



Sea-ice extent and its trend provide limited metrics of model performance

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Abstract. We examine how the evaluation of modelled sea-ice coverage against reality is affected by uncertainties in the retrieval of sea-ice coverage from satellite, by the usage of sea-ice extent to overcome these uncertainties, and by internal variability. We find that for Arctic summer sea ice, model biases in sea-ice extent can be qualitatively different from biases in sea-ice area. This is because about half of the CMIP5 models and satellite retrievals based on the Bootstrap and the ASI algorithm show a compact ice cover in summer with large areas of high-concentration sea ice, while the other half of the CMIP5 models and satellite retrievals based on the NASA Team algorithm show a loose ice cover. For the Arctic winter sea-ice cover, differences in grid geometry can cause synthetic biases in sea-ice extent that are larger than the observational uncertainty. Comparing the uncertainty arising directly from the satellite retrievals with those that arise from internal variability, we find that the latter by far dominates the uncertainty estimate for trends in sea-ice extent and area: most of the differences between modelled and observed trends can simply be explained by internal variability. For absolute sea-ice area and sea-ice extent, however, internal variability cannot explain the difference between model and observations for about half the CMIP5 models that we analyse here. All models that we examined have regional biases, as expressed by the root-mean-square error in concentration, that are larger than the differences between individual satellite algorithms.

1 Introduction

The evaluation of climate-model simulations against reality is important both to build confidence in future projections from these models and to understand and improve their possible shortcomings. For a useful evaluation, two quantities must be known: first, the real evolution of the variable that is to be evaluated, and second, the degree to which one can expect agreement between simulation and reality in light of the internal variability of the climate system. In this contribution we examine how the evaluation of modelled sea-ice coverage is affected by the incomplete knowledge of both quantities and by the standard approach that is taken to overcome this incomplete knowledge.

The incomplete knowledge of the actual state of the sea-ice cover arises primarily from the difficulty in accurately determining sea-ice concentration from space, which is the only feasible method to obtain daily global data. Because of wide-spread cloud coverage, most often the passive microwave signature of the ocean surface as retrieved from satellites is used to derive the most likely sea-ice concentration in a specific area. This passive microwave signature is, however, strongly affected by meltwater at the ice surface and also by surface temperature, wind speed, humidity and other atmospheric properties. Because of these influencing factors, different retrieval algorithms result in different estimates of sea-ice concentration in a particular area (see, for example, Comiso et al., 1997; Kwok, 2002; Meier, 2005; Andersen et al., 2007).

These long-known discrepancies between sea-ice concentration estimates from different algorithms imply some uncertainty in our knowledge of the “true” sea-ice coverage. To still allow for the comparison of model simulations against a

reliable “true” state of sea-ice coverage, most studies that aim at evaluating multiple models against reality have resorted to using a quantity called sea-ice extent that differs only minimally between the various algorithms. This quantity measures the total area of the ocean surface in which significant amounts of sea ice exist. To calculate sea-ice extent in gridded data, one usually adds the area of all grid cells with an ice concentration of more than 15 %. Hence, sea-ice extent in a certain area would be the same for an algorithm that sees a sea-ice concentration of, for example, 40 % and for an algorithm that sees a sea-ice concentration of 60 %. While sea-ice extent was initially only used to assess the observed long-term evolution of the sea-ice cover (e.g. Zwally et al., 1983; Parkinson et al., 1987), it has now become common practice to use sea-ice extent also as the primary (and often sole) variable to assess the quality of modelled sea-ice coverage (e.g. Stroeve et al., 2007, 2012; Massonnet et al., 2012).

Sea-ice extent is always larger than the more direct integrative measure sea-ice area, which is simply the total area of the sea-ice cover and as such a much more direct measure of ice coverage. Important physical quantities such as Arctic-wide average albedo, open-water fraction and thus ocean–atmosphere heat exchange depend therefore much more directly on sea-ice area than on the non-linear measure sea-ice extent. This was already acknowledged by early works on satellite remote sensing (cf. Zwally et al., 1983). The focus on sea-ice extent is, as described, nevertheless understandable since this parameter can be more reliably observed from ships, airplanes and satellites than sea-ice area. This then allows both for a better assessment of the long-term (including pre-satellite) evolution of the ice cover and reduces the uncertainty of the observational data against which model simulations are compared.

This reduction in uncertainty in the observational data comes, however, at a price, in that sea-ice extent can give misleading results regarding model quality. Consider the trivial, fictitious observed sea-ice cover in three grid cells shown in Fig. 1a. Compared to these observations, a model could simulate a smaller sea-ice area that nevertheless results in a larger sea-ice extent because of a slight shift in the location or the spatial distribution of the sea-ice cover (Fig. 1b). A model could also simulate a larger sea-ice area with a smaller sea-ice extent (Fig. 1c). Hence, small shifts in the location of the modelled sea-ice pack, in particular in the marginal ice zone with its strong gradients in sea-ice concentration, can result in misleading results regarding the actual bias in modelled sea-ice cover.

In addition to these grid-independent issues, there is also a grid-dependent issue related to the usage of sea-ice extent vs. sea-ice area. Generally, higher grid resolution causes a lower sea-ice extent. At very high resolution, sea-ice extent converges to the same value as sea-ice area, since then almost all grid cells will either be fully ice covered or fully ice free.

We became aware of these issues when we analysed results from the Max Planck Institute for Meteorology Earth System

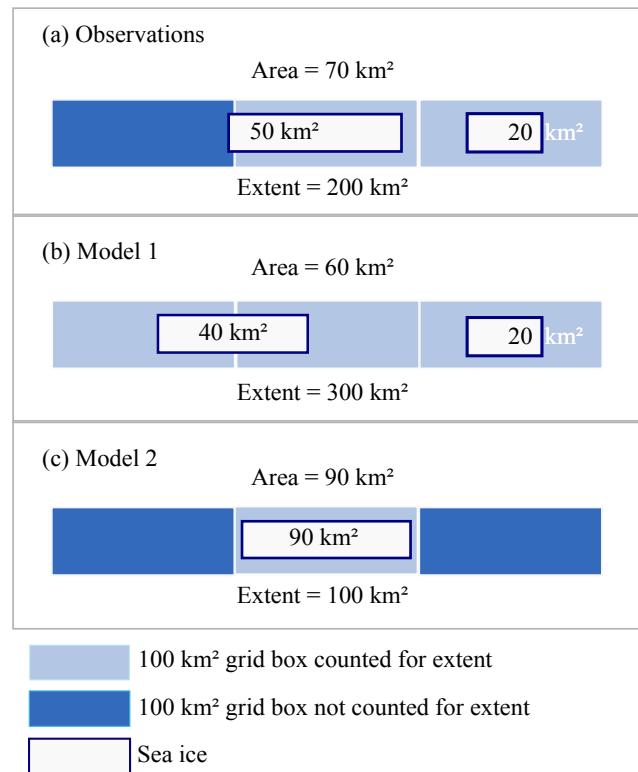


Fig. 1. A fictitious example to illustrate the possible non-intuitive relationship between sea-ice area and sea-ice extent. **(a)** In the observations, the ice pack is distributed such that two grid cells are covered by more than 15 % ice. **(b)** In a fictitious model simulation, less sea ice than in the observations is distributed such that three grid cells are covered by more than 15 % ice. **(c)** In a fictitious model simulation, more sea ice than in the observations is distributed such that only one grid cell is covered by more than 15 % ice.

Model MPI-ESM: compared to observations, this model has about 6 % too small a September Arctic sea-ice extent, but 20 % too small a sea-ice area (Notz et al., 2013). In contrast, this model’s predecessor ECHAM5/MPIOM had about 20 % too large a September Arctic sea-ice extent, but only about 7 % too large a sea-ice area. This gave rise to the question of whether too strong a focus on sea-ice extent can give misleading results regarding the quality of modelled sea-ice coverage, and which implications this has for quantitative model evaluation.

In this contribution, we examine these questions by analysing output from models that have contributed to the Coupled Model Intercomparison Project, phase 5 (CMIP5). Our aim is to give the reader a quantitative assessment, and an explanation, for the different outcomes in model–data comparison studies based on sea-ice extent vs. sea-ice area and their trends. Because positive and negative regional biases cancel each other out in the calculation of either sea-ice extent or sea-ice area, we additionally analyse these measures’ relationship to the mean absolute bias in sea-ice

concentration, which avoids such cancellation of errors. We also touch upon the issue of local biases in sea-ice concentration, which are relevant for a more detailed analysis of model quality. Our aim is to allow the reader an informed assessment of which parameter to use for a specific purpose and how to handle the related observational uncertainty. In particular, we put our findings into the context of uncertainty that arises because of the internal variability of the Arctic climate system.

The satellite products and the model data that we use are introduced in Sect. 2. In Sect. 3.1, we analyse the compactness of the modelled and satellite-retrieved sea-ice cover, which is important to understand the analysis of the different biases in sea-ice extent, area, and in their trends, discussed in Sect. 3.2. In Sect. 3.3, we examine the impact of grid resolution, followed by an analysis of cancelling negative and positive biases in Sect. 3.4. Section 3.5 then contains an analysis of the impact of internal variability on the assessment of model quality. In Sect. 3.6 we briefly touch upon some issues related to the non-linearity of sea-ice extent. We discuss the implications of these findings for model-evaluation purposes in Sect. 4. Our main findings are then summarised in Sect. 5.

2 Models and data

For our analysis, we focus on the period 1979–2005, which is the overlapping period of the most-widely used satellite records of sea-ice coverage and the “historical” simulations of the CMIP5 protocol (Taylor et al., 2012). These historical simulations are forced by the observed evolution of greenhouse gases, solar radiation, etc. For all 117 historical simulations from 26 different models that we consider here, time series of monthly mean sea-ice extent and area are calculated from their monthly mean sea-ice concentration fields. The sea-ice extent is calculated as the total area of all grid cells with at least 15 % sea-ice concentration. For sea-ice area, the area of all grid cells is multiplied by their sea-ice concentration and then added. For sea-ice area and extent, linear trends are calculated as a least-squares fit to the time series. Ensemble-mean and multi-model mean time series of sea-ice extent and sea-ice area are calculated as the ensemble-mean and the multi-model mean of the individual simulations’ time-series of these two parameters, and not from the ensemble-mean or multi-model mean concentration fields (compare Sect. 3.6).

The model results are compared against satellite retrievals of sea-ice concentration. As described in the introduction, different algorithms result in different estimates of sea-ice concentration because they are based on different transfer functions to derive sea-ice concentration from the measured passive-microwave signature. These differences are best documented (e.g. Comiso et al., 1997; Kwok, 2002) for the two satellite algorithms for sea-ice concentration that are most widely used for model-data intercomparison studies:

the Bootstrap algorithm (Comiso, 1986) and the NASA Team algorithm (Cavalieri et al., 1984) that forms the basis for the NSIDC Sea-Ice Index (Fetterer et al., 2002, updated 2012). Both provide sea-ice concentration data from 1979 onwards, and will be used throughout this study to exemplify the shortcomings of a direct comparison of modelled sea-ice extent to one particular satellite algorithm. Additionally, we consider retrievals based on the ASI algorithm (Kaleschke et al., 2001; Spreen et al., 2008), which provides sea-ice concentration based on SSM/I data from 1991 onwards and based on AMSR-E data from 2002 onwards.

Sea-ice concentration retrieved through the Bootstrap algorithm is, especially in summertime, probably closer to the real sea-ice concentration than that from the NASA Team algorithm, because the latter has been found to be biased low compared to independent observations (e.g., Agnew and Howell, 2003; Partington et al., 2003). The Bootstrap algorithm, in contrast, results in estimates of sea-ice concentration that are very close to the “Climate Data Record of Passive Microwave Sea Ice Concentration” (CDR, Meier et al., 2011) that is a merged product of different algorithms with the aim to provide a consistent time series of sea-ice concentration. In summer, estimates of sea-ice area of the Bootstrap algorithm also agree favourably with estimates based on the ASI algorithm from SSMI satellite data and the higher resolved AMSR-E satellite data, while estimates of sea-ice area based on the NASA Team algorithm are significantly lower (Fig. 2). Since all passive-microwave algorithms will see surface melt ponds as open water, their estimates of sea-ice concentration in summer have been found to be lower than independent observations. Comiso and Nishio (2008) have therefore suggested to synthetically increase sea-ice extent by a 25 km-wide margin during the melt season. In line with existing model–satellite intercomparison studies we will not take such a measure for our model-satellite intercomparison in Sect. 3. We will, however, return to the issue of the low-bias in satellite retrievals in Sect. 4. There we will also discuss in more detail the greater uncertainty of the retrieved sea-ice area and the differences between the various algorithms shown in Fig. 2.

3 Results

3.1 The frequency distribution of sea-ice concentration

The Bootstrap and the NASA Team algorithms result in similar estimates of mean September Arctic sea-ice extent for the period 1979–2005, namely 7.3 million km² for the Bootstrap algorithm and 6.9 million km² for the NASA Team algorithm. It is usually assumed that this difference is small enough to allow for the meaningful, quantitative comparison of modelled sea-ice extent against the estimated extent from an individual satellite retrieval. The difference in September mean sea-ice area for the same period is much larger,

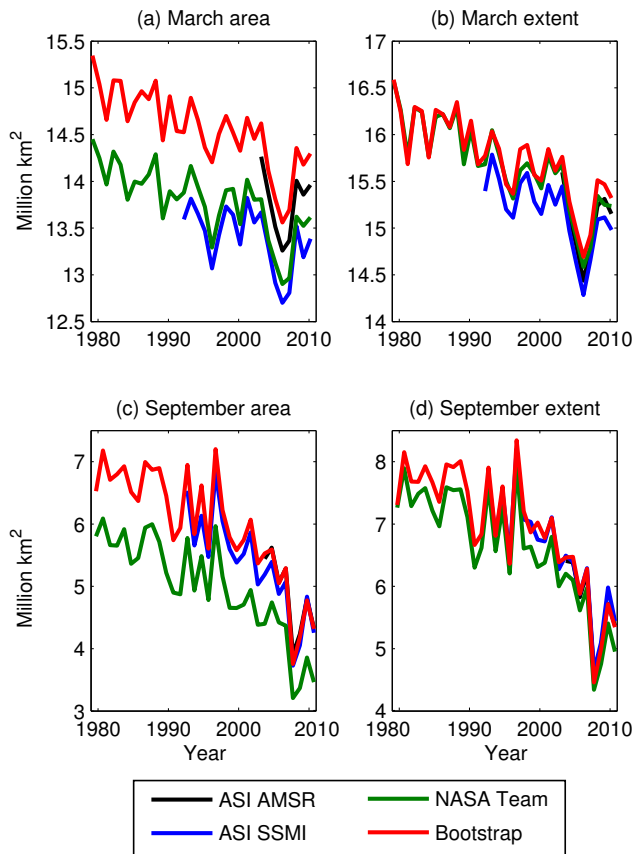


Fig. 2. September and March sea-ice area and sea-ice extent as retrieved from satellite for the period 1979–2010. Different colors denote different algorithms or satellites. Area and extent were calculated based on sea-ice concentration fields on EASE grids with 25 km resolution (NASA Team and Bootstrap, based on SMMR and SMM/I, 1979–2010), 12 km resolution (ASI SSM/I, 1992–2010) and 6 km resolution (ASI AMSR-E, 2002–2010).

with 6.3 million km² for the Bootstrap algorithm compared to only 5.2 million km² for the NASA Team algorithm. This much larger difference is the main reason why the sea-ice area estimate of an individual satellite retrieval is usually not used for model-evaluation purposes. Such large relative difference arises, however, only in summer: in March, both the estimates of sea-ice area and of sea-ice extent are similar between the two algorithms, as the mean 1979–2010 sea-ice extent is 15.9 million km² for Bootstrap and 15.8 million km² for NASA Team, while sea-ice area is 14.6 million km² for Bootstrap and 13.9 million km² for NASA Team.

Since our focus here is on sea-ice extent vs. sea-ice area, it is important to understand the cause for the different agreement between these two measures for the satellite algorithms. For this purpose, we consider the frequency distribution of sea-ice concentration that is displayed by the two algorithms. Of particular importance for the estimate of sea-ice area is the amount of ice-covered grid cells that have a very high ice concentration. According to the Bootstrap algorithm the

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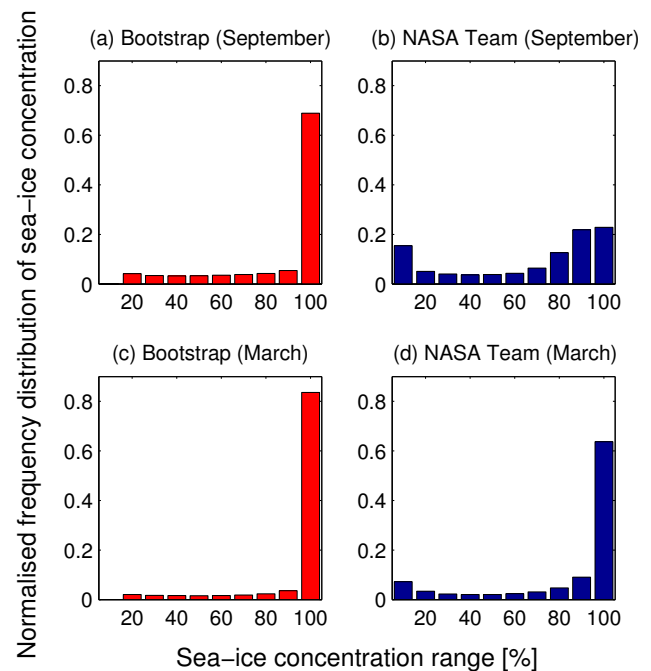


Fig. 3. Histogram of 1979–2005 sea-ice concentration in all areas with at least 0.1 % sea-ice concentration. (a, c) Satellite retrievals based on the Bootstrap algorithm and (b, d) satellite retrievals based on the NASA Team algorithm for (a, b) September and (c, d) March. The numbers on the x axis denote the upper limit of each bar: e.g. 20 denotes the concentration range 10 to 20 %.

ice cover is very compact in summer, with about 70 % of all ice-covered grid cells having more than 90 % ice concentration (Fig. 3a). In contrast, according to the NASA Team algorithm the ice cover is quite loose, with only about 20 % of all ice-covered grid cells having such high ice concentration in summer (Fig. 3b). This difference comes primarily about by the different treatment of sea ice that is covered by surface meltwater (Meier and Notz, 2010; L. T. Pedersen, personal communication, 2013): while both algorithms interpret the meltwater-covered sea ice as open water, the Bootstrap algorithm more strongly compensates for this well-known bias compared to the NASA Team algorithm. The two versions of the ASI algorithm that were analysed for the present study show a similarly compact ice cover as the Bootstrap algorithm.

The large difference between the NASA Team and the Bootstrap algorithms in the estimated frequency of high sea-ice concentration causes their large difference in estimated sea-ice area. In wintertime, the estimated frequency of high sea-ice concentration is much more similar for the two algorithms (Fig. 3c, d), which explains the smaller difference of estimated sea-ice area for that season. Differences in estimated sea-ice extent come about by different estimates of the frequency of low sea-ice concentration. Since at this end of the spectrum differences between the two algorithms are

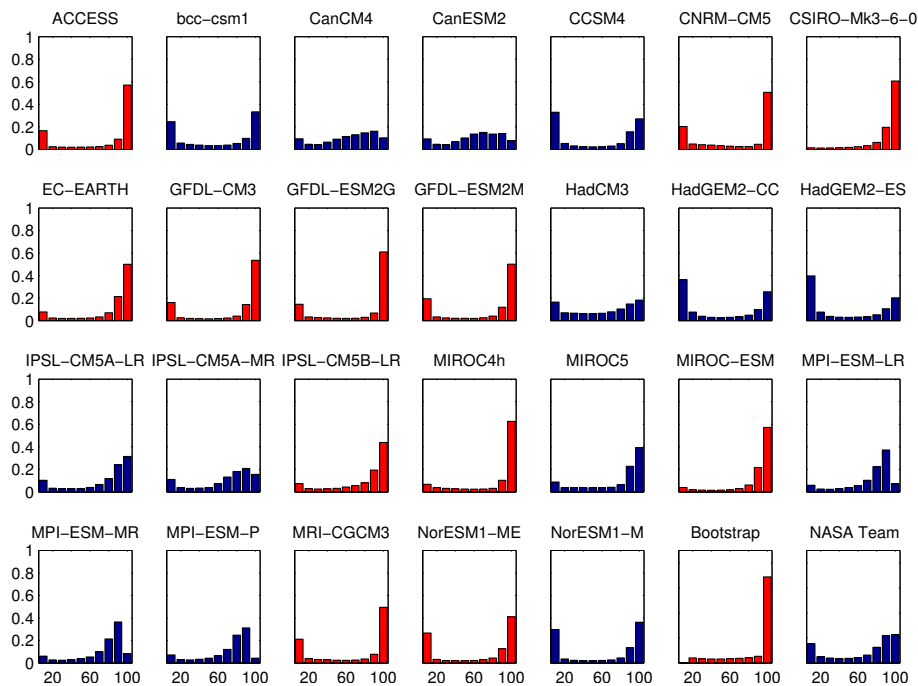


Fig. 4. Histogram of 1979–2005 September sea-ice concentration in all grid cells with at least 0.1 % sea-ice concentration in CMIP5 model simulations. The numbers on the x axis denote the upper limit of each bar: e.g. 20 denotes the concentration range 10 to 20 %. Red panels denote histograms with a compact sea-ice cover, while blue panels denote histograms with a loose sea-ice cover. For models with multiple simulations, the ensemble mean is shown.

small both in summer and winter, both algorithms result in similar estimates of sea-ice extent.

Examining the frequency distribution of summer sea-ice concentration in the CMIP5 model simulations, we find that these simulations can be divided into two groups. One group simulates a compact ice cover in summer (red panels in Fig. 4), while the other group simulates a loose ice cover (blue panels in Fig. 4). In winter, all models simulate a compact ice cover (not shown). Somewhat arbitrarily, we chose a normalised frequency of 0.4 for the 90...100 % concentration band as the dividing line between simulations with a compact ice cover and simulations with a loose ice cover. An alternative definition could be based on the ratio of the amount of sea ice in the highest concentration and that in the second-highest class. Depending on the demarcation line for this ratio, this would slightly modify the composition of the two classes without qualitatively affecting the results discussed in the following.

It would be interesting to examine why roughly half of the CMIP5 models produce a compact ice cover while the other half does not, in particular since this might allow further insights into the quality of the satellite retrievals. Some initial analyses point towards the relative distribution of melting between lateral melt and thinning in individual models to play some role, but a conclusive analysis of this question is beyond the scope of this paper.

What is important, however, is to reiterate the fact that the occurrence of a compact vs. a loose ice cover has different implications in the models compared to the satellite retrievals: in the models, this terminology does indeed refer to the actual simulated state of the ice cover. In the satellite retrievals, however, this differentiation is above all a reflection of the different treatment of surface meltwater by the different algorithms. An algorithm that interprets more of that meltwater as ice free will necessarily result in an “observed” loose ice cover, though this then has little to say about the real properties of the ice pack.

3.2 Extent vs. area

By nature of the definition of sea-ice extent, differences between sea-ice extent and sea-ice area are comparably small for compact sea ice, because of the large number of grid cells with a very high ice concentration. In contrast, the difference between extent and area is usually much larger for a loose ice cover (see Fig. 5a–c).

This has direct consequences for the analysis of model biases based on these two measures. We find for simulations with a compact sea-ice cover that biases relative to the Bootstrap retrieval are similar for sea-ice area and sea-ice extent (red dots are close to red line in Fig. 6a). In particular, all simulations with a compact sea-ice cover that are within $\pm 10\%$ of the retrieved sea-ice extent are also within $\pm 10\%$

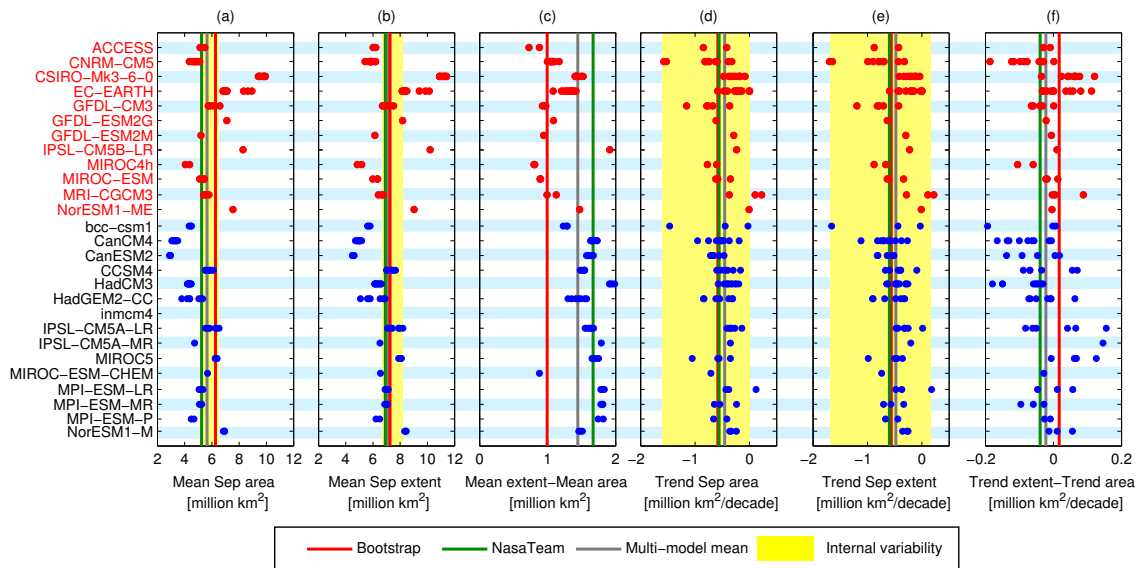


Fig. 5. Overview of the September sea-ice coverage in the 117 historical CMIP5 simulations analysed for this study. Each individual dot corresponds to a single simulation. The vertical lines show the values of the observational record and the mean of all simulations. The yellow shading indicates estimated internal variability. All data refer to the period 1979–2005. **(a)** Mean September sea-ice area, **(b)** mean September sea-ice extent, **(c)** difference between mean September sea-ice extent and mean September sea-ice area, **(d)** linear trend in September sea-ice area, **(e)** linear trend in September sea-ice extent, **(f)** difference between trend in September sea-ice extent and trend in September sea-ice area. Models with a compact ice cover are labelled in red.

of the retrieved sea-ice area. For the simulations with a loose ice cover, we find that those models that underestimate sea-ice extent relative to the Bootstrap retrieval have a stronger percentage bias in sea-ice area than they have in sea-ice extent, while those simulations that overestimate sea-ice extent have a smaller percentage bias in sea-ice area than in extent (Fig. 6a). A number of simulations with a loose ice cover that fall within $\pm 10\%$ of the retrieved sea-ice extent are clearly outside the $\pm 10\%$ range of the retrieved sea-ice area, and vice versa. Hence, a focus on sea-ice extent can give misleading results regarding model quality compared to a focus on sea-ice area (see also Fig. 5a, b, where a number of simulations with loose ice match the Bootstrap sea-ice extent well but are below Bootstrap sea-ice area).

Relative to the satellite-retrieved estimates based on the NASA Team algorithm, we find that biases for sea-ice extent are similar to biases for sea-ice area for simulations with a loose ice cover (blue dots close to green line in Fig. 6a). Simulations with a compact ice cover that overestimate the mean sea-ice extent compared to the NASA Team algorithm in contrast have a stronger percentage bias in sea-ice area, and vice versa.

For March, all simulations and both satellite retrievals have a compact ice cover. Hence, percentage biases in sea-ice area are for all simulations almost identical to the biases in sea-ice extent (Fig. 6b).

To understand this behaviour of simulations with a compact ice cover vs. those with a loose ice cover, we need to

consider that the former have a small difference between sea-ice extent and sea-ice area, while the latter have a larger difference. Figure 7 illustrates how this explains the different behaviour of the two model families: if any of the loose-ice simulations with their comparably large difference between sea-ice extent and sea-ice area results in too small a mean sea-ice extent, this simulations' bias in sea-ice area will be comparably large. If, however, the simulation resulted in too large a sea-ice extent, its bias in sea-ice area would be comparably smaller – simply because the difference between extent and area is larger in the simulations than in the observations. For simulations with a compact ice cover, biases in extent and area relative to the Bootstrap algorithm are very similar, because these simulations' difference between sea-ice extent and sea-ice area is similar to that of the Bootstrap observations. Compared to observations based on the NASA Team algorithm, the simulations with a compact ice cover have generally a lower difference between extent and area, which explains their contrasting behaviour relative to the NASA Team algorithm.

In winter, all simulations result in a compact sea-ice cover. Therefore, in winter they have a difference between sea-ice extent and sea-ice area similar to the Bootstrap observations, which explains the consistent wintertime biases of all model simulations.

Examining trends in sea-ice area and sea-ice extent, we find that the Bootstrap retrieval gives almost the same number for both these measures, namely an average loss of

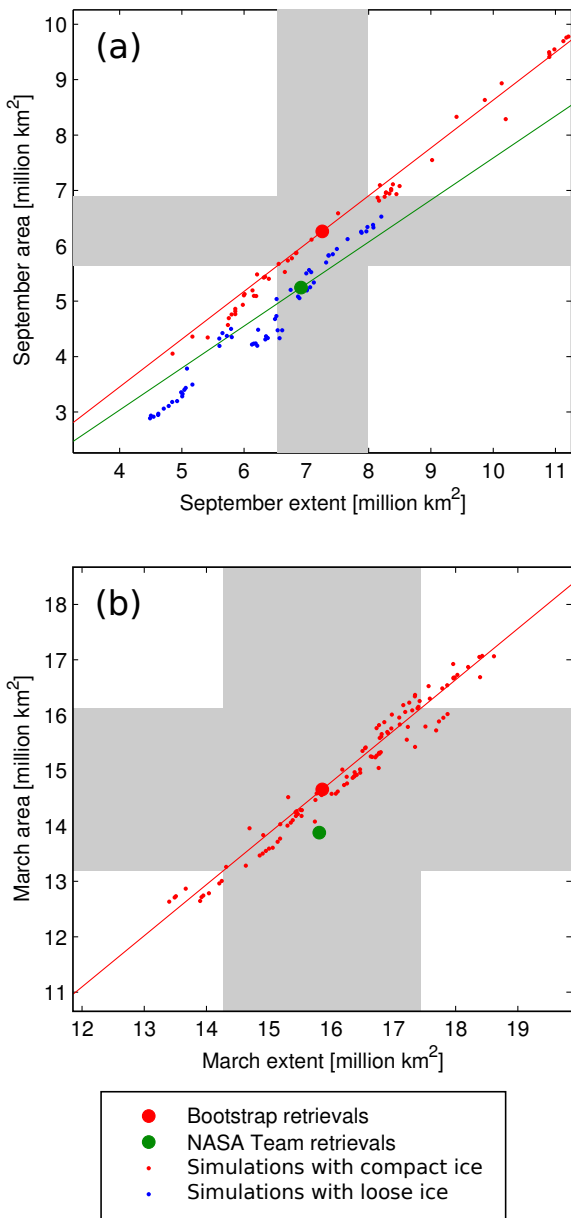


Fig. 6. (a) September and (b) March sea-ice area vs. sea-ice extent in models and satellite retrievals. The red line connects all value pairs that have the same percentage bias in sea-ice extent and in sea-ice area relative to the Bootstrap retrievals. The gray shading indicates a $\pm 10\%$ range around the values obtained from the Bootstrap retrievals. Note that in March all simulations have compact ice, which is why there are no blue dots in (b).

0.56 million km² per decade in sea-ice extent and a loss of 0.58 million km² per decade in sea-ice area during the period 1979–2005. The models, in contrast, show inconsistent behaviour, with both smaller and larger trends in sea-ice area than in extent (Fig. 5d, f). The consistent trends in the satellite retrieval can be understood by analysing the individual trends for different ice-concentration ranges (Fig. 8). Almost

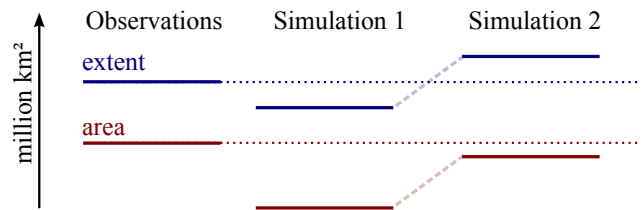


Fig. 7. Schematic to explain the findings in Fig. 6: because of the smaller difference between sea-ice extent and sea-ice area in observations with a compact ice cover than in simulations with a loose ice cover, models with a loose ice cover and slightly too large a simulated sea-ice extent result in a comparably small bias in simulated sea-ice area. The difference between simulated extent and simulated area is the same for both simulations.

all the ice loss in the Bootstrap retrievals happens within the ice-concentration range 90 to 100 %, with no compensating increase in lower ice-concentration ranges (second to last panel in Fig. 8). An ice loss at these high concentrations will have roughly the same impact on sea-ice area and on sea-ice extent. For most models, in contrast, the ice loss is spread over a wider range of sea-ice concentrations. In addition, the grid cells with high ice concentration often only lose some of their ice, which then causes an increase in the number of grid cells with intermediate ice concentration. This compensation then causes a smaller loss of sea-ice extent than of sea-ice area. Some models, however, also show a faster loss in sea-ice extent than in sea-ice area. This behaviour can be understood if a significant amount of grid cells with intermediate sea-ice concentration become ice free in a simulation. The entire area of these grid cells is then lost in terms of sea-ice extent, while only the fraction of these grid cells that was ice-covered is lost from sea-ice area.

The different biases in trends of area and extent in models vs. the satellite retrievals obviously have consequences for the assessment of model quality (Fig. 9a). A number of simulations result in trends that lie within $\pm 20\%$ of the Bootstrap retrieved trends in sea-ice extent, while they lie outside the $\pm 20\%$ range for the simulated trends in sea-ice area. In particular, models that have too fast a loss in sea-ice extent compared to Bootstrap retrievals sometimes have too slow a loss in sea-ice area compared to the Bootstrap retrievals. The same holds for the trends in winter sea-ice coverage (Fig. 9b). Hence, again, an assessment of model quality based on an analysis of trends in sea-ice extent can give misleading results.

3.3 Grid resolution

While the different histograms of sea-ice concentration explain most of the findings discussed so far, differences in model grids might also be relevant for different biases in sea-ice extent and in sea-ice area. As discussed in the introduction, one would generally expect a smaller difference

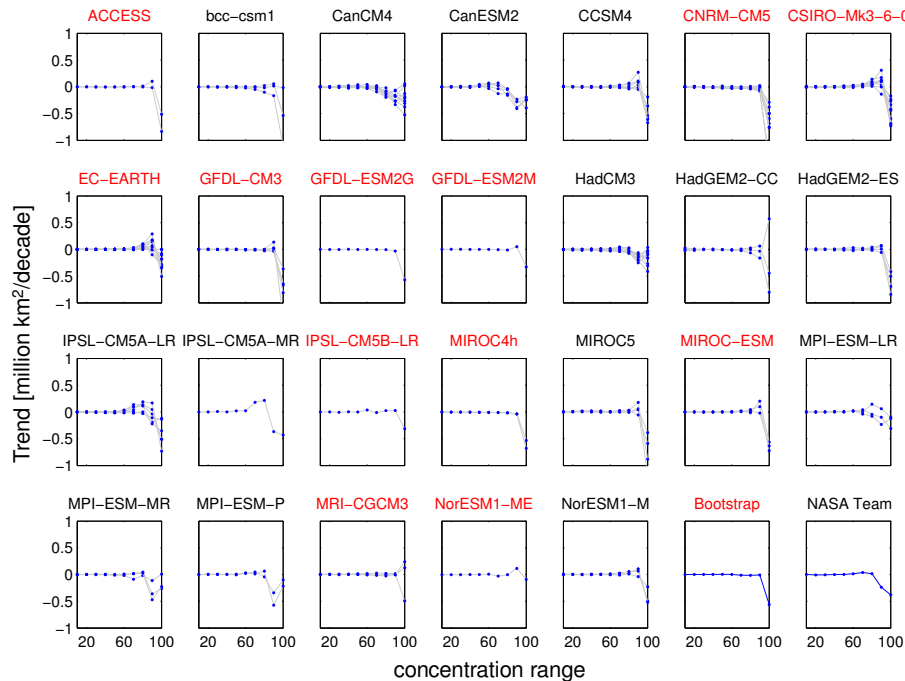


Fig. 8. Trends in September sea-ice area per ice-concentration category. The numbers on the x axis denote the upper limit of each bar: e.g. 20 denotes the concentration range 10 to 20.

between sea-ice extent and sea-ice area for higher grid resolution. The comparably high resolution of the satellite data set might therefore have contributed to the comparably small difference between sea-ice area and sea-ice extent for the Bootstrap algorithm (Fig. 5c).

To examine this possibility, we bilinearly interpolated the gridded Bootstrap-derived sea-ice concentration field for each month of the year 2007 from the original 25 km EASE grid to each individual model grid and then calculated area and extent on the model grids. We find that sea-ice area usually agrees well between the original grid and the individual model grids, with a multi-model mean difference of less than 50 000 km² all year round (blue line in Fig. 10). Individual models typically show a mean difference of less than 200 000 km² all year round, where the difference compared to the original EASE grid comes primarily about through roundoff errors, which is also exemplified by the fact that both positive and negative differences occur. Sea-ice extent as calculated from the interpolated sea-ice concentration on the lower-resolved model grids, however, is always larger than the one on the original 25 km EASE grid. In particular in winter, the multi-model mean difference reaches more than 800 000 km², decreasing to less than 200 000 km² around the summer minimum (red line in Fig. 10). For the calculation of sea-ice extent, grid resolution and grid geometry can hence strongly affect the comparison between model simulations and satellite retrievals for the large ice cover that is still typical for wintertime.

3.4 Cancelling biases

So far, we have examined possible misinterpretations that can arise when using sea-ice extent instead of sea-ice area for model-evaluation purposes. However, both measures allow for cancelling biases and hence render a regional assessment of model quality difficult: a model that has a large positive bias in sea-ice concentration in one region and a large negative bias in another region might simulate a better overall sea-ice area than a model that has weak negative biases in both regions. Therefore, an analysis of the mean absolute bias in sea-ice concentration gives a better indication of regional model performance compared to either sea-ice extent or sea-ice area.

We calculated for the period 1979 until 2005 the area-weighted, monthly mean bias and the area-weighted, monthly mean absolute bias in sea-ice concentration in the CMIP5 simulations relative to the Bootstrap retrievals. Doing so, we obviously find very good correlation between the mean percentage bias in the integrative measures extent or area and the mean bias in sea-ice concentration (compare Fig. 11a, b vs. c): for the mean bias in concentration, regional errors cancel in a similar way as they do for extent and area. Therefore, a linear regression of the biases in area vs. biases in mean concentration results in a high value of $R^2 = 0.93$. Because of the non-linearity of sea-ice extent, the linear regression of sea-ice extent on sea-ice concentration gives a slightly lower value of $R^2 = 0.85$. The fact that R^2 is not 1

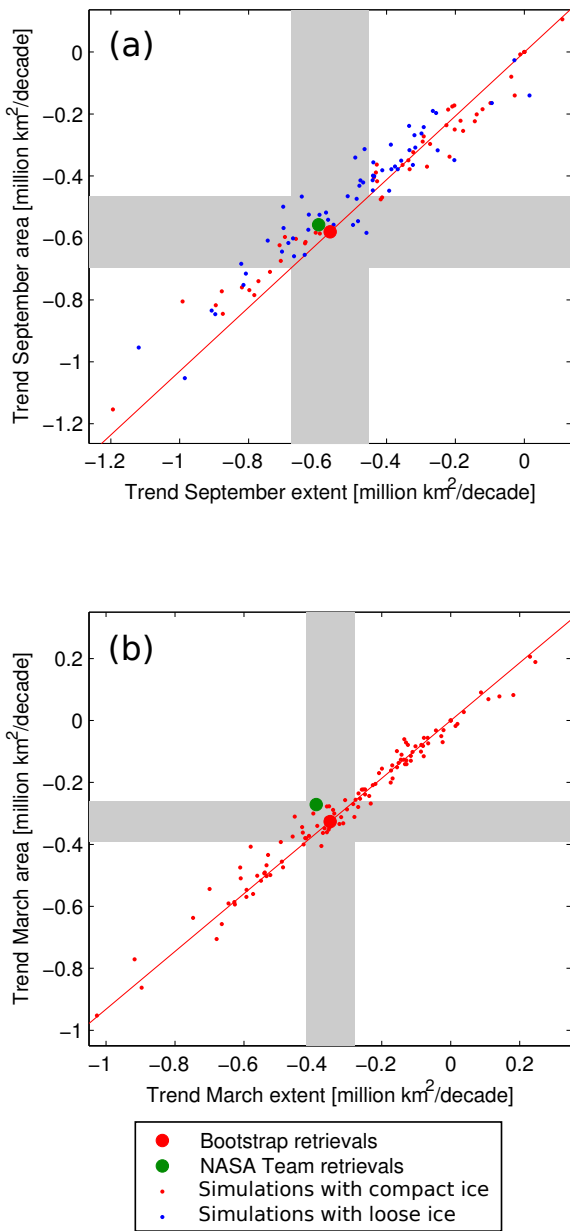


Fig. 9. (a) September and (b) March trends in sea-ice area vs. trends in sea-ice extent for the period 1979–2005. The red line connects all value pairs that have the same percentage bias in sea-ice extent and in sea-ice area relative to the Bootstrap retrievals. The gray shading indicates a $\pm 20\%$ range around the trends obtained from the Bootstrap retrievals.

for the linear regression of area vs. mean concentration is primarily related to interpolation issues during the calculation of mean biases.

For the absolute biases in sea-ice concentration that prevent the cancellation of regional biases, however, correlation with the absolute percentage bias in the integrative measures sea-ice extent and sea-ice area is low, giving $R^2 \approx 0.5$ for both measures: some models with almost no bias in sea-ice

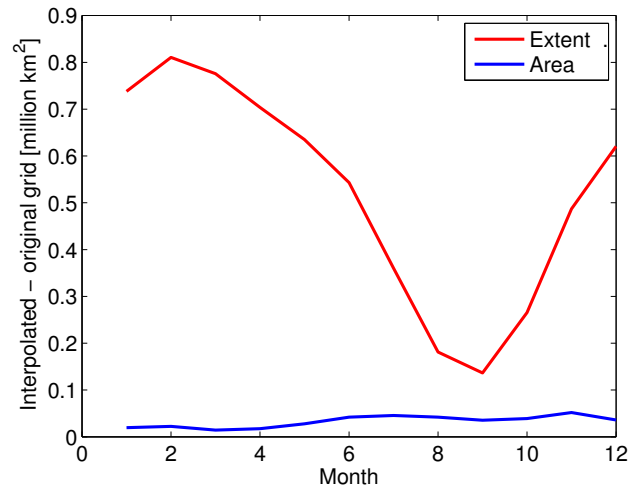


Fig. 10. Mean difference of sea-ice area and sea-ice extent between the original 25 km EASE-Grid and all CMIP5 model grids throughout the year 2007. For each month, the Bootstrap-derived sea-ice concentration was interpolated onto all individual model grids, from which then sea-ice extent and sea-ice area were calculated. The differences of all grids relative to the original EASE-Grid were averaged for this figure.

extent or area still have comparably large mean absolute concentration biases.

For model-evaluation purposes this suggests that additional insights can be gained by considering not only sea-ice area, but also the root mean square bias of the sea-ice concentration fields. This allows for some estimate of the quality of modelled regional sea-ice distributions, while the integrated measure sea-ice area allows for an estimate of the quality of the overall sea-ice volume that is formed through the convergence and divergence of heat fluxes across the entire Arctic. Both measures would be particularly insightful if the magnitude and timing of their seasonal distribution were assessed.

3.5 Internal variability

In the previous sections, we have shown that the more reliably measurable sea-ice extent can give misleading results regarding model quality compared to the geophysically more meaningful sea-ice area. We will now examine how important these differences are in the light of internal variability. Such internal variability, which captures the chaotic nature of the climate system, often permits a broad range of possible responses in a specific variable to a specified evolution of the external forcing. For example, in a previous study examining the Earth-System Model MPI-ESM, we found in one of its CMIP5 historical simulations an increase in the sea-ice cover in the Arctic during the period 1979–2005, while another historical simulation showed a decrease almost as large as observed (Notz et al., 2013). Both simulations were driven by the same external forcing in greenhouse-gas concentration,

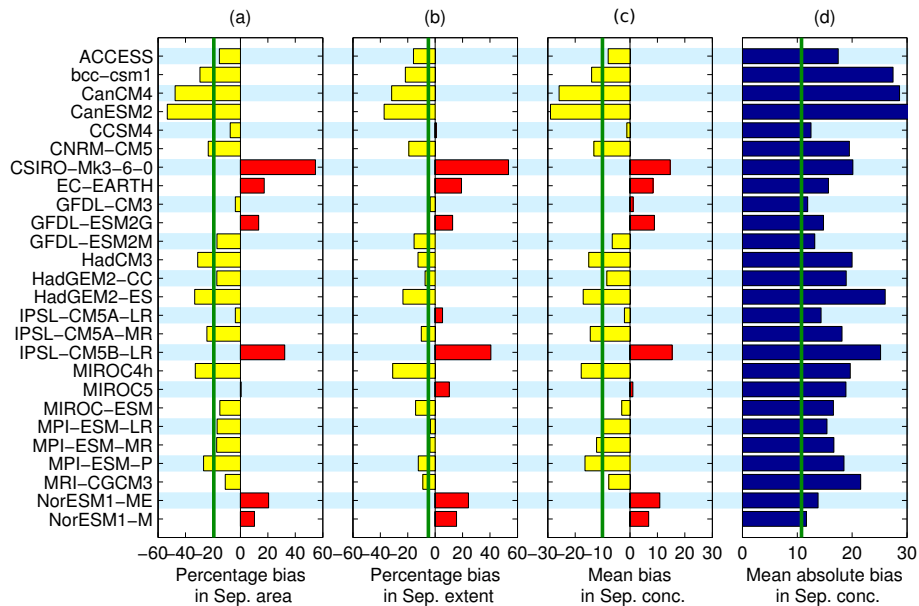


Fig. 11. Overview of biases in September sea-ice coverage in the 117 “historical” CMIP5 simulations analysed for this study relative to Bootstrap satellite retrievals. **(a)** Mean bias in September sea-ice area. **(b)** Mean bias in September sea-ice extent. **(c)** Mean bias in sea-ice concentration. **(d)** Mean absolute bias in sea-ice concentration. The vertical green lines denote the respective bias of the NASA Team retrieval relative to the Bootstrap retrieval.

solar activity, aerosol load etc. The only difference between the simulations were the initial weather conditions on the simulated 1 January 1850, which was the starting date for the simulations. This exemplifies the well-known fact that because of the chaotic nature of the climate system, the trend in the response of the climate system to a given trend in the external forcing can vary drastically on short timescales.

Because of this large internal variability of the Arctic climate system it is often impossible to judge whether a difference in sea-ice coverage between a model simulation and observations is simply random or caused by a model deficiency (cf. Winton, 2011). While there are observational estimates of decadal-scale internal variability of the Arctic sea-ice cover (cf. Notz and Marotzke, 2012), a reasonable range of sea-ice trends for previous decades can obviously not robustly be inferred from observations, since only one single trend has been realised by the real world. It is, however, possible to estimate from ensemble model simulations how much of a modelled trend is caused by the external forcing and how much of it is caused by internal variability, and to then translate these results to the real world (e.g. Kay et al., 2011; Day et al., 2012).

Here, we use a simple, straight-forward method to estimate a reasonable range of observed sea-ice area and sea-ice extent and of their trends from our CMIP5 simulation ensemble: we assume that this reasonable range is given by the maximum spread of ensemble simulations of all those models that encompass the observed evolution within their ensemble members. While this would ideally be done on a model-by-model

basis, many models that we examine here do only provide a single ensemble member. We therefore generalise the spread from models that do provide multiple ensemble members to all simulations that we consider here.

Using this approach to examine mean September sea-ice area for the period 1979–2005 (yellow shading in Fig. 5a), we find an up to 1 million km² ensemble spread for those models that match the Bootstrap-observed value of 6.3 million km² in at least one of their ensemble members. This spread is comparable to the difference between the Bootstrap- and the NASA-Team-derived sea-ice area. Hence, for the period considered here the reasonable range of mean September sea-ice area as derived from model simulations is similar to the uncertainty range of the satellite observations. Simulations that fall outside of this range are most likely incompatible with the observed external forcing. Based on this reasoning, 14 of the 26 models that we analysed have too small a sea-ice area for that period in all their ensemble members, while 5 have too large a sea-ice area in all their ensemble members. The mean of all simulations, 5.6 million km², lies within the reasonable range.

For mean September sea-ice extent (Fig. 5b), the spread of individual ensemble members of those models whose simulations encompass the Bootstrap estimate of 7.3 million km² is 1.5 million km². Hence the model spread is about four times as large as the difference between the Bootstrap estimate and the 6.9 million km² estimate for the NASA Team algorithm. Of the 26 models that we analysed, 12 have too small a sea-ice extent for that period in all their

ensemble members, while 4 have too large a sea-ice extent in all their ensemble members. The mean of all simulations, 7.1 million km², lies again within the reasonable range.

The large number of model simulations that fall outside the reasonable range for both sea-ice extent and sea-ice area indicates that the mean value of these two measures is in principle helpful for model-evaluation purposes, notwithstanding the differences that can arise for individual models for the two measures as discussed above. In contrast, the internal variability of the trends is so large that trends of individual simulations can hardly be used for model-evaluation purposes (Fig. 5d, e): for the period 1979–2005, many models which generated one simulation with a sea-ice trend similar to the observed one simulate for identical forcing and slightly different initial conditions trends that are twice as strongly negative, or trends that are even positive. Hence, any trend that falls within this range might be the consequence of internal variability affecting the modelled trend rather than a model deficiency. Using such criterion, almost all simulations that we consider here show a trend for the period 1979–2005 that is consistent with the observed increase in greenhouse-gas emissions. Since 2005, Arctic sea-ice coverage in summer has decreased rapidly. The trend in September sea-ice coverage for the extended period 1979–2012, however, remains below 1 million km² ice loss per decade both for extent and area. As such, the trend remains comfortably within our estimated range of modelled trends modified by internal variability. Hence, also for the extended temporal range until 2012 we cannot positively identify the modelled trends as inconsistent with the applied forcing.

In their evaluation of CMIP5 simulations, Stroeve et al. (2012) estimate a range for the trend in sea-ice extent that is consistent with the observed external forcing by calculating the standard deviation of the observations around the linear trend. Since the observed trend might be extraordinary for the observed forcing, we here instead assume that the reasonable range for the trend is given by the much larger ensemble spread of those models that encompass the observed trend within their ensemble spread. We then take this model ensemble spread to represent the range of possible trends that are consistent with an externally forced trend modified by internal variability over the previous decades. Since we find that almost all simulations that we consider here fall within this wider range of reasonable trends, we conclude that an assessment based on the difference between the observed trend and individual ensemble simulations only allows for very limited insights into model quality.

3.6 Non-linearity

For completing our discussion of the usage of sea-ice extent for model evaluation, we should finally note that for any comparison of modelled mean sea-ice extent with observations, the non-linearity of sea-ice extent must carefully be taken into account. Mean sea-ice extent should normally be

calculated as the mean of the sea-ice extents of the individual simulations, and not as the sea-ice extent of the mean concentration of the simulations. Consider, for example, two simulations, one with 0% ice concentration in a certain region and the other with 35% ice concentration in that same region. The mean ice concentration of these simulations is larger than 15%, and the sea-ice extent of the mean of the two simulations will be identical to the sea-ice extent of the simulation with the higher sea-ice concentration. The same issue arises when directly comparing sea-ice extent from daily observations with monthly mean fields of model output: the monthly-mean sea-ice extent as derived from a monthly-mean sea-ice concentration field will usually be larger than the monthly mean of daily estimates of sea-ice extent. Therefore for the purpose of this paper, all daily satellite data sets were averaged to monthly data before calculating sea-ice extent. Since sea-ice area scales linearly with ice coverage, these issues do not apply for any study using sea-ice area as a metric for model quality.

4 Discussion

In the previous section, we have shown that for a number of reasons the sole consideration of sea-ice extent for the evaluation of model quality can give misleading results. We therefore recommend that future studies that aim at evaluating the performance of sea ice move away from the sole consideration of sea-ice extent and also consider the model performance for the more meaningful integrative quantity sea-ice area.

In doing so, differences between different satellite algorithms will play a more prominent role than for sea-ice extent (see Fig. 2). Hence, such comparison will need to take more the form of a comparison of observational data with a specific uncertainty vs. model simulations with a specific internal variability. To quantify the uncertainty of the satellite data, we compared in more detail the four satellite algorithms shown in Fig. 2. We find that despite their large difference in retrieved sea-ice area, these algorithms have a similar year-to-year variability, which becomes apparent if anomalies of all satellite algorithms relative to the retrieved area in 2010 are plotted together (see Fig. 12a, b). Hence, the difference between the satellite products is largely caused by a constant offset and there is larger certainty in anomalies in sea-ice area than there is in its absolute value. This is important for any model simulation with assimilated sea-ice concentration fields: one should expect such a model to at least retrieve the anomaly structure of the satellite time series, which can be very reliably estimated.

To quantify the uncertainty of sea-ice area retrievals and of the retrieved trends, we calculated the mean seasonal cycle of sea-ice area and of trends in sea-ice area for the period 2003–2010, for which all four satellite products contain data (see Fig. 12c, d). We then for each month simply subtracted

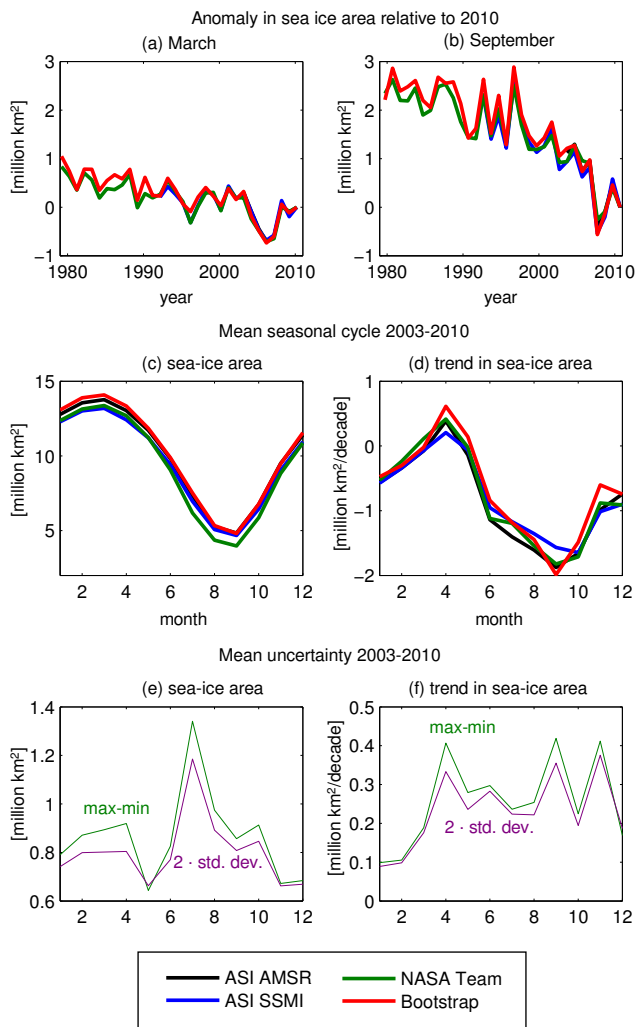


Fig. 12. (a) March and (b) September anomalies in sea-ice area as retrieved from satellites for the period 1979–2010. Different colours denote different algorithms or satellites. (c) Seasonal cycle in sea-ice area and (d) in sea-ice-area trend as retrieved from satellites for the period 2003–2010. (e) Uncertainty in retrieved sea-ice area and (f) in retrieved trend of sea-ice area.

the minimum value from the maximum value to obtain a time series of uncertainties based on passive microwave data. Doing so, we find that apart from July, differences in estimated sea-ice area are less than 1 million km² (green curve in Fig. 12e). The same is found for an estimate of twice the standard deviation (purple curve in Fig. 12e). Hence, a value of 1 million km² can be taken as a rough approximation of the uncertainty of retrieved sea-ice area throughout the year. This uncertainty is comparable to the one found by Comiso et al. (1997) in his comparison of estimated sea-ice area for the Bootstrap and the NASA Team algorithm. The true uncertainty is probably larger than this value, since we here only examine the differences between individual passive-microwave algorithm. Additional uncertainties that are com-

mon to all these algorithms are not reflected by this number. Such uncertainties include, for example, changes in snow-surface properties, seasonal changes in cloud cover, and the impact of thin ice.

Repeating a similar analysis for sea-ice trends, we find that uncertainties from passive-microwave products are less than 0.4 million km² decade⁻¹ throughout the year, with smaller values in wintertime (Fig. 12f). Hence, this value can be taken as an approximation of the uncertainty of retrieved trends in sea-ice area.

A number of models have smaller biases in sea-ice area than 1 million km² relative to satellite retrievals. For these models, biases in this integrative measure could therefore simply be explained by the uncertainty range of the satellite retrievals. For the absolute biases in mean concentration, however, all models show larger biases towards satellite retrievals than the retrievals do among each other. The integrated regional biases in the models are hence not explicable by measurement uncertainty.

For a more detailed analysis of modelled sea-ice coverage, the regional distribution of biases must be analysed. Therefore, the mapping of differences in modelled mean sea-ice concentration is a standard tool in examining model quality. However, again the interpretation of such an analysis hinges on the reliability of the underlying concentration field as obtained from satellite retrievals: in particular in summer, large differences arise between different algorithms (Fig. 13a). To allow for a rough quantification of the uncertainty of retrieved sea-ice concentration from satellite, we have calculated for each month the median of the gridded difference between sea-ice concentration obtained from the NASA Team algorithm and that obtained from the Bootstrap algorithm (Fig. 13b). This then allows one to estimate if a certain regional difference between model and satellite retrieval in a specific month still lies within the observational uncertainty. The figure confirms our analysis of the integrative measures discussed in the previous subsections: during wintertime, estimates of sea-ice concentration are very similar for different satellite products, while a median uncertainty of around 10 % is typical for summer and early autumn. Note that this assessment only gives a somewhat crude estimate of the reliability of retrieved sea-ice concentration from satellites: locally, differences between the two products considered here can exceed 50 % throughout the year.

Our analysis has also shown that internal variability gives rise to much larger uncertainty in the estimate of model quality than do the differences between individual satellite retrievals. This is particularly true for the assessment of modelled trends in sea-ice coverage, which usually vary rapidly in time (see also Notz et al., 2013). In the light of this finding, for model evaluation purposes an integrative assessment of the quality of modelled processes and statistical distributions is more insightful than a simple comparison of modelled time series. This includes, for example, an assessment of seasonal changes in the ice-thickness distribution, the response of the

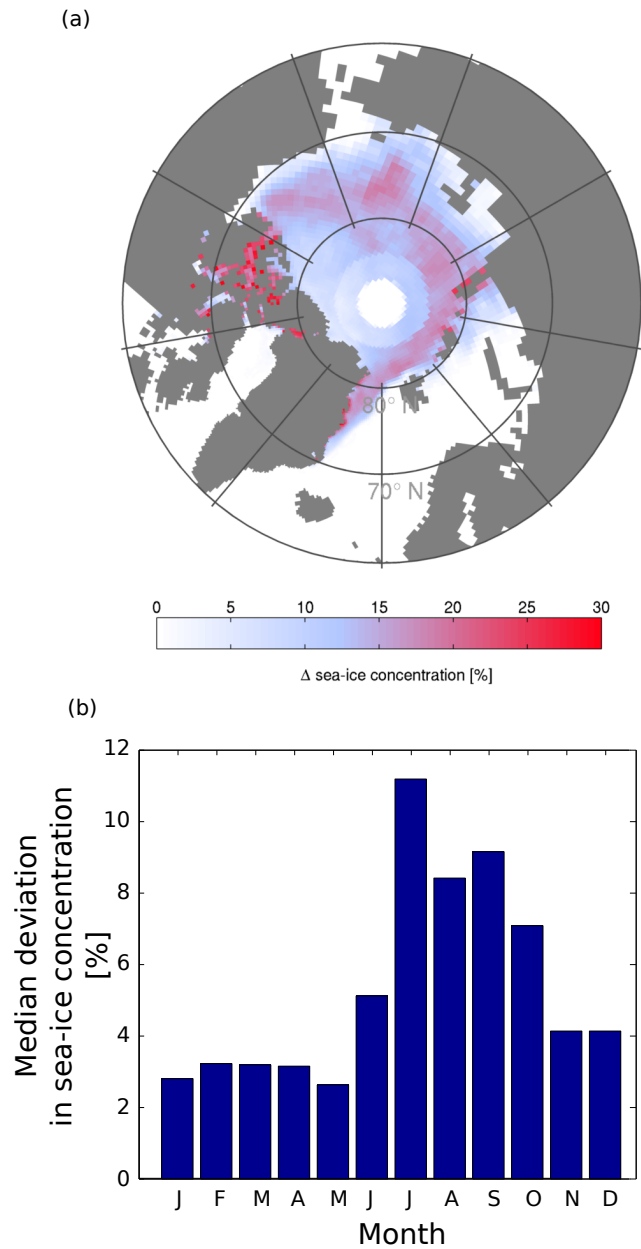


Fig. 13. (a) Mean difference in September sea-ice concentration between Bootstrap retrieval and NASA Team retrieval for the period 1979–2007 (Bootstrap minus NASA Team). (b) Monthly median deviation in sea-ice concentration between Bootstrap retrieval and NASA Team retrieval for the period 1979–2007.

ice cover to divergent wind fields, and an assessment of the statistical distribution of sea-ice concentration as carried out as part of the present study. Through such focused analysis, ideally across a number of satellite algorithms, we can identify shortcomings in these algorithms and at the same time work towards identifying deficits in our sea-ice model physics.

5 Conclusions

In this paper, we have discussed how the evaluation of modelled sea-ice coverage against observations is affected by the incomplete knowledge of the real evolution of the sea-ice cover, by internal variability, and by technical issues such as differences in model grids. For the quantitative assessment of model quality, all these factors need to be taken into account. Our results can be summarised as following:

5.1 Evaluation of sea-ice coverage

1. Summer biases between a particular model and a particular satellite retrieval can be different for sea-ice extent and for sea-ice area. This is because some models and some algorithms see the summer Arctic sea-ice cover as compact with a high fraction of high-concentration sea ice, while others do not. In winter, all algorithms and all models see the Arctic sea-ice cover as compact.
2. Simulations with a compact ice cover have a similar bias in sea-ice extent and in sea-ice area relative to satellite retrievals based on the Bootstrap algorithm or the ASI algorithm. Relative to these algorithms, simulations with a loose ice cover with a negative bias in sea-ice extent usually have an absolute larger bias in sea-ice area, while simulations with a positive bias in sea-ice extent usually have an absolute smaller bias in sea-ice area.
3. Internal variability of sea-ice area as estimated from CMIP5 simulations is comparable to the observational uncertainty as estimated from different passive-microwave algorithms, while internal variability of sea-ice extent from the simulations is about four times as large as the observational uncertainty.
4. For sea-ice area, 19 of the 26 models that we examined here and for sea-ice extent, 16 of the 26 models have all their ensemble members outside of the reasonable range that we estimated from the ensemble spread from those models that capture the observed value in at least one of their ensemble members.
5. The error that is introduced in the calculation of sea-ice extent by different grid geometries can be larger than the observational uncertainty in months with a large ice coverage.
6. Because biases in sea-ice extent can give misleading results regarding model quality, we recommend that biases in sea-ice area are also taken into account in the assessment of model quality. Based on differences between individual passive-microwave retrievals, we estimate the uncertainty in satellite-retrieved sea-ice area to be 1 million km² throughout

the year. The uncertainty in retrieved trends is less than $0.4 \text{ million km}^2 \text{ decade}^{-1}$ throughout the year. The median uncertainties in retrieved sea-ice concentration range from below 5% throughout winter and spring to about 10% in summer. These numbers will have to be re-assessed (and probably increased) once reliable data sets of Arctic sea-ice coverage become available that are not based on passive microwave data.

7. There is little correlation between biases in the integrative measures sea-ice extent and sea-ice area compared to the mean absolute bias in sea-ice concentration. This is caused by the fact that for the integrative measures, regional positive and negative biases can cancel. The average absolute bias in sea-ice concentration relative to observations is therefore a useful additional estimator of model quality.

5.2 Evaluation of trends

1. Internal variability of sea-ice trends as estimated from the ensemble spread of CMIP5 model simulations is so large that almost all differences in trends between observations and simulations of CMIP5 models for the period 1979–2005 (and, indeed, until 2012, see Sect. 3.5) could be caused by internal variability. Many models show in one simulation a much stronger trend than has been observed, while a different simulation with the same model and the same forcing shows for slightly different initial conditions a much weaker trend than has been observed.
2. If despite the large internal variability differences between modelled and observed trends are of quantitative interest, one must note that model simulations with too fast a retreat of sea-ice extent have generally a smaller bias in simulated sea-ice-area trends relative to Bootstrap retrievals. Models that simulate too slow a retreat of sea-ice extent have generally a larger bias in sea-ice area trends. This is independent of the compactness of the ice cover.

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D. Notz: Evaluation of modelled sea-ice concentration

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