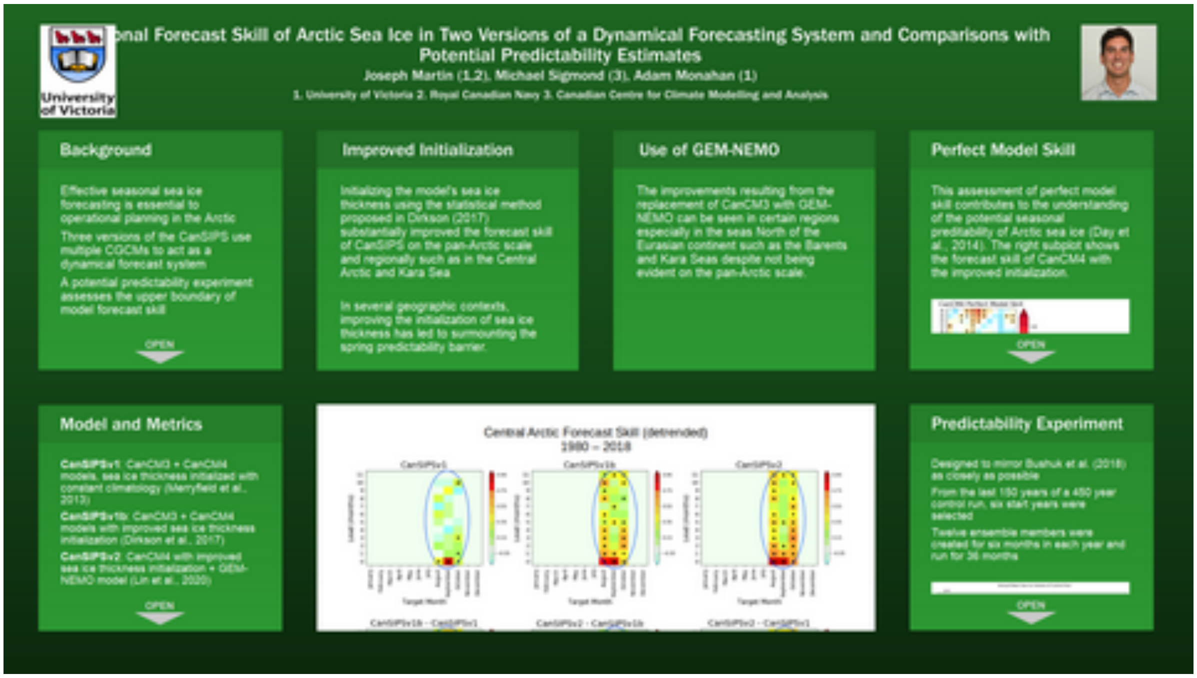
Seasonal Forecast Skill of Arctic Sea Ice in Two Versions of a Dynamical Forecasting System and Comparisons with Potential Predictability Estimates



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BACKGROUND

Effective seasonal sea ice forecasting is essential to operational planning in the Arctic

Three versions of the CanSIPS use multiple CGCMs to act as a dynamical forecast system

A potential predictability experiment assesses the upper boundary of model forecast skill

Motivation

With the decline in global sea ice, interest has increased in the potential to operate in Arctic waters without the requirement for expensive ice breaking vessels. These operations will require a robust seasonal sea ice forecasting capability in order to facilitate operational planning. This study assesses the potential of using Coupled Global Circulation Models (CGCMs) for this purpose.

Spring Predictability Barrier

The spring predictability barrier is a challenge described in the literature (Day, 2014; Bushuk, 2020) of spring initialized sea ice forecasts accurately predicting autumn months. The related target months and lead times are outlined in rectangles in the figures.

Related Work

Sigmond et al. (2013) assessed the forecast skill of CanSIPSv1 on a pan-Arctic scale. In considering the skill of detrended forecasts, there was clear presence of a spring predictability barrier and notable difficulty outperforming an anomaly persistence forecast. Sigmond et al. (2013) suggested that more accurate initializations of sea ice thickness may improve the model's skill with regards to September forecasts.

Based on the contention that accurate sea ice thickness initialization would improve the skill of September forecasts, Dirkson et al. (2017) proposed three statistical models to model thickness for initialization given sparse observations. The SMv3 method extrapolates trends from the local sea ice concentration and applies them to the local sea ice thickness climatology. This method is applied in both models in CanSIPSv1b and one model in CanSIPSv2.

A potential predictability experiment looks to assess the skill of a "perfect model" - one in which it is assumed that the model physics perfectly reflect the observed phenomena and there is near-perfect knowledge of the initial conditions. Perfect model skill metrics therefore represents the upper limit of a system's predictability. Bushuk et al. (2018) conducted such an experiment for GFDL's FLOR model. From a control integration, six start years were picked representing high, medium, and low anomalies from climatological sea ice volume. Twelve member ensembles were initialized in six months of each start year and run for three years. Forecast skill was then quantified by each ensemble member taking a turn as the observations which the mean of the other members is used to "predict". Significant skill was found for lead times as large as 35 months for both pan-Arctic and most regional perfect model forecasts.

IMPROVED INITIALIZATION

Initializing the model's sea ice thickness using the statistical method proposed in Dirkson (2017) substantially improved the forecast skill of CanSIPS on the pan-Arctic scale and regionally such as in the Central Arctic and Kara Sea.

In several geographic contexts, improving the initialization of sea ice thickness has led to surmounting the spring predictability barrier.

USE OF GEM-NEMO

The improvements resulting from the replacement of CanCM3 with GEM-NEMO can be seen in certain regions especially in the seas North of the Eurasian continent such as the Barents and Kara Seas despite not being evident on the pan-Arctic scale.

PERFECT MODEL SKILL

This assessment of perfect model skill contributes to the understanding of the potential seasonal preditability of Arctic sea ice (Day et al., 2016). The right subplot shows the forecast skill of CanCM4 with the improved initialization.

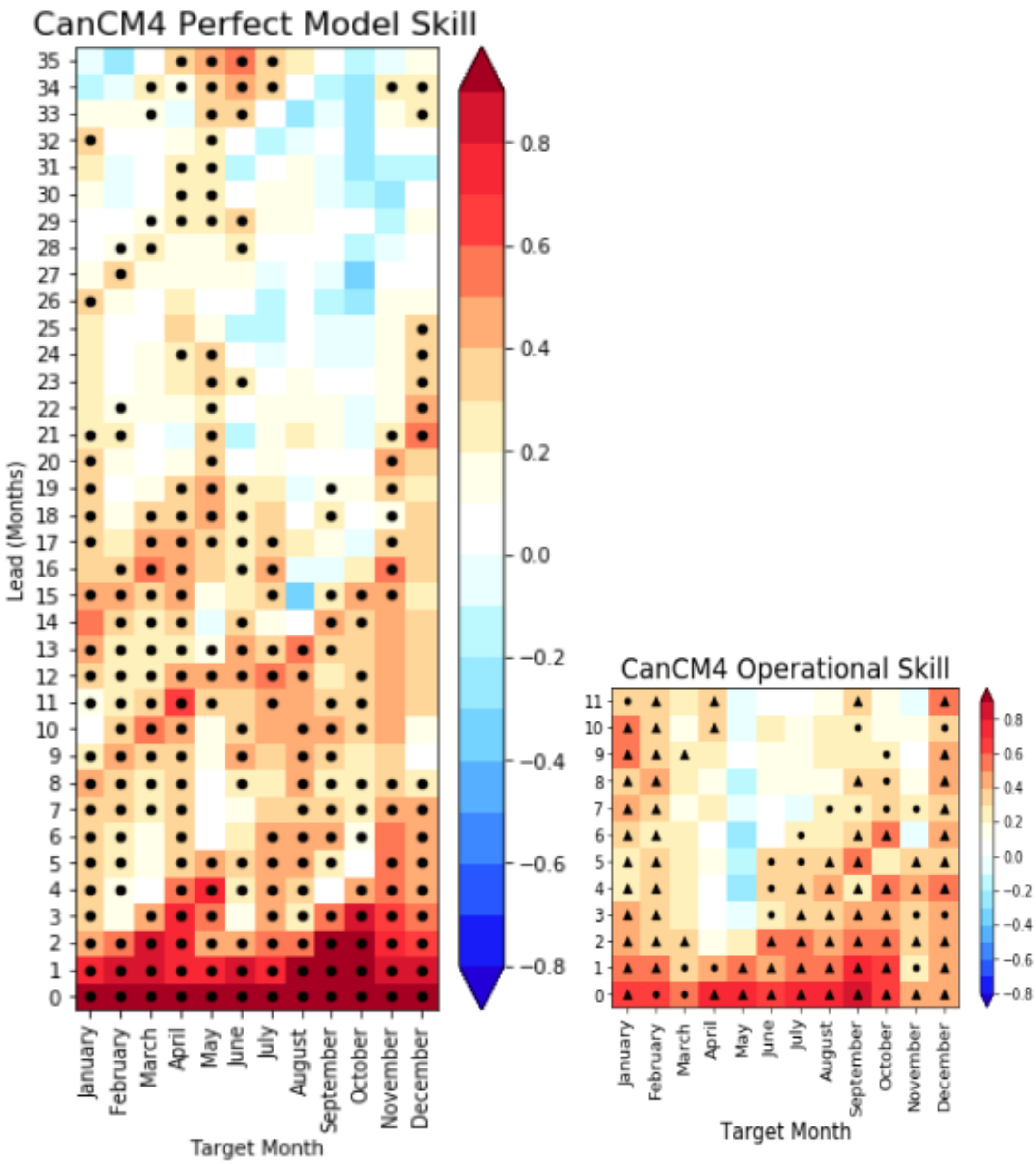


Figure 1 - CanCM4 perfect model skill (left) and CanCM4 operational model skill (right). Dots indicate statistically significant skills. Triangles in the OP model indicate statistically significant skills that outperform persistence. In some cases, operational model skill is greater than perfect model skill which may be the result of sampling error.

MODEL AND METRICS

CanSIPSv1: CanCM3 + CanCM4 models, sea ice thickness initialized with constant climatology (Merryfield et al., 2013)

CanSIPSv1b: CanCM3 + CanCM4 models with improved sea ice thickness initialization (Dirkson et al., 2017)

CanSIPSv2: CanCM4 with improved sea ice thickness initialization + GEM-NEMO model (Lin et al., 2020)

The Canadian Seasonal and Interannual Prediction System (CanSIPS) is a multi-model dynamical forecasting system developed by Environment and Climate Change Canada.

Metrics

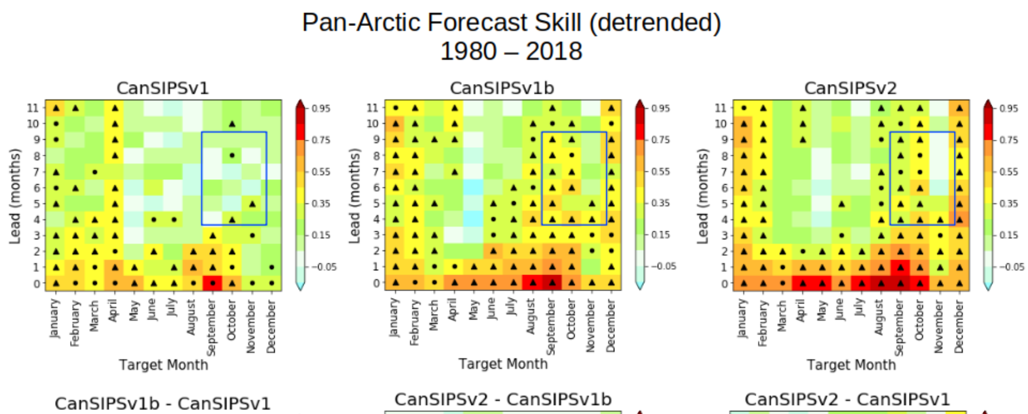
The Anomaly Correlation Coefficient (ACC) measures the covariability of two time series. It is used throughout this study to quantify the forecast skill of the model.

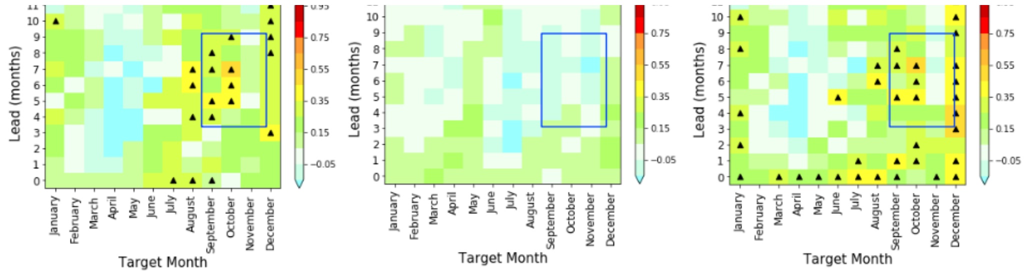
$$ACC(\tau) = \frac{\Sigma_{j=1}^{M}\Sigma_{j=1}^{N}(\langle \mathbf{x}_{\hat{i}j}(\tau)\rangle - \mu(\tau))(x_{ij} - \mu(\tau))}{\sqrt{\Sigma_{j=1}^{M}\Sigma_{j=1}^{N}(\langle \mathbf{x}_{\hat{i}j}(\tau)\rangle - \mu(\tau))^2}\sqrt{\Sigma_{j=1}^{M}\Sigma_{j=1}^{N}(x_{ij}(\tau) - \mu(\tau))^2}}$$

As a result of the clear downward trend in Arctic sea ice over the past decades, the forecast skill as quantified by the ACC may be high despite capturing little of the short time scale variability (Sigmond et al., 2013).

In order to better exhibit the predictive capabilities of the models considered, both the predictions and observations of all time series (except the potential predictability) were subjected to linear detrending before the ACCs were calculated.

In all figures (except the potential predictability experiment), the forecast skill is compared to the skill of an anomaly persistence forecast. An anomaly persistence forecast is one in which the initialization month's anomaly from the climatological mean is applied to the target month's climatological mean. As a long-used (Namias, 1964) method of seasonal forecasting, which with modern computing is relatively trivial, it is used as a baseline from which to assess the added skill of computationally expensive models such as CanSIPS.

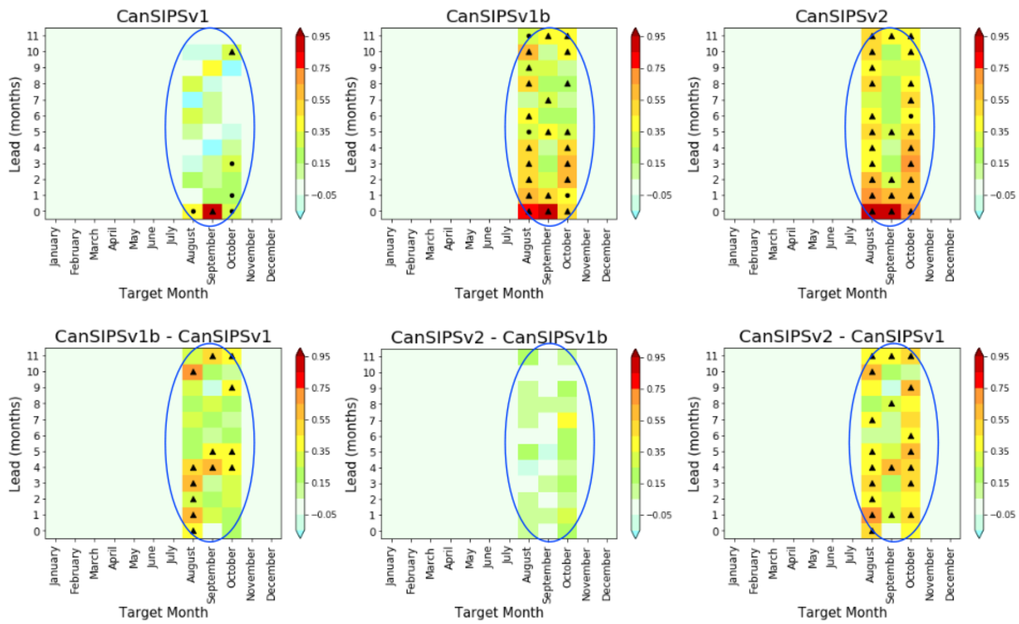




▲ Statistical significance at the 95% confidence level and more skillful than persistence
● Statistical significance at the 95% confidence level, but **not** more skillful than persistence

Skill of forecasts of the spring prediction barrier is increased by improved thickness initialization

Central Arctic Forecast Skill (detrended)
1980 – 2018



▲ Statistical significance at the 95% confidence level and more skillful than persistence
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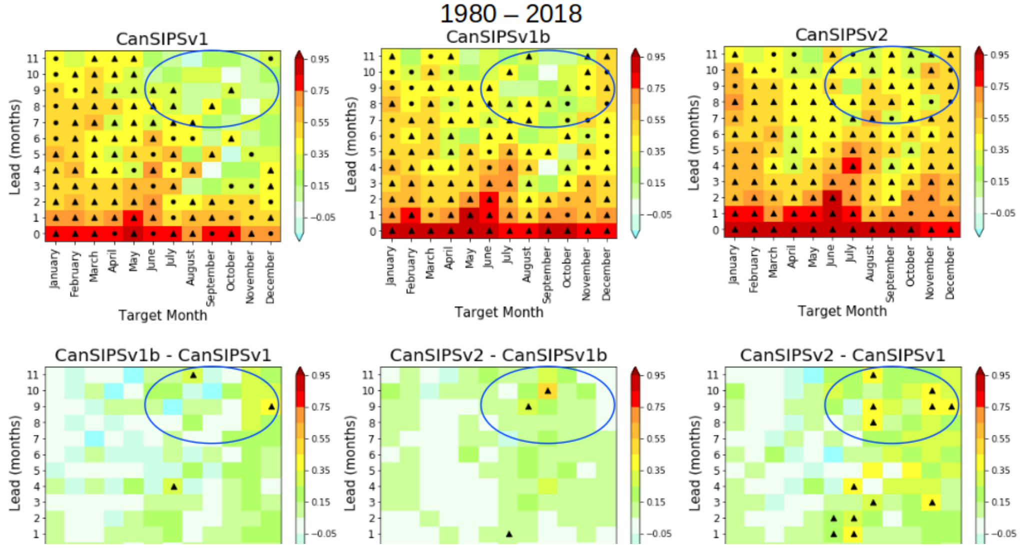
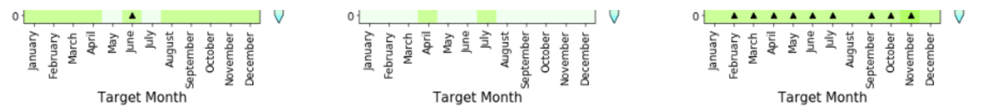
The skill of a variety of Central Arctic forecasts is increased by improved thickness initialization

Barents Sea Forecast Skill (detrended)
1980 – 2018





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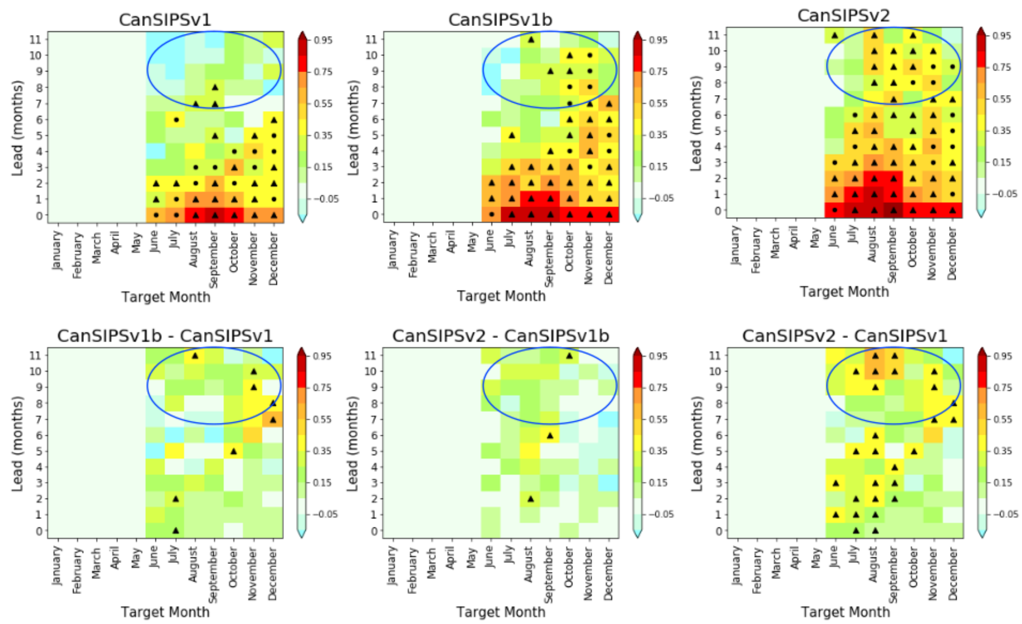
The skill of long lead time Barents Sea forecasts is increased by improved thickness initialization as well as the replacement of CanCM3 with GEM-NEMO

Kara Sea Forecast Skill (detrended)
1980 – 2018



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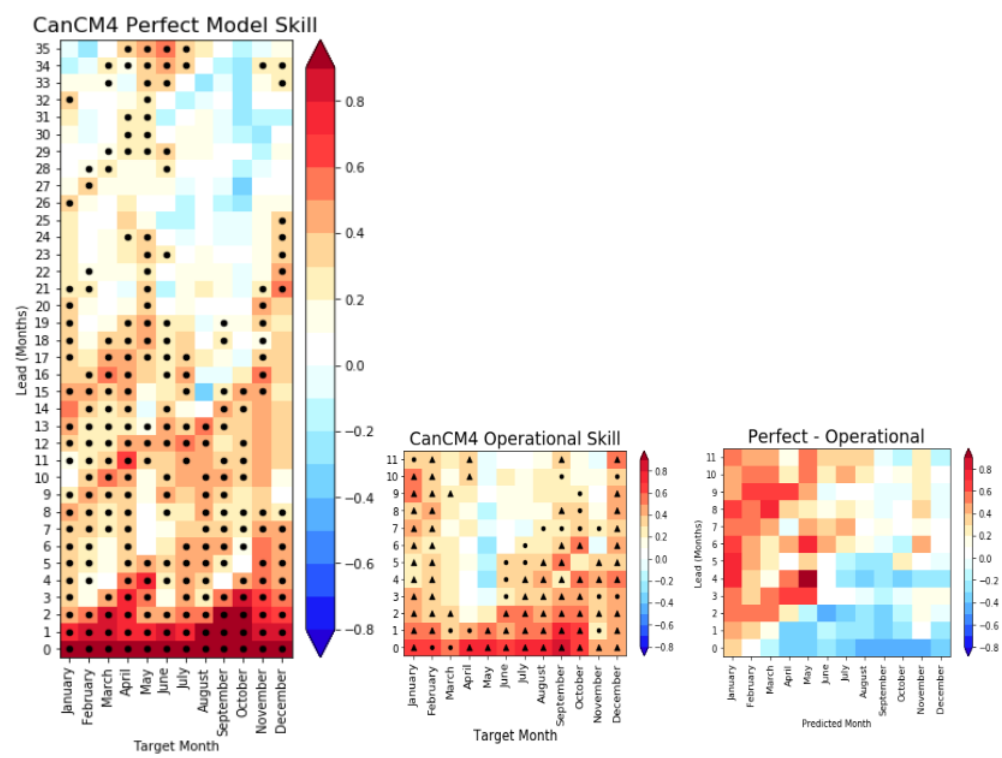
The skill of long lead time Kara Sea forecasts is increased by improved thickness initialization as well as the replacement of CanCM3 with GEM-NEMO



▲ Statistical significance at the 95% confidence level and more skillful than persistence
● Statistical significance at the 95% confidence level, but **not** more skillful than persistence

Perfect model skill (left) and operational model skill (right) for CanCM4. These results suggest that the operational model is apporoaching it's upper boundary of potential predictability.

PREDICTABILITY EXPERIMENT

Designed to mirror Bushuk et al. (2019) as closely as possible

From the last 150 years of a 450 year control run, six start years were selected

Twelve ensemble members were created for six months in each year and run for 36 months

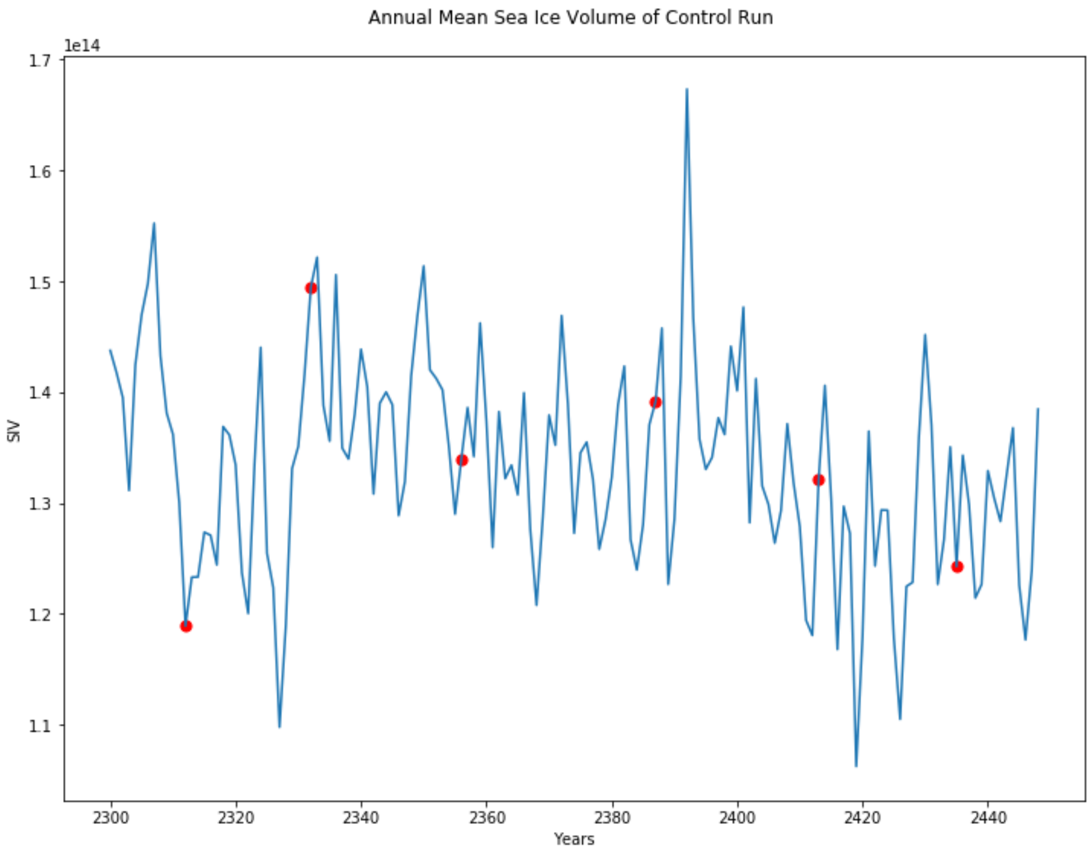


Figure 2 - Sea ice volume timeseries of last 150 years of control run from which six start years were selected. Years were separated into six sextiles by anomaly and one year selected from each in order to prevent artificially high skill from high anomaly years being selected by chance.

The CanCM4 model was run for a 450 year control integration using forcings representative of 1990 conditions. From the final 150 years of the control integration, six start years were chosen. These years (shown in Figure 1) were chosen one each from sextiles organized by sea ice volume anomaly. For each year, twelve-member ensembles were initialized for the months January, March, May, September, and November and run for 36 months.

In assessing perfect model skill, each ensemble member was in turn designated the "truth" with the others designated 'forecasts". The ACC was then calculated by comparing the forecast ensemble mean to the truth. Note that for perfect model analysis, the anomalies are calculated relative to the climatological mean of the control integration, not of the ensemble member itself.

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