Science and Technology Infusion Climate Bulletin
NOAA's National Weather Service
41st NOAA Annual Climate Diagnostics and Prediction Workshop
Orono, ME, 3-6 October 2016

Prediction of Seasonal Arctic Sea Ice Extent Using the NMME

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1. Introduction

Arctic sea ice decline is a well-documented topic with many studies outlining the September minimum as decreasing by more than 10% per decade since satellite observations began in 1979. Within the past few decades, the rate of decline has been shown to be increasing significantly due to both thinning ice and longer melt seasons. When it comes to prediction of the Arctic sea ice extent (SIE), there is potential for skillful predictions mainly attributed to individual modeling system's ability to predict the long-term trend (Sigmond *et al.* 2013, Wang *et al.* 2013, Chevallier *et al.* 2013, Holland *et al.* 2011, *etc.*).

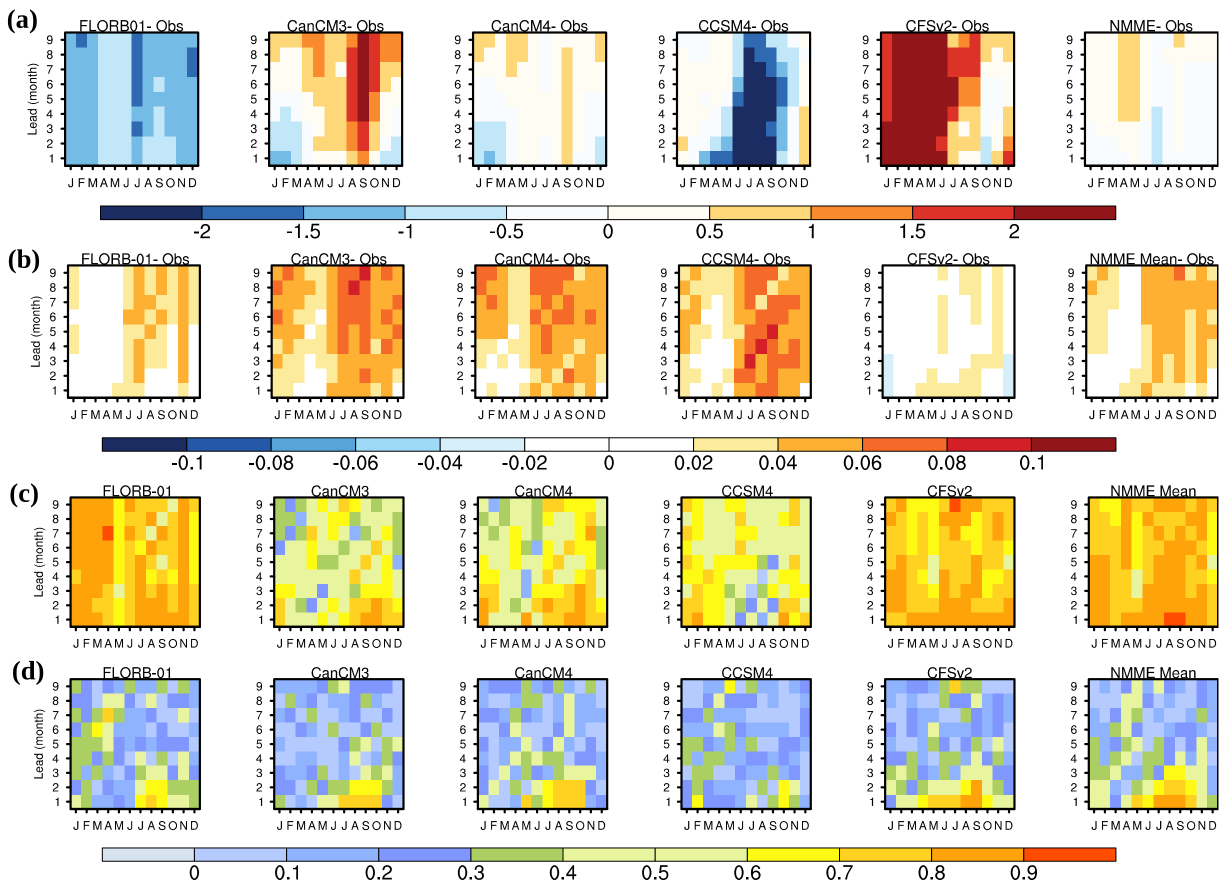

Fig. 1 Model bias (model minus observations) including the NMME for (a) Total SIE [10^6 km^2] and (b) the Y2Y SIE [10^6 km^2]. (c) and (d) are ACC for total SIE and Y2Y, respectively.

SIE prediction skill has been assessed by a variety of dynamical, statistical, and heuristic models. For other variables, it has been shown that predictions using the ensemble means from different models tend to outperform any individual system [Merryfield *et al.* 2013; Stroeve *et al.* 2014]. The North American Multi-Model Ensemble (NMME) takes advantage of the multi-model approach by utilizing a multi-agency team to

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collect and organize global model data on a somewhat uniform spatial and temporal scale. This study seeks to expand on previous multi-platform studies by utilizing output from five NMME models to determine the skill in predicting Arctic SIE based on the long term trend and year-to-year (Y2Y) variability.

2. Data

There are 5 models that currently provide sea ice predictions to the NMME archive. Each hindcast simulation is initialized and allowed to run for either 12 months (CanCM3, CanCM4, FLORB-01, and CCSM4) or 9 months (CFSv2). To maintain consistency for all models and in creating an NMME average, all of the models are evaluated during the 1982-2011 time period, which represents the time when all 5 models have results and for a 9 month forecast extent. Observations derived from NASA Bootstrap version of the National Snow Ice Data Center NASA GSFC sea ice concentration are utilized in order to calculate the skill metrics.

3. Summary of results

Figure 1 shows the model bias for (a) total SIE and (b) Y2Y SIE. Overall, the NMME predictions of total SIE have less error than the individual predictions. In contrast, the Y2Y difference evaluates SIE prediction irrespective of the long-term trend. For all individual models and the NMME, the Y2Y differences show a generally positive bias, meaning that from one year to the next, the models tend to predict more SIE than observed. While the Y2Y values are not providing information on the long-term trend, this result implies the models are not capturing the magnitude of the loss of SIE from one year to the next. The NMME Y2Y bias shows improvement over CanCM3, CanCM4, and CCSM4, with CFSv2 and FLORB-01 having overall the best Y2Y prediction.

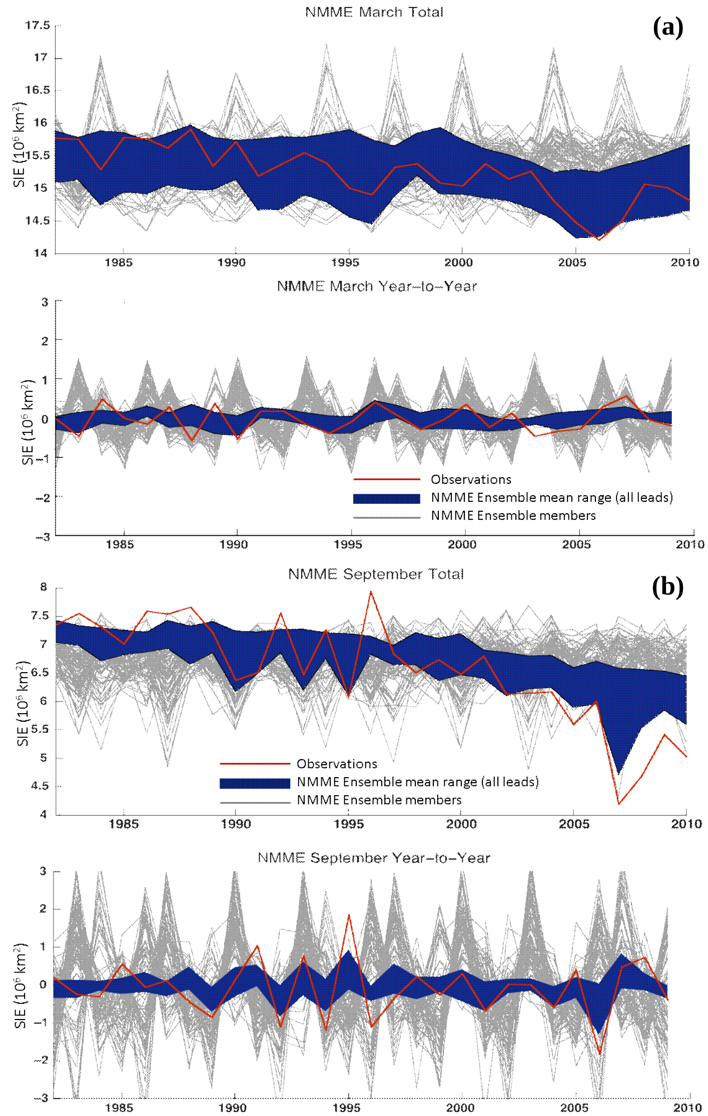

Fig. 2 Time series for NMME SIE in March (a) and September (b) for total (top) and Y2Y (bottom) SIE with observations (red line), the range of ensemble means at all lead times (blue shading), and individual ensemble members (grey lines).

To further quantify prediction skill, Figure 1 also shows the ACC values for the (c) total SIE and (d) Y2Y SIE. One primary feature across all models is the smaller ACC in Y2Y variability compared to the prediction of total SIE. For both total and Y2Y SIE, the NMME predictions result in generally higher ACC compared to the individual. The higher ACC with NMME is evident for predictions of Y2Y variability, especially for lead times greater than 3 months. The NMME also noticeably improves upon CanCM3, CanCM4, and CCSM4 for predictions of total SIE. Overall, relative to the skill of individual models, the NMME offers the most bias reduction for predictions of total SIE, and the correlations are highest for the prediction of Y2Y SIE.

Figure 2 compares the total and Y2Y SIE observational data (red) to the range of ensemble means (blue) and all members (grey) from NMME for 1982-2010. All forecast lead times are shown leading up to the March or September target month. The biases seen in Figure 1 are also reflected within this analysis, except now it is easier to view the evolution of the model forecasts as the SIE changes over time. For predictions of March total SIE, the observations largely fall within the spread of the NMME. The observations also largely lie within the spread of predictions for March Y2Y SIE. However, for the Y2Y SIE predictions, the variance of the individual members is clearly larger than the observed variability across the NMME.

In contrast to March, predictions for September total SIE show that there are periods of time when the observations clearly lie outside of the spread of the model predictions. This is particularly true in the years following the large sea ice melt in 2007, when the NMME underestimated the degree of sea ice loss. Only during the recent period did the spread of forecasts from these models contain the observed September SIE. As for the March total SIE, the NMME predictions of September SIE appears to encompass the observed variability more often than any individual model. For the September Y2Y SIE, the observations largely lie within the spread of the model forecasts with the exception of the more extreme Y2Y years. But even in those instances, it appears the variance of the Y2Y individual members largely captures the variance of the observational data.

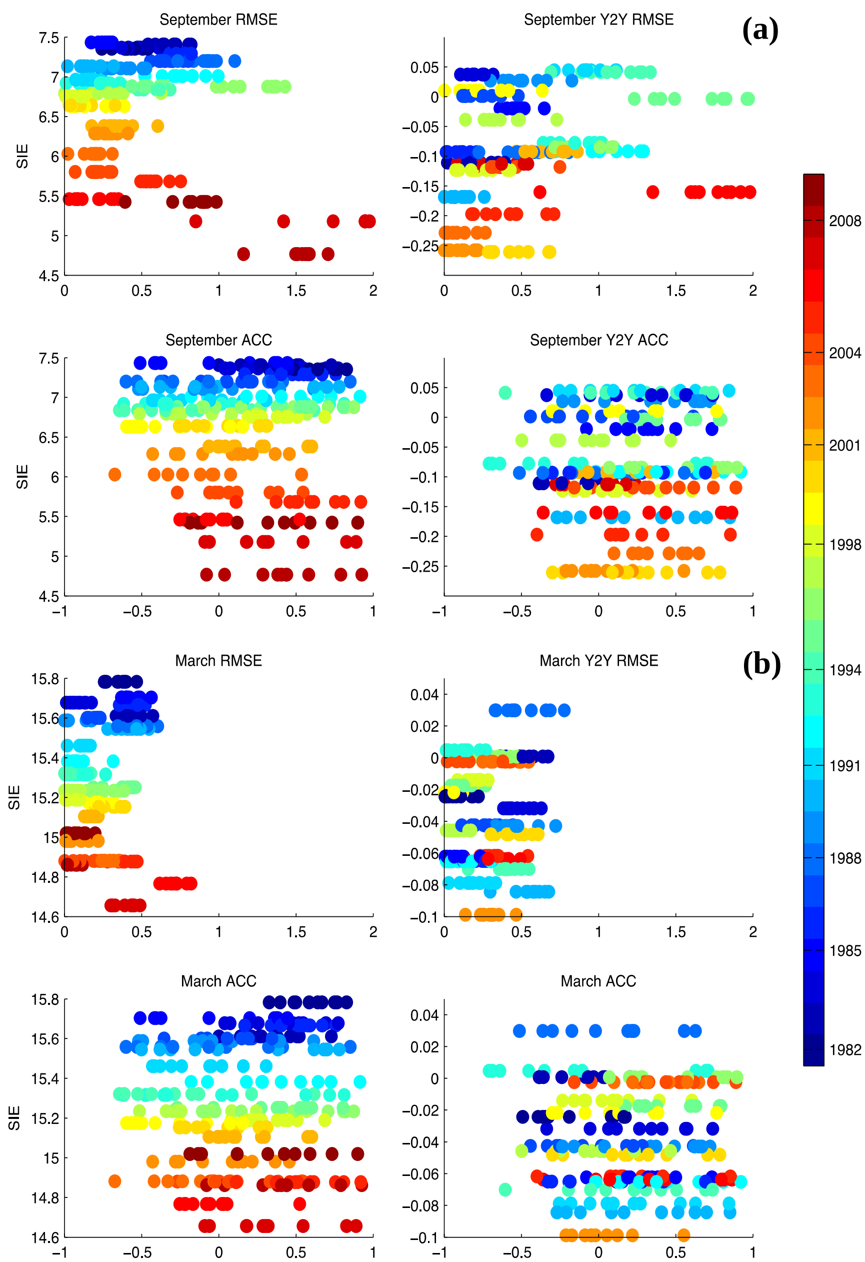

Fig. 3 September (a) and March (b) root-mean-square error (RMSE; top) and ACC (bottom) versus total SIE (left) and Y2Y (right) with year indicated by the colors.

Both the total and Y2Y time series in Figure 2 are smoothed using a 10-year running mean and presented versus model ACC and RMSE values. These scatterplots (Figure 3) show the skill for the 9 forecast lead times with respect to the total or Y2Y SIE. The associated 10-year period is indicated by the color shading, with reds (blues) indicating later (earlier) periods. Over these running 10-year periods, the ACC values in both September and March do not show any clear tendency over time. The RMSE tells a different story especially during September when the RMSE values are considerably larger during the more recent decades than the ones prior. The RMSE for Y2Y SIE does not show the same temporal trend, with the larger errors inclusive of decades with the largest Y2Y departures shown in Figure 2. Because Y2Y changes are independent of the longer-term trends, this suggests that errors in the prediction of the total SIE are increasing over time because the NMME is not adequately capturing the trend or variability in recent years. In contrast, March does not show the same clear trend over time, and in general, the amplitude of RMSE for both total and Y2Y SIE is smaller in March compared to September, likely due to smaller trends and year-to-year variability during a month when the SIE is typically maximized.

4. Discussion

The NMME approach provides the most gain over individual models through decreased bias for predictions of total SIE and increased correlations of Y2Y SIE variability. There is a tendency for all models and the NMME to over-predict Y2Y SIE from one year to the next. The struggle of the models to predict the following year SIE change, along with the increasingly larger errors for September SIE predictions in recent decades, suggest that prediction of the trend remains a fundamental challenge for most coupled modeling systems. Regardless, it is clear that the average of multiple models generally exceeds the skill of any one modeling system, so the NMME demonstrates value for the prediction of Arctic SIE.

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