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Memory of Arctic sea ice in model simulations, observations, and reanalyses

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Why, what, and how?

Do climate models overestimate the memory of sea ice?

Previous studies [1-3] have identified a large predictability gap between perfect model experiments and real-world forecasts of Arctic sea ice. This could indicate a strong potential for improvement of operational sea ice predictions or hint at a systematic overestimation of sea ice predictability in current climate models. Here, we assess the inherent memory of sea ice and compare it between models, observations, and reanalyses.

Sea ice concentration datasets

We analyze monthly sea ice concentration data in the time period 1979-2018 in the following datasets:

Model data	Observational data	Reanalysis data
· Max Planck Institute Grand Ensemble (**MPI-GE**, 100 members) [4] · **CMIP6** multi-model ensemble (241 members, MPI-ESM excluded) [5]	· **NSIDC** data with **Bootstrap** retrieval algorithm [6] · **NSIDC** data with **NASA Team** retrieval algorithm [6] · **OSI SAF** data [7]	· **ERA5** [8] · **ERA-Interim** [9]

Quantification of memory

We quantify memory of Arctic sea ice in terms of lagged correlations of sea ice area anomalies on seasonal to annual time scales. In order to remove long-term trends, we detrend the time series of individual months by applying a Nadaraya–Watson kernel regression with a bandwidth of 5 years.

Memory of pan-Arctic sea ice area

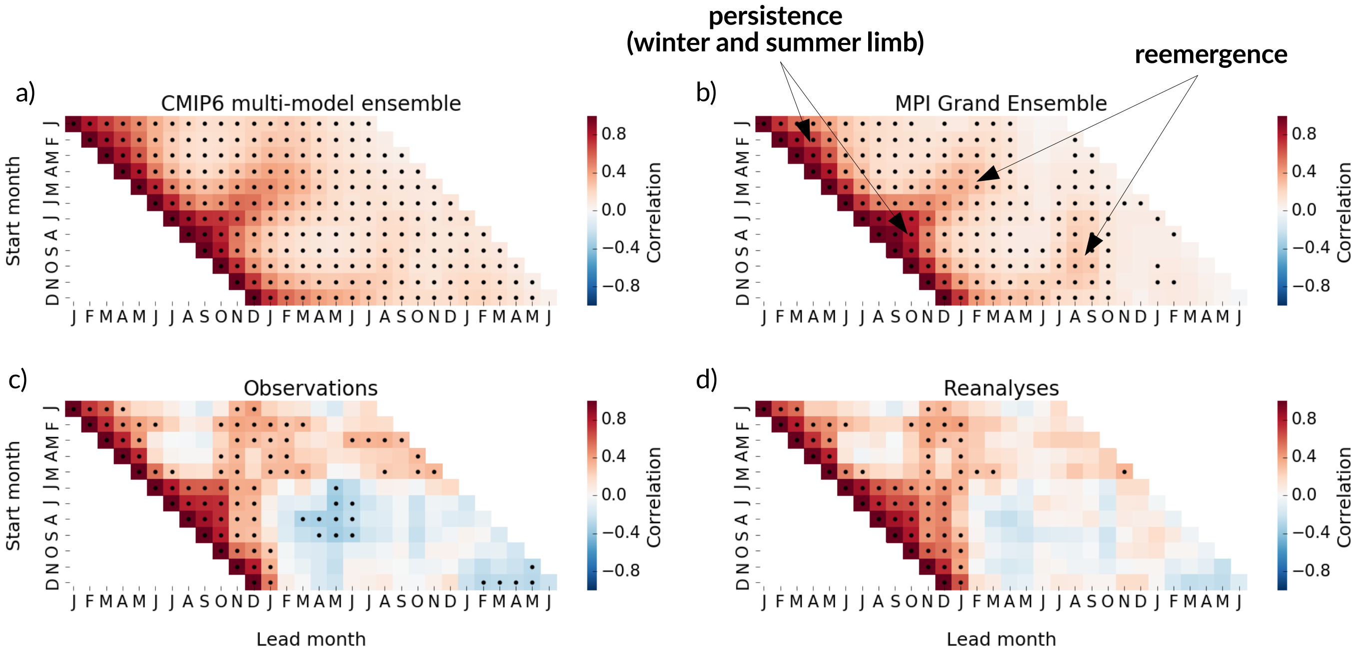


***Figure 1:** Lagged correlations of monthly pan-Arctic sea ice area anomalies in a) the CMIP6 multi-model ensemble, b) the MPI Grand Ensemble, c) the observational products (NSIDC Bootstrap, NSIDC NASA Team and OSI SAF Climate Data Records), and d) the reanalysis products (ERA5 and ERA-Interim). Correlation values of individual ensemble members (in a) and b)) or data products (in c) and d)) are combined using a Fisher's z-transformation. Black dots indicate statistical significance on the 99 % level for model ensembles and the 95 % level for observations and reanalyses.*

The memory of pan-Arctic sea ice area is characterized by two **persistence** regimes (winter/summer limb) and patterns of **reemergence** → consistent with previous literature [10-12].

Overall, models, reanalyses and observations show similar memory properties, in particular on short persistence time scales. The largest **discrepancies are found in the memory transferred from the summer limb months into the following year**. While models show a summer-to-summer reemergence of memory, the observations indicate a negative correlation between anomalies in summer and the following spring.

Ranking of observations and reanalyses in model variability range

Looking at the ranking of observed correlation values within the internal model variability range for individual time lags, a large **accumulation of time lags with overestimated model memory** (blue cells with triangles in Fig. 2) is found in the **"summer long-term memory regime"** (=memory from the summer limb months into the following year and beyond). Additionally, smaller patterns of time lags with model over-/underestimation can be identified.

The reanalysis data show similar patterns than the observations, but less pronounced, i.e. correlations tend to be closer to the ensemble mean value.

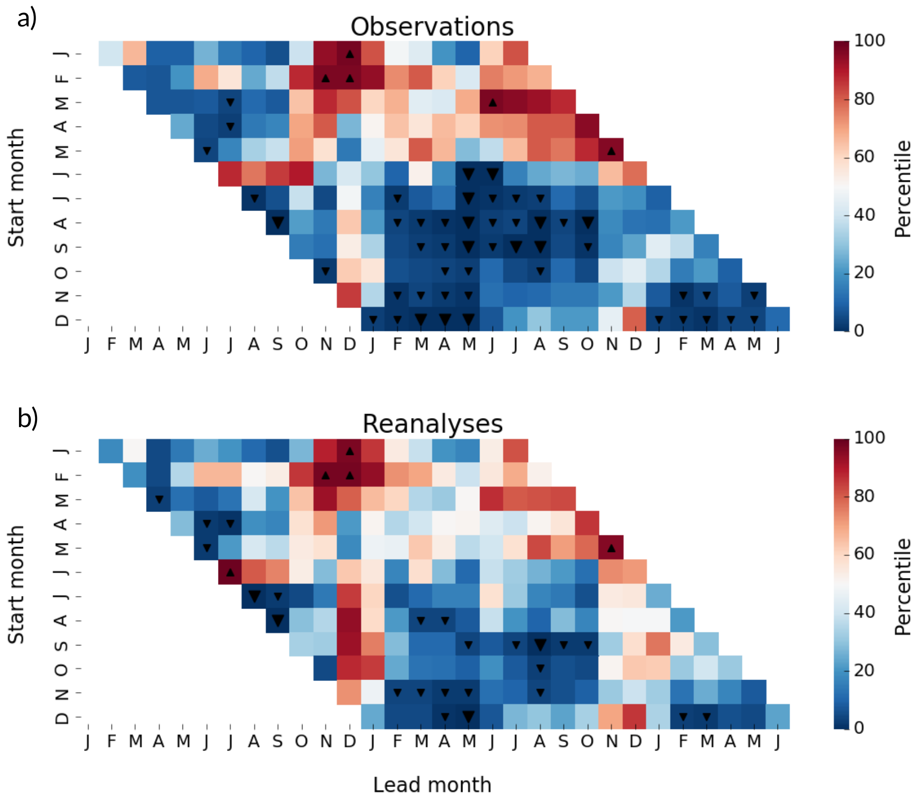
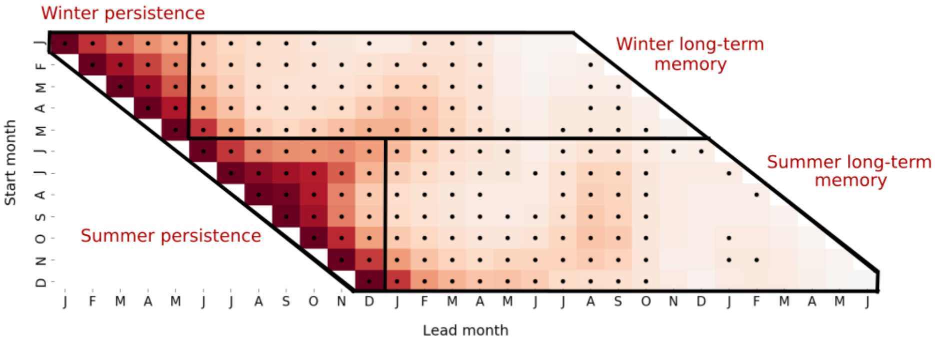


Figure 2: *Percentile of MPI-GE members with lower correlation values than the corresponding correlation in a) observational data and b) reanalysis data (combined data products as in Fig. 1). Downward and upward triangles mark values within the 5th and 95th percentile. Correlation values which are outside the model range (0th and 100th percentile) are marked with a larger triangle.*

Memory regimes

How do the individual datasets compare for different memory regimes?

Defintion of memory regimes:



Despite some spread between the correlation values of individual datasets, they all lie within the model ensemble (CMIP6 and MPI-GE) ranges for the winter persistence, summer persistence and winter long-term memory regimes.
For the **summer long-term memory regime, all observational products are outside/below the model range** and reanalysis products are on the lower side of the model range.

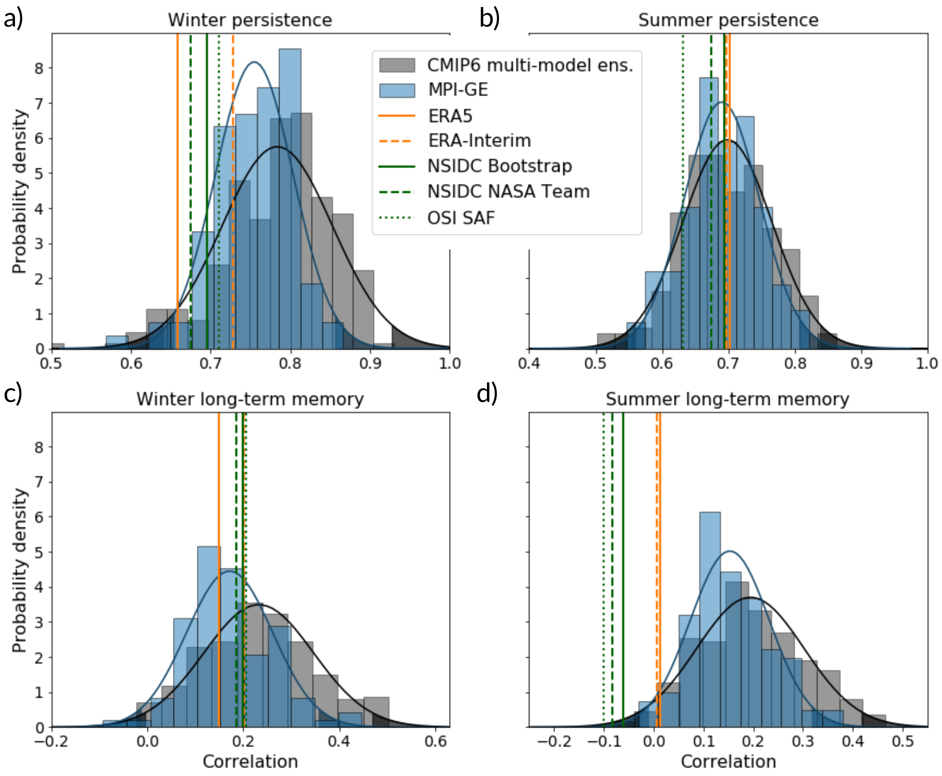
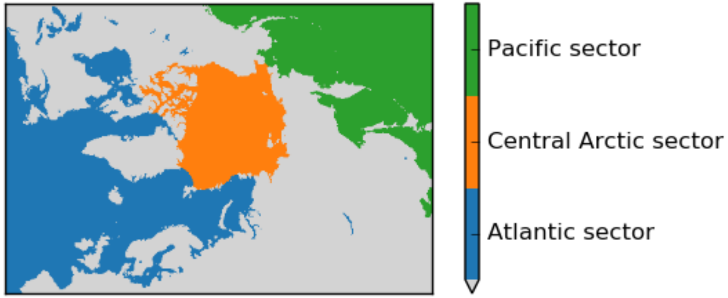


Figure 3: *Distribution of mean correlation for the four different memory regimes shown as histograms for the CMIP6 multi-model ensemble (gray) and the MPI Grand Ensemble (blue), and as lines for the reanalysis (orange) and observational datasets (green). The black and blue lines show normal distribution fits to the CMIP6 and MPI-GE data, respectively. Shadings indicate the 2σ-range.*

Memory of regional sea ice area

The location of the sea ice edge and its seasonal cycle largely determine memory properties of regional sea ice area. Generally, regional-scale memory features are similar in model, observational, and reanalysis data. **Differences** exist, but **are less prominent than on the pan-Arctic scale**. In contrast to the pan-Arctic scale, indications of negative correlations in the model and of summer-to-summer reemergence in the observations can be found on the scale of sectors or individual basins (not shown here).

Defintion of regions:



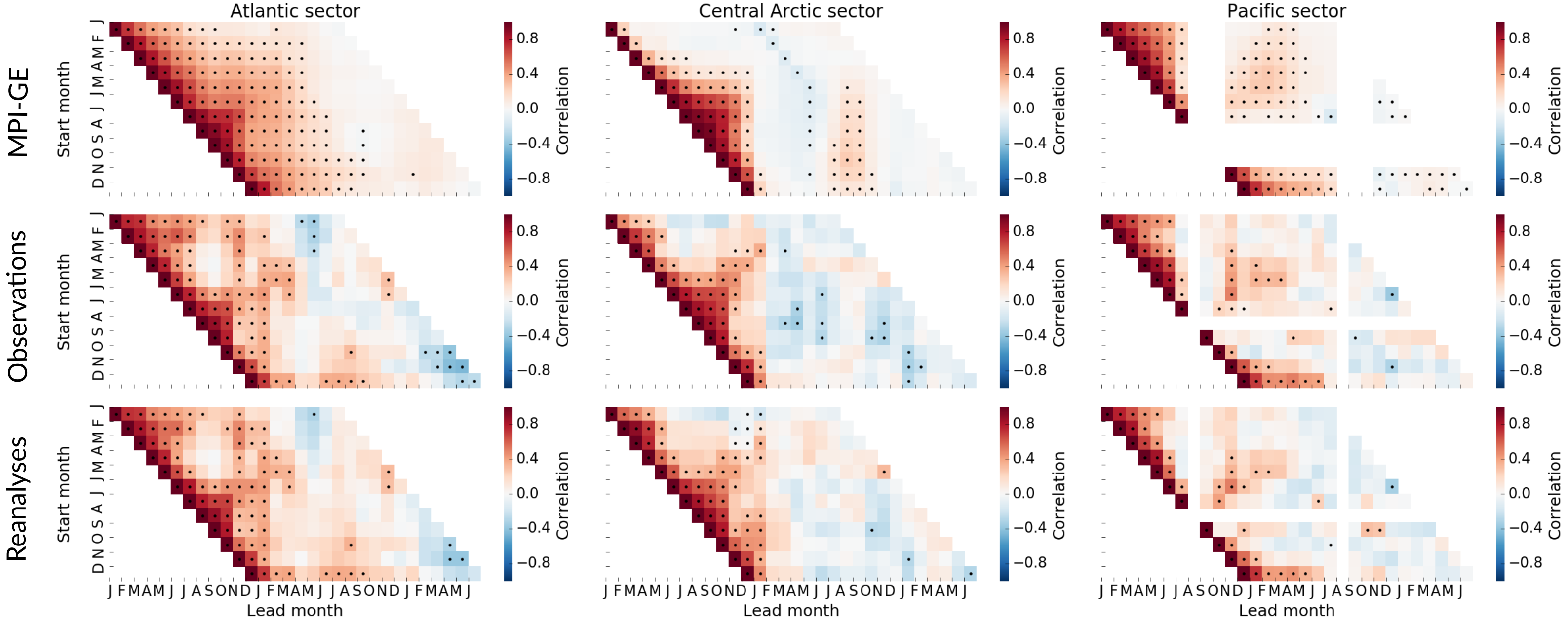


Figure 4: *Lagged correlations as in Figure 1 b)-d) but for regional sea ice areas anomalies (Atlantic, central Arctic and Pacific sector).*

Conclusions

- Generally, model simulations, observations and reanalyses show similar memory for Arctic sea ice area, particularly on short persistence time-scales.
- The memory of pan-Arctic sea ice area from the summer limb months into the following year and beyond („summer long-term memory regime“) is significantly higher in model simulations (CMIP6 and MPI Grand Ensemble) than observed.
- Reanalysis data tend to show correlation values that lie in between observational and model mean values, underpinning the hybrid nature of reanalyses combining observations and model behaviour.
- Model simulations agree better with observations on a regional than on the pan-Arctic scale.
- The overestimation of memory of pan-Arctic sea ice area in the summer long-term memory regime could explain some of the predictability gap between perfect model experiments and real-world forecasts.

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