentrations in the ESICR (Fig. 6). The near 100% sea ice-ESICR and NIC ice chart difference is negative around -10% during Antarctic winter. During the Antarctic summer the difference over ice is near -20%.

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The standard deviation of the difference between the ESICR and the NIC ice charts shown in (figure Fig. 7) is higher and has more inter-annual variability in Antarctica than in the Arctic except for the

1 comparison over open water. The standard deviation of where the difference for the open water case is 2 between 0 and 5_% from 20063 onwards. 3 4 3.2 The SMMR and SSM/I overlap 5 The overlap period between SMMR and SSM/I during July and August 1987 is short because 15 days 6 prior and after the actual date is needed in order to establish the tie-points properly. Subtracting 15 days 7 in each end of the overlap period leaves only a few days where the tie-points are fully established. For 8 the periods where the tie-points are not fully developed the tie-points for SMMR and for SSM/I cover 9 different time periods and they are therefore expected to differ. Figure 8 and 9 show the overall bias 10 between SMMR and SSM/I including the periods where tie-points are based on less than one month 11 data, for NH and SH, respectively. On the nNorthern hHemisphere (Fig 8)the overlap is during the sea 12 ice minimum in 1987 which means that there are a limited number of ice data points the bias is 13 belowsmall (less than 4 %) and this may be due to melt ponds with diurnal variability in their 14 signatures and the two instruments different orbits and coverage. 15 16 The SMMR and SSM/I overlap period coincides with the ice maximum on the sSouthern hHemisphere 17 which is ideal for comparison (Fig. 9) and the bias is even smaller than on the northern hemisphere 18 (less than 2 %). However, the comparison is limited by the very short overlap just as for the Northern 19 Hemisphere. Inspecting the differences geographically (not shown) indicates that when environmental 20 conditions have not changed significantly during SMMR and SSM/I passes then the SSM/I is slightly 21 higher over open water while over ice it is close to neutral. The open water bias is probably due to the 22 higher sensitivity of the 19.35 GHz channel on SSM/I to water vapor than the 18.0 GHz channel on 23 SMMR. 24 25 3.3 Ice chart and ESICR comparison discussion 26 The NIC ice charts are produced manually on the basis of satellite and reconnaissance data for ship 27 navigation support and they do not contain estimates of uncertainty. However, the uncertainties The 28 uncertainties in the NIC sea ice charts is are described in Dedrick et al. (2001). Another study of the 29 differences in the between ice charts from two Greenland and Norwegian ice centers covering the same 30 region other producers are show relatively large with standard deviation of the difference between

overlapping and coincident Greenland and Norwegian ice charts (up to 30%) discrepancies in ice concentration STD of the difference especially at intermediate concentrations (Breivik et al., 2015). Compared to microwave radiometer ice concentrations (the OSI-SAF operational algorithm in Andersen et al., (2006B)) the ice concentration in Greenland ice charts is systematically about 30% higher at intermediate concentrations. Trials with the ice concentration model described in section 2.5.39 shows that the estimates from most sea ice concentration algorithms including the Bootstrap and the Bristol is agree very well withabout the 1:1 proportional to the actual ice concentration and that there are very small differences between the overall response of different algorithms (ice concentration differences < 1% on 1000 km scale not including noise). The ...e. different algorithms thus yield the same ice concentrations given the same brightness temperature input. We did not find a similar investigation comparing NIC and other overlapping and coincident ice charts. However, we note that the methodology for making the Greenland, Norwegian and NIC ice charts is similar. The bias between ice charts and radiometer ice concentrations at intermediate concentrations could can be caused by two effects: 1)-The estimated radiometer ice concentrations are lower than real ice concentration for new ice and if the surface is melting or refrozen after melting. Both and both new ice and melting refreezing is abundant in regions with intermediate ice concentrations, i.e and this will thus lead to -the radiometer is-underestimating the real ice concentration. A hybrid algorithm such as OSI-SAF mitigates biases due to melting-refreezing to some extent but usage of hemispheric tie points cannot account for existing regional differences in melt progress. 2) The ice charts ice concentration is a subjective estimate which is made for the safety of navigation and the overestimation of the ice concentration in the ice chart stem from "better-safe-than-sorry" practices within the ice charting community. 3.4 The ESICR metrics In the following we are giving examples of the ESICR dataset for estimating sea ice climate statistics and trends. The applied climate period here is the full length of the ESICR from Oct. 1978 to the end of 2014. First we show the long term trend in sea ice extent and secondly the trend in open water days in regions covered part of the season by sea ice. TWe givehe examples are given for both the northern and

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the southern-hemispheres.

2 In this context, tHere thhe sea ice extent is defined as the area covered by sea ice within the ice edge. 3 The ice edge is defined as the 30% contour. I and ice concentrations greater than 30% are considered as 4 ice covered while concentrations less than 30% are considered open water. This threshold is higher 5 than e.g. the 15% threshold used in Parkinson and Cavalieri, (2008). The higher threshold is needed 6 here because we are not using weather filters in the processing and therefore there may be more noise 7 over open water. The noise level over open water depends on the success of the Tb correction and the 8 levels of cloud liquid water, i.e. partly the quality of the NWP data. 9 10 For the Arctic there is a negative trend in the monthly mean extent for all months of the year (Table 11 3A). The negative slope is largest in September: -94 000±9700 km²/year and smallest in May: -32 12 000±4600 km²/year. The monthly trends for the Arctic are shown in Table 3A. 13 14 For the Antarctic there is a positive trend in the monthly mean extent for all months of the year (Table 15 3B). The positive slope is largest in April, October and December: at 33 000 km²/year and the smallest in February: 13 000±5400 km²/yr. The monthly trends for the Antarctica are shown in Table 3B. 16 17 Below we have looked at two periods of the 35 year ESICR: the entire 35 year period from autumn 18 19 1978 to the end of 2014 and the shorter recent 10 year period from 2004 to the end of 2014. The latter 20 shorter period represents the period where most of the sea ice extent changes are taking place in both 21 the southern and northern hemisphere. 22 23 Figure 10 shows tThe sea ice extent for the Arctic for both the long and the short records is shown in 24 Figure 10 together with the September 2012 sea ice extent in Figure 10. The lower two panels are 25 showingdisplay the seasonal variability of the sea ice extent and the long term mean monthly sea ice 26 extent in March and in September, which is the months with maximum and minimum extent, 27 respectively. In this panel we have included the extent for the most recent 11 year of ESICR (2004-28 2014) for comparison. September 2012 was the lowest sea ice extent on record in the Arctic since 29 beginning of the satellite era. Over the 35 years of ESICR there is a negative trend in sea ice extent for 30 all months of the year with the largest negative trend during the summer and the beginning of autumn

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1	(Jul-Oct). i.e. the third quarter of the year (Q3).
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3	Figure 11 shows tThe sea ice extent for the Antarctic for both the long and the short record-together
4	with the September 2012 sea ice extent is shown in Figure 11. The lower two panels are showing the
5	seasonal variability of the sea ice extent and the long term mean monthly sea ice extent in March and ir
6	September-which is the minimum and maximum extent respectively. The sea ice extent has
7	experienced an overall positive trend around Antarctica especially downstream of the Weddell and the
8	Ross Seas in the eloekwise cyclonic atmospheric circulation along the ice edge.
9	
10	In order to determine assess the length of the ice season period of open waters for a given pixel, the
11	annual spatial distribution of dates of freeze-up and break-up were calculated using a simple
12	methodology, yet the results are comparable to Parkinson (2014). The freeze-up date for a given point
13	is defined as the date where the sea ice concentration exceeds elimbs from below to above 30% and
14	remains so for at least 5 days. Similarly, Tthe break-up date for a given point is defined as the date
15	where the sea ice concentration falls from above to below 30% and remains so for at least 5 days.
16	
17	The values for the ice concentration threshold and length of period were chosen by manually tuning for
18	convergence: ice concentrations lower than 30% and periods less than 5 days were found to produce
19	noise in the spatial distribution of freeze up/break up dates, which settles at the chosen values, though
20	somewhat less so in the short 10 year record.
21	
22	Since the sea ice does not retreat and expand completely every year, not all areas experience the same
23	number of freeze-ups and break-ups over an equal period of years. Therefore, some regions may
24	experience relatively few freeze-ups and break-ups, thus reducing the confidence in the trend of the
25	region. As a consequence, only areas having experienced more than 6 freeze-ups/break-ups in each
26	period are considered.
27	
28	Figure 12 is showing the decadal trend in open water days in the Arctic region covered by sea ice part
29	of the year. The open water days are calculated as the difference in days between freeze-up and break-
30	up and the -

2 The decadal trends in the open water days are shown for both the long and the short climate record in 3 Ffigure 12-left and right, respectively. 4 5 Over the long record of 35 years the ice season has been shortened number of open water days have 6 been extended by at least 60 days in the Davis Strait and in large parts of the Barents Sea. The ice 7 season (the opposite of open water days) has been shortened consistently all over the Arctic except in 8 the Bering Strait region and the Greenland Sea. The shortening of the ice season is due both to a delay 9 of the freeze-up and earlier breakup in combination (not shown). This is consistent with e.g. Close et al. 10 (2015). While this pattern is largely consistent for the short and the long periods in the Baffin Bay, and 11 the Barents, Kara and Laptev Seas, there are large differences in the open- water days trend in the 12 Davis Strait and in the Beaufort Sea and Bering Strait region. The short period has substantial negative 13 trends in these regions (more than 15 days / decade) while the long period has positive trends. 14 However, the statistical significance of the trends for the short period is much lower than for the long 15 period. 16 17 Figure 13 is showing tThe significance of the trends in number of open water days is shown in figure 18 Figure 13-here as a test of the null-hypothesis, i.e. testing the probability of no trend. This means that a 19 low probability indicates that the trend is in fact significant. It is noted that while the trend is significant 20 in most regions-for the long record the trends are not significant for the short record. This is due to the 21 relatively short record of 10 years which is influenced by short term natural variability for example 22 shifts in the mean location of the atmospheric pressure systems. 23 24 Figure 14 shows tThere is a negative he decadal trend in the number of open water days around 25 Antarctica in regions with a seasonal sea ice cover (Fig. 14), except in the Bellingshausen Sea/ 26 Amundsen Sea and the Indian Ocean. Tshows a Tthe trend is significant in large regions in the 27 Weddell Sea and in the Ross Sea for the long record (Figure. 15), but for the short record the trends are 28 more sporadically significant for the short record because of the fewer data points. For the short record 29 one or two unusual years can change the trend. As for the Arctic the open water days is calculated as the 30 difference in days between freeze-up and breakup.

The trend in open water days is shown for both the long and the short record. 2 3 4 5 the null-hypothesis, i.e. testing the probability of no trend. It is noted that while the 6 7 8 or two unusual years can change the trend. 9 10 The negative trend in the number of open water days inon the long record in the Ross and in the 11 Weddell Seas indicates that the ice is staying longer in these areas now than before. Along the ice edge 12 in the Ross Sea, in East Antarctica, the Weddell Sea and in all of the Bellingshausen Sea we findthere 13 is a positive trend in the number of open water days, i.e. a shortening of the ice season. This means that 14 the ice which is either advected into or formed in these regions is staying there for shorter time now 15 than before and it indicates that these regions have experienced warming during the 35 years of the 16 record. Even though there is an overall positive trend in the sea ice extent around Antarctica there is an 17 indication that the warming is closing in on the poleAntarctica. 18 19 4.0 Conclusions 20 A sea ice climate record covering the period from autumn 1978 to the end of 2014 has been produced 21 based on past microwave radiometer data from SMMR, SSM/I and SSMIS. The climate record has 22 been produced according to 4 principles to ensure consistency and to minimize the sensitivity to noise 23 sources: 24 25 1) Finding algorithms with low sensitivities to geophysical noise. Two algorithms have been selected in 26 combination based on the evaluation in Andersen et al., (2007), the Bristol over ice and the Bootstrap 27 in frequency mode over open water. An independent evaluation of algorithms in Ivanova et al. (2015) 28 pointed at the same two algorithms. 29 30 2) Regional error reduction correcting the brightness temperatures for water vapor in the atmosphere

Kommentar [RTT1]: revise

1	and wind over open water. The scheme described in Andersen et al. (2006B) is used to reduce the noise
2	over both ice and water.
3	
4	3) Calibrate the algorithms to the actual ice and water signatures and sensor drift using dynamical tie-
5	points. The result of using dynamical tie-points has been demonstrated here at the transition from
6	SMMR to SSM/I with satisfactory results. In addition, we do not see any jumps at sensor transitions or
7	long term trends in the comparison to the independent ice chart dataset.
8	
9	4) Quantify the residual uncertainties. A forward model for the residual uncertainties has been
10	developed and applied. The total uncertainty as a combination of the tie-point variability and the
11	representativeness uncertainty is a function of the ice concentration and it is applied on each individual
12	measurement.
13	
14	It is clear that the sea ice covers on both hemispheres have undergone large changes over the 35 year
15	period. In the Arctic the linear trend at sea ice minimum month in September is -94 000 km²/yr.
16	
17	Around Antarctica there has been an increase of the total sea ice extent during all months especially
18	downstream of the Weddell Sea and in the Ross SeasHowever, these extensions are relatively short
19	lived meaning that the ice which is extending across the long term mean extent (primarily driven by
20	advection) near sea ice extent maximum into the Atlantic and the Pacific ocean is removed by melt or
21	advection relatively quickly. However, there are regional differences and the ice extent has decreased
22	along the Antarctic Peninsula in the Bellinghausen and the Amundsen Seas.
23	
24	4.1 Future work
25	The sea ice climate record will be updated at irregular intervals. The next update is planned for autumn
26	2016. In addition, the daily OSI SAF sea ice concentration product and the ESICR is using the same
27	algorithm and methodology with only minor differences due to the tie-point selection period which is
28	either the last 30 days (operational) or 15 days before and after (reprocessing).
29	
30	In order to extend the sea ice climate record with past data it is being investigated if it is possible to

1	retrieve the Nimbus 5 Electrically Scanning Microwave Radiometer (ESMR) 19 GHz swath data from	
2	1972 to 1977. These single channel data are significantly different from SMMR and SSM/I - SSMIS	
3	data and a new sea ice algorithm would have to be used.	
4		
5	The next update of the ESICR dataset will include development from the ESA sea ice climate change	
6	initiative project working towards improved sea ice climate record methodologies (Ivanova et al.,	
7	<u>2015)</u> .	
8		
9	Acknowledgements	
10	We would like to thank Irene Rubinstein, Walter Meier, and Georg Heygster for their constructive and	
11	helpful comments on the manuscript. The work was completed with support from EUMETSAT's	
12	Ocean and Sea Ice Satellite Application Facility. The SMMR data were provided by the NSIDC, the	
13	SSM/I data by Remote Sensing Systems, the SSMIS data were processed at NOAA and the numerical	
14	weather prediction model data by the ECMWF.	
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1 2 **Tables** 3 4 5 Table 1

Table 1. The different satellite missions carrying the SMMR, SSM/I and SSMIS instrument and the

6 periods they cover.

7

8 Table 2. The STD of the difference between the simulated SSM/I - SSMIS satellite ice concentration

9 and the reference ice concentration resampled to different grid resolutions in percent.

10

11 Table 3A. The mean monthly sea ice extent, long term trend and standard error of the trend in the

12 Arctic. All figures are in millions of km².

13

14 Table 3B. The mean monthly sea ice extent, long term trend and standard error of the trend in the

15 Arctic. All figures are in millions of km².

16 17

Sensor	Launch	End
Nimbus 7 SMMR	October 1978	August 1987
DMSP F8 SSM/I	June 1987	December 1991
DMSP F10 SSM/I	December 1990	November 1997
DMSP F11 SSM/I	November 1991	May 2000
DMSP F13 SSM/I	March 1995	November 2009
DMSP F14 SSM/I	May 1997	August 2008
DMSP F15 SSM/I	December 1999	-
DMSP F16 SSMIS	October 2003	-
DMSP F17 SSMIS	November 2006	-
DMSP F18 SSMIS	October 2009	-
DMSP F19 SSMIS	April 2014	-

Table 1. The different satellite missions carrying the SMMR, SSM/I and SSMIS instrument and the periods they cover.

18 19 20

	1 km	5 km	10 km	12 km	25 km	50 km
CF	18	16	14	13	10	7
Bristol	17	15	13	12	10	6
OSISAF	17	15	13	12	9	6

Table 2. The STD of the difference between the simulated SSM/I - SSMIS satellite ice concentration and the reference ice concentration resampled to different grid resolutions in percent.

Month	Mean [10 ⁶ km ²]	Trend [10 ⁶ km ² /yr]	Trend std err
Jan	14.641	-0.045	0.0040
Feb	15.505	-0.045	0.0043
Mar	15.620	-0.041	0.0042
Apr	14.772	-0.036	0.0048
May	13.403	-0.032	0.0046
Jun	11.899	-0.053	0.0044
Jul	09.667	-0.079	0.0060
Aug	07.458	-0.084	0.0083
Sep	06.881	-0.094	0.0097
Oct	09.053	-0.077	0.0089
Nov	11.138	-0.055	0.0052
Dec	13.241	-0.044	0.0043

Table 3A. The mean monthly sea ice extent, long term trend and standard error of the trend in the Arctic. All figures are in millions of km².

Month	Mean [10 ⁶ km ²]	Trend [10 ⁶ km ² /yr]	Trend std err
Jan	04.566	0.022	0.0092
Feb	02.911	0.013	0.0054
Mar	04.105	0.022	0.0072
Apr	06.860	0.033	0.0099
May	10.135	0.032	0.0089
Jun	13.229	0.029	0.0072
Jul	15.622	0.022	0.0055
Aug	17.129	0.022	0.0059
Sep	17.684	0.029	0.0089
Oct	17.278	0.033	0.0070
Nov	15.164	0.020	0.0065
Dec	09.932	0.033	0.0115

Table 3B. The mean monthly sea ice extent, long term trend and standard error of the trend in the Arctic. All figures are in millions of km².

2 3	Figures
4	Captions:
5	Figure 1. The 1 km cloud free MODIS image 3000 x 2200 km. The scene is situated north of McMurdo
6	Station and east of the Ross Sea, Antarctica. Ice concentrations between 0% (black) and 100% (white).
7	The scene is recorded at 03.30 UTC 2008/02/24 by the Aqua satellite. The scene center is at 69.5S,
8	165W.
9	
10	Figure 2. The simulated ice concentrations using the SSM/I sensor specifications and the OSI SAF
11	hybrid ice concentration algorithm and the data in figure 1 as input. Ice concentrations between 0%
12	(black) and 100% (white).
13	
14	Figure 3. The total uncertainty in blue and its two components the smear in red and the tie-point
15	uncertainty in green as a function of ice concentration.
16	
17	Figure 4. The Arctic ESICR - NIC ice chart difference for areas of ice in red, for areas of open water in
18	black and the total, i.e. both ice and water, in blue.
19	
20	Figure 5. The Arctic ESICR - NIC ice chart standard deviation of the difference for areas of ice in red,
21	for areas of open water in black and the total, i.e. both ice and water, in blue.
22	
23	Figure 6. The Antarctic ESICR NIC ice chart difference for areas of ice in red, for areas of open water
24	in black and the total, i.e. both ice and water, in blue.
25	
26	Figure 7. The ESICR and NIC ice chart standard deviation of the difference around Antarctica. The
27	blue curve is showing the total standard deviation of the difference for both areas of open water and
28	ice. The red curve is for ice and the black curve is for water. No ice charts were available to us from
29	1994 to 2003.
30	
31	Figure 8. The overlapping SMMR SSM/I difference in the Arctic during summer melt. The blue
32	curve is the total bias and the red curve is showing the ice bias.

2 Figure 9. The overlapping SMMR - SSM/I difference around Antarctica during austral winter. The blue 3 curve is the total bias and the red curve is showing the ice bias. 4 5 Figure 10. The upper panel: the September 2012 sea ice extent in the Arctic compared to the mean 6 extent for the long (left) and the short record (right) shown with the red line. The blue lines on either 7 side of the mean extent line are the 5 and 95 percentiles of ice extent. The lower two panels are 8 showing the annual cycle of sea ice extent. The shaded areas are the 5 and 95% percentiles. The lower 9 panel is showing the long term (1978-2014) Arctic sea ice extent near its maximum in March and near 10 its minimum in September. 11 12 Figure 11. The upper panel: the September 2012 sea ice extent in the Antarctic compared to the mean 13 extent for the long and the short record shown with the red line. The blue lines on either side of the 14 mean extent line are the 5 and 95 percentiles of ice extent. The lower two panels are showing the annual cycle of sea ice extent. The shaded areas are the 5 and 95% percentiles. The lower panel is 15 16 showing the long term (1978-2014) Antarctic sea ice extent near its maximum in March and near its 17 minimum in September. 18 19 Figure 12. Show the linear trend in open water days in the Arctic for the long record (1978 2014) to the 20 left and the short record (2004-2014) to the right. 21 22 Figure 13. The probability that the trend in figure 12 is not significant (test of the null-hypothesis). A 23 low value (< 5) indicates that the trend is significant. 24 25 Figure 14. Show the linear trend in open water days in the Antarctic for the long record (1978-2014) to 26 the left and the short record (2004-2014) to the right. 27 28 Figure 15. The probability that the trend in figure 14 is not significant (test of the null-hypothesis). A 29 low value (< 5%) indicates that the trend is in fact significant.

1

Figure 1. The 1 km cloud free MODIS image 3000 x 2200 km. The scene is situated north of McMurdo Station and east of the Ross Sea, Antarctica. Ice concentrations between 0% (black) and 100% (white). The scene is recorded at 03.30 UTC 2008/02/24 by the Aqua satellite. The scene centre is at 69.5S, 165W.

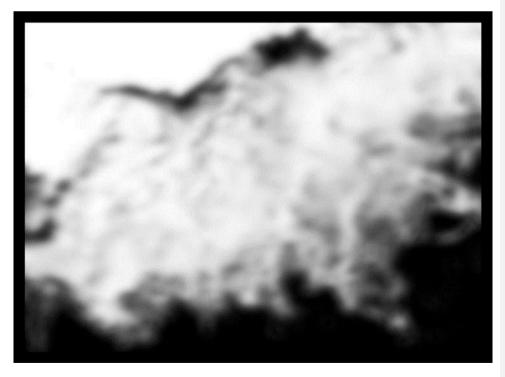


Figure 2. The simulated ice concentrations using the SSM/I sensor specifications and the OSI-SAF hybrid ice concentration algorithm and the data in Ffigure 1 as input. Ice concentrations between 0% (black) and 100% (white).

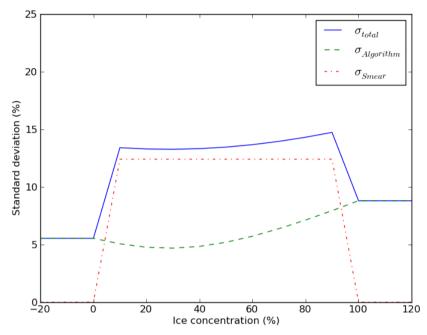
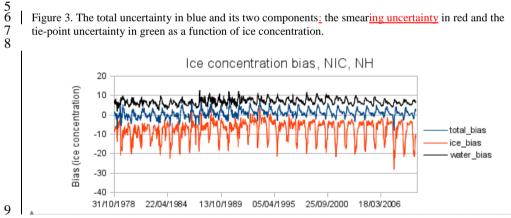


Figure 3. The total uncertainty in blue and its two components: the smearing uncertainty in red and the tie-point uncertainty in green as a function of ice concentration.

Formateret: Skrifttype: 10 pkt



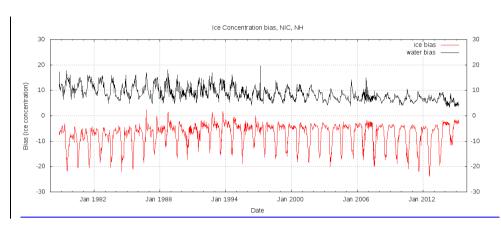


Figure 4. The Arctic ESICR - NIC ice chart difference for areas of ice in red, for areas of open water in black and the total, i.e. both ice and water, in blue.

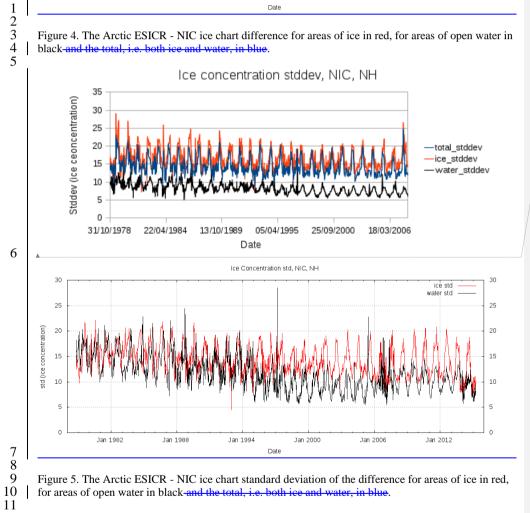
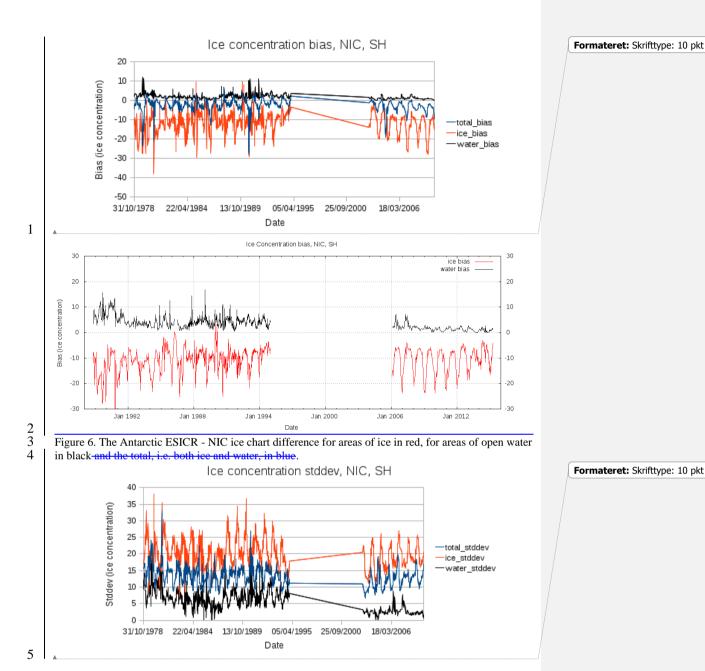
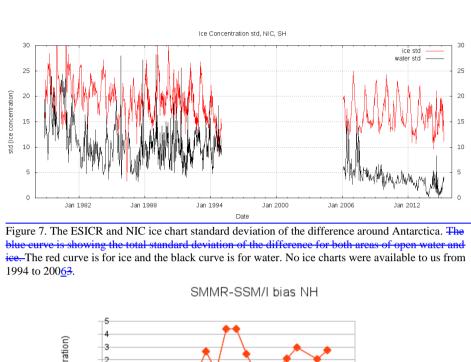


Figure 5. The Arctic ESICR - NIC ice chart standard deviation of the difference for areas of ice in red, for areas of open water in black and the total, i.e. both ice and water, in blue.





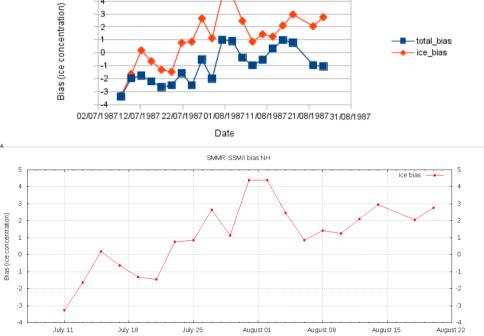


Figure 8. The overlapping SMMR - SSM/I difference in the Arctic during summer melt. The blue curve is the total bias and tThe red curve is showing the ice bias.

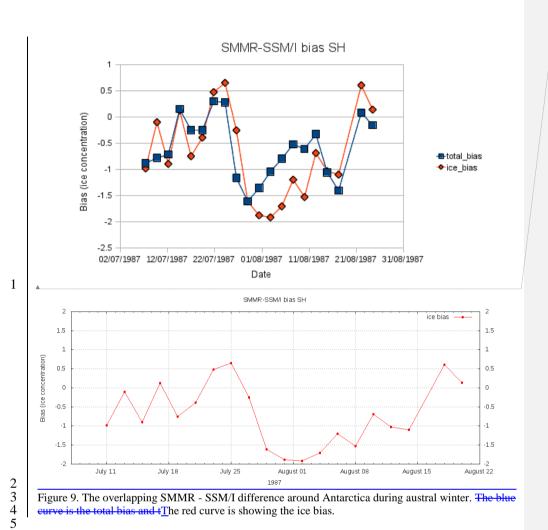
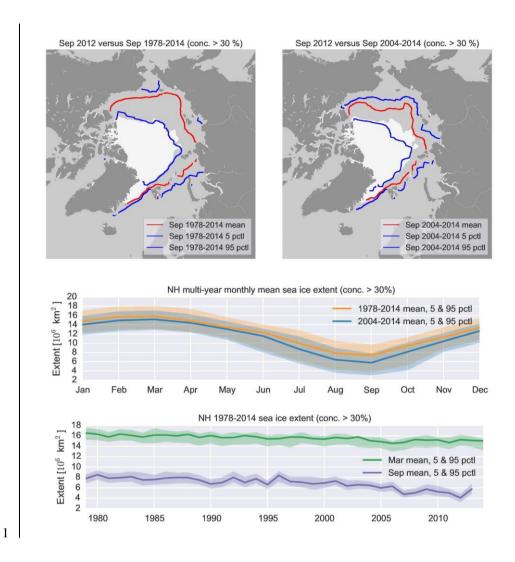
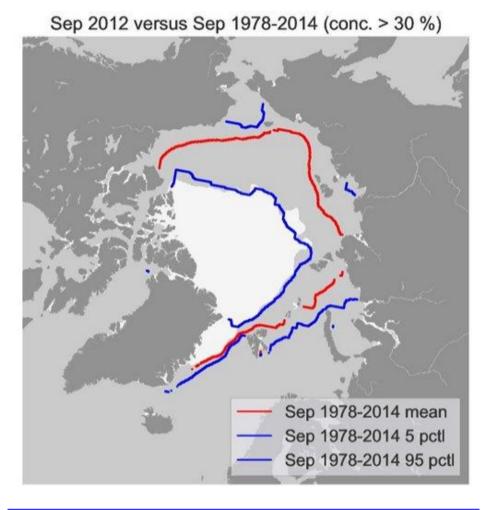


Figure 9. The overlapping SMMR - SSM/I difference around Antarctica during austral winter. The blue curve is the total bias and tThe red curve is showing the ice bias.





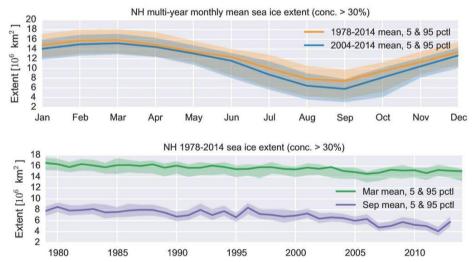


Figure 10. The upper panel: the September 2012 sea ice extent in the Arctic compared to the mean extent for the long (left) and the short record (right) shown with the red line. The blue lines on either

side of the mean extent line (<u>red</u>) are the 5 and 95 percentiles of ice extent. The lower two panels are showing the annual cycle of sea ice extent. The shaded areas are the 5 and 95% percentiles <u>of the interannual and daily variability, respectively</u>. The lower panel is showing the long term (1978-2014) Arctic sea ice extent near its maximum in March and near its minimum in September.

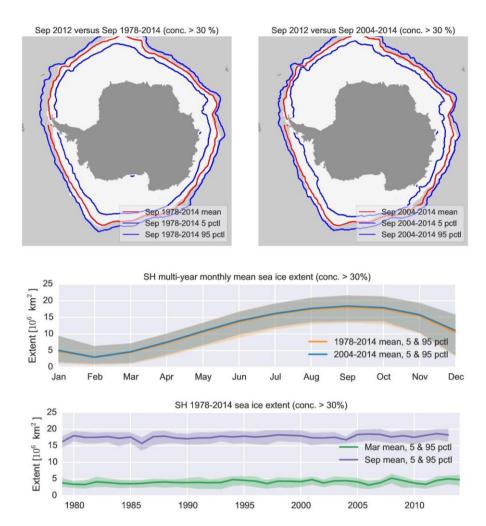


Figure 11. The upper panel: the September 2012 sea ice extent in the Antarctic compared to the mean extent for the long and the short record shown with the red line. The blue lines on either side of the mean extent line are the 5 and 95 percentiles of ice extent. The lower two panels are showing the annual cycle of sea ice extent. The shaded areas are the 5 and 95% percentiles of the inter-annual and daily variability, respectively. The lower panel is showing the long term (1978-2014) Antarctic sea ice extent near its maximum in March and near its minimum in September.

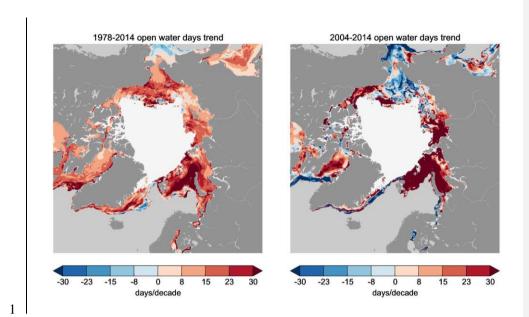
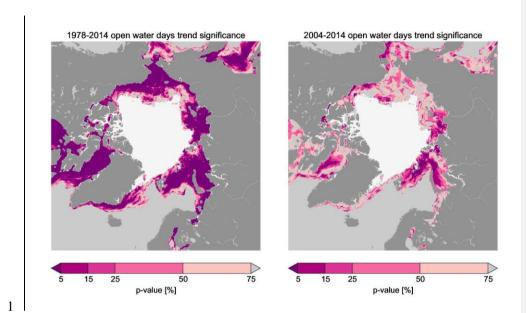


Figure 12. Show the linear trend in open water days in the Arctic for the long record (1978-2014) to the left and the short record (2004-2014) to the right.



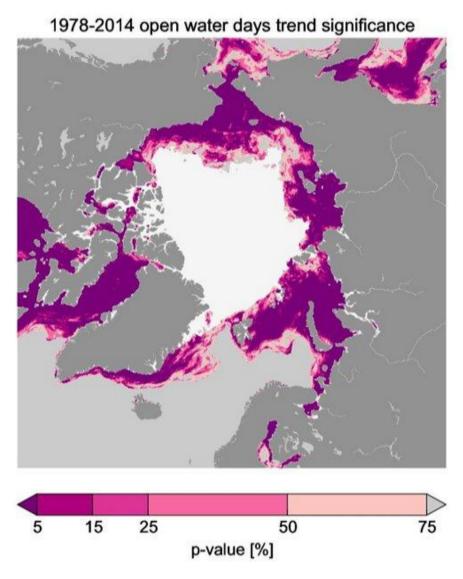
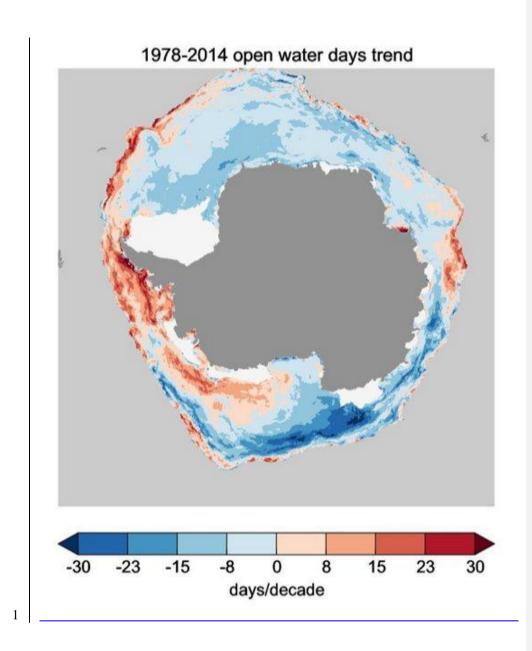


Figure 13. The probability that the trend in Figure 12 is not significant (test of the null-hypothesis). A low value (< 5) indicates that the trend is significant.



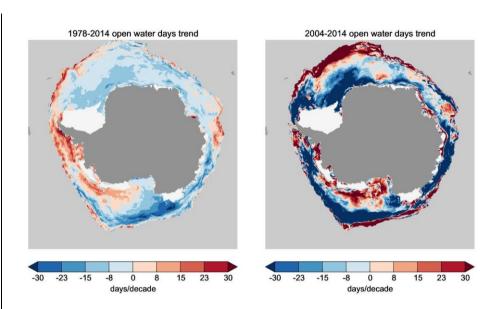
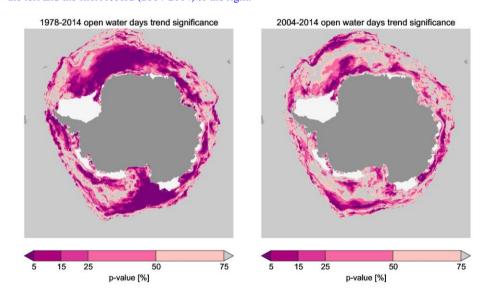


Figure 14. Show the linear trend in open water days in the Antarctic for the long record (1978-2014) to the left and the short record (2004-2014) to the right.



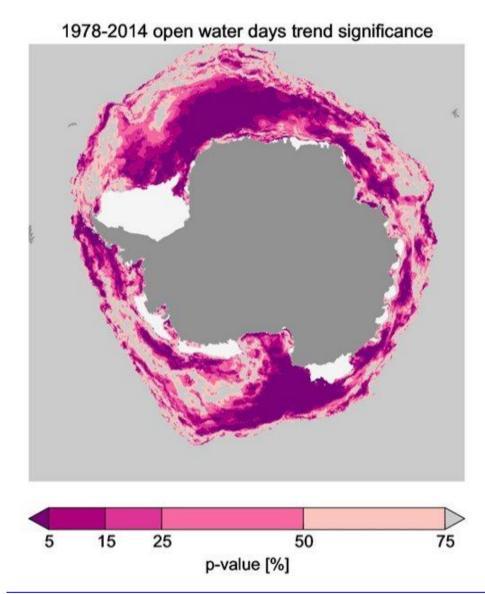


Figure 15. The probability that the trend in Figure 14 is not significant (test of the null-hypothesis). A low value (< 5%) indicates that the trend is in fact significant.