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Title
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Large-scale Climate Modes Drive Low-Frequency Regional Arctic Sea Ice Variability

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ABSTRACT: Summer Arctic sea ice is declining rapidly but with superimposed variability on multiple timescales that introduces large uncertainties into projections of future sea ice loss. To better understand what drives at least part of this variability, we show how a simple linear model can link dominant modes of climate variability to low-frequency regional Arctic sea ice concentration (SIC) anomalies. Focusing on September, we find skillful projections from global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) at lead times of 4-20 years, with up to 58% of the low-frequency variability explained by our linear model at a 5-year lead time. The dominant driver of low-frequency SIC variability is the Interdecadal Pacific Oscillation (IPO) which is positively correlated with SIC anomalies in all regions up to a lead time of 15 years, but with large uncertainty between GCMs and internal variability realization. The Niño 3.4 Index has good agreement between GCMs of being positively correlated with low-frequency SIC anomalies for up to approximately 12 years. The Atlantic Multidecadal Oscillation is simulated as being negatively correlated for up to approximately 10 years. No other climate modes investigated were found to be of high importance in driving low-frequency Arctic SIC anomalies. Our results suggest that, based on the 2022 phases of dominant climate variability modes, enhanced loss of sea ice area across the Arctic is likely during the next decade.

SIGNIFICANCE STATEMENT: The purpose of this study is to better understand the drivers of low-frequency variability of Arctic sea ice. Teasing out the complicated relationships within the climate system takes a large number of examples. Here we use 42 of the latest generation of global climate models to construct a simple linear model based on dominant named climate features to predict regional low-frequency sea ice anomalies at a lead time of 2-20 years. In 2022, these modes of variability happen to be in the phases most conducive to low Arctic sea ice concentration anomalies. Given the context of the longer-term trend of sea ice loss due to global warming, our results suggest accelerated Arctic sea ice loss in the next decade.

1. Introduction

Over the past four decades, summer Arctic sea ice has rapidly declined and is projected to continue to decline in the future (Wang and Overland 2012; Notz and Stroeve 2016; Sigmond et al. 2018). However, large variability on multiple timescales is superimposed on this declining trend, which can lead to 10-20 year periods of accelerated sea ice loss but also to a period of over a decade of no sea ice loss (Kay et al. 2011; Swart et al. 2015). Hence, it is not unexpected that no new record low September sea ice area has occurred since 2012 (Francis and Wu 2020), in particular as September internal variability is currently elevated due to the decrease in the mean sea ice state (Goosse et al. 2009; Jahn 2018; Mioduszewski et al. 2019). The shelf seas have been the focus of the observed decline as well as of the impact of internal variability, with lower average sea ice concentration and thinner ice making the area a hotspot of internal variability over the past few decades (Lindsay and Zhang 2006; England et al. 2019; VanAchter et al. 2020; Årthun et al. 2021). The shelf seas are also coincident with areas of interest for shipping (Eguíluz et al. 2016; Melia et al. 2017), natural resource exploration (Petrick et al. 2017), and ecological changes (Kovacs et al. 2011). However, the current characteristics of variability are likely transitory as the shelf seas in the next few decades will become more reliably ice-free throughout the summer (Barnhart et al. 2016; Crawford et al. 2021), ending the dominant role of internal variability in projection uncertainty for this region (Bonan et al. 2021).

The internal variability of Arctic sea ice acts on multiple timescales and has therefore been challenging to cleanly separate from the forced response (Stroeve et al. 2007; Kay et al. 2011; Swart et al. 2015; Dörr et al. 2023). High-frequency drivers such as atmospheric temperature and wind anomalies are generally considered dominant over lower-frequency drivers (Ding et al. 2019; Olonscheck et al. 2019), but separating the drivers is difficult due to large spatial and temporal heterogeneity in variability (Onarheim et al. 2018). By defining low-frequency variability as periods of at least 2 years, approximately one quarter of September pan-Arctic internal variability can be accounted for by low-frequency variability in a sample of global climate models (GCMs) (Wyburn-Powell et al. 2022). Although low-frequency variability is only a small component of internal variability, it promises some longer term predictability, as the influence of initial conditions and high-frequency drivers of variability decay rapidly beyond the current season (Blanchard-Wrigglesworth et al. 2011; Bonan et al. 2019; Bushuk et al. 2019), and have been shown to be useful to a maximum of two year lead time (Day et al. 2014; Yeager et al. 2015; Bushuk and Giannakis 2017; Holland et al. 2019; Gregory et al. 2021; Wang et al. 2021).

There is some prospect of summer Arctic sea ice predictability at lead times greater than 2 years due to ocean heat transports (Zhang and Wallace 2015; Docquier et al. 2021) and climate modes of variability (Guemas et al. 2016). However, results so far seem to be model dependent (Tietsche et al. 2014; Blanchard-Wrigglesworth and Bushuk 2019), and our current length of observations is likely too short to verify such relationships (Bonan and Blanchard-Wrigglesworth 2020). Despite these challenges, extra-tropical modes of sea level pressure variability have been suggested to have an influence on the Arctic sea ice variability, but so far only with strong evidence on high-frequency timescales (Ukita et al. 2007; Serreze et al. 2007; L'Heureux et al. 2008; Zhang et al. 2019; Liu et al. 2021). Tropical teleconnections have also been identified as influencing Arctic sea ice loss, primarily associated with Pacific sea surface temperatures (SSTs) (Hu et al. 2016; Li et al. 2018a; Screen and Deser 2019; Ding et al. 2019; Kim et al. 2020; Clancy et al. 2021; Jeong et al. 2022b; Simon et al. 2022), but also with Atlantic variability (Day et al. 2012; Miles et al. 2014; Meehl et al. 2018; Li et al. 2018b). These insights into low-frequency drivers of variability show promise, but skillful regional predictions combining multiple modes of variability at low-frequency timescales has so far been elusive.

Assessing drivers of low-frequency variability in the climate system is difficult to do without large quantities of consistent data, such as that available from single model initial-condition large ensembles (Deser et al. 2020; Milinski et al. 2020). This requirement for assessing drivers of low-frequency Arctic sea ice variability stems from a multitude of drivers likely interacting on heterogeneous spatial and temporal scales to cause this variability (Zhang et al. 2020). This has, so far, lead to a lack of consensus of many of the drivers at time periods in excess of 2 years, especially as GCMs and observations have been shown to represent these relationships differently. We therefore leverage all available GCMs from the Coupled Model Intercomparison Project Phase 6 (CMIP6) archive to investigate model consensus of these low-frequency relationships. Additionally, we do not prescribe the nature of any of these relationships such as linearity and independence, and seek high spatial and temporal specificity. To enable interpretation of these potentially complex relationships in the climate system we use machine learning which has been used successfully before to explain patterns of surface climate variability (e.g. Barnes et al. 2019; Labe and Barnes 2022). With this coherent approach to determine the drivers of low-frequency Arctic sea ice variability on multiple timescales and locations, we determine the modes of variability which are simulated to have the largest impact and use the resulting model to make predictions of low frequency SIC variability over the next decade.

2. Methods

a. Data sources

In order to gather sufficient data of both climate modes of variability and associated sea ice concentrations, we use 42 GCMs with historical CMIP6 forcing (O'neill et al. 2016). These GCMs are those for which both monthly sea ice concentration is available and the full suite of climate mode data has been processed using the Climate Variability Diagnostics Package (CVDP) (Phillips et al. 2014). In total we use 609 realizations, from 42 GCMs and 23 modeling centers; a full list can be found in Table 1. The only other simulations which could provide a similarly large quantity of data would be future scenarios or pre-industrial control simulations. However, as the mean-state and variability of the Arctic sea ice (VanAchter et al. 2020; Årthun et al. 2021) and some aspects of the rest of the climate system such as ENSO (Brown et al. 2020) or AMOC (Weijer et al. 2020) differ from present conditions in both the pre-industrial and future climate states, this approach would be less appropriate to analyze current variability. Within the historical period we use the 74-year time period 1941-2014 for sea ice concentration (SIC), which we average over regions of the Arctic as defined by the National Snow and Ice Data Center (NSIDC) Multisensor Analyzed Sea Ice Extent - Northern Hemisphere (Fetterer et al. 2010) (see Figure 1d). These seven regions cover the vast majority of the sea ice found during the summer, although we do exclude the Canadian Arctic Archipelago due to complex coastal zones which are typically poorly represented in GCMs (Long et al. 2021). We linearly detrend the average SIC for each region (for the period 1920-2014) and then apply a 2-year lowpass filter to exclude the high-frequency interannual variability and leave only the low-frequency anomalies (see Figure 1a-c). This low-pass filtered regional sea ice concentration data becomes the predictands in our regression analysis.

We use nine variables from the CVDP to assess their influence on regional SIC anomalies in our regression analysis. We obtain seasonal values for all variability modes except the Interdecadal Pacific Oscillation (IPO) where we use a single annual value. The seasonal or annual modes are linearly detrended and standardized (if not already in such a format) but no other data transformations are made. We use data from 1920-2014 to facilitate lagging the SIC data between 2 and 20 years from the CVDP data. When we present the linear effects of each mode of variability, the modes which have seasonal values are summed to produce a combined effect. The eight variables used from the CVDP and their abbreviations are listed below:

- AMO: Atlantic Multidecadal Oscillation
- NAO: North Atlantic Oscillation
- ATN: Atlantic Niño
- NINO34: Niño 3.4 Index

Table 1. Global climate model output used in this analysis

Modeling Center	GCM Name	Members	Citation
CSIRO-ARCCSS	ACCESS-CM2	5	Dix et al. 2019
CSIRO	ACCESS-ESM1.5	40	Ziehn et al. 2019
BCC	BCC-CSM2-MR	3	Wu et al. 2018
BCC	BCC-ESM1	3	Zhang et al. 2018
CAMS	CAMS-CSM1.0	3	Rong 2019
NCAR	CESM2-FV2	3	Danabasoglu 2019a
NCAR	CESM2-LENS	50	Danabasoglu 2019b
NCAR	CESM2-WACCM	3	Danabasoglu 2019d
NCAR	CESM2-WACCM-FV2	3	Danabasoglu 2019c
THU	CIESM	3	Huang 2019
CMCC	CMCC-CM2-SR5	11	Lovato and Peano 2020
CNRM-CERFACS	CNRM-CM6-1	21	Voldoire 2018
CNRM-CERFACS	CNRM-ESM2-1	6	Seferian 2018
CCCma	CanESM5	65	Swart et al. 2019b
CCCma	CanESM5-CanOE	3	Swart et al. 2019a
E3SM-Project	E3SM1.0	4	Bader et al. 2019
EC-Earth-Consortium	EC-Earth3	23	EC-Earth-Consortium 2019a
EC-Earth-Consortium	EC-Earth3-CC	10	EC-Earth-Consortium 2021
EC-Earth-Consortium	EC-Earth3-Veg	7	EC-Earth-Consortium 2019b
EC-Earth-Consortium	EC-Earth3-Veg-LR	3	EC-Earth-Consortium 2020
FIO-QLNM	FIO-ESM2.0	3	Song et al. 2019
NOAA-GFDL	GFDL-ESM4	3	Krasting et al. 2018
NASA-GISS	GISS-E2-1-G	46	NASA Goddard Institute for Space Studies 2018
NASA-GISS	GISS-E2-1-H	25	NASA Goddard Institute for Space Studies 2019b
NASA-GISS	GISS-E2-2-G	11	NASA Goddard Institute for Space Studies 2019a
NASA-GISS	GISS-E2-2-H	5	NASA Goddard Institute for Space Studies 2019c
MOHC	HadGEM3-GC31-LL	5	Ridley et al. 2019a
MOHC	HadGEM3-GC31-MM	4	Ridley et al. 2019b
INM	INM-CM5-0	10	Volodin et al. 2019
IPSL	IPSL-CM6A-LR	32	Boucher et al. 2018
MIROC	MIROC-ES2H	3	Watanabe et al. 2021
MIROC	MIROC-ES2L	31	Hajima et al. 2019
MIROC	MIROC6	50	Tatebe and Watanabe 2018
HAMMOZ-Consortium	MPI-ESM1.2-HAM	3	Neubauer et al. 2019
MPI-M	MPI-ESM1.2-HR	10	Schupfner et al. 2019
MPI-M	MPI-ESM1.2-LR	30	Wieners et al. 2019
MRI	MRI-ESM2.0	12	Yukimoto et al. 2019
NUIST	NESM3	5	Cao and Wang 2019
NCC	NorCPM1	30	Bethke et al. 2019
NCC	NorESM2-LM	3	Seland et al. 2019
NCC	NorESM2-MM	3	Bentsen et al. 2019
MOHC	UKESM1.0-LL	16	Tang et al. 2019

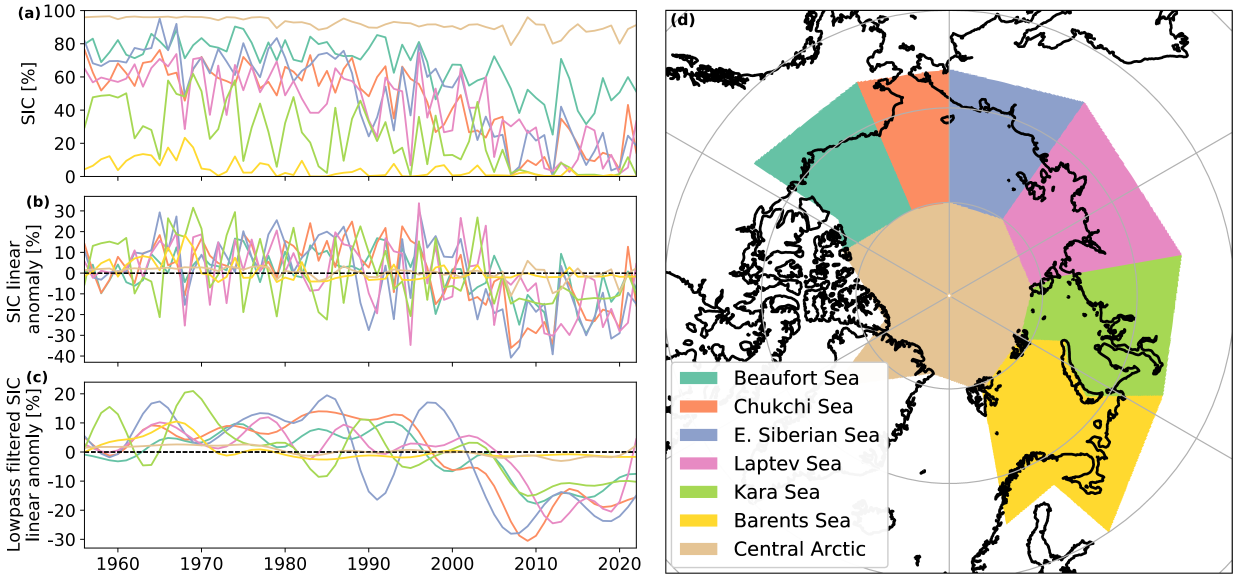

FIG. 1. **Observed September sea ice concentrations for the seven Arctic regions used in this analysis.** The observational HadISST1 sea ice concentration data shown for (a) the regional average, (b) the linearly detrended version of (a), and (c) a 2-year lowpass filter applied on (b). What is shown in (c) is the data used in the analysis presented here. The outline of the different regions considered are shown in (d) and defined as for the National Snow and Ice Data Center (NSIDC) Multisensor Analyzed Sea Ice Extent - Northern Hemisphere (MASIE-NH) dataset (Fetterer et al. 2010).

- PDO: Pacific Decadal Oscillation
- NPO: North Pacific Oscillation
- PNA: Pacific/North American Teleconnection
- IPO: Interdecadal Pacific Oscillation

In addition to these modes of variability, we also include the seasonal values of the global average surface temperature (TAS), as motivated in section d.

Several additional modes of variability were also available from the CVDP but were not included in the final analysis. The modes investigated but not used are as follows: the Indian Ocean Dipole, the Atlantic Meridional Mode, the Southern Annular Mode, the North Pacific

Index. All of these modes of variability had no measurable effect on the regression model. Furthermore, including the Northern Annular Mode lead to over-fitting with the highly related NAO.

Observational SIC is taken from the Hadley Centre Sea Ice and Sea Surface Temperature data set (HadISST1) (Rayner et al. 2003) for the period 1956-2022. We use the HadISST1 SIC record before the beginning of the satellite era in 1978 to enable longer analyses in our correlation analysis in section e. 1956 is the starting year of the SIC data we use as variability is degraded substantially before 1956 due to interpolations for September-March (Rayner et al. 2003). However, when calculating a linear trend for detrending, we use SIC data for 1920-2014 in order to be consistent with the GCMs. The HadISSST1 data, similarly to the SIC in the GCMs, is divided into regions, linearly detrended and interannual variability is removed with a 2-year lowpass filter. For observed climate variability data we also obtain these from the CVDP where we use the HadISST1 dataset to calculate sea surface temperature-derived variables, the NCEP-NCAR record for sea level pressures (Kalnay et al. 1996), and GISTEMP version 4 for global surface temperatures (Lenssen et al. 2019). Similarly to the CVDP output variables for the GCMs, we apply a linear detrending and standardization to the variables not already in this format.

b. Machine Learning Methods

The aim of using machine learning is to determine the relationship between the climate variability modes and the lagged effects on regional Arctic SIC gain and loss. We provide the CVDP variables as feature inputs to regress SIC anomalies 2 to 20 years later, for a given region and month of SIC anomalies. To do this, many realizations are required to provide sufficient training data; our one realization of reality from observations does not provide a long enough time period in which to disentangle the relationships between climate variability modes and regional SIC anomalies. We compute regressions both for an individual GCM large ensemble (LE) which we require to have at least 20 members (12 large ensembles in total), and also two CMIP6 multi-model large ensembles comprising of GCMs with at least 3 members (n=42) or 30 members (n=8), referred to as MMLE 3+ and MMLE 30+ respectively. For each LE we divide the members into training, validation, and testing sets with 75%, 15%, 10% of members respectively, similar to theoretical ’optimal’ splits for 33 variables such as 72/13/15% from Joseph 2022. For the MMLE 3+ we select all of the GCMs which provide at least 3 realizations, then we use the first member for the training data set, the second member for the validation set, and leave the third and any other members for testing. For the MMLE 30+ we pool the first 23 members from all 8 GCMs for training, we use the next 4 members for validation, and the final 3 or more members for testing. As we use 74 years of data for each ensemble member the smallest LE uses 74 years with 21 ensemble members, yielding an effective 1554 years for training - far in excess of observations and typically longer than pre-industrial control runs from any individual GCM. On the other extreme, the MMLE 30+ maximizes the number of effective training years at 13,320, allowing us to determine whether substantially increasing the training data provides any gain in predictive skill.

We make use of 8 climate modes of variability and TAS, where all except the IPO have four seasonal values. Hence our total is 33 input feature variables in our regression analysis. Our objective is to assess the effect of each of these variables as a function of time preceding the target regional SIC anomalies for a given month. Therefore, we train our machine learning models on a single region, month, and lag time. This granularity of regression analysis allows us to determine the different links between climate modes and SIC anomalies across regions, SIC anomaly months, and lag time, without prescribing assumptions regarding regional or temporal evolution. The SIC anomalies are in % points, hence when comparing the influence of modes of variability across regions, the % point change should be scaled by the variability of that region. Our model has no knowledge of the initial anomaly of SIC, but as the memory for the summer at lead times in excess of 1 year is considered negligible (Giesse et al. 2021), this omission is considered unimportant at the timescales we consider. Furthermore, this would add additional complexity to our model by adding degrees of freedom which would require more data to constrain.

For the 12 LE and 2 MMLE data sets, we devise four experiments with different machine learning model configurations to investigate the effect of nonlinearities and interdependence between climate variability modes in skillful prediction of regional SIC anomalies. All of the four machine learning models use a fully-connected neural network with the same L1 loss function to encourage sparseness and an Adam optimizer for suitability to the four diverse experiments. There is no bias used for models 1 and 2 as this allows direct analysis of the linear effect of the input variables and is permissible as we are using standardized values for our features. With these four machine learning models, as detailed below, we can separate the effect of linear/nonlinear activation functions from the effect of additional neural network layers which allows one climate variable to interact with another:

- Model 1 - Model layers: 33-1 with linear activation functions and no bias.
- Model 2 - Model layers: 33-1 with nonlinear (ReLU) activation functions and no bias.
- Model 3 - Model layers: 33-6-6-1 with linear activation functions.
- Model 4 - Model layers: 33-6-6-1 with nonlinear (ReLU) activation functions.

By comparing the predictive skill of model 1 versus 2 and model 3 versus 4 we can identify the effect of increasing the model complexity from a linear to nonlinear activation functions. This is because the only difference between those two groups is the activation function. Then, separately, we can determine the difference in allowing interdependence between climate modes of variability by comparing the predictive skill of models 1 versus 3 as well as model 2 versus 4. This interdependence is facilitated by either a simple model where each of the 33 neurons in the input layer connects directly with the output layer (as in models 1 and 2), or to connect the input layer to two hidden layers of 6 fully-connected neurons before reaching the output layer.

c. Assessing Predictive Skill

We define that the threshold for our machine learning model to be useful at a given lag time is for its Pearson correlation coefficient for the validation data to exceed persistence. The persistence correlation coefficient in this instance is calculated from the 2-year lowpass filtered regional SIC anomalies lagged between 2 and 20 years, the same lag times as used for our regression analysis. When using the correlation coefficient, it is important to note that, especially at longer lag times, there may be a high correlation between the linear model output and the validation data, but this skill may be present with a smaller amplitude than for the validation data.

As we do not have sufficiently long periods of observations, we cannot train a separate machine learning model on the observations. Instead, by pooling several regions and SIC anomaly months, we calculate the proportion of positively and negatively correlated modes of variability with the most extreme 10% of SIC positive and negative anomalies. This is not a way of verifying the GCM predictive models per se, rather it shows the range of correlations present within a large ensemble and allows observation to be placed alongside that range. Observations would be expected to typically fall within the large ensemble distribution, but as we do not know how atypical our one realization of reality is, we cannot ascribe meaning to differences from the ensemble mean (Notz 2015). Similarly, when in section e we provide predictions of past and future regional SIC anomalies, good agreement to observations does not explicitly validate our results.

d. Sensitivities to time period and forcing

We use a linear detrending for both the SIC and the CVDP variables over the period 1920-2014 as this is a simple process to understand and does not make specific assumptions about the time period in question. This is not perfect as the forced response during this period was not entirely linear (see Figure 1 from Mcbride et al. 2021). This means that some of the very low-frequency variability of the forced response is incorporated into the anomalies of SIC and CVDP variables, rather than being removed by detrending. Therefore, some predictability is due to the shape of the forced response, primarily represented by our input variable of global average surface temperature (TAS), and likely, to a small extent, the SST-derived variables of NINO34, PDO, ATN, AMO, and the IPO. As the simple linear model used in our results considers each variable independently, we can consider TAS similarly to a residual term in the model which does not affect the conclusions we draw about other modes of variability.

To verify that our results from the period 1920-2014 are robust to different forcing conditions, we compare results with a more linear forcing scenario for the historical period 1970-2014 and a constant pre-industrial forcing scenario. For the 1970-2014 time period the global surface temperature and sea ice area trends are both highly linear (Notz and Stroeve 2016; Mcbride et al.

2021). Consequently, we find that the linear response to TAS in our models is far smaller than in 1920-2014 (see Figure S1, compared with Figure 4). The 1970-2014 time period only uses 24 years of data (compared with 74 for 1920-2014) and hence the linear response is much more noisy than for 1920-2014 and infrequently exceeds persistence. Therefore, although we get a broadly similar linear responses for each climate mode, the low skill and erratic results mean we cannot use this time period. Pre-industrial control runs (of which 35 GCMs are available to provide 222 training years) use constant 1850 forcing and hence TAS trends are near zero over a 74-year time periods. The influence of TAS is indeed found to be much smaller than for 1920-2014 (see Figure S2 compared with Figure 4). Very similar linear coefficients to the 1920-2014 time period are found, and are much less erratic and higher skill than the 1970-2014 time period, likely due an order of magnitude more training data. However, the pre-industrial control results provide much smaller linear responses, likely due to the 1850 mean-state exhibiting less variability than the 21st century, due to the long-term thinning of the Arctic sea ice (Kwok and Rothrock 2009). We therefore use the 1920-2014 time period, despite the TAS nonlinearity, as it both captures similar SIC variability to the present day and enables the use of sufficient training data.

3. Results

a. A simple linear model captures drivers of low-frequency variability

Predictions of regional low-frequency Arctic sea ice concentration anomalies can be produced from climate modes of variability using a linear model, which are skillful when compared with persistence. In general, we find that the simple linear variant of the machine learning models (model 1) produces the highest predictive skill of the four models across GCMs, regions and seasons. When validating our linear model we find it generally exceeds the skill from persistence for lead times beyond approximately 4 years, but is dependent on the GCM (see Figure 2 for the Chukchi Sea in September). The highest predictive skill is found at approximately a 5-year lead time when the skill of persistence has decayed close to zero while the skill of the linear model declines more slowly with lead time. This temporal pattern of persistence, as well as the superiority of the linear model, is found across regions and months with nonzero skill (see section b).

The simple linear model with no hidden layers (model 1) and the neural network with two hidden layers and linear activation functions (model 3) are nearly identical in their performance across different LEs and MMLEs (see Figure 2). Model 2 with no hidden layers and nonlinear activation functions consistently performs poorly, with model 4 preforming similarly to model 2 except for LEs and MMLEs with high amounts of training data. The high performance of models 1 and 3 imply that nonlinearities are not required to produce a skillful predictive model. Furthermore, if nonlinearities are included in a model, the nonlinear interactions only become as skillful as the simple linear model at short lead time and with the largest datasets such as the MMLE 30+ which has 184 members used for training. The benefit of including the effect of covariance of climate modes, achieved by including hidden layers in the machine learning model, is not of benefit in our analysis again except in the case of very large training data. In general, we observe a monotonic decline in validation r^2 across the machine learning models, providing the LE or MMLE has sufficiently numerous training members, approximately 30.

b. Hotspots of low-frequency variability predictive skill

The summer and autumn marginal seas are generally able to produce the highest skill at a 5-year lead time, however the predictive skill varies considerably between GCM. Based on the MMLE 3+, which takes into account the full suite of CMIP6 GCMs with at least 3 ensemble members, the pattern of highest predictability is found in the Beaufort Sea in September, with decaying skill for regions further from the Pacific and for months more distant from September (Figure 3). The MMLE 3+ model is unable to produce high predictive skill in the Barents Sea for any season, and the Kara sea appears to have distinct peaks of predictive skill in July and late autumn.

For models using individual GCMs, the temporal and regional patters of predictive skill are often noisy for neighboring regions and months, unlike the clearer MMLE models. The high predictive skill values of the LEs typically exceed that of the MMLE 3+ for the best regions, but

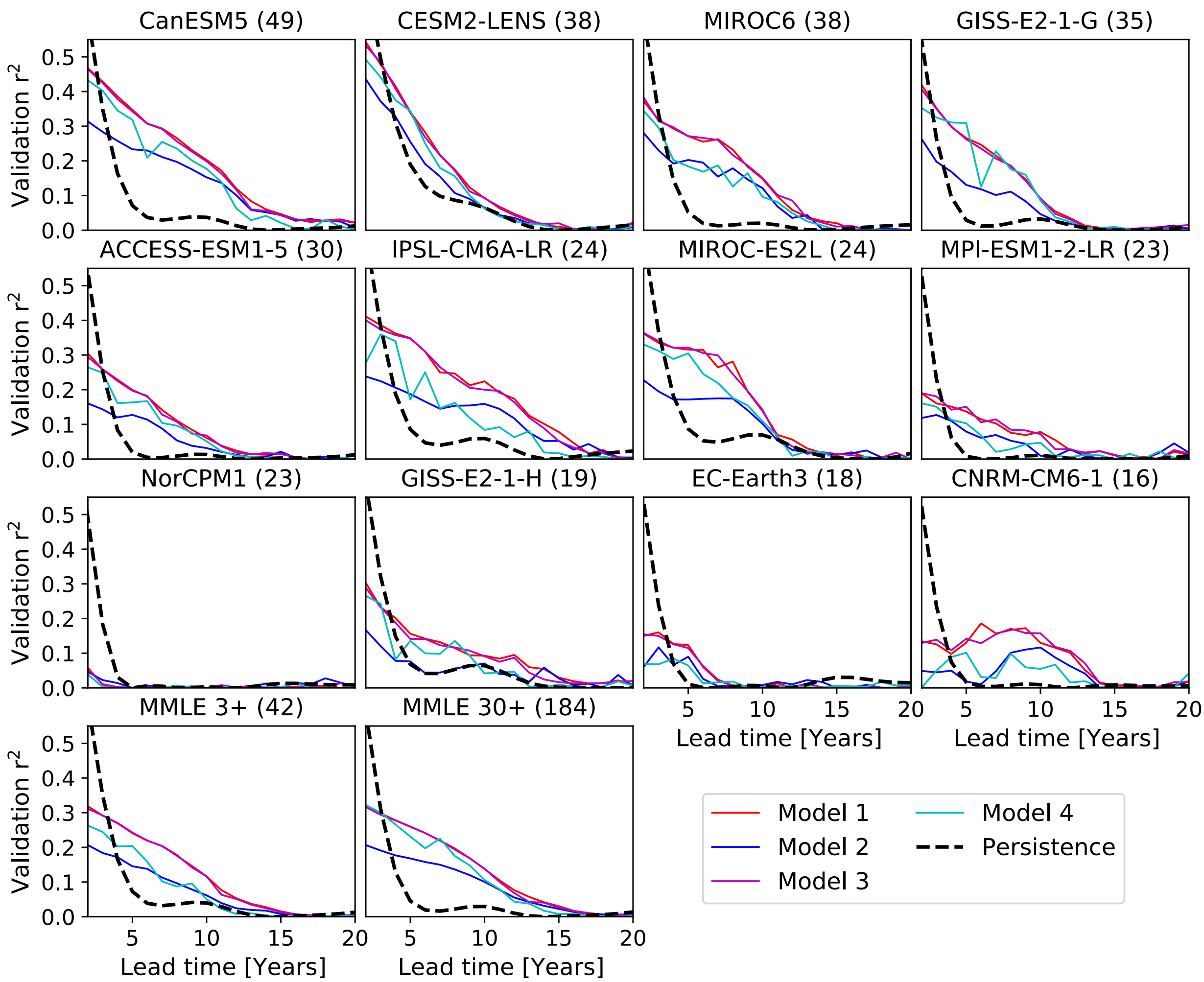

FIG. 2. **The effect of machine learning algorithm complexity on predictive skill.** Pearson correlation coefficients in the Chukchi Sea in September for the validation data for four machine learning models as shown for the 12 LEs and 2 MMLE datasets. Model 1 refers to the simple linear model (red), model 2 to the simple nonlinear model (blue), and Model 3 and Model 4 to the fully-connected 33-6-6-1 neural network with linear (purple) and nonlinear (cyan) activation functions, respectively. The black dashed line indicates the average persistence for that lag time for the GCM or GCMs used. Where the model validation r^2 values exceed persistence the model has predictive skill. Numbers in parentheses indicate the number of ensemble members used in training.

with less coherence between regions and months. Selecting the LE with the highest skill for a region and month may be appropriate, but each LE's specific spatial and temporal limitations should be taken into account. The MMLE 3+ has lower predictive skill than the best LEs, but is influenced by all 42 CMIP6 GCMs. Therefore, high predictive skill in the MMLE 3+ should be seen as less sensitive to individual GCM biases as it is representative of the general agreement between all GCMs. Some LEs such as CanESM5 and ACCESS-ESM1-5 exhibit unusual patterns of high predictability in the Kara and Chukchi Seas in the winter. Other LEs such as CESM2-LENS, GISS-E2-1-H and MIROC-ES2L have particular regions which are far more predictable than others. For example, the CESM2-LENS simulates high persistence for the Chukchi Sea but not for the Beaufort Sea (see Figure S4 for 5-year persistence) which causes the large disparity in predictive skill between these two regions. As September is of particular interest as the typical minimum annual pan-Arctic sea ice cover, and relatively high validation r^2 values occur across regions for September in the MMLE 3+, this is our focus in subsequent analyses.

c. Linear drivers of regional sea ice anomalies

Using a linear model trained on 42 CMIP6 GCMs (the MMLE 3+ model), we can establish the consensus across GCMs for the independent effect of each mode of variability on regional September SIC anomalies. The lead times where the MMLE 3+ model has no predictive skill is before a 4-year lead time for all regions except the Central Arctic where it is not until a 5-year lag time that the validation r^2 exceeds persistence (see the dotted lines in Figure 4). The most important mode of variability is the IPO, which is strongly positively correlated with the SIC in all regions, especially in the East Siberian and Beaufort Seas (Figure 4). The IPO decays in influence over time, reaching near zero influence on SIC at approximately a 15-year lead time. The global average surface temperature (TAS) also has a very large coefficients, but as this is not a mode of variability and is considered to integrate modes of variability not represented (see section d for a more detailed explanation), we do not discuss in detail the influence of TAS further.

Aside from the large influence of the IPO, the Niño 3.4 index (NINO34) and the Atlantic Multidecadal Oscillation (AMO) both display a very consistent sign of influence which decays with time. The NINO34 and AMO both have smaller influences than the dominant IPO, approximately one third and one quarter respectively for a given one standard deviation anomaly in each mode

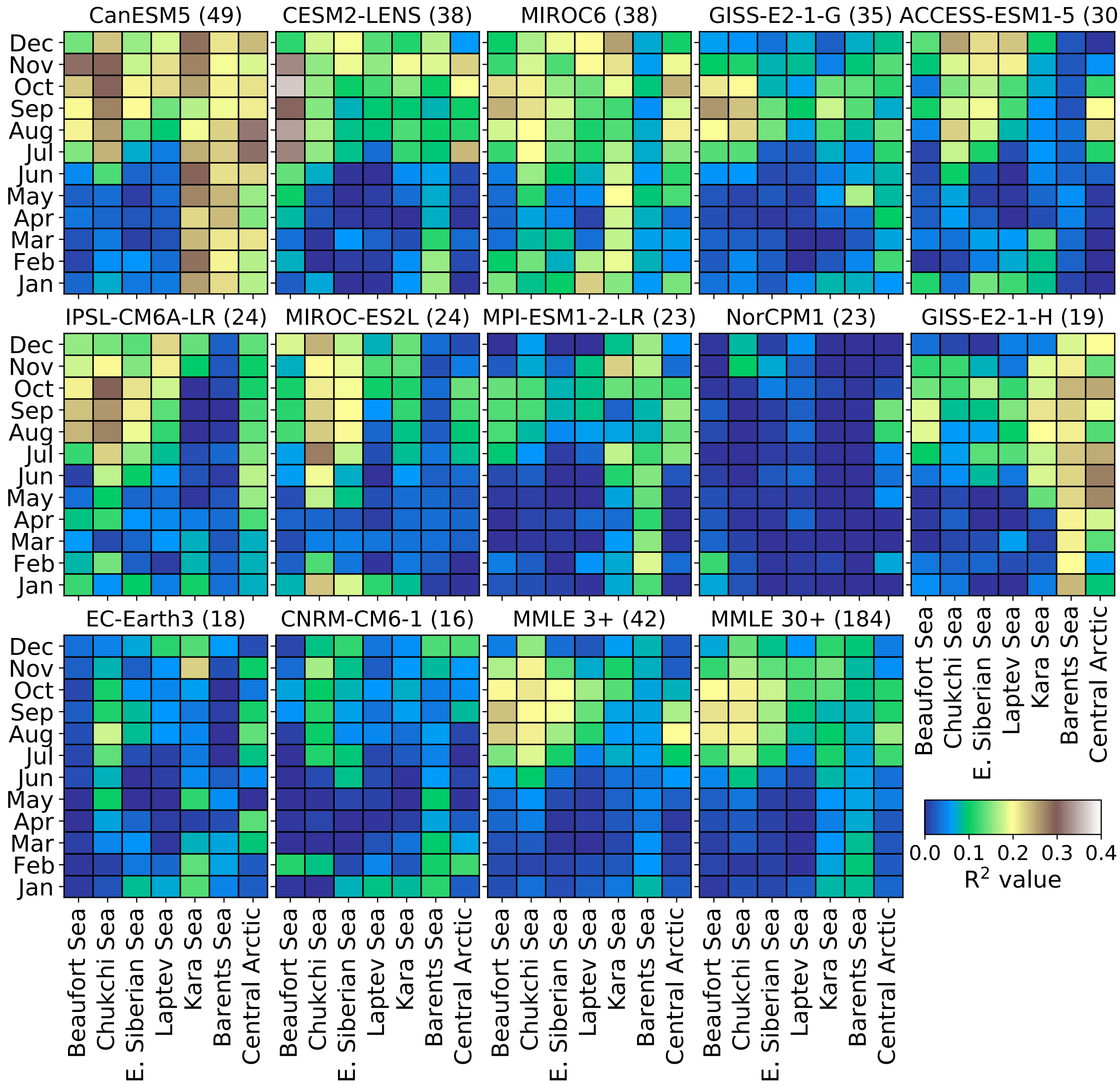

FIG. 3. **5-year lagged predictive skill for multiple global climate models and the CMIP6 multi-model ensembles.** Pearson correlation coefficients are shown for the validation data minus persistence at a 5-year lag time between the input climate modes and sea ice concentration anomalies. Persistence is removed to indicate the regions and months for each LE or MMLE where predictive skill is high, rather than where explained variability is high. Numbers in parentheses indicate the total number of ensemble members used for training.

of variability. Like the IPO and TAS, the influence of the AMO and NINO34 decays relatively monotonically with time. As the skill of persistence also declines nearly monotonically, and the IPO, TAS, NINO34 and AMO all display low-frequency variability, this increases confidence in the

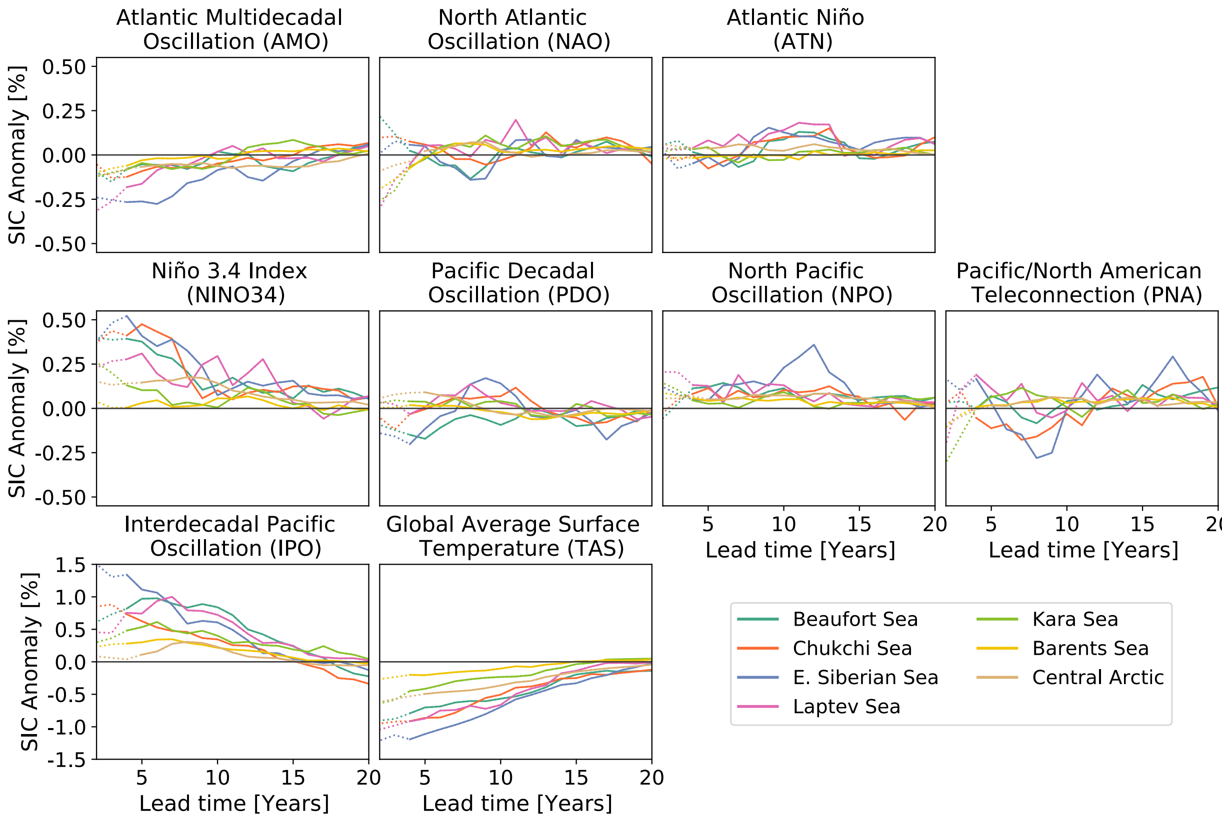

FIG. 4. **Linear drivers of September regional sea ice concentration anomalies.** Linear response of a +1 standard deviation anomaly of each of the 8 climate modes and global average surface temperature on sea ice concentration anomalies in each of the seven Arctic regions. Positive SIC anomaly values indicate a positive SIC anomaly results from the +1 standard deviation anomaly in the climate mode of variability. The IPO only provides one annual value, the other climate modes provide seasonal data and the sum of all seasons is shown here. Solid lines indicate that the validation r^2 value exceeds persistence for a given region and lead time, dashed lines indicate where there is no predictive skill beyond persistence. Predictive skill occurs for 4- to 20- year lead times for all regions except for the Central Arctic which has predictive skill for 5- to 20-year lead times.

validity of these relationships found in the MMLE 3+. The low-frequency oscillations of the other sea surface temperature-derived indices of the Pacific Decadal Oscillation (PDO), and to a lesser extent the Atlantic Niño (ATN), implies the potential for longer-term predictability as with the IPO, TAS, NINO34 and AMO. However the influence of these modes is small at most time periods and does not display a monotonic decline with time. This suggests these two modes are not highly important in driving low-frequency Arctic sea ice variability, but consistency or lack thereof between

LEs (see section d) may clarify whether the relationships in the MMLE 3+ are small and independently consistent in magnitude between GCMs, or small due to disagreement between GCMs.

The modes of variability based on sea level pressure patterns are generally of a small and highly erratic influence on low-frequency variability of Arctic sea ice. The North Atlantic Oscillation (NAO) and the Pacific/North American Teleconnection (PNA) do have large, regionally distinct effects, on very short time periods. However, their influence decays to near zero at a 4-year lead time which is the threshold for the linear model skill exceeding persistence. At lead times beyond 4 years both modes become erratic and close to zero influence implying they are not important drives of low-frequency variability. The North Pacific Oscillation (NPO) is somewhat less erratic than the NAO and PNA, and its influence remains positive for all regions and time periods. However, as the influence of the NPO is small in magnitude, does not decay with time, and has a suddenly large influence in the East Siberian Sea at a 12-year lead time, this linear driver seems unlikely to be representing a robust physical relationship.

d. Low-frequency driver representation across global climate models

Comparing the independent results from 12 LEs aids our interpretation of the linear drivers of SIC anomalies captured in the MMLE 3+. We do this by comparing the datasets for both the medium-term for lead times of 4-9 years (Figure 5a) and the longer-term for lead times of 10-15 years (Figure 5b). Although the LE analysis only includes 12 of the 42 GCMs that went into the MMLE 3+ liner model, we can get a sense of the consistency between the CMIP6-suite of GCMs. This informs our interpretation of the two dominant modes of variability, namely the IPO and NINO34 as the LEs are highly consistent in sign for NINO34 but vary considerably for the IPO, for both periods. Although the influence of the IPO is seen to gradually decrease over time for the MMLE 3+, the individual LEs show large magnitudes of influence on SIC for both time periods and the sign is highly inconsistent between LEs. This shows that the positive influence of the NINO34 should be seen as a common feature of CMIP6 GCMs, but there is little consensus regarding the IPO. The strong positive medium-term influence of the IPO in the

MMLE 3+ which is larger than the any of the 12 LEs, must therefore be due to the 30 GCMs not part of the 12 LEs. This highlights the importance of taking a multi-model approach for the detection of low-frequency variability as two GCMs selected at random may produce opposite results.

The AMO has reasonably good agreement between the LEs with almost all indicating negative influence on regional SIC in the medium-term. For the longer-term, the LEs broadly agree with the sign in the medium-term, although for the full MMLE 3+ the coefficient is near zero due to lower consensus; most but not all of the LEs indicate a large negative value. The PDO in the MMLE 3+ has near zero influence for both time periods, by looking at the spread between the LEs we can see that none of the LEs indicate the PDO as being particularly influential and the disagreement in sign further reduces the overall effect for the MMLE 3+. For the other modes of variability we find that almost all of the LEs coefficients are small in magnitude and with little agreement on sign, further indicating that the MMLE 3+ near zero coefficients are a good representation of the CMIP6 consensus of the modes of variability being unimportant at those lead times.

The average magnitude of influence across all modes of variability differs considerably between individual LEs. For example CESM2-LENS often produces the largest magnitudes for a given mode and NorCPM1 the smallest. Such systematic differences may play out due to differences in the mean state and magnitude of variability by GCM. This may well be the case considering the SIC anomaly is recorded in percentage points and CEMS2-LENS has a low biased summer mean-state (DuVivier et al. 2020) and consequently large variability. Conversely, NorCPM1 has been noted as having a high biased sea ice thickness (Bethke et al. 2021), which may explain why NorCPM1 is an outlier for small low-frequency SIC variability. Again, this indicates care must be taken to understand the effect of limitations to the results from individual LEs. Although many of the CMIP6-suite GCMs are related (Knutti et al. 2013), and their biases may not average out, taking the results from the MMLE 3+ can reduce the risk of extreme outliers.

Using the remaining ensemble members from our MMLE 3+ trained and validated linear model, we find a wide variety GCMs and members which most closely match the MMLE

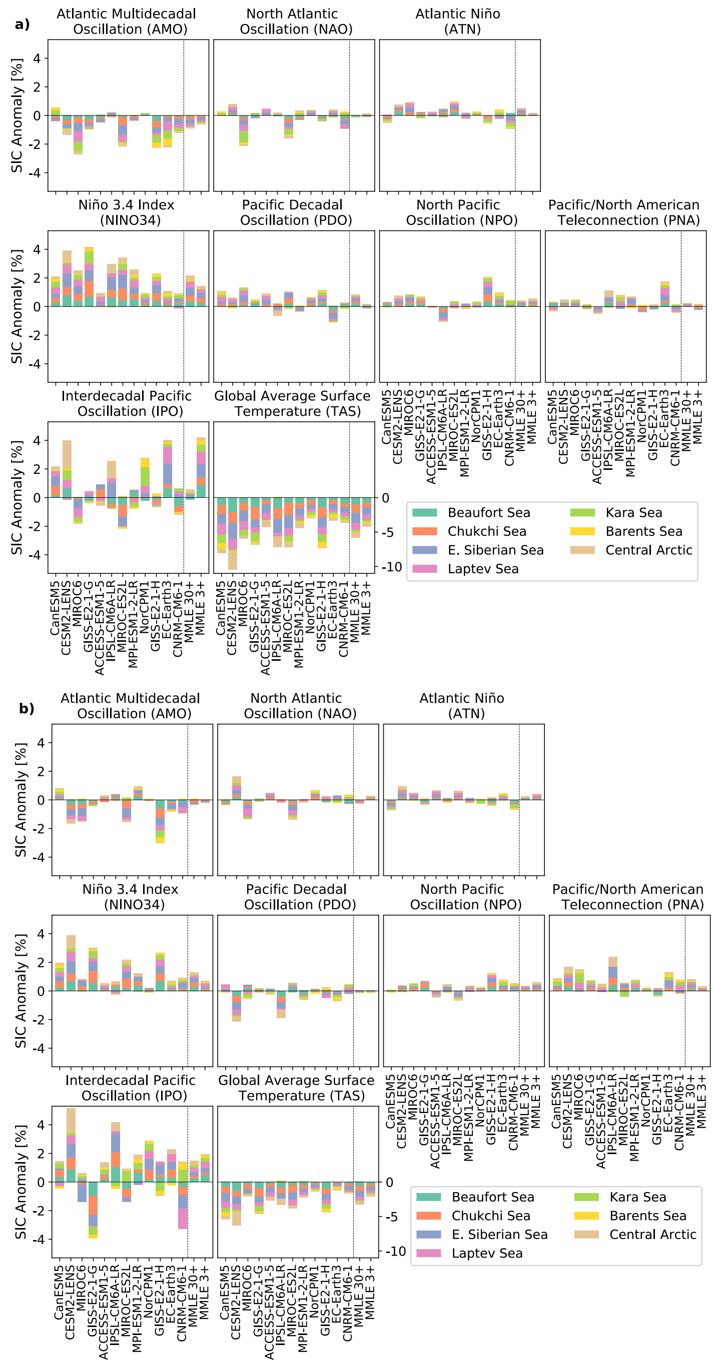

FIG. 5. **The linear effect on regional SIC for 12 large ensembles and the two multi-model large ensembles.** Linear response in September sea ice concentration for a +1 standard deviation anomaly of each climate mode, as in Figure 4, but averaged over two distinct lead times. Bars are the linear response averaged over 4 to 9-year lead times in a) and 10 to 15-years in b). Agreement within the CMIP6-suite of GCMs is high where bars are similar in magnitude and sign. Note the different y-axis scale for the global average surface temperature.

3+. All of the GCMs listed have equal weighting in training the MMLE 3+, so each test member from all GCMs can be treated equally. There is a large amount of variability between ensemble members from the same GCM (see Figure 6). Additionally CESM2-LENS has far more variation between the micro-perturbations (atmospheric state), than between ensemble members with different ocean states (macro-perturbations) (see Figure S3), as also found by Kay et al. 2022 for pan- Arctic volume variability. This indicates that for a 74-year time period the specific manifestation of the relationships between climate variability modes and regional Arctic SIC anomalies can be highly dependent on the initial climate state.

When using the MMLE3+ model on the test members of a given GCM, there are large differences in test r^2 values across the ensemble members. This limits our ability to determine which GCMs are most like the CMIP6 consensus if they have small ensemble sizes which cannot populate the full range of potential values (Notz 2015). Observational comparison with a similar time period will therefore be difficult as observations could be expected, rather unhelpfully, to fall somewhere between 0 and 0.5 r^2 if the actual climate system has relationships like the MMLE 3+. However, the MMLE 3+ model appears to be well generalized to multiple GCMs as the test r^2 values appear very similar if a linear model is trained on all 42 GCMs as for the MMLE 3+ (blue circles in Figure 6) or only on other members from the same GCM as for the LE (red triangles).

e. Observational comparisons

Correlations between the climate modes and extreme SIC anomalies show observations broadly fall within what is simulated for the LEs, but validation is difficult due to the large differences between realizations. In order to directly compare observations with ensemble members, we compute the correlation between the 6 most extreme regional SIC anomaly years in the period 1956-2022 and correlate whether each mode of variability was in a positive or negative phase. To make a more representative sample, we pool the seven regions (except the Barents Sea where summer variability is near zero), averaged over a 10- to 15-year lead time. However, the correla-

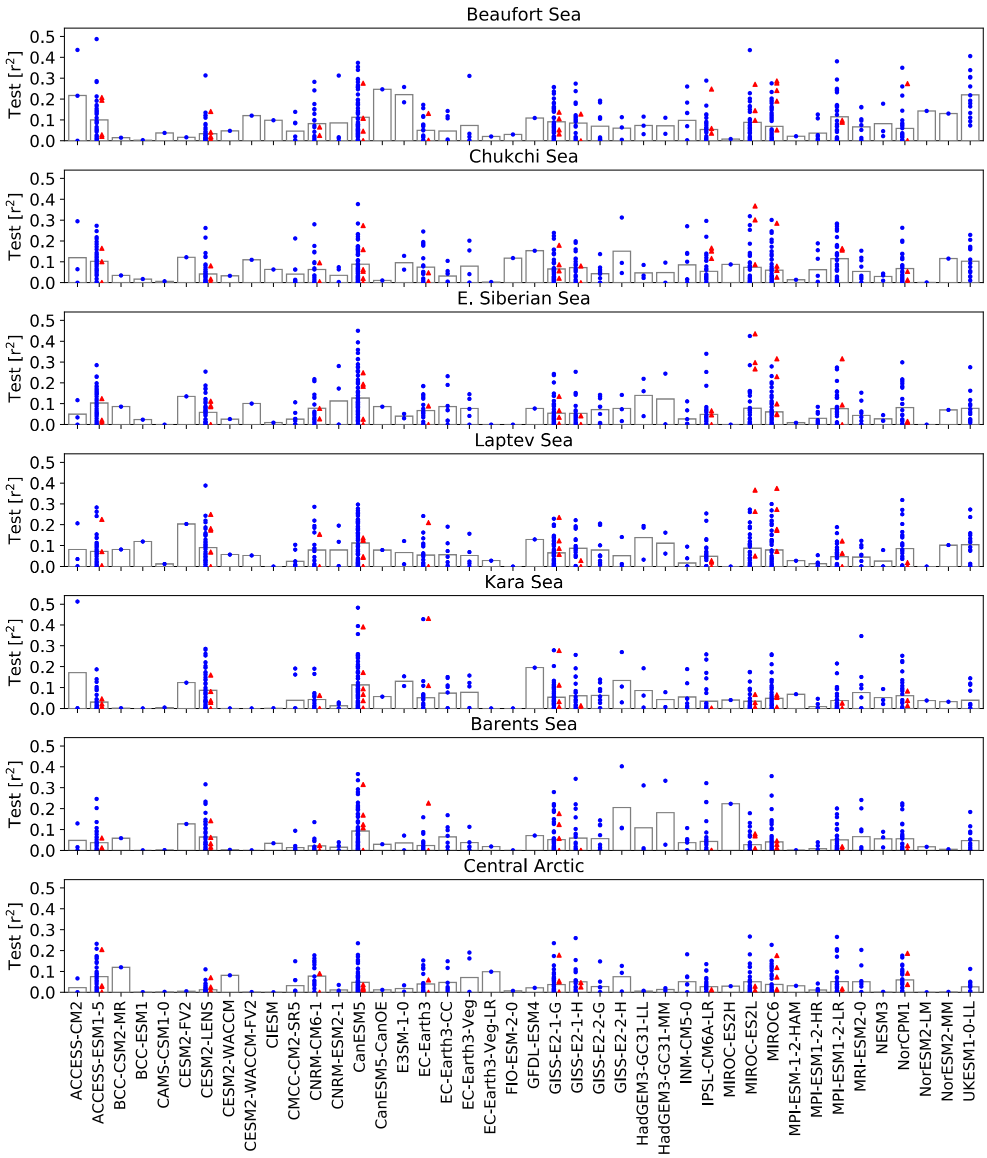

FIG. 6. **September r^2 values for the test ensemble members from either the multi-model large ensemble (3+, blue) or the 12 single GCM large ensembles (red).** The performance of the test members (third and later ensemble members) for the 42 GCMs included in the MMLE 3+ model are shown as blue circles, ensemble mean values are indicated by gray bars. The red triangles indicate the performance of the test members for the individually trained linear models for each of the 12 LEs, where 10% of the LE members were reserved for testing against the linear model trained and validated on the first 75% and 15% of members from each GCM. Where the red triangles and blue circles for a given GCM have a similar distribution, the MMLE 3+ is equally good at capturing the relationships between climate modes and SIC as the LE, indicating the MMLE 3+ is well generalized. The r^2 values are for a 5-year lead time minus persistence.

tions should not be seen as comparable to the linear model as each season is weighted equally and the correlations are binary, unlike the abilities of the linear model which applies lower weights to less important seasons and has a continuous rather than binary representation of relationships. Observations fall within the ensemble spread for all modes of variability except for the PNA for all LEs and NINO34 for all LEs except CanESM5 (see Figure 7). This suggests that the observations and GCMs match well in terms of the influence of modes of variability on regional SIC anomalies, except for the PNA and NINO34. As NINO34 is a large contribution to regional SIC anomalies in the LE and MMLE 3+ linear models, the far stronger correlation of observations may mean in our one realization of reality the NINO34 index has played a larger role than simulated in many climate models. Again, the large spread between realizations within a large ensemble highlights the extremely large range that observations would be expected to fall within (particularly for the IPO), and hence the difficulty of validating the simulated low-frequency drivers with observations.

f. Future projections

Our limited time period of observations may not be representative of a typical climate realization and therefore may arbitrarily match well or poorly to a specific machine learning model trained on GCMs. However, validation of our LE and MMLE 3+ models against the period 1956-2022 may have some implications for how well we can expect projections over the next 4-20 years to hold up. The r^2 values of the MMLE 3+ validated against the observations (Figure 8 prediction columns) is similar to that of the MMLE 3+ validated against the second large ensemble members (Figure 3). The MMLE 3+ and the best LEs when used for hindcasting SIC anomalies from observed climate modes, often achieve r^2 values of between 0.2-0.4 above persistence, but is highly regionally dependent. As the MMLE 3+ typically has the highest or near highest validation skill against the observations, we use these for future projections in the following.

For all regions of the Arctic, our linear model predicts below trend sea ice concentrations over the coming decade. The seven regions have different time evolutions of the projected SIC anomalies, however all regions for the MMLE 3+ projections show accelerated SIC loss

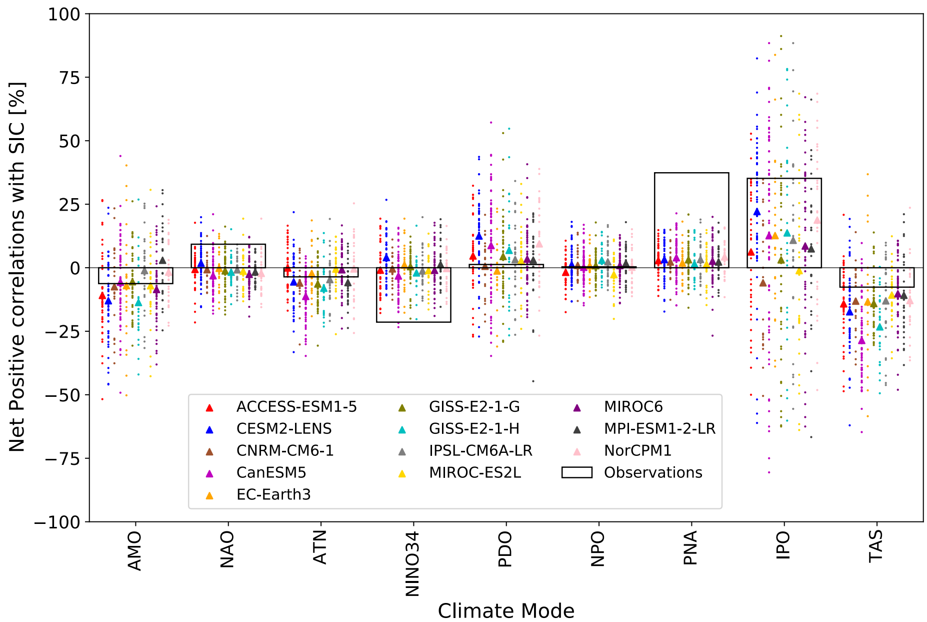

FIG. 7. **Correlations between ensemble members and observations between modes of variability and extreme SIC anomaly events.** The 6 most extreme SIC positive and negative anomalies are found for each ensemble member and September observations over the period 1956-2014. For a lead time of 10-15 years the positive and negative correlations with each mode of variability is summed. These data are the average for the Beaufort, Chukchi, East Siberian, Kara and Laptev Seas and the Central Arctic. Each colored dot indicates the correlations for a single ensemble member, with the same colored triangle indicating the ensemble mean. The observed value for each variable is shown with a black hollow bar. When observations lie within a given GCM ensemble member distribution, the correlation in the observations is consistent with that simulated in the GCM.

due to low-frequency variability over the 20 years following 2022 (see Figure 8). Taking the pan-Arctic as a whole, the predicted negative anomaly from the linear trend is the largest anomaly at a 5-year lead time during the period 1956-2022. Therefore, our MMLE 3+ model predicts current climate modes as being particularly conducive to a large low-frequency SIC anomaly. This is fairly consistent across LEs, with the only large outlier being the CESM2-LENS which predicts an extreme accelerated loss due to being a large outlier in Central Arctic projections. This outlier is likely due to thin biased ice as discussed in section d. Comparing the persistence of CESM2-LENS with CESM2-lessmelt runs which have thicker sea ice (Kay et al. 2022), the lessmelt CESM2 variant is more in line with the persistence in other GCMs (see Figure S4).

This indicates the low thickness bias likely caused the enhanced simulated variability outlier.

The contributions to this predicted accelerated SIC loss throughout the Arctic in the coming decade is dominated by the large negative anomalies in 2022 in both the IPO and NINO34 and the positive phase of the AMO. Furthermore, the above trend surface temperature warming in 2022 is also modeled as being a large contribution in the year 2027 (see Figure 8q,r). Only the negative phase of the PDO in 2022 is expected to counter the accelerated sea ice loss by leading to positive SIC anomalies in the Pacific sector. The remaining modes of variability are either in near neutral phase in 2022 or have small influences on the linear model and hence do not feature as contributing to future anomalies. The alignment of modes of variability phases in 2022 combine to simulate a negative anomaly to the linear trend larger than any anomaly predicted during the period 1956-2021.

4. Discussion

The quantity and quality of GCM data available from CMIP6 simulations is unprecedented (Davy and Outten 2020), allowing us to investigate whether nonlinearities and climate mode covariance is essential to produce skillful SIC projections. The fact that linear relationships were found to be sufficient for skillful projections shows promise for using the dominant modes of variability we identified of the IPO, NINO34 and the AMO. Nonlinearities and covariance in the effect of climate modes on Arctic sea ice is likely to exist (e.g. Heo et al. 2021), but may require additional data or more prescriptive methods to improve skill beyond that by achieved using simple linear relationships. By using 42 GCMs in our MMLE 3+ linear model, we did not degrade our skill when compared with training our linear model on a single GCM (see section d). This shows that a generalized linear model can be obtained from a variety of GCMs differing in model physics, model biases and ocean states, but that this generalized linear model still has a large range of predictive skill outcomes dependent on realization.

Previous studies have primarily focused on seasonal or interannual timescales of variability, with the notable exceptions of the IPO and AMO which have been considered on decadal timescales. We found the IPO to be the most influential mode of variability on all lead times between 4 and 20 years. In previous research the IPO has not featured except as found by Screen and Deser 2019 for the GCM CESM1-LE. This agreed with the positive correlation in our MMLE 3+ linear model that was strongest in the CESM2-LENS large ensemble. The moderate disagreement in sign and longevity of the IPO's influence on SIC in CMIP6 LEs follows on from research that CMIP5 GCMs generally poorly simulate the effect of the IPO (Baxter et al. 2019; Ding et al. 2019; Topál et al. 2020). In addition to the lack of consensus between GCMs broadly, the correlation appears highly sensitive to realization (see Figure 7). Additional focus on this mode with a wider variety of modeling applications appears needed and is particularly pressing given the strong current negative phase (see Figure 8q). The AMO was found in our MMLE 3+ linear model to be negatively correlated with all regions of the Arctic sea ice, which shows good agreement with previous studies (e.g. Day et al. 2012; Miles et al. 2014; Li et al. 2018b) for the pan-Arctic or Atlantic sector on decadal timescales. However, the AMO itself may have a forced component (Murphy et al. 2021; Klavans et al. 2022), and its oscillatory timescale varies considerably between GCMs (Lee et al. 2021), potentially limiting the use of the AMO as an independent variable. However, the fact that the pre-industrial control simulations (see Figure S2) match well with the MMLE 3+ for 1920-2014 for the AMO, IPO and NINO34 suggests that forcing context is not highly important.

El Niño and La Niña have been shown to be influential on Arctic sea ice and generally suggest that NINO34 is positively correlated with SIC except for the Beaufort Sea (e.g. Clancy et al. 2021; Hu et al. 2016; Jeong et al. 2022b). However, the lead times considered previously were shorter than our 4-20 year timescale, making our positively correlated influence hard to directly compare with previous research. Furthermore, previous literature on shorter timescales have noted the importance of the type of El Niño regime (Jeong et al. 2022a; Lee et al. 2023) and the likely nonlinear climate response from NINO34 (Hoerling et al. 1997). The PDO was previously not found to be highly important by itself (Zhang et al. 2020) and its weak influence may also have changed over time (Kim et al. 2020); similarly we also only found a small influence of the PDO. The ATN is the only negligible mode of variability derived from SSTs, but has not previously been identified as specific driver of Arctic sea ice variability. However the tropical Atlantic was been suggested to influence Arctic sea ice (Meehl et al. 2018), hence the unimportant nature of the ATN does not preclude other aspects of tropical Atlantic being important. Consistent with the previous lack of evidence of influence beyond interannual timescales, the sea level pressure-derived modes of variability (the NAO, NPO and PNA) were found to have negligible effect at lead times of 4-20 years. Previous research has shown the effect of the NAO to decay to zero after approximately 2 years (Ukita et al. 2007), this timescale and the regional correlations (e.g. Serreze et al. 2007; Döscher et al. 2010) align with our findings given the smoothing inherent in our lowpass filtered data. This provides confidence in our linear model's ability to capture higher frequency variability but dismiss low-frequency influence from these modes of variability.

5. Conclusions

We have shown that low-frequency variability of regional Arctic sea ice can be modeled using linear drivers consisting of climate modes of variability. We achieve predictions superior to persistence for most regions for a lead time of 4-20 years and find that the climate modes of variability can be considered independently without reducing skill. By comparing the linear responses between twelve large ensembles from CMIP6 and a multi-model large ensemble comprising of 42 GCMs, we find where there is consensus of the dominant linear drivers of low-frequency sea ice variability except in the case of the Interdecadal Pacific Oscillation (IPO). In the pan-Arctic we are able to explain up to 58% of observed low-frequency sea ice concentration variability at lead times of 5 years. However, the ability of a GCM or a multi-model large ensemble to predict unseen ensemble members or observations can vary wildly depending on the realization of internal variability. Hence, this both complicates the analysis of small samples of GCMs and the application and verification of these relationships with observations.

The most important modes of variability we found were the IPO, Nino 3.4 Index (NINO34) and the Atlantic Mutidecadal Oscillation (AMO). The multi-model large ensemble linear model showed the IPO to have a strong positive correlation with this being most pronounced in the East Siberian, Beaufort and Laptev Seas at lead times of up to 14 years. Although this large magnitude of influence of the IPO was found across GCMs, the sign and regional influence was especially dependent on the GCM used and the specific realization of internal variability. NINO34 was found to be positively correlated with SIC anomalies in all regions, particularly in the Pacific sector. This correlation was robust between GCMs, but disagreement occurred regarding the longevity of this positive correlation. The AMO was the only other mode of variability considered important for long periods of time, being modeled as highly negatively correlated with SIC across all regions for up to approximately 10 years. However, the agreement across CMIP6 GCMs for the AMO was less consistent than NINO34.

When using our linear model to make predictions, we find a near 'perfect storm' of modes of variability in the year 2021/2022 to induce an acceleration to the sea ice loss trend over the next decade. The primary influences of this projected acceleration of low-frequency variability driven sea ice loss are an above trend global average surface temperature warming, a negative IPO, La Niña conditions, and a positive AMO. For the pan-Arctic, the projected low-frequency deviation from the long-term trend due to current climate mode phase configurations is expected to be the largest since at least 1956. Of course, the sea ice anomalies that will actually be observed are still dominated by interannual variability, which makes up roughly three quarters of the total variability. Thus, while we cannot say with confidence that a new record low September extent will occur over the next decade, the modeled low-frequency variability suggests that extreme low SIC values will be more likely over the coming decade, as they will enhance rather than oppose the long-term negative trend.

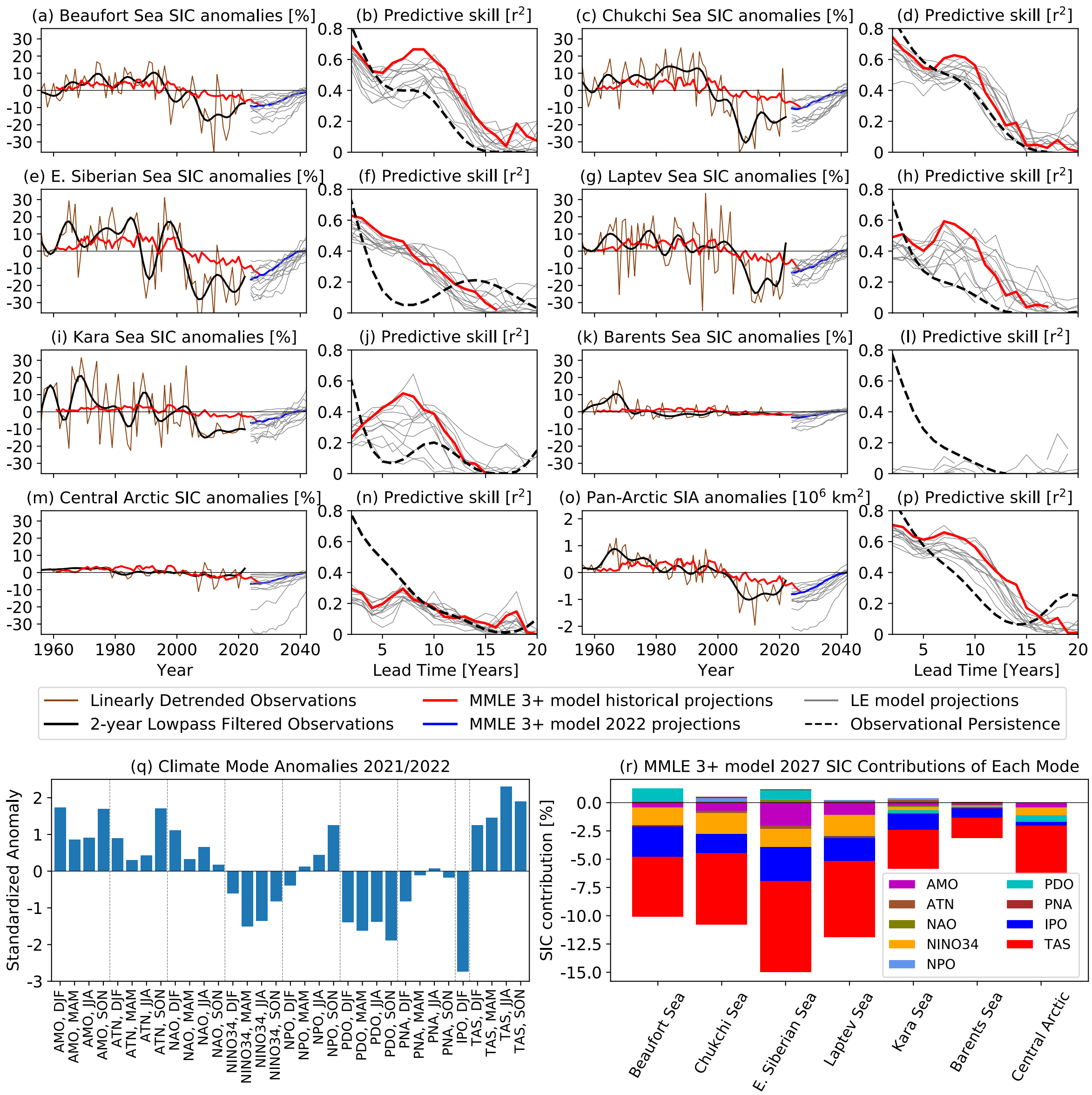

FIG. 8. **Linear model projections of SIC anomalies based on observed climate modes.** The projection subplots a,c,e,g,i,k,m,o show the observed 1956-2022 regional or pan-Arctic SIC anomalies (brown), the 2-year lowpass filtered anomalies (black), the MML3+ linear model historical hindcasts on a 5-year lead time (red), and the future projections based on the climate mode anomalies observed in 2022 (or 2021 for the SON season) using the MMLE 3+ (blue) and individual LEs (grey). The prediction skill subplots b,d,f,h,j,l,n,p show the observed persistence in dashed back lines while the MMLE 3+ and LE hindcast performances for 1976-2022 at 2- to 20- year lead times are shown in red and gray respectively. The subplot q depicts the observed climate mode anomalies for the year 2022 (or 2021 for season SON). Subplot r shows the MMLE 3+ contribution to the projected anomalies in 2027 based on 2022 data of each of the modes of variability.

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Data availability statement. The data used in this study is freely available at https://esgf-node.llnl.gov/projects/ cmip6/ for the CMIP6 global climate model data except for the CESM2-LENS, which is available at https://www.cesm.ucar.edu/community-projects/lens2/data-sets. The CVDP data is available at https://www.cesm.ucar.edu/ projects/cvdp/data-repository. The observational sea ice concentration data is freely available from https://nsidc.org/data/g02202/versions/4. Upon publication, all code required to replicate this study will be made open-access at Zenodo, currently it is available at https://github.com/chrisrwp/low-frequency-variability. Additionally the linear model coefficients and the observational CVDP output data processed for this analysis will be made available at the Arctic Data Center upon acceptance of this manuscript.

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Supplementary Material

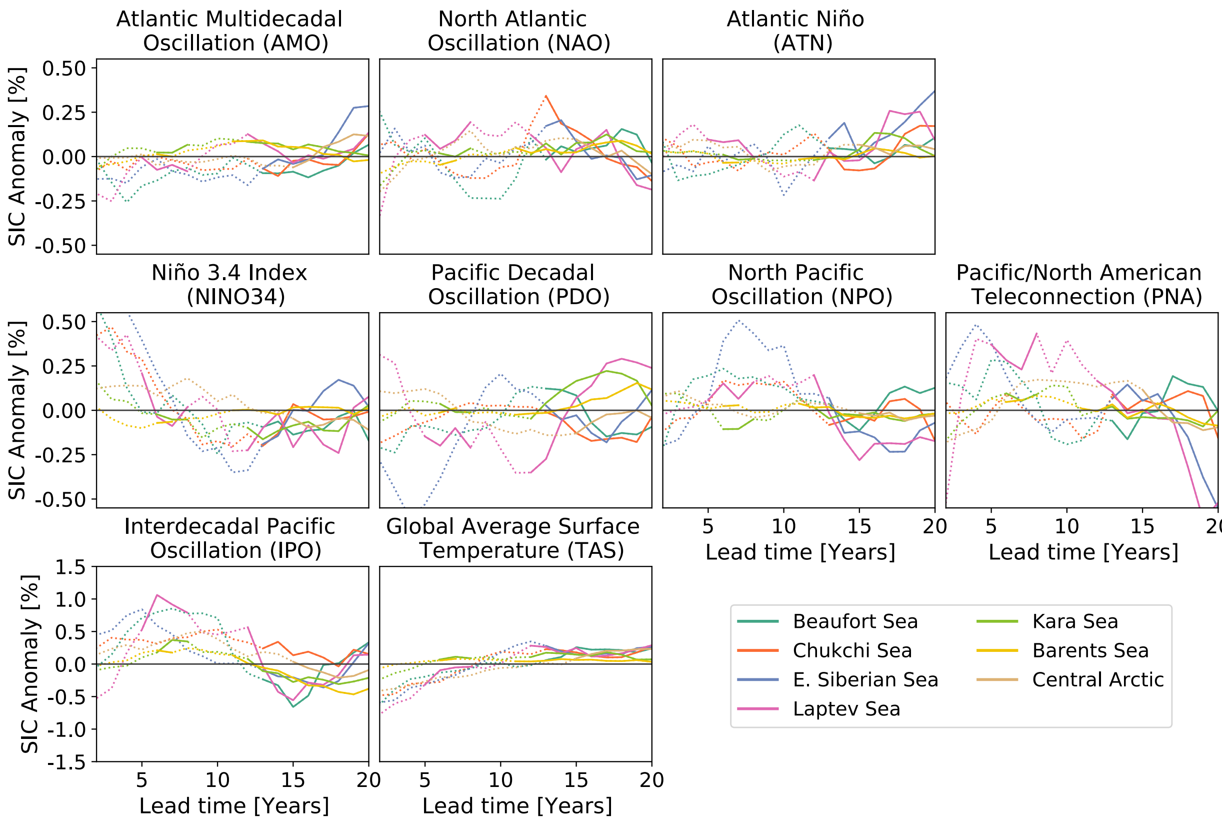


FIG. S1. **Linear drivers of regional sea ice concentration anomalies for a reduced time period.** Same as Figure 4, except for the reduced time period of 1970-2014 instead of 1920-2014. By comparing this figure with 4, we can see that the modes of variability have a similar influence as for the 1920-2014 time period, although the results are far more noisy and predictive skill does not exceed persistence for as much of the lead times as for the period 1920-2014.

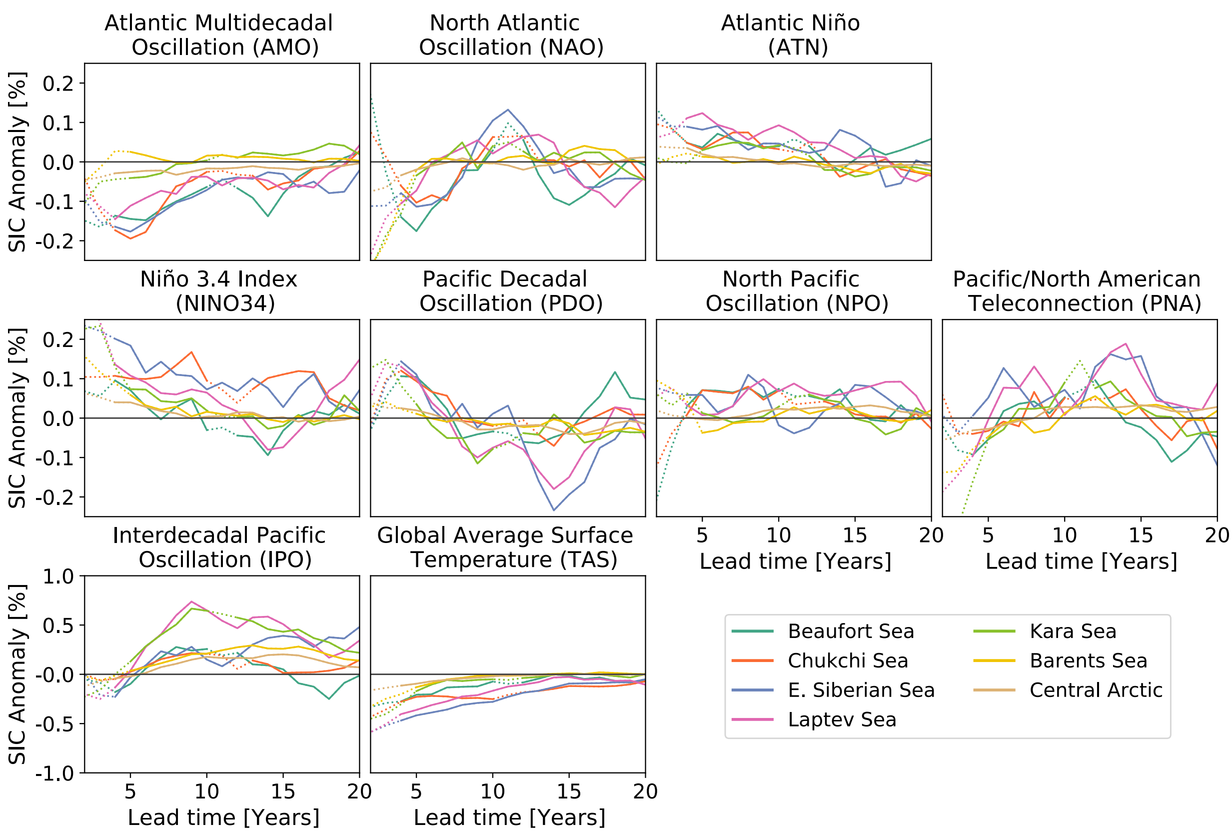


FIG. S2. **Linear drivers of regional sea ice concentration anomalies for pre-industrial control runs.** Same as Figure 4 and S1, except here using the 1850 control simulations instead of the period 1920-2014 in the historical simulations. As for Fig. S1, the influence of the climate variability modes are very similar as for the period 1920-2014 (Fig. 4), but the coefficients are smaller, likely due to the lower variability in the pre-industrial mean state. Instead of different ensemble members, the available 35 GCMs are each split into several members of 74 year length each, with the first 222 years used for training and the following 74 years for validation.

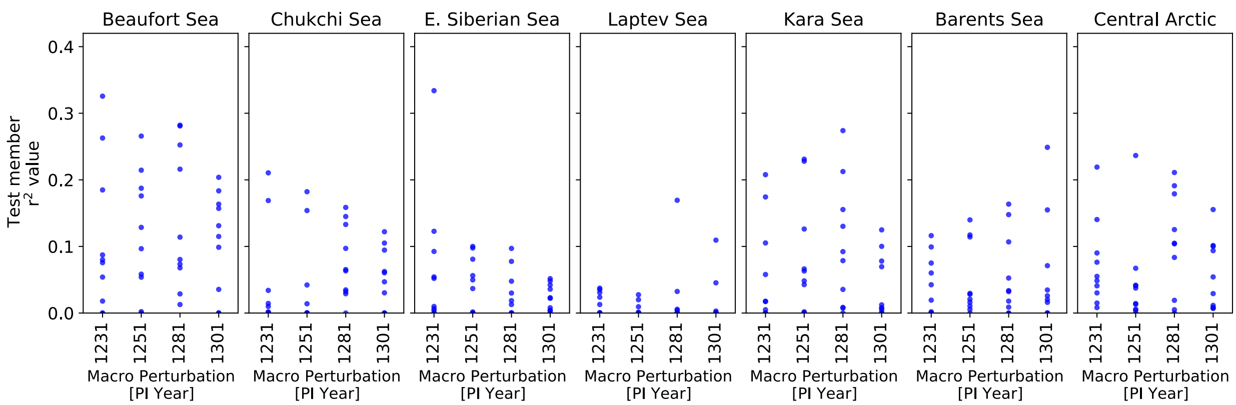
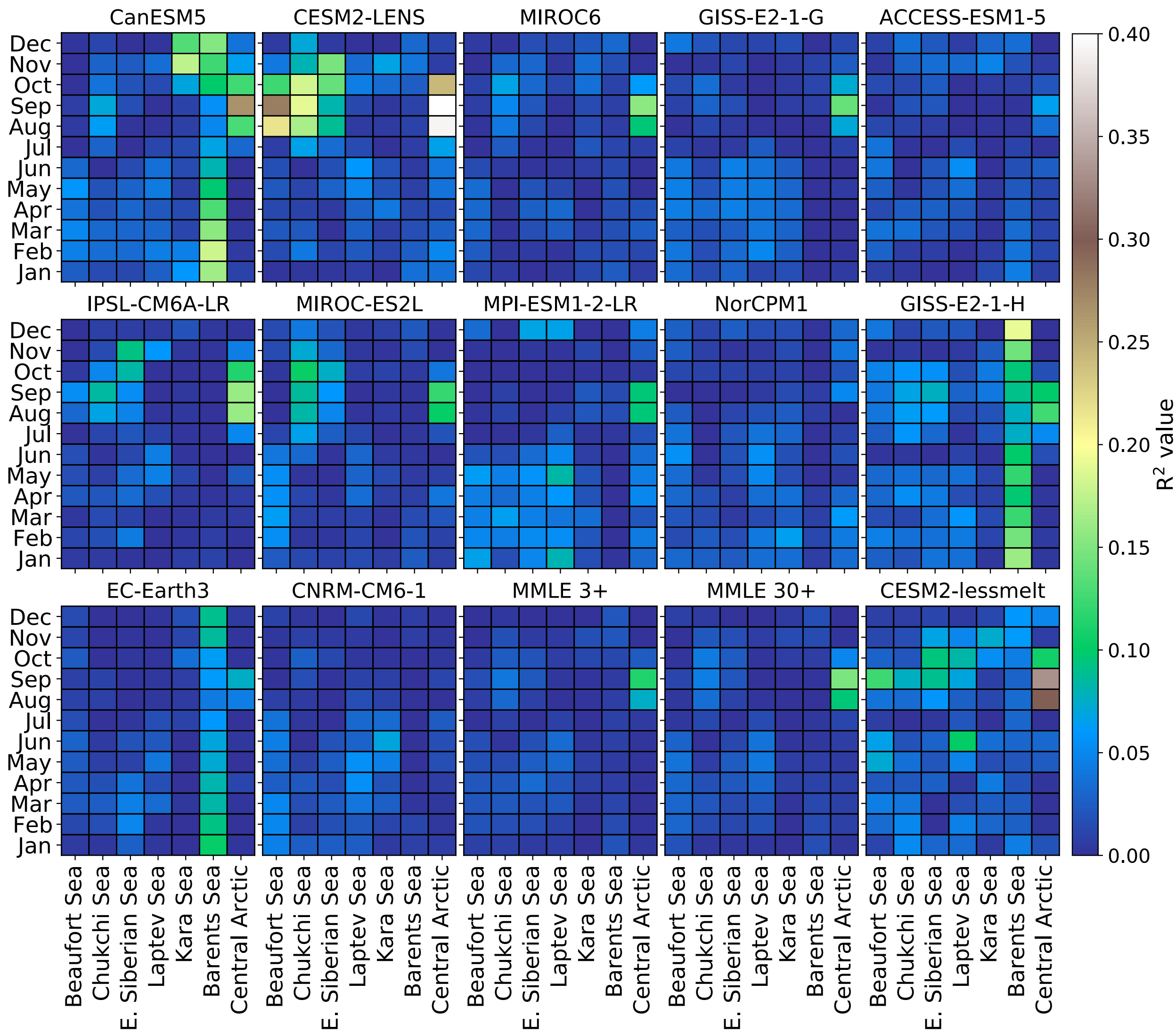


FIG. S3. **Influence of macro versus micro initializations in the CESM2-LENS on September test member r^2 values**. Of the 48 test members from the CESM2-LENS, 12 are created through macro initializations by choosing different start years from the pre-industrial simulation, and hence differ in their ocean and atmospheric state. Of those 12, four (here shown on the x-axis by branch year) have 9 additional ensemble members branched from them, which all only differ slightly in their atmospheric state due to small atmospheric perturbations, i.e., referred to as micro initializations. Here we show these latter 40 simulations (blue circles), to assess whether macro or micro initializations dominate the possible r^2 values (with persistence removed). As the four distributions of 10 realizations for each macro initialization are very similar, this shows that the ocean state (macro perturbation) has a much smaller impact on prediction skill than atmospheric micro perturbations.



1039 FIG. S4. **Persistence r^2 values for LEs, MMLEs, and CESM2-lessmelt at a 5-year lag time.** This figure shows the persistence r2 value that was subtracted from the absolute value of the validation r^2 in Figure 3. Additionally the CESM2-lessmelt persistence is shown for comparison with CESM2-LENS. CESM2-lessmelt has a thicker sea ice mean state than CESM2-LEMS and, as shown in this figure, has a smaller persistence validation r^2 value, although this value is still an outlier compared with the other GCMs.