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Sources of multi-decadal variability in Arctic sea ice extent

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Abstract
The observed dramatic decrease in September sea ice extent (SIE) has been widely discussed in the scientific literature. Though there is qualitative agreement between observations and ensemble members of the Third Coupled Model Intercomparison Project (CMIP3), it is concerning that the observed trend (1979–2010) is not captured by any ensemble member. The potential sources of this discrepancy include: observational uncertainty, physical model limitations and vigorous natural climate variability. The latter has received less attention and is difficult to assess using the relatively short observational sea ice records. In this study multi-centennial pre-industrial control simulations with five CMIP3 climate models are used to investigate the role that the Arctic oscillation (AO), the Atlantic multi-decadal oscillation (AMO) and the Atlantic meridional overturning circulation (AMOC) play in decadal sea ice variability. Further, we use the models to determine the impact that these sources of variability have had on SIE over both the era of satellite observation (1979–2010) and an extended observational record (1953–2010). There is little evidence of a relationship between the AO and SIE in the models. However, we find that both the AMO and AMOC indices are significantly correlated with SIE in all the models considered. Using sensitivity statistics derived from the models, assuming a linear relationship, we attribute 0.5–3.1%/decade of the 10.1%/decade decline in September SIE (1979–2010) to AMO driven variability.

Keywords: sea ice extent, Atlantic multi-decadal oscillation, Arctic oscillation, Atlantic meridional overturning circulation, Arctic, climate variability

S Online supplementary data available from stacks.iop.org/ERL/7/034011/mmedia

1. Introduction

Satellite monitoring since the late 1970s has shown that total Arctic sea ice extent (SIE) has been declining, and at an accelerating rate since the 1990s (Serreze *et al* 2007). This decline in SIE is predicted to continue until the Arctic is seasonally ice-free at some point in the 21st century (Boe *et al* 2009b, Wang and Overland 2009). The observed September SIE trend is not captured by the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model mean, which was used to project 21st century sea ice decline for the Intergovernmental Panel on Climate Change (IPCC) 4th Assessment Report (AR4) (Stroeve *et al* 2007).

Observational uncertainty, climate model insensitivity and vigorous natural variability have all been suggested as potential sources of discrepancy between observed and CMIP3 modelled trends (Serreze *et al* 2007, Kattsov *et al* 2011). If natural variability has played a large role in the observed decline, it is possible that it is a statistically rare

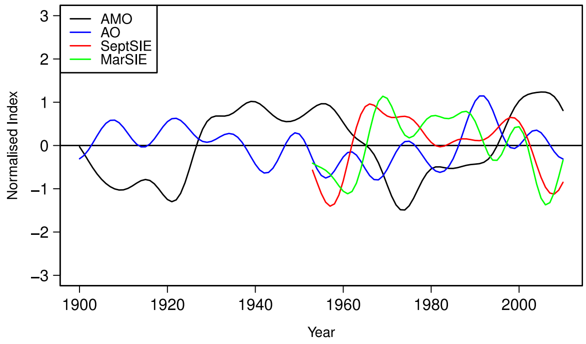

Figure 1. Normalized AMO index (Enfield *et al* 2001), AO index (calculated from Allan and Ansell (2006)), September and March SIE (Meier *et al* 2007). The time series were detrended (apart from the AO index), then passed through a 10 year low pass filter.

event which is simply not captured by the relatively small size of the CMIP3 ensemble (Kattsov *et al* 2011). Stroeve *et al* (2011b) suggest that accelerated decline since 1990 may be a response to natural variability which may not continue. Boe *et al* (2009a) demonstrated that, over the course of the 21st century, the climatological sea ice thickness and local feedback strength cause some spread in model sensitivity. However, the satellite observation period for sea ice (1979–2010) is too short to calculate a value for sea ice sensitivity to anthropogenic forcing, to compare with these models (Winton 2011). Thus, understanding the sources and magnitude of natural sea ice variability is important to determine the proportion of the observed decline which can be attributed to anthropogenic forcing, and also to investigate possible limitations of model simulations. Kay *et al* (2011) use multiple simulations of the climate model CCSM4 for the period 1979–2005 to determine that 44% of the observed September SIE trend over this period can be explained by natural variability. In this study we look at the potential sources of this natural variability.

Atmospheric sources of variability include large-scale sea level pressure (SLP) anomalies and associated anomalous winds, which have been associated with sea ice motion (Rigor *et al* 2002, Ogi *et al* 2010). In particular, it has been suggested that positive phases of the leading mode of winter Northern hemisphere SLP variability, the Arctic oscillation (AO) are associated with thinning in the east Arctic and outflow through the Fram Strait since 1979 (Rigor *et al* 2002). However a shift towards a more neutral state followed by the extreme negative shift in the 2009/2010 winter AO index did not result in a higher September SIE, rather the third lowest on record, leading to suggestions that this relationship may be changing (Stroeve *et al* 2011a) (see figure 1).

Oceanic sources of variability are also thought to have had a significant impact on SIE. These include the Atlantic multi-decadal oscillation (AMO) a 65–80 year oscillation in North Atlantic sea surface temperature (SST) (Schlesinger and Ramankutty 1994). This is a major source of natural variability in the North Atlantic and is thought to be driven by Atlantic meridional overturning circulation (AMOC) variability (Delworth and Mann 2000, Zhang 2007). Mahajan *et al* (2011), using a 1000 year integration of GFDL-CM2.1, found areas of significant anti-correlation between both the AMO and AMOC indices and Arctic sea ice concentration in all seasons. There is also evidence of a low frequency AMO like oscillation in historical observations of sea ice conditions in the Nordic and Arctic Marginal seas (Polyakov *et al* 2003, Divine and Dick 2006). The AMO index has shifted from a negative to positive state over the period of satellite sea ice observation, indicating that natural variability in the AMO could be responsible for some of the observed trend in SIE (see figure 1).

In this letter we use five CMIP3 coupled general circulation models (GCMs) with pre-industrial forcing to investigate the impact of the AO, AMO and AMOC on SIE. The methods, models and data sets are described in section 2. In section 3, we present results from a correlation analysis between the indices of climate variability and SIE. Based on these results, we use a linear regression model in section 4 to estimate the impact of the AMO on March and September SIE over the period 1953–2010.

2. Methods and data

We perform correlation analyses on observations and climate model output to investigate which modes of internal variability may be related to SIE. We use control simulations, for which external forcing is held fixed, in order to eliminate the confounding effects of time-varying forcings. An initial investigation with the HadCM3 and MIROC3.2.2 models, using subintervals of multi-millennial length control runs, reveals that O(500) years of data are required in order to generate statistically robust results (see figure S1 available at stacks.iop.org/ERL/7/034011/mmedia). Therefore, in addition to these two models, we use results for CSIRO-MK3.5, GFDL-CM2.1 and GISS-ER which are the only models for which suitably long control integrations can be obtained from the CMIP3 database (Meehl *et al* 2007).

The winter AO index is defined as the principal component of the leading Empirical Orthogonal Function (EOF) of the winter (JFM) sea level pressure (SLP) field. Correlation analysis is performed between the winter AO index and September SIE from the five GCM simulations. All five models produce a good representation of the observed AO pattern (Zhu and Wang 2010).

For the five GCMs, we also perform correlation analyses between the annual mean AMOC strength (defined as the maximum of the basin meridional stream function at 40°N) and AMO index (defined as the weighted average of Atlantic SST between 0°N and 70°N), and between both of these indices and March and September SIE. This is in order to determine the inter-model robustness of the relationships described by Mahajan *et al* (2011). Details of the AMOC, AMO and SIE climatologies in these models are described in the supplementary material (available at stacks.iop.org/ERL/7/034011/mmedia).

The significance of all correlations was calculated using a t-test with $N_{\mathrm{eff}} - 2$ degrees of freedom. N_{eff} is the number of effective degrees of freedom of the combined dataset, e.g. AO index and SIE. $N_{\mathrm{eff}} = N/[1+2\sum_{i=1}^{N} C_{\mathrm{index},i} C_{\mathrm{SIE},i}]$, where N is

Table 1. Correlation between AO index, AMOC, AMO and September SIE for five GCMs and detrended observations. All correlations are significant at the 90% level except starred values. The lag time which maximizes the correlation between the variable and SIE is included, where SIE is the lagging variable.

Model	*r*(AO, SIE)	*r*(AMOC, SIE)(lag)	*r*(AMO, SIE)	*r*(AHT, SIE)(lag)
CSIRO-MK3.5	−0.08*	−0.40(0)	−0.44	−0.59(1)
GFDL-CM2.1	0.11	−0.11(3)	−0.31	
GISS-ER	0.12	−0.14(0)	−0.13	−0.20(−1)
HadCM3	0.05*	−0.12(2)	−0.17	
MIROC3.2.2	−0.04*	−0.17(2)	−0.21	−0.31(2)
Observed	−0.09		−0.42	

the simulation length in years and $C_{x,i}$ is the auto-correlation of the time series x with lag i (Livezey and Chen 1983).

Least squares regression analysis was performed to relate March and September SIE to the AMO index in the GCMs. The slope coefficients are then used in section 4 to estimate the impact of the observed AMO on SIE over the periods 1953–2010 and 1979–2010 based on the observed AMO variability. The observed AMO index used here is that of Enfield *et al* (2001), which has been detrended and so can be thought of as the natural signal. The observed SIE data set used for comparison is the Meier *et al* (2007) record which is primarily based on HadISST, which utilizes early satellite, airborne and ship observations prior to 1979 (Rayner *et al* 2003). To account for an inconsistency occurring between 1996 and 1997 where HadISST sea ice concentration is based on a different product, Meier *et al* (2007) modify their data set to use the NASA team sea ice algorithm (Cavalieri *et al* 2003) for the whole period post-1979.

SIE trends in the CMIP3 20C3M and A1B simulations are discussed with respect to natural variability in section 4. We follow Stroeve *et al* (2007) in only using those models whose observed SIE is within 20% of the observed 1953–95 values.

3. Multi-model Analysis

3.1. AO

The correlation between the observed AO index (Allan and Ansell 2006) and detrended September SIE is −0.09 which is not significant at the 90% level (see table 1). This indicates that despite the arguments of Rigor *et al* (2002) that the AO affects sea ice dynamics, it does not appear to have had a detectable effect on the SIE record. There is also no significant anti-correlation in any of the five GCMs studied here (table 1). That is not to say that the AO has no effect on ice dynamics in the GCMs, for example ice depth and concentration in MIROC3.2.2 do vary significantly with the AO.

We checked for robustness by calculating correlation coefficients in MIROC3.2.2 over multiple time periods of the same length as the observations (58 years). Using a Kolmogorov–Smirnov test we find that the correlations are well approximated by the Gaussian Distribution $N(-0.04, 0.13)$ (see figure S1 available at stacks.iop.org/ERL/7/034011/mmedia). Correlations in this sample are as strong or stronger than the observed correlation ($r = -0.09$) in ~35% of these 58 year subsets. This suggests that either:

(i) There is no long term relationship between AO index and September SIE, but some short periods will exhibit correlations of the observed magnitude by chance, or;
(ii) September SIE in the GCMs considered is unrealistically unresponsive to changes in the surface pressure field due to missing physical processes.

Based on the observed data and model analysis we conclude that the former is more likely. Our results are broadly in agreement with Holland and Stroeve (2011), who found similarly weak correlations between the AO index and September SIE in the CCSM3 climate model.

3.2. AMO and AMOC

Mahajan *et al* (2011) found significant correlations between the annual AMO index and SIE in GFDL-CM2.1, analysing annual mean SIE rather than monthly mean values as we do here. Similarly, we find significant correlations between the annual AMO and March and September SIE in all five model simulations. Highly significant correlations were also found between the detrended time series of the observed annual AMO index and March ($r = -0.42$) and September ($r = -0.42$) SIE data set.

We also find significant correlations between the AMOC index and both September and March SIE in all models except for GFDL-CM2.1, where the September correlation is not significant (tables 1 and 2). Mahajan *et al* (2011) did find a significant correlation in this model, but their analysis only considered annual SIE rather than monthly as we do here. In some models, performing the correlation with the SIE lagging the AMOC index by 1–5 years leads to higher correlations. The strength of the correlation varies substantially between the models, as does the lag time leading to the highest correlation for both September and March SIE. It appears that as a general rule those models with high (low) *r*(AMOC:SIE) have high (low) *r*(AMO:SIE). Similarly models with high (low) *r*(AMO:SepSIE) have high (low) *r*(AMO:MarSIE).

Of the models considered Atlantic northward heat transport was only available for 3. In these models, variations in the overturning impact SIE by varying the northward heat transport to the high latitudes, where a higher (lower) AMOC index corresponds with higher (lower) northward heat transport in the North Atlantic. The strength of the correlation between the AMOC and SIE is thus related to the variability of heat transport at the Greenland–Scotland ridge (~70°N). For

Table 2. Correlation between AMOC, AMO and March SIE for five GCMs and detrended observations. All correlations are significant at the 90% level. The lag time which maximizes the correlation between the variable and SIE is included, where SIE is the lagging variable.

Model	*r*(AMOC, SIE)(lag)	*r*(AMO, SIE)	*r*(AHT70, SIE)(lag)
CSIRO-MK3.5	−0.56(3)	−0.57	−0.57(1)
GFDL-CM2.1	−0.17(3)	−0.37	
GISS-ER	−0.18(4)	−0.25	−0.20(−1)
HadCM3	−0.26(0)	−0.49	
MIROC3.2.2	−0.28(5)	−0.33	−0.31(3)
Observations		−0.42	

example CSIRO-MK3.5 has a high correlation between the AMOC and September SIE ($r = -0.4$) and relatively variable heat transport ($\sigma = 24$TW) at 70N, but GISS EH has a much smaller correlation ($r = -0.1$) and variability is an order of magnitude smaller ($\sigma = 6$TW) (see tables 1 and 2).

Previously, it has been suggested that the AMO is driven by AMOC variability as their observed cycles are in phase (Knight *et al* 2005, Zhang 2007). In all five models considered here, the AMOC and AMO are significantly correlated with correlations between 0.1 and 0.5. The lag time leading to the largest correlation between the AMOC and the AMO is also variable between the models (0–3 years). As such, the AMO can be thought of as a surface fingerprint of the AMOC variability and in this sense it is appropriate to think of the relationships between SIE and the AMO and AMOC as two ways to look at the same phenomena.

Through the mechanism described, the AMO can be thought of as driving sea ice variability. To determine the size of the effect of the AMO on September and March SIE a linear regression analysis is performed between annual AMO and monthly mean SIE. These calculations yield a range of slope parameters -1.8 to -0.7×10^6 km^2 °C^{-1} for March and -1.5 to -0.4×10^6 km^2 °C^{-1} for September with the GFDL model producing the largest coefficients (see figure 2). This inter-model spread is likely caused by differences in both AMO and ocean northward heat transport variability and may be the result of differing ocean model resolution (see table S1 available at stacks.iop.org/ERL/7/034011/mmedia). Both will affect the flow of Atlantic water into the Arctic, which is important since warmer ocean temperatures lead to more melting and reduced sea ice growth (e.g. in the Barents Sea: Årthun *et al* 2012). The response of SIE to fluctuations in the AMO is larger in March than September in all models. This is probably because in March sea ice extends into the North Atlantic and is thus more affected by anomalous northward heat transport in the North Atlantic than September sea ice, which is entirely contained in the Arctic basin and thus only effected by relatively small anomalous heat transport across the Greenland–Scotland ridge. However, when expressed in terms of the percentage of the multi-year monthly mean extent, α is similar for March and September.

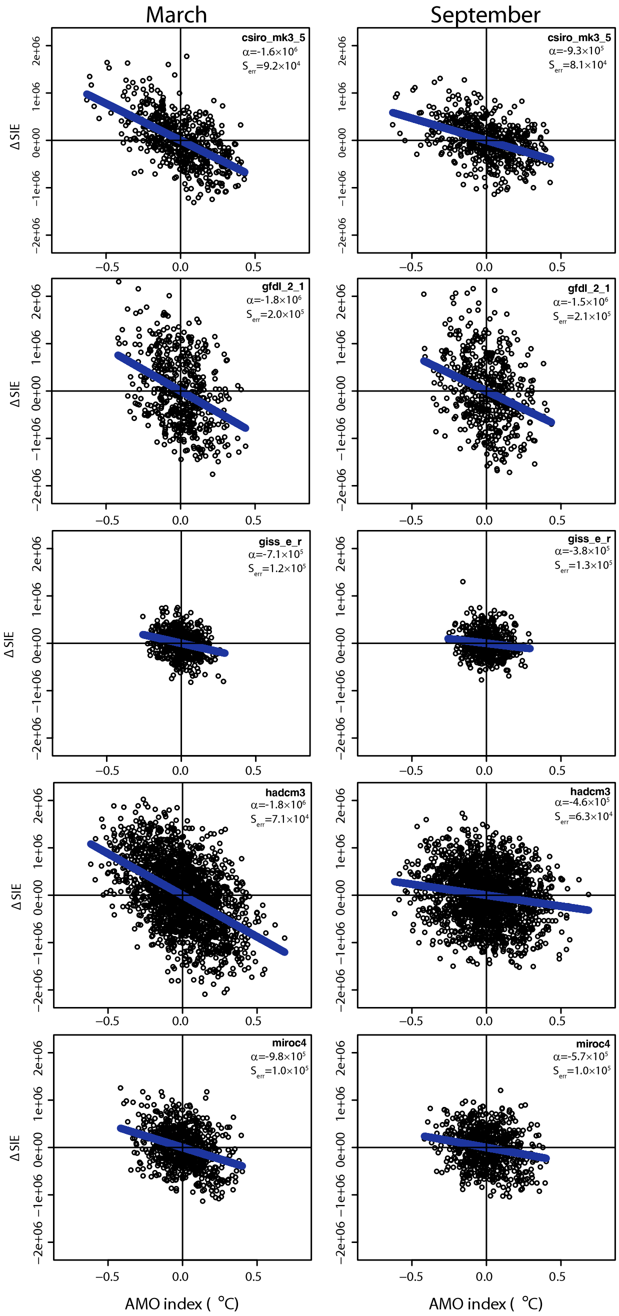

Figure 2. Scatter plots of the annual AMO index and March (left column) or September (right column) for each simulation. The blue line is the least squares linear best fit. The slope coefficient (α) and standard error (S_{err}) are stated in km^2 °C^{-1}. Slope coefficients for all models are significantly different from 0 at the 99% level, using a student *t*-test.

4. Estimating the AMO driven component of sea ice decline

We use a simple linear model $\Delta SIE_{AMO} = \alpha \Delta AMO$ to estimate the component of sea ice decline forced by natural AMO variability. We estimate α from regression slope

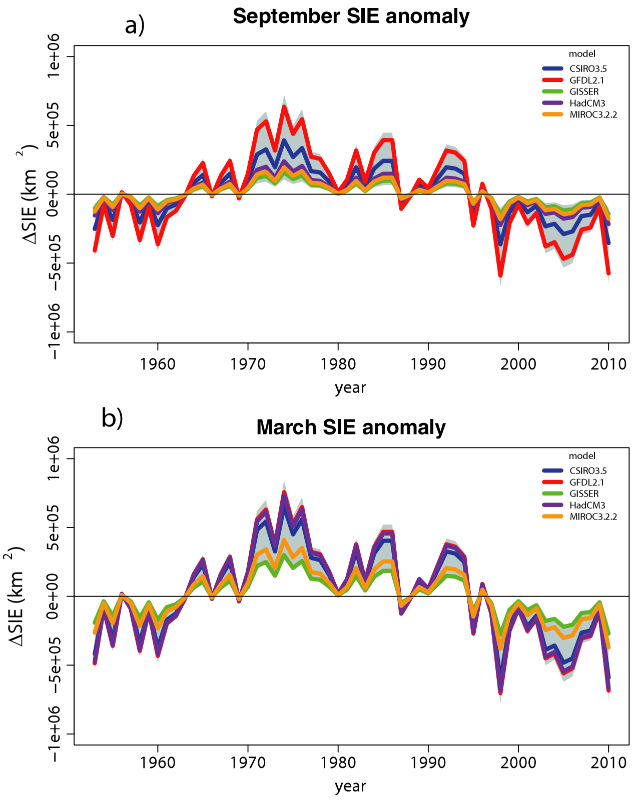

Figure 3. Estimates of the September (a) and March (b) SIE perturbation, ΔSIE, caused by the AMO for the period 1953–2010. These were calculated from a linear model using the observed AMO index as a predictor of ΔSIE using the sensitivity from five GCMs. The range of values for ΔSIE, taking into account both model and regression uncertainty are shown in grey.

coefficients, calculated from each of the five GCMs in turn and use these values together with the observed AMO values to calculate the SIE anomaly due to the AMO, ΔSIE_{AMO}. By considering the model and regression uncertainty in α we calculate a range of values for the change in SIE per decade due to the AMO, calculated as a percentage of the observed SIE at the start year. Using this method we estimate that, for September sea ice, a decline of 0.5–3.1%/decade out of the total observed decline of 10.1%/decade for 1979–2010 is related to the AMO. Over the longer observational period (1953–2010) this contribution is 0.2–0.5%/decade out of the 6.9%/decade trend (see figure 3(a)).

Repeating this calculation for March, we find the trend associated with the AMO is 0.6–1.8%/decade of the observed decline of 2.5%/decade for the period 1979–2010 (see figure 3(b)). Again this is an order of magnitude larger than that for the 1953–2010 period, of which 0.1–0.3%/decade of the observed decline of 1.4%/decade is associated with the AMO.

As the AMO changed from a negative to positive phase during the period 1979–2010, the North Atlantic SST trend is strong and the AMO index increases by 0.48 °C, corresponding with an abrupt decline in SIE (figure 1). During this time the linear model estimates a strong trend in SIE. The longer period, 1953–2010 captures nearly a full AMO cycle, thus the trend in AMO is smaller with an increase in the AMO index of 0.11 °C, causing a smaller SIE trend in the linear model. These results indicate that some, if not most of the acceleration in trend between the two periods considered is due to the AMO, but the observed decline is substantially more rapid than our estimated range for the AMO driven component.

The results above indicate that the AMO may explain some of the discrepancy between observed and modelled SIE. The September SIE trend in the 20C3M and A1B CMIP3 ensemble members have a smaller range for the period 1953–2010 (0.3–4.8%/decade) than for the shorter 1979–2010 period (0.6–9.6%/decade). Focusing on the five CCSM3 ensemble members, the range of trends for the model years 1953–2010 is a decline of 3.8–4.2%/decade compared to 2.5–9.6%/decade (1979–2010). Since the upper bound of this range increases as well as the lower bound decreasing in the latter period, this indicates that it is not simply that larger anthropogenic forcing post-1979 leads to an accelerated trend, but also that vigorous decadal variability such as that associated with the AMO can have a strong effect when SIE trends are calculated over short timescales. March SIE modelled trends show similar behaviour where the range widens from −2.4–1.1%/decade (1953–2010) to −2.0–5.2%/decade (1979–2010) between these periods.

5. Conclusions

Understanding the sources of natural sea ice variability is important to determine the proportion of the observed decline in sea ice which can be attributed to anthropogenic forcing, and also to investigate possible limitations of model simulations. To this end, we have used long GCM simulations with constant pre-industrial forcing to investigate the sea ice variability due to the AO, AMOC and AMO.

We find little evidence for a relationship between the AO and September SIE in either the observations or the five models. Further, from modelling we find that over short periods ($\leq$58 years) there will be apparently significant correlations between the AO and SIE purely by chance, indicating the need for long term observations. However, missing physical processes in the GCMs may cause a lack of sensitivity to changes in atmospheric circulation.

In agreement with Mahajan *et al* (2011), we find that a significant correlation between the annual AMO index and SIE and is a robust feature of the five models. Correlation between the AMOC and SIE is also a consistent feature of all 5 pre-industrial simulations, except for September in GFDL-CM2.1. In the models considered variations in the AMO and AMOC are associated with variations in the North Atlantic heat transported to the Arctic, it is through this mechanism that North Atlantic variability impacts SIE. However, the lag time which maximizes the correlation between AMOC and SIE differs between models. The lack of long term, century scale monthly sea ice or AMOC estimates does not allow us to robustly infer this relationship from observations.

The method used here shows that for the period 1979–2010, 0.5–3.1%/decade of the observed decline of

10.1%/decade is associated with the natural cycle of the AMO, consistent with Kay *et al* (2011). During this period the AMO has moved from a negative phase, associated with anomalously cold North Atlantic SSTs, to a positive phase, associated with anomalously warm SSTs. The effect of the AMO over the extended observational period 1953–2010 is much smaller since the record both begins and ends in a negative AMO state. This suggests that despite increased observational uncertainty in the pre-satellite era, the trend in SIE over this longer period is more likely to be representative of the anthropogenically forced component. Looking at the longer term trends is also more comparable with the multi-model mean in multi-model ensembles which have reduced variability as decadal variability in the models cancels.

Our results are clearly dependent on the models used for this study, which were chosen for the availability of long integrations necessary for the calculation of robust correlation statistics. A larger ensemble of control simulations would give a better indication of the robustness of the relationships studied here and of sea ice sensitivity to internal variability. It is also unclear whether present day control simulations would exhibit different sensitivity compared to pre-industrial. There was good qualitative agreement in the models concerning the nature of the relationship between the AMO and SIE, however there was some spread in sensitivity. Performing the same analysis with the CMIP5 models, which include more elaborate sea ice schemes would be an informative follow up to this study.

Acknowledgments

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