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Key Points:
- The first occurrence of an ice-free Arctic is found to have a prediction uncertainty of two decades due to internal variability
- Common metrics of the past and present mean sea ice state do not allow a reduction of the prediction uncertainty due to internal variability
- For characterizing internal variability, the benefit per additional ensemble members is reduced after the first 10-15 ensemble members

Supporting Information:
- Supporting Information S1

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How predictable is the timing of a summer ice-free Arctic?

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Abstract Climate model simulations give a large range of over 100 years for predictions of when the Arctic could first become ice free in the summer, and many studies have attempted to narrow this uncertainty range. However, given the chaotic nature of the climate system, what amount of spread in the prediction of an ice-free summer Arctic is inevitable? Based on results from large ensemble simulations with the Community Earth System Model, we show that internal variability alone leads to a prediction uncertainty of about two decades, while scenario uncertainty between the strong (Representative Concentration Pathway (RCP) 8.5) and medium (RCP4.5) forcing scenarios adds at least another 5 years. Common metrics of the past and present mean sea ice state (such as ice extent, volume, and thickness) as well as global mean temperatures do not allow a reduction of the prediction uncertainty from internal variability.

1. Introduction

The timing of an ice-free Arctic Ocean, commonly defined as 1 million km^2 or less sea ice coverage [*Wang and Overland*, 2009], has generated a lot of interest both with stakeholders and the scientific community [*Boe et al.*, 2009; *Wang and Overland*, 2009; *Mahlstein and Knutti*, 2012; *Massonnet et al.*, 2012; *Overland and Wang*, 2013; *Liu et al.*, 2013; *Hezel et al.*, 2014; *Notz*, 2015]. Climate model simulations from Coupled Model Intercomparison Project Phase 5 (CMIP5) did not constrain the date of an ice-free summer to less than 100 years, even when only the strongest forcing scenario (Representative Concentration Pathway (RCP) 8.5) was considered, with predictions ranging from 2005 to beyond 2100 [*Notz*, 2015]. Part of this spread is due to significant model biases in some of the CMIP5 models [*Stroeve et al.*, 2012], while another part is due to internal variability [*Kay et al.*, 2011; *Swart et al.*, 2015; *Notz*, 2015]. Scenario uncertainty further widens the prediction uncertainty of an ice-free Arctic [*Stroeve et al.*, 2012; *Liu et al.*, 2013]. As the Arctic September sea ice is still quite far from an ice-free threshold, the prediction of the timing of an ice-free summer Arctic is not a question of initial value predictability, which is limited to about 3 years for sea ice [*Blanchard-Wrigglesworth et al.*, 2011]. Rather, the predictability of an ice-free Arctic is due to the forced response of the sea ice cover to the increasing greenhouse gas forcing, which is often referred to as predictability of the second kind or forced predictability [*Lorenz*, 1975]. And just as initial value predictions, such as weather forecasts, are inherently limited due to the chaotic nature of the weather [*Lorenz*, 1963], internal variability inherently limits the forced predictability of the statistics of the climate system [*Deser et al.*, 2012a, 2012b]. Previous studies have attempted to narrow the wide range of CMIP5 predictions of an ice-free Arctic by using model selection based on certain metrics [*Wang and Overland*, 2009; *Massonnet et al.*, 2012; *Overland and Wang*, 2013] or emergent constraints determined from model simulations [*Boe et al.*, 2009; *Mahlstein and Knutti*, 2012; *Liu et al.*, 2013], which both have limitations [*Stroeve and Notz*, 2015], as well as through statistical methods [*Runge et al.*, 2016]. However, the fundamental question of how much we can actually narrow the prediction uncertainty of the timing of an ice-free Arctic, due to the inherent uncertainty introduced by internal variability, has not been answered. Here we address this fundamental question and ask: how well are we able to predict the timing of when the Arctic will first reach ice-free conditions? Using ensemble simulations from the Community Earth System Model (CESM) forced by the strong (RCP8.5) and medium (RCP4.5) emission scenarios for the 21st century [*Kay et al.*, 2015; *Sanderson et al.*, 2015], we answer this essential question, discuss the prediction uncertainty from internal variability and scenario uncertainty, assess the number of ensemble members needed to robustly diagnose the impact of internal variability on sea ice projection uncertainty, place the CESM results in the context of CMIP5 results, and investigate whether the present sea ice state can be used to narrow the prediction uncertainty introduced by internal variability.

2. Methods

The CESM large ensemble (LE) [*Kay et al.*, 2015] and the CESM medium ensemble (ME) [*Sanderson et al.*, 2015] with CESM1-CAM5 are ideally suited to address questions about the impact of internal variability and scenario uncertainty on climate predictions. They consist of 40 and 15 ensemble members, respectively, and are forced by two different scenarios for the 21st century, the strong forcing scenario (RCP8.5) and the medium forcing scenario (RCP4.5) [*Meinshausen et al.*, 2011], respectively. All ensemble members use the identical model and within each ensemble are forced by the same forcing (historical and RCP8.5 for the CESM LE and RCP4.5 for the CESM ME). The only difference between them is a roundoff-level perturbation to the initial conditions of the CESM LE in 1920, which grows due to the chaotic nature of the climate system and leads to distinct internal variability in each ensemble member (see supporting information Text S1 for more details on the ensembles and the CESM). Furthermore, the CESM LE and ME simulations are well suited to study Arctic sea ice predictability as the CESM1-CAM5 simulates a realistic present-day Arctic sea ice state, with the satellite observations falling within the ensemble spread (see supporting information Figures S1 and S2 for the simulated mean sea ice thickness pattern and seasonal cycle; the CESM LE sea ice trends have been previously discussed by *Swart et al.* [2015] and *Barnhart et al.* [2016]).

3. Results

3.1. Influence of Internal Variability on the Timing of an Ice-Free Arctic

Internal variability leads to a substantial spread in the ensemble simulations of the September sea ice extent in the CESM LE and ME simulations (Figures 1a and 1b). The range of dates when each ensemble member's monthly mean September sea ice extent reaches (or crosses) the 1 million km^2 "ice-free" threshold for the first time is 2032–2053 under the strong forcing scenario used in the CESM LE and 2043–2058 under the medium forcing scenario used in the CESM ME (Figure 1c). This means that due to internal variability alone, the timing of an ice-free summer Arctic has a prediction uncertainty of up to 21 years. The year when a September ice-free Arctic is first realized and the associated prediction uncertainty due to internal variability changes somewhat if we look at other definitions of "ice free" that have been used in the literature, but the influence of internal variability is large in all of these cases: It narrows to 14 years for the 5 year running mean sea ice extent (2040–2054), to 16 years if we look at the first year of a 5 year period where the Arctic is consecutively ice free in September (2040–2056), and extends to 24 years if we assess the first year of a 10 year period of consecutively ice-free Septembers (2040–2064) (see Table 1 for the impact in the CESM ME). The large uncertainty due to internal variability is also not only present for the 1 million km^2 ice-free threshold, but similar uncertainty ranges are found for the first time other sea ice extent thresholds are crossed (shown for values between 5.5 and 0.5 million km^2 in the supporting information Figure S4, which shows ensemble spreads of 14–22 years in the CESM LE and 15–28 years in the CESM ME). In the following we focus our discussion on the first time the September monthly mean of each ensemble member reaches or crosses the 1 million km^2 ice-free threshold, but the results are generally similar for other definitions and thresholds.

3.2. Combined Influence of Internal Variability and Scenario Uncertainty

In addition to complicating the prediction of when the Arctic could first reach an ice-free September under a given forcing scenario, the large internal variability also complicates the distinction between the sea ice evolution in the strong (RCP8.5) and medium (RCP4.5) emission scenario used in the CESM LE and CESM ME, respectively (Figure 1c and supporting information Figure S4). In fact, the CESM ME prediction of an ice-free Arctic (2043–2058) overlaps with the CESM LE predictions (2032–2053) by 11 years. This gives a combined scenario and internal variability prediction uncertainty for an ice-free Arctic of 26 years, an extension of only 5 years compared to the internal variability uncertainty range in the CESM LE. For other definitions of ice free, however, the scenario uncertainty is much larger, as consecutive 5–10 years of ice-free Septembers do not occur in all of the CESM ME ensemble members before the end of the simulations in 2080 (Table 1). This reflects the very different sea ice regime in the Arctic in the later part of the 21st century under the two forcing scenarios: Under the strong forcing scenario, the Arctic Ocean in the CESM LE is consistently ice free in September starting in the late 2060s (Figures 1a–1c). Under the medium forcing scenario, consistently ice-free

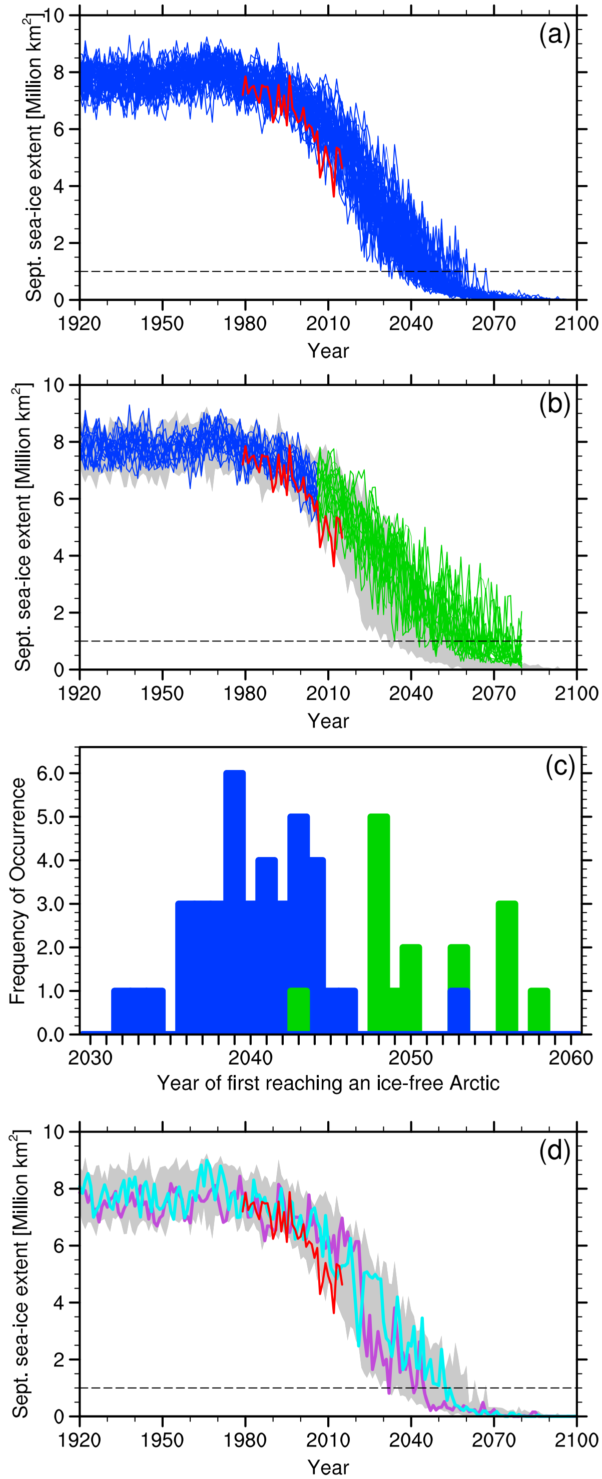

Figure 1. September sea ice extent from the (a) 40-member CESM LE for RCP8.5 and the (b) 15-member CESM ME for RCP4.5 (see supporting information Figure S3 for individual plots for all CESM LE ensemble members to see the details of their evolution). The ensemble spread of the CESM LE is shown in Figure 1b under the CESM ME as grey shading, to allow a direct comparison of the two ensembles. The ice-free 1 million km^2 threshold is shown as the black dashed line, and the observed sea ice extent from National Snow and Ice Data Center (NSIDC) [*Fetterer et al.*, 2002] is shown as the red line in Figures 1a, 1b, and 1d. (c) The histogram of the first year when the September mean ice extent crosses the 1 million km^2 ice-free threshold for the CESM LE (blue) and the CESM ME (green), with yearly bin sizes. (d) The trajectories of sea ice extent for the first (purple) and last (cyan) ensemble member to cross the ice-free threshold of 1 million km^2 (dashed black line).

Table 1. Range of Years From CESM and CMIP5 Ensembles When an Ice-Free September in the Arctic is First Reached, Based on Different Definitions of Ice Free Used in the Literature[a]

Model	Monthly Mean	5 Year Running Mean	5 Consecutive Years	10 Consecutive Years
CESM LE [40]	2032–2053 (21)	2040–2054 (14)	2040–2056 (16)	2040–2064 (24)
CESM ME [15]	2043–2058 (15)	2047–2078 (31)	2053 – past 2080 (>27)	2064 – past 2080 (>16)
CSIRO [10]	past 2100	past 2100	past 2100	past 2100
EC-EARTH [10]	2058–2065 (7)	2058–2068 (10)	2058–2069 (11)	2060–2069 (9)
CCSM4 [6]	2060–2075 (15)	2066–2075 (9)	2067–2080 (13)	2076–2089 (13)
CanESM2 [5]	2015–2028 (13)	2027–2035 (8)	2032–2044 (12)	2032–2044 (12)
CNRM-CM5 [5]	2027–2037 (10)	2036–2048 (12)	2035–2051 (16)	2041–2051 (10)

[a]The ensemble spread is given in parentheses after the year range, and the ensemble size is given in square parentheses after the model name CSIRO.

summers only occur in a few ensemble members before the end of the CESM ME simulations in 2080 (Table 1), and large interannual September sea ice variability of several million square kilometers persists in most ensemble members. This highlights that while internal variability hides the influence of different emission scenarios on Arctic sea ice in the first half of the 21st century, future emissions have a big impact on the state of the Arctic sea ice cover in the second half of the 21st century.

3.3. How Many Ensemble Members Do We Need?

Large ensembles are computationally expensive but, as shown earlier, allow a robust statistical assessment of the prediction uncertainty due to internal variability. Another way to assess internal variability is the use of analytical models applied to the long unforced control simulations from climate models [e.g., *Thompson et al.*, 2015]. However, one of the main assumptions of the analytical model suggested by *Thompson et al.* [2015] is that the standard deviation of the variable of interest does not change in response to anthropogenic forcing. As the standard deviation of sea ice extent changes as the climate warms [*Goosse et al.*, 2009] (also see supporting information Table S1), this analytical model can therefore not be used for sea ice, and we need large ensembles to assess the impact of internal variability on sea ice. But how large do these ensembles need to be?

We can estimate how well a particular ensemble samples the range of internal variability by assessing its histogram. For the CESM LE, we find that it appears to be normally distributed (Figure 2a; see supporting information Text S2 for more details). Compared to a normal Gaussian distribution with the same standard deviation and mean, even the CESM LE with 40 members does not yet have a fully filled-in Gaussian distribution, which suggests that the ensemble spread might increase further with more ensemble members (Figure 2a). The L_1 and L_2 error norms are two objective measures of the distance between a distribution from the CESM LE

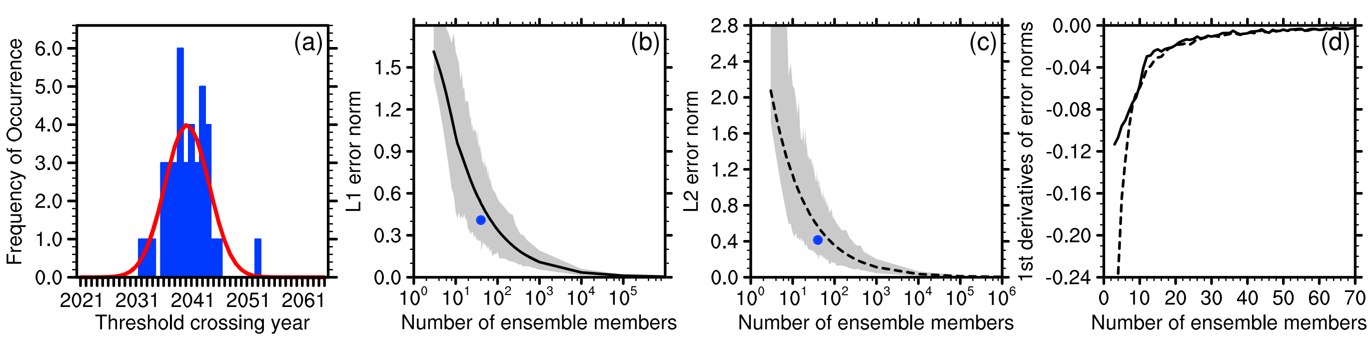

Figure 2. (a) A normal Gaussian distribution (red line) with the same standard deviation and average as the CESM LE for the first year of an ice-free September (shown as blue histogram). The difference between the distribution from the CESM LE and the Gaussian distribution shown in Figure 2a is measured using the (b) L_1 and (c) L_2 error norms (blue dots), while the average theoretical evolution of L_1 and L_2 error norms for ensembles of various sizes (from 3 to 1,000,000) drawn from the Gaussian distribution shown in Figure 2a is shown as black lines. The ensemble spread from randomly sampling the Gaussian 5000 times for these ensemble sizes is indicated by the grey shading. (d) The slope of the L_1 (solid line) and L_2 (dashed line) error norms in Figures 2b and 2c (calculated as second-order first derivatives of the average error norms) shows how fast the error norm drops off per additional ensemble member (shown for the first 70 ensemble members; after that the curve continues to approach zero).

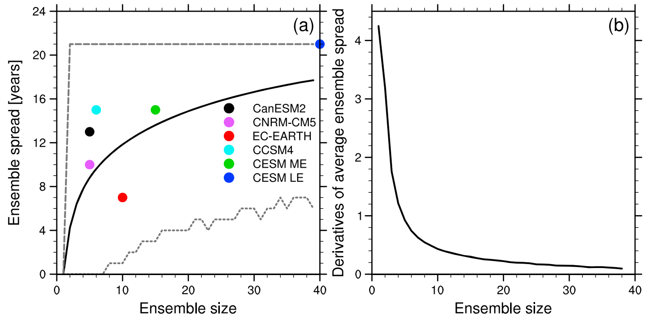

Figure 3. (a) Bootstrapped CESM LE average (solid black), maximum (dashed grey), and minimum (dotted grey) ensemble spread for different ensemble sizes, based on 500,000 random bootstrap samples (with replacement) of different ensemble sizes from the 40 member CESM LE, showing how the possible ensemble spread can vary for an ensemble of a given size. Colored dots show the ensemble spread simulated by the CMIP5 models and the CESM ME, to assess whether their ensemble spread is consistent with the CESM LE. (b) The slope of the average CESM ensemble spread curve in Figure 3a (calculated as second-order first derivative of the average ensemble spread), which provides information on the additional average ensemble spread gained per additional ensemble member.

and a Gaussian distribution with the same mean and standard deviation as the CESM LE (see supporting information Text S2 for more detail on the L_1 and L_2 error norms). Error norm analysis shows that the initial error reduction is largest for the first 10–15 ensemble members and flattens significantly after that (Figures 2b–2d). Another way to estimate how many ensemble members we need is to randomly sample the 40-member CESM LE ensemble many times to construct smaller ensembles and to analyze the statistics of these bootstrapped random ensembles of sizes 2–39. This reveals that the ensemble spread for small ensembles can vary substantially depending on the random sampling of possible climate states by the ensemble members (Figure 3a). The slope of the average expected ensemble spread of ice-free years is largest for the first 5 ensemble members (Figure 3b), with a slower increase per additional ensemble member to about 15 ensemble members, and an even smaller increase per additional ensemble member after that.

Given computational resource constraints associated with large ensembles, the bootstrapping and error norm analysis suggest that, at least for thresholds of sea ice extent, ensembles of size 10–15 might be a good cost-benefit compromise that should provide a reasonable estimate of the influence of internal variability. However, larger ensembles always provide better statistics, and the analysis shown here was only possible due to the existence of the large 40-member ensemble with the CESM and is based on its representation of internal variability. It would therefore be very valuable to have large ensembles from other models, to compare the range of simulated internal variability and to better generalize the lessons learned from the CESM LE.

3.4. How Representative is the Internal Variability in the CESM LE Compared to CMIP5 Ensembles?

How representative is the internal variability and the resulting ensemble spread from the CESM LE compared to other simulations? In the CMIP5 archive, five climate models contributed five or more ensemble members of historical and RCP8.5 simulations. As shown in Figure 4a, these five models simulate very different trajectories of Arctic sea ice extent for the 21st century under RCP8.5 forcing and span almost the full range of the CMIP5 model predictions of when an ice-free Arctic is first reached (Table 1 and Figure 4b). The ensemble spread of the year of first reaching an ice-free Arctic varies between 7 and 15 years for these individual CMIP5 models. This is considerably smaller than the 21 year range found in the 40-member CESM LE but comparable to the 15 years found in the RCP4.5 forced CESM ME. However, as shown in Figure 3a, the possible bootstrapped ensemble spread for ensembles of size 5–10 drawn from the CESM LE data brackets the ensemble spread of the CMIP5 models. This indicates that the simulated CESM LE ensemble spread is consistent with the spreads from smaller ensembles in the CMIP5 archive. A comparison of the standard deviations of the September sea ice extent also does not suggest that the CESM internal sea ice variability is inconsistent with the smaller CMIP5 ensembles (supporting information Table S1). The lack of any kind of near-normal distribution of ice-free years in the CMIP5 models (Figure 4b) suggests that the ensembles contributed to CMIP5 were too small to adequately sample the internal variability. Larger ensembles using the RCP8.5 forcing in other models are needed to further assess how representative the internal variability in the CESM LE is.

3.5. Can We Reduce the Prediction Uncertainty Based on Present-Day Conditions?

Given the substantial ensemble spread in the simulation of when an ice-free year is first reached in the CESM LE and CESM ME, can we determine which ensemble member will go ice free first based on the past, present, or future sea ice state in the simulation? If so, this would provide a reduction in the prediction uncertainty. An analysis of several characteristics of the past, current, and near-future sea ice state variables (i.e., trends

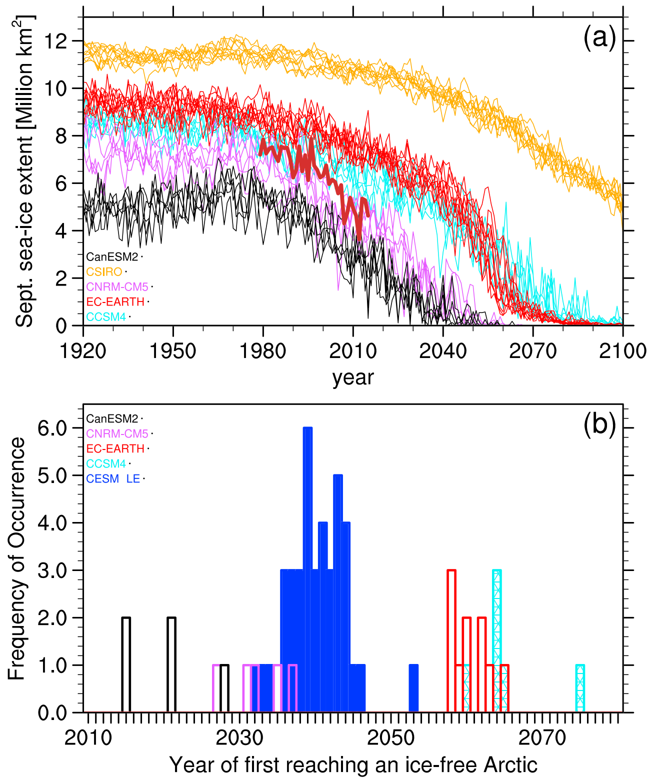

Figure 4. (a) September sea ice extent from the CMIP5 models that have an ensemble size of 5 or greater for RCP8.5 and the historical simulations and the NSIDC sea ice extent (thick brown line), as well as (b) a histogram of the year when the 1 million km^2 ice-free threshold is first crossed for the September mean in the CMIP5 models compared to the CESM LE.

and decadal averages of ice thickness, sea ice extent, area, and sea ice volume, for annual, decadal, winter, and summer means) shows that these have no predictive skill as to the order in which ensemble members reach ice-free conditions within the CESM LE and ME (see supporting information Figures S5 and S6 for some sample plots for the CESM LE). An examination of the ensemble members that reach ice-free conditions first and last (Figure 1d) clearly shows that the September sea ice extent trajectories cross at least once, if not several times, between 2015 and when ice-free conditions are reached (see supporting information Figure S3 for trajectories of all ensemble members). So while it might be possible to use emergent constraints to narrow the prediction uncertainty in the CMIP5 simulations due to the large differences in mean-state bias across the different models [*Liu et al.*, 2013], it is not possible to use the same constraints to narrow the uncertainty due to internal variability within the CESM or within the individual ensembles from CMIP5 models (supporting information Figure S5). In fact, the previous narrowing of the prediction of an ice-free Arctic from the CMIP5 simulations to 5 years (2054–2058) [*Liu et al.*, 2013] was likely too strong and is not supported by our analysis of the CESM LE (with an uncertainty range of 21 years) and the multiple ensemble members of the CMIP5 models we examined (7–15 years). It might have been a result of using only one ensemble member from each CMIP5 model and highlights how important it is to consider the influence of internal variability. The metrics defined in *Massonnet et al.* [2012] on the other hand used all available ensemble members from each model and found a prediction uncertainty of two to three decades for the timing of an ice-free Arctic, including both model and internal variability uncertainty.

The global or Arctic temperatures in the year individual ensemble members go ice free differ considerably across ensemble members of the CESM and of the CMIP5 models (see supporting information Figure S7). So while 2°C might be the threshold for an ice-free September Arctic using 10 year mean sea ice extents and global temperature anomalies in the CMIP3 models [*Mahlstein and Knutti*, 2012], for the annual time series of the CESM and CMIP5 ensemble members neither the global nor the Arctic temperature shows such a threshold. This strongly suggests that the temperature in a given year is not responsible for the timing of when individual ensemble members reach an ice-free state, and global or Arctic temperatures can therefore also not be used to narrow down the uncertainty introduced by internal variability for the prediction of when the Arctic could first be ice free in September.

4. Conclusions

Our results from the 40-member CESM LE and the 15-member CESM ME show that due to internal variability alone, we cannot predict the timing of a summer ice-free Arctic with an uncertainty of less than 21 years. The much smaller ensembles (5–10 members) from the CMIP5 archive show uncertainty ranges of 7–15 years due to internal variability, which are consistent with the expectation for smaller ensembles from the bootstrapped CESM LE. Past, present, and near-future sea ice volume, trends, area, extent, and thickness, as well as global temperature metrics do not allow us to narrow the prediction uncertainty due to internal variability within individual models. Hence, accurate predictions of the exact year or even the exact decade we could first reach a summer ice-free Arctic decades in advance are not possible. When attempting to narrow down the large prediction uncertainty of over 100 years due to CMIP5 model differences, care needs to be taken to adequately account for the role of internal variability.

Scenario uncertainty between the strong (RCP8.5) and medium (RCP4.5) forced simulations further adds to the prediction uncertainty from internal variability, with an additional 5 years for the first time the Arctic has less than 1 million km^2. However, the occurrence of consecutively ice-free Septembers varies significantly between the strong and medium emission scenarios, with ice-free summers the norm after the late 2060s in the strong forced CESM LE and the exception in the medium forced CESM ME. Prior to the middle of the 21st century, large internal variability hides the influence of scenario uncertainty. The continued decline of the Arctic sea ice cover over the 21st century, however, is not the result of internal variability and occurs in all ensemble members from the CESM and CMIP5.

Based on the CESM LE, many ensemble members are needed to characterize the statistics of internal variability in sea ice simulations, but the benefit per additional ensemble members is reduced after the first 10–15 ensemble members. And while ensembles of 10–15 ensemble members do not provide information on the full impact of internal variability, they might be a reasonable cost-benefit compromise for future model intercomparisons, in particular if other large ensembles can confirm the lessons learned from the CESM LE.

Acknowledgments
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