The authors would like to thank the **Anonymous Referee #1** for the valuable comments that helped improving quality of the paper.

In the **major comment** the Reviewer points out some weaknesses of the presented dynamic tie-points approach. We will address them point-by-point first and then continue with the other comments (the answers are marked by **A**):

1. It would probably help to strengthen the entire chapter 4.5 by showing in more detail, how the retrieved SIC for single days changes when the dynamic tie points are used. How does it affect different regions?

A: The dynamic tie-points are only dynamic in time, not in space, so the effect on a single day map will be only through (small) offsets in the tie-point for water and ice, and thus small differences in SIC that will be hardly visible if shown as a map. The signature of ice including geophysical noise is not the same as it was in the past. Both sea ice extent and area and the geophysical noise parameters (sea ice emissivity, atmospheric parameters) have climatic trends. When computing sea ice climate record it is essential to ensure long-term stability and to avoid sensitivity to noise parameters with climatic trends. This is achieved with dynamic tie-points. Further, the dynamic approach is needed when accurately quantifying SIC uncertainties. In addition, it is an effective way of dealing with inter-calibration of satellite instruments and sensor drift. We will make the text clearer on this aspect (Sect. 4.5 and 5.6) and add horizontal lines corresponding to fixed tie-points in Fig. 8, so that the reader can see the effect of temporal variations of the dynamical approach as opposed to horizontal lines of the static tie-points.

**2.** According to my understanding, the suggested smoothing and averaging of TB for NT>95% areas just artificially removes the average 5% uncertainty that is being reported for NT. If not so, the authors need to discuss this in more detail.

A: The 15-day window for the tie-point average indeed causes smoothing, but the full range of NT SIC 95-100% is used (limited to a maximum of 5000 samples per day for the tie-points) to calculate the average. Then, the scatter of all selected NT>95% points (up to a maximum of 15 000 from all the swath files in the 15-day window) is used to calculate the tie-point uncertainty, which contributes to the total SIC uncertainty.

The criterion for selecting the tie-points is to ensure areas with near 100% ice concentration. We are using NT, which has a different sensitivity to geophysical noise than Bristol. This point is not crucial and we could have used Bristol instead in the selection of the near 100% ice signature. However, by incorporating the NT SIC for this selection we also avoid "tuning" of the final hybrid algorithm too much towards the two algorithms that compose it, which is of particular importance in the marginal ice zone.

The 15-day averaging period ensures that temporal regional noise, e.g. frontal systems, does not affect the tie-points and the ice concentrations estimates in other regions without such frontal systems on a day-to-day basis.

Yet the 15-day averaging is sufficiently short to capture systematic seasonal changes happening on a hemispheric scale, e.g. the different stages of summer melt or fall freeze-up.

The selection of only 5000 samples per day is to ensure that one day is not weighted higher than others when there are differences in the number of data-points from day to day. 5000 data points are easily achieved yet enough for a statistical mean. This will be clarified in the text (Sect. 4.5) accordingly.

**3.** Could a tie-point "recipe" (or a data base, i.e. monthly tie points instead of fixed values as provided in Table A1) be derived from the authors' research? Such an outcome would increase the impact of the presented research substantially.

A: The authors agree on the value of such details and will provide a step-by-step description of the dynamic tie-points retrieval (a new Appendix will be added) so that the results will be reproducible.

As stated in the paper, tie-points will vary with calibration of the input data/version number and source, so our tie-points should not be used with other versions of the input data with potential different calibration. The "recipe" on the other hand can be applied to all versions/calibrations of the input data.

**4.** In the end, the paper runs a bit short in discussing this most innovative aspect. A more detailed discussion will definitely be an asset in this regard.

A: The discussion section (Sect. 5.6) will be strengthened (based on the answers provided above) accordingly in the revised version of the paper.

#### **Detailed comments**

Ch1 P1272, L2: "globally" . . . rather: "polar regions"? A: Adjusted accordingly P1272, L3: Second sentence requires re-phrasing. A: Adjusted accordingly P1272, L12 and L14: "were" and "was" . . . change to "are" and "is" ... use present. A: Adjusted accordingly P1272, L29: remove "in turn" A: Adjusted accordingly P1272, L24: abbreviation SD is not introduced A: Adjusted accordingly

P1272, L13 - P1274, L17: The listing of error sources is somewhat hard to follow. First, it is stated that there are two main error sources (emissivity variability, atmosphere). But then, more are introduced: thin ice, melt ponds. I suggest this paragraph to be rearranged or to prepend an enumeration of all error sources before the details are described.

A: The paragraph will be rearranged

P1272, L16: What are "internal properties"?

A: This is the method applied to retrieve sea ice concentration from input brightness temperatures, which distinguishes each algorithm among the others. The text will be adjusted accordingly.

P1272, L20: start new sentence after semicolon.

A: Adjusted accordingly

P1272, L27: specify what is meant by "tie-point signature".

A: Predefined Tb for ice. The text will be adjusted accordingly.

## Ch2

P1275, L10: "principle" is a bit fuzzy here.

A: The channels: which ones and how the algorithms employ them – is meant here. The text will be adjusted accordingly.

P1276, L28: The term "Round Robin Data Package" needs some additional explanation.

A: Now introduced in the last paragraph of the introduction.

P1278, L7: RRDP has already been introduced.

A: Adjusted accordingly

P1278, L16: PolarView and MyOcean need a reference (or a description)

A: References added

P1278, L19: change "got refrozen" to "refroze".

A: Adjusted accordingly

FIGURE1: Circles are hard to distinguish from squares in the present form.

A: Fig. 1 and 2 will be adjusted accordingly

P1279, L8-L11: I suggest that you indicate FYI, MYI as well as A and B types in the figure.

A: Fig. 1 and 2 will be adjusted accordingly

P1279, L14: I cannot see that OW pixels are mostly grouped within one point. I rather see a line as well.

A: What was meant here is that the majority of the points is grouped around one point, however it is not easy to see from the plot, how many points are concentrated there and how many are spread along the line. The points stretching to the line are caused by atmospheric water vapor, liquid water- and ice clouds, surface temperature variability and surface roughening by wind.

We will clarify this point in the text.

P1279, L15: ...also indicate the OW tie point. What is "geophysical noise"?

A: The noise induced by geophysical parameters such as atmospheric water vapor, liquid water- and ice clouds, surface temperature variability and surface roughening by wind (all collectively called geophysical noise). This will be added to the text.

FIGURE1: I think it would be beneficial to see the bootstrap 100% ice and OW lines in this figure.

A: Fig. 1 and 2 will be adjusted accordingly.

P1279, L25ff: Please indicate all the lines and points that you describe in the figure. Otherwise it is hard to follow your argumentation.

A: Fig. 1 and 2 will be adjusted accordingly

P1281, L27: "geophysical noise" see above.

A: Adjusted accordingly

## Ch3.3

The reader might wonder why the authors didn't use MODIS SIC to evaluate their algorithms, at least for case studies.

A: We used MODIS sea ice concentration data for comparison, but only for the summer period to assess the algorithms performance over melt ponds. We did not do more as our primary focus was to evaluate high and low sea ice concentration data. We were not aware of a sufficiently quality-controlled MODIS sea ice concentration product to be used as a validation data set. For MODIS there is also the problem with cloud contamination, as the cloud filters developed for lower latitudes are not working

that reliably in the polar latitudes. Moreover, identification of ice/water in the images depends on thresholds, which will take us back to the problem of dynamic tie-points. We will clarify the point in the revised version of the paper.

## Ch3.4

P1282, L20-22: Some explanation is required here on how "large areas of 100% homogeneous thin ice" can be manually identified from ASAR data!

A: "Visually" was meant rather than "manually". By visual inspection (the same procedure as when producing ice charts), large homogenous areas of near 100% thin ice were identified as areas with a darker and homogenous texture. The text will be adjusted accordingly. Admittedly, visual interpretation comes with its own bias.

P1282, L26: "measurements" . . . rather "pixels", or "data points"? A: Adjusted accordingly.

## Ch3.6

P1284, L5: RRDP introduced again.A: Corrected.P1284, L12: . . . considered "the" following aspects. . .A: Adjusted accordingly.

## Ch4.1

P1285, L3: remove parentheses.

A: Adjusted accordingly.

P1285, last line: Again, remove parentheses. Make a full sentence of this statement instead.

A: Adjusted accordingly.

P1286, L6-10: Why does the bias influence the ability to estimate the SD? This needs to be explained in more detail.

A: More detailed explanation will be provided in the text. The large positive bias affects the SD in combination with a cut-off at 100% (which was not clear from the text before). For example, if real SIC is 75%, an algorithm with a positive bias of 20% will have average SIC of 95%, and by cutting-off all the values above 100% it reduces the scatter to only the values in 95-100% interval. For an algorithm with smaller bias and no cut-off the full scatter will be represented by SD.

P1286, L10: intermediate OR high, intermediate AND high? Parentheses unclear.

A: SIC > 75% is meant, only "high" will be kept.

P1286, L18-19: Last sentence needs to be re-arranged.

A: Adjusted accordingly.

Figure3: Legend: Change "Stdev" to "SD" to be consistent.

A: Adjusted accordingly.

## Ch4.2.

P1287, L12: State the coefficients in a full sentence, rather than in parentheses.

A: Adjusted accordingly.

P1287, L16-18. Be more specific in explaining why polarization and gradient ratios are less sensitive to surface temperature variations.

A: The NT algorithm is based on polarisation and gradient ratios of Tbs, which more or less cancels out the physical temperature (Cavalieri et al. 1984). However, this is only true when there is only one surface temperature, so in cases of mixed ice types it

may not be the case. With more different effective temperatures of fractions of the surface they do not all cancel out and we are left with a residual temperature effect in the ratio and thus in SIC inferred from the ratio. For the N90, in the case when emissivity of two ice types is similar, then a change in temperature will have same effect in both H and V channels.

However, in the revised version of the paper we will remove this discussion, which was based on the correlation coefficients between SIC obtained by the PM algorithms and ice surface fraction from MODIS. We believe the correlation can be caused by at least two factors – effect of melt ponds and variations in Tb of the ice surface between melt ponds – and this study does not allow to separate the two.

## Ch4.3

P1288, L7: Maybe the findings of Kwok et al. (2007) might be worth mentioning here (Kwok, R., J. C. Comiso, S. Martin, and R. Drucker (2007): Ross Sea polynyas: Response of ice concentration retrievals to large areas of thin ice, J. Geophys. Res., 112, C12012, doi:10.1029/2006JC003967).

A: Adjusted accordingly. This reference will be also added to the Introduction.

## Ch4.5

P1290, L5: "microwave emission". There has been a paper by Willmes et al. in 2014 (The Cryosphere, 8, 891-904, doi:10.5194/tc-8-891-2014) which investigated the microwave emissivity variability. Maybe their findings could be discussed in this context? (see also P1273, L13)

A: This work will be cited in the Introduction and mentioned in the discussion section (Sect. 4.5).

P1290, L8: Which data is the "two-week running window" applied to? Brightness temperatures? This suggestion needs some more explanation. It causes a smoothing in the input data that avoids an un-beloved scatter in the output data. Wouldn't it be more practical to stay with the scatter and use it for an uncertainty flag instead? As presented, the tie-point retrieval is dynamic in terms of season. Would it be useful to be also dynamic in terms of region? How large would regionally adjusted tie-point variations be in comparison to seasonal adjustments?

A: The "two-week running window" is applied to the input brightness temperatures. Only selected data points are used, namely the ones where NASA Team algorithm gives SIC > 95%. The ice tie-point was subsequently calculated as average Tb value of these selected data points.

The 15-days sliding window was mostly chosen for the OW end with the purpose of smoothing out the synoptic scales of weather perturbations. At the same time, the onset of ice emissivity changes due to snow melting should be reflected. We believe longer time windows will induce additional (too much) smoothing over the ice, and that shorter time-periods will introduce too much noise (over open water).

However the scatter of all 15000 NT>95% points (from all the swath files in the averaging period) is used to calculate the tie-point uncertainty, which contributes to the total SIC per-pixel uncertainty.

As for the dynamic tie-points in terms of region, the aim of this study is to identify a proper algorithm for climate dataset, which requires transparent description of techniques and uncertainties. It would be difficult to come up with proper uncertainty estimation in case we divide our region of interest - more or less arbitrarily - into sub-regions.

One might argue that different tie-points for multiyear ice and first-year ice can still be used. However, computation of the uncertainty at the boundary of both regions will become problematic. How shall one treat mixed pixels? And - most importantly - one would need a validated quality-controlled ice type dataset spanning the entire period. We would recommend that regional (dynamic) tie-points would be an ideal tool for regional applications and for near-real time SIC retrieval of spatially limited areas but not for a climate dataset.

This section (Sect. 4.5) will be made clearer in the text.

P1290, L14: Please specify what is meant by "inside monthly climatology of ice".

A: Within the limits of monthly climatology of sea ice extent. For the present study, we used a monthly climatology of maximum sea ice cover from NSIDC (http://nsidc.org/data/smmr\_ssmi\_ancillary/ocean\_masks.html), and covering period 1979-2007. This climatology was then expanded by a distance of 350 km. This information will also be added to the revised manuscript.

## Ch5.2

P1293, L9-10: How were the applied SIC thresholds (70% and 90%) chosen?

A: Different weights were tested on the thin ice dataset. The optimal values were chosen so that the hybrid algorithm performs better over thin ice, and at the same time keeps its performance in other conditions at the same level as the original OSISAF algorithm.

This will be also added to the text.

## Ch5.3

P1294, L15-17: So is the chosen method feasible in this regard?

A: Yes, the NT algorithm showed to be sensitive to melt ponds. The text will be adjusted.

## Ch5.5

P1295, L18: "surface temperature" where does this information come from?

A: It is the same surface air temperature at 2 m from ECMWF ERA-Interim as the one used earlier for correction over low SIC. It will be renamed to 2m-temperature in the text to avoid confusion.

P1295, L19: "100%" SIC?

A: Yes. It is added now.

P1295, L20: "the atmospheric influence over ice is small". . . is there are reference for this statement?

A: The ERA Interim data we used showed that total water vapor and cloud liquid water content over ice were much smaller than over ocean. The atmosphere over ice is generally much colder than over the ocean, and cold air can contain much less moisture (including clouds) than warmer air. In addition, the emissivity is typically much larger for sea ice than for open water. Hence a change in the atmospheric water vapor of, e.g., 2 kg/m<sup>2</sup>, imposes a different (smaller) change in the brightness temperature measured over sea ice compared to the one measured over open water (Oelke 1997).

We believe the reason why the simple surface temperature correction did not work so well is that a) microwave radiation penetrates dry snow and partly also the sea ice and b) this penetration is a function of wavelength; accordingly different wavelengths

penetrate to different depths in the ice and thus should encounter radiation based on different temperatures.

This will be clarified in the text.

# Ch5.6

P1295, L23: ". . .during the RRDP" needs re-phrasing. A: adjusted accordingly

# Ch6

P1296, L22: Can an algorithm have "low sensitivity to the tie-points"? Would that be useful?

A: Expressed inaccurately in the current text of the paper, this should be: "an algorithm can be less sensitive to uncertainties in tie-points". Low sensitivity to tie-points in general is not necessarily a good thing, since it is the tie-points that allow us to compute SIC.

P1296, L19 (1 of 2): Which are the error source that cannot be correct for? According to my understanding, none is corrected for in the presented research but an algorithm setup with the lowest sensitivity suggested.

A: More precisely: "The error sources that cannot be corrected for by the atmospheric correction procedure suggested".

By the error sources that cannot be corrected for we mean cloud liquid water and precipitation – these are found to be less reliable in ERA Interim and thus the suggested atmospheric correction will not be optimal for these. This is both found in literature (Andersen et al. 2006) and confirmed by our work. We address this in the Sect. 3.5.

In the present research we correct for atmospheric and surface effects using a Radiative Transfer Model (RTM) (Wentz (1997)). Fields of 10m-wind speed, total columnar water vapor, and air temperature at 2m from the ECMWF ERA-Interim Numerical Weather Prediction (NWP) re-analysis are used in this process. The correction is described in the Sect. 3.5, the results are presented in the Sect. 4.4. and the effect of the correction is demonstrated by Fig. 7.

In the revised version of the manuscript we will make the point clearer.

P1296, L19 (2 of 2): A dynamic tie-point retrieval could provide a correction for sensor drift, inter-sensor differences and maybe emissivity variations. But this is not what is being achieved with the suggested data smoothing. This issue could be pointed out more clearly.

A: The reason for the 15-days smoothing is only to reduce noise in the tie-points, especially the ones for open water, as there is quite a lot of variation from day to day. It is the longer-term variations that we want to correct for. The main point of the dynamic tie-points is the fact that the tie-points follow the seasonal cycle of signatures including the atmosphere.

# References

Andersen, S., Tonboe, R., Kern, S., and Schyberg, H.: Improved retrieval of sea ice total concentration from spaceborne passive microwave observations using numerical weather prediction model fields: An intercomparison of nine algorithms, Remote Sens. Environ., 104, 374-392, 2006.

Cavalieri D. J., Gloersen, P., and Campbell, W. J.: Determination of sea ice parameters with the NIMBUS 7 SMMR, J. Geophys. Res., 89, D4, 5355–5369, 1984.

Oelke, C., Atmospheric signatures in sea ice concentration estimates from passive microwaves: modelled and observed, Int. J. Rem. Sens., 18, 1113-1136, 1997.

Wentz, F. J.: A well-calibrated ocean algorithm for SSM/I. J. Geophys. Res., 102, 8703-8718, 1997.

The authors would like to thank **Dr. W. Meier** for the valuable comments that helped improving quality of the paper.

We will address the comments point-by-point (the answers are marked by A):

**1271, 15**: I know there may be a length limitation in the Abstract, but if possible you should at least briefly describe the optimal approach. As it stands now, it says an optimal approach has been suggested, but no information on what that approach may be. Just another sentence saying that it is based on the combination of two algorithms, atmospheric correction, and dynamic tiepoints.

A: adjusted accordingly.

**1274, 13**: thin ice concentration estimation significant for ice volume? How big of an effect is this? Because the ice is thin, it seems like it would have a minimal effect on volume. Even at 1 million sq km of 30 cm ice being "missed", that's only 300 cubic km in volume. I guess, especially with low volumes that are seen now, that could be up to 5%, though I think generally it would be more like 1%. I doubt ice volume estimates are accurate to even close to 1%. And that underestimation is in some sense temporary because the ice (during winter growth) will fairly quickly thicken to >30% and not be underestimated (or at least underestimated as much). I guess the main thing here is not that it's irrelevant but the other effect – on air-sea heat (and moisture) exchange is much more important than the volume. So perhaps just separate out those two, e.g, "significant effect on air-sea exchange" and "also effects ice volume estimates".

A: the authors agree with this remark and changed the text accordingly.

**1277, 1**: The RRDP is introduced here without any explanation, so it's a bit confusing as to what the authors are referring. The RRDP is later explained, page 1284, lines 1-9, but the reader is left in a bit of limbo for 7 pages. I would recommend explaining RRDP as it is first mentioned.

A: The RRDP is now introduced in the last paragraph of the introduction.

**1278, 29** - **1279, 4**: This text is really simply describing the contents of the figure, so it would be best left to be in the caption and not in the main text of the manuscript.

A: adjusted accordingly.

**1286, 5**: "ECICE algorithm was adjusted. . .in this study". Why was it adjusted? How was it adjusted? More info is needed here.

A: The wording was not clear in our text. The ECICE was originally developed for the Northern Hemisphere and we used this original version of the algorithm for both hemispheres. ECICE can be adjusted to the Southern Ocean by introducing a new set of probability distributions of the input parameters for each one of the intended ice types. This was not done in this research.

This is clarified in the text now.

**1286, 20** – **1287, 21 (1 of 7)**: I'm a little confused on the melt pond analysis. If I understand correctly, the authors are comparing the retrieved PM concentrations with the concentration of non-ponded ice retrieved from MODIS and finding that PM is overestimating concentration. In this framework, I can see why the PM overestimates, and I don't think that's not necessarily a bad thing.

A: Yes, we compare sea ice concentration from the PM algorithms with the ice surface fraction (free from melt ponds) as obtained from MODIS, and find that they are highly correlated. We also find that for these areas (ice between melt ponds and open water = concentration of the non-ponded ice) the sea ice concentration is overestimated by the PM algorithms. This contradicts what one would expect from theory because it seems as if PM algorithms retrieve sea ice where they should see open water according to theory because of the limited penetration depth of microwaves into liquid water. One potential explanation for this could be the effect of wetness of the surface on the Tbs causing thus higher SIC values.

**1286, 20 – 1287, 21 (2 of 7)**: The authors assume that PM see melt ponds as open water, and to some degree that makes sense because generally the penetration depth of PM is small. However, I'm not convinced that a melt pond is the same as open ocean water in the PM signature. Melt ponds are quite different than ocean water (e.g., in leads) – ponds are fresh water on top of ice cover. So I would expect that there could be a different signature.

A: We agree that generally salinity should affect dielectric properties of a medium. However, for such high frequencies as used in the algorithms (19 GHz and higher) and in cold waters the salinity was found to play a less significant role (Meissner and Wentz, 2012; Ulaby et al., 1986).

One may still argue that the observed signature of open water differs from that of summer melt (one might need a more specific definition of summer melt though), first year ice, flooded multi-year ice, frozen melt ponds, crust, dry multi-year ice and open water as reported by Eppler et al. 1992. However, in application to satellite passive microwave measurements, this is rather uncertain. The footprint size in this case is so large (70\*45 km for the 19.3 GHz channel on SSM/I) that an unresolvable mixture of surfaces might be present in it. In addition, footprint mismatch uncertainty is common for all the algorithms using more than one frequency, and we believe the difference in signature between melt ponds on ice floes and open water between ice floes will be within this uncertainty.

**1286, 20** - **1287, 21 (3 of 7)**: It could be that the algorithm are "tuned" through tiepoint selection to see melt ponds as ice-covered.

A: The overestimation by the algorithms we saw was presumably corresponding to the areas between melt-ponds, so in this case they (correctly) interpreted melt-ponds as open water with the set of tie-points used. However, the difference in dielectric properties of the sea ice between winter and summer seems to trigger overestimation of the sea ice concentration.

**1286, 20** – **1287, 21 (4 of 7)**: Fundamentally, what I'm saying is that the authors seem to be suggesting that PM algorithms should detect ponds as open water and that concentration retrievals should reflect only non-ponded ice – i.e., if there is 10% open

water and 40% pond coverage, the authors seem to suggest that an accurate concentration retrieval would be 50%.

A: Yes, this is our conclusion, which is applicable to the sea ice algorithms based purely on satellite passive microwave observations from the existing (or formerly existing) instruments.

**1286, 20 – 1287, 21 (5 of 7)**: I'm not sure that this is optimal. Ponded ice is still ice, so I would say that 10% open water and 40% would be best retrieved as 90% ice concentration. Now, granted, 90% ice with 40% pond coverage is very different than 90% ice with no ponds. However, 90% ice with 40% ponds is very different than 50% ice and 50% open water – whether it be for navigational support (not that it's advisable to use PM for navigation), calculating radiative fluxes, input into models, etc.

A: We agree with this point. For many applications ponded ice is preferred to be identified as ice rather than water. However, we believe the algorithms considered are incapable of doing it.

Our main points here are: a) satellite microwave radiometry is incapable to estimate SIC correctly if a certain fraction of the sea ice is submerged under water and b) it might be more straightforward to stay with what the sensor actually can do, and this is to estimate ice surface fraction. The latter will be similar to the well known SIC during most of the year - except in the melting season, when it will be a more accurate and more transparent estimation of the actual ice surface fraction. Why do known algorithms using satellite microwave radiometry retrieve close to 100% ice concentration in an area with only 70% ice surface fraction? This is not transparent and not easy to understand and can only be because the radiometric signature of the ice between the melt ponds has changed such that the plus in the open water at the surface does not count anymore that much. It can be assumed that this change in radiometric signature changes for different algorithms, which is why we have different scatter plots in Figure 4. As we are aiming for a climate data record we rather would like to provide the information the sensor can actually retrieve. Infrared temperature based retrievals of the sea surface temperature do also not aim to provide an estimate of the water temperature at 20 m depth. Moreover, infrared temperature based retrievals of the sea surface temperature have data gaps where there are clouds which cannot be penetrated by the infrared signal of the surface. These gaps need to be interpolated or simply stay as gaps. Here, with SIC we have the same setting: the microwave signal of the sea ice underneath the melt pond does not reach to the sensor. We have a data gap.

**1286, 20 – 1287, 21 (6 of 7)**: I suppose this is somewhat of a value judgment, but to me a better approach is to try to get the concentration as accurate as possible and let melt ponds be calculated separately (e.g., with the MODIS product).

A: We support this opinion. Data fusion might be necessary to retrieve more accurate sea ice concentration estimates in summer. In this work we have not approached this challenge as our purpose was to explore methods suitable for a consistent climate dataset, which would provide daily maps covering whole Arctic and Antarctic and cover longer time periods, which would be hard to achieve with MODIS due to the cloudiness, darkness and the length of available time series of the input data

(launched in 2002). If the reviewers' approach would be to try to get the concentration as accurate as possible then we are on the right track because this is exactly what we are aiming for: to get an estimate of the ice surface fraction year-round with best accuracy and in a most transparent way within the physical limitations given by the sensors' viewing techniques.

**1286, 20** – **1287, 21 (7 of 7)**: The authors' approach is no less legitimate I suppose, but I think some further discussion is warranted, either here and/or in the discussion, pg. 1293, line 16 through pg. 1294, line 17, to discuss the ramifications of how ponds are addressed (or are attempted to be addressed) in the PM algorithms.

**A:** In addition to providing our opinions here (please see above) we will extend the discussion section in the paper to cover these 7 points.

**1291, 12**: I see he tie-point variation is 8-10 K in Figure 8 and that that is 8-10% of the average tie point, but this is from the Bristol "y-component", right? But many algorithms use simple ice tie points, which are 200-250 K. Would the 8-10 K apply there, in which case it would be more like 3-5%, or would the variation be more than 8-10 K? For the open water, which is a simple surface type tie point (Fig. 8 b and d), the variation looks to be only 3-4 K. I would expect the OW tie point to have less variation than ice tie points, but I wonder if the 8-10% variation from the Bristol is a function of the combined y-component tie point approach or if it would apply to simple ice tie points – i.e., is the variation for those 8-10% as well, meaning 15-20K?

A: Yes, we show Bristol tie-points for ice because in the hybrid algorithm it is used for high SICs. The value of 8-10% variation is also valid for simple tie-points. Fig. 1 here shows Tb19V and Tb37V (ice tie-points) from Bootstrap F algorithm, where the variation is about 20-30K.

In the updated version of the paper we will substitute the Bristol tie-points for ice by the ones from Bootstrap F because we found these to be easier to interpret as they are Tbs in K (while Bristol is using rotated axes, which are harder to relate to). Even though Bristol is used for consolidated ice, we still can use Bootstrap F example here to make our point about the dynamic tie-points.



Figure A2.1. Examples of tie point time series for the Bootstrap F algorithm the Northern (left panels) and Southern (right panels) hemispheres: Tb19v and Tb37v ice tie points and slopes. Light grey to dark grey vertical bars denote the progressing melt season from May to September in the Northern and from November to March in the Southern hemisphere.

**1291, 19**: Table B1 is quite interesting and points out an important issue to consider – sea ice trends due not to changes in sea ice but due to sensor drift, intercalibration, and trends in atmospheric variables that effect the sea ice retrieval. However, the numbers presented in the table do not give a real good sense of how big of an effect this is. In other words, how different is the sea ice trend than reported due to these effects. I don't suggest the authors actually try to explicitly calculate this, but it's hard to get a sense of what general (e.g., order of magnitude) effect because the trends vary (even in sign) between sensors and the OW and ice tie-points also vary differently. To put it succinctly, if the current data say the Antarctic September sea ice trend is instead \_-1% per decade? I suspect not, but it would be useful to have some sense of what these effects are on the overall trend estimates.

A: The authors agree with this point, the table raises more questions than it answers. Since we at the moment, indeed, cannot provide an estimate of significance of the effect, we choose to remove this table.

**1298, 5**: something seems to be missing here - ". . .temperature is the only one." The only one what? The only parameter that Bristol is sensitive to?

A: Rephrased: "Over ice the chosen Bristol algorithm is sensitive to the snow and ice temperature profile as well as to ice emissivity variations. Surface temperature is quantified in most NWP models, which means that there is a potential for correction".

**1298, 24-28**: The authors make the important point that the Near 90 GHz are subject to greater errors due to the atmosphere, particularly near the ice edge and over open water. However, they do have a distinct advantage (at least the algorithms that use only the near 90 GHz channels) in that the higher frequency channels have much smaller sensor footprints, higher resolution – roughly double the spatial resolution. This may or may not offset the atmospheric issues, but I think it is a salient point. While the time series for such products is not as long, the 1991-present timespan is potentially value for climate studies.

A: The finer spatial resolution achieved by the higher frequency channels does not offset the weather-induced SIC biases over open water and near the ice edge. Model data used in the RTM to correct for the influence of surface wind speed, water vapor and air temperature have a coarser spatial resolution and hence will cause artifacts in the RTM-based correction of the input brightness temperatures. The remaining weather effects we cannot correct for (cloud liquid water and precipitation) will become even worse and more difficult to correct for because the model is even less capable to provide the information for this parameters at the same spatial scale as would be required and in addition the finer grid resolution increases the amplitude of the impact of e.g. cloud liquid water because gradients in these parameters are captured "better" and are less smeared.

This will be mentioned in the text (the Discussion section).

**Figure 4**: Both figures on the bottom row are labeled "Near90". Should one of these be "NASA Team"?

A: Yes, the bottom right panel should be "NASA Team", the misprint is corrected.

**Figure 4:** The bias correction mentioned in the caption is not discussed in the manuscript text. What is this and why is this done? This should be better explained within the main text.

A: From an inter-comparison between Envisat ASAR wide swath mode imagery, insitu sea ice surface observations, weather station reports and the daily MODIS melt pond fraction and sea ice concentration dataset it was found that the MODIS sea ice concentration is negatively biased by 3 % and that the MODIS melt pond fraction is positively biased by 8 %. An investigation of the 8-day composite dataset of the MODIS melt pond fraction and sea ice concentration with regard to their seasonal development during late spring / early summer confirmed the existence of such biases. Hence, it was decided to apply these bias corrections suggested first by Mäkynen et al. [2014].

#### **Minor Comments:**

# A: The text of the revised paper is adjusted with regard to all the suggested minor comments:

1278, 19: remove "got"
1279, 24: suggest "slope of one" instead of "slope of unit"
1281, 16: "substitution" instead of "substitute"
1281, 23: change to ". . .SIC values, though this does not apply. . ."
1288, 19: ". . ., see the introduction. . ." to ". . .; see the introduction. . ."
1288, 28: remove "real"
1290, 26: "An example of the ice tie-point. . ."
1291, 17: suggest "unrealistic" or "artificial" instead of "undesirable". Also either "an artificial trend" or "artificial trends"
1292, 12: suggest "significant" or "substantial" or "large" instead of "severe"
1292, 18: "algorithm for a climate dataset" or "algorithm for climate datasets"
1293, 6: "Similar" instead of "Similarly"
1294, 7: ". . . this effect: the OSISAF algorithm. . ."
1295, 2: suggest "limitation" instead of "drawback"
1297, 17: "all 10 algorithms. . ."

#### References

Eppler, D. T., L. D. Farmer, A. W. Lohanick, M. R. Anderson, D. J. Cavalieri, J. Comiso, P. Gloersen, C. Garrity, T. C. Grenfell, M. Hallikainen, J. A. Maslanik, C. Mätzler, R. A. Melloh, I. Rubinstein, and C. T. Swift: Passive Microwave Signatures of Sea Ice, in: Microwave remote sensing of sea ice (ed F. D. Carsey), American Geophysical Union, Washington, D. C, 47-71, doi:10.1029/GM068p0047, 1992.

Mäkynen, M., Kern, S., Rösel, A., and Pedersen, L.T.: On the Estimation of Melt Pond Fraction on the Arctic Sea Ice With ENVISAT WSM Images, IEEE T. Geosci. Remote, 52, 7366–7379, 2014.

Meissner, T., and F. J. Wentz: The emissivity of the ocean surface between 6 - 90 GHz over a large range of wind speeds and Earth incidence angles, IEEE Transactions on Geoscience and Remote Sensing, 50(8), 3004-3026, 2012.

Ulaby F. T., Moore, R. K., and A. K. Fung 1986. Microwave Remote Sensing. Active and Passive. Norwood, MA: Artech House Inc, 1986.

The authors would like to thank **Dr. J. C. Comiso** for the valuable comments that helped improving quality of the paper.

We will address the comments point-by-point (the answers are marked by A).

# **General Comments:**

1. The primary objective of this study is to evaluate the performance of several sea ice concentration algorithms, identify the strengths and weaknesses of a selected few and come up with an optimal hybrid algorithm that takes advantage of the techniques used in the higher performing versions. First, the authors selected 13 from 30 algorithms and evaluated the merits of each based on statistical and sensitivity analysis in conjunction with a set of validation data. The hybrid algorithm as put together by the authors may be an improvement over some of the other algorithms but they fail to properly provide a convincing evidence that what they ended up with is indeed the optimal and most accurate algorithm. Also, although the criteria used for choosing the hybrid algorithm are reasonable they are not exhaustive enough to take into consideration some of the weaknesses of the techniques they decided to implement.

A: The authors agree that it would be too ambitious to say that the outcome of this study is an optimal and most accurate algorithm, but this is indeed the impression the manuscript gives. There is obviously still potential for development in passive microwave algorithms.

In the revised version of the manuscript we alter the focus: we emphasize that it does not aim at developing an optimal algorithm but rather identify the need for it and investigate some of the criteria that should be employed. We will adjust the title, abstract and conclusions accordingly, as well as where relevant in the main text of the paper.

**2.** They even failed to test other algorithms properly or at least use them as they are normally implemented for the production of sea ice data sets.

A: Please see the detailed answer to the Technical Corrections below where we explain the reason for testing the Bootstrap Algorithm in its two modes. For all the other algorithms their original versions were implemented. However, the RRDP tiepoints were used instead of the original ones and no weather filters were applied. This was done to achieve a fair comparison of the algorithms. Please understand that what we aimed to do here in the framework of the ESA-CCI Sea Ice ECV project is a novel and fair way to inter-compare different retrieval techniques without (sometimes) subjective tuning to tie-points or application of (too) general filters.

**3.** Furthermore, the authors failed to show how they handle other parts of the ocean where the algorithm does not work properly. Since it is a global algorithm and meant for climate studies, the authors should demonstrate that they are not retrieving sea ice in areas where they are not supposed to be found. In particular, strongly disturbed areas in the open seas as may be caused by strong winds and bad weather and coastal areas contaminated by land could have signatures similar to those of ice covered ocean. They tried to address the first but there is no demonstration that their technique really work everywhere.

A: The validation dataset locations in Arctic and Antarctic for open water are shown in the figures 1 and 2 of the paper, it covers different areas, including the areas where there normally should not be any ice (blue squares in the figures' left panels). This dataset only for the shown years (2007 and 2008) contains about 30 000 data points, which we consider to be sufficient, bearing in mind such extensive validation datasets have not been produced and used before for validation of sea ice concentration algorithms. The other years are covered less, approximately 4 000 data points per year, except the SMMR period with about 1000 points per year, but the full dataset extends from 1978 to 2011. We are confident that these locations represent the full amplitude of weather influence on measured brightness temperatures and hence retrieved sea ice concentrations.

The reviewer could perhaps take into account that the present paper does not aim to "sell" the algorithm and to provide a complete set of validation results. These have to and will be addressed in another paper. The present paper basically deals with the challenge to select the most suitable combination of algorithms for a long-term climate sea ice concentration data set.

These details will be added to the revised manuscript (Sect. 3.2).

**4.** A good land mask is also needed to exclude land areas that may change with time due to iceberg calving or surging.

A: The authors do agree that for production of a final SIC dataset it is important to implement a good land mask and correction of pixels closely located to land. The land mask should take into account the fact that different algorithms use different passive microwave channels with different footprint size. Implementation and application of such masks and corrections would solve this concern. However, production of a final SIC dataset is out of scope of this paper. For the consistent validation exercise completed here, such areas (in the vicinity of land) were not selected for the validation and evaluation of the algorithms. The primary focus was on 0 % and 100 % sea ice concentration (turned out to be 15 % and 75 % for the reasons mentioned in the paper) in open waters. Therefore contamination of SIC estimates by land has no effect on the results.

The authors wish to underline that they are well aware of the problem the reviewer is mentioning. The reviewer might be pleased to learn that it is planned to include the approach published by Maass and Kaleschke (2010) into the production chain of the next version of the SICCI SIC product. This method allows correcting for land contamination independently of frequency used. As implementation of this approach has been planned since the beginning of the SICCI project we did not find it necessary to evaluate the different algorithms also for their capability (or incapability) to retrieve accurate SIC adjacent to land.

The reviewer is mentioning land area changes due to iceberg calving - so primarily the Southern Hemisphere. The authors are also aware of this problem. An annually or even monthly revised outline of the ice shelf and glacier borders would be a target solution here. But it is beyond the scope of this paper to find the optimal solution for these problems because this is something outside the SIC retrieval approach and more similar to the problem with land contamination. Hence for the same reason as stated above we don't find it appropriate to discuss this issue in the context of this paper. This will be mentioned in the discussion section of the revised manuscript. **5.** They correctly indicate that there are large errors in areas of meltponding and over thin ice regions but a real solution to the problem was not presented.

A: The manuscript may not offer solutions for such well-known problems as melt ponds or thin ice, but its merit would be in revealing more information about the causes of these problems and presenting a new approach to address them.

What has been done in the current study with respect to melt ponding on sea ice, and could be valued, is the approach that resulted in the data shown in Figure 4. Here we had to use another data source (MODIS) that is more capable of characterizing melt ponds on ice surface. For the solution of the melt-pond issue we would suggest that one could either use visible data and/or accept that passive microwave measurements interpret melt ponds as open water.

Another aspect of the study that should contribute to developing of an optimal method is the use of thin ice thickness in evaluating the algorithms in presence of thin ice (Figure 5). This identification of the sensitivity of different algorithms is new information.

These would probably be valued more if viewed as an endeavor to shed more light on a few long-standing difficulties in the way of developing a generic algorithm rather than offering an "optimal algorithm".

**6.** The scientific merit of this study is good and well founded and the creation of a robust algorithm that is acceptable to everybody would be highly desirable. However, the paper needs to be revised extensively as indicated below before its publication. First of all, the authors should be commended for pursuing this noteworthy project. Since the launch of SMMR, there has been some progress in making refinements to the algorithms but the same techniques are basically made leading to just minor improvements in the accuracy of the retrievals. It is not until now that an attempt is being made to evaluate the various existing algorithms and come up with a hybrid version that could better than any of the existing ones.

The question is: how well did they succeed in coming up with such an optimal version? I find it disappointing that there are no comparison of real products. Ideally, the authors should give examples of products that demonstrate problems with existing algorithms. They should then show that their hybrid version eliminates or at least minimizes such problems. This should be done for various seasons and both hemispheres. They should also show some time series of ice extents and ice areas and demonstrate how the new technique provides significantly improvements in accuracy and reliability.

A: The text of the paper will be substantially changed in order to clarify the points raised by Dr. Comiso and, as we pointed out above, we will re-formulate the main impression the paper gives from "optimal algorithm" to what it was aiming at originally, namely to inter-compare and validate different algorithms using a reference dataset (which is public and free for everyone to use). The hybrid algorithm has according to these criteria some (minor) improvements relative to the original Bootstrap algorithm but is in essence very similar.

When it comes to comparing real products, we find this to be out of scope of this particular study because this would mean evaluation of all the processing steps involved in production of a SIC dataset. To mention only some, these would be land-mask and land spillover correction, gridding, ocean-masks (climatologies of ice extent are often used to dismiss OW areas far away from ice). While all these evaluations

would be very important, it would have been impossible to cover in one paper. Also, validation of time series of area and extent (and making a conclusion on how much improvement is achieved by using the hybrid algorithm) would require accurate daily validation maps for the length of the required time period, which do not exist yet.

The novelty of this study is the use of a limited but very accurate reference datasets (the RRDP) and addressing some of the major problems, common to all algorithms, and inter-compare these algorithms in a transparent and objective way. Our attempt of being objective can be seen in our efforts to keep algorithms like the ASI and the NT2 in the loop even though they cut off SIC at 100% or 102%. We constructed artificial 75% and 15% sea ice concentration datasets to evaluate potential biases across ALL algorithms considered. We tackle known problematic areas such as thin ice and melt ponds. For the first time we can now visualize - using real ice thickness information - how different algorithms are biased towards too low SIC values over thin ice. For the first time we visualize how different algorithms fail to provide a physically reasonable estimate of the net ice surface fraction during summer conditions. Maybe the reviewer could see that this goes beyond showing time series or maps of sea ice concentration (anomalies) of different algorithms with different tie-points applied to different sets of brightness temperatures using different weather filters.

7. In making the evaluations, the authors did not do a good job in their analysis of the various algorithms. For example, they separated the Bootstrap Algorithm as has been described in literature into two algorithms: one using the 18V versus the 37V set, which they call CV, and the other using the 37H versus the 37V set, which they call P. The two sets needs to be combined and are usually used to complement each other with the P-set utilized mainly in highly consolidated area where ice can be retrieved at a high accuracy (using this set). The CV set is then used for the rest of the data to take care of areas where the P-set does not do a good job such as in ice cover areas affected by layering in the snow and ice cover. Separating the two sets in an algorithm would compromise the overall accuracy of the retrieval.

A: Please see the detailed answer to the Technical Corrections below where we provide the justification for testing the Bootstrap Algorithm in its two modes. We found that even though this algorithm showed very good performance, it was somewhat better, if we used Bristol over areas of consolidated ice instead of Bootstrap P, while keeping Bootstrap F for lower concentrations. This point will be added to the discussion section.

**8.** Their assessments of atmospheric and emissivity effects is also not so accurate. The scatter plots show that the data points in the consolidated ice region form a well defined cluster that are basically confined along a line that is then used as a reference or "tie points" for 100% sea ice. With a few exceptions, the effect of different weather conditions and different surface emissivity of sea ice is to cause the data points to move along this line. Hence, the accuracy is not altered as long as the tie point for ice is estimated properly. The other issue is in the use of stability through statistical analysis as the key criteria for validation. Stability may not be a good measure in many cases since a poor retrieval of sea ice cover can be consistently wrong. There should be a direct comparison with real data on sea ice concentration in two dimension to illustrate that the algorithm captures the spatial distribution of sea ice properly. I saw an earlier data set using the recommended technique and I find sea ice concentrations north of Greenland that are less than 95% in winter or substantially

less than other parts of the Arctic basin.

A: The presented RRDP exercise shows that varying emissivity does not only generate variations along the line but also perpendicular to the line (as do some atmospheric effects). These effects are in fact the main reason for algorithm uncertainty, and in our dynamic tie-points approach we use this variability to estimate the uncertainty. Earlier papers on ice emissivity, such as (Cavalieri 1994), show exactly that some ice types (or mixtures of ice types) have emissivities that differ from the 'ice line'.

It is correct that stability can be systematically wrong, which is the reason why we use a reference dataset that is distributed all over the Arctic (and the Southern Ocean).

Since this study is devoted to algorithm inter-comparison, the prototype dataset, which is the one the reviewer is referring to in the last sentence of his comment above, should not be included into the discussion. The authors stress again that the present paper is not about the validation of the SICCI SIC retrieval algorithm but about the challenging steps to decide which hybrid of which algorithms could have the best performance and why.

**9.** Finally, they failed to provide solutions to basic requirements of a good sea ice concentration climate data set. One requirement is a land/ocean mask that would separate land covered areas which are not of interest from the ocean region which is partly covered by sea ice. Such mask should take into consideration the different requirements of different sensors which usually have different resolutions. Another requirement is a technique that takes into account of land contamination in ocean pixels. In this case, the contamination of pixels near coastal areas by land causes the algorithm to estimate non-zero ice concentrations in such areas where sea ice is not expected (e.g., coast of Spain). Some visual comparisons of actual ice concentration maps would also be useful. The impacts of not taking care of these requirements can be more serious than some of the issues, including the atmospheric effects, that the authors are so worried about.

A: The aim of this paper was to document the algorithms' skills rather then a final dataset quality assessment. The difference is that the dataset production chain contains several implementation and processing steps, which we do not aim to address here. Such steps can be for example, use of climatological masks, correcting land contamination effects and gridding from swath to daily maps. This study is devoted to a systematic evaluation of the algorithms. For this purpose a limited but very accurate reference dataset (the RRDP) was built. Therefore we do not show inter-comparison of maps.

We will make this point clear in the revised manuscript.

**10.** A third requirement which they actually tried to address is that of an open ocean mask or weather filter. They use RTM for this purpose and indicate improvements in the distribution of the open water data. However, they should demonstrate that they are consistent in removing all erroneous data with their technique and also ensure that they are not deleting data (e.g., 15% to 30%) that is used to define the ice edge.

A: The concept of RTM correction was introduced in order to avoid removing ice. The drawback of this approach compared to weather filter is that it does not remove all atmosphere over the ocean, which leaves some noise that cannot be corrected for (cloud liquid water, and some from wind speed and water vapor).

We will provide more explanations to make relevant sections (3.5, 4.4 and 5.5) clear in the revised manuscript.

# **Specific Comments:**

**p. 1272, line 6:** I agree that the uncertainties in the summer are high but they are primarily caused by surface melt and meltponding. Large errors at the ice edge do not happen only in summer but in other seasons as well and they are basically caused by variations in the emissivity of new ice and the effect of side lobes that causes a smearing of ice edge location as the satellite crosses the ice/ocean boundary from different directions.

A: The authors agree that this formulation is not clear enough in the text. The message was that the uncertainties are large in summer and at the ice edge, but in the explanation of the reasons that follows it is not very clear which are more relevant to each of these situations. For example, atmospheric contribution and wind roughening are more of a problem for low and intermediate SIC values, while emissivity variations meant in this particular context are relevant for consolidated ice areas. The summer issues (surface melt) are addressed in more detail later in the Introduction (p. 1273, line 23). We do not address smearing and footprint mismatch uncertainties in this paper because this would more naturally belong to a paper on production of a final dataset, where all the uncertainty components should be discussed. Note however that the passive microwave data used in the evaluation were footprint matched.

The text will be re-formulated in the revised version of the paper.

**p. 1272, line 21:** In consolidated regions in the Arctic, the accuracy in the retrieval that takes into account spatial variations in emissivity and temperature is about 2.5% (see, Comiso, 2009, Vol. 29, p. 203, J. Remote sensing of Japan).

A: This work will be cited in the Introduction.

**p. 1272, line 28:** The statement that starts with "The apparent. . ." is incorrect. Kwok (2002) did not make an assessment of emissivity fluctuations in the Arctic – such assessments were done by others including Comiso (1983) and Eppler (1992). It is hard to tell which one is secondary and which one is primary. It is more accurate to say that for retrieved concentrations higher than 97%, the actual percentage of open water may range from 0 to 3% because of uncertainties in the 100% ice tie point.

A: Wrong citation was inserted after this statement; it should be Andersen et al 2007 instead of Kwok 2002 (which is cited earlier in the text). Will be corrected in the revised manuscript.

**p. 1273, line 4:** The impact of water vapor and cloud liquid water is to change the effective emissivity of the surface. Such effect is already included in the determination of "tie points" for sea ice and water.

A: This is correct, the effect is included; especially when the tie-points are sampled in various areas they should cover various local weather conditions. However, it is still an averaged value that is used in an algorithm (except ECICE which works with distributions) when calculating SIC. This gives one value for each tie-point per day. There will be variation of real Tbs around this value, and part of them is explained by the mentioned atmospheric effects that deviate from that average value. The atmospheric correction suggested in this study decreases this deviation (not for cloud liquid water though, which is explained in the text).

**p. 1273, line 6:** Wind effects on surface water signature is not as much within the ice pack as in the open seas. In the open seas, weather filter or ocean mask is normally used. Within the pack, the change is less significant but is included in the estimate of the ocean tie-point.

A: The effect is indeed less significant within the ice pack, mainly because one would expect much smaller fetch for wind to work in the openings/leads in consolidated ice. However, for the areas of low sea ice concentration or open water (where ocean mask is not applied) the weather filters remove also part of actual ice, and not only false ice retrievals, as we show in the Figure 6. Therefore, we emphasize the importance of this effect and suggest applying atmospheric correction. Development of the existing weather filters to solve this issue could be an alternative solution.

It could be questioned whether the wind effect which is included in the estimate of the ocean tie-point is the valid one to be used within the sea ice cover. The ocean tie-point is estimated for open water well away from the ice edge. Hence the fetch is long enough to provide the full spectrum of waves and foam coverage. Inside the sea ice cover the same wind speed will cause a different set of water surface modulation with potentially a different wave spectrum and less foam and hence a different radiometric signature compared to the open ocean.

**p. 1273, line 29:** Meltponding is indeed a big issue but note that it is a problem for only two months. For this period a special algorithm needs to be designed to improve ability to obtain more accurate results.

A: We agree that development of a new algorithm (for example, based on optical measurements) would be beneficial to support passive microwave measurements in summer months.

We will add this point to the discussion section.

**p. 1274, line 7:** Thin ice is a problem because the microwave emissivity changes with thickness and there are two basic types, namely, nilas and pancakes the signature of which are also different. Effects on heat fluxes are also different. There needs to be a means to identify thin ice unambiguously to be able to utilize any thickness algorithm from passive microwave data.

A: This is a valuable remark, however we would like to keep this paragraph unaltered in terms of amount of detail, since it was not the purpose of this study to retrieve sea ice thickness from passive microwave data. We merely assessed SIC over areas where we identified the fact of presence of thin ice from SMOS and SAR.

**p. 1275, line 18:** The Bootstrap algorithm should not be split into two since it takes advantage of both polarization mode and the frequency mode. The frequency mode is relatively stable but it has problems including more sensitivity to temperature and emissivity than the polarization mode. On the other hand, the polarization mode does a better job in highly concentrated (near 100%) sea ice cover.

A: Please see our detailed answer to the Technical Corrections.

**p. 1283, lines 15-20:** There should be a demonstration that the use of RTM for the ocean mask or weather filter works everywhere. Using a model to generate geophysical product is not a reliable technique especially if the atmospheric parameters needed as input by the model also comes from other models or historical data.

**A:** The result of RTM correction shown in the Figure 7 of the paper was obtained using the following locations:





We assume these locations cover different weather types (for some it is more common to have storms and strong winds, and some are typically more quiet). Total amount of points sampled in these locations amounts to 2320 and covers whole year of 2008, SSM/I. The improvement due to the RTM correction shown in the Figure 7 of the paper is an average measure for all these samples – we show that the standard deviation of SIC obtained from the algorithms becomes significantly smaller after the correction. Please note that some of these points were only used in summer, since there is ice at these locations during winter.

This explanation will be added to the text of the paper.

**p. 1284, lines 7-11:** It is a mistake to consider only 15% and 75% cases. Most of the pixels within the pack have ICs close to 100%. Ability to detect the high concentration data effectively is very important.

A: Yes, the high concentration areas are important on their own, and accurate SIC retrievals for such areas would be much appreciated in a number of applications. In this study we aimed at inter-comparison of as many as possible of the main available algorithms (or groups of algorithms), which includes NASA Team2, ECICE and ASI. These algorithms though could not be added to the experiment for 100% SIC for the reasons explained in the paper. Therefore we made such choice – a tradeoff – to use 75% and include all the algorithms but thus miss the opportunity to address areas of SIC close to 100%. However this seems like a fine trade-off because an algorithm inter-comparison study focused particularly on high SIC has already been published (Andersen et al 2007). Please see also our answer to the Technical Corrections for more details.

**p. 1287, line 10-14:** Is it true that the NASA team IC does not go beyond 100%? If so, the ice tie point used is not correct and the estimated IC would be an underestimate of the real IC. The high IC for CalVal is in part caused by the high variability of the emissivity of summer ice and also to take into account the expected bias due to meltponding. The error gets significantly reduced in August when the surface starts to become dry and the emissivity becomes more stable.

A: No, it is not true that NT does not go beyond 100%.

Actually if NT did not go beyond 100% the tie-point would be underestimated by our criterion (NT>95%) and the actual ice concentration would then be overestimated. In winter most of the data points that have NT>95% will actually have SIC very close to 100% (99-100%) since very little open water exists during winter. During other parts of the year (especially during summer) the average SIC for NT>95% might well be slightly lower than 100% (perhaps 97-98%) and our tie-point may cause a small overestimation of some ice concentrations by up to 3% in those periods. We consider this an acceptable possible bias (unknown) and a significant improvement over having a bias of up to 30% or larger.

The high SIC during summer for CalVal (>130% in some locations) is due to changes in emissivity as well as changes in effective temperature. We do not believe it is the correct approach to handle melt ponds by 'overestimation' of the ice in between the melt ponds to make them look like ice. This will only provide the 'desired' result at one melt pond fraction and will still overestimate the ice concentration where the MPF is less than expected, and underestimate the ice concentration where the MPF is larger than expected. **p. 1288, lines 5-20:** None of the existing algorithms does a good job on thin ice. Within the pack, thin ice forms in leads and polynyas and they are usually narrow and not easily resolved by the passive microwave sensors (especially SSM/I). The fraction of thin ice in most cases are usually relatively small and not much to worry about. Where it counts would be in large coastal and deep ocean polynyas where the open water or thin ice is represented by a significant number of pixels. In these cases, ability to identify them in the ice concentration maps (because of the bias) is actually an advantage since they are areas where heat fluxes are significantly different. Producing an ice concentration map that treats thin ice (including grease ice) on an equal footing as the thicker ice types would produce maps that are mainly 100% within the ice pack. A newly formed lead within the pack normally freeze within hours and would not be represented by such a map and an important information would be lost.

A: The thin ice we relate to in this study is newly formed ice in fall, but yes, large polynyas are of relevance as well. It can be important to be able to distinguish this ice as ice and not areas of open water because ice formation is an indicator of starting freezing season with all the relevant processes. For example, increased ocean salinity, or terminated wind energy transmission to the ocean. However, we agree that with passive microwave standard algorithms there is no way to distinguish thin ice from low concentration ice. More over, if areas of thin ice are interpreted as reduced concentration we should say so. This issue is similar to melt ponds in a way that there is no simple solution, and one should be aware of the limitation, which we demonstrate by the Figure 5.

In general, it can be of interest to distinguish leads with open water from the ones with thin ice. For example, if a lead is wide enough to be affected by wind and provoke ocean convection; or for studying of brine rejection effects on the ocean stratification. But such division should be very hard to achieve by passive microwave methods alone.

The authors suggest that in case of thin ice it might again be required to rely on data fusion techniques and instead of using only microwave radiometry to include independent data which permit discrimination between thin and thick ice and hence provide the desired information where an apparently (too) low SIC is caused by actual lower ice concentration or where it is caused by thin ice or perhaps even both.

What is new here is that we manage to quantify the effect and thus allow sea ice modelers with a thickness distribution to assimilate ice concentration data in a more proper way.

**p. 1280, lines 1-20:** Losing <30% ice concentration is not acceptable and also, the authors must demonstrate for sure that there are no residuals. The other techniques used by other algorithms (e.g., NT2 and Bootstrap for AMSR data) are probably more effective and should be examined.

A: We did investigate the traditional weather filters (as used by the NT2 and Bootstrap algorithms) (see Figure 6) and found that they remove ice sometimes up to 30%. We agree that this is normally unacceptable and therefore we decided NOT to use these filters. Instead we decided to perform atmospheric correction of the measured Tbs using reanalysis atmospheric data (ERA Interim). This procedure

reduces the atmospheric noise considerably but does not remove it completely. There will therefore be some residual atmospheric noise over the ocean. We argue that this noise is more acceptable in an ice concentration algorithm than the removal of ice, but agree that this is debatable and for some applications the removal of ice may be preferable. We did investigate the performance of NT2 at low concentrations and the 'weather correction' of this algorithm turned out to not perform very well (see e.g. Figure 3).

Relevant sections on the weather filters and atmospheric correction will be made clearer in the text (Sect. 3.5, 4.4 and 5.5).

**Technical Corrections:** The Bootstrap Algorithm should be implemented as designed. Both P (37H and 37V) and CV (18V and 37V) techniques should be utilized in concert as described by the author especially when making the comparisons with other techniques.

A: The authors understand the concern regarding testing the two modes of the Bootstrap Algorithm separately, and would like to clarify this issue in more details, which they hope will justify their choice. They also admit that this point is not explained very well in the current version of the paper. This will be addressed properly in the updated version.

Here we offer a step-by-step procedure of the decision-making:

1. Since accurate intermediate SIC reference data are not available we have created validation datasets at 0% and 100%.

2. We validate SIC obtained by the algorithms using the obtained validation datasets for 0% and 100% and find out that some of the algorithms are hard to validate at these values because they cut-off the SIC at 0% and 100% (NASA Team2, ECICE), are affected by a combination of large bias and nonlinearity at high SIC (ASI). These effects cut part of standard deviation (see examples in Figure 2 and Table 1 here: SIC100%, NASA Team 2 and ASI), while we aim at evaluating the full variability around these reference values (0 and 100%). We implement the algorithms (except these 3) without cut-offs, allowing thus SIC values below 0% and above 100% as well.

In order to be able to include these three algorithms in the inter-comparison, we produce artificial datasets (the procedure is described in the paper) of SIC 15% and 75%, and used them instead of 0% and 100% datasets respectively. We find that the algorithms' performance at 15% is representative of that of 0%, and so is 75% to 100%. Therefore we show only the 15% and 75%. By "representative" here we mean that the algorithms' ranking does not change significantly (Tables 1 and 2 here) even though the absolute values of standard deviations are different. We only show Northern Hemisphere here because the Bootstrap P scheme is originally used in this hemisphere (Comiso 1995).



Figure A3.2. SIC obtained by NT2, ASI and BR algorithms (BR is shown for reference) from the Tbs over areas of SIC 100%, SSM/I, 2008, winter.

Table A3.1. Standard deviations for SIC datasets: 75% (2008) and 100% (2007-2011, except NT2, which is provided for 2008). SSM/I and AMSR-E, Northern Hemisphere, winter.

Algorithm	SIC 75%	SIC 100%
Bristol	3.1	4.3
OSISAF*	3.1	4.3
NT+CV	3.1	4.4
CV+N90	3.4	4.6
NASA Team2	3.7	1.7
6H	3.7	5.4
NASA Team	3.9	5.7
ASI	4.1	1.8
CV	4.5	6.4
Bootstrap P	4.7	6.2
Near90	5.4	7.0

\*Please note that at SIC 75% and 100% OSISAF = Bristol

Algorithm	SIC 15%	SIC 0%
6Н	2.8	3.0
CV	3.8	4.4
CV+NT	4.5	5.2
OSISAF	4.7	5.3
NASA Team	5.4	6.2
Bristol	6.6	7.7
NASA Team2	7.3	7.4
Bootstrap P	13.5	15.8
CV+N90	15.6	19.2
ASI	28.5	30.7
Near90	28.8	34.9

Table A3.2. Standard deviations for SIC datasets: 15% (2008, SSM/I and AMSR-E) and 0% (1978 – 2011, SMMR, SSM/I and AMSR-E, except NT2, which is provided for 2008). Northern Hemisphere, all year round.

3. The Polarization scheme (mode) of the original Bootstrap algorithm is applied only when Tb19V is above the AD line (ice line) minus 5K, that is when

$$Tb19V - (t1a + sad*Tb37V - 5) > 0,$$
(1)

where t1a and sad are intercept and slope of the ice line (please see [Comiso 1995] for details). Otherwise the Frequency mode is applied.

The threshold defined by this line can be converted to a SIC value, which amounts to values shown in the Table 3 as obtained from our RRDP tie-points set. Both of our test datasets, 15% and 75% SIC, are well below these values, and therefore only Frequency mode would be chosen by the original Bootstrap scheme. However, we show the Bootstrap Polarization mode in the paper anyway.

4. Thus, we did not show in the paper the tests of Bootstrap P for what it is originally meant – near 100% SIC. We show this test here (Figure 3), and it is indicating that Bootstrap P performs quite well, but Bristol showed somewhat lower standard deviations and therefore was selected for the hybrid algorithm. Please note that the 100% SIC reference dataset may still have some small fraction of residual open water. This however, does not jeopardize our use of the minimum standard deviation as a measure of algorithm performance, since we are only looking for the relative differences between algorithms.



Figure A3.3. Standard deviations from SIC 100% validation dataset: average 2007 – 2011, SSM/I and AMSR-E, winter, Northern Hemisphere.

#### References

Cavalieri, D. J.: A microwave technique for mapping thin sea ice, J. Geophys. Res., vol. 99, no. C6, 12561–12572, 1994

Comiso, J. C.: SSM/I Sea Ice Concentrations Using the Bootstrap Algorithm, NASA Reference Publication 1380, NASA Center for Aerospace Information, 800 Elkridge Landing Road, Linthicum Heights, MD 21090-2934, (301) 62 1-0390, 1995.

Maass, N., and L. Kaleschke: Improving passive microwave sea ice concentration algorithms for coastal areas: applications to the Baltic Sea, *Tellus*, vol. 62A, 393-410, 2010.

		Notalia Ivanova 27/5/2045 00:20
1	Sea ice algorithms inter-comparison and evaluation:	Deleted: Passive microwave s
2	towards further identification of challenges and optimal	Natalia Ivanova 10/6/2015 12:55 Deleted: valid
3	approach using passive microwave observations	Natalia 22/5/2015 11:02
4 5	Natalia Ivanova <sup>1</sup> , Leif T. Pedersen <sup>2</sup> , Rasmus T. Tonboe <sup>2</sup> , Stefan Kern <sup>3</sup> , Georg Heygster <sup>4</sup> , Thomas Lavergne <sup>5</sup> , Atle Sørensen <sup>5</sup> , Roberto Saldo <sup>6</sup> , Gorm Dybkjær <sup>2</sup> ,	<b>Deleted:</b> Satellite passive microwave measurements of sea ice concentration: an optimal algorithm and challenges
6 7	Ludovic Brucker <sup>7, 8</sup> , and Mohammed Shokr <sup>9</sup>	
8	(1){Nansen Environmental and Remote Sensing Center, Bergen, Norway}	Natalia 17/6/2015 11:55
9	(2){Danish Meteorological Institute, Copenhagen, Denmark}	Deleted:
10	(3){University of Hamburg, Hamburg, Germany}	
11	(4){University of Bremen, Bremen, Germany}	
12	(5) {Norwegian Meteorological Institute, Oslo, Norway}	Natalia Ivanova 24/3/2015 09:12
13	(6){Technical University of Denmark, Lyngby, Denmark}	Deleted: Met-Norway, Oslo, Norway
14 15	(7){NASA Goddard Space Flight Center, Cryospheric Sciences Laboratory, Code 615, Greenbelt, Maryland 20771, USA}	
16 17	(8){Universities Space Research Association, Goddard Earth Sciences Technology and Research Studies and Investigations, Columbia, Maryland 21044, USA}	
18	(9){Environment Canada, Ontario, Canada}	
19		
20	Correspondence to: N. Ivanova (natalia.ivanova@nersc.no)	
21		
22		
23		
24		
25		
26		
	1	

2 Abstract

3 Sea ice concentration has been retrieved in Polar Regions with satellite microwave 4 radiometers for over 30 years. However, the question remains open, what is the optimal sea 5 ice concentration retrieval method for climate monitoring. This paper presents some of the key results of an extensive algorithm inter-comparison and evaluation experiment. Thirty sea 6 7 ice algorithms entered the experiment where their skills were evaluated systematically over 8 low and high sea ice concentrations; thin ice and areas covered by melt ponds. A selection of 9 thirteen algorithms is shown in the article to demonstrate the results. Based on the findings, a hybrid approach is suggested to retrieve sea ice concentration globally for climate monitoring 10 purposes. This approach consists of a combination of two algorithms, dynamic tie points 11 12 implementation, and atmospheric correction of input brightness temperatures. The method 13 minimizes inter-sensor calibration discrepancies and sensitivity to error sources with seasonal to inter-annual variations and potential climatic trends, such as atmospheric water vapour and 14 15 water surface roughening by wind,

Natalia Ivanova 31/5/2015 22:43
Deleted: measured ...etrieved globally ...n ... [1]

#### 

#### 

16

#### 17 **1** Introduction

From a <u>perspective of climate change</u> it is important to know how fast the total volume of sea ice is changing. In addition to sea ice thickness (Kern et al., 2015), this requires reliable estimates of sea ice concentration (SIC). Consistency in sea ice climate records is <u>crucial for</u> understanding of internal variability and external forcing (e.g. Notz and Marotzke, 2012) in the observed sea ice retreat in the Arctic (Cavalieri and Parkinson, 2012) and expansion in the Antarctic (Parkinson and Cavalieri, 2012).

24 Accuracy and precision serve as measures of performance of a SIC algorithm. Accuracy 25 (expressed by bias) is the difference between the mean retrieval and the true value. Precision (expressed by standard deviation, SD) is the range within which repeated retrievals of the 26 27 same quantity scatter around the mean value (see also Brucker et al., 2014, where precision is 28 addressed in detail). Average accuracy of commonly known algorithms, such as NASA Team 29 (Cavalieri et al., 1984) and Bootstrap (Comiso, 1986), is reported to be within  $\pm 5\%$  in winter 30 in a compact (high concentration) ice pack. Accuracy of the Bootstrap scheme applied to 31 AMSR-E (Advanced Microwave Scanning Radiometer for Earth Observing System) data,

Natalia Ivanova 27/5/2015 09:37 **Deleted:** perspective... it is important to k ... [4]

Natalia Ivanova 31/5/2015 22:53 Deleted: P...ecision and accuracy ...erve a....[5]

Natalia 3/6/2015 12:27 Deleted: Natalia Ivanova 31/5/2015 22:53 Deleted: Accuracy (represented by the bias) is the difference between the mean retrieval and the true value. Natalia Ivanova 15/6/2015 09:50 Formatted

1	expressed as standard deviation of the scatter around the ice line, was estimated at 2.5%. The	
2	accuracy including combined effect of surface temperature and emissivity variability was 4%	/
3	(Comiso 2009). A comparison of seven algorithms to a trusted dataset of Synthetic Aperture	
4	Radar (SAR) and ship-based observations in the Arctic showed precision of 3-5%, including	
5	sensor noise (Andersen et al., 2007), In summer and at the ice edge the retrievals are more	/
6	uncertain, and accuracy can be as poor as ±20% (Meier and Notz, 2010). Inter-comparison of	$\overline{\}$
7	eleven <u>SIC</u> algorithms in the Arctic showed differences in SIC retrievals of 2.0-2.5% in	/
8	winter in the areas of consolidated ice (5-12% for intermediate SIC) and 2-8% in summer	
9	reaching up to 12% in the Canadian Archipelago area (Ivanova et al., 2014). The large	
10	uncertainty in retrievals, of the summer period is, caused by increased variability in sea ice	
11	emissivity due to the surface wetness and presence of melt ponds. Part of the uncertainty at	$\langle \rangle$
12	low and intermediate SICs, which is relevant both for summer and for the marginal ice zone	$\langle \rangle$
13	at any time, is caused by atmospheric contributions and wind roughening of open water areas,	/
14	as shown for the Arctic by Andersen et al. (2006). Marginal ice zone, is characterized by	
15	increased uncertainties due to smearing and footprint mismatch effects. The uncertainties over	/
16	consolidated ice during Arctic winter were explained by variations in sea ice emissivity /	/
17	(Andersen et al., 2007).	
17 18	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have	
17 18 19	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2)	
17 18 19 20	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical	
17 18 19 20 21	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs)	
<ol> <li>17</li> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> </ol>	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and	
<ol> <li>17</li> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> </ol>	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations, and the method applied to retrieve SIC from them, which	
<ol> <li>17</li> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> </ol>	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations, and the method applied to retrieve SIC from them, which distinguishes each algorithm among the others (explained in Sect. 2.1). Kwok (2002) and	
<ol> <li>17</li> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> </ol>	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations, and the method applied to retrieve SIC from them, which distinguishes each algorithm among the others (explained in Sect. 2.1). Kwok (2002) and Andersen et al. (2007) showed that SIC algorithms do not reflect the near 100% ice	
<ol> <li>17</li> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> </ol>	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations, and the method applied to retrieve SIC from them, which distinguishes each algorithm among the others (explained in Sect. 2.1). Kwok (2002) and Andersen et al. (2007) showed that SIC algorithms do not reflect the near 100% ice concentration variability in the Arctic adequately. Variability due to actual ice concentration	
<ol> <li>17</li> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> <li>27</li> </ol>	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations, and the method applied to retrieve SIC from them, which distinguishes each algorithm among the others (explained in Sect. 2.1). Kwok (2002) and Andersen et al. (2007) showed that SIC algorithms do not reflect the near 100% ice concentration variability in the Arctic adequately Variability due to actual ice concentration changes in the order of less than 3% is below the noise floor of the algorithms. Heat and	
<ol> <li>17</li> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> <li>27</li> <li>28</li> </ol>	(Andersen et al., 2007). In this study we focus on the following four error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice depends on the selection of input brightness temperatures. (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations, and the method applied to retrieve SIC from them, which distinguishes each algorithm among the others (explained in Sect. 2.1). Kwok (2002) and Andersen et al. (2007) showed that SIC algorithms do not reflect the near 100% ice concentration variability in the Arctic adequately Variability due to actual ice concentration changes in the order of less than 3% is below the noise floor of the algorithms. Heat and moisture fluxes between the surface (ocean or ice) and the atmosphere are sensitive to small	
<ol> <li>17</li> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> <li>27</li> <li>28</li> <li>29</li> </ol>	(Andersen et al., 2007). In this, study we focus on the following four, error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations, and the method applied to retrieve SIC from them, which distinguishes each algorithm among the others (explained in Sect. 2.1). Kwok (2002) and Andersen et al. (2007) showed that SIC algorithms do not reflect the near 100% ice concentration variability in the Arctic adequately, Variability due to actual ice concentration changes in the order of less than 3% is below the noise floor of the algorithms. Heat and moisture fluxes between the surface (ocean or ice) and the atmosphere are sensitive to small variations in the near 100% ice cover (Marcq and Weiss, 2012). This unresolved SIC	
<ol> <li>17</li> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> <li>27</li> <li>28</li> <li>29</li> <li>30</li> </ol>	(Andersen et al., 2007). In this, study we focus on the following four, error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The sensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations, and the method applied to retrieve SIC from them, which distinguishes each algorithm among the others (explained in Sect. 2.1). Kwok (2002) and Andersen et al. (2007) showed that SIC algorithms do not reflect the near 100% ice concentration variability in the Arctic adequately, Variability due to actual ice concentration changes in the order of less than 3% is below the noise floor of the algorithms. Heat and moisture fluxes between the surface (ocean or ice) and the atmosphere are sensitive to small variations in the near 100% ice cover (Marcq and Weiss, 2012). This unresolved SIC variability, can thus be of significant importance for sea ice models (and consequently coupled	
17         18         19         20         21         22         23         24         25         26         27         28         29         30         31	(Andersen et al., 2007). In this, study we focus on the following four, error sources, to which the algorithms have different responses: 1) sensitivity to emissivity and physical temperature of sea ice, 2) atmospheric effects, 3) melt ponds, and 4) thin ice. The gensitivity to emissivity and physical temperature of sea ice_depends on the selection of input brightness temperatures (Tbs) available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations, and the method applied to retrieve SIC from them, which distinguishes each algorithm among the others, (explained in Sect. 2.1). Kwok (2002) and Andersen et al. (2007) showed that SIC algorithms do not reflect the near 100% ice concentration variability in the Arctic adequately, Variability due to actual ice concentration changes in the order of less than 3% is below the noise floor of the algorithms. Heat and moisture fluxes between the surface (ocean or ice) and the atmosphere are sensitive to small variations in the near 100% ice cover (Marcq and Weiss, 2012). This unresolved SIC variability, can thus be of significant importance for sea ice models (and consequently coupled climate models) when assimilating these data without proper handling of the uncertainties.	

Deleted: theprecision of 3%, includ [8]
Natalia 22/5/2015 13:38
Deleted:
Natalia Ivanova 15/6/2015 14:35
Deleted:etrievals are more uncertain, ar
Natalia 22/5/2015 11:42
<b>Deleted:</b> These uncertainties are in general caused by atmospheric contributions, wind roughening of open water areas, variations in sea ice emissivity, sensor noise (Andersen et al. 2006, Andersen et al. 2007).
Natalia Ivanova 10/6/2015 15:10
Deleted: sea ice
Natalia 3/6/2015 12:38
Deleted: among the algorithms
Natalia Ivanova 10/6/2015 14:48

Natalia 3/6/2015 12:39 Deleted: e...presented work...tudy we wit ... [1] Natalia Ivanova 27/5/2015 09:49 Deleted: There are...he following fourtwd ... [12]

Natalia 3/6/2015 12:40

Deleted: see...xplained in Sect. 2.11 for d....[13] Natalia Ivanova 27/5/2015 09:43

**Deleted:** Input brightness temperatures are available at electromagnetic frequencies between 6 and near 90 GHz in vertical (V) and horizontal (H) polarisations. ...wok (2002) and Andersen e....[14]

Tb for ice) and only secondarily to actual SIC fluctuations (Andersen et al., 2007). 2 3 The second error source is represented by atmospheric effects, such as water vapour, cloud liquid water (CLW) and wind roughening of the water surface. It causes the observed Tb to 4 5 increase and to change as a function of polarisation and frequency, season and location (Andersen et al., 2006). This effect is usually larger during summer and early fall and over 6 7 open water (also in the marginal ice zone) because of the larger amounts of water vapour and 8 <u>CLW</u> in the atmosphere, and generally more open water areas present. 9 Algorithms with different sensitivities to surface emissivity and atmospheric effects produce 10 different estimates of trends in sea ice area and extent on seasonal and decadal time scales (Andersen et al., 2007). Effect of diurnal, regional and inter-annual variability of atmospheric 11 12 forcing on surface microwave emissivity was also reported in a model study of Willmes et al. 13 (2014). This means that not only sea ice area has a climatic trend, but atmospheric and surface parameters affecting the microwave emission may also have a trend. Such parameters can be 14 15 wind patterns, atmospheric water vapour and CLW (Wentz et al., 2007), snow depth and snow properties, and the fraction of multiyear ice (MYI), 16 However, some algorithms are less sensitive than others to these effects (Andersen et al., 17 18 2006; Oelke, 1997), and it is thus important to select an algorithm with low sensitivity to 19 them. It is particularly important to have low sensitivity to error sources, which it is currently 20 impossible to correct for, e.g. extinction and emission by <u>CLW</u> or sea ice emissivity 21 variability. We therefore designed a set of experiments to test a number of aspects related to 22 SIC algorithm performance, ultimately to allow us to select an optimal algorithm for retrieval 23 of a SIC climate data record. 24 Melt\_ponds on Arctic summer sea ice represent an additional source of errors due to their 25 microwave radiometric signatures being similar to open water. Virtually all SIC algorithms

primarily attributed to snow/ice surface emissivity variability around the tie point (predefined

1

based on the passive microwave channels around 19, 37, and 90 GHz are very sensitive to
presence of melt water on the ice. The penetration <u>depth</u> of microwave radiation into liquid
water is a few millimetres at most (Ulaby et al., 1986), and therefore it is impossible to
distinguish between ocean water (in leads) and melt water (on the ice). This is the primary
reason why most SIC algorithms are less reliable during summer and potentially
underestimate the actual SIC (Fetterer and Untersteiner, 1998; Cavalieri et al., 1990; Comiso

32 and Kwok, 1996). Melt ponds may exhibit a diurnal cycle with interchanging periods of open

#### Natalia Ivanova 14/6/2015 14:20 **Deleted:** ie-point...e point (predefined Tb ... [15] Natalia 22/5/2015 13:15 **Deleted:** Kwok, 2002 Natalia Ivanova 27/5/2015 09:55 **Deleted:** the ...epresented by atmospheric ... [16]

Natalia 3/6/2015 12:43 Deleted: as well as Natalia Ivanova 27/5/2015 09:53 Deleted: change ...as a function of polaris ... [17]

#### Deleted: as well as Natalia Ivanova 27/5/2015 09:55 Deleted: In addition to atmospheric extinction, wind roughening of the water surface causes the surface emissivity to change towards the values typical for sea ice (Andersen et al., 2006) Natalia Ivanova 15/6/2015 15:44 Deleted: on...and atmospheric effects pro ... [18] Natalia 3/6/2015 16:02 Deleted: also Natalia Ivanova 27/5/2015 09:58 Deleted: trends in ... tmospheric and surfa ... [19] Natalia 3/6/2015 16:04 Deleted: Trends in Natalia Ivanova 10/6/2015 15:25 Deleted: liquid water content...LW (Wen .. [20] Natalia 3/6/2015 16:04 Deleted: could have such effects Natalia Ivanova 27/5/2015 10:07 Deleted: for ... hich it is currently at the p....[21]

Natalia Ivanova 27/5/2015 10:11 Deleted:

Natalia 3/6/2015 16:07 Deleted: depth of

Natalia Ivanova 30/3/2015 13:50 Deleted: ....1990; Comiso and Kwok, 199....[22]

water and thin ice. This further complicates the SIC retrieval using satellite microwave
 radiometry during summer and increases the level of uncertainty. <u>Some SIC algorithms have</u>

3 been shown to underestimate SIC by up to 40% in the areas with melt\_ponds (Rösel et al., 2012b).

Thin ice is known to be another challenge for the passive microwave algorithms as they 5 underestimate SIC in such areas (Heygster et al., 2014; Kwok et al., 2007; Cavalieri, 1994). 6 7 Recent studies of aerial (Naoki et al., 2008) and satellite (Heygster et al., 2014) passive microwave measurements show an increase in  $\underline{Tb}$  with sea ice thickness (<30 cm), which is 8 9 more pronounced for lower frequencies and horizontal polarisation. Since an instantaneous amount of thin ice can reach as much as <u>1 million km<sup>2</sup></u> (total amount globally, Grenfell et al., 10 1992), the effect of SIC underestimation can be significant for ice area estimates, air-sea heat 11 12 and moisture exchange and modelled ice dynamics. It may also affect ice volume estimates. It 13 is suggested that the dependency of Tb on the sea ice thickness is due to changes in near-14 surface dielectric properties caused, in turn, by changes of brine salinity with thickness and 15 temperature (Naoki et al., 2008).

For the first time this many (thirty) SIC algorithms have been evaluated in a consistent and 16 17 systematic manner including both hemispheres, and their performance tested with regard to high and low SIC, areas with melt ponds, thin ice, atmospheric influence and tie points; and 18 covering the observing characteristics of the Scanning Multichannel Microwave Radiometer 19 20 (SMMR), Special Sensor Microwave/Imager (SSM/I) and AMSR-E. The novelty of the presented approach to algorithm inter-comparison is in the implementation of all the 21 22 algorithms with the same the points, which helps avoiding subjective tuning, and without applying weather filters, which have their weaknesses (also addressed in this study). When 23 24 evaluating the algorithms we have in particular focused on achieving low sensitivity to the 25 error sources over ice and open water, performance in areas covered by melt ponds in summer and thin ice in autumn. We suggest that an optimal algorithm should be adaptable to: 1) 26 27 dynamic tie points in order to reduce inter-instrument biases and sensitivity to error sources with potential climatological trends and/or seasonal and inter-annual variations and 2) 28 29 regional error reduction using meteorological data and forward models.

30 The algorithms evaluation was carried out in the context of European Space Agency Climate

- 31 Change Initiative<u>, Sea Ice</u> (ESA SICCI) and is described in the following sections. Sect. 2
- 32 describes the algorithms and the basis for selection of the thirteen algorithms to be shown in

Natalia Ivanova 15/6/2015 15:49 Deleted: sSea ice Natalia Ivanova 10/6/2015 15:44 Deleted: are known Natalia Ivanova 27/5/2015 10:13 Deleted:

Natalia Ivanova 10/6/2015 15:46 Deleted: A Natalia Ivanova 25/3/2015 13:42 Deleted: brightness temperature Natalia Ivanova 10/6/2015 15:47 Deleted: < 30cm Natalia Ivanova 10/6/2015 15:47 Deleted: 1 million km<sup>2</sup> Natalia Ivanova 10/6/2015 15:47 Formatted: Superscript Natalia Ivanova 31/3/2015 10:08 Deleted: volume Natalia Ivanova 25/3/2015 13:42 Deleted: brightness temperature Natalia Ivanova 15/6/2015 15:51 Deleted: assessed

#### Natalia Ivanova 27/5/2015 10:14 Deleted: Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point Natalia 3/6/2015 16:3 Deleted: properties Natalia Ivanova 10/6/2015 14:54 Deleted: Advanced Microwave Scanning Radiometer for the Earth Observing System Natalia Ivanova 10/6/2015 14:54 Deleted: ) Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point Natalia Ivanova 10/6/2015 15:51 Deleted: of Natalia Ivanova 27/5/2015 10:16 Deleted: Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point Natalia Ivanova 15/6/2015 22:44 Deleted: climatological trends in error sources and Natalia Ivanova 15/6/2015 22:47 Deleted: Sea Ice

1 the following sections. Sect. 3 describes the data and methods. Sect. 4 presents the main

2 results of the work: algorithms <u>inter-comparison and evaluation</u>, suggested atmospheric

3 correction and dynamic tie points approach. All the input data and obtained results are

4 <u>collocated and composed into a reference dataset called round robin data package (RRDP).</u>

5 This is done in order to achieve equal treatment of all the algorithms during the inter-

6 <u>comparison and evaluation, as well as to provide an opportunity for further tests in a</u>

- 7 consistent manner. This dataset is available from the Integrated Climate Data Center (ICDC,
- 8 <u>http://icdc.zmaw.de/1/projekte/esa-cci-sea-ice-ecv0.html).</u> The discussion and conclusions are
- 9 provided in Sect. 5 and Sect. 6 respectively.
- 10

#### 11 2 The algorithms

12 During the experiment we implemented 30 SIC algorithms and found that they form groups 13 according to the selection of channels and how these are used in each algorithm. We also 14 found that algorithms within each group had very similar sensitivities to atmospheric effects 15 and surface emissivity variations. This is in agreement with sensitivity studies (Tonboe, 2010; Tonboe et al., 2011) using simulated <u>Tbs</u> generated by coupling a thermodynamic ice/snow 16 model to the Microwave Emissivity Model for Layered Snow Packs. To avoid redundancy we 17 18 only include here a selection of 13 sea ice algorithms (Table 1), which were chosen as 19 representatives of the groups.

#### 20 2.1 Selected algorithms

21 The first group of algorithms, represented by Bootstrap polarisation mode (BP, Comiso, 22 1986), includes polarisation algorithms. These algorithms primarily use 19 or 37 GHz 23 polarisation difference (difference between Tbs in vertical and horizontal polarisations of the 24 same frequency) or polarisation ratio (polarisation difference divided by the sum of the two Tbs). The next group uses 19V and 37V channels and is represented here by CalVal (CV, 25 Ramseier, 1991). Commonly known algorithms in this group are NORSEX (Svendsen et al., 26 1983), Bootstrap Frequency Mode (BF, Comiso, 1986) and UMass-AES (Swift et al., 1985). 27 28 Bristol (BR, Smith, 1996) represents the group that uses both polarisation and spectral 29 gradient information from the channels 19V, 37V and 37H. The NASA Team algorithm (NT, 30 Cavalieri et al., 1984) uses polarisation ratio at 19 GHz and gradient ratio at 19V and 37V. 31 ASI, a non-linear algorithm (Kaleschke et al., 2001), and Near 90 GHz linear (N90, Ivanova

Natalia Ivanova 15/6/2015 22:49 Deleted: validation and Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point

Natalia Ivanova 16/6/2015 10:30 Deleted: have Natalia Ivanova 25/3/2015 14:01 Deleted: their main principle Natalia Ivanova 16/6/2015 10:30 Deleted: ve Natalia Ivanova 27/5/2015 10:21 Deleted: , which Natalia Ivanova 25/3/2015 13:42 Deleted: brightness temperature

-	Natalia Ivanova 27/5/2015 10:23
	Deleted: the
-	Natalia Ivanova 25/3/2015 13:42
	Deleted: brightness temperature
1	Natalia Ivanova 25/3/2015 13:43
	Deleted: brightness temperature
/	Natalia Ivanova 16/6/2015 10:38
/	Deleted: by deploying using
1	Natalia Ivanova 16/6/2015 10:39
	Deleted:
λ	Natalia Ivanova 16/6/2015 10:39
1	Deleted: the
λ	Natalia Ivanova 10/6/2015 16:03
	Deleted: (
-	Natalia Ivanova 10/6/2015 16:03
	Deleted: )

1 et al., 2013) use the polarisation difference at near 90 GHz, both based on Svendsen et al. (1987). These are also called near 90 GHz or high-frequency algorithms. ESMR, named after 2 the single channel 18H radiometer on board Nimbus-5 operating from 1972 to 1977 (e.g. 3 Parkinson et al., 2004), and 6H (Pedersen, 1994) are one-channel algorithms using horizontal 4 polarisation at 18/19 GHz and 6 GHz respectively. ECICE (Shokr et al., 2008) and NASA 5 Team 2 (NT2, Markus and Cavalieri, 2000) represent a special class of more complex 6 7 algorithms where more channels are used and additional data may be needed as input. Finally 8 we consider combinations of algorithms (hybrid algorithms), where one of the algorithms is 9 expected to have low sensitivity to atmospheric effects over open water, and the other is 10 expected to have a better performance over ice. This group includes the NT+CV\_algorithm 11 (Ivanova et al., 2013): an average of NT and CV, the CV+N90 algorithm (Ivanova et al., 2013): an average of N90 and CV, and the OSISAF algorithm (Eastwood (ed.), 2012): a 12 weighted combination of BR over ice and BF over open water (note that BF is identical to 13 14 CV). The Bootstrap algorithm is tested in its two modes separately for the reasons explained 15 in Sect. 5.1.

All the algorithms were evaluated without applying open water/weather filter, since our aim
 was a comparison of the algorithms themselves. We consider performance of an open
 water/weather filter separately in Sect. 4.4.

#### 19 2.2 T<u>ie point</u>s

A necessary parameter for practically every algorithm is a set of tie points - typical Tbs of sea 20 ice (100% SIC) and open water (0% SIC), Under certain conditions, such as wind-roughened 21 water surface or thin sea ice, it is difficult to define a single tie point to represent the surface. 22 23 In nature, Tb may have a range of variability for the same ice type or open water due to 24 varying emissivity, atmospheric conditions, and temperature of the emitting layer. Therefore 25 the <u>scatter of retrieved SIC</u> near the tie points, which correspond to 0% and 100%, may lead 26 to negative or larger than 100% SICs. The ECICE algorithm uses the probability distribution 27 of the radiometric observations from each surface, instead of a single tie point,

In order to obtain an unbiased comparison of the algorithms, we developed a special set of tie points (Appendix A) based on <u>the RRDP for both hemispheres and for each of the three</u> radiometers: AMSR-E, SSM/I and SMMR. This enabled us to compare the algorithms directly without biases between the algorithms caused by differences in tie points. The set of Natalia Ivanova 10/6/2015 16:04 **Deleted:** (...amed after the single channe[ ... [23]

Natalia Ivanova 16/6/2015 10:41 Deleted: where

Natalia Ivanova 27/5/2015 10:32 Moved (insertion) [7]

#### Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point

Natalia 3/6/2015 16:40 Deleted: that Natalia Ivanova 16/6/2015 11:50 Deleted: concentrations...ICs. ...he ECI(.... [27]

Natalia Ivanova 16/6/2015 11:50 Deleted: have...developed a special set o.... [28]
1	the RRDP tie points differs from the original tie points provided with the algorithms. This is	
2	caused by the fact that we use different versions of the satellite data, which may have	Natalia Ivanova 14/6/2015 14:20  Deleted: ie-pointe points differs from the [29]
3	different calibrations. Also, the tie points published with the algorithms are typically valid for	
4	one instrument and need to be derived for each new sensor. In this study the RRDP, tie points	
5	were used for all the algorithms except ASI, NASA Team 2 and ECICE where such	Natalia 18/5/2015 10:36
6	traditional tie points were not applicable, and therefore the original implementations of these	Natalia Ivanova 14/6/2015 14:20
7	algorithms were used	Deleted: ie-pointe points wereareuse
		Natalia Ivanova 27/5/2015 10:32
8		without applying open water/weather filter, since our aim was a comparison of the algorithms themselves
9	3 <u>D</u> ata and <u>methods</u>	We consider performance of an open water/weather filter separately in Sect. 4.4.
		Natalia Ivanova 16/6/2015 11:57
10	3.1 Input data	Deleted: The data and[31] Natalia Ivanova 16/6/2015 13:23
11	Single swath Tbs were used as input to the algorithms. The SMMR data were obtained from	Deleted: The i
12	the US National Snow and Ice Data Centre – NSIDC (25 October 1978 to 20 August 1987,	Natalia Ivanova 25/3/2015 13:43
13	Njoku, 2003), EUMETSAT CM-SAF provided the SSM/I data (covering 9 July 1987 to 31	
14	December 2008, Fennig et al., 2013), and AMSR-E data were from NSIDC (from 19 June	
15	2002 to 3 October 2011; Ashcroft and Wentz, 2003). The footprints of all the channels were	/
16	matched and projected onto following footprints: the 6 GHz footprint of 75 km $\times$ 43 km for	
17	AMSR; SSM/I and SMMR channels were averaged to approximately 75 km x 75 km areas	
18	for all channels, except 6 GHz and 10 GHz of SMMR, which were used in their original	
19	resolution of 148 km $\times$ 95 km and 91 km $\times$ 59 km respectively.	
20	It is important to note that different datasets may have different calibration, and it can even be	
21	the case for different versions of the same dataset. Therefore the results presented in the	
22	following (especially the derived tie points) should be applied to other datasets with caution	
	iono wing (especially the derived <u>to point</u> s) should be uppred to other datasets whitedation.	Natalia Ivanova 14/6/2015 14:20
23	3.2 Validation data	Natalia Ivanova 16/6/2015 13:23
24	Ideally grow algorithm should be avaluated even onen water at interve distance distances	Deleted: The v
24 25	ideally, every algorithm should be evaluated over open water, at intermediate concentrations	
25 26	and <u>over</u> 100% ice cover. In practise, it is difficult to find high quality reference data at	Natalia Ivanova 16/6/2015 12:01
26	intermediate concentrations, especially for large areas covering entire satellite footprint (e.g.,	Deleted: at near100% ice cover. In prad[34]
27	$70 \text{ km} \times 45 \text{ km}$ for SSM/I at 19.3 GHz) and covering all seasons and ice types. Since the	/ //

relationship between SIC and <u>Tbs</u> at all frequencies is assumed linear (except for the various

noise contributions and a slight nonlinearity of the ASI algorithm), we argue that errors at

28

1 intermediate concentrations can be found by linear interpolation between errors at 0% and 100%. Thus the RRDP was built for validation of the algorithms at 0% and 100% SIC. 2 3 For the Open Water (OW) validation dataset (SIC = 0%), areas of open water were found 4 using ice charts from Danish Meteorological Institute (DMI) and the US National Ice Center 5 (NIC). The validation dataset for 0% SIC covered the following time periods: 1978-1987 (SMMR), 1987-2008 (SSM/I), and 2002-2011 (AMSR-E). For this paper we used the subsets 6 7 of 1978-1985 for SMMR, 1988-2008 for SSM/I and the full AMSR-E dataset. To create the Closed Ice (CI) validation dataset (SIC = 100%), areas of convergence were 8 9 identified in ENVISAT ASAR (Advanced SAR) derived sea ice drift fields available from the 10 PolarView (http://www.polarview.org) and MyOcean (http://www.myocean.eu) projects, The basic assumption for the convergence method to provide 100% sea ice is that during winter 11 12 after 24 hours of net convergence the open water areas (leads) have either closed or refroze. 13 During summer, this assumption does not hold due to the presence of melt ponds and the lack of refreezing. The CI dataset is therefore only valid for accurate tests during winter (October-14 15 April in the Northern Hemisphere and May-September in the Southern Hemisphere). The CI dataset covered years 2007-2008 for SSM/I and 2007-2011 for AMSR-E. SMMR was not 16 17 included, because there were no SAR data available at that time. Note that the CI reference 18 dataset may still have some small fraction of residual open water. This however, does not 19 jeopardize our use of the minimum standard deviation as a measure of algorithm performance, 20 since we are only looking for the relative differences between algorithms. 21 Fig. 1 (Northern Hemisphere) and Fig. 2 (Southern Hemisphere) show the coverage of a 22 subset of the RRDP for the SSM/I instrument during winters of 2007 and 2008, which 23 contains about 30,000 data points. The dataset also includes the areas where there normally 24 should not be any ice (blue triangles in the left panels of the figures) in order to test the ability 25 of the algorithms to capture these correctly. The coverage of the RRDP is displayed both in 26 terms of Tbs in the 6 channels of the SSM/I instrument (main panels), and spatial distribution 27 (embedded maps). The other years, mentioned above and not shown in the figures, include 28 approximately 4,000 data points per year, except the SMMR period with about 1,000 points 29 per year, but the full dataset extends from 1978 to 2011. We are confident that these locations 30 represent the full amplitude of weather influence on measured Tbs and hence retrieved SICs. 31 The left panels of Fig. 1 and Fig. 2 show the RRDP SSM/I subset in a classic (Tb37v,

32 Tb19v)-space, which is the one sustaining the BF algorithm (or CV). The ice line extends

	Natalia Ivanova 27/5/2015 10:37
	Deleted: as
$\mathbf{i}$	Natalia Ivanova 27/5/2015 10:37
	<b>Deleted:</b> combination of performances at
N	Notolia lyanaya 27/5/2015 10:28
	Natalia Ivanova 27/5/2015 10.36
1	Deleted:
$\left( \right)$	Natalia Ivanova 25/3/2015 14:35
	Deleted: a Round Robin Data Package (
	Natalia Ivanova 25/3/2015 14:35
	Related: )
	Netelia lueneuro 20/2/2015 00:46
	Natalia Ivanova 50/5/2015 09.46
/	Deleted: (
1	Natalia Ivanova 30/3/2015 09:46
/	Deleted: )
1	Natalia Ivanova 26/3/2015 14:51
	Deleted: got
/ _	Natalia Ivanova 26/3/2015 14:51
/	Deleted: "
Λ	Natalia Ivanova 16/6/2015 12:04
	Deleted: ,
-	Natalia Ivanova 14/6/2015 14:16
	Deleted: -
1	Natalia Ivanova 27/5/2015 10:40
	<b>Deleted:</b> the time of SMMR
	Natalia Ivanova 10/6/2015 16:56
	Deleted:
//	Natalia Ivanova 10/6/2015 16:56
"	Deleted: Fig.
/ /	Natalia Ivanova 16/6/2015 12:07
	Deleted: seasons
	Natalia 3/6/2015 16:41
	Deleted: right
1	Deleted: right Natalia Ivanova 25/3/2015 13:43
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures (
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: )
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: i varia of
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Nutritio 20100015 10:42
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16 Moved down [2]: In all panels, square symbols
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16 Moved down [2]: In all panels, square symbols are used for the OW dataset, and circles are used for the CI dataset. In the Td datasets the OW combole
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16 Moved down [2]: In all panels, square symbols are used for the OW dataset, and circles are used for the CI dataset. In the Tb diagrams, the OW symbols are coloured according to Tb22v values (left colour
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16 Moved down [2]: In all panels, square symbols are used for the OW dataset, and circles are used for the CI dataset. In the Tb diagrams, the OW symbols are coloured according to Tb22v values (left colour scale), while the CI symbols are coloured according
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16 Moved down [2]: In all panels, square symbols are used for the OW dataset, and circles are used for the CI dataset. In the Tb diagrams, the OW symbols are coloured according to Tb22v values (left colour scale), while the CI symbols are coloured according to Tb37h values (right colour scale). The colouring of CI methods in the values of the Values (left values in the values in th
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16 Moved down [2]: In all panels, square symbols are used for the OW dataset, and circles are used for the CI dataset. In the Tb diagrams, the OW symbols are coloured according to Tb22v values (left colour scale), while the CI symbols are coloured according to Tb37h values (right colour scale). The colouring of CI symbols is also used in the embedded maps.
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16 Moved down [2]: In all panels, square symbols are used for the OW dataset, and circles are used for the CI dataset. In the Tb diagrams, the OW symbols are coloured according to Tb22v values (left colour scale), while the CI symbols are colouring of CI symbols is also used in the embedded maps. Natalia Ivanova 16/6/2015 12:10
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16 Moved down [2]: In all panels, square symbols are used for the OW dataset, and circles are used for the CI dataset. In the Tb diagrams, the OW symbols are coloured according to Tb22v values (left colour scale), while the CI symbols are coloured according to Tb37h values (right colour scale). The colouring of CI symbols is also used in the embedded maps. Natalia Ivanova 16/6/2015 12:10 Deleted: .
	Deleted: right Natalia Ivanova 25/3/2015 13:43 Deleted: Brightness Temperatures ( Natalia Ivanova 25/3/2015 13:43 Deleted: ) Natalia Ivanova 27/5/2015 10:42 Deleted: in terms of Natalia 3/6/2015 16:42 Deleted: sea ice concentrations Natalia Ivanova 31/3/2015 10:16 Moved down [2]: In all panels, square symbols are used for the OW dataset, and circles are used for the CI dataset. In the Tb diagrams, the OW symbols are coloured according to Tb22v values (left colour scale), while the CI symbols are colouring of CI symbols is also used in the embedded maps. Natalia Ivanova 16/6/2015 12:10 Deleted: . Natalia Ivanova 16/6/2015 12:10

Deleted:

9

Natalia Ivanova 27/5/2015 10:43

1 along different ice types. In the Northern Hemisphere, ice types vary from MYI with lower values of Tb37h (colouring) to first-year ice (FYI) with higher values of Tb37h. In the 2 3 Southern Hemisphere, the ice line extends between ice types A, representing FYI, and B, sea ice with a heavy snow cover (Gloersen et al., 1992). The so-called FYI and MYI tie points 4 5 would typically lie along this line. The location of these different ice types can be seen on the embedded maps, and matches the expected distribution of older and younger ice in the 6 7 Northern Hemisphere. In the (Tb37v, Tb19v)-space, the OW symbols are grouped mostly in 8 one point (OW tie point), but also present some spread due to the noise induced by 9 geophysical parameters such as atmospheric water vapour, liquid water- and jce clouds, 10 surface temperature variability and surface roughening by wind (all collectively called 11 geophysical noise). Note that the majority of the symbols is grouped around one point and a 12 lot less are spread along the line, however this is not easy to see from the plots because many points are hidden behind each other. The Tb22v colouring of the OW symbols illustrates how 13 14 the variability of the OW signature is mostly driven by factors impacting also the 22 GHz 15 channel (atmospheric water vapour content). The length and orientation of the OW spread, 16 and especially the distance from the OW points to the line of ice points, determines the 17 strength of algorithms built on these frequencies (e.g. BF or CV) at low SIC. The right panels show the same areas but in a (Tb85v, Tb85h)-space. The ice line is very well 18 defined (limited lateral spread), almost with a slope of one, However, it is difficult to define 19 20 an OW point in this axis, since samples are now spread along a line. This "weather line" even intersects the ice line, illustrating that algorithms based purely in the (Tb85v, Tb85h)-space 21 (like the ASI and N90 algorithms) have difficulties at discriminating open water from sea ice 22 23 under certain atmospheric conditions (Kern, 2004). 24 The embedded maps display the winter location of the OW samples (same location for the 25 whole RRDP, for all instruments). In both hemispheres, these locations follow sea ice retreat 26 in summer months to always capture ocean/atmosphere conditions in the vicinity of sea ice 27 (not shown). The absence of data near the North Pole is due to the ENVISAT ASAR not covering areas north of  $87_{\bullet}^{0}$  The somewhat limited coverage of the sea ice samples of the 28 29 Pacific sector in the Northern Hemisphere and many areas in the Southern Hemisphere is due 30 to scene acquisition strategies of the ENVISAT mission. 31 After validation of the algorithms using the obtained datasets at 0% and 100% we found that

32 some of the algorithms are hard to validate at these values because they are not designed to

# Natalia Ivanova 10/6/2015 15:35

Deleted: multi-year sea ice (MYI) ... YI w ... [35]

Natalia 3/6/2015 16:42

Deleted: Please n... ote that the majority o ... [36]

_	Natalia Ivanova 16/6/2015 12:13
	Deleted: ice concentrations
_	Natalia Ivanova 16/6/2015 12:13
	Deleted: hand side
	Natalia 3/6/2015 16:43
1	Deleted: sthe same data[37]
1	Natalia Ivanova 27/5/2015 10:45
	Deleted:pace. The ice line is very well [38]
	Natalia 3/6/2015 16:44
7	Deleted: On the other hand
1	Natalia Ivanova 27/5/2015 10:46
	Deleted:pace (like the ASI and N90[39]

enable retrievals outside the SIC range of 0% -100% (NASA Team2, ECICE) or are affected 1 2 by a combination of large bias and nonlinearity at high SIC (ASI). This complicates comparison of these algorithms directly to other algorithms because these effects cut part of 3 4 SD of the retrieved SIC, while we aim at evaluating the full variability around these reference 5 values (0% and 100%). We implemented the algorithms (except these three) without cut-offs, allowing thus SIC values below 0% and above 100% as well. In order to be able to include 6 7 these three algorithms in the inter-comparison, we have produced reference datasets of Tbs in 8 every channel that correspond to values of SIC 15% and 75% for an additional evaluation. We 9 find that the algorithms' performance at 15% is representative of that at 0%, and so is 75% to 10 100%. Therefore we show the results of evaluation only at SIC 15% and 75%. By "representative" here we mean that the algorithms' ranking does not change significantly 11 (more details in Sect. 4.1. and Table 2) even though the absolute values of SD are different. 12 13 The SIC 15% dataset was constructed by mixing the average FYI signature (Tb) with the OW

14 dataset, i.e.

15

# $Tb15 = 0.85 * Tb0(t) + 0.15 * Tb100(\overline{FY}),$

where Tb0 (OW Tb) is multiplied by 0.85 (85% water) and is varying with time, while Tb100 16 (ICE Tb) is multiplied by 0.15 (15% ice) and is an average value of the FYI signature, 17 constant for all data points from the RRDP (see above) for a given year. By using the SIC 18 19 15% dataset we aim at testing sensitivity of the algorithms to the atmospheric influence, over 20 the ocean and not to variability in emissivity of ice. Therefore we keep Tb of ice constant.

The SIC 75% dataset was generated similarly to the SIC 15% dataset, but with full variability 21 22 of ice and 25% of the average OW signature:

# 23

## $Tb75 = 0.75 * Tb100(t) + 0.25 * Tb0(\overline{OW}).$

For the SIC 75%, dataset the variability in Tbs is driven by variability at SIC 100% 24 (Tb100(t)), and not at SIC 0%. We keep SIC 0% Tb (Tb0) constant at the average value of the 25 OW signature for a given year in order to avoid the influence of seasonally varying 26 27 atmospheric conditions, which would have happened if we mixed variable SIC 100% Tbs with variable SIC 0% Tbs. As a consequence, the SIC 75% dataset will reflect a lower 28 29 atmospheric variability than we would have to expect from a real SIC 75% dataset. Since the 30 CI dataset is only valid for the winter season, the same applies for this SIC 75% dataset.

# Deleted: cut-off the SIC at 0% and 100%

### Natalia Ivanova 24/5/2015 17:49

Deleted: Some algorithms have a special way of estimating tie-points and a non-linear way of dealing with ice concentrations near 0% and 100% or they use simple truncation at 0% and 100% This complicates comparison of these algorithms directly to other algorithms because the standard deviation of the retrieved ice concentration is affected by the treatment at the 0% and 100% reference points. Therefore, we have produced reference datasets of brightness temperatures in every channel that correspond to values of SIC 15% and 75% for an additional evaluation. A bias at these intermediate reference points will indicate a bias at intermediate concentrations in general. Natalia Ivanova 25/3/2015 13:43

### Deleted: brightness temperature Natalia Ivanova 9/6/2015 10:08 Formatted: Right Natalia Ivanova 9/6/2015 10:08 Deleted: Natalia Ivanova 25/3/2015 13:43 Deleted: brightness temperature Natalia Ivanova 10/6/2015 18:40 Deleted: the added 15% FYI signature is an average value Natalia Ivanova 10/6/2015 18:40 Deleted: es Natalia Ivanova 9/6/2015 10:08 Formatted: Right Natalia Ivanova 9/6/2015 10:09 Deleted: Natalia Ivanova 9/6/2015 10:09 Deleted: Natalia Ivanova 10/6/2015 18:41 Deleted: SIC Natalia Ivanova 25/3/2015 13:43 Deleted: brightness temperature Natalia Ivanova 10/6/2015 18:42 Deleted: We keep SIC 0% brightness temperature constant in order to avoid mixing the atmospheres Natalia Ivanova 25/3/2015 13:43 Deleted: brightness temperature Natalia Ivanova 25/3/2015 13:43

Deleted: brightness temperature

11

(1)

 $(2)^{\bullet}$ 

1 Jt is noteworthy that we originally had designed a reference dataset of SIC 85%, but the positive biases of the ASI and NASA Team 2 algorithms were larger than 15% and thus part 2 of the SD was still cut-off at 100%. Therefore it was necessary to use a SIC 75% dataset 3 4 instead. The performance of the algorithms was consistent between the SIC 75%, 85% and 5 100% datasets, and therefore we consider such substitution acceptable. This way of mixing Tbs is not entirely physical since we are mixing Tbs seen through two different atmospheres. 6 7 However, since the majority of the signal originates from either open water or ice, and we use 8 fixed Tbs for the remaining fraction, we consider the results to be still reasonably 9 representative for algorithm performance evaluation. 10 Normally, SIC products are truncated at 0% and 100% to allow only physically meaningful SIC values, though this does not apply to ECICE because it employs the inequality constraint 11 of 0% < SIC < 100% in its optimization formulation. However, as the intention here is to 12 investigate the statistical properties of the retrievals, we will analyse actual SIC as retrieved 13 14 with the algorithms, without truncation, which means the retrieved values can be negative or 15 above 100%. Instrument and geophysical noise cause the Tbs to vary around the chosen tie 16 points, and it cannot be avoided that at least a part of this noise is translated into some noise in

18 3.3 Reference dataset for melt pond sensitivity assessment

the retrieved SIC.

17

19 Daily gridded SIC and melt pond fraction (MPF) reference dataset for the Arctic (Rösel et al., 20 2012a) was derived from clear-sky measurements of reflectances in channels 1, 3 and 4 of the 21 MODerate resolution Imaging Spectroradiometer (MODIS) in June\_August 2009. The MPF 22 is determined from classification based on a mixed-pixel approach. It is assumed that the reflectance measured over each MODIS  $500 \text{ m} \times 500 \text{ m}$ , grid cell comprises contributions 23 24 from three surface types: melt ponds, open water, sea ice/snow (Rösel et al., 2012a). By using 25 known reflectance values (e.g. Tschudi et al., 2008) a neural network was built, trained, and 26 applied (Rösel et al., 2012a). MPF is given as fraction of sea ice area (not grid cell) covered 27 by melt ponds. For the sensitivity analysis in this work, a total of 8152 data points were selected from this dataset, so that <u>SD</u> of <u>MPF</u> over each <u>100 km × 100 km</u> area was less than 28 29 5%, SIC variations were less than 5%, SIC itself was larger than 95% and cloud cover less 30 than 10%.

### Natalia Ivanova 27/5/2015 11:00

**Deleted:** The 15% and 75% reference datasets are constructed to be able to compare algorithms and their standard deviation at intermediate concentrations and to compare algorithms with nonlinearities near 100% ice concentration (e.g. ASI) and algorithms with large positive biases when implemented without open water filter (e.g. ASI and NASA Team 2)...t is noteworthy that we (....[41])

Natalia Ivanova 25/3/2015 13:43 Deleted: brightness temperature...bs to va ... [43]

#### Natalia Ivanova 14/6/2015 14:16 Deleted: -

Natalia Ivanova 16/6/2015 13:18 **Deleted:** of...June-, July, and ...ugust 20(....[44])

The MODIS data were undergone a bias correction (Mäkynen et al., 2014) based on an inter comparison between ENVISAT ASAR wide swath mode (WSM) imagery, in-situ sea ice
 surface observations, weather station reports and the daily MODIS MPF and SIC dataset. It
 was found that the MODIS SIC was negatively biased by 3% and MPF was positively biased
 by 8%. An investigation of the 8-day composite dataset of the MODIS MPF and SIC dataset
 with regard to their seasonal development during late spring/early summer confirmed the
 existence of such biases.

8 MODIS SIC was only used for the summer period to evaluate the algorithms performance 9 over melt ponds, but not for the SIC validation. This is due to lack of a sufficiently quality-10 controlled MODIS SIC product with potential of a validation dataset. The cloud filters 11 developed for lower latitudes are not reliable enough in the polar latitudes. Moreover, 12 identification of ice/water in the images depends on thresholds, which will bring the problem 13 of tie points. The validation of the MPF dataset by Rösel et al. (2012a) revealed accuracy of 14 5% to 10%. Because of the methodology used, the MPF is tied to the other two surface types: 15 open water in leads and openings between the ice floes and sea ice / snow. Therefore it can be 16 assumed that the accuracy of the fraction of these two other surface types is of the same 17 magnitude as that of the MPF: 5% to 10%, which can be considered as not sufficient for 18 quantitative SIC evaluation.

### 19 **3.4** Reference dataset for the thin ice tests

20 Sensitivity of the algorithms to thickness of thin ( $\leq 50 \text{ cm}$ ) sea ice was evaluated using a thin 21 ice thickness dataset for the Arctic Ocean, compiled for this particular purpose. To produce 22 this dataset, large (100 km diameter) homogenous areas of ~100% thin ice were identified as 23 areas with dark and homogenous texture by visual inspection of 175 ENVISAT ASAR WSM 24 scenes. The same procedure as when producing ice charts was applied. Thin ice thickness was 25 subsequently derived for these areas using ESA's L-band Soil Moisture and Ocean Salinity 26 (SMOS) observations (Huntemann et al., 2014; Heygster et al., 2014). The dataset covers the time period from 1 October to 12 December 2010 and consists of 991 sea ice thickness data 27 points. For these selected grid cells AMSR-E <u>Tb</u>s were extracted and used as input to the SIC 28 29 algorithms.

Natalia Ivanova 2/4/2015 16:49
Deleted: . For this purpose a
Natalia Ivanova 2/4/2015 16:49
Deleted: was compiled by
Natalia Ivanova 30/3/2015 11:11
Deleted: manually
Natalia Ivanova 2/4/2015 16:51
<b>Deleted:</b> identifying large (100 km diameter) areas of ~100% homogenous thin ice areas in the Arctic Ocean using
Natalia Ivanova 16/6/2015 13:25
Deleted: (Advanced Synthetic Aperture Radar, Wide Swath Mode) data (175
Natalia Ivanova 2/4/2015 16:53
Deleted: )
Natalia Ivanova 2/4/2015 16:47
Deleted:, and
Natalia Ivanova 2/4/2015 16:47
Deleted: subsequently deriving
Natalia Ivanova 2/4/2015 16:47
Deleted: t
Natalia 3/6/2015 16:49
Deleted: sensor
Natalia Ivanova 30/3/2015 11:14
Deleted: measurements of
Natalia Ivanova 25/3/2015 13:43

Deleted: brightness temperature

1	3.5 <u>Substitution of weather filters by atmospheric correction</u>		Natalia Ivanova 24/5/2015 15:59 Deleted: andaAmospheric corr[45]
2	SIC retrievals can be contaminated due to wind roughening of the ocean surface, atmospheric		
3	water vapour and <u>CLW</u> , as well as precipitation. Traditionally, the atmospheric effects on the		Natalia Ivanava 20/E/2015 12:26
4	SIC retrievals are <u>removed</u> by applying an open water/weather filter based on gradient ratios	/	Deleted: cloud liquid waterLW, as well [46]
5	of <u>Tbs</u> for SMMR (Gloersen and Cavalieri, 1986) and SSM/I (Cavalieri et al., 1995):		
6	SMMR: $SIC = 0$ if $GR(18/37) > 0.07$ (3)*	$\leftarrow$	Natalia Ivanova 9/6/2015 10:09
7	$SSM/I: SIC = 0  if \ GR(19/37) > 0.05 \ and/or \ GR(19/22) > 0.045,$ (4)		Natalia Ivanova 9/6/2015 10:09
8	where the gradient ratios of Tb18 $\underline{v}$ (Tb19 $\underline{v}$ ) and Tb37 $\underline{v}$ (GR(18/37) and GR(19/37)) are most		Formatted: Right Natalia Ivanova 9/6/2015 10:09
9	sensitive to <u>CLW</u> and the gradient ratio of Tb19v, and Tb22v, (GR(19/22)) mainly detects		Deleted:
10	water vapour. We tested the performance of this technique (more details in Sect. 4.4), and		<b>Deleted:</b> V(Tb19vV and[47]
11	found that it is removing not only atmospheric effects but also ice itself, which we found to be		Natalia 3/6/2015 18:53
12	unacceptable for a SIC algorithm.		Deleted: id that it is removing not only [48]
13	Therefore we chose not to use the open water/weather filters, but implement an alternative		
14	solution, following Andersen et al. (2006) and Kern (2004), The suggested method consists of		Natalia Ivanava 22/E/2015 12:21
15	applying a more direct atmospheric correction methodology, where the input SSM/I_Tbs in all	Λ	Deleted:         Fllowing Andersen et al. (200([49])
16	the channels used by the algorithms, are corrected with regard to atmospheric and surface		
17	effects using a Radiative Transfer Model (RTM).		Natalia 8/6/2015 00:50
18	$Tb_{corr} = Tb_{measured} - (Tb_{atm} - Tb_{ref}) $ (5)		Deleted: of Natalia Ivanova 27/5/2015 16:48
19	$Tb_{atm} = Tb(f, p, WS, WV, CLW, SST, T_{ice}, SIC, FMYI) $ (6)		Deleted: ( Natalia 8/6/2015 09:57
20	$Tb_{ref} = Tb(f, p, 0, 0, 0, SST_{ref}, T_{ice \ ref}, SIC, FMYI), $ (7)	١	Deleted: Wentz (1997) Natalia Ivanova 9/6/2015 09:30 Formatted: Right
21	where f - frequency, p - polarisation, WS - wind speed, WV - water vapour, SST - sea_		Natalia Ivanova 9/6/2015 09:29
22	surface temperature, $T_{ice_{r}}$ – ice temperature, and FMYI – MYI fraction (Meissner and Wentz,		Deleted: , (5)
23	2012 and Wentz, 1997). Tb <sub>corr</sub> is measured Tb minus the difference between simulations		Deleted: Tice
24	with $(Tb_{atm})$ and without $(Tb_{ref})$ atmospheric effects (Meissner and Wentz, 2012 and Wentz,		Natalia Ivanova 9/6/2015 09:39
25	1997). In order to calculate $Tb_{ref}$ , zero values were assigned to WS, WV and CLW, while		<b>Deleted:</b> and simulations with calm wind and clear sky.)
26	$SST_{ref} = 271.5K_{and} T_{ice ref} = 265K_{and} T_{ice ref} = 265K_$	_	Natalia 5/6/2015 12:57
27	water vapour, and <u>2 m</u> air temperature from the ECMWF ERA-Interim Numerical Weather		Deleted: Natalia Ivanova 16/6/2015 13:31
28	Prediction (NWP) re-analysis were used in this process. Following the results of Andersen et		Deleted: F
29	al. (2006) we did not use $\underline{CLW}$ and precipitation from the NWP data because these are	$\sum$	<b>Deleted:</b> at 2 m
30	considered to be less consistent with the observed <u>Tbs</u> (also confirmed by our own analysis).		Natalia Ivanova 16/6/2015 13:31 Deleted: ae used in this process (3-hour

1 <u>Therefore CLW is 0 also when calculating  $Tb_{atm}$  in this case.</u> The NWP model grid <u>cells are</u>

2 collocated with the AMSR-E/SSM/I swath <u>Tbs</u> in time and space. Using the 3-hourly NWP

3 fields we ensure a time difference between the NWP data and the satellite data to be within4 | 1.5 h.

- 5 In order to evaluate the effect of suggested atmospheric correction for SSM/I we selected six
- 6 test cites in the Arctic, which are subject to different weather types: for some it is more
- 7 common to have storms and strong winds, and some are typically guieter. The total amount of
- 8 points sampled at these locations is 2320 and covers the entire year 2008. The results obtained
- 9 were similar for AMSR-E (not shown here).

# 10 **3.6** The validation/evaluation procedure

11 The structure of the section o

15 The criteria for the validation and evaluation procedure were aimed at minimizing the sensitivity to the atmospheric effects and surface emissivity variations as described in the 16 17 Introduction. In addition, we considered the following aspects: 1) data record length: algorithms using near 90 GHz channels cannot be used before 1991 when the first functional 18 19 SSM/I 85 GHz radiometer started to provide consistent data, 2) spatial resolution: ranges from 20 over 100 km to less than 10 km for different channels and instruments, 3) performance along 21 the ice edge, where new ice formation is common in winter, and 4) performance during the 22 summer melt. Additional criteria for the algorithm selection were: the possibility of reducing 23 regional error using, e.g., NWP data and forward models; and the possibility to use dynamic 24 tie points. The latter is to reduce sensitivity to inter-sensor calibration differences and error 25 sources, which may be characterized by seasonal and inter-annual variability and/or have 26 global and regional climatological trends. 27

### Natalia Ivanova 16/6/2015 13:33 Deleted: points Natalia Ivanova 25/3/2015 13:44 Deleted: brightness temperature

Natalia 3/6/2015 16:54
Deleted:
Natalia 3/6/2015 16:54
Deleted: more quiet
Natalia Ivanova 25/3/2015 13:44
Deleted: Brightness temperature
Natalia Ivanova 25/3/2015 14:35
Deleted: a so-called Round Robin Data Package (
Natalia Ivanova 25/3/2015 14:35
Deleted: )
Natalia Ivanova 27/5/2015 16:50
Deleted: B
Natalia Ivanova 10/6/2015 19:32
Deleted: to retrieve SIC
Natalia Ivanova 10/6/2015 19:28
<b>Deleted:</b> It is noted that the RRDP, including all
the reference data, collocated brightness
request to anyone interested in inter-comparing,
improving or developing SIC algorithms (http://esa-
seatce-cct.org).
Natalia Ivanova 16/6/2015 13:54
Formatted: Indent: Left: 0 cm
Deleted: based on the desire to
Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: time
Natalia (Valiova 27/5/2015 10.51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 2/6/2015 16:51
Deleted:     based on the desire to       Natalia     3/6/2015 16:54       Deleted:     ation       Natalia     3/6/2015 16:54
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: ation
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: in
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: ies
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: ies Natalia Ivanova 27/5/2015 16:52 Deleted: e
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: ies Natalia Ivanova 27/5/2015 16:52 Deleted: e
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: e
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: attenuation Natalia Ivanova 14/6/2015 14:20
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: attenuation Natalia Ivanova 14/6/2015 14:20 Deleted: e soit
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point Natalia Ivanova 16/6/2015 14:51
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: attenuation Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point Natalia Ivanova 16/6/2015 13:51 Deleted: c
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: attenuation Natalia Ivanova 14/6/2015 14:20 Deleted: ic-point Natalia Ivanova 16/6/2015 13:51 Deleted: to Natalia Ivanova 16/6/2015 13:51 Deleted: to
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: ic-point Natalia Ivanova 16/6/2015 13:51 Deleted: c
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: ice-point Natalia Ivanova 16/6/2015 13:51 Deleted: c Natalia Ivanova 16/6/2015 13:51 Deleted: c
Natalia Ivanova 27/5/2015 16:51 Deleted: based on the desire to Natalia 3/6/2015 16:54 Deleted: ation Natalia 3/6/2015 16:54 Deleted: of Natalia Ivanova 27/5/2015 16:51 Deleted: e the Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: e Natalia Ivanova 27/5/2015 16:52 Deleted: attenuation Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point Natalia Ivanova 16/6/2015 13:51 Deleted: to Natalia Ivanova 16/6/2015 13:51 Deleted: e Natalia Ivanova 16/6/2015 13:47 Deleted: e

Deleted: s in error sources (Andersen et al, 2006)

2	4.1 The SIC algorithms inter-comparison and evaluation
3	To <u>evaluate</u> performance of the algorithms, <u>SD (Table 2) and bias (not shown) relative to the</u>
4	validation datasets (Sect. 3.2) were calculated for summer and winter separately. The
5	algorithms in the Table 2 are sorted by the average SD of all the cases, starting with the
6	smallest one, These values are averages weighted by the number of years when data were
7	available for each instrument, thus giving more weight to SSM/I as the one providing the
8	longest dataset. SSM/I data were available during 21 years (1988-2008) for the low-
9	frequency algorithms, i.e. the algorithms using frequencies up to 37 GHz (except 6H because
10	this channel was not available on SSM/I), and for high-frequency algorithms during 17 years
11	(1992-2008). SMMR did not have high frequencies and thus only applies to the low-
12	frequency algorithms (8.7 years, November 1978-1987). The reference column (Ref) in the
13	Table 2 contains SD of the full SIC 0% and SIC 100% datasets. It shows that the SD of the
14	algorithms relative to each other, that is the algorithms ranking, does not change significantly
15	when substituting SIC 100% dataset with SIC 75%, and SIC 0% dataset with SIC 15%.
16	However, the absolute values of SD are altered
17	The high-frequency algorithms ASI and N90 have a clear difference in SDs at low and high
1.0	SIC This is also true for the CVI NOO also within that the conception is smaller as this had wid
18	SIC, Init is also true for the CV+1N90 algorithm, but the separation is smaller as this hybrid
18 19	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms
18 19 20	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms mainly originate from the low <u>SIC</u> cases, where the atmospheric influence is more
18 19 20 21	algorithm also contains a low-frequency component. The large $SDs$ for these algorithms mainly originate from the low $SIC$ cases, where the atmospheric influence is more pronounced than it is for the low-frequency algorithms. Winter $SDs$ for most of the
18 19 20 21 22	algorithm also contains a low-frequency component. The large $SDs$ for these algorithms mainly originate from the low $SIC$ cases, where the atmospheric influence is more pronounced than it is for the low-frequency algorithms. Winter $SDs$ for most of the algorithms tend to be lower than the ones of summer in the same category of $SIC$ and
18 19 20 21 22 23	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms mainly originate from the low <u>SIC</u> cases, where the atmospheric influence is more pronounced than <u>it is</u> for <u>the</u> low-frequency algorithms. Winter <u>SDs</u> for most of the algorithms tend to be lower than the ones of summer_in the same category of <u>SIC</u> and instrument.
18 19 20 21 22 23 24	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms mainly originate from the low <u>SIC</u> cases, where the atmospheric influence is more pronounced than <u>it is</u> for <u>the</u> low-frequency algorithms. Winter <u>SDs</u> for most of the algorithms tend to be lower than the ones of summer_in the same category of <u>SIC</u> and instrument. We chose to not show the biases here because we put more weight on SD in the algorithm
18 19 20 21 22 23 24 25	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms mainly originate from the low <u>SIC</u> cases, where the atmospheric influence is more pronounced than <u>it is</u> for <u>the</u> low-frequency algorithms. Winter <u>SDs</u> for most of the algorithms tend to be lower than the ones of summer_in the same category of <u>SIC</u> and instrument. We chose to not show the biases here because we put more weight on SD in the algorithm evaluation. The bias was found to be similar within low- and high-frequency algorithm.
<ol> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> </ol>	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms mainly originate from the low <u>SIC</u> cases, where the atmospheric influence is more pronounced than <u>it is</u> for <u>the</u> low-frequency algorithms. Winter <u>SDs</u> for most of the algorithms tend to be lower than the ones of summer_in the same category of <u>SIC</u> and instrument. <u>We chose to not show the biases here because we put more weight on SD in the algorithm</u> <u>evaluation. The bias was found to be similar within low- and high-frequency algorithm</u> , categories and it was sensitive to the choice of tie points, which made it less suitable for the
<ol> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> <li>27</li> </ol>	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms mainly originate from the low <u>SIC</u> cases, where the atmospheric influence is more pronounced than <u>it is</u> for <u>the</u> low-frequency algorithms. Winter <u>SDs</u> for most of the algorithms tend to be lower than the ones of summer_in the same category of <u>SIC</u> and instrument. We chose to not show the biases here because we put more weight on SD in the algorithm evaluation. The bias was found to be similar within low- and high-frequency algorithm, categories and it was sensitive to the choice of tie points, which made it less suitable for the evaluation procedure. In the Northern Hemisphere the stronger negative biases <u>were</u>
<ol> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> <li>27</li> <li>28</li> </ol>	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms mainly originate from the low <u>SIC</u> cases, where the atmospheric influence is more pronounced than <u>it is</u> for <u>the</u> low-frequency algorithms. Winter <u>SDs</u> for most of the algorithms tend to be lower than the ones of summer_in the same category of <u>SIC</u> and instrument. We chose to not show the biases here because we put more weight on SD in the algorithm evaluation. The bias was found to be similar within low- and high-frequency algorithm, categories and it was sensitive to the choice of tie points, which made it less suitable for the evaluation procedure. In the Northern Hemisphere the stronger negative biases <u>were</u> <u>dominated</u> by the high <u>SIC</u> cases (with the exception of the N90, CV+N90, NT2 and ASI),
<ol> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> <li>27</li> <li>28</li> <li>29</li> </ol>	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms mainly originate from the low <u>SIC</u> cases, where the atmospheric influence is more pronounced than <u>it is</u> for <u>the</u> low-frequency algorithms. Winter <u>SDs</u> for most of the algorithms tend to be lower than the ones of summer_in the same category of <u>SIC</u> and instrument. <u>We chose to not show the biases here because we put more weight on SD in the algorithm</u> <u>evaluation. The bias was found to be similar within low- and high-frequency algorithm</u> , categories and it was sensitive to the choice of tie points, which made it less suitable for the evaluation procedure. In the Northern Hemisphere the stronger negative biases <u>were</u> <u>dominated</u> by the high <u>SIC</u> cases (with the exception of the N90, CV+N90, NT2 and ASI), while stronger positive biases <u>were dominated</u> by the low <u>SIC</u> cases. Algorithms ASI, NT2
<ol> <li>18</li> <li>19</li> <li>20</li> <li>21</li> <li>22</li> <li>23</li> <li>24</li> <li>25</li> <li>26</li> <li>27</li> <li>28</li> <li>29</li> <li>30</li> </ol>	algorithm also contains a low-frequency component. The large <u>SDs</u> for these algorithms mainly originate from the low <u>SIC</u> cases, where the atmospheric influence is more pronounced than <u>it is</u> for <u>the</u> low-frequency algorithms. Winter <u>SDs</u> for most of the algorithms tend to be lower than the ones of summer_in the same category of <u>SIC</u> and instrument. We chose to not show the biases here because we put more weight on SD in the algorithm evaluation. The bias was found to be similar within low- and high-frequency algorithm, categories and it was sensitive to the choice of tie points, which made it less suitable for the evaluation procedure. In the Northern Hemisphere the stronger negative biases <u>were</u> <u>dominated</u> by the high <u>SIC</u> cases (with the exception of the N90, CV+N90, NT2 and ASI), while stronger positive biases <u>were</u> <u>dominated</u> by the low <u>SIC</u> cases. Algorithms ASI, NT2 and ECICE <u>were</u> positively biased for all the cases in both hemispheres. Note that the

Natalia Ivanova 28/5/2015 10:49
Deleted: assess
Natalia 18/5/2015 11:33
Deleted: bias and
Natalia Ivanova 25/3/2015 13:12
Deleted: standard deviation
Natalia 18/5/2015 11:34
Deleted: from
Natalia Ivanova 28/5/2015 10:49
<b>Deleted:</b> for the Northern and (Fig. 3 upper panels) and the Southern (Fig. 3 bottom panels) hemispheres for the instruments AMSR-E, SSM/I and SMMR (shown in different symbols in the figures) during
Natalia 18/5/2015 11:34
Deleted: (empty symbols)nd winter set
Natalia Ivanova 30/3/2015 11:18
Deleted: (of all the cases) values of the
Natalia 18/5/2015 11:35
Deleted: biasD of all the cases, starting
Natalia Ivanova 27/5/2015 16:56
<b>Deleted:</b> averages of standard deviations [54]

# Natalia Ivanova 28/5/2015 12:09

Natalia 3/6/2015 16:56 Deleted: s

1	both hemispheres in this study. These three algorithms are the only ones for which it was not	
2	possible to use the RRDP tie points as was done for the other algorithms, and this may explain	
3	part of the bias (see Sect. 4.5 for further discussion on tie points). For the algorithms with	7
4	large biases and cut-offs at SIC 100%, the bias reduces our ability to estimate their SD	/
5	properly using the chosen approach and thus makes them look better than they really are at	/
6	high SIC (>75%), For example, if real SIC is 75%, an algorithm with a positive bias of 20%	
7	will have average SIC of 95%, and by cutting-off all the values above 100% it reduces the	
8	scatter, and thus SD, to only the values in 95-100% interval. In contrast, for an algorithm with	
9	same bias and no cut-off the full scatter will be preserved and represented by a higher SD.	
10	At SIC 15% the CV (BF) algorithm had the second lowest SD (3.8% in the Northern	
11	Hemisphere and 3.5% in the Southern Hemisphere) after the 6H algorithm. Even though the	
12	6H showed such a low SD, we did not consider it as a suitable algorithm for a climate dataset	
13	because this algorithm could not be applied to SSM/I data, which shortens the time series	
14	significantly. At SIC 75% the BR algorithm had the lowest SD of 3.1% in the Northern	
15	Hemisphere and 2.9% in the Southern Hemisphere.	
16	Difference in <u>SD</u> between summer and winter (only SIC 15%) was lowest for the algorithms	
17	NT, NT+CV, BR, CV and OSISAF (average over both hemispheres and all three instruments	/
18	amounted to 0.2-0.3%), The algorithms ESMR, ECICE, 6H, NT2 and CV+N90, had higher,	$\parallel$
19	summer-winter differences (0.4-0.5%), while the remaining algorithms (BP, N90 and ASI)	/
20	showed the highest values of 0.8–1.2%	

# 21 4.2 Melt Ponds

The SIC and <u>MPF</u> from MODIS were collocated with daily SIC retrieved by the algorithms in the Arctic Ocean for June\_August 2009 to investigate the sensitivity of the algorithms to melt ponds. Due to the low penetration depth, we expect that passive microwave SIC algorithms interpret melt ponds as open water and hence in summer they provide the net ice surface fraction (*C*), which excludes leads and melt ponds, rather than traditional SIC. Therefore we compute corresponding parameter from the MODIS data:

28

 $C = (1 - W) = SIC_{MODIS} - SIC_{MODIS} + MPF,_{\bullet}$ 

where *W* is surface fraction of water (leads + melt\_ponds), Fig. 3, shows SIC calculated by four selected SIC algorithms (CV, BR, N90 and NT) as a function of C. Note that because of Natalia Ivanova 14/6/2015 14:20

Deleted: ie-point ... e points as was done f ... [57]

Natalia Ivanova 11/5/2015 16:00 Deleted: melt pond fraction estimates...P[ ... [59]

17

(8)

the limitation to MSIC > 95% the variation in the net ice <u>surface</u> fraction is almost solely due
 to the variation in MPF, which was varying from 0 to 50% for the selected dataset.

3 There is a pronounced overestimation of the net ice <u>surface</u> fraction by the <u>CV</u> and <u>BR</u>

4 algorithms that compose the OSISAF combination (however only BR is used for high SIC).

5 For example, at C = 90% the average SIC is 128% (<u>CV</u>), 115% (<u>BR</u>), 103% (N90) and 100%

6 (NT). The slopes of the regression lines are close to one (0.9–1.2 for the shown algorithms),

7 which agrees with the assumption that melt ponds are interpreted as open water by microwave

8 radiometry, The NT algorithm shows SIC values closest to C (the least bias of the four

9 algorithms), which adds to our argument for using this algorithm for defining areas of high

10 SIC (NT > 95%) for retrieval of the dynamic tie points (Sect. 4.5).

### 11 4.3 Thin ice

12 Sensitivity of selected SIC algorithms (CV, BR, OSISAF, N90, NT and 6H) to thin sea ice 13 thickness was investigated. Fig. 4 shows SIC obtained by these algorithms as a function of sea ice thickness from SMOS (Sect. 3,4). The data are shown as averages for each sea ice 14 15 thickness bin of 5 cm width with the number of measurements in each bin shown on the figure (total number of measurements is 991). The grey shading shows SD, which is 16 calculated from all the SIC retrievals in the given bin. These SDs are calculated for each 17 18 algorithm individually, but overlap each other on the figure. Since in the OSISAF 19 combination, the <u>BR algorithm</u> has weight of 1 for high <u>SIC</u>, these algorithms show identical 20 results; therefore <u>BR</u> is not visible.

21 The SIC is known to be  $\sim 100\%$  for the cases selected, therefore one would expect all the 22 curves to be horizontal and placed at high SIC. However, this is not going to be the case 23 following published knowledge suggesting that SIC is underestimated for thin ice (Kwok et 24 al., 2007, Grenfell et al., 1992). Hence, we are interested in the point where a given algorithm 25 is no longer affected by the ice thickness. All the algorithms underestimate the SIC for ice thickness of up to 25 cm. Note that most of the algorithms also show a negative bias of about 26 27 5% for ice thickness above 30 cm, i.e. ice which is not termed thin ice anymore. This could be 28 caused by the fact that the thin ice identified in SAR images is on average smoother/less 29 deformed and most likely has less snow than the ice used for the derivation of the sea ice tje 30 points applied in the algorithms.

Natalia Ivanova 10/6/2015 19:56 Deleted: area

Natalia Ivanova 10/6/2015 19:56 Deleted: area ...urface fraction by the Cal ... [63]

Natalia Ivanova 16/6/2015 14:54 Deleted: sea ice...IC algorithms (CV, BR ... [64]

Natalia Ivanova 28/5/2015 13:02 Deleted: near ...orizontal and placed at hi

1 Out of the five algorithms shown, N90 levels off, that is the SIC value varies by less than 5%

2 between the neighbouring bins of SIT, at the lowest thicknesses (20-25 cm). The OSISAF

3 and CV follow at the thicknesses of 25–30 cm, and NT and 6H at 30–35 cm. The slightly

4 better performance of CV relative to OSISAF suggests a shift in the mixing of BR and CV in

5 a new algorithm (using CV at higher intermediate concentrations)<sup> $\frac{1}{2}$ </sup> see the introduction of the

6 SICCI algorithm in the discussion section. More details on the algorithm's performance over

7 thin ice can be found in Heygster et al. (2014).

# 8 4.4 Atmospheric correction

9 First we implemented traditional open water/weather filters (Eqs. 3, and 4), which work as ice-

10 water classifiers. These filters set pixels to SIC 0% when they are classified as ones subjected

11 to a high atmospheric influence over open water. This efficiently removes noise due to the

12 weather influence in open water regions.

13 However, we found, as did also Andersen et al. (2006), that open water/weather filters also 14 eliminate low concentration ice (up to 30%). This is illustrated in Fig. 5, where intermediate 15 concentration datasets were generated using equations similar to Eq. (1) from the same Tbs as 16 used for the algorithms inter-comparison (Sect. 4.1). The filter identifies correctly the pixels, which do not contain any ice (SIC = 0%): practically all pixels are located outside the red 17 square in the upper left plot. The filter keeps almost all the pixels containing sea ice (SIC = 18 19 30%): almost all pixels are located inside the red square in the bottom right plot; only a 20 handful values fall outside the range defined by the red box and is set to 0%. However for the 21 cases of SIC 15% and 20%, which are shown here as an example, the filter sets SIC to 0% for 22 all the pixels outside the red square in the upper right and bottom left plots, which 23 corresponds to 27% of the total amount of pixels (3320) for the SIC 15% and to 9% for the 24 SIC 20%. 25 In order to avoid this truncation of real SIC by the open water/weather filter, we investigated

an alternative approach where we applied atmospheric correction to the <u>Tbs</u>, as described in Sect. 3.5, before using them as input to the algorithms. The correction reduced the <u>Tb</u> variance by 22–35 % (<u>19\_GHz</u>, and 37\_<u>GHz</u>, channels) and up to 40% (near 90\_<u>GHz</u>, channels) when water vapour, wind speed and 2\_m\_temperature were used in the correction scheme. Adding <u>CLW</u>, as the fourth parameter worsened the results (19\_<u>GHz</u>, and 37\_<u>GHz</u>, channels).

31 CLW has high spatial and temporal variability and the current ERA Interim resolution and

#### Natalia Ivanova 28/5/2015 13:03 Deleted: ear...0 levels off. that is the SIC

Natalia Ivanova 28/5/2015 13:20 Deleted: W... implemented the ...radition .... [67]

Natalia Ivanova 16/6/2015 14:55

Natalia Ivanova 16/6/2015 14:56

Deleted: y...atmospheric correction to the ... [69]

performance for CLW is not <u>suitable</u> for this correction. In the following the satellite data are
 therefore not corrected for the influence of CLW.

#### 3 To illustrate the effect of the correction, we compared the SD of SIC computed from Tbs with and without correction for water vapour, wind speed and 2 m temperature (Fig. 6). The top 4 5 plots show histograms of the SIC over open water for the OSISAF algorithm before the correction (left) and after (right). The distribution becomes clearly less noisy and tends to be 6 7 more Gaussian-shaped. To show the effect of the correction on performance of all the algorithms (Table 1, except NT2 and ECICE), the <u>SD of SIC</u> is shown in the bottom plot. The 8 <u>SD</u> has decreased by 48–65% (of the original value) after the atmospheric correction for all 9 10 the shown algorithms. The improvement due to the RTM correction shown in the Fig. 6 is an average measure for all the 2320 samples. It should be noted that the tie points need to be 11 adjusted to the atmospherically corrected data. The tie points given in Appendix A are for 12 13 uncorrected data.

14 **4.5 Dynamic tie points** 

As mentioned in the Introduction, not only sea ice <u>area/extent is characterised by seasonal</u> variability and has a trend, but so do also atmospheric and surface effects influencing the <u>measured</u> microwave emission. In order to compensate for these effects, we suggest that in an optimal approach tie points should be derived dynamically.

In order to generate dynamically adjusted daily tie points we first define the sampling areas
for consolidated ice and open water at a distance of 100 km from the coasts. The area for the

21 ice tie point is defined so that SIC is larger than 95% according to the NT algorithm and it is

22 within the limits of maximum sea ice extent climatology (NSIDC, 1979–2007). The NT

23 algorithm was chosen for this purpose because it is a standard relatively simple algorithm

24 with little sensitivity to ice temperature variations (Cavalieri et al., 1984). The data for the

25 open water tie point were selected geographically along two belts in the Northern and

26 <u>Southern hemispheres defined by the maximum sea ice extent climatology, (200 km wide belt</u>

27 <u>starting 150 km away from the climatology). Data points south of 50N were not used. Total of</u>
28 15,000 data points per day were selected.

28 <u>15,000 data points per day were selected.</u>

29 Then 5,000 Tb measurements (every day) in these areas were randomly selected among the
 30 total of 15,000 data points and averaged using a 15-day running window (± 7 days) to reduce

31 potential noise in daily values. Selection of only 5,000 samples per day is to ensure that no.

Natalia Ivanova 16/6/2015 14:56 Deleted: sufficient

Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point

Natalia Ivanova 12/5/2015 12:47 Deleted: has ...s characterised by seasona( ... [71]

Natalia Ivanova 31/3/2015 10:47 Deleted: We suggest using a two-week running window (± 7 days) to reduce potential noise in daily values. In order to generate the 100% ice tie-point we used areas with...he area for the ice tie p....[72] Natalia Ivanova 31/3/2015 10:49 Moved (insertion) [3] Natalia Ivanova 28/5/2015 16:31 Deleted: NASA Team Natalia Ivanova 12/5/2015 10:29 Moved (insertion) [6] Natalia Ivanova 14/6/2015 14:20 Deleted: ie-point...e point were selected ....[73]

Natalia 18/5/2015 10:42
Deleted: 1...,000 of ... b measurements (e ... [74]
Natalia Ivanova 28/5/2015 16:33

Deleted: t

1	days are weighted higher than others when there are differences in the number of data points		De	eted: oneays iresweight	ed l ⊿Q
2	from day to day. The 15-days window allows smoothing out the synoptic scales of weather		Мо	ved up [3]: The NASA Team a	algo
3	perturbations and at the same time capture the onset of ice emissivity changes due to summer		cho: rela	sen for this purpose because it is a tively simple algorithm with little	ı sta sen
4	melt or fall freeze-up, We believe that longer time windows will induce additional (too much)		Na	talia 18/5/2015 11:30	et al
5	smoothing over the ice, while shorter time-periods will introduce too much noise (over open	///	De	eted:	
6	water). The scatter of all the obtained 15,000 data points per day was used as a tie point		Na	talia Ivanova 12/5/2015 10:	29
7	uncertainty, which contributes to the total per-pixel daily uncertainty retrieved for SIC.		poir in t	it were selected geographically allow Northern and Southern hemisp?	en v ong here
8	An example of ice tie point is presented in Fig. 7, top and middle panels, by Tb19v and Tb37v		by t (200 clin	he monthly maximum climatologi ) km wide belt starting 150 km aw hatology). Data points south of 50	ical vay N iı
0	and in the bottom panels by slope of the ice line according to the Bootstran scheme. We chose		Nor	thern Hemisphere were not used.	00
10	and in the obtain panets by stope of the recenting to the bootstrap scheme, we enose		De <sup>l</sup>	eted: The ice tie-point was subs	23 sequ
10	to not show the tie points of the Bristol algorithm because the polarization and frequency		calc	ulated as the average brightness to	emp
11	information from 19V, 37V and 37H channels is transformed into a 2D plane defined by x		Na	talia Ivanova 12/5/2015 10:	41
12	and y components (see Smith (1996) for more details), which are harder to relate to than Tbs.		Del fror	eted: Only samples at a distance n the coast regions, and inside mo	e of onth'
13	The open water tie points are not shown here as they have less seasonal variability (within 5		clin in tl	atology of ice were used. The pro- ne order of 15000 data points in a	oced two
14	K). The dynamic tie point for ice is represented by an average of the fraction of FYI and MYI		peri	od. talia 19/5/2015 15:31	
15	in the samples of all ( $\pm 7 days$ ) selected ice conditions ( $NT > 95\%$ ). Due to the change in the		De	eted: snow melting We believ	ve tl
16	relative amount of FYI and MYI in the Arctic Ocean in recent years, the average ice tie point		Na De	talia Ivanova 31/3/2015 11: eted: )	17
17	will move along the ice-line in the Tb space.		Na	talia 18/5/2015 10:43	
			De	eted: . However, the scatter o	of al
18	Fig, 7, demonstrates that the <u>tie points</u> are not constant values as it is assumed traditionally		Na De	talia 19/5/2015 15:28 eted: Fig. 8 shows examples of	dvn
19	(static tie points from the RRDP, also averaged FYI and MYI values, are shown by horizontal		poir plat	its for overlapping periods of the l forms: f10, f11, f13, f14 and f15.	DM The
20	<u>lines</u> ), but rather geophysical parameters showing seasonal and inter-annual variations. This		tie-p frac	point for ice is represented by an a tion of FYI and MYI in the sampl	iver les c
21	applies particularly to the melt season, which is highlighted by the grey vertical bars for three		(±7	days) selected ice conditions (NI talia Ivanova 14/6/2015 14	r > 20
22	selected years in Fig. 7, bottom plots. Therefore the dynamic approach is more suitable for the		De	eted: ie-point e point is preser	nted
23	SIC algorithms. The jce tie point may vary by about <u>30 K</u> during one year, which amounts to		Na De	talia 19/5/2015 15:27	
24	approximately 8–10% of the average value. Sensor drift and inter-sensor differences are also		Na	talia Ivanova 12/5/2015 12:	16
25	important aspects, which might cause an unrealistic trend in the retrieved SIC when static tie	$\langle       \rangle$	Del SIC	eted: algorithm, the algorithm u in the OSISAF combination. In	ised
20	registe and amplied. The dynamic tic neight anneach compared for these offects.	$\langle       \rangle$	Na	talia 19/5/2015 15:29	
20	points are applied. The dynamic <u>ue point</u> approach compensates for these effects.		De	eted:	20
27	A detailed description of the procedure to obtain dynamic tie points is given in the Appendix		De	eted: ie-point	20
28	B. The tie points will vary with calibration of the input data/version number and source, so the		Na De	talia Ivanova 10/6/2015 20:	01
29	tie points obtained here should not be used with other versions of the input data with potential	$\mathcal{N}$	Na	talia Ivanova 10/6/2015 20:	01
30	different calibration. The procedure on the other hand can be applied to all	1	De	eted:78demonstrates that	the
31	versions/calibrations of the input data.		De	eted: altie-pointe points is	give
32			Na	talia Ivanova 12/5/2015 12:	21
		/	- Do'	oroce A table of the trand values	e for

am algorithm was t is a standard little sensitivity to lieri et al. 1984).

# 10:29

he open water tie-lly along two belts mispheres defined ological ice extent m away from the of 50N in the sed.

subsequently ess temperature 10:41

stance of 100 km le monthly ne procedure yielded in a two-week

elieve that .... [76] 11:17

ter of all th ... [77]

es of dynamic tie-f the DMSP SSM/I f15. The dynamic y an average of the samples of all is  $(NT > 95 \dots [78])$ 

14:20 resented in ... [79]

nm used for high In…e chot ... [80]

that the tie ... [82]

16:39

ts is given i ... [83] 12:21

... [81]

**Deleted:** A table of the trend values for the tie-points from Fig. 8 is included as Appendix I [... [84]

2	5.1 The SIC algorithms inter-comparison and evaluation	Natalia 17/6/2015 11:44
3	Based on validation datasets of SIC 15% and 75% we used variability (SD) in the SIC	
4	produced by the different algorithms as a measure of the sensitivity to geophysical error	Natalia Ivanova 25/3/2015 13:13
5	sources and instrumental noise. The errors from geophysical sources over open water are	
6	generated by wind induced surface roughness, surface and atmospheric temperature	
7	variability and atmospheric water vapour and CLW. Over ice, the errors are dominated by	
8	snow and ice emissivity and temperature variability, where parameters such as snow depth,	
9	and to some extent variability in snow density and ice emissivity are important (Tonboe and	
10	Andersen, 2004). The atmosphere plays only a minor role over ice except at near 90 GHz.	
11	where liquid water/ice clouds may still be a significant error source, especially in the	//
12	Marginal Ice Zone. At the same time near 90 GHz data might be less sensitive to changes in	
13	physical properties in ice and snow because of the smaller penetration depth relative, to the	
14	other frequencies used.	
15	The algorithms 6H, <u>CV</u> , <u>BR</u> , <u>OSISAF</u> , <u>NT</u> and <u>NT+CV</u> , showed the lowest <u>SD</u> s <u>(Table 2)</u> .	Natalia Ivanova 28/5/2015 16:50
16	The 6 GHz channel was not available on SSM/I, which provides the longest time series, and	Deleted: OSISAF, CalValV, Bristol [87]
17	therefore the 6H algorithm was not considered to be an optimal SIC algorithm for a climate	
18	dataset. Bristol showed the lowest SD over high SIC (only winter is considered) while CV	//
19	had the lowest <u>SD</u> for the low <u>SIC</u> cases, which suggests that combining these two algorithms	
20	would provide a good basis for an optimal <u>SIC</u> algorithm.	
21	The differences in <u>SD</u> s between summer and winter are reflecting the sensitivity of different	Natalia Ivanova 25/3/2015 13:13
22	algorithms to wind, atmospheric humidity and other seasonally changing quantities. $\underline{In}$	Deleted: standard deviationDs between [88]
23	addition, some of these quantities may have climatological trends. Therefore small difference	
24	between the summer and winter <u>SDs</u> is an asset for an algorithm. The algorithms <u>NT</u> ,	///
25	NT+CV, BR, CV and OSISAF showed the lowest summer-winter differences in SD (0.2-	//
26	0.3% on average for both hemispheres and all three instruments)	
27	Note that the two modes of the Bootstrap Algorithm in this study were tested separately. The	Natalia 3/6/2015 16:57
28	frequency mode (BF) of the original algorithm is applied only when Tb19v is below the ice	Deleted: Please n
29	line minus 5 K (Comiso 1995), which is the case for both 15% and 75% case. Otherwise the	
30	polarisation mode (BP) should be applied. Thus, we did not show the tests of BP for what it is	
31	originally meant - SIC near 100%. This algorithm was still evaluated along with all the others	

## Natalia 17/6/2015 11:44

1	for SIC 100%, and the test indicated that BP performed quite well, but BR showed somewhat
2	lower SDs (by about 2%) and therefore was selected for the hybrid algorithm.
3	Evaluation of typical processing chain components, such as climatological masks, land
4	contamination correction and gridding from swath to daily maps, is not covered by this study.
5	This work is devoted to a systematic evaluation of algorithms using a limited but very

- 6 accurate reference dataset (the RRDP). For the consistent evaluation exercise completed here,
- 7 areas in the vicinity of land were excluded.

### 8 5.2 The SICCI algorithm

9 During the algorithm evaluation and inter-comparison exercise the SICCI algorithm was introduced. It is a slightly modified version of the OSISAF algorithm in order to achieve 10 better performance over areas with thin ice. Similar to the OSISAF algorithm, it is constructed 11 as a weighted combination of CV and BR algorithms. In order to take more advantage of the 12 13 better performance of CV for thin ice, the weights are defined as follows. For SIC below 70%, as obtained by CV, the weight of this algorithm is  $w_{CV} = 1$ , while for high values 14 ( $\geq$ 90%) it is  $w_{CV} = 0$ . Different weights were tested on the thin ice dataset. The optimal 15 values were chosen so that the hybrid algorithm performs better over thin ice, and at the same 16 time keeps its performance in other conditions at the same level as the original OSISAF 17 18 algorithm. For the values between 70% and 90% the weight for CV is defined as

$$w_{CV} = 1 - \frac{SIC_{CV} - 0.7}{0.2},$$

where  $SIC_{CV}$  is SIC (between 0 and 1) obtained by CV. The weight of BR is  $1 - w_{CV}$ . In the original OSISAF algorithm, values of 0% and 40% were used,

## 22 5.3 Melt ponds

23	Fig. <u>3</u> , illustrates that the four algorithms shown ( <u>but this is also valid for</u> all other algorithms)
24	are sensitive to the <u>MPF</u> , which may mean that melt_ponds are interpreted as open water by
25	the algorithms. This is because microwave penetration into water is very small. Rösel et al.
26	(2012b) showed that in areas with melt_ponds SIC algorithms (ASI, NT2 and Bootstrap)
27	underestimate SIC by up to 40% (corresponding to a MPF close to 40%). One may still argue
28	that melt ponds should have different signature from that of open water due to the difference
29	in their salinity. However, for such high frequencies as used in the algorithms (19 GHz and

Natalia 3/6/2015 16:58 Deleted:

Natalia Ivanova 10/6/2015 20:10 Deleted: validation Natalia Ivanova 28/5/2015 17:13 Deleted: for Natalia Ivanova 3/4/2015 23:00 Deleted: ly Natalia Ivanova 16/6/2015 16:16 Deleted: the Natalia Ivanova 28/5/2015 17:13 Deleted: Natalia Ivanova 28/5/2015 17:13 Deleted: Natalia Ivanova 10/6/2015 20:11 Deleted: intermediate Natalia Ivanova 9/6/2015 10:09 Formatted: Right Natalia Ivanova 9/6/2015 10:09 Deleted: Natalia Ivanova 9/6/2015 09:50 Deleted: 3 Natalia Ivanova 25/5/2015 12:58 Deleted: Natalia Ivanova 25/5/2015 12:58 Deleted: instead of 70% and 90% suggested here Natalia Ivanova 21/5/2015 21:15 Deleted: 4 Natalia Ivanova 28/5/2015 17:17 Deleted: as well as Natalia Ivanova 28/5/2015 17:20 Deleted: melt pond fraction Natalia Ivanova 28/5/2015 17:20 Deleted: Natalia Ivanova 10/6/2015 20:11 Deleted: a Natalia Ivanova 14/6/2015 14:17 Deleted: Natalia Ivanova 28/5/2015 17:20 Deleted: infested areas passive microwave Natalia Ivanova 10/6/2015 20:12 Deleted: of

(<u>9</u>)<sup>◀</sup>

higher) and in cold water the salinity was found to play a less significant role (Meissner and
 Wentz, 2012; see also Ulaby et al., 1986). In addition, the footprint size is so large (e.g. 70 km
 × 45 km for 19.3 GHz channel on SSM/I) that an unresolvable mixture of surfaces might be
 present in it.

5 For some applications it is important to interpret ponded ice as ice and not as open water. However, we believe that satellite microwave radiometry is incapable to estimate SIC 6 7 correctly if a certain fraction of the sea ice is submerged under water. Therefore, we suggest accepting what microwave sensors actually can do; to estimate the net ice surface fraction. 8 9 The latter is similar to the well known SIC during most of the year until melt ponds have 10 formed on top of the ice in the melting season. Additional data sources (for example MODIS) could be used to supplement summer retrievals of SIC. Unlike with microwave radiometry, 11 12 open water in leads and openings between the ice floes can be discriminated from open water 13 in melt ponds on ice floes by means of their different optical spectral properties. The algorithms shown in Fig. 3 overestimate SIC, which can be caused by higher Tbs in the 14 15 areas between melt ponds. During summer these areas comprise wet snow and/or bare ice 16 with a different physical structure than during winter. Therefore these areas have radiometric 17 properties potentially different from those of winter, when the RRDP ice tie points were 18 developed. This is demonstrated by Fig. 7 where the grey bars highlight that seasonal changes 19 in the dynamic tie points to be used in the SICCI algorithm vary particularly during the 20 summer months. The comparison of passive microwave algorithms and MODIS SIC in Rösel 21 et al. (2012b) showed that in the areas without melt ponds the passive microwave SIC was 22 larger than that of MODIS. Note also, however, that the tje points used here differ from those in Rösel et al. (2012b). This complicates a quantitative comparison of their results with ours 23 24 and, in turn, calls for such kind of systematic, consistent evaluation and inter-comparison as shown in the present paper. Using the dynamic tie points approach (Sect. 4.5) decreases this 25

effect: the OSISAF algorithm on average overestimated SIC by 24% when fixed RRDP tie points were used (same as in the Fig. 3) and by 17% with dynamical tie points (this example is not shown in the figure). However, even with dynamic tie points, it is likely that the areas selected to derive the 100% ice tie point during summer contain melt ponds. If this would be the case and if the selected area would have an average melt\_pond fraction of 10%, then the 100% ice tie point would not represent 100% ice but a net ice surface fraction of only 90%. Natalia Ivanova 12/5/2015 08:52

Deleted: However, t...e algorithms shown ... [89]

1	done using pixels with NT SIC $> 95\%$ . This algorithm is less sensitive to the surface
2	temperature variations because it is based on polarization and gradient ratios of Tbs, which
3	more or less cancels out the physical temperature (Cavalieri et al. 1984). In addition, it is
4	interpreting melt ponds as open water (Sect. 4.2). This means that using NT SIC $> 95\%$ we
5	select areas with reasonably low MPF to determine the signature of ice, which helps to avoid
6	introducing a bias to the tie points with measurements containing melt ponds,

# 7 5.4 Thin ice

8 All the algorithms shown for the thin ice test (Fig. 4) underestimate the SIC for ice 9 thicknesses up to 35 cm, which confirms findings by others (see Introduction). The 6H 10 algorithm showed the highest sensitivity to the sea ice thickness, which is in agreement with 11 Scott et al. (2014) showing that Tbs at 6 GHz can be used to estimate thin ice thickness. The 12 least sensitivity to thickness of thin ice was observed for the N90 algorithm, the SIC obtained 13 by this algorithm was independent of SIT values already at thicknesses of 20-25 cm, This is 14 caused most likely by a smaller penetration depth in the near 90 GHz channels (shorter wave length) (see also Grenfell et al., 1998). OSISAF and CV had the second least sensitivity 15 16 (levelled off at 25-30 cm), which adds more weight to the choice of an OSISAF-like combination as an optimal algorithm. We suggest that, when areas of thin ice are interpreted 17 18 as reduced concentration, this should be clearly stated along with an eventual SIC product. 19 This issue is similar to melt ponds in a way that there is no simple solution, and one should be 20 aware of the limitation, which we demonstrate by the Fig. 4. In this study we manage to 21 quantify the effect and thus allow modellers to assimilate SIC data in a more proper way. 22 Implementation of an algorithm that accounts for thin ice (Röhrs and Kaleschke, 2012; Röhrs 23 et al., 2012; Naoki et al., 2008; Grenfell et al., 1992) as an additional module to this optimal 24 algorithm could be a potential improvement. For shorter datasets, a thin ice detection 25 technique developed for AMSR-E and SSMIS (Mäkynen and Similä, 2015) can be 26 incorporated in order to provide a thin-ice flag.

### 27 5.5 Atmospheric correction

28 Using the RTM of Wentz (1997), we concluded that over open water, most of the algorithms

- 29 were sensitive to <u>CLW</u> although the sensitivities of CV and 6H were small (not shown).
- 30 However, we found that CLW and precipitation are less reliable in ERA Interim data and
- 31 therefore represent error sources, which we cannot correct for using the suggested method.

Natalia Ivaliova 30/3/2013 19.30
<b>Deleted:</b> This estimate should be provided by a method which is sensitive to melt ponds in order to
Natalia Ivanova 14/6/2015 14:20
Deleted: ie-point
Natalia Ivanova 14/6/2015 14:15
Deleted: -
Natalia Ivanova 28/5/2015 17:35
Deleted: infested measurements
Natalia Ivanova 21/5/2015 21:15
Deleted: 5
Natalia Ivanova 10/6/2015 20:25
Deleted: (
Natalia Ivanova 10/6/2015 20:25
Deleted: it is suitable to measure retrieve
Natalia Ivanova 28/5/2015 17:35
Deleted: ,
Natalia Ivanova 10/6/2015 20:26
Deleted: thicknesses
Natalia Ivanova 28/5/2015 17:36
Deleted: It
Natalia Ivanova 28/5/2015 17:36
Deleted: most likely
Natalia Ivanova 28/5/2015 17:36
Deleted: CalVal
Natalia Ivanova 10/6/2015 20:27
Deleted: ,
Natalia Ivanova 10/6/2015 20:27
Deleted: ,
Natalia Ivanova 10/6/2015 20:27
Deleted: an
Natalia Ivanova 10/6/2015 20:27
Deleted: of this drawback
Natalia Ivanova 28/5/2015 17:38
Deleted: emission and radiative transfer model (
Natalia Ivanova 28/5/2015 17:38
Deleted: )
Natalia Ivanova 28/5/2015 17:40
Deleted: are
Natalia Ivanova 28/5/2015 17:38
Deleted: cloud liquid water
Natalia Ivanova 16/6/2015 16:24
Deleted: a
Natalia Ivanova 16/5/2015 19:43
Deleted: W

This is also confirmed in literature (Andersen et al., 2006). Therefore, it is important to select
a less sensitive algorithm (e.g., CV). The algorithms BP, ASI and N90 were very sensitive to
this component (not shown). Most of the algorithms were sensitive to water vapour over open
water, especially BP, ASI and N90. Some of the algorithms show some sensitivity to wind
(ocean surface roughness), e.g. NT and BR. But we corrected for the water vapour and wind
roughening by applying the RTM correction (see Fig. 6).

7 It was found that atmospheric correction of Tbs for wind speed, water vapour and temperature reduces the <u>SD</u> in retrieved SIC for all tested algorithms at low <u>SIC</u>. In addition, the shape of 8 9 SIC distribution got closer to Gaussian after the correction (Fig. 6). The OSISAF combination 10 (19V/37V) improved significantly after correction over open water. Over ice the atmospheric 11 influence is small, as was shown by the ERA Interim data we used - total water vapour and 12 CLW content over ice were much smaller than over ocean. The atmosphere over ice is 13 generally much colder than over ocean, and cold air can contain much less moisture 14 (including clouds) than warmer air. In addition, when the emissivitiy is much larger over sea 15 ice (e.g. FYI) than open water, a change in the atmospheric water vapour imposes a smaller 16 change in the Tb measured over sea ice compared to the one measured over open water 17 (Oelke, 1997). Correction for the effect of surface temperature variations at SIC 100%, where 18 2 m temperature was used as a proxy, was not effective, This can be explained by the fact that 19 different wavelengths penetrate to different depth in the ice and thus should retrieve different 20 temperatures.

The limitation of the applied correction is that, even though it reduces the atmospheric noise considerably, it does not remove it completely. There will therefore be some residual atmospheric noise over the ocean. We argue that this noise is more acceptable in a SIC algorithm than the removal of ice, but admit that this is debatable and for some applications the removal of ice may be preferable.

# 26 5.6 Dynamic tie points,

The advantages of the suggested dynamical approach to retrieve tie points can be listed as
follows, Firstly, it ensures long-term stability in sea ice climate record and decreases
sensitivity to noise parameters with climatic trends. This is of importance because both sea ice
area/extent and the geophysical noise parameters (sea ice emissivity, atmospheric parameters)
have climatic trends. Also, as model study by Willmes et al. (2014) showed, emissivity of

	Natalia Ivanova 16/5/2015 19:43
	<b>Deleted:</b> the representation of cloud liquid water in the NWP data were not suitable for correction of brightness temperatures, which makes
	Natalia Ivanova 28/5/2015 17:39
	Deleted: ootstrap
	Natalia Ivanova 28/5/2015 17:39
$\langle  $	Deleted: ear
	Natalia Ivanova 28/5/2015 17:40
	Deleted: are
	Natalia Ivanova 28/5/2015 17:40
	Deleted: the
	Natalia 3/6/2015 16:59
	Deleted: we corrected for
	Natalia Ivanova 21/5/2015 21:15
V	Deleted: 7
$\left( \right)$	Natalia Ivanova 25/3/2015 13:44
N	Deleted: brightness temperature
	Notolia lyapova 16/6/2015 16:26
	Natalia Ivaliova 10/0/2015 10.20
	Natalia Ivanova 16/6/2015 16:26
	Deleted: e
	Natalia Ivanova 16/6/2015 16:26
	Deleted: s
	Natalia Ivanova 21/5/2015 21:16
	Deleted: 7
	Natalia 3/6/2015 16:59
	Deleted: T
	Natalia Ivanova 14/6/2015 13:40
	<b>Deleted:</b> A simple correction using surface temperature at 100%
	Natalia Ivanova 14/6/2015 13:41
	Deleted:

/	Natalia Ivanova 14/6/2015 14:20	
	Deleted: ie-point	
/	Natalia 18/5/2015 10:52	
	Deleted:	[90]
1	Natalia Ivanova 14/6/2015 14:20	
	Deleted: ie-point	
	Natalia Ivanova 10/6/2015 20:30	
	Deleted: include	
	Natalia Ivanova 10/6/2015 20:30	
	Deleted: ing	
-	Natalia Ivanova 28/5/2015 17:51	
	Deleted: /area	
-	Natalia Ivanova 16/6/2015 16:29	
	Deleted: s	

1	FYL covered by snow is characterized by seasonal and regional variations caused by	
2	atmospherically driven snow metamorphism, Secondly, the dynamical tie points are needed	$\setminus$
3	when accurately quantifying the SIC uncertainties. Thirdly, the dynamic tie point method in	$\bigwedge$
4	principle compensates for inter-sensor differences in a consistent manner, so no additional	$\left( \right)$
5	attempt was considered necessary to compensate explicitly for sensor drift or inter-sensor	
6	calibration differences (the SSM/I data have been inter-calibrated but not with the SMMR	
7	dataset).	
8	The seasonal cycle in the tie points can be tracked across platforms (Fig. 7). Thus, the tie	
9	points are naturally changing geophysical parameters (or quantities obtained from such	
10	parameters), and should be dynamic as opposed to the traditional static approach. The	
11	variation amounts to approximately 20-30 K, which corresponds to about 8-12% of the	
12	average value, and the peaks in the variation occur in summer. Thus, increased variability in	
13	late spring/early summer connected to melt onset and consequent snow metamorphoses,	
14	reported by Willmes et al. (2014), is confirmed in our study.	
15	The dynamic tie points approach is only applied in time, not in space. The aim of this study is	
16	to identify an optimal SIC algorithm for a climate dataset, which requires transparent	
17	description of techniques and uncertainties. It would be difficult to come up with proper	
18	uncertainty estimate in case we divide our region of interest - more or less arbitrarily - into	
19	sub-regions.	
20	One might argue that different tie points for MYI and FYI can still be used. However,	

One might argue that different tie points for MYI and FYI can still be used. However,
 computation of the uncertainty at the boundary of both regions will become problematic. How
 shall one treat mixed pixels? And - most importantly - one would need a validated quality controlled ice type dataset spanning the entire period. Therefore, we would recommend that
 regional (dynamic) tie points would be an ideal tool for regional applications and for near-real
 time SIC retrieval of spatially limited areas, but not for a climate dataset.

# 27 6 Conclusions

26

A SIC algorithm for climate time series should have low sensitivity to error sources, especially those that we cannot correct for (CLW and precipitation, see Sect. 5.5) and those, which may have climatic trends. When correcting for errors it is important to adjust the tie points in order to avoid introducing artificial trends from the auxiliary data sources (e.g. NWP data). Therefore the preferred algorithm should allow adjusting the tie points dynamically.

Natalia Ivanova 28/5/2015 17:51
Deleted:
Natalia Ivanova 28/5/2015 17:51
Deleted: ice
Natalia Ivanova 28/5/2015 17:52
Deleted:
Natalia Ivanova 28/5/2015 17:52
Deleted:
Natalia Ivanova 28/5/2015 17:51
Deleted: TP's
Natalia Ivanova 14/6/2015 14:20
Deleted: ie-point
Natalia 18/5/2015 11:21
<b>Deleted:</b> We argue that if a geophysical parameter causes a trend in the parameters shown in Fig. 8, this trend should be practically the same across all DMSP platforms. However, the trend would not agree if it were caused by a combination of sensor drift and trend in geophysical parameter. The trends seem to agree according to the table in the Appendix B (see Sect. 4.5). It could still be considered as good practice to combine data from different platforms not only for better data coverage but also for mitigating across-platform biases.
Natalia Ivanova 14/6/2015 14:20
Deleted: ie-point
Natalia 19/5/2015 15:33
Deleted: Figure
Natalia Ivanova 21/5/2015 21:16
Deleted: X
Natalia Ivanova 14/6/2015 14:20
Deleted: 8 Natalia Ivanova 14/6/2015 14:20

Natalia Ivanova 14/6/2015 14:20
Deleted: ie-point
Natalia Ivanova 30/3/2015 20:15
<b>Deleted:</b> have relatively low sensitivity to the tie- points and it should be possible
Natalia Ivanova 30/3/2015 20:15
Deleted: to adjust
Natalia Ivanova 14/6/2015 14:20
Deleted: ie-point

1	The latter is necessary to compensate for climatic changes in the radiometric signature of ice		
2	and water; and eventual instrumental drift and inter-instrument bias, In addition, this		
3	algorithm should be accurate over the whole range of <u>SIC</u> from 0% to 100%. Along the ice	/	Deleted: es In addition, this algorithm s[91]
4	edge spatial resolution and sensitivity to new ice and atmospheric effects is of particular		
5	concern. In order to produce a long climate data record, it is also important that the algorithm		
6	is based on a selection of channels for which the processing of long time-series is possible,		
7	which are currently $19\_GHz$ and 37 GHz. The comprehensive algorithm inter-comparison		
8	study reported here leads to following conclusions:		
9	- The CalVal algorithm is among the best (low <u>SD</u> , <u>Table 2a</u> ) of the simple algorithms at low		Natalia Ivanova 28/5/2015 18:00
10	<u>SIC</u> and over open water.		Deleted: te CalVal algorithm is among
11	- The Bristol algorithm is the best (lowest SD, Table 2b) for high SIC.		Natalia Ivanova 28/5/2015 18:00
12	- OSISAF-like combination of CalVal and Bristol is a good choice for an overall algorithm,		<b>Deleted:</b> te Bristol algorithm is the best [93]
13	using CalVal at low <u>SIC</u> and Bristol at high <u>SIC</u> .		Natalia Ivanova 16/6/2015 16:43
14	In addition we conclude that:		Deleted: concentrationsIC and Bristol ( [94]
15	- Melt ponds are interpreted as open water by all algorithms.		Natalia Ivanova 28/5/2015 18:00
16	- Thin ice is seen as reduced <u>SIC</u> by all algorithms.		Deleted:         mlt        [95]           Natalia Ivanova 28/5/2015 18:00
17	- After atmospheric correction of Tbs, low SIC become less uncertain (less noisy) than high		Deleted: tin ice is seen as reduced conc
18	<u>SIC.</u>		Deleted: ater atmospheric correction of [97]
19	- Near 90 GHz algorithms are very sensitive to atmospheric effects at low SIC.		Natalia Ivanova 28/5/2015 18:03
20	- All 10 algorithms shown in the Fig. 6 improve substantially when Tbs are corrected for		Deleted: n Natalia Ivanova 28/5/2015 18:03
21	atmospheric <u>effects</u> using RTM with NWP data. The additional 3 algorithms by nature could		Deleted: al the0 algorithms tested
22	not be corrected/tested for this.		
23	- The dynamic tie points approach can reduce systematic biases in SIC and alleviate the		Natalia Ivanova 28/5/2015 18:04
24	seasonal variability in <u>SIC</u> accuracy.		Deleted: te dynamic tie-pointe points [99]
25	It is clear from these conclusions that there is no one single algorithm that is superior in all		Natalia Ivanova 28/5/2015 18:05
26	criteria, and it seems that a combination of algorithms (e.g., OSISAF or SICCI) is a good		Deleted: tone single algorithm that is s[100]
27	choice. An additional advantage of using a set of $19 \underline{\text{ GHz}}$ and 37 GHz algorithms is that the		
28	dataset extends from fall 1978 until today and into the foreseeable future.		

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17	Over ice the Bristol algorithm, chosen for the high SIC retrievals, is sensitive to the snow and ice temperature profile as well as to ice emissivity variations. Surface temperature vis quantified in most NWP models, which means that there is a potential for correction. The Bristol algorithm performance over melting ice is good because the SIC as a function of net
2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17	ice temperature profile as well as to ice emissivity variations. <u>Surface temperature vis</u> <u>quantified in most NWP models, which means that there is a potential for correction. The</u> Bristol <u>algorithm</u> performance over melting ice is good because the SIC as a function of net
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17	<u>quantified in most NWP models, which means that there is a potential for correction. The</u> Bristol <u>algorithm</u> performance over melting ice is good because the SIC as a function of net
4 5 6 7 8 9 10 11 12 13 14 15 16 17	Bristol <u>algorithm</u> performance over melting ice is good because the SIC as a function of net
5 6 7 8 9 10 11 12 13 14 15 16 17	
6 7 8 9 10 11 12 13 14 15 16 17	ice <u>surface</u> fraction has a slope close to <u>one</u> . The Bristol algorithm as other algorithms has a
<ul> <li>7</li> <li>8</li> <li>9</li> <li>10</li> <li>11</li> <li>12</li> <li>13</li> <li>14</li> <li>15</li> <li>16</li> <li>17</li> </ul>	clear seasonal cycle in the apparent ice concentration at 100% SIC when using static tie
<ul> <li>8</li> <li>9</li> <li>10</li> <li>11</li> <li>12</li> <li>13</li> <li>14</li> <li>15</li> <li>16</li> <li>17</li> </ul>	points. This means that dynamic tie points are an advantage when using Bristol (as with most
<ol> <li>9</li> <li>10</li> <li>11</li> <li>12</li> <li>13</li> <li>14</li> <li>15</li> <li>16</li> <li>17</li> </ol>	of the other algorithms).
<ol> <li>10</li> <li>11</li> <li>12</li> <li>13</li> <li>14</li> <li>15</li> <li>16</li> <li>17</li> </ol>	Over open water the CalVal algorithm, chosen for the low SIC retrievals, is among the
<ol> <li>11</li> <li>12</li> <li>13</li> <li>14</li> <li>15</li> <li>16</li> <li>17</li> </ol>	algorithms with the lowest overall sensitivity to error sources including surface temperature,
12 13 14 15 16 17	wind, and atmospheric water vapour. Importantly, the CalVal is relatively insensitive to
<ol> <li>13</li> <li>14</li> <li>15</li> <li>16</li> <li>17</li> </ol>	<u>CLW</u> , which is a parameter we cannot correct for due to the uncertainty of this parameter in <b>Deleted:</b> In particularmportantly, the <b>(102)</b>
14 15 16 17	the NWP data at high latitudes. The response of CalVal to atmospheric correction gives a
15 16 17	substantial reduction in the noise level. The response of CalVal to thin ice is better than that
16 17	of the other 19 GHz and 37 GHz algorithms and comparable to near 90 GHz algorithms.
17	Therefore we suggest that an OSISAF or SICCI type of algorithm with dynamic tie points and Natalia Ivanova 28/5/2015 18:34
	atmospheric correction <u>could</u> be <u>a good choice</u> for <u>SIC</u> climate dataset retrievals. The
18	selection of tie points should be done with careful attention to the melt pond issues in order to
19	avoid melt_pond contamination of the tie points in summer. Correction for wind speed, water
20	vapour and surface temperature provides, a clear noise reduction, but we found no
21	improvement from correcting for NWP <u>CLW</u> .
22	In spite of their high resolution and good skill over ice, the near 90_GHz algorithms have
23	some <u>limitations</u> for a SIC climate dataset because the near 90 GHz data were not available
24	before 1991, and they are very sensitive to the <u>atmospheric</u> error sources over open water and <b>Deleted:</b> drawbacksimitations for a SI[104]
25	near ice edge such as <u>CLW</u> . Finer spatial resolution achieved by the high-frequency channels
26	does not offset the weather-induced SIC biases over open water and near ice edge. Model data
27	used in the RTM to correct for the influence of surface wind speed, water vapor and air
28	temperature have a coarser spatial resolution and hence will cause artifacts in the RTM-based
29	correction. The remaining weather effects we cannot correct for (CLW and precipitation) will
30	become even worse and more difficult to correct for because the model is even less capable to
31	
32	provide the information for this parameters at the same spatial scale as would be required.

In the presented work we suggested a number of parameters, which could be used in order to
 select an optimal approach to retrieval of SIC climate dataset. We also suggested an approach
 that satisfies these requirements. However, we do not claim the suggested approach to be the
 best one taking into account that there is still a lot of potential for improvement in passive
 <u>microwave methods.</u>

6

7

8

## Appendix A: The RRDP tie points

Table A1. The RRDP tie points: brightness temperatures in K

AMSR-E

Northern Hemisphere										
		AMSR-E			SSM/I			SMMR		
	OW FYI MYI				OW FYI MYI			FYI	MYI	
6V	161.35	251.99	246.04				153.79	251.99	246.04	
6H	82.13	232.08	221.19				86.49	232.08	221.19	
10V	167.34	251.34	239.61				161.81	251.34	239.61	
10H	88.26	234.01	216.31				95.59	234.01	216.31	
18V	183.72	252.15	226.26	185.04	252.79	223.64	176.99	252.15	226.26	
18H	108.46	237.54	207.78	117.16	238.20	206.46	111.45	237.54	207.78	
22V	196.41	250.87	216.67	200.19	250.46	216.72	185.93	250.87	216.67	
22H	128.23	236.72	199.60				135.98	236.72	199.60	
37V	209.81	247.13	196.91	208.72	244.68	190.14	207.48	247.13	196.91	
37H	145.29	235.01	184.94	149.39	233.25	179.68	147.67	235.01	184.94	
Near90 <sub></sub> V	243.20	232.01	187.60	243.67	225.54	180.55				
Near90 <mark>H</mark>	196.94	222.39	178.90	205.73	217.21	173.59				
	Southern Hemisphere									

SSM/I

Natalia Ivanova 15/6/2015 11:34 Deleted: 85 Natalia Ivanova 15/6/2015 11:34 Deleted: 85

Natalia Ivanova 16/6/2015 16:51

Natalia Ivanova 16/6/2015 16:51

Natalia Ivanova 16/6/2015 16:52

Deleted: Tie-point

Deleted: Tie-point

Deleted: B

**SMMR** 

	OW	FYI	MYI	OW	FYI	MYI	OW	FYI	MYI
6V	159.69	257.04	254.18				148.60	257.04	254.18
6H	80.15	236.52	225.37				83.47	236.52	225.37
10V	166.31	257.23	251.65				159.12	257.23	251.65
10H	86.62	238.50	221.47				93.80	238.50	221.47
18V	185.34	258.58	246.10	185.02	259.92	246.27	175.39	258.58	246.10
18H	110.83	242.80	217.65	118.00	244.57	221.95	110.67	242.80	217.65
22V	201.53	257.56	240.65	198.66	257.85	242.01	186.10	257.56	240.65
<b>22</b> H	137.19	242.61	213.79				129.63	242.61	213.79
37V	212.57	253.84	226.51	209.59	254.39	226.46	207.57	253.84	226.51
37H	149.07	239.96	204.66	152.24	241.63	207.57	149.60	239.96	204.66
Near90 <sub>V</sub>	247.59	242.81	210.22	242.41	244.84	211.98			
Near90 <sub></sub> H	207.20	232.40	197.78	206.12	235.76	200.88			

1	Natalia Ivanova 15/6/2015 11:35
	Deleted: 85
1	Natalia Ivanova 15/6/2015 11:35
	Deleted: 85

Natalia Ivanova 15/5/2015 19:56

Natalia 17/6/2015 11:45

Deleted:

1 2

3

# Appendix B: Retrieval of the dynamic tie points

4 Computing of the dynamic tie points involves two steps. First, a large number of
5 characteristic Tb samples are selected for each day. Then, these data samples are aggregated
6 over a temporal sliding window.

7 <u>The open water tie point</u>

8 The open water data samples are selected geographically within the limits of two 200 km

9 wide belts, one in each hemisphere. Each belt follows the mask of maximum sea ice extent

10 climatology, which was first extended 150 km away from the pole of the respective

11 hemisphere. A land mask extending 100 km into open sea ensures that the open water

12 signatures are not contaminated by land spill-over effects. In the Northern Hemisphere, data

13 points south of 50N are discarded. A maximum of 5,000 randomly selected open water data

14 samples are kept per day,

- 1 The daily open water tie point is computed as the average Tb of all selected open water data
- 2 samples in a centred temporal sliding window (± 7 days). The open water tie point is
- 3 <u>computed separately for each hemisphere.</u>

4 The sea ice tie point

5 The sea ice data samples are selected geographically within maximum sea ice extent
6 climatology for each hemisphere. The ice tie point data must in addition correspond to a SIC
7 greater than 95%, as retrieved by the NASA Team algorithm using the tie points from the
8 Appendix A. Additional masks ensure that samples are taken away from the coastal regions.
9 A maximum of 5,000 sea ice data samples are kept per day.
10 The daily sea ice tie point is computed over the same temporal sliding window as the open

- water tie point, and is computed separately for each hemisphere. The slope and offset of the 11 12 ice line are computed using Principal Component Analysis. The ice line is the line in Tb space 13 that goes through the FYI and MYI points (type-A and type-B ice in the Southern Hemisphere, see Fig. 1 and 2). Since the total SIC is our target (and not the partial 14 15 concentrations of ice types), alternative versions of the CV and Bristol algorithms that rely on 16 the slope and offset of the ice line were implemented. Additional criteria would be needed for 17 further splitting the sea ice data samples into tie points based on ice types, this is not 18 considered here.
- A similar approach to deriving dynamic tie points is implemented for the sea ice
   concentration reprocessed dataset, and operational products of the EUMETSAT OSISAF.
- 21

# 22 Acknowledgements

23 This work was completed in the context of ESA Climate Change Initiative, Sea Ice project

- 24 (SICCI) and was funded by ESA. The work of S. Kern was supported by the Center of
- 25 Excellence for Climate System Analysis and Prediction (CliSAP). Support from the
- 26 International Space Science Institute (ISSI), Bern, Switzerland, under project No. 245: Heil P.

and S. Kern, 'Towards an integrated retrieval of Antarctic sea ice volume' is acknowledged.

27 and 5. Refit, Fowards an integrated refitival of Financial sea fee volume <u>is additioned sea</u>.
 28 The EUMETSAT OSISAF (http://osisaf.met.no) granted access to an implementation of its

29 SIC processing software, in particular the dynamic tie point retrieval process (see Appendix

- 30 <u>B)</u>.
- 31

Natalia Ivanova 16/6/2015 16:54 Deleted: i Natalia Ivanova 28/5/2015 18:39 Deleted: scope Natalia Ivanova 16/6/2015 16:54 Deleted: Sea Ice

### 1 References

- 2 Andersen, S., Tonboe, R., Kern, S., and Schyberg, H.: Improved retrieval of sea ice total
- 3 concentration from spaceborne passive microwave observations using numerical weather
- 4 prediction model fields: An intercomparison of nine algorithms, Remote Sens. Environ., 104,
- 5 374-392, 2006.



- Andersen, S., Tonboe, R., Kaleschke, L., Heygster, G., and Pedersen, L. T.: Intercomparison
  of passive microwave sea ice concentration retrievals over the high-concentration Arctic sea
  ice, J. Geophys. Res., 112, C08004, doi:10.1029/2006JC003543, 2007.
- 9 Ashcroft, P. and Wentz F. J.: AMSR-E/Aqua L2A Global Swath Spatially-Resampled
- Brightness Temperatures. Version 2, NASA DAAC at the National Snow and Ice Data
  Center, Boulder, Colorado USA, doi: 10.5067/AMSR-E/AE\_L2A.002, 2003.
- Brucker, L., Cavalieri, D. J., Markus, T., and Ivanoff, A.: NASA Team 2 Sea Ice
   Concentration Algorithm Retrieval Uncertainty, IEEE T. Geosci. Remote, 52, 7336–7352,
- 14 doi: 10.1109/TGRS.2014.2311376, 2014.
- Cavalieri, D. J., Gloersen, P., and Campbell, W. J.: Determination of sea ice parameters with
  the NIMBUS 7 SMMR, J. Geophys. Res., 89, D4, 5355–5369, 1984.
- 17 Cavalieri, D.\_J., Burns, B.\_A., and Onstott, R.\_G.: Investigation of the effects of summer melt
- 18 on the calculation of sea ice concentration using active and passive microwave data, J.
- 19 Geophys. Res., 95, 5359–5369, 1990.
- Cavalieri, D. J., Germain, K. S., and Swift, C. T.: Reduction of weather effects in the
  calculation of sea ice concentration with the DMSP SSM/I, J. Glaciol., 41, <u>455-464</u>, 1995.
- Cavalieri, D. J. and Parkinson, C. L.: Arctic sea ice variability and trends, 1979–2010, The
   Cryosphere, 6, 881-889, doi:10.5194/tc-6-881-2012, 2012.
- Comiso, J. C.: Characteristics of arctic winter sea ice from satellite multispectral microwave
  observations, J. Geophys. Res., 91, 975–994, 1986.
- 26 Comiso, J. C.: SSM/I Sea Ice Concentrations Using the Bootstrap Algorithm, NASA
- 27 Reference Publication 1380, NASA Center for Aerospace Information, 800 Elkridge Landing
- 28 Road, Linthicum Heights, MD 21090-2934, (301) 62 1-0390, 1995.
- Comiso, J. C. and Kwok, R.: Surface and radiative characteristics of the summer Arctic sea
  ice cover from multisensor satellite observations, J. Geophys. Res., 101, 28397–28416, 1996.

1	Comiso, J. C.: Enhanced Sea Ice Concentrations and Ice Extents from AMSR-E Data, J.	
2	Remote Sens. of Japan, 29, 199–215, doi:10.11440/rssj.29.199, 2009.	
3	Eastwood, S. (Ed.): Ocean & Sea Ice SAF (OSISAF) Sea Ice Product Manual. Version 3.8.,	
4	available at: http://osisaf.met.no, last access: May 2012.	
5	Fennig <sub>2</sub> K., Andersson, A., and Schröder, M.: Fundamental Climate Data Record of SSM/I	
6	Brightness Temperatures, Satellite Application Facility on Climate Monitoring,	Natalia Ivanova 31/3/2015 11:40
7	<u>doi</u> :10.5676/EUM_SAF_CM/FCDR_SSMI/V001, 2013.	Deleted:
8	Fetterer <sub>a</sub> F. and Untersteiner, N.: Observations of melt ponds on Arctic sea ice. J. Geophys.	Natalia Ivanova 31/3/2015 11:27 Deleted: DOI
9	Res., 103, 24821–24835, 1998.	Natalia Ivanova 21/2/2015 11:20
10	Gloersen, P., and Cavalieri, D. J.: Reduction of Weather Effects in the Calculation of Sea Ice	Deleted: , C11
11	Concentration From Microwave Radiances, J. Geophys. Res., 91, 3913-3919, 1986.	
12	Gloersen, P., Campbell, W. J., Cavalieri, D. J., Comiso, J. C., Parkinson, C. L., and Zwally H.	Natalia Ivanova 31/3/2015 11:40 Deleted: C3,
13	J.: Arctic and Antarctic Sea Ice, 1978-1987: satellite passive microwave observations and	
14	analysis, NASA SP-511, NASA, Washington, D.C., 1992.	
15	Grenfell, T. C., Barber, D. G., Fung, A. K., Gow, A. J., Jezek, K. C., Knapp, E. J., Nghiem, S.	Deleted: (
16	V., Onstott, R. G., Perovich, D. K., Roesler, C. S., Swift, C. T., and Tanis, F.: Evolution of	Natalia Ivanova 31/3/2015 11:40 Deleted: NASA)
17	electromagnetic signatures of sea ice from initial formation to the establishment of thick first-	
18	year ice, IEEE Trans. Geosci. Rem. Sens., 36(5), 1642-1654, 1998.	
19	Grenfell, T. C., Cavalieri, D. J., Comiso, J. C., Drinkwater, M. R., Onstott, R. G., Rubinstein,	
20	I., Steffen, K., and Winebrenner, D. P.: Considerations for Microwave Remote Sensing of	
21	Thin Sea Ice, in: Microwave Remote Sensing of Sea Ice (ed F. D. Carsey), American	
22	Geophysical Union, Washington, D.C. doi: 10.1029/GM068p0291, 1992.	Natalia Ivanova 31/3/2015 11:41
23	Heygster, G., Huntemann, M., Ivanova, N., Saldo, R., and Pedersen, L. T.: Response of	Deleted:
24		Natalia Ivanova 31/3/2015 11:41
25	passive microwave sea ice concentration algorithms to thin ice, Proceedings Geoscience and	Deleted: DOI
25	passive microwave sea ice concentration algorithms to thin ice, Proceedings Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International, 13-18 July, Quebec City,	Deleted: DOI
25 26	passive microwave sea ice concentration algorithms to thin ice, Proceedings Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International, 13-18 July, Quebec City, QC, 3618 – 3621, doi:10.1109/IGARSS.2014.6947266, 2014.	Deleted: DOI
25 26 27	passive microwave sea ice concentration algorithms to thin ice, Proceedings Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International, 13-18 July, Quebec City, QC, 3618 – 3621, <u>doi</u> :10.1109/IGARSS.2014.6947266, 2014. Huntemann, M., Heygster, G., Kaleschke, L., Krumpen, T., Mäkynen, M., and Drusch, M.:	Deleted: DOI Natalia Ivanova 31/3/2015 11:41 Deleted: pages
25 26 27 28	<ul> <li>passive microwave sea ice concentration algorithms to thin ice, Proceedings Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International, 13-18 July, Quebec City, QC, 3618 – 3621, doi:10.1109/IGARSS.2014.6947266, 2014.</li> <li>Huntemann, M., Heygster, G., Kaleschke, L., Krumpen, T., Mäkynen, M., and Drusch, M.: Empirical sea ice thickness retrieval during the freeze up period from SMOS high incident</li> </ul>	Deleted: DOI Natalia Ivanova 31/3/2015 11:41 Deleted: pages Natalia Ivanova 31/3/2015 11:41 Deleted: DOI

1	Ivanova, N., Johannessen, O. M., Pedersen, L. T., and Tonboe, R. T.: Retrieval of Arctic Sea		
2	Ice Parameters by Satellite Passive Microwave Sensors: A Comparison of Eleven Sea Ice		
3	Algorithms, IEEE T. Geosci. Remote, 52, 7233-7246, doi:10.1109/TGRS.2014.2310136,		Natalia Ivanova 31/3/2015 11:42
4	2014.	$\backslash$	Deleted: rans
5	Ivanova, N., Pedersen, L. T., and Tonboe, R., T.: Product Validation & Algorithm Selection		Deleted: Sens.
6	Report (PVASR): Sea Ice Concentration, version 1.0, 20 June 2013, Doc Ref: SICCI-PVASR		Natalia Ivanova 31/3/2015 11:43 Deleted: , 11
7	(SIC), European Space Agency, http://esa-seaice-cci.org, 2013.		
8	Kaleschke, L., Lüpkes, C., Vihma, T., Haarpaintner, J., Bochert, A., Hartmann, J., and		Natalia Ivanova 10/6/2015 20:39
9	Heygster, G.: SSM/I Sea Ice Remote Sensing for Mesoscale Ocean-Atmosphere Interaction		Deleted: u
10	Analysis, Can. J. Remote Sens., 27, 5, 526–537, 2001.		
11	Kern, S.: A new method for medium-resolution sea ice analysis using weather-influence		
12	corrected Special Sensor Microwave/Imager 85 GHz data, Int. J. Remote Sens., 25, 4555-		
13	4582, 2004.	$\backslash$	Deleted:
14	Kern, S., Khvorostovsky, K., Skourup, H., Rinne, E., Parsakhoo, Z. S., Djepa, V.,		Natalia Ivanova 31/3/2015 11:43 Deleted: , 21
15	Wadhams, P., and Sandven, S.: The impact of snow depth, snow density and ice density on		Natalia Ivanova 10/6/2015 20:40
16	sea ice thickness retrieval from satellite radar altimetry: results from the ESA-CCI Sea Ice		Deleted:
17	ECV Project Round Robin Exercise, The Cryosphere, 9, 37-52, doi:10.5194/tc-9-37-2015,		
18	<u>2015.</u>		
19	Kwok, R.: Sea ice concentration estimates from satellite passive microwave radiometry and		
20	openings from SAR ice motion, Geophys. Res. Lett., 29, doi:10.1029/2002GL014787,		
21	2002.		Natalia Ivanova 31/3/2015 11:29 Deleted: 9,
22	Kwok, R., Comiso, J. C., Martin, S., and Drucker, R.; Ross Sea polynyas; Response of ice		Natalia Ivanova 31/3/2015 11:29
23	concentration retrievals to large areas of thin ice. J. Geophys. Res., 112, C12012		
24	doi:10.1029/2006JC003967, 2007.		
25	Mäkynen, M. and Similä, M.: Thin Ice Detection in the Barents and Kara Seas With AMSR-E		
26	and SSMIS Radiometer Data, IEEE T. Geosci. Remote, IEEE Early Access Articles, DOI:		
27	<u>10.1109/TGRS.2015.2416393, 2015.</u>		
28	Mäkynen, M., Kern, S., Rösel, A., and Pedersen, L.T.: On the Estimation of Melt Pond		
29	Fraction on the Arctic Sea Ice With ENVISAT WSM Images, IEEE T. Geosci. Remote, 52,		

**30** <u>7366–7379, 2014.</u>

31/3/2015 11:43 31/3/2015 11:43

31/3/2015 11:43 31/3/2015 11:43 10/6/2015 20:40

31/3/2015 11:29 31/3/2015 11:29

Marcq, S. and Weiss, J.: Influence of sea ice lead-width distribution on turbulent heat transfer
between the ocean and the atmosphere, The Cryosphere, 6, 143-156, DOI: 10.5194/tc-6-143-
<u>2012, 2012.</u>
Markus, T., and Cavalieri, D. J.: An enhancement of the NASA Team sea ice algorithm, IEEE
Trans. Geosci. Remote Sens., 38, 1387–1398, 2000.
Meier, W., and Notz, D.: A note on the accuracy and reliability of satellite-derived passive
microwave estimates of sea-ice extent. Clic Arctic sea ice working group. Consensus
document, CLIC International Project Office, Tromsø, Norway, 28 October 2010.
Meissner, T., and Wentz, F. J.: The emissivity of the ocean surface between 6 - 90 GHz over a
large range of wind speeds and Earth incidence angles, IEEE Transactions on Geoscience and
Remote Sensing, 50(8), 3004-3026, 2012
Naoki, K., Ukita, J., Nishio, F., Nakayama, M., Comiso, J. C., and Gasiewski, A: Thin sea ice
thickness as inferred from passive microwave and in situ observations, J. Geophys. Res., 113,
2156-2202, 2008.
Njoku, E. G.: Nimbus-7 SMMR Pathfinder Brightness Temperatures. 25, October 1978-20,
August 1987, NASA DAAC at the National Snow and Ice Data Center, NASA, Boulder,
Colorado, USA, 2003.
Notz, D. and Marotzke, J.: Observations reveal external driver for Arctic sea-ice retreat.
Geophys. Res. Lett., 39, L08502, doi: 10.1029/2012GL051094, 2012.
NSIDC (National Snow and Ice Data Center): Monthly Ocean Masks and Maximum Extent
Masks, http://nsidc.org/data/smmr_ssmi_ancillary/ocean_masks.html
Oelke, C., Atmospheric signatures in sea ice concentration estimates from passive
microwaves: modelled and observed, Int. J. Rem. Sens., 18(5), 1113-1136, 1997.
Parkinson, C. L., and Cavalieri, D. J.: Antarctic sea ice variability and trends, 1979-2010, The
Cryosphere, 6, 871-880, doi:10.5194/tc-6-871-2012, 2012.
Parkinson, C. L., Comiso, J. C., and Zwally, H. J.: Nimbus-5 ESMR Polar Gridded Sea Ice
Concentrations, 1978-2011, edited by: Meier, W. and Stroeve, J. NASA DAAC at the

- 29 Pedersen, L.T.: Merging microwave radiometer data and meteorological data for improved
- 30 sea ice concentrations, EARSeL Adv, in Remote Sens, 3, <u>81-89</u>, 1994.

Natalia Ivanova 31/3/2015 11:48 Deleted: 3 Natalia Ivanova 31/3/2015 11:31 Deleted: Natalia Ivanova 31/3/2015 11:49 Deleted: Mäkynen, M., Kern, S., Rösel, A., and Pedersen, L.T.: On the Estimation of Melt Pond Fraction on the Arctic Sea Ice With ENVISAT WSM Images, IEEE Trans. Geosci. Remote Sens., 52, 11, 7366–7379, 2014. Natalia Ivanova 31/3/2015 11:49 Deleted: C2 Natalia Ivanova 31/3/2015 11:49 Deleted: Natalia Ivanova 31/3/2015 11:49 Deleted: .10. Natalia Ivanova 31/3/2015 11:49 Deleted: .08 Natalia Ivanova 31/3/2015 11:49 Deleted: ]. Boulder, Colorado USA: Natalia Ivanova 31/3/2015 11:50 Moved (insertion) [4] Natalia Ivanova 31/3/2015 11:51 Deleted: [ Natalia Ivanova 31/3/2015 11:51 Deleted: ] Natalia Ivanova 31/3/2015 11:51 Deleted: Natalia Ivanova 31/3/2015 11:52 Deleted: E Natalia Ivanova 31/3/2015 11:52 Deleted: W. Natalia Ivanova 31/3/2015 11:52 Deleted: J. Natalia Ivanova 31/3/2015 11:52 Deleted: . Boulder, Colorado USA Natalia Ivanova 31/3/2015 11:50 Deleted: Natalia Ivanova 31/3/2015 11:50 Moved up [4]: Parkinson, C. L. and Cavalieri, D. J .: Antarctic sea ice variability and trends, 1979-2010, The Cryosphere, 6, 871-880, 2012. Natalia Ivanova 31/3/2015 11:32 Deleted: ances Natalia Ivanova 31/3/2015 11:32 Deleted: ing Natalia Ivanova 31/3/2015 11:32 Deleted: Vol. Natalia Ivanova 31/3/2015 11:32 Deleted: No. 2-XII

- Ramseier, R. O.: Sea Ice Validation, in: <u>DMSP special sensor microwave/imager</u>
   calibration/validation, <u>edited by: Hollinger, J. P.,</u> Naval Research Laboratory, <u>Washington,</u>
   <u>D.C.</u> 1991.
- 4 Röhrs, J., and Kaleschke, L.: An algorithm to detect sea ice leads by using AMSR-E passive
  5 microwave imagery, The Cryosphere, 6, 343-352, doi:10.5194/tc-6-343-2012, 2012.
- 6 Röhrs, J., Kaleschke, L., Bröhan, D., and Siligam, P. K.: Corrigendum to "An algorithm to
- 7 detect sea ice leads by using AMSR-E passive microwave imagery" published in The
- 8 <u>Cryosphere, 6, 343–352, 2012, The Cryosphere, 6, 365-365, doi:10.5194/tc-6-365-2012,</u>
- 9 <u>2012.</u>
- Rösel, A., Kaleschke, L., and Birnbaum, G.: Melt ponds on Arctic sea ice determined from
  MODIS satellite data using an artificial neural network, The Cryosphere, 6, 431-446,
  doi:10.5194/tc-6-431-2012, 2012a.
- 13 Rösel, A., Kaleschke, L., and Kern, S.: Influence of melt ponds on microwave sensor's sea ice
- 14 concentration retrieval algorithms, Proceedings Geoscience and Remote Sensing Symposium
- 15 (IGARSS), 2012 IEEE International, <u>23-27 July 2012</u>, Munich, <u>2012b</u>.
- 16 Scott, K. A., Buehner, M., and Carrieres, T.: An Assessment of Sea-Ice Thickness Along the
- 17 Labrador Coast From AMSR-E and MODIS Data for Operational Data Assimilation, IEEE T.
- 18 Geosci, Remote, 52, 2726–2737, doi: 10.1109/TGRS.2013.2265091,2014.
- 19 Shokr, M., Lambe, A., and Agnew, T.: A new algorithm (ECICE) to estimate ice
- 20 concentration from remote sensing observations: an application to 85-GHz passive microwave
- 21 data, IEEE T, Geosci. Remote, 46, 4104–4121, doi: 10.1109/TGRS.2008.2000624, 2008.
- 22 Smith, D. M.: Extraction of winter total sea-ice concentration in the Greenland and Barents
- 23 Seas from SSM/I data, Int. J. Remote Sens., 17, 2625–2646, 1996.
- 24 Svendsen, E., Kloster, K., Farrelly, B., Johannessen, O. M., Johannessen, J. A., Campbell, W.
- 25 J., Gloersen, P., Cavalieri, D., and Matzler, C.: Norwegian Remote Sensing Experiment'
- 26 Evaluation of the Nimbus 7 Scanning Multichannel Microwave Radiometer for Sea Ice
- 27 Research, J. Geophys. Res., 88, 2781-2791, 1983.
- 28 Swift, C., Fedor, L., and Ramseier, R.: An Algorithm to Measure Sea Ice Concentration With
- 29 Microwave Radiometers, J. Geophys. Res., 90, 1087–1099, 1985.

Natalia Ivanova 31/3/2015 11:53 Moved down [5]: J. P. Hollinger, ed., Natalia Ivanova 31/3/2015 11:53 Moved (insertion) [5] Natalia Ivanova 31/3/2015 11:53 Deleted: J. P. Natalia Ivanova 31/3/2015 11:53 Deleted: ed., Washington, DC, Natalia Ivanova 14/6/2015 15:04 Deleted: \_\_\_\_\_\_\_\_[106]

Natalia Ivanova 31/3/2015 11:59 Deleted: July 23-27 Natalia Ivanova 31/3/2015 11:59 Deleted: Transactions Natalia Ivanova 31/3/2015 11:59 Deleted: on Natalia Ivanova 31/3/2015 11:59 Deleted: ence and Natalia Ivanova 31/3/2015 11:59 Deleted: Sensing Natalia Ivanova 31/3/2015 11:59 Deleted: 5 Natalia Ivanova 10/6/2015 20:43 Formatted: German Natalia Ivanova 31/3/2015 12:00 Deleted: rans Natalia Ivanova 31/3/2015 12:00 Deleted: Sens. Natalia Ivanova 31/3/2015 12:00 Deleted: 12 Natalia Ivanova 10/6/2015 20:44 Formatted: German Natalia Ivanova 31/3/2015 12:00 Deleted: Natalia Ivanova 31/3/2015 12:00 Deleted: 13 Natalia Ivanova 31/3/2015 12:00 Deleted: C5. Natalia Ivanova 31/3/2015 12:00 Deleted: C1

1	Tophoe R $T \cdot T$	e simulated	sea ice thermal micros	vave emission at window and sounding	
2	frequencies. Tellu	s A. 62. 333-	344, 2010.	wave emission at window and sounding	
2 3 4 5 6 7 8 9	frequencies. Tellu Tonboe, R. T., and to emissivity vari Scientific Report ( Tonboe, R. T., Dy temperature and m Tschudi, M. A., M arctic sea ice using	s A, 62, 333- d Andersen, S ations of the D4-03, <u>Danish</u> bkjær, G., <u>an</u> nicrowave eff Maslanik, J. <i>A</i> g MODIS obs	344, 2010. S.: Modelled radiomete e Arctic sea ice snow <u>h Meteorological Institu</u> <u>d</u> Høyer, J. L.: Simulat fective temperature. Tel A., and Perovich, D. K servation, Remote Sens	er algorithm ice concentration sensitivity cover, Danish Meteorological Institute ite, Copenhagen, Denmark, 2004. cions of the snow covered sea ice surface llus A, <u>63</u> , 1028-1037, 2011. : Derivation of melt pond coverage on s. Environ., 112, 2605–2614, 2008.	Natalia Ivanova 31/3/2015 11:35 Deleted: . Natalia Ivanova 31/3/2015 11:35 Deleted: 63
10	<u>Ulaby, F. T., Moo</u>	ore, R. K., ar	nd A. K. Fung 1986. N	Microwave Remote Sensing. Active and	
11 12 13	Passive. Norwood Wentz, F. J.: A we 1997.	<u>, MA: Artech</u> ell-calibrated	<u>h House Inc, 1986.</u> ocean algorithm for SS	SM/I. J. Geophys. Res., 102 <u>, 8703-8718,</u>	Natalia Ivanova 31/3/2015 12:01 Deleted: , C4
14 15	Wentz, F. J., Ricc Global Warming I	iardulli, L., H Bring?, Scien	Hilburn, K. A., and Me ce, 317, 233-235, 2007	ears, C. A.: How Much More Rain Will	
16 17 18	Willmes, S., Nico covered first-year 891–904, doi:10.5	olaus, M., ar sea ice from 194/tc-8-891	nd Haas, C.: The mic late winter to early sun -2014, 2014.	prowave emissivity variability of snow nmer: a model study, The Cryosphere, 8,	
19 20	<b>v</b>				Natalia Ivanova 28/5/2015 18:39 Deleted:
21					
22					
23					
24					
25	Table 1. <u>The SIC</u>	algorithms sh	own in this study.		Natalia Ivanova 16/6/2015 16:56
I	Algorithm	Acronym	Reference	Channels	Deleted: The selection of thirteen Natalia Ivanova 16/6/2015 16:56
	Bootstrap P	BP	Comiso, 1986	37V, 37H <b>P</b>	Deleted: sea ice
	CalVal	CV	Ramseier, 1991	19V, 37V <b>F</b>	
				38	

Bristol	BR	Smith, 1996	19V, 37V, 37H <b>PF</b>
NASA Team	NT	Cavalieri et al., 1984	19V, 19H, 37V <b>PF</b>
ASI	ASI	Kaleschke et al., 2001	85V, 85H <b>P</b>
Near 90GHz linear	N90	Jvanova et al., 2013	85V, 85H <b>P</b>
ESMR	ESMR	Parkinson et al., 2004	19H
6Н	6H	Pedersen, 1994	6H
ECICE	ECICE	Shokr et al., 2008	19V&19H or 37V&37H <b>P</b>
NASA Team 2	NT2	Markus and Cavalieri, 2000	19V, 19H, 37V, 85V, 85H <b>PF</b>
NT+CV	NT+CV	Jvanova et al., 2013	19V, 19H, 37V <b>PF</b>
CV+N90	CV+N90	Jvanova et al., 2013	19V, 37V, 85V, 85H <b>PF</b>
OSISAF	OSISAF	Eastwood (ed.) <sub>2</sub> 2012	19V, 37V, 37H <b>PF</b>

*P* indicates that the algorithm is based on the polarisation difference or ratio at a single frequency; *F* indicates
 that the algorithm uses two different frequencies at the same polarisation (i.e., a spectral gradient). The names of the high-frequency algorithms (and the algorithms partially using high frequencies) are shown in bold, while the rest are low-frequency algorithms.

# 6 Table 2a. SIC SD (in %). Low SIC: 15% (0% for SMMR), winter (W) and summer (S). No

	open water filter applied.	Ref – SD for the full SIC 0% dataset.
I		

Northern Hemisphere											
		AMS	SR-E	<u>SSM/I</u>		<u>SMMR</u>					
Algorithm	Avrg SD	<u>S</u>	W	<u>S</u>	W	<u>S</u>	W	Ref			
<u>6H</u>	<u>2.8</u>	<u>2.0</u>	<u>2.5</u>			<u>2.8</u>	<u>3.8</u>	<u>3.0</u>			
CV	<u>3.8</u>	<u>3.6</u>	<u>3.5</u>	<u>4.6</u>	<u>3.8</u>	<u>3.5</u>	<u>3.9</u>	<u>4.8</u>			
<u>NT+CV</u>	<u>4.5</u>	<u>4.6</u>	<u>4.4</u>	<u>5.1</u>	<u>4.6</u>	<u>3.9</u>	<u>4.2</u>	<u>5.5</u>			
OSISAF	<u>4.7</u>	<u>5.3</u>	4.8	<u>5.4</u>	<u>4.7</u>	<u>3.8</u>	<u>4.1</u>	<u>5.2</u>			
NT	<u>5.4</u>	<u>5.8</u>	<u>5.5</u>	<u>5.9</u>	<u>5.5</u>	<u>4.7</u>	<u>4.8</u>	<u>6.6</u>			

BR	<u>6.6</u>	<u>7.1</u>	<u>6.7</u>	<u>6.6</u>	<u>6.1</u>	<u>6.4</u>	<u>6.4</u>	<u>7.8</u>		
ESMR	<u>7.2</u>	<u>7.6</u>	<u>7.0</u>	<u>7.9</u>	<u>6.9</u>	<u>7.1</u>	<u>6.5</u>			
<u>NT2</u>	<u>7.3</u>	<u>6.3</u>	<u>6.7</u>	<u>8.9</u>	<u>7.2</u>					
ECICE	<u>9.4</u>	<u>10.7</u>	<u>10.0</u>	8.8	<u>8.2</u>					
BP	<u>13.5</u>	<u>14.5</u>	<u>13.1</u>	<u>12.4</u>	<u>11.4</u>	<u>15.2</u>	<u>14.1</u>	<u>15.5</u>		
<u>CV+N90</u>	<u>15.8</u>	<u>15.6</u>	<u>15.6</u>	<u>16.5</u>	<u>15.3</u>			<u>19.8</u>		
ASI	<u>28.5</u>	<u>31.3</u>	<u>30.1</u>	<u>27.0</u>	<u>25.7</u>					
<u>N90</u>	<u>28.8</u>	<u>28.9</u>	<u>28.8</u>	<u>29.6</u>	<u>27.8</u>			<u>35.9</u>		
Southern Hemisphere										
		AMS	<u>SR-E</u>	<u>SS</u>	<u>M/I</u>	<u>SM</u>				
Algorithm	Avrg SD	<u>S</u>	W	<u>S</u>	W	<u>S</u>	W	Ref		
<u>6H</u>	<u>2.2</u>	<u>2.1</u>	<u>2.4</u>			<u>1.9</u>	<u>2.2</u>	<u>2.3</u>		
CV	<u>3.5</u>	<u>3.4</u>	<u>3.4</u>	<u>3.9</u>	<u>4.0</u>	<u>3.0</u>	<u>3.2</u>	<u>3.9</u>		
<u>NT+CV</u>	<u>3.9</u>	<u>3.9</u>	<u>3.9</u>	<u>4.4</u>	<u>4.5</u>	<u>3.1</u>	<u>3.4</u>	<u>4.4</u>		
OSISAF	<u>4.3</u>	<u>4.8</u>	<u>4.8</u>	<u>4.9</u>	<u>5.0</u>	<u>3.2</u>	<u>3.4</u>	<u>4.3</u>		
<u>NT</u>	<u>4.4</u>	4.6	4.6	<u>5.0</u>	<u>5.2</u>	<u>3.4</u>	<u>3.7</u>	<u>5.0</u>		
BR	<u>6.1</u>	<u>6.7</u>	<u>6.5</u>	<u>6.3</u>	<u>6.2</u>	<u>5.5</u>	<u>5.7</u>	<u>6.9</u>		
<u>NT2</u>	<u>6.2</u>	<u>6.3</u>	<u>6.3</u>	<u>6.2</u>	<u>6.0</u>					
<u>ESMR</u>	<u>6.7</u>	<u>7.3</u>	<u>7.1</u>	<u>6.9</u>	<u>6.9</u>	<u>6.0</u>	<u>6.1</u>			
ECICE	<u>9.8</u>	<u>11.1</u>	<u>10.7</u>	<u>8.8</u>	<u>8.5</u>					
BP	<u>16.2</u>	<u>17.0</u>	<u>16.2</u>	<u>14.4</u>	<u>14.1</u>	<u>17.</u> 6	<u>18.0</u>	<u>17.7</u>		
<u>CV+N90</u>	<u>18.9</u>	<u>20.5</u>	<u>19.8</u>	<u>18.0</u>	<u>17.5</u>			<u>22.0</u>		
ASI	<u>28.9</u>	<u>32.5</u>	<u>31.1</u>	26.3	<u>25.6</u>					
<u>N90</u>	<u>35.0</u>	<u>38.4</u>	<u>36.9</u>	32.7	32.0			<u>40.8</u>		

# 1 <u>Table 2b. SIC SD (in %). High SIC: 75%, winter. No open water filter applied. Ref – SD for</u>

2 <u>the full SIC 100% dataset.</u>

	Northern	Hemisphe	ere		Southern Hemisphere					
Alg	<u>Avrg</u> <u>SD</u>	<u>AMSR-</u> <u>E</u>	<u>SSM/I</u>	<u>Ref</u>	Alg	<u>Avrg</u> <u>SD</u>	<u>AMSR-</u> <u>E</u>	<u>SSM/I</u>	Ref	
BR	<u>3.1</u>	<u>3.1</u>	<u>3.1</u>	<u>4.3</u>	BR	<u>2.9</u>	2.8	<u>3.0</u>	<u>4.5</u>	
<u>OSISAF</u>	<u>3.1</u>	<u>3.1</u>	<u>3.1</u>	<u>4.3</u>	<u>OSISAF</u>	<u>2.9</u>	<u>2.8</u>	<u>3.0</u>	<u>4.5</u>	
<u>NT+CV</u>	<u>3.1</u>	<u>3.1</u>	<u>3.2</u>	<u>4.4</u>	<u>6H</u>	<u>2.9</u>	<u>2.9</u>		<u>4.8</u>	
<u>CV+N90</u>	<u>3.4</u>	<u>3.3</u>	<u>3.5</u>	<u>4.6</u>	<u>NT+CV</u>	<u>3.0</u>	<u>2.8</u>	<u>3.1</u>	<u>4.7</u>	
<u>NT2</u>	<u>3.7</u>	<u>3.9</u>	<u>3.6</u>		<u>CV</u>	<u>3.4</u>	<u>3.0</u>	<u>3.7</u>	<u>5.4</u>	
<u>6H</u>	<u>3.7</u>	<u>3.7</u>		<u>5.4</u>	<u>NT</u>	<u>4.3</u>	<u>4.2</u>	<u>4.4</u>	<u>6.6</u>	
<u>NT</u>	<u>3.8</u>	<u>4.0</u>	<u>3.7</u>	<u>5.7</u>	<u>CV+N90</u>	<u>4.6</u>	<u>4.8</u>	<u>4.5</u>	<u>5.9</u>	
ASI	<u>3.9</u>	<u>4.7</u>	<u>3.5</u>		<u>ECICE</u>	<u>4.9</u>	<u>5.4</u>	<u>4.6</u>		
<u>CV</u>	<u>4.5</u>	<u>4.5</u>	<u>4.5</u>	<u>6.4</u>	<u>ASI</u>	<u>4.9</u>	<u>5.9</u>	<u>4.3</u>		
BP	<u>4.6</u>	<u>5.2</u>	<u>4.3</u>	<u>6.2</u>	<u>NT2</u>	<u>5.8</u>	<u>5.7</u>	<u>5.8</u>		
<u>ESMR</u>	<u>4.7</u>	<u>3.0</u>	<u>5.4</u>		<u>ESMR</u>	<u>7.1</u>	<u>3.9</u>	<u>8.6</u>		
<u>N90</u>	<u>5.4</u>	<u>5.2</u>	<u>5.5</u>	<u>7.0</u>	<u>N90</u>	<u>8.1</u>	<u>8.4</u>	<u>7.9</u>	<u>10.4</u>	
ECICE	<u>8.1</u>	<u>7.4</u>	<u>8.5</u>		BP	<u>9.0</u>	<u>8.7</u>	<u>9.2</u>	<u>13.1</u>	

3



Figure 1. Coverage graphs for the SSM/I subset of <u>the</u> Northern Hemisphere RRDP in winters 2007 and 2008. Both the Tb and spatial coverage are displayed. In all panels, <u>triangle symbols</u> are used for the QW<sub>v</sub> locations, and circles for CI<sub>v</sub> In the Tb diagrams, the OW symbols are coloured according to Tb22v values (left colour scale), while the CI symbols are coloured according to Tb37h values (right colour scale). The colouring of CI symbols is also used in the embedded map. Solid and dashed lines show ice and OW lines respectively.



10 Figure 2. Same as Fig. 1, but in the Southern Hemisphere.





Deleted: ie-point


Figure <u>4</u>, SIC calculated by the <u>SIC</u> algorithms as a function of SMOS ice thickness in areas
of the Arctic Ocean, which are known to be ~100% thin ice during the time period from 1
October to 12 December 2010. Grey shading shows <u>SDs</u> of the algorithms. Number of
measurements in each bin is shown above the x-axis (total number is 991). In this SIC range
OSISAF is the same as BR.

-	Natalia Ivanova 21/5/2015 21:12
	Deleted: 5
	Natalia Ivanova 16/6/2015 17:02
	Deleted: implemented
	Natalia Ivanova 25/3/2015 13:13
	Deleted: standard deviation





Figure 5, Demonstration of the open water/weather filter performance: gradient ratio (GR)
19/22 is plotted as a function of GR19/37 for SSM/I data in 2008 (entire, year) for the
Northern Hemisphere for SIC of 0%, 15%, 20% and 30%. The red square shows the value
range outside which the open water/weather filter sets SIC values to 0% (open water).

Natalia Ivanova 21/5/2015 21:12
Deleted: 6
Natalia Ivanova 16/6/2015 17:03
Deleted: full



- and with RTM correction (upper panel, right). The histograms contain 21 bins of 2% SIC.
- Bottom plot: decrease in <u>SDs for 10 SIC algorithms</u> due to the <u>atmospheric</u> correction of the
- measured Tbs.

Natalia Ivanova 21/5/2015 21:12
Deleted: 7
Natalia Ivanova 16/6/2015 17:04
Deleted: for
Natalia Ivanova 16/6/2015 17:04
Deleted: the OSISAF algorithm
Natalia Ivanova 16/6/2015 17:04
Deleted: full
Natalia Ivanova 25/3/2015 13:13
Deleted: standard deviation
Natalia Ivanova 16/6/2015 17:05
Deleted: atmagnharia influence on the







Figure 7, Examples of tie points time series for the Bootstrap F algorithm in the Northern (left panels) and Southern (right panels) hemispheres: Tb19y and Tb37v, ice tie points (upper and middle plots respectively) and slopes (bottom plots). The vertical bars in light grey to dark grey colours denote the progressing melt season from May to September in the Northern and from November to March in the Southern hemisphere.

Natalia Ivanova 21/5/2015 21:12
Deleted: 8
Natalia Ivanova 14/6/2015 14:20
Deleted: ie-point
Natalia Ivanova 12/5/2015 11:46
Deleted: BR
Natalia Ivanova 12/5/2015 12:10
Deleted: ice tie-point for
Natalia Ivanova 12/5/2015 12:11
Deleted: a
Natalia Ivanova 12/5/2015 12:11
Deleted: c
Natalia Ivanova 12/5/2015 12:11
Deleted: and BF open water tie-point (
Natalia Ivanova 10/6/2015 20:48
Deleted: V
Natalia Ivanova 10/6/2015 20:48
Deleted: V
Natalia Ivanova 12/5/2015 12:11
<b>Deleted:</b> ) for the Northern (b) and Southern (d) hemispheres