Large-Scale Climate Modes as Drivers of Low-Frequency Regional Arctic Sea Ice Variability

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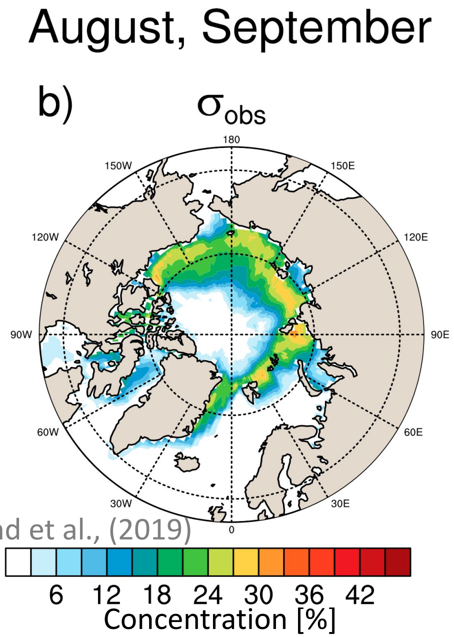
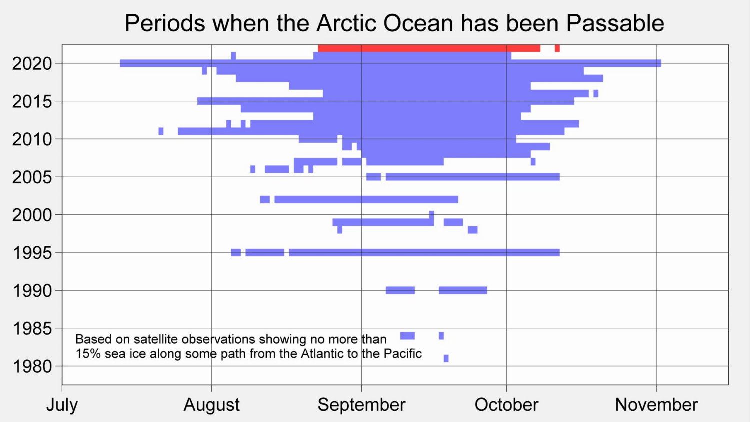
The Importance of Internal Variability

- The regions of the Arctic currently experiencing the largest internal variability coincide with:
  - The regions of most rapid declines
  - Regions important for ship navigability



England et al., (2019)



Rohde (2022)

The Importance of Internal Variability

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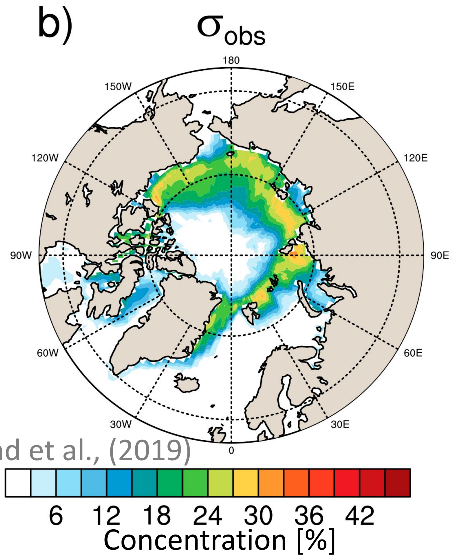
- Internal variability dominates projection and model uncertainty for the marginal/shelf seas.

August, September



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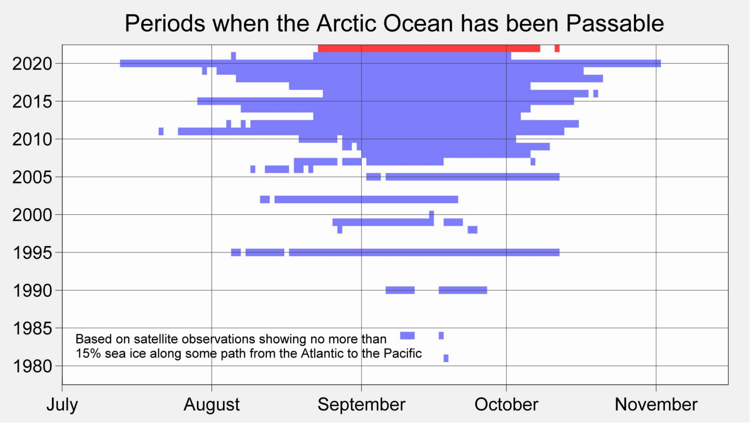

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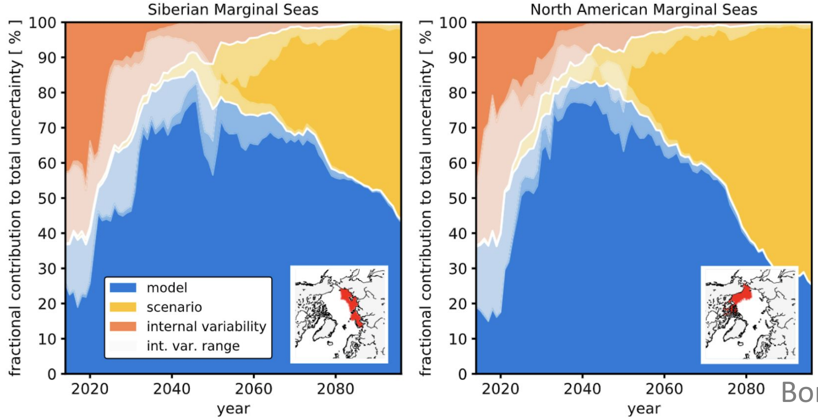
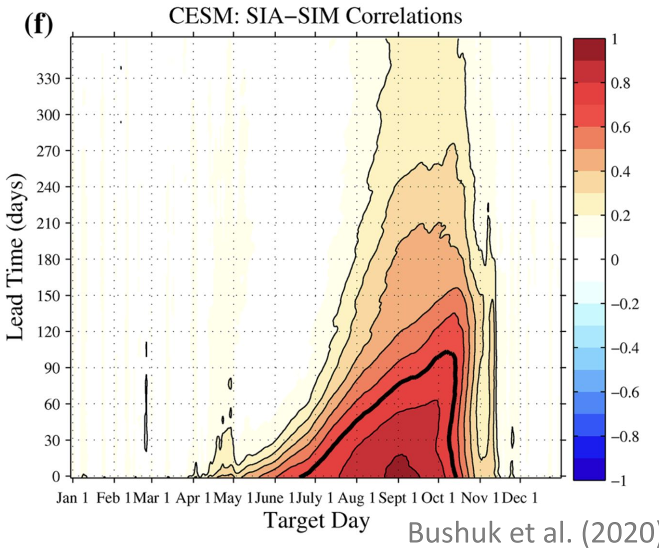


Bonan et al. (2021)

Low-Frequency Variability

- Periods >2 years. Typically accounts for ~1/3 - 1/4 of internal variability (Wyburn-Powell et al., 2022), but varies substantially between global climate models (GCMs).

- A spring predictability barrier has been shown to limit predictability for regional Arctic sea ice e.g. (Bonan et al.,2019; Bushuk et al., 2020).



Bushuk et al. (2020)

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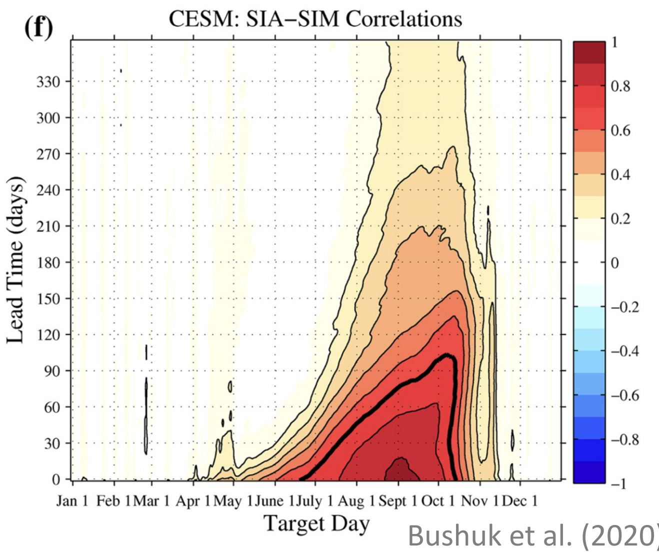
- A spring predictability barrier has been shown to limit predictability for regional Arctic sea ice e.g. (Bonan et al.,2019; Bushuk et al., 2020).
- However, at longer time periods predictability may emerge e.g. related to the IPO (Screen & Deser, 2019).
- **Objective: Identify modes of climate variability that affect Arctic sea ice anomalies across the Arctic, at lead times of 3-20 years**



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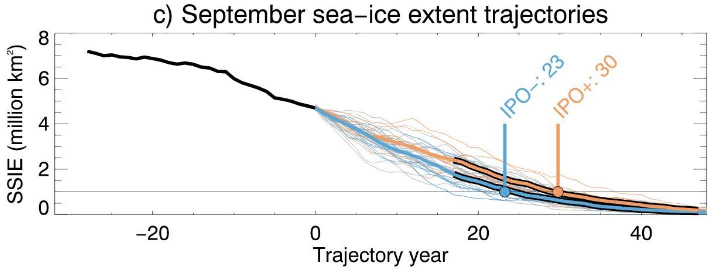
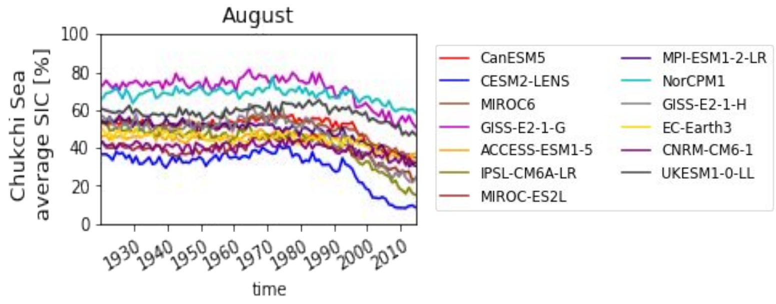


Screen & Deser (2019)

Datasets

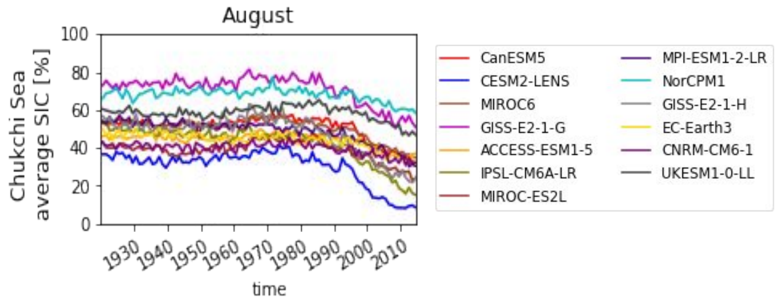
- Sea ice concentration from CMIP6 historical runs, for GCMs which also have data from the Climate Variability Diagnostics Package (CVDP). 42 GCMs with 3+ members, 9 with 30+ members.

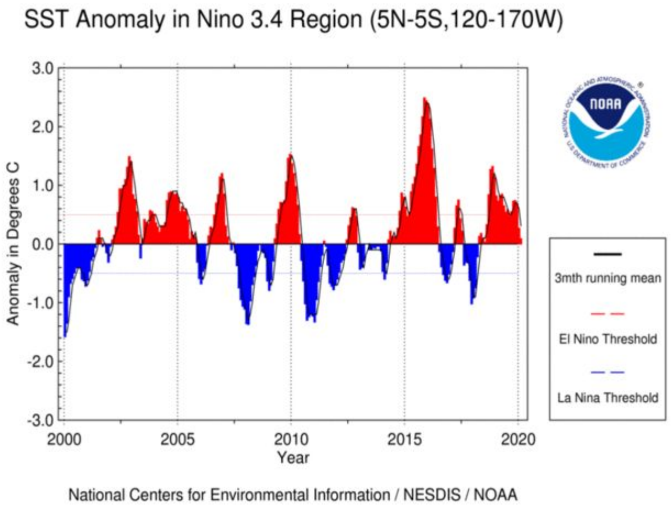


Datasets

- Sea ice concentration from CMIP6 historical runs, for GCMs which also have data from the Climate Variability Diagnostics Package (CVDP). 42 GCMs with 3+ members, 8 with 30+ members.

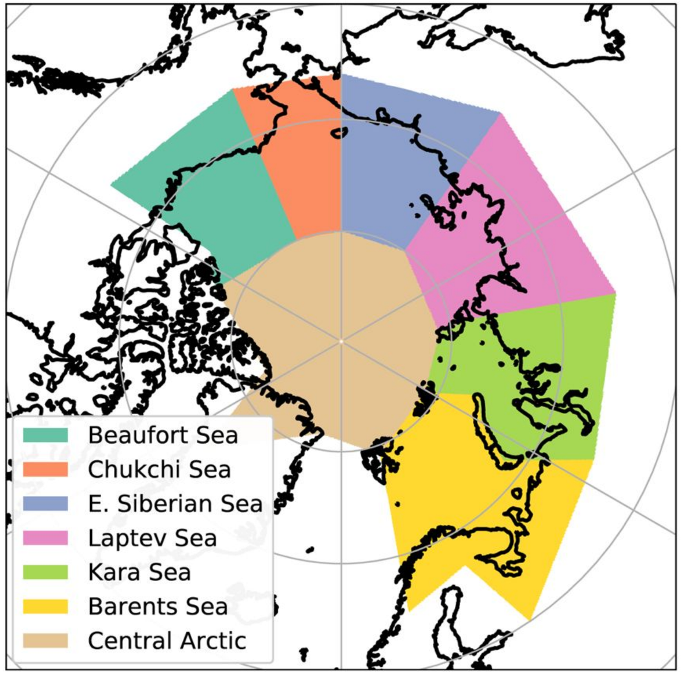
- 14 seasonal Climate modes of variability from the CVDP:
  - Atlantic Meridional Mode (AMM)
  - Atlantic Multidecadal Oscillation (AMO)
  - Atlantic Meridional Overturning Circulation (AMOC)
  - Atlantic Niño (ATN)
  - Indian Ocean Dipole (IOD)
  - Interdecadal Pacific Oscillation (IPO)
  - Northern Annular Mode (NAM)
  - North Atlantic Oscillation (NAO)
  - Niño 3.4 Index (NINO34)
  - North Pacific Index (NPI)
  - North Pacific Oscillation (NPO)
  - Pacific Decadal Oscillation (PDO)
  - Pacific/N. American Telecon. (PNA)
  - Southern Annular Mode (SAM)
  - Global Average Surface Temperature (TAS)





Use of Data

- We calculate the regional sea ice concentration (SIC) for 7 regions (see figure).
- For each region, we remove the interannual variability by detrending and taking a 2-year lowpass filter.
- The seasonal CVDP variables are detrended and standardized, but are not lowpass filtered. There are 4 seasonal values for each of the 14 variables.

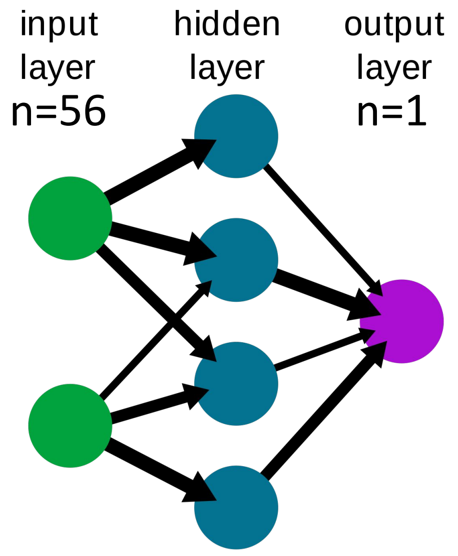


Wyburn-Powell & Jahn (in prep.)

Analysis Method

- Regress 56 Input features of climate variability modes, on to 1 output layer of the target SIC anomaly (in % points).
- Our machine learning models are trained on 1 region for 1 month of SIC anomalies at a time.
- Training/validation/test split 75/15/10%. Either using a large ensemble (LE) or multi-model large ensemble (MMLE):
  - LE – A single GCM split by member
  - MMLE – We select all GCMs with at least 3 ensemble members (42 GCMs) or at least 30 members (8 GCMs).

A simple neural network



Four Machine Learning Model Configurations

- We want to determine what complexity of ML model is required to capture the links between climate variability modes and SIC anomalies.
  - Model 1 – Simple linear regression. 56-1 with linear activation functions.
  - Model 2 – Simple nonlinear regression. 56-1 with ReLU activation functions.

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  - Model 3 – Linear neural net. 56-8-8-1 with linear activation functions.
  - Model 4 – Nonlinear neural net. 56-8-8-1 with ReLU activation functions.

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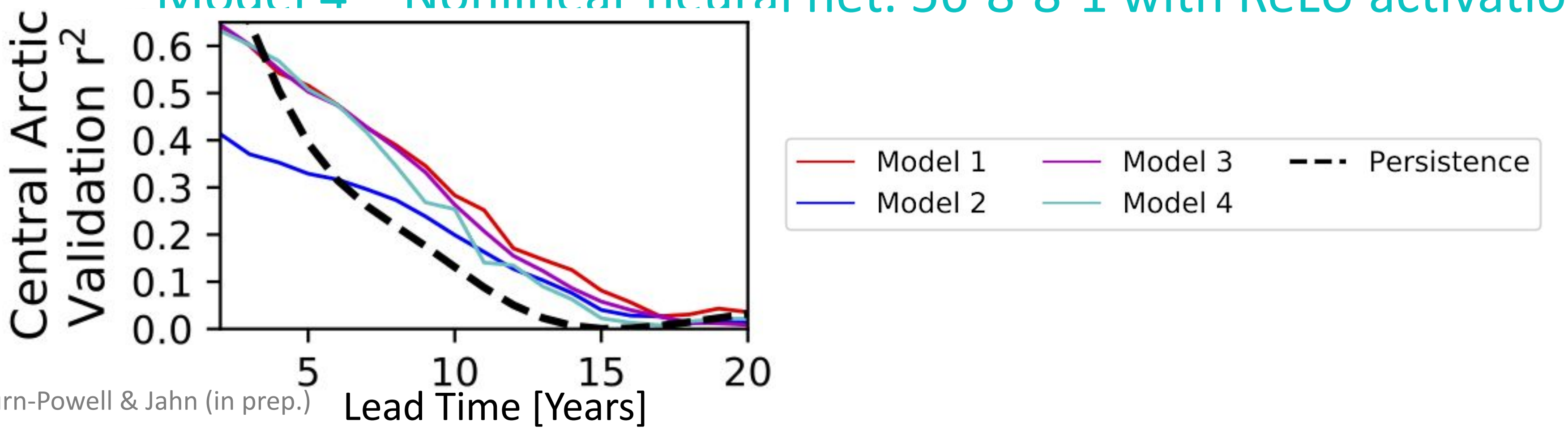

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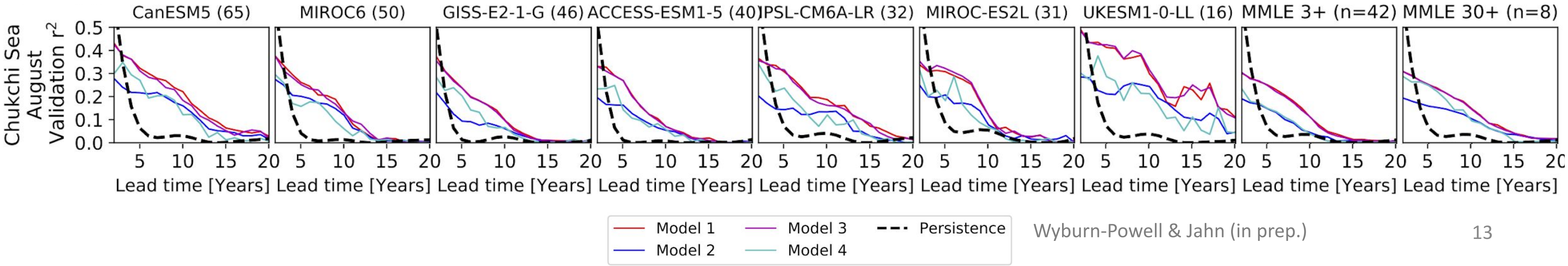
A simple linear model is the best

- Typically, the linear models 1 and 3 perform almost identically. Therefore, the impact of climate variability modes on SIC can be considered independently, with limited non-linear effects.



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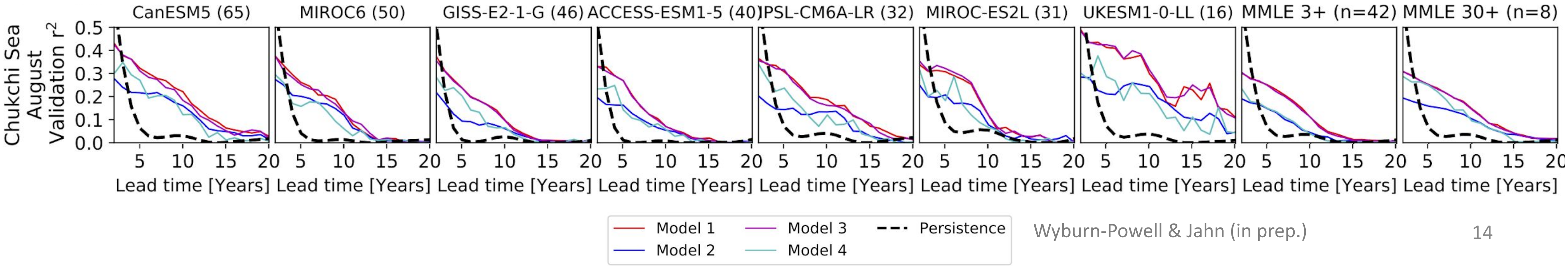
A simple linear model is the best

- Typically, the linear models 1 and 3 perform almost identically. Therefore, the impact of climate variability modes on SIC can be considered independently, with limited non-linear effects.
- Model 2 (56-1, nonlinear) performs the worst, so if you have nonlinearities, a simple model (0 hidden layers) will not yield high predictability.
- Model 4 (56-8-8-1, ReLU) also performs poorly, especially for the smaller ensemble sizes, but can do better than model 2 at short lead time and for large ensemble sizes.



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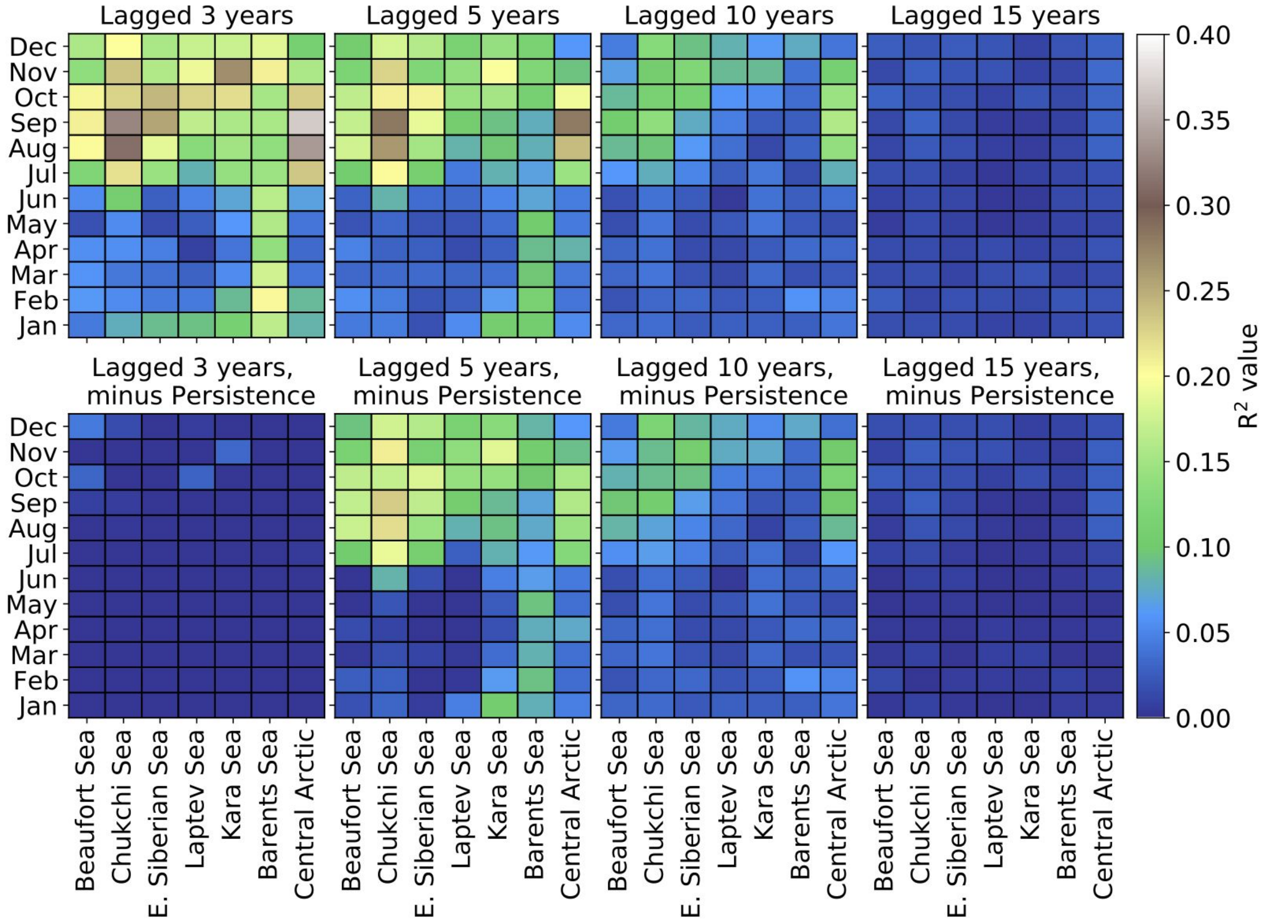
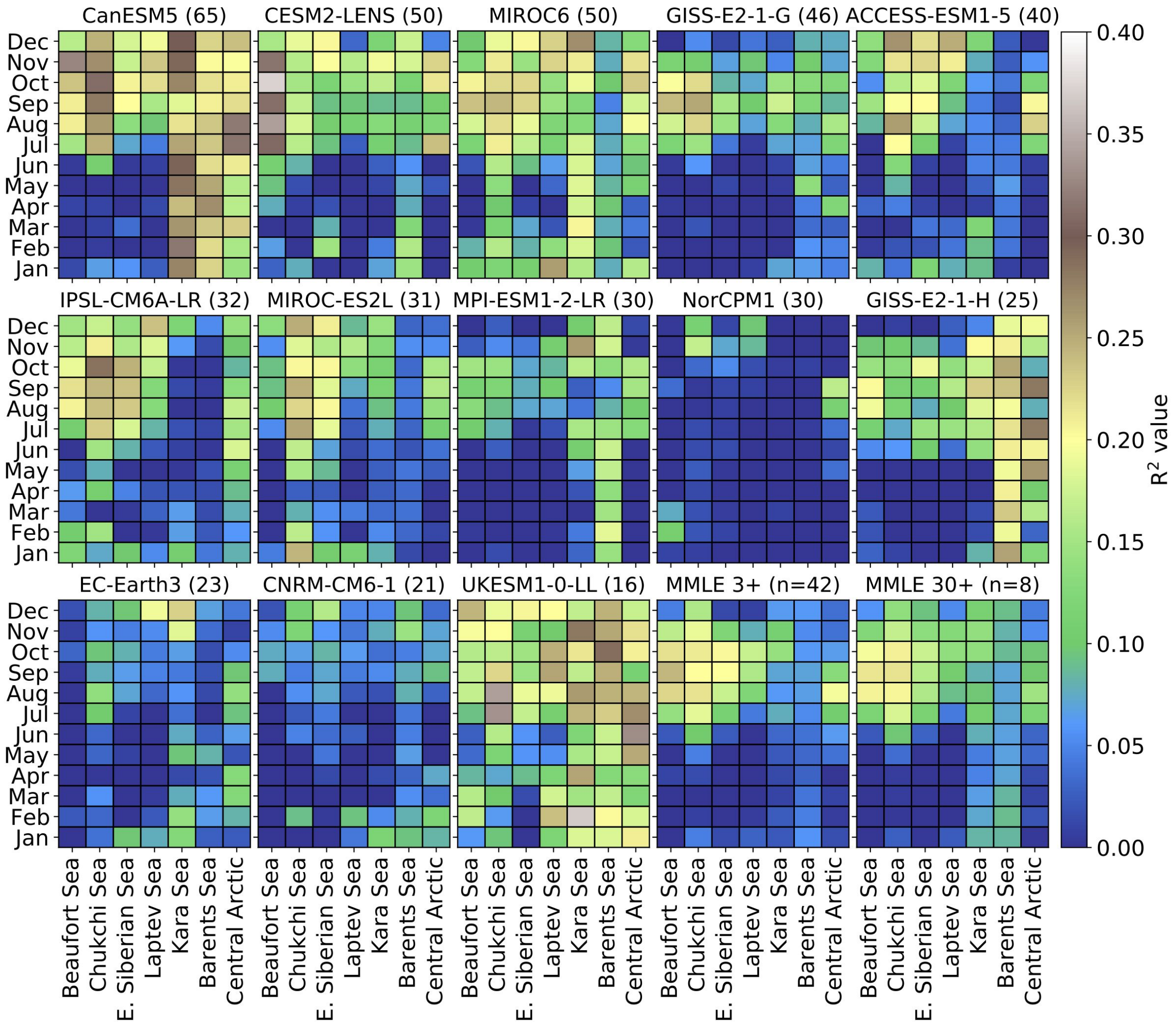
Assessing Predictive Skill with Persistence

- We can measure predictive skill as the validation r^2 value minus the r^2 value from persistence.
- At a 5-year lag time we typically obtain the highest r^2 value above persistence.
- CESM2-LENS has very high persistence so it usually performs worse in predictive skill in comparison to other GCMs.



GCM predictive skill by region and month

- Looking at a 5-year lag time, we select the regions where a GCM achieves at least 0.2 r^2 above persistence.
- We will focus on the Chukchi Sea as a common region of high predictive skill – however CESM2-LENS performs poorly in this region.



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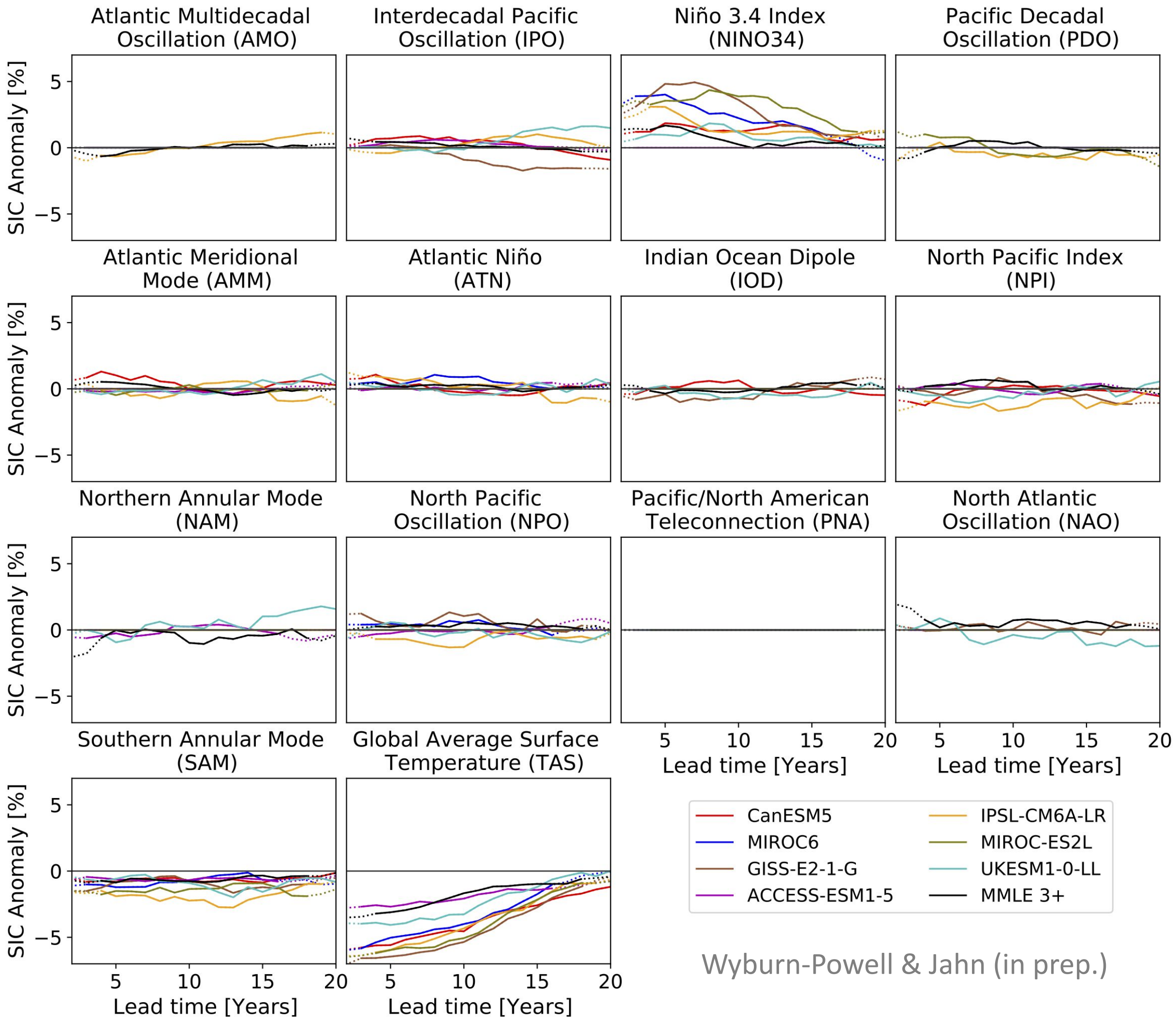
Climate Variability Modes and the August Chukchi Sea

- Two dominant climate variability modes are Niño 3.4 Index and Global Average Surface Temperature, common across GCMs.
- Some climate modes have high confidence of small influences such as the SAM
- Other modes such as the AMO, PDO, NAM do not appear as important for most GCMs



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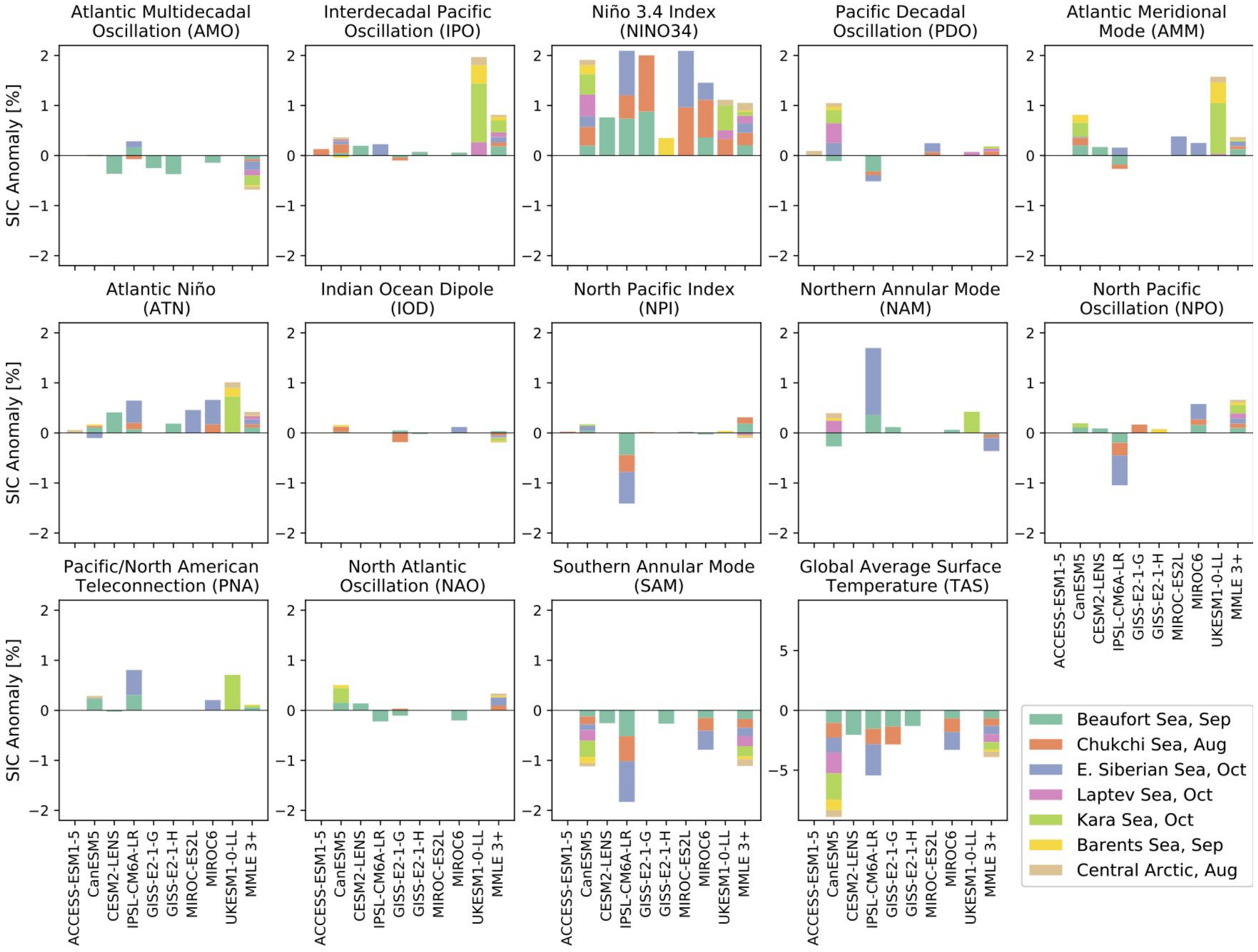
Summary across regions

- Most GCMs and regions have the same sign of climate mode influence.
- Similar to the Chukchi Sea, NINO34 and TAS are the strongest influences across regions.
- Some surprises are the SAM's strong and consistent negative correlation, and the small influence of the AMO.



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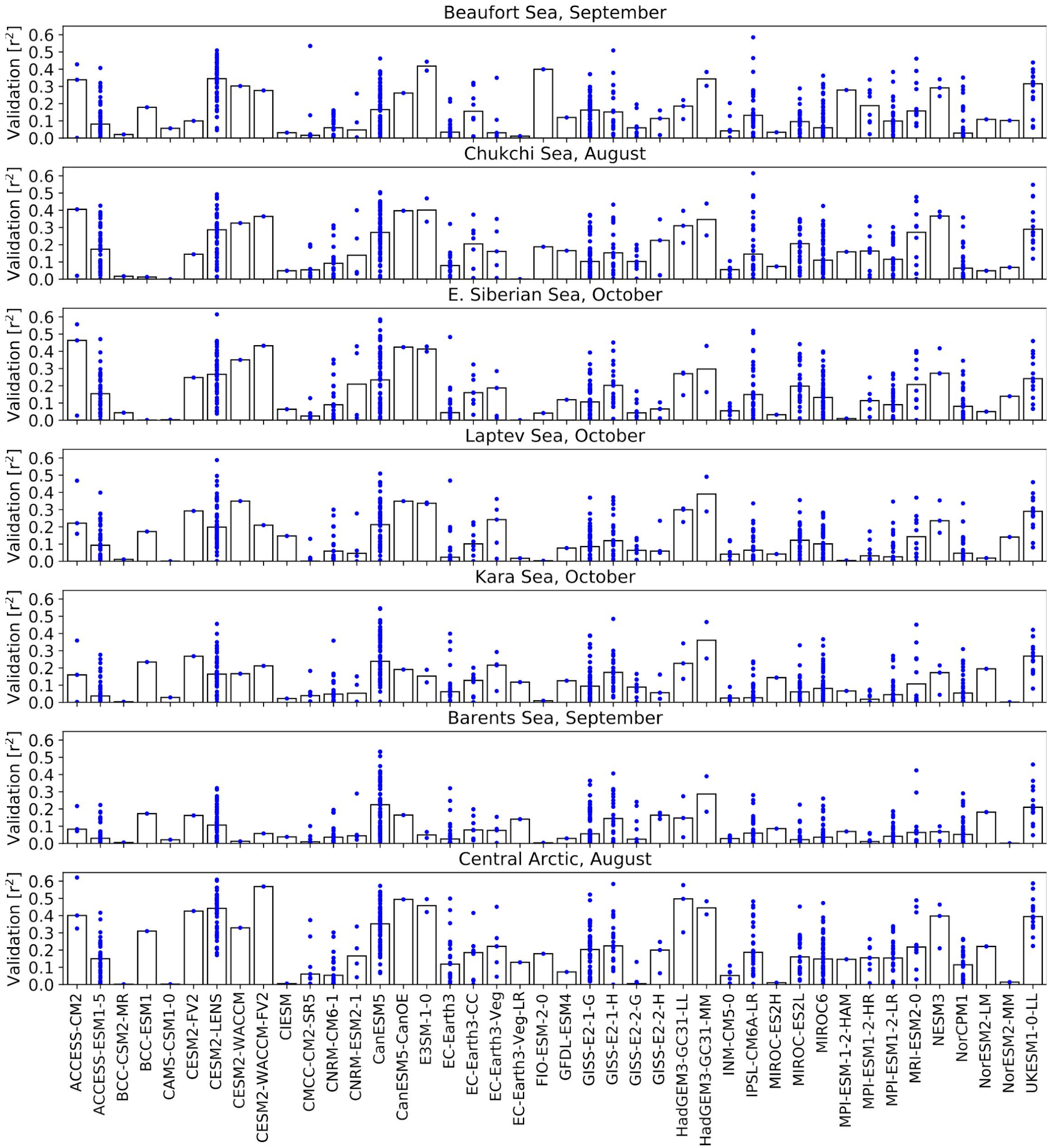
Comparison of all GCMs

- Generally, GCMs have similar predictive skill across regions.
- There are large differences between ensemble members within a GCM.
- This implies verification with observations may prove difficult.



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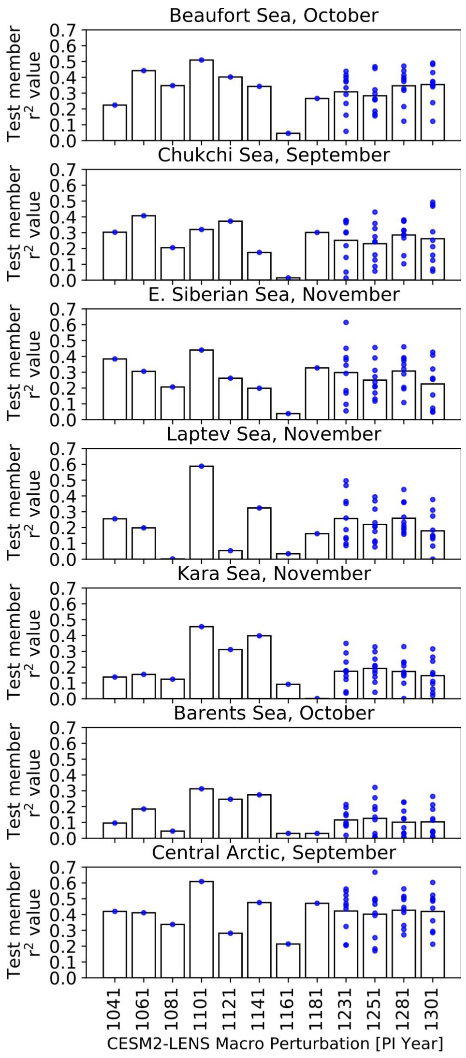
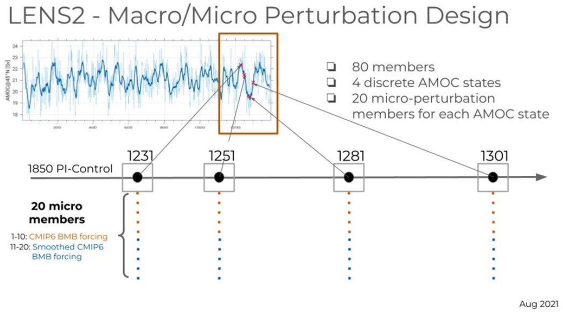
Conclusions

- A simple linear model best captures climate variability modes' effect on regional Arctic sea ice anomalies.
- The dominant modes of variability are: Global average temperature which is strongly negatively correlated with SIC anomalies across regions, and Niño3.4 index is next most important, and positively correlated.
- Other modes of variability have some regional or GCM dependence on their magnitude of influence, but generally have the same sign across GCMs and regions.
- CESM2-LENS exhibits highly predictable properties, but has high persistence in comparison to other GCMs, reducing skill.

CESM2-LENS micro/macro-Perturbations

- Micro perturbations have far larger variation than between the average of the macro perturbations
- This would suggest that our findings are not dependent on ocean state, but again showing vastly different performance based on specific realization.
- Therefore, we should not draw conclusions about model performance or obs agreement based on a single test





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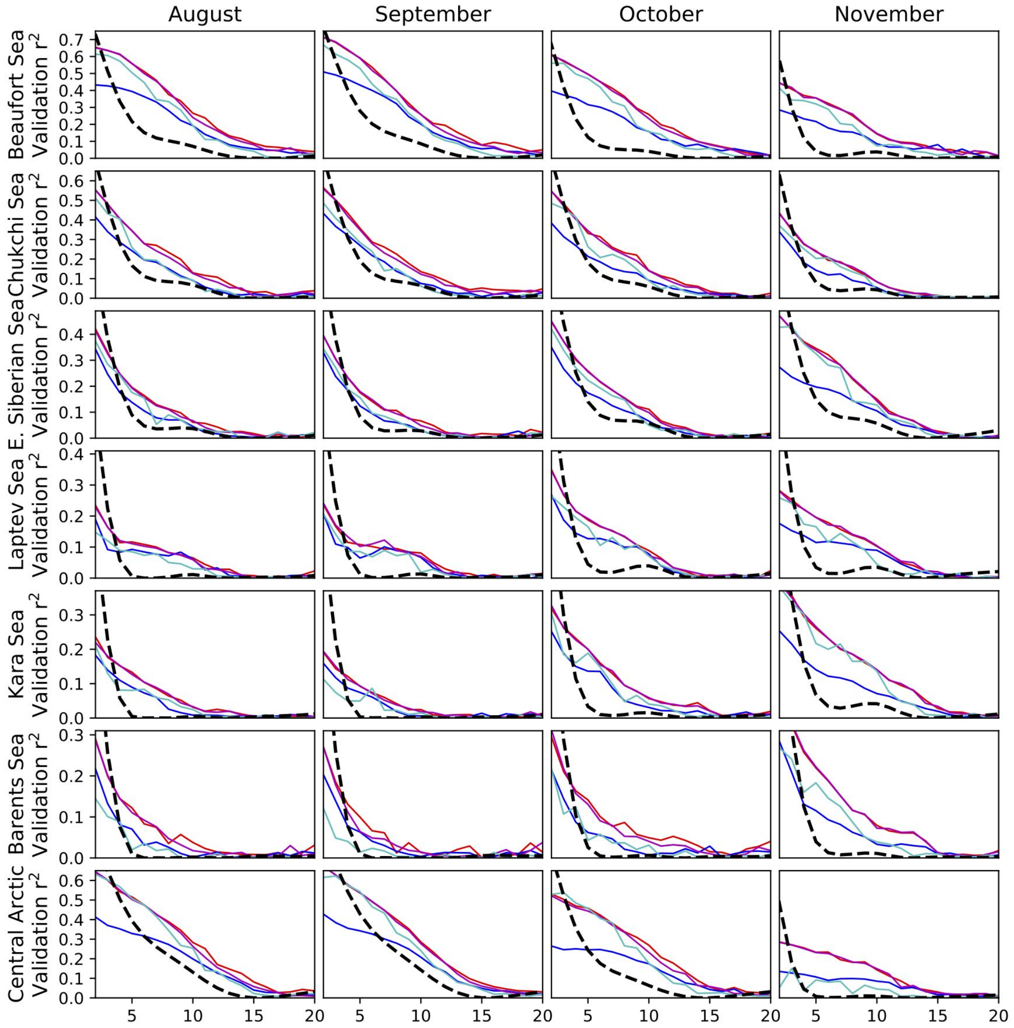
Assessing Predictive Skill with Persistence

- CESM2-LENS has very high persistence so it usually performs worse in predictive skill when compared with other GCMs.
- Typically a 5 year lag time is where the largest gap between validation r^2 and persistence exists.



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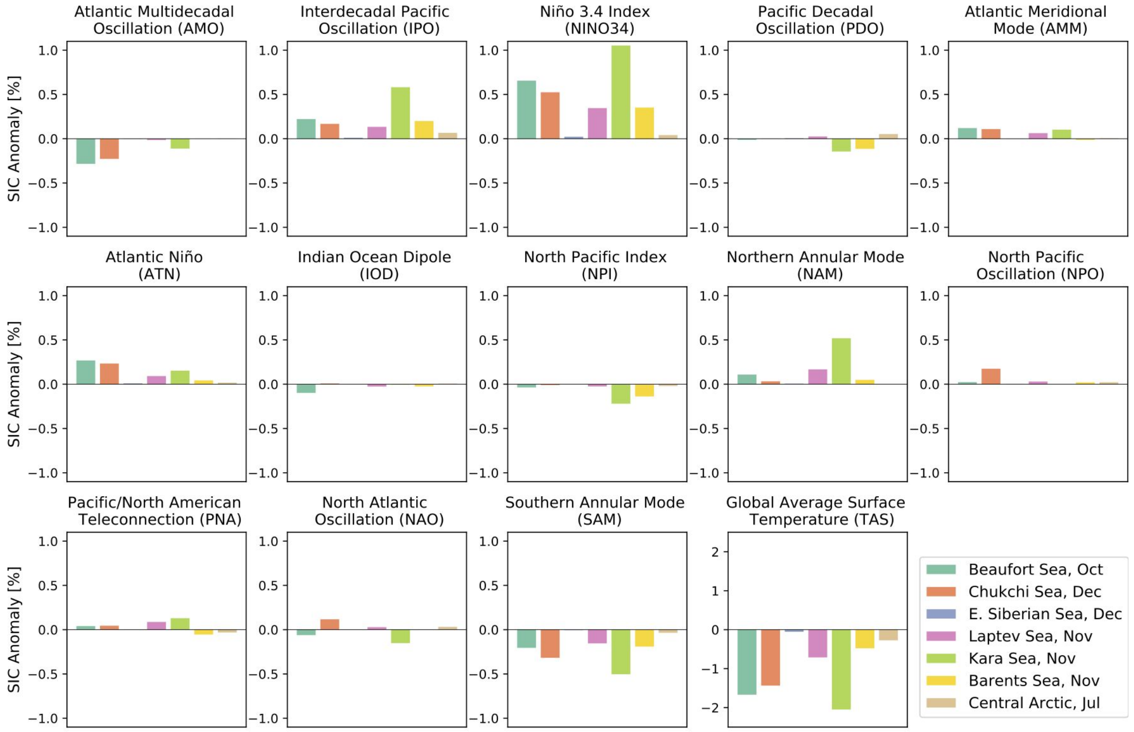
Summary across regions, CESM2-LENS

- Similar to the other large ensemble GCMs, both global average surface temperature and Niño 3.4 Index are the most dominant climate variability modes.
- The PDO has a regional importance, interestingly away from the Pacific sector.



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