Realism of simulated internal variability in September Arctic sea ice

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Abstract

Arctic summer sea ice has decreased dramatically over the last few decades, with a substantial part of this decline attributed to internal variability. However, models show large differences in their simulated internal variability, increasing projection uncertainty and complications with model-observation comparisons. Here we will present results that aim to quantify the contribution of internal variability in different models which provide large ensemble simulations, and compare them with estimates from observations. In particular, we are comparing five models from the CLIVAR multi-model large ensemble (CanESM2, CESM1, CSIRO MK36, GFDL ESM2M, and MPI ESM1) with observations. So far, we have found a large range in simulated pan-Arctic sea ice area standard deviation from 0.35 million km2 (CSIRO MK36) to 0.74 million km2 (CESM1) for mean September areas between 4.00-4.25 million km2. Spatially, the detrended standard deviation in the central Arctic is consistently over-represented in models compared to observations. Conversely, the marginal seas are simulated to have slightly below to several times below observed detrended standard deviation. Further analysis on a more regional scale will be done over the coming months to further characterize the realism of simulated internal variability in Arctic sea ice.

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1) Objective

- The observed decline in September sea ice is faster than most CMIP5 models, but if internal variability is considered, the rate of decline between the two are not inconsistent (Swart et al., 2015).
- Internal variability varies considerably between CMIP5 models (Olonscheck & Notz, 2017), but with only one realization of reality it is difficult to assess the accuracy of models' simulated internal variability.
- We use ensembles from the Multi-model Large Ensemble Archive (Deser et al., 2020), shown in figure 1, and a synthetic ensemble of observations to answer the question:

Is internal variability accurately represented in CMIP5 models' September sea ice area?

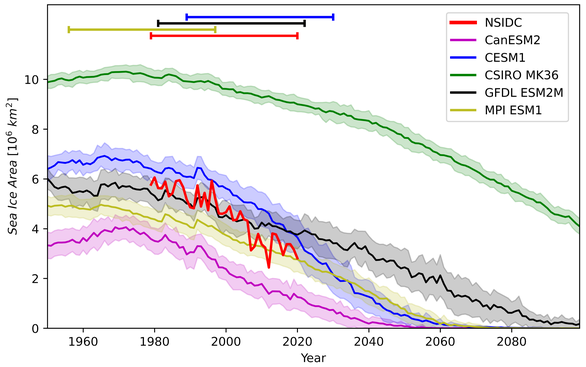

Figure 1. September sea ice area in five CMIP5 large ensembles (1950-2100) with RCP 8.5 forcing, as per legend. Observations in red. Thick lines are ensemble means, lighter shading indicates ±1 standard deviation. Bold lines with caps indicate the 41-year period when the ensemble mean has the same mean state as observations for 1979-2020.

2) Method

Data sets

- Observations: NSIDC Sea Ice Index Version 3 (Fetterer et al., 2017).
- CMIP5 LEs: CLIVAR Multi-Model Large Ensemble Archive (Deser et al., 2020). RCP8.5 runs: CanESM2, CESM1, CSIRO MK36, GFDL ESM2M, and MPI ESM1.
- Time period: September sea ice area, 1979-2020 for equivalent forcing, also the 41-year period with mean sea ice area equal to observations (figure 1a).

Resampling to assess internal variability

- Forced response is assumed to be the linear trend, internal variability is the anomalies of the detrended timeseries.
- 1000 equally possible scenarios are created by resampling anomalies from observations and ensemble members, following McKinnon et al. (2017; 2018). Figure 2a shows the spread of the gradient of resampled observations.
- The standard deviation of the 1000 simulations is one possible metric of internal variability, as is the standard deviation of non-resampled large ensemble members.

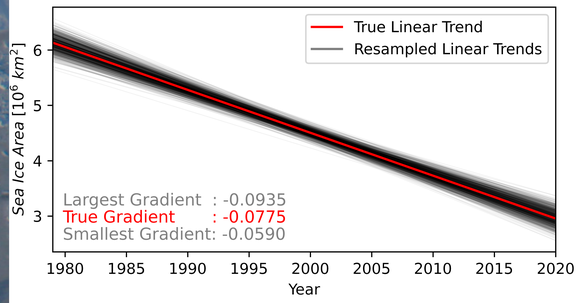

Figure 2. Gradients of the 1000 resampled observations of September sea ice area.

3) Results

- **Models typically have a resampled standard deviation 15% higher than resampled observations** (Fig 3, Table 1 rows I, V).
- **All models except CSIRO have at least one member with standard deviations larger and smaller than resampled observations** (not shown here).

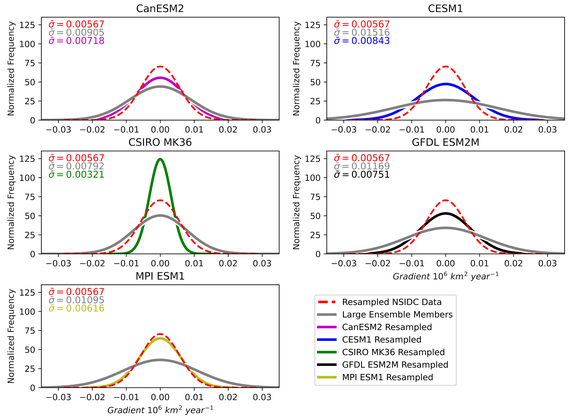

Figure 3. Normal distributions of the gradients of September sea ice area. Red: resampled observations, grey: non-resampled ensemble members, colored as per legend: mean resampled ensemble member.

- Large ensemble standard deviation (across non-resampled members) is **approximately 69% larger** than individual members' resampled standard deviations (Table 1 rows II and VI).
- **Changing the period of observation minimally changes the results** (Table 1 column H).

		A	B	C	D	E	F	G	H
	Variable	NSIDC	CLIVAR Average	CanESM2	CESM1	CSIRO MK36	GFDL ESM2M	MPI ESM1	CESM, GFDL, MPI
	1979-2020								
I	Mean Mem Resamp / NSIDC Resamp	0.00567	1.15	1.27	1.49	0.57	1.32	1.09	1.30
II	Non-resamp Mem / Mean Mem Resamp		1.69	1.26	1.80	2.47	1.56	1.78	1.71
III	Non-resamp Mem / NSIDC Resamp		1.93	1.60	2.67	1.40	2.06	1.93	2.22
	Equivalent to 1979-2020								
IV	Equivalent Years	*1979-2020*	N/A	*N/A*	*1989-2030*	*N/A*	*1981-2022*	*1956-1997*	
V	Mean Mem Resamp / NSIDC Resamp	0.00567			1.62		1.32	1.02	1.32
VI	Non-resamp Mem / Mean Mem Resamp				1.62		1.57	1.99	1.73
VII	Non-resamp Mem / NSIDC Resamp				2.63		2.07	2.02	2.24

Table 1. Ratio of standard deviations of sea ice area gradients for the following: average resampled ensemble member (Mean Mem Resamp) resampled observations (NSIDC Resamp), non-resampled large ensemble members (Non-resamp Mem).

4) Conclusions

1. **Resampled CMIP5 large ensembles have average standard deviations ~15% higher than resampled observations for September.** However, excluding CSIRO, observations are consistent with the range of standard deviations captured by ensembles.
2. **Large ensemble standard deviation is approximately double that of resampled observations.** This implies only a portion of internal variability is captured by the resampling technique.
3. **Ratios of internal variability are robust for near-contemporary Pan-Arctic areas.** Conclusions 1 and 2 are not highly dependent on the mean sea ice area.

Resampling indicates the internal variability of selected CMIP5 models is not inconsistent with observations

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