September Arctic sea ice predicted to disappear near 2°C global warming above present

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[1] The decline of Arctic sea ice is one of the most visible signs of climate change over the past several decades. Arctic sea ice area shows large interannual variability due to the numerous factors, but on longer time scales the total sea ice area is approximately linearly related to Arctic surface air temperature in models and observations. Overall, models however strongly underestimate the recent sea ice decline. Here we show that this can be explained with two interlinked biases. Most climate models simulate a smaller sea ice area reduction per degree local surface warming. Arctic polar amplification, the ratio between Arctic and global temperature, is also underestimated but a number of models are within the uncertainty estimated from natural variability. A recalibration of an ensemble of global climate models using observations over 28 years provides a scenario independent relationship and yields about 2°C change in annual mean global surface temperature above present as the most likely global temperature threshold for September sea ice to disappear, but with substantial associated uncertainty. Natural variability in the Arctic is large and needs to be considered both for such recalibrations as well as for model evaluation, in particular when observed trends are relatively short.

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1. Introduction

[2] The September Arctic sea ice minimum in 2007 was widely portrayed as a visible sign of climate change happening more quickly than anticipated. A strong response to coupled effects of wind circulation and temperature led to the extraordinary minimum in sea ice extent [*Comiso et al.*, 2008; *Kauker et al.*, 2009; *Parkinson and Kellogg*, 1979; *Stroeve et al.*, 2008]. Interannual variability plays an important role in controlling sea ice in any particular year, yet on longer time scales the annual ice loss in terms of area per degree warming is surprisingly constant in models and observations [*Amstrup et al.*, 2010; *Armour et al.*, 2011; *National Research Council*, 2010; *Gregory et al.*, 2002; *Ridley et al.*, 2007; *Washington et al.*, 2009; *Winton*, 2006, 2011]. Figure 1 illustrates this linear dependency for global mean temperatures (Figures 1a and 1b) and Arctic mean (north of 65°N) temperature (Figures 1c and 1d) for annual means and September using the CMIP3 models (for model details see section 2). The linearity is stronger when using only Arctic temperatures. In addition Table 1 lists the goodness-of-fit for all models for the linear approximation between annual global mean surface temperature and September sea ice area. For all models but one (INGV ECHAM) a linear fit is suitable to describe the relationship between the two quantities (for more information see auxiliary material Figure S1).[1] The mean correlation between Arctic surface temperature and annual Arctic sea ice area on average is −0.98 across all A1B scenario runs based on 10-year running means (Figure 1c), and −0.96 for the mean correlation of global mean surface temperature and September Arctic sea ice area (Figure 1b). The correlation in the observations is −0.97 for the time period 1980–2007 for the equivalent of Figure 1c and −0.96 for the equivalent of Figure 1b in the observations. When the sea ice area becomes very small, the ice loss per degree warming decreases in a number of models. Some models suggest that in a nearly ice-free Arctic in summer, sea ice will remain in some areas even if temperatures are increased further [*Wang and Overland*, 2009]. The reason for this behavior could be that once the Arctic is seasonally ice-free or almost ice-free, the maximum ice thickness decreases more slowly [*Budyko*, 1966] as a result of two processes. Sea ice with a very small thickness initially grows quickly at the beginning of the cold season compared to multiyear ice. Significant amounts of snow accumulate on multiyear ice and insulate the ice from the cold atmosphere which slows down its growth [*Notz*, 2009]. Furthermore, if the sea ice area becomes small a large fraction of the sea ice left is perennial which has a greater thickness than first-year sea ice, and takes longer to melt for the same area. The linear relationship is therefore analyzed

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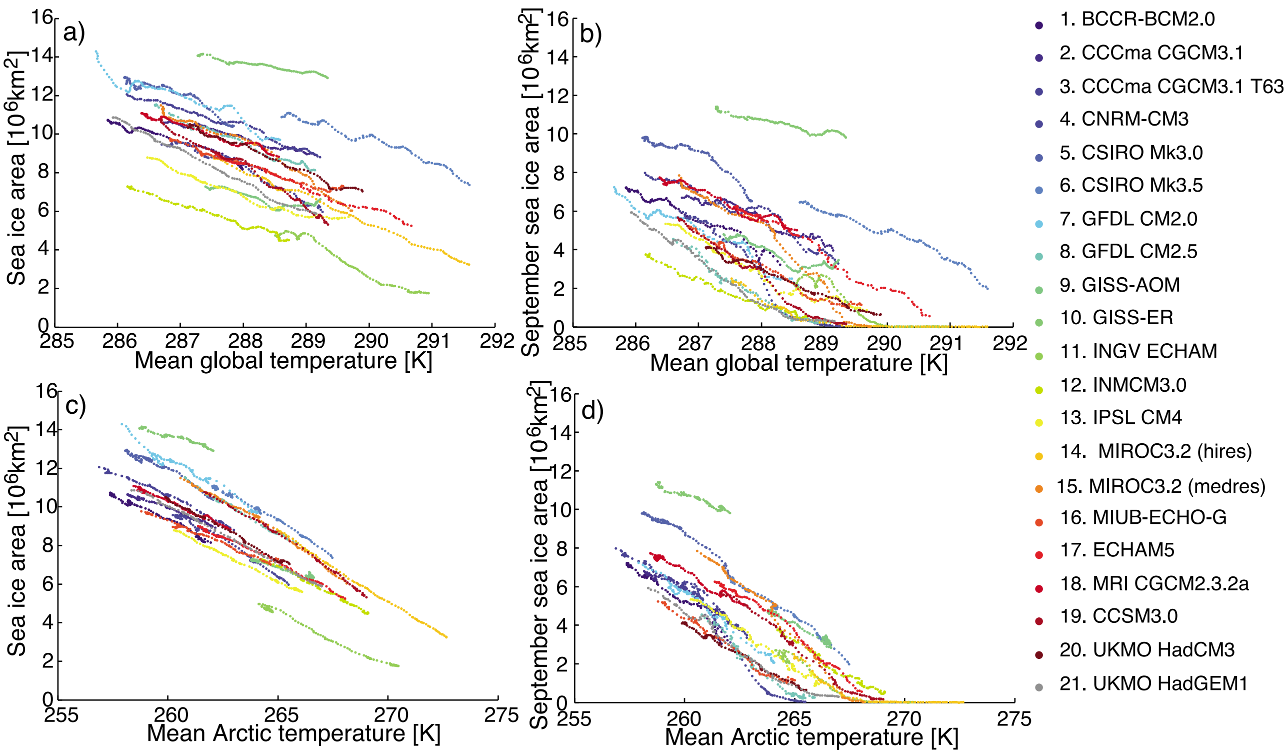

Figure 1. Linearity of Arctic sea ice and temperature of model data for the time period 1980–2099. (a) Annual mean sea ice area versus mean global temperature, (b) September sea ice area versus mean global temperature, (c) annual mean sea ice area versus mean Arctic temperature and (d) September sea ice area versus mean Arctic temperature in an A1B scenario. The slope in panel b represents the value of γ of the models and the slope in panel d represents the value of α of the models. Each color indicates a different model from the CMIP3 ensemble (for details see section 2). The numbers of each model in the legend can be used to identify the models in Figure 3. All results shown are based on 10-year running means.

only for sea ice area greater than 1.0 million km^2. This threshold will be referred to as nearly ice-free throughout the paper, since the Arctic is largely ice free even though some ice remains north of Greenland and Canada [see *Wang and Overland*, 2009]. The linearity between sea ice and temperature is supported by recent model results that find little evidence for tipping points and that simulate recovery of the sea ice within a few years even after strong perturbations [*Amstrup et al.*, 2010; *Armour et al.*, 2011; *Notz*, 2009; *Sedláček et al.*, 2012; *Tietsche et al.*, 2011; *Winton*, 2006]. In this study we make use of this near linear relationship between warming and September sea ice loss to estimate when the Arctic will be ice-free in September. Similar relationships between past and future sea ice trends were used to constrain model results in the Arctic in earlier studies [*Boé et al.*, 2010; *Zhang*, 2010].

2. Data

[3] This study uses the twentieth century and the SRES emission scenario simulations of 21 atmosphere ocean general circulation models (AOGCM) available from the World Climate Research Program (WCRP) Coupled Model Intercomparison Project Phase 3 (CMIP3) [*Meehl et al.*, 2007; *Randall et al.*, 2007]. The CMIP3 multimodel data set is a collection of AOGCM simulations that were assessed in the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) [*Intergovernmental Panel on Climate Change* (*IPCC*), 2007]. No pre-selection of the models was applied. For comparisons between the different CMIP3 models always the first initial condition ensemble member is used. All simulations are regridded to a common

Table 1. Goodness-of-Fit for the Linear Approximation Between Annual Global Mean Surface Temperature and September Arctic Sea Ice Area for the CMIP3 Models

Model	Goodness-of-Fit
BCCR-BCM2.0www1111	0.9599
CCCma CGCM3.1	0.9502
CCCma CGCM3.1 T63	0.9580
CNRM-CM3	0.9256
CSIRO Mk3.0	0.8817
CSIRO Mk3.5	0.9633
GFDL CM2.0	0.9651
GFDL CM2.1	0.9497
GISS-AOM	0.7596
GISS-ER	0.9508
INGV ECHAM	0.4576
INMCM3.0	0.9832
IPSL CM4	0.9408
MIROC3.2 (hires)	0.9584
MIROC3.2 (medres)	0.9556
MIUB-ECHO-G	0.9726
ECHAM5	0.9831
MRI CGCM2.3.2a	0.9627
CCSM3.0	0.9821
UKMO HadCM3	0.9848
UKMO HadGEM1	0.9928

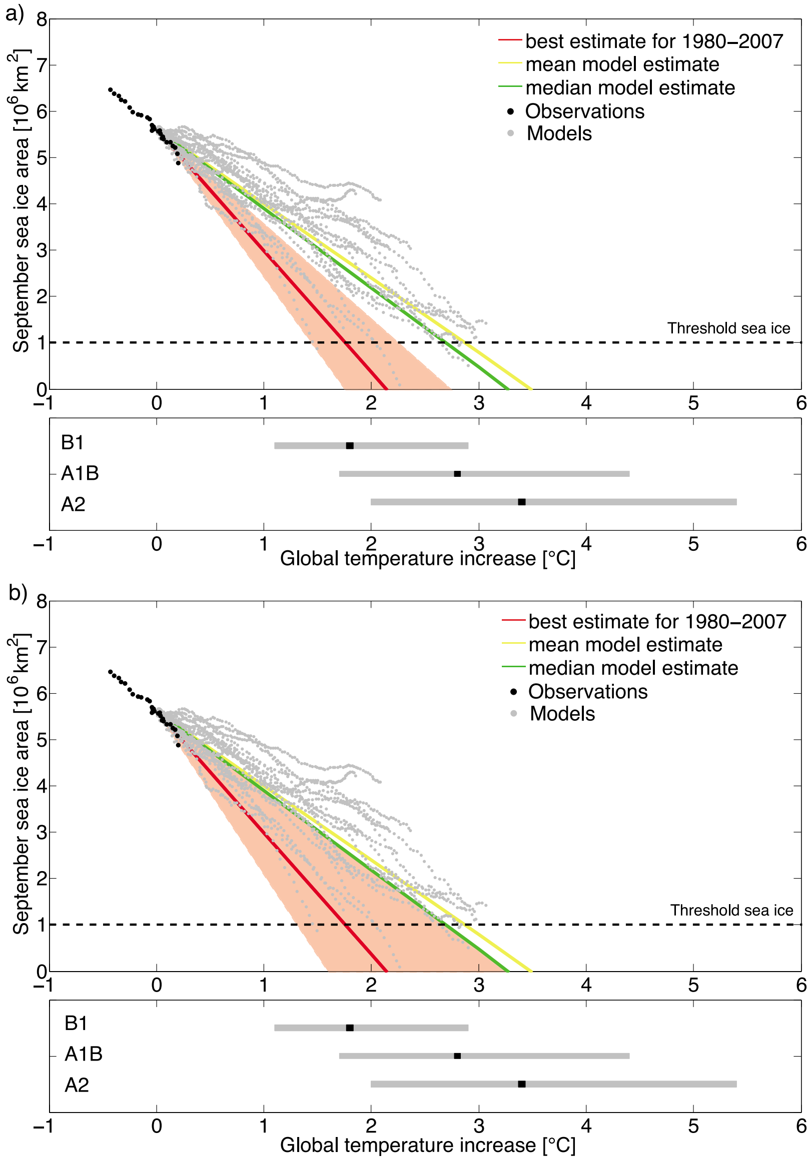

Figure 2. Predicted decline of Arctic September sea ice area with increasing global temperature. Shaded areas depict the uncertainty range (red based on observations from 1980 to 2007). The models are calibrated to start at the current observational point (1980–2007) and show points for sea ice larger than 1.0 million km^2. The difference between Figures 2a and 2b is the method to calculate the uncertainty ranges: Figure 2a uses the internal variability from models whereas Figure 2b uses the model spread (one standard deviation). For more details of the uncertainty estimation see section 3.2. Warming in 2090–2099 and associated uncertainties for three SRES non-intervention emission scenarios are indicated at the bottom [*IPCC*, 2007]. Models and observations are based on 10-year running means. Please note that for illustration purposes the observations are shown over the time period 1970–2007.

T42 grid. The Arctic is defined in this study as the area north of 65°N. For sea ice observations the Met Office Hadley Centre's sea ice and sea surface temperature data set (HadISST) [*Rayner et al.*, 2003] is used. Due to data coverage issues only the time period after 1979 is used. For illustration purposes in Figures 2 and 4 data onwards from 1970 are shown, but note that all analysis and results are based on data after 1979. In this study the sea ice area is defined as the total area of sea ice simulated/observed. For temperature the gridded data from NASA (GISTEMP [*Hansen et al.*, 2006] and http://data.giss.nasa.gov/gistemp) are used. Note that for this data set the central Arctic Ocean data coverage is low before 1980 and local interpolation uncertainties are substantial, but long-term trends averaged over the whole Arctic as used here are less affected by observational uncertainties.

3. Recalibration of Sea Ice Decline Estimated by Models

[4] All but one climate model show that the close to linear relationship between September sea ice area and global surface temperature is robust and persists throughout the

21st century. There is no fundamental reason why the relationship must be linear, so this is purely an empirical result. There might be some nonlinearities that the models do not capture and have not been observed yet, but there is currently no evidence for that. So the approximation with linear trends is not perfect, but good enough for the purpose of this study. Observed trends are consistent with that linear relationship. Assuming that the linearity holds in the future as indicated by the models, the relationship can therefore be used in combination with the observed trend to estimate at what global temperature increase the Arctic will be nearly ice-free in September. It is important to note that the method applied here is useful only for long time-scale projections, as described here. The linearity does not hold on shorter time scales when interannual or decadal variability is included. Future September Arctic sea ice area $\mathrm{SI_f}$ is given by

$$\begin{aligned}\mathrm{SI_f} &= \mathrm{SI_{1980-1999}} + (\Delta\mathrm{Sea\ ice}/\Delta\mathrm{T_{Global}}) \cdot \Delta\mathrm{T} \\ &= \mathrm{SI_{1980-1999}} + \gamma \cdot \Delta\mathrm{T},\end{aligned} \tag{1}$$

where $\mathrm{SI_{1980-1999}}$ is the observed September sea ice area (mean of 1980–1999) and $\Delta\mathrm{T}$ is the global temperature increase relative to 1980–1999. $\Delta\mathrm{Sea\ ice}/\Delta\mathrm{T_{Global}}$ is hereafter called γ and represents the observed change in September sea ice per degree global warming. γ is basically the slope shown in Figure 1b, but note that the models are only used to confirm that the relationship is in fact linear over the whole time period, and the slope itself is based on observations. For the time period 1980–2007 the observations give $-2.62{\cdot}10^6$ km^2/°C for γ. As γ is not exactly constant over time this number is multiplied by a factor of 0.92, which takes into account the decrease of γ over time as the observational period is short and climate variability large (see below). This correction factor is determined by how γ changes in the CMIP3 models on average (see section 3.2). The decrease of γ with time could be due to the fact that sea ice volume and sea ice area are not entirely linearly related. As sea ice volume decreases, the sea ice area decreases at a slower rate. However, as sea ice area becomes smaller, sea ice area and sea ice volume decrease at a similar rate (not shown). Therefore, the relationship between sea ice volume and surface temperature is not quite linear. The more important point, however, is that there is an uncertainty associated with γ. The observations provide only one estimate of γ, therefore climate models have to be used to estimate the contribution of internal variability to γ. Two different approaches are used to estimate the uncertainty, hereafter called $\gamma_{\mathrm{unc.}}$ The first approach is simply to look at the CMIP3 model spread of γ during the specific time period, and provides an estimate of the uncertainty of γ due to both internal variability as well as model uncertainty. The second approach uses four climate models that have at least four initial condition ensemble members, i.e., only models that have run at least four simulations over the specific time period. For each model the spread across the individual ensembles is estimated by calculating the standard deviation. γ_{unc} is the average across these four standard deviations (for details of the error propagation see section 4). This second method provides an uncertainty estimate for γ just based on internal variability in the climate system, but does not include model uncertainty. Figure 2 summarizes these findings by showing the predicted sea ice loss as a function of temperature. We find that a temperature increase of about 2°C above present (1980–1999 average) leads to a near ice-free Arctic. A temperature increase of 2°C will be reached in 2070 in an A1B scenario. *Boé et al.* [2009b] estimate an ice-free Arctic during September in 2070, supporting the results of the approximations shown. An early study by *Parkinson and Kellogg* [1979] suggest an ice-free Arctic in August and September at a global temperature increase of about 2°C (Arctic increase of 5°C) above 1950–1964, which would imply a temperature increase of about 1.4°C above present. This result however is based on only one model with prescribed surface temperatures. For comparison, the uncalibrated ensemble projects a near ice-free Arctic at 3–3.5°C. The internal variability (see section 3.2 for details) is used to assess the lower bound of the uncertainty associated with the extrapolation (Figure 2a). Alternatively, the uncertainty ranges of the extrapolation can be estimated using the model spread of γ as a basis of the error propagation (Figure 2b), which results in larger uncertainty ranges. The two approaches based on internal variability and model spread can be interpreted as a lower and upper bound on the uncertainty.

3.1. Understanding the Biases in Sea Ice Trends of Climate Models

[5] The above presented recalibration approach provides our best estimate of when sea ice is most likely to disappear based on the current understanding of the climate system and its implementation in models, as well as the assumption that the observed changes are largely attributable to external forcing. However, it provides no insight into why models differ, and why the ensemble as a whole underestimates the sea ice decline. The overall sensitivity of sea ice to global temperature γ can be decomposed into two quantities: Arctic polar amplification and local sea ice sensitivity. Note that these are linked and will be discussed in greater detail below. Future September sea ice area $\mathrm{SI_f}$ is then given by

$$\begin{aligned}\mathrm{SI_f} &= \mathrm{SI_{1980-1999}} + ((\Delta\mathrm{Sea\ ice}/\Delta\mathrm{T_{Arctic}}) \cdot (\Delta\mathrm{T_{Arctic}}/\Delta\mathrm{T_{Global}})) \cdot \Delta\mathrm{T} \\ &= \mathrm{SI_{1980-1999}} + (\alpha \cdot \beta) \cdot \Delta\mathrm{T},\end{aligned} \tag{2}$$

where $\mathrm{SI_{1980-1999}}$ is the observed September sea ice area (mean of 1980–1999) and $\Delta\mathrm{T}$ is the global temperature increase relative to 1980–1999. $\Delta\mathrm{Sea\ ice}/\Delta\mathrm{T_{Arctic}}$ is hereafter called α and denotes the change in September sea ice area per degree Arctic warming. $\Delta\mathrm{T_{Arctic}}/\Delta\mathrm{T_{Global}}$ is termed β and describes the well known Arctic polar amplification, the ratio between Arctic temperature increase and global temperature increase. The product $\alpha{\cdot}\beta$ is the change in sea ice area per degree global warming γ. Figure 3 visualizes α and β and their uncertainties. The best estimate for α and β is calculated from observational data. The goal is to use the longest time period possible with high quality data. In the case of α, the longest time period is 28 years (1980–2007, see section 2). In the case of β only surface temperature is required and two time periods are used, first the same as for α and a second period that is extended to 50 years (1960–2009). The best estimates based on observations yield $-9.86{\cdot}10^5$ km^2/°C for α and 2.8 and 2.16 for the 28 yr and 50 yr period for β, respectively. Those β values are additionally multiplied by a factor (0.94 and 0.88, respectively) that takes into account that β is not constant over time (see

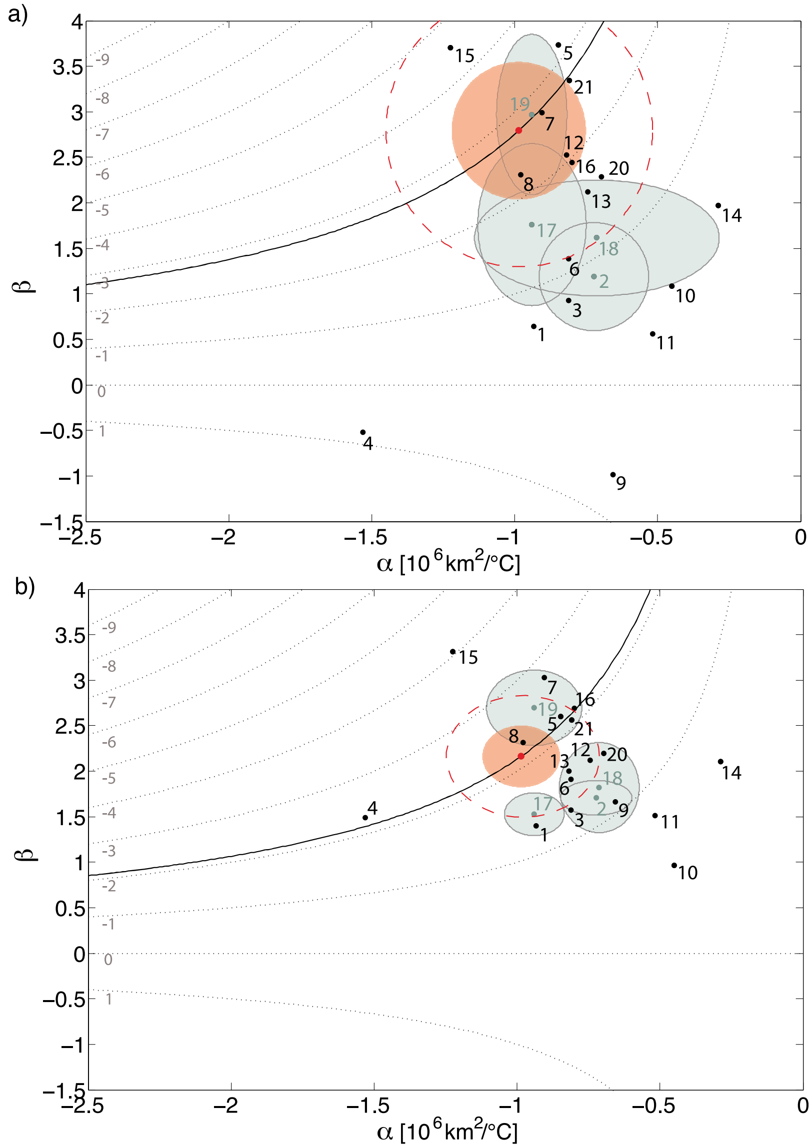

Figure 3. Sea ice temperature sensitivity α versus Arctic polar amplification β for the CMIP3 models (black dots; see Figure 1 for model numbers) and the observations (red). The gray shaded ellipses illustrate the internal variability (one standard deviation) of the four models with at least four ensembles (gray dots). The red shaded area is the mean spread of the above mentioned models' internal variability centered at the observations; the dashed red curve shows two standard deviation of the variability. The lines indicate isolines of constant $\alpha \cdot \beta$ (in million km^2/°C). The solid isoline marks the observations. Figure 3a shows the short time period of 28 years (1980–2007). Figure 3b shows the 50-years time period (1960–2009). Note that α_{obs} in Figure 3b is taken from the 28-year period as in panel a since sea ice observations used in this study start only in 1980. The estimated variability however is based on the model data and covers 50 years. The numbers for the models correspond to the legend of Figure 1.

section 3.2). α on the other hand can be expected to be reasonably constant over time, since Arctic and global temperatures are correlated in the future as suggested by models [*Winton*, 2006]. The uncertainty due to internal climate variability that is associated with α and β can only be characterized by initial condition ensemble members of climate models (gray ellipses in Figure 3). The ensemble spread is based on the variability of α respective β of four climate models that have at least four initial condition ensemble members, as previously done for γ. The ensemble spread is again the standard deviation across ensemble members and is estimated for each model and then averaged. It provides an estimate of the uncertainty in the observations caused by internal variability (red ellipse in Figure 3). The vast majority of models show a lower overall sea ice decline per unit global temperature ($\alpha \cdot \beta$) than the observations (see Figure 3). Only a few models have a similar total slope ($\alpha \cdot \beta$) as the observations and are located close to the solid line, marking the isoline of the observed $\alpha \cdot \beta$. A few models are too sensitive, but clearly most of the models are not sensitive enough and are far to the right and below the solid line. Four of the six models closest to observations are identical to those selected by *Wang and Overland* [2009]. For the 28 yr time period (Figure 3a) the variability is considerably larger than for the 50 yr time period (Figure 3b) and a few models are consistent with the observations and produce results, which lie within the estimated variability. However, for the longer time period only one model (model 8 – GFDL CM2.5) is within the one standard deviation uncertainty range. Irrespective of the time period considered, all but two models (models 4 and 15: CNRM-CM3 and MIROC3.2(medres)) simulate a sensitivity of the sea ice to a temperature increase (α) that is too weak. But at least for some models the discrepancy with the observations might be due to natural variability [*Stroeve et al.*, 2007; *Winton*, 2011] when considering a two standard deviation uncertainty range. Arctic Polar amplification (β) is remarkably insensitive to the scenario for a model average [*IPCC*, 2007, Figure 10.6a], but most models underestimate the Arctic polar amplification compared to observations, in particular for the shorter period. Two models (models 4 and 9: CNRM-CM3 and GISS-AOM) even feature a negative Arctic polar amplification over the past 28 years (Figure 3). One of the reasons why most of the models underestimate $\alpha{\cdot}\beta$ could be that the majority of the models simulate sea ice that is overly thick. The thickness of the sea ice in the unforced state is related to the sea ice extent in the future [*Boé et al.*, 2010].

[6] The separation of the sea ice decrease into the influence of local temperature on sea ice, as proxy for local feedbacks and energy budget, and the well-established Arctic polar amplification is convenient and helps to understand the differences between models and observations (see Figure 3). However, the two quantities are clearly not independent; a low magnitude of α likely implies a low β (see below). A number of models strongly underestimate both the magnitude of α and β and their $\alpha{\cdot}\beta$ is outside the two standard deviation range of variability estimated around the observations, confirming earlier claims that models underestimate the observed sea ice decrease [*Boé et al.*, 2009b; *Stroeve et al.*, 2007; *Wang and Overland*, 2009]. However, natural variability of α and β estimated for the short observational period is large and hence some models are not inconsistent with observations. It is therefore essential that natural variability is carefully considered before models are being dismissed as being wrong, in particular for regional scales and short observational trends.

[7] While our results provide strong evidence for a tight coupling of surface temperature and Arctic sea ice area, it is not possible to argue that one quantity is driving the other because processes leading to Arctic polar amplification and the associated sea ice loss are complex and involve many feedbacks. It is likely that the ocean transport and warming play an important role in sea ice decline [*Boé et al.*, 2009a; *Mahlstein and Knutti*, 2011; *Polyakov et al.*, 2010; *Ridley et al.*, 2007; *Spielhagen et al.*, 2011] and therefore control to some extent Arctic polar amplification. Furthermore, it is known that sea ice plays a central role in Arctic temperature amplification [*Screen and Simmonds*, 2010b; *Serreze and Barry*, 2011]. Arctic sea ice loss and Arctic polar amplification are related through various physical processes that cannot easily be separated. A model which has a small absolute value for α (Arctic September sea ice loss per degree warming in the Arctic) likely features low β (Arctic polar amplification). A small magnitude of α leads to a smaller ice loss, which in turn leads to a smaller heat transfer into the ocean during summer season. Hence, in winter less energy is available that can be transferred into the atmosphere from the ocean through radiative cooling as well as latent and sensible heat fluxes [*Screen and Simmonds*, 2010a], thereby resulting in a lower Arctic polar amplification. The seasonal heat transfer of ocean heat into the atmosphere is central for Arctic temperature increase. It is important to note that β should not be considered as the driving process for sea ice loss. Temperature affects sea ice, and sea ice affects temperature, so it is impossible to separate cause and effect in this study. The Arctic polar amplification itself is both a result and a driver of ice loss. The separation into α and β in this study is simply a way to link the results to quantities like Arctic polar amplification that are commonly used in model evaluation and for example in paleoclimate studies [*Miller et al.*, 2010]. Although we use α and β for the recalibration, it is not possible to attribute model biases to either α or β or specific physical processes, and we make no assumption of which of the two terms is the driving process or the response. Note also that our analysis does not allow to separate whether the Arctic polar amplification in models is biased as a result of an incorrect simulation of feedbacks or as a consequence of missing or underestimated forcing agents [*Shindell and Faluvegi*, 2009].

[8] The predicted end-of-summer sea ice loss as a function of global temperature as described in equation (2) is shown again in Figure 4 using several observationally calibrated regressions. The different linear approximations of the decline of September sea ice calibrated to observations for 28 and 50 years (see section 4) are displayed. Unsurprisingly, the approximation based on 28 years also shows that most likely a global temperature increase of 2°C above 1980–1999 leads to a near ice-free Arctic during September, as for the simpler calibration described in equation (1). Comparing the best estimates based on the two different time periods, the global temperature increase needed to melt the September sea ice is about 0.5°C larger for the longer time period. This is solely due to the difference in β, as this is the only difference between the two estimates. The internal variability as shown in Figure 3 (see section 3.2 for details) is again used to assess the lower bound of the uncertainty associated with the extrapolation (Figure 4a). Alternatively, the uncertainty ranges of the extrapolation can be estimated using the model spread of α and β as a basis of the error propagation (Figure 4b), which results in larger uncertainty ranges. In particular the upper end of the range is sensitive to how uncertainty is estimated. The second uncertainty estimate assumes that the current climate models span a plausible range of uncertainty and in our view is too pessimistic given that some models show rather unrealistic behavior in both sea ice and Arctic polar amplification (see Figure 3). As for γ the two approaches of uncertainty estimation represent a lower and an upper bound on the uncertainty. A detailed description of the uncertainty quantification is given in section 3.2. Compared to the uncertainty estimate based on γ the ranges derived from constraining α and β separately are significantly larger. This is not surprising since in the latter case the uncertainty is estimated for two terms that are treated independently but in reality are not. The uncertainty ranges

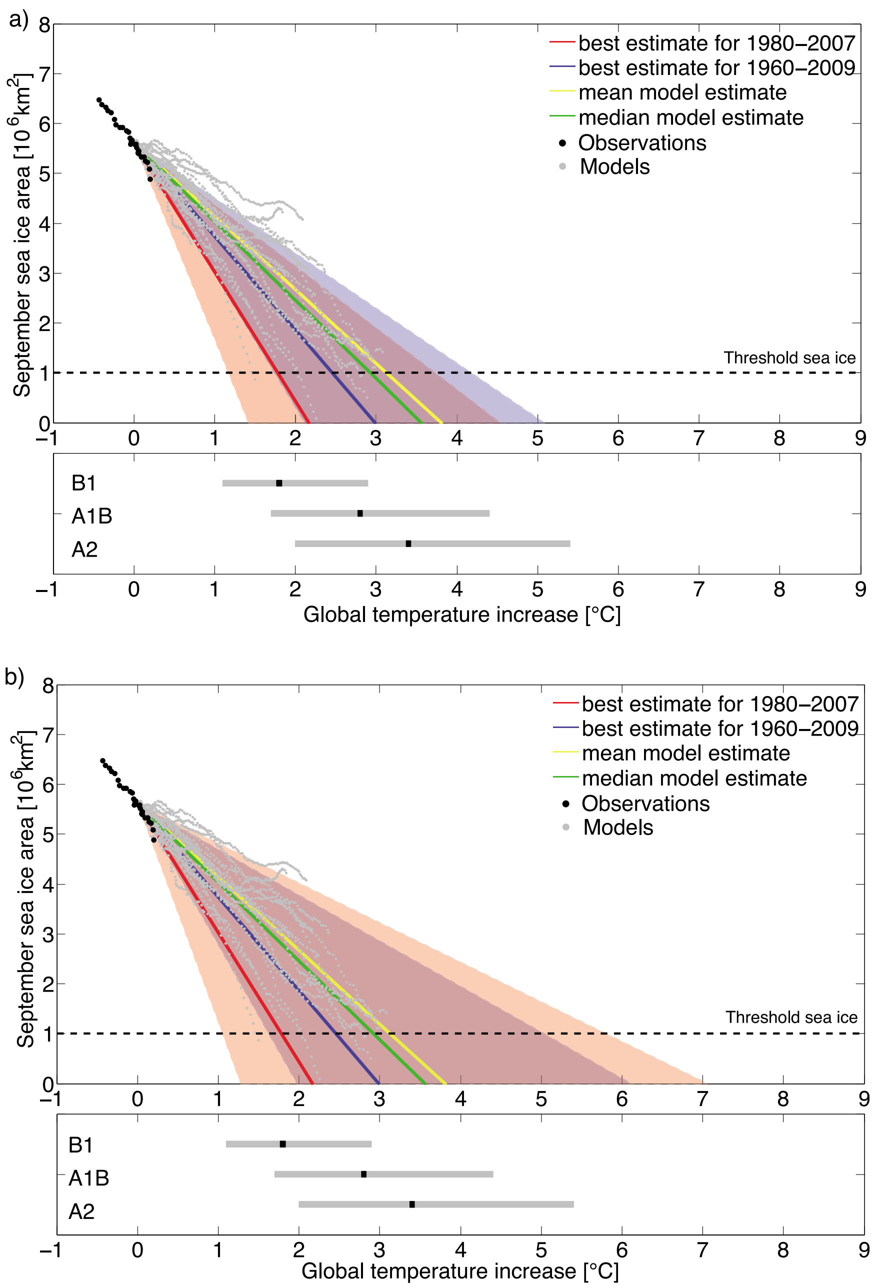

Figure 4. Predicted decline of Arctic September sea ice area with increasing global temperature as in Figure 1. Shaded areas depict the uncertainty range (red based on observations from 1980 to 2007 and blue from 1960 to 2010). The time period in the legend indicates the time window that is used to estimate β. The models are calibrated to start at the current observational point (1980–2007) and show points for sea ice larger than 1.0 million km^2. The difference between Figures 4a and 4b is the method to calculate the uncertainty ranges: Figure 4a uses the internal variability from models whereas Figure 4b uses the model spread (one standard deviation). For more details of the uncertainty estimation see section 3.2. Warming in 2090–2099 and associated uncertainties for three SRES non-intervention emission scenarios are indicated at the bottom [*IPCC*, 2007]. Models and observations are based on 10-year running means. Please note that for illustration purposes the observations are shown over the time period 1970–2007.

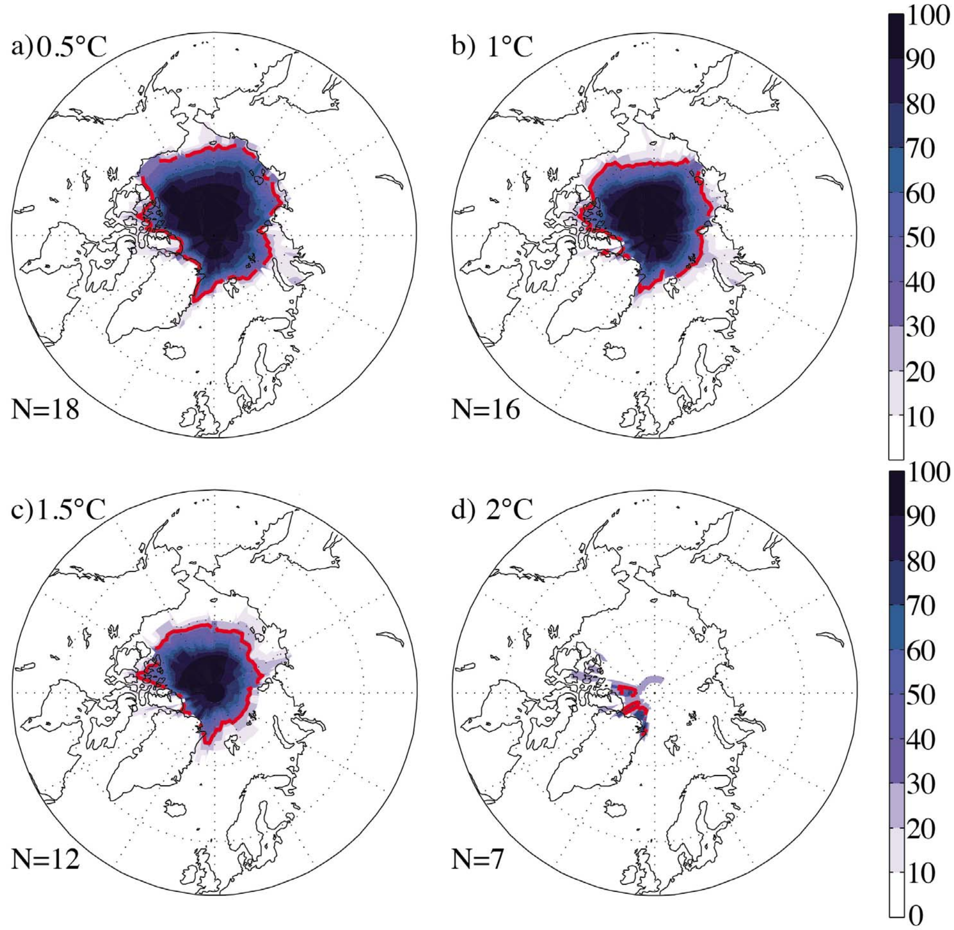

Figure 5. Spatial development of predicted September sea ice decline. Shown is the percentage of climate models with sea ice in a specific grid cell for (a) 0.5°C, (b) 1°C, (c) 1.5°C and (d) 2°C above present. The number N denotes the number of models included. As a number of models simulate a sea ice area that is too large compared to observations, only those models were included which simulate a sea ice area indicated by the extrapolation. The red line shows the 33.3% isoline. The area outside the red line is therefore likely to be ice-free (see text).

presented in Figure 4 are therefore probably too pessimistic and should be interpreted as a sensitivity test. The uncertainty presented in Figure 2 is expected to be more realistic.

3.2. Uncertainty Estimation

[9] Equation (3) shows the error propagation with increasing temperature levels as follows:

$$\mathrm{SI_f} \pm \Delta\mathrm{SI_f} = \mathrm{SI}_{1980-1999} + \gamma \cdot \Delta\mathrm{T}(1 \pm \gamma_{\mathrm{rel}}), \qquad (3)$$

where γ_{rel} is the absolute value of $\gamma_{\mathrm{unc}}/\gamma$. The uncertainty term is obtained by ensemble studies of different climate models or CMIP3 model spread. In case of the ensemble study, the idea is that the variability over a specific time period can be represented by the spread across members of one climate model. Therefore, four climate models which have multiple model members (NCAR CCSM3, CCCma CGCM3.1, MPI ECHAM5 and MRI CCM2.3.2a) are used to estimate the spread across the members. The ensemble spread is then averaged across models. To account for the change in γ over time, the mean γ across all CMIP3 models of the period 2010–2099 (γ_{f}) is divided by the mean γ of the time period 1980–2007 (γ_{c}). This scaling factor is then used to estimate the future sea ice loss per degree temperature increase (γ) from the observed estimate as shown in equation (4):

$$\gamma = \gamma_{\mathrm{Obs}}(1980 - 2007) \cdot (\gamma_{\mathrm{f}}/\gamma_{\mathrm{c}}) \qquad (4)$$

The scaling factor is close to one and therefore the results are not sensitive to this step. Furthermore, *Winton* [2011] shows that γ is reasonable constant over time based on annual sea ice. Figures 1b and 1d suggest that this is also true for September sea ice, but with somewhat larger noise.

[10] In the same way the error propagation is computed for the approach taken in equation (2):

$$\mathrm{SI_f} \pm \Delta\mathrm{SI_f} = \mathrm{SI}_{1980-1999} + \alpha \cdot \beta \cdot \Delta\mathrm{T}[1 \pm (\alpha_{\mathrm{rel}} + \beta_{\mathrm{rel}})], \qquad (5)$$

where α_{rel} is the absolute value of $\alpha_{\mathrm{unc}}/\alpha$ and β_{rel} is $\beta_{\mathrm{unc}}/\beta$. The uncertainty terms are again determined either by ensemble studies of different climate models or based on the model spread. The Arctic polar amplification β is similar for different scenarios but may change slightly over time. To account for this, the mean Arctic polar amplification across all models of the period 2010–2099 (β_f) is divided by the mean Arctic polar amplification of the time period 1980–2007 (β_c). This scaling factor is again used to estimate the future Arctic polar amplification from the observed estimate as shown in equation (6):

$$\beta = \beta_{\mathrm{Obs}(1980-2007)} \cdot (\beta_f/\beta_c) \tag{6}$$

This effect however is small, the scaling is close to one and the results are not sensitive to this step.

[11] However, there are multiple possibilities how to propagate uncertainty. Instead of quantifying the uncertainty around the observed value, one could argue that the observed value is rather at the upper end of the range of the forced sensitivity in the future [*Kay et al.*, 2011]. This would imply that the state of an ice-free Arctic in September is reached at a slightly higher global temperature increase than suggested by our best estimate.

3.3. Spatial Representations of September Sea Ice Cover

[12] The discussion so far has focused on area-averaged quantities. An interesting question is the spatial distribution of Arctic sea ice, and how it evolves over time. The difficulty is that standard pattern scaling approaches fail for sea ice, since it is a retreating front rather than a spatial pattern that decreases in magnitude. A first order estimate, however, can be obtained based on the recalibrated sea ice extrapolation presented in Figure 2 and by sampling the ensemble along the extrapolation. A certain level of warming, e.g., 1°C above the reference period, corresponds to a best estimate of total September sea ice area based on the red line in Figure 2. We can now for each model find the 20 yr time period matching that area, and aggregate those spatial distributions. In other words, model periods with equal September sea ice area are aggregated, even though their specific temperature increase is different. The four different cases 0.5°C, 1°C, 1.5°C and 2°C above present are shown in Figure 5 and show the percentage of models that have sea ice cover in a specific grid cell (note that grid cells with a sea ice fraction less than 15% are not shown in Figure 5). The maps therefore represent the spatial distributions that correspond to a given warming and given sea ice area, based on the recalibrated ensemble. The 33% isoline is marked in red in Figure 5. The area outside of this isoline is "likely" (using IPCC terminology) to be ice-free as at least 66% of the models show ice-free conditions.

[13] Without applying the recalibration presented here, some models simulate a sea ice area that is too large, but when averaging across the multi model ensemble, the ice edge agrees reasonably well with the observations over recent decades, for March as well as September [*Arzel et al.*, 2006]. Therefore, and also by comparing the two observed extreme minima in 2007 and 2011 with Figure 5, the spatial September sea ice retreat simulated by the models appears to be reasonably consistent with observations.

4. Summary and Conclusions

[14] In this study we find that current models indicate a near linear relationship between temperature and Arctic sea ice area that can be used to estimate at what global temperature increase the Arctic will be nearly ice-free during September based on observations. In contrast to earlier studies [*Boé et al.*, 2009b; *Wang and Overland*, 2009], these projections are independent of the assumed emission scenario. A slower warming will simply delay but not avert the outcome. Overall the CMIP3 models underestimate the past and future sea ice decline for two interlinked reasons. They underestimate the loss of sea ice per degree local warming (α), and underestimate the Arctic polar amplification (β). However, we find a large natural variability in Arctic polar amplification and argue that at least half of the models simulate a plausible realization of Arctic polar amplification. In case of α at least some models simulate a realistic relationship between local temperature and sea ice [*Hall and Qu*, 2006].

[15] A number of previous studies have evaluated and to some extent calibrated the CMIP3 models with observations [*Huber et al.*, 2011; *Knutti et al.*, 2006], but in many cases the relationships between observable quantities and projections are vague, and observations cannot clearly constrain the ensemble more tightly [*Knutti*, 2010; *Knutti et al.*, 2010; *Räisänen et al.*, 2010]. The majority of successful approaches are regionally limited to the Arctic system. Different approaches have been used, but most are based on the idea of finding a quantity that can be observed today that correlates with a quantity in the future across the multimodel data set [*Boé et al.*, 2009a, 2009b; *Hall and Qu*, 2006; *Mahlstein and Knutti*, 2011], or defining a set of criteria for a model to be 'acceptable' [*Wang and Overland*, 2009]. Defining criteria for a subset of 'better' models is easy to communicate, but somewhat subjective, as every model can be ruled out if enough criteria are defined. This is particularly problematic if the number of models is small, and if the models are not independent, both of which is true for the CMIP ensemble [*Masson and Knutti*, 2011; *Pirtle et al.*, 2010]. Selecting a subset also assumes that the ensemble is reasonable sample of the model uncertainty. This may or may not be true, but certainly the CMIP ensembles were never designed in any way to represent uncertainty. Rather they are an ensemble of opportunity. Recalibrating the ensemble as a whole using observations as done here is likely to be less sensitive to the sample of models, since only the relationship in the models or across models is used, but not individual models. The Arctic system including sea ice appears to be one of the few examples where model evaluation can successfully constrain or recalibrate projections, independent of the approach or variable that is used. The relationships are also well understood in terms of physical processes, correlations are unlikely to be spurious or a consequence of screening predictors [*DelSole and Shukla*, 2009] and the model biases are much larger than the estimated variability, thus minimizing the chance of inappropriate weighting [*Weigel et al.*, 2010]. The results from different approaches consistently show that the models are underestimating sea ice decline and Arctic polar amplification in the past, and very likely in the future as well. This study provides strong evidence supporting that conclusion. The calibrated sea ice extrapolation based on observations since 1980 suggests a most likely threshold for a near ice-free Arctic in September of about 2°C above present, about half of the model mean value estimated by CMIP3. Note that a large uncertainty is associated with this

estimate due to large internal climate variability in the Arctic [*Mahlstein et al.*, 2011]. A recent study claimed that "the warming commitment associated with existing atmospheric greenhouse gas levels means it is very likely that in the coming decades the summer Arctic Ocean will become ice-free" [*Allison et al.*, 2009]. The commitment warming from current total radiative forcing (about 1.6 Wm^{-2}) is about 0.5°C. The commitment warming from current greenhouse gas concentrations (about 2.9 Wm^{-2}, assuming no aerosol forcing) would be about 2.4°C. That number is above the 2°C limit for near ice-free conditions estimated here, but the uncertainty range is large (1.6–3.5°C for a climate sensitivity range of 2–4.5°C). So the Arctic may be ice free with existing greenhouse gas concentrations, but current models and observational evidence do not support the "very likely" statement. The uncertainty caused by internal variability and models is simply too large. A more appropriate comparison however is to look at economically plausible emission scenarios. If emissions were to continue to increase strongly (e.g., as in an SRES A1B or A2 scenario), it appears likely that the Arctic will be nearly ice-free in summer at the end of this century. Yet, if global temperature increase was to be stabilized at 2°C above preindustrial (1.2°C above 1980–1999) [*Washington et al.*, 2009] the Arctic could likely be prevented from becoming ice-free and about half of the current sea ice area could remain during summer.

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