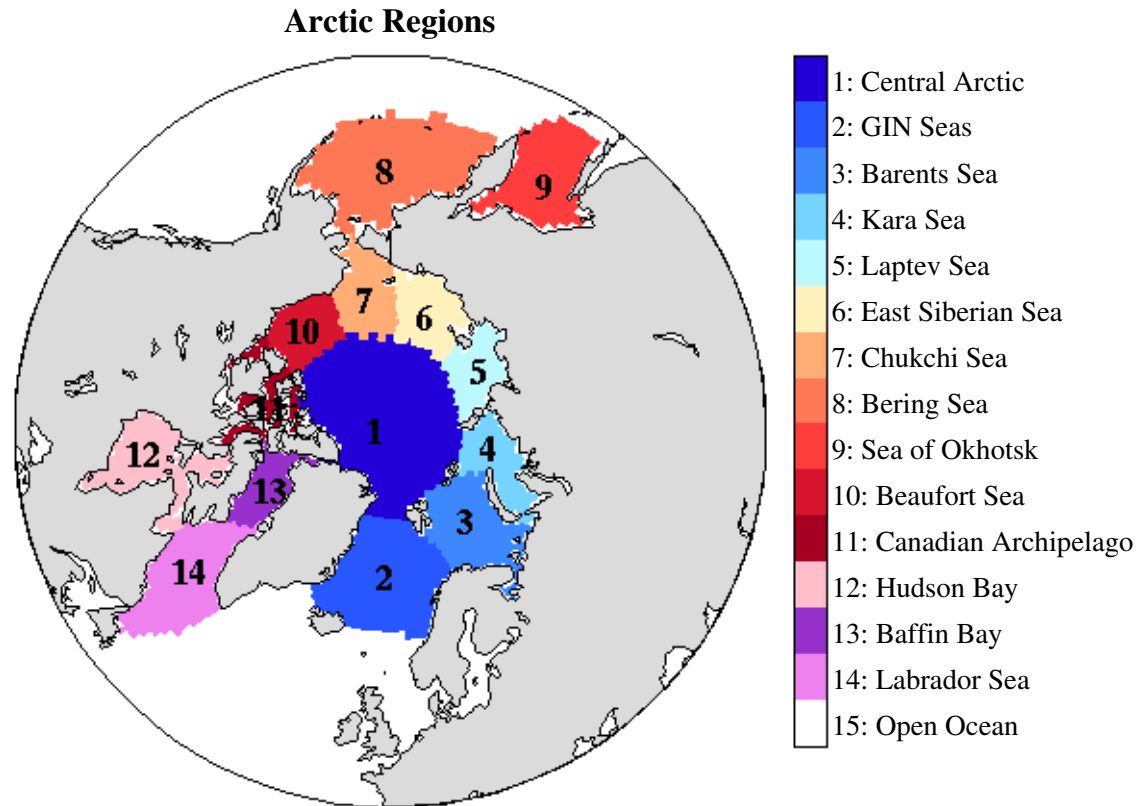


Regional Arctic sea-ice prediction: Potential versus operational seasonal forecast skill

Mitch Bushuk
GFDL and Princeton University

With contributions from:
Rym Msadek, Michael Winton,
Gabriel Vecchi, Anthony Rosati,
Xiaosong Yang, Rich Gudgel

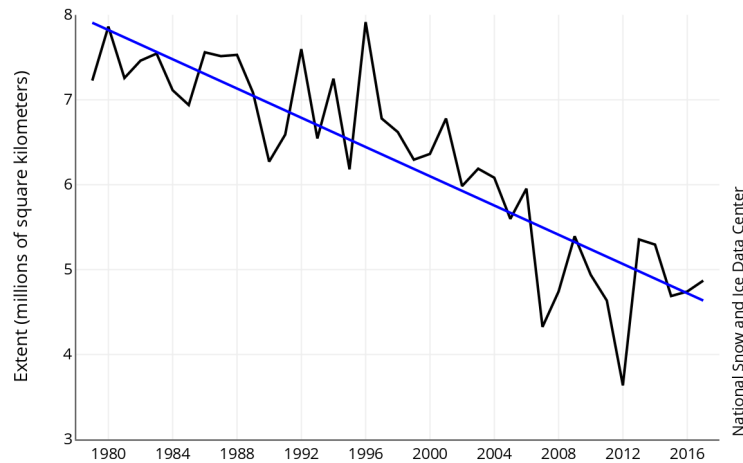
Conference on Subseasonal to
Decadal Prediction
S2D Session B6
Sept 20, 2018



The Changing Arctic Sea-Ice Cover

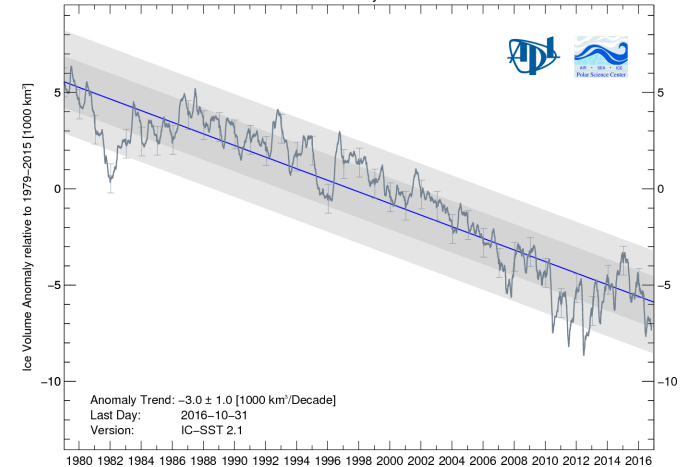
Negative extent trend

September 1979 - 2017

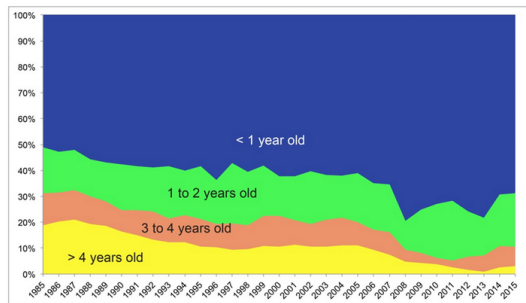


Negative volume trend

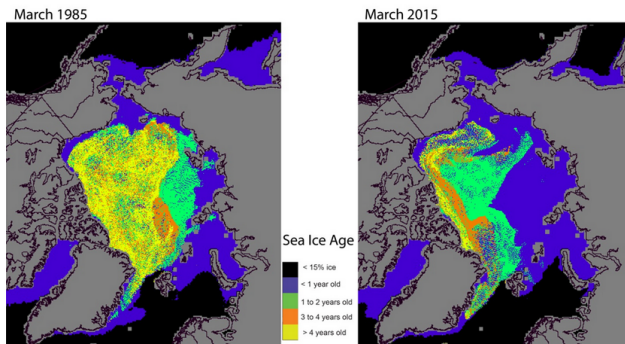
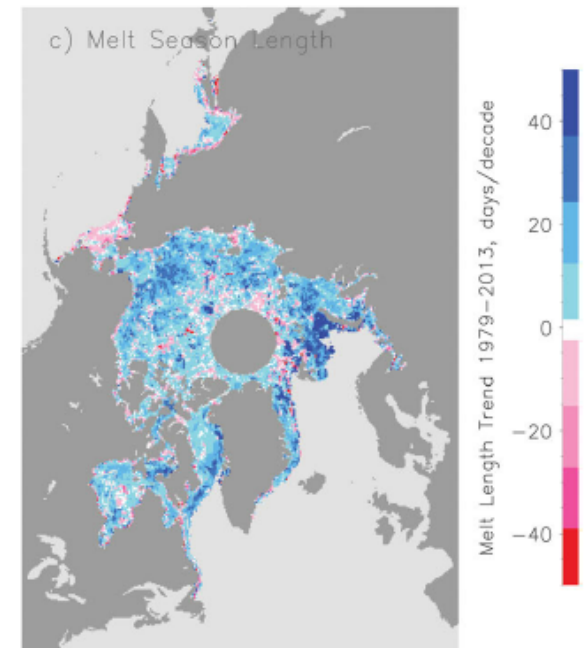
Arctic Sea Ice Volume Anomaly and Trend from PIOMAS



Younger and thinner ice cover

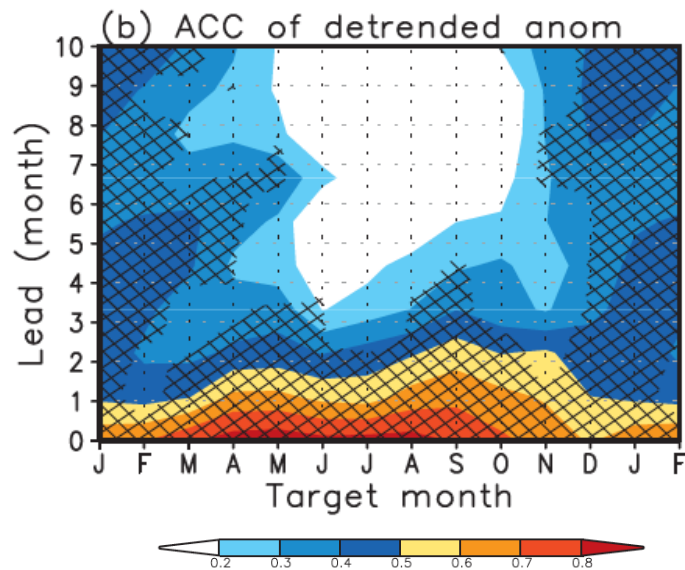


Longer melt seasons

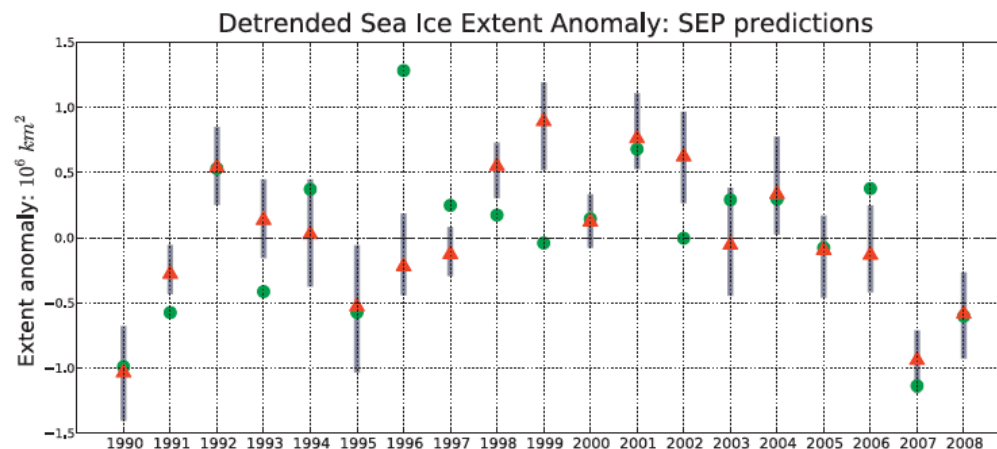


Operational Pan-Arctic Seasonal Sea Ice Predictions

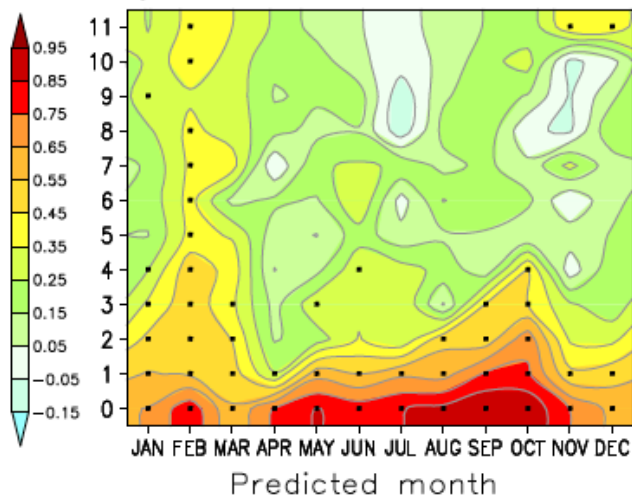
- GCM-based hindcast skill for detrended SIE: 0-6 months



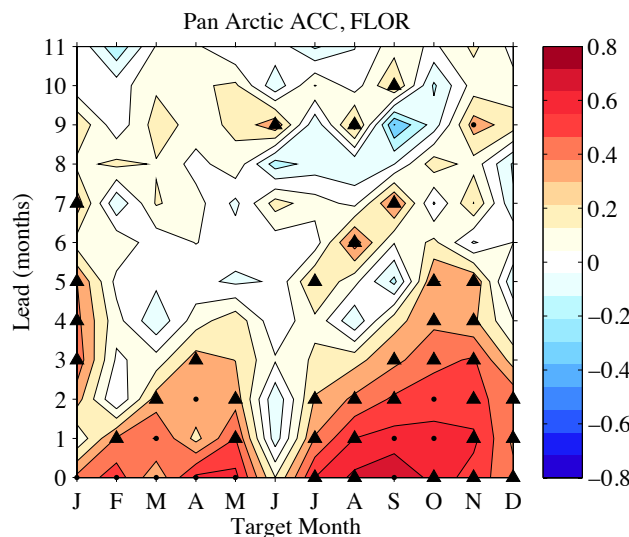
Wang et al. 2013, *Mon. Wea. Rev.*



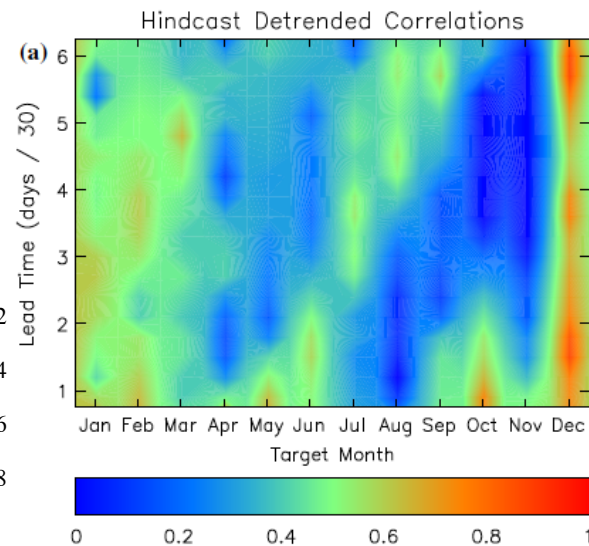
Chevallier et al. 2013, *J. Climate*



Merryfield et al. 2013, *GRL*;
Sigmond et al. 2013, *GRL*



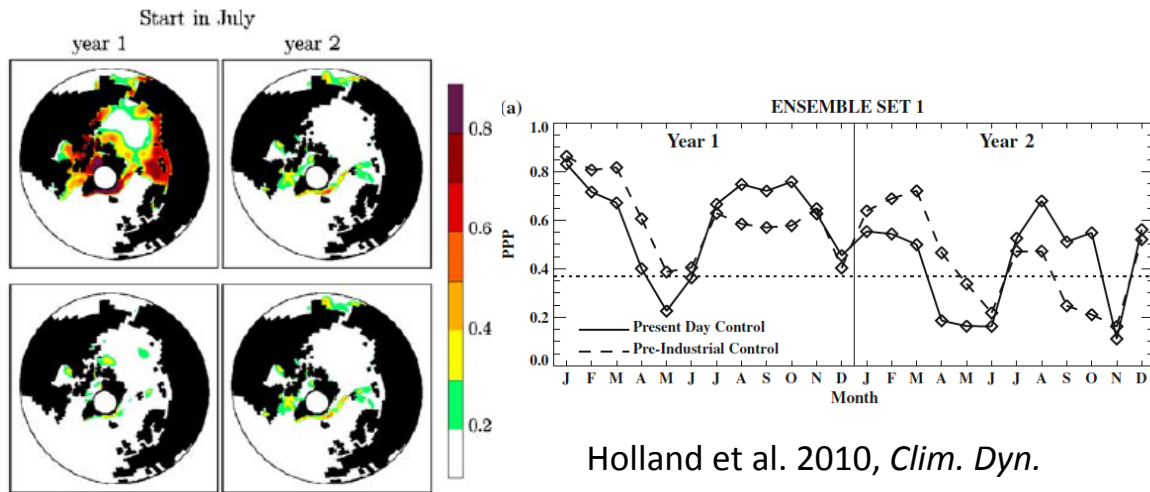
Msadek et al. 2014, *GRL*;
Bushuk et al. 2017, *GRL*



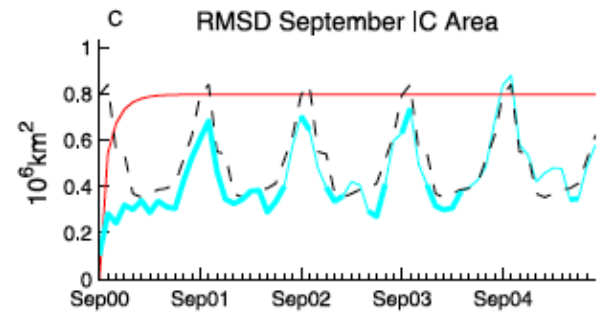
Peterson et al. 2015, *Clim. Dyn.*

Perfect Model Pan-Arctic Sea Ice Predictions

- Perfect model skill: 12-24 months

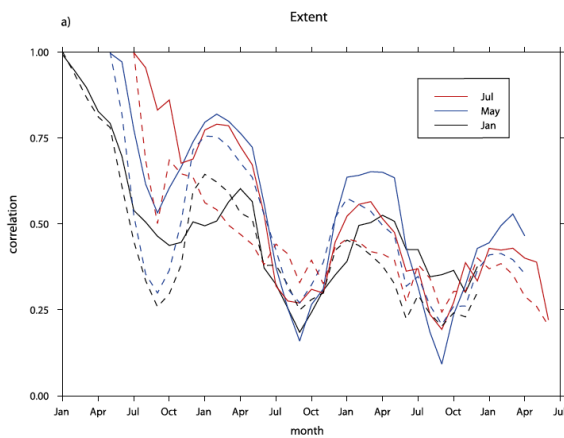


Holland et al. 2010, *Clim. Dyn.*

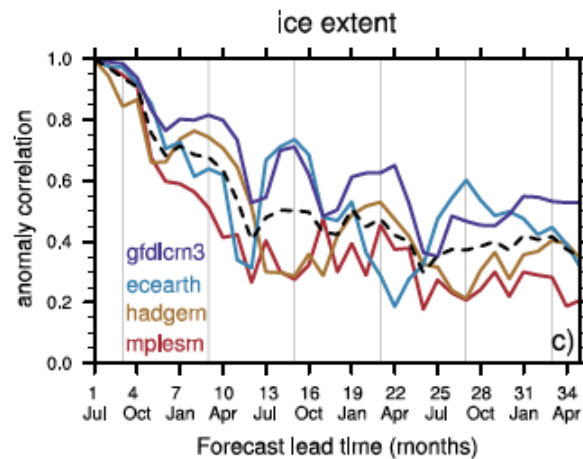


Blanchard-Wrigglesworth et al. 2011, *GRL*

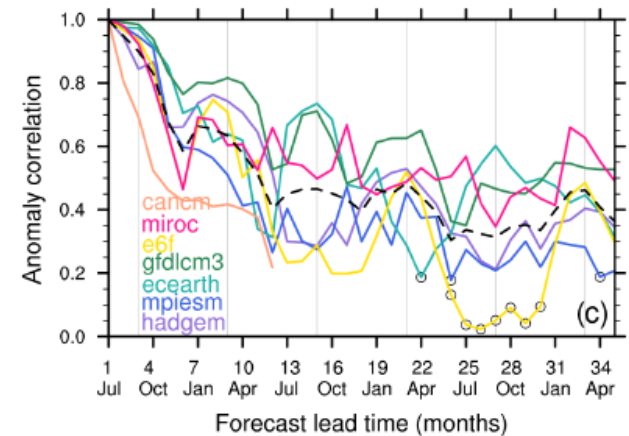
Koenig and Mikolajewicz
2009, *Clim. Dyn.*



Day et al. 2014, *J. Climate*



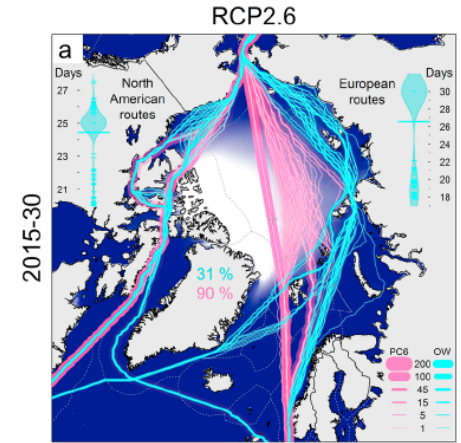
Tietsche et al. 2014, *GRL*



Day et al. 2016, *GMD*

Motivating questions/ideas for this work

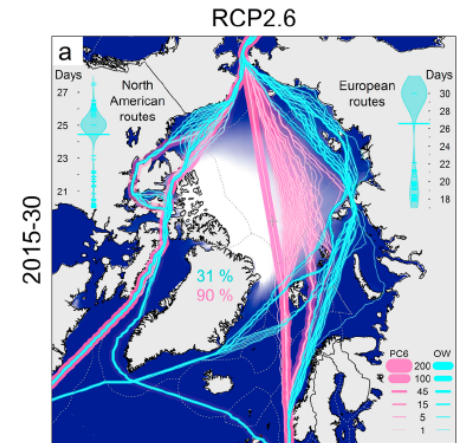
(1) Regional Arctic sea ice predictability: How skillful are operational and perfect model regional predictions?



Motivating questions/ideas for this work

(1) Regional Arctic sea ice predictability: How skillful are operational and perfect model regional predictions?

(2) Assess operational and perfect model skill within a common dynamical prediction system

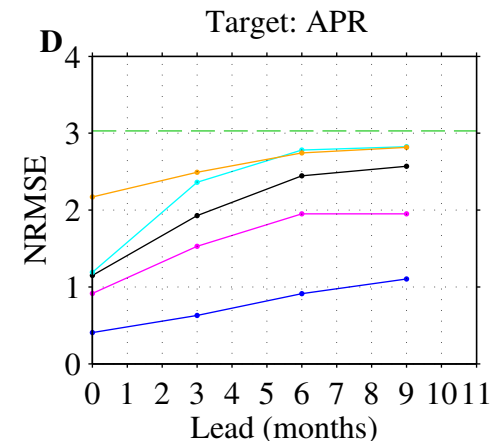
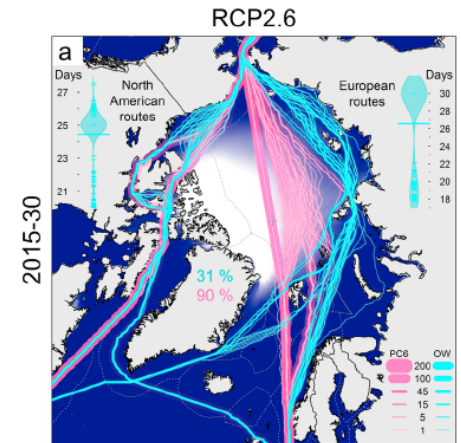


Motivating questions/ideas for this work

(1) Regional Arctic sea ice predictability: How skillful are operational and perfect model regional predictions?

(2) Assess operational and perfect model skill within a common dynamical prediction system

(3) How do we improve regional sea ice predictions?



The Dynamical Forecast Model

GFDL-FLOR¹: Forecast-oriented Low Ocean Resolution

- Fully-coupled global model
- Atmosphere and Land (50km)
- Ocean and Sea Ice (1°)



```
graph TD; A[GFDL-FLOR1: Forecast-oriented Low Ocean Resolution] --> B[Operational Predictions]; A --> C[Perfect Model Predictions];
```

Operational Predictions

Perfect Model Predictions

1: Vecchi et al. 2014, *J. Climate*

The Dynamical Forecast Model

GFDL-FLOR¹: Forecast-oriented Low Ocean Resolution

- Fully-coupled global model
- Atmosphere and Land (50km)
- Ocean and Sea Ice (1°)

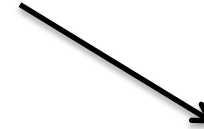


Operational Predictions

Initialized from ECDA²:

Ensemble Kalman Filter Coupled Data Assimilation

- Ocean assimilates satellite SST, ARGO, CTD, XBT, other WOD profiles
- Atmosphere assimilates NCEP reanalysis
- No assimilation of sea ice data



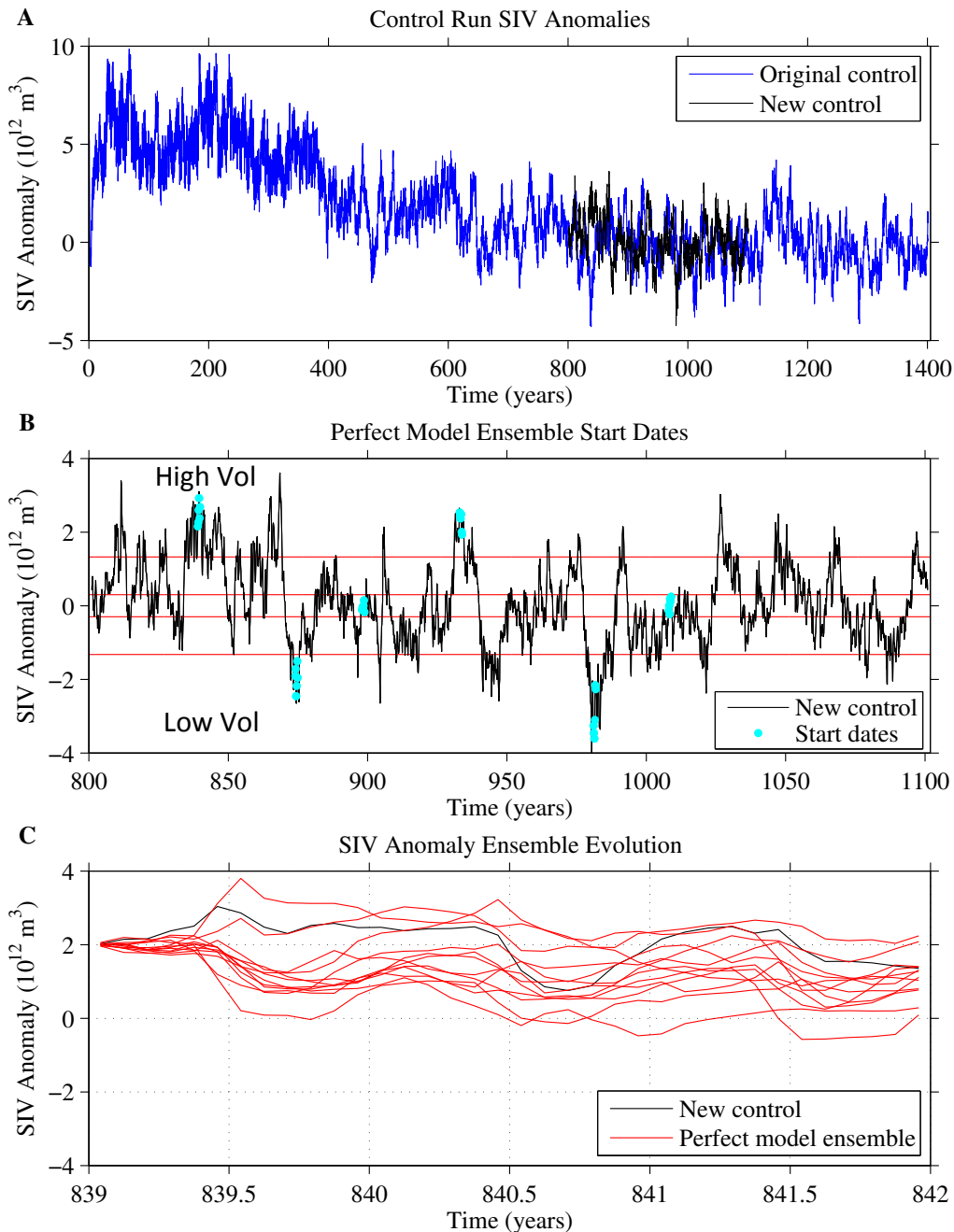
Perfect Model Predictions

Retrospective Forecasts

- Forecasts initialized on the first of each month; run for one year
- 12-member ensemble
- Retrospective forecasts spanning 1980-2017

1: Vecchi et al. 2014, *J. Climate*; 2: Zhang et al. 2007 *Mon. Wea. Rev.*

Perfect Model Predictions with GFDL-FLOR



- **Start Months**
Jan, Mar, May, Jul, Sep, Nov
- **Start Years**
839, 874, 898, 933, 981, 1008
- **Ensemble members**
12
- **Integration time**
3 years

Key Design Aspects

- Experiments run from well equilibrated climate of 1990 control run
- Seasonal coverage of start dates allows for study of skill at different lead times
- Performed with same model as seasonal forecast system. Allows for direct comparison of perfect model and operational skill

Bushuk et al. 2018, *Clim. Dyn.*

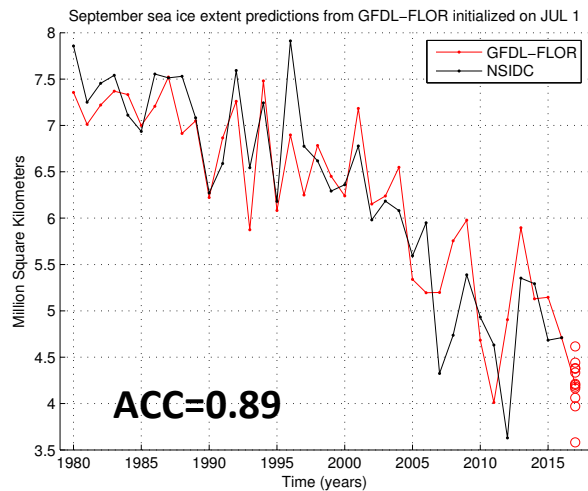
Operational Predictions of Pan-Arctic SIE

Target month: Month we are trying to predict

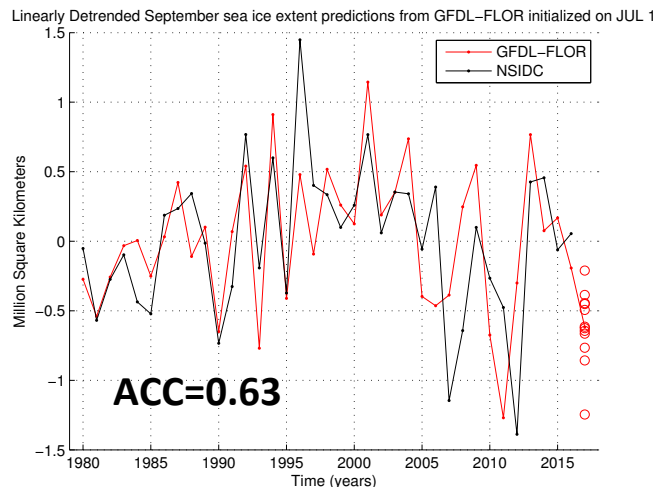
Lead time: Number of months prior to target month that forecast was initialized

Anomaly correlation coefficient (ACC): Correlation between observed and predicted SIE

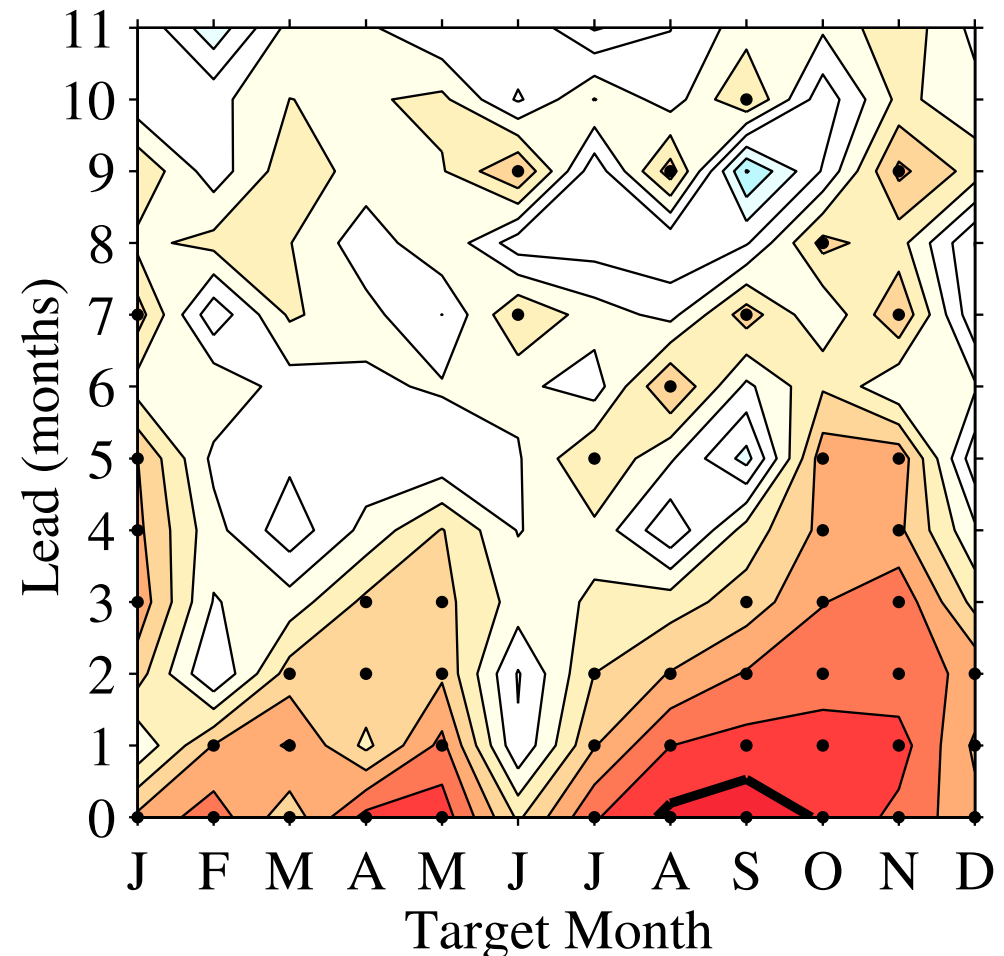
Target: September; Lead: 2



Detrended

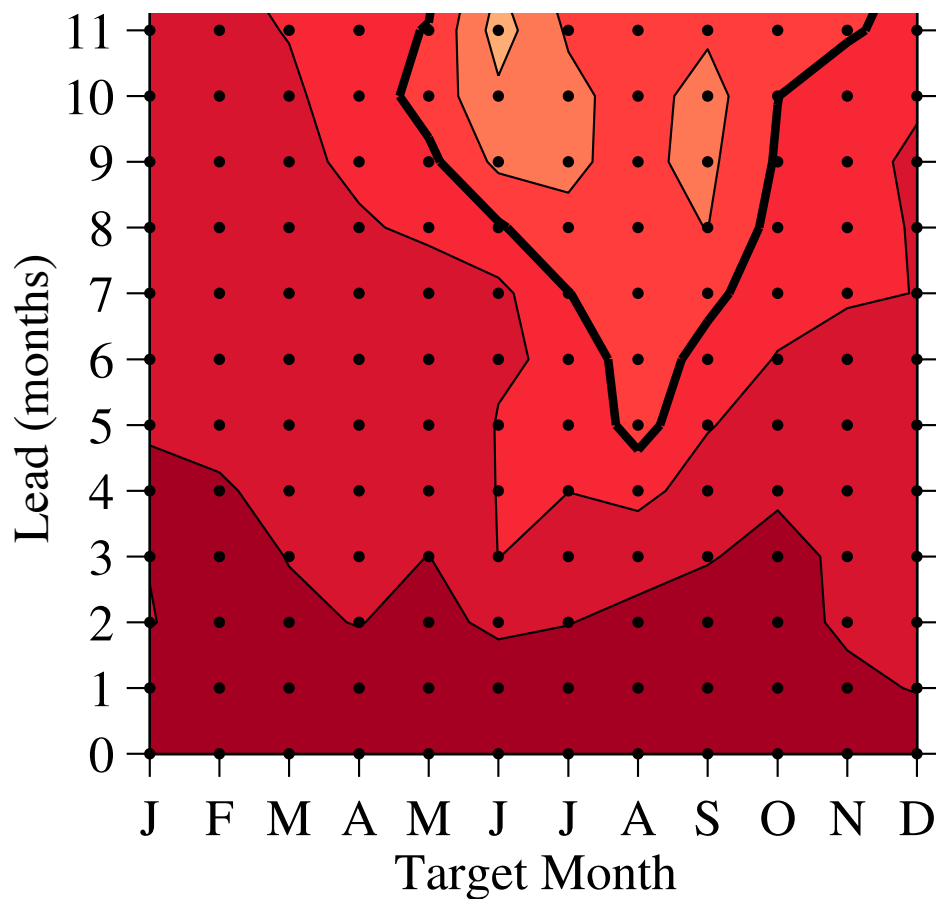


Initialized Forecast Skill (ACC)

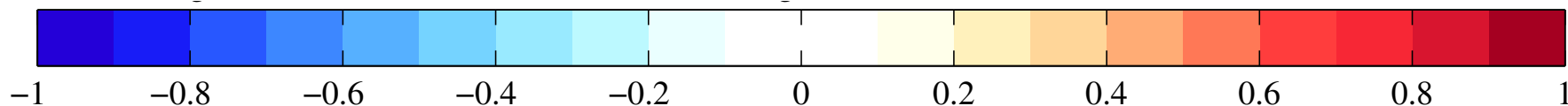
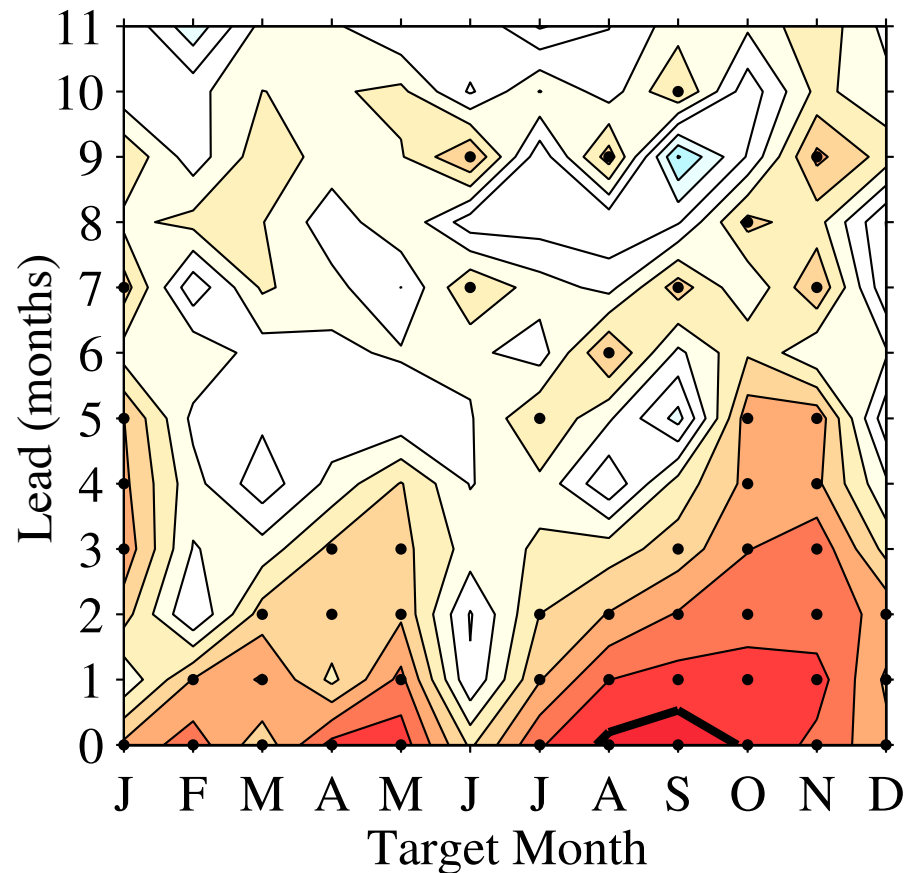


Comparison of Perfect Model and Operational Skill: Pan-Arctic SIE

Perfect Model Skill (ACC)



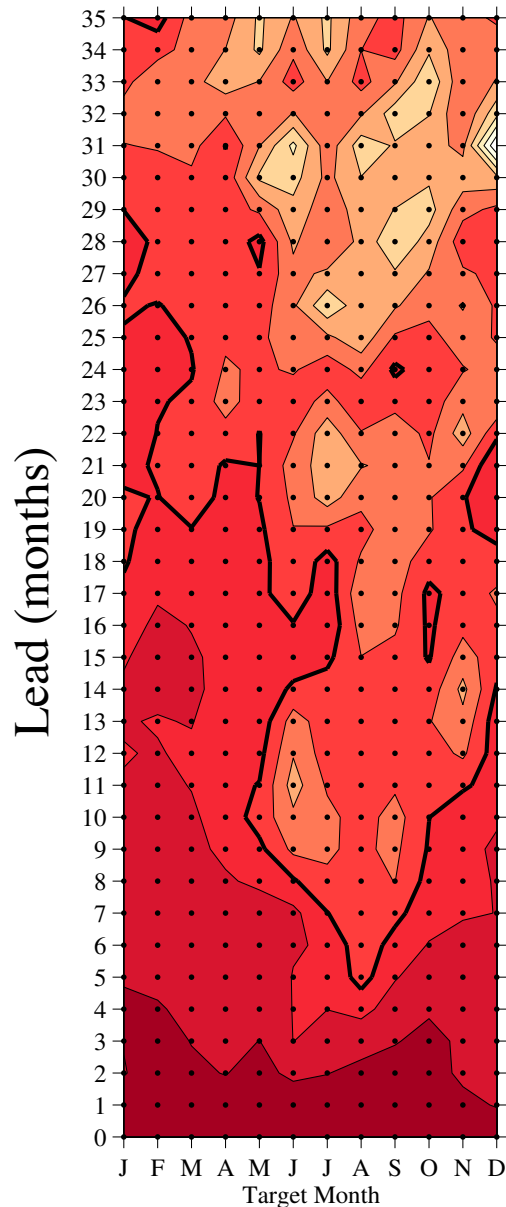
Initialized Forecast Skill (ACC)



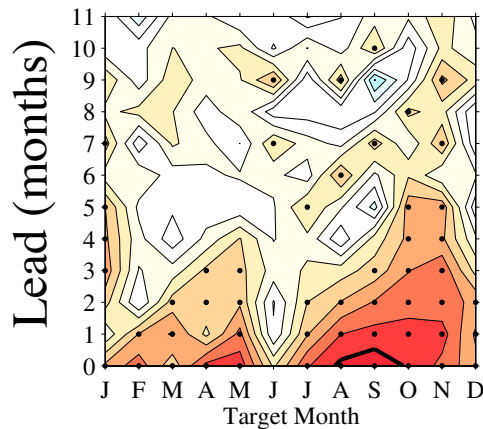
● : Statistically significant prediction skill

The Prediction Skill Gap: Pan-Arctic SIE

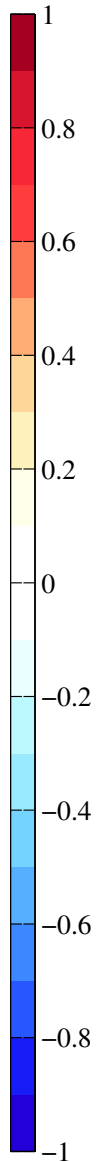
Perfect Model Skill (ACC)



Initialized Forecast Skill (ACC)

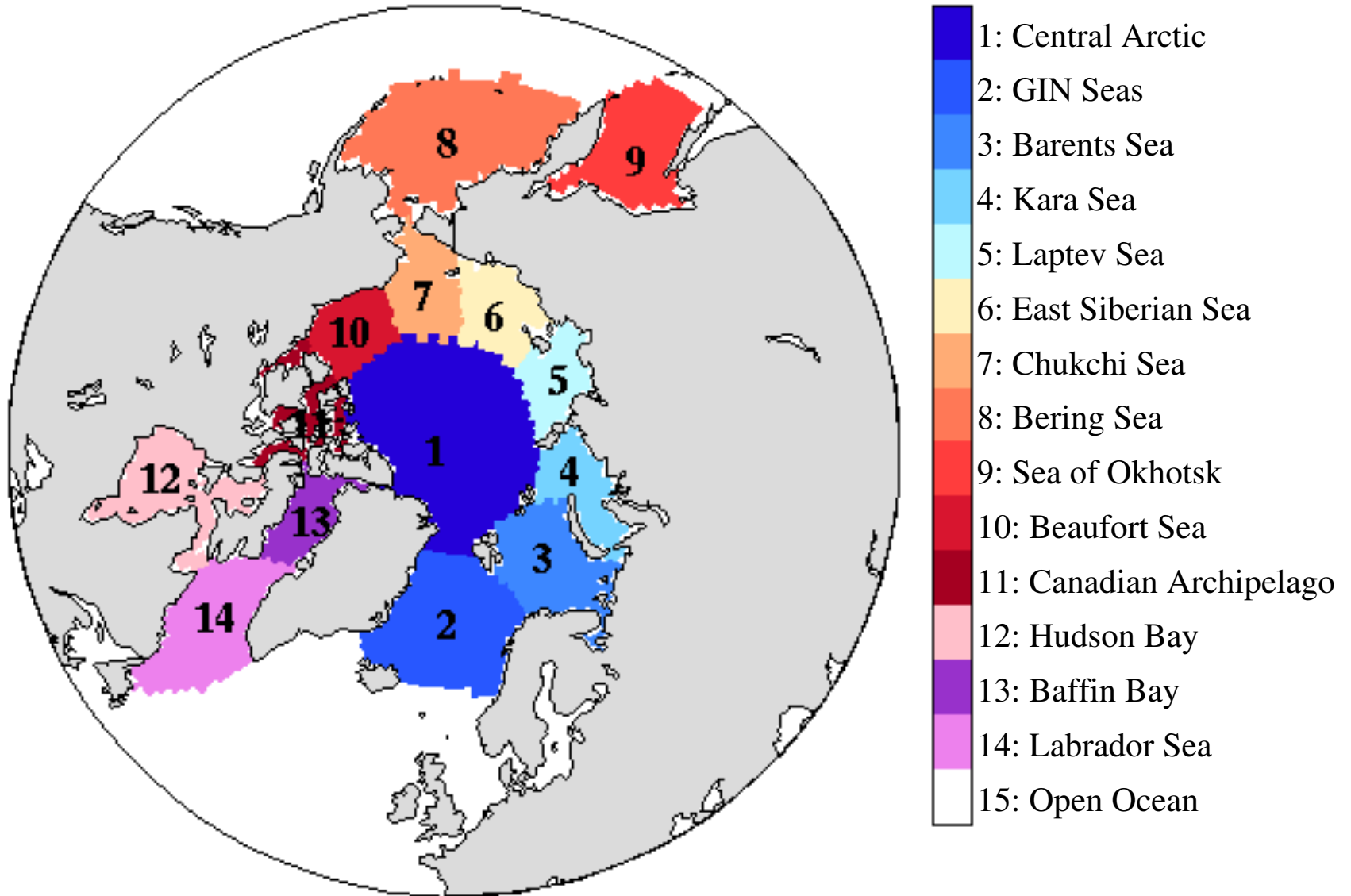


Black contour:
ACC=0.7



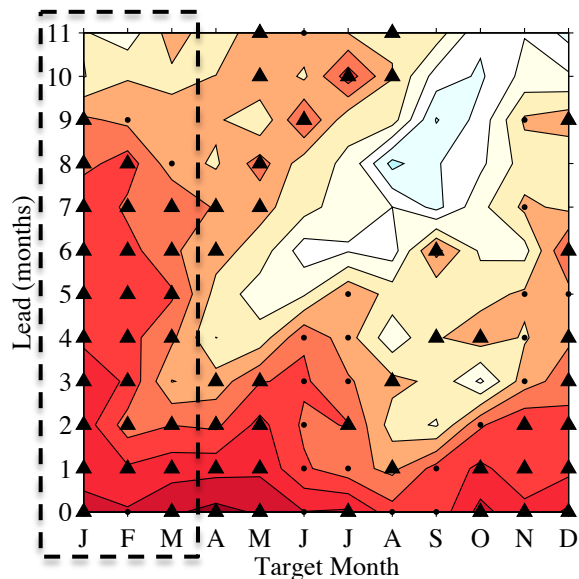
Regional Prediction Skill

Arctic Regions

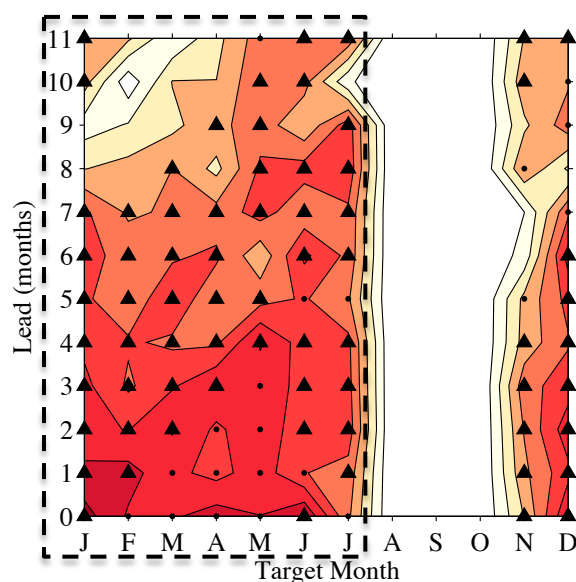


Operational Prediction Skill For Winter Ice Regions (Region # in parentheses)

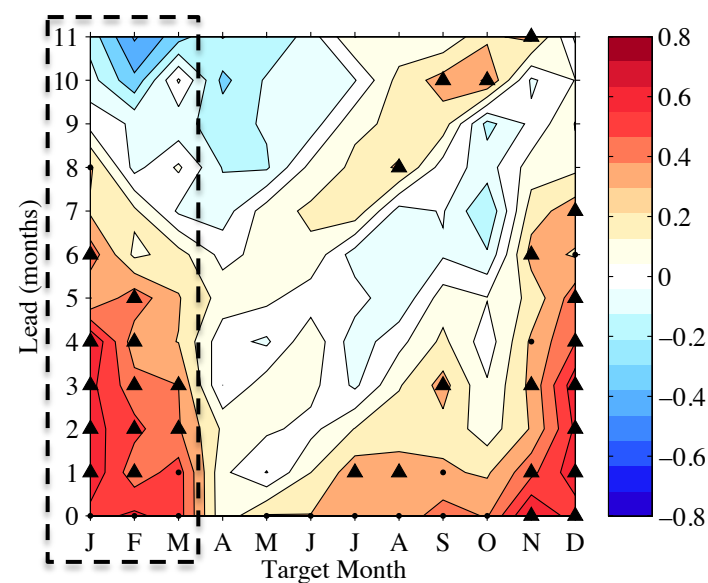
Barents Sea (3)



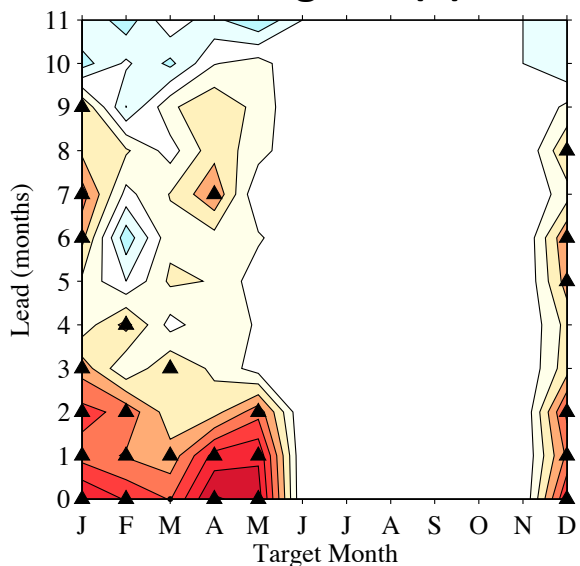
Labrador Sea (14)



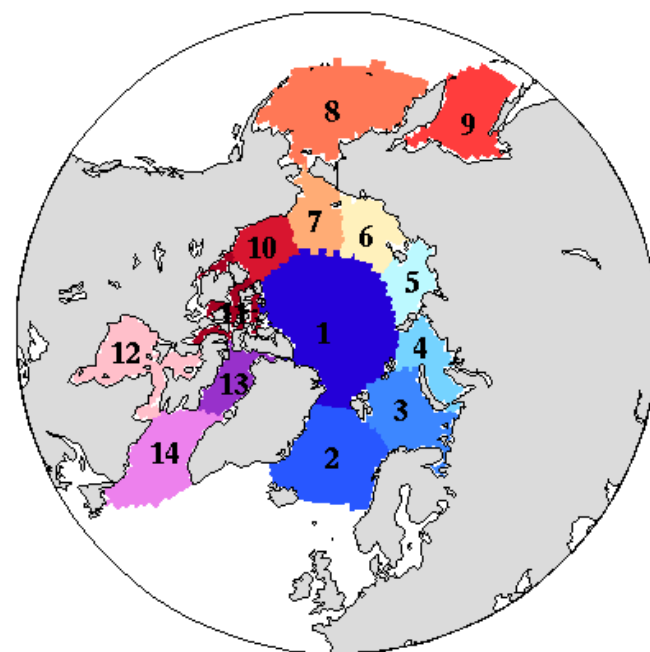
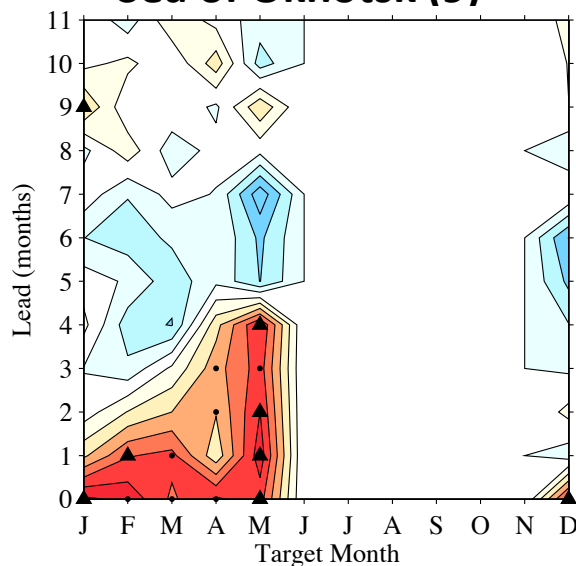
GIN Seas (2)



Bering Sea (8)

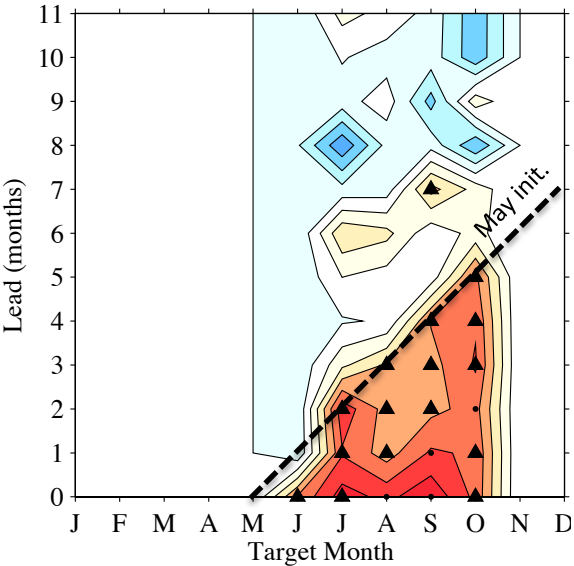


Sea of Okhotsk (9)

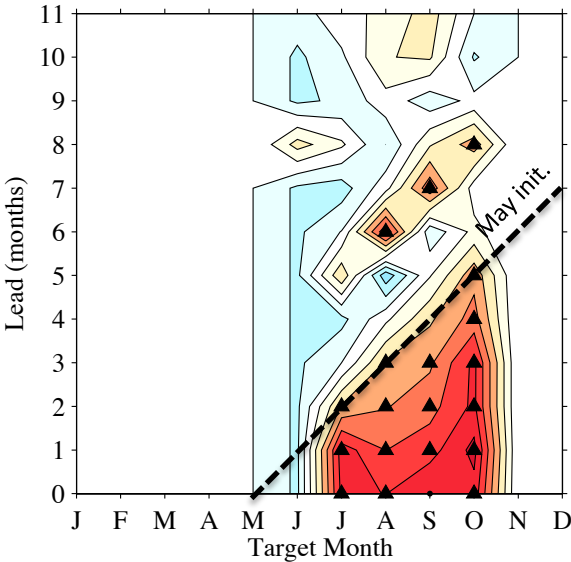


Operational Prediction Skill For Summer Ice Regions (Region # in parentheses)

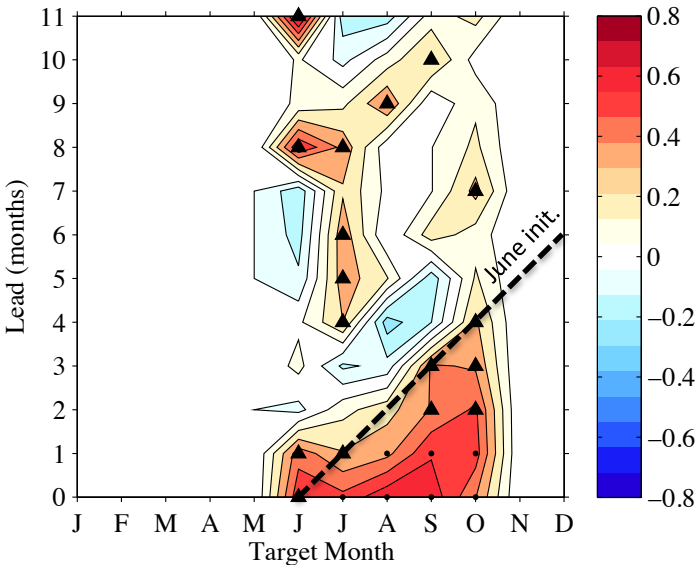
Laptev Sea (5)



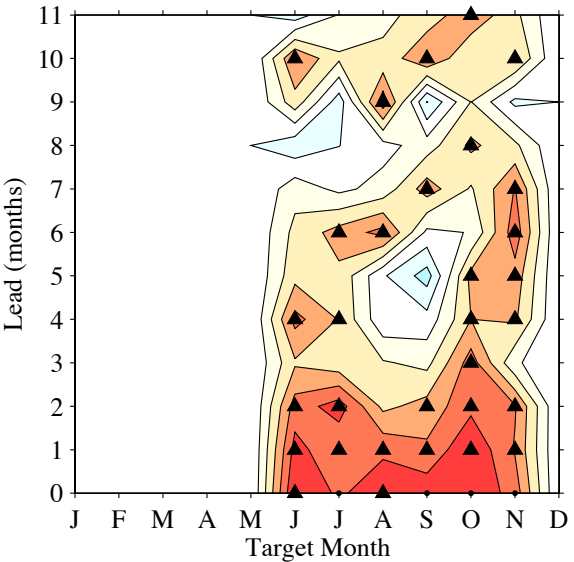
East Siberian Sea (6)



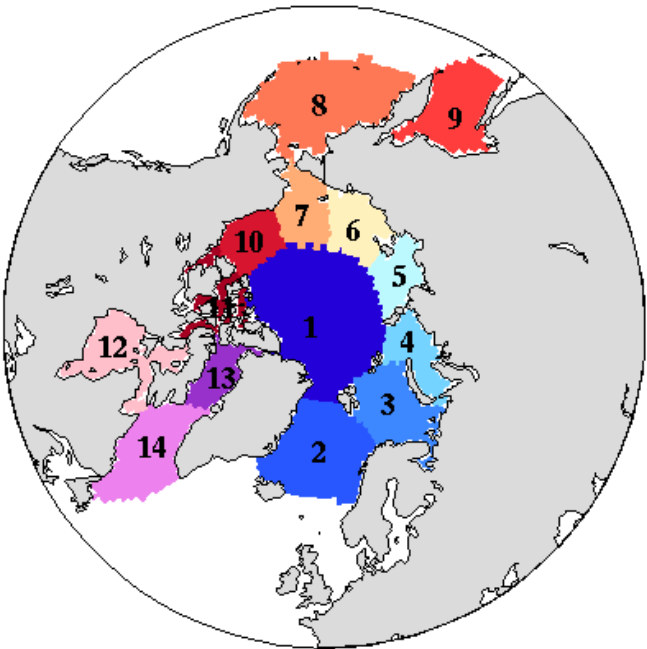
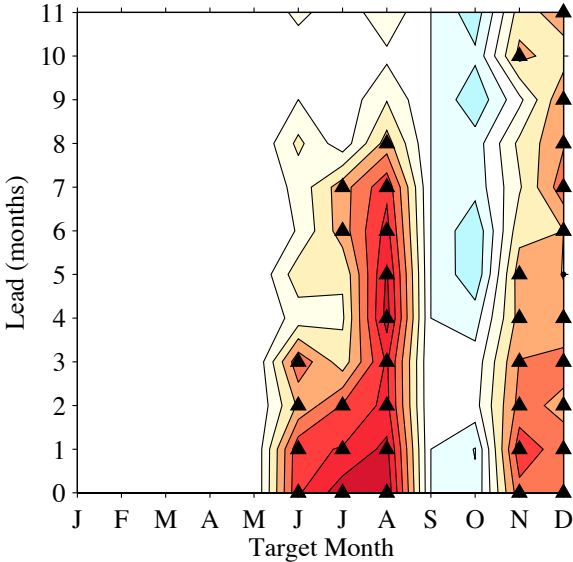
Beaufort Sea (10)



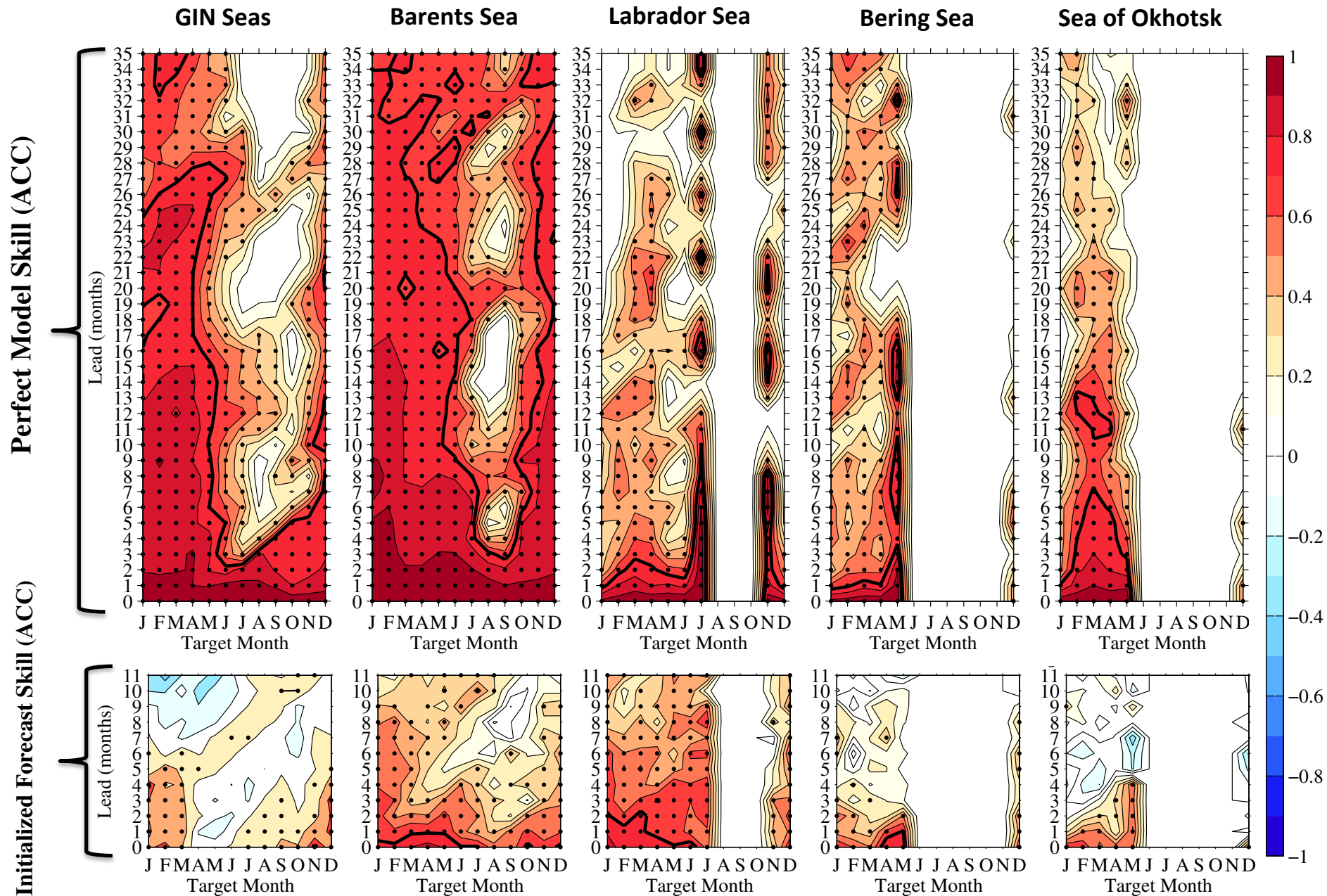
Chukchi Sea (7)



Hudson Bay (12)



The Prediction Skill Gap: Regional Winter SIE



The Prediction Skill Gap: Regional Summer SIE

Kara Sea

Laptev Sea

East Siberian Sea

Chukchi Sea

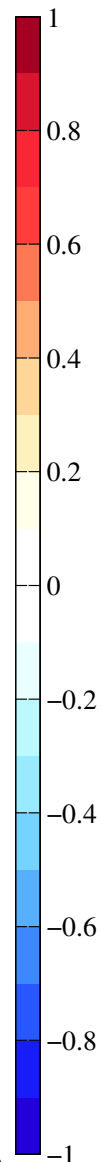
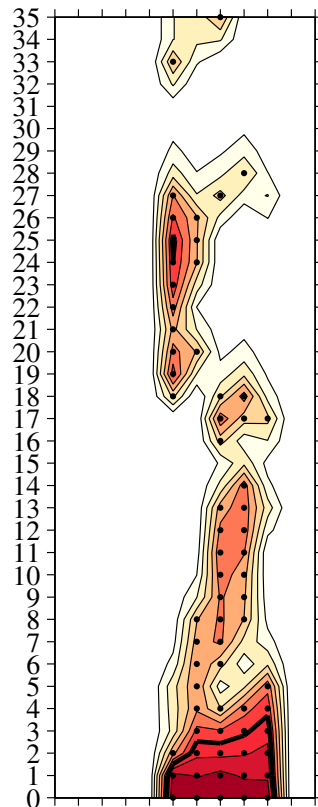
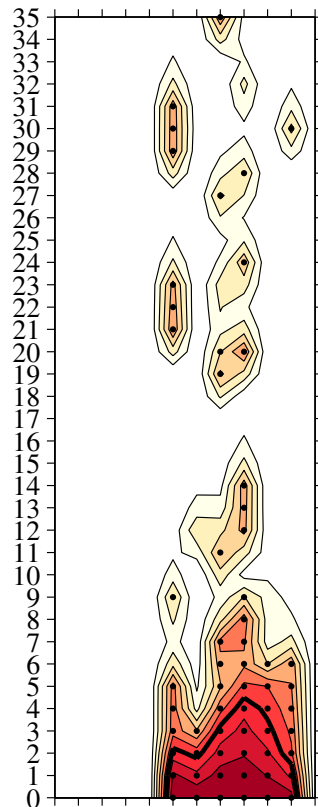
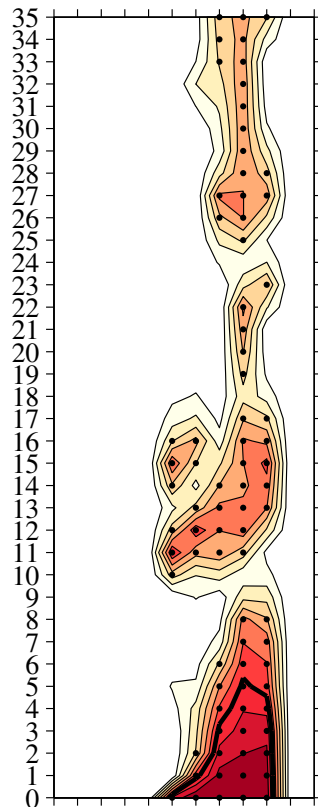
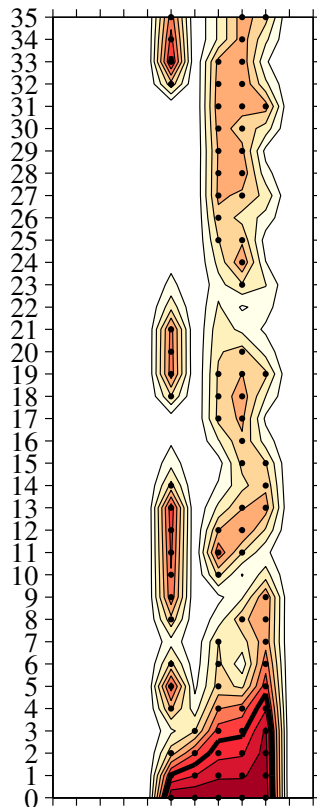
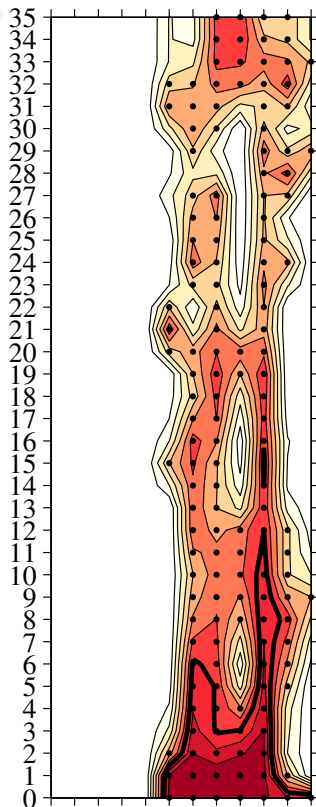
Beaufort Sea

Perfect Model Skill (ACC)

Initialized Forecast Skill (ACC)

Lead (months)

Lead (months)



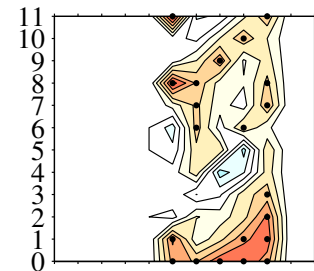
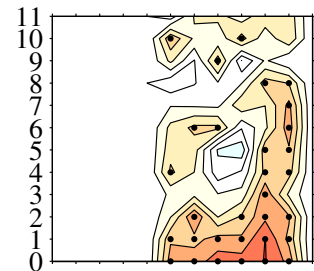
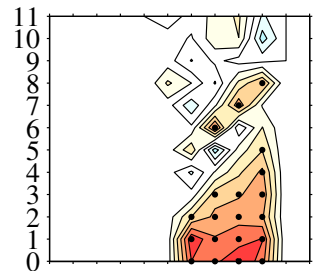
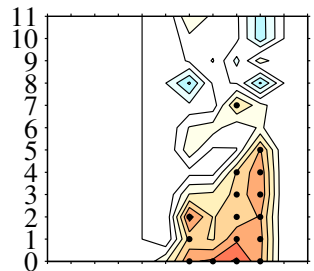
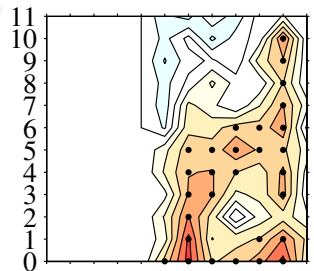
J F M A M J J A S O N D
Target Month

J F M A M J J A S O N D
Target Month

J F M A M J J A S O N D
Target Month

J F M A M J J A S O N D
Target Month

J F M A M J J A S O N D
Target Month



J F M A M J J A S O N D
Target Month

J F M A M J J A S O N D
Target Month

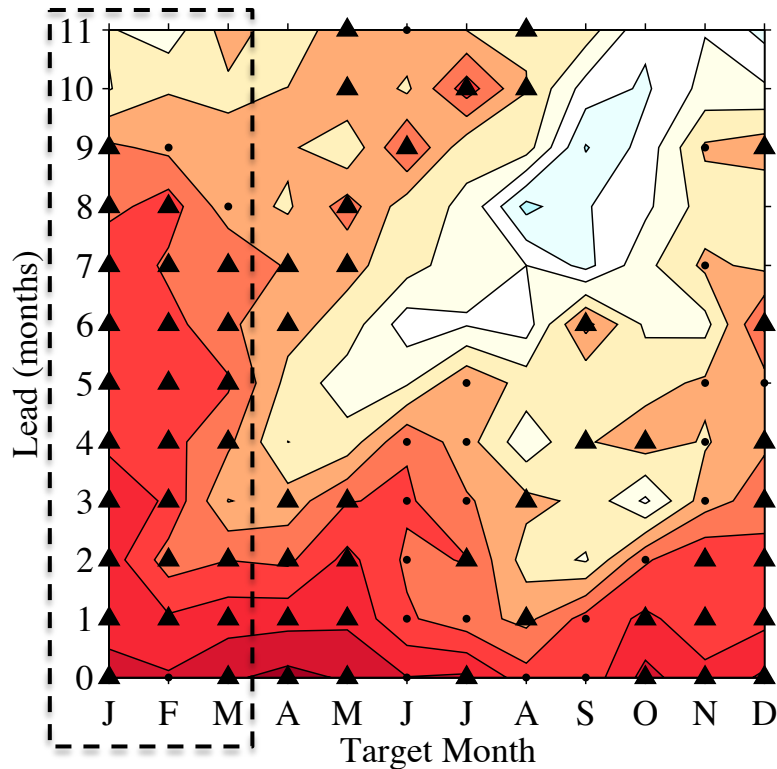
J F M A M J J A S O N D
Target Month

J F M A M J J A S O N D
Target Month

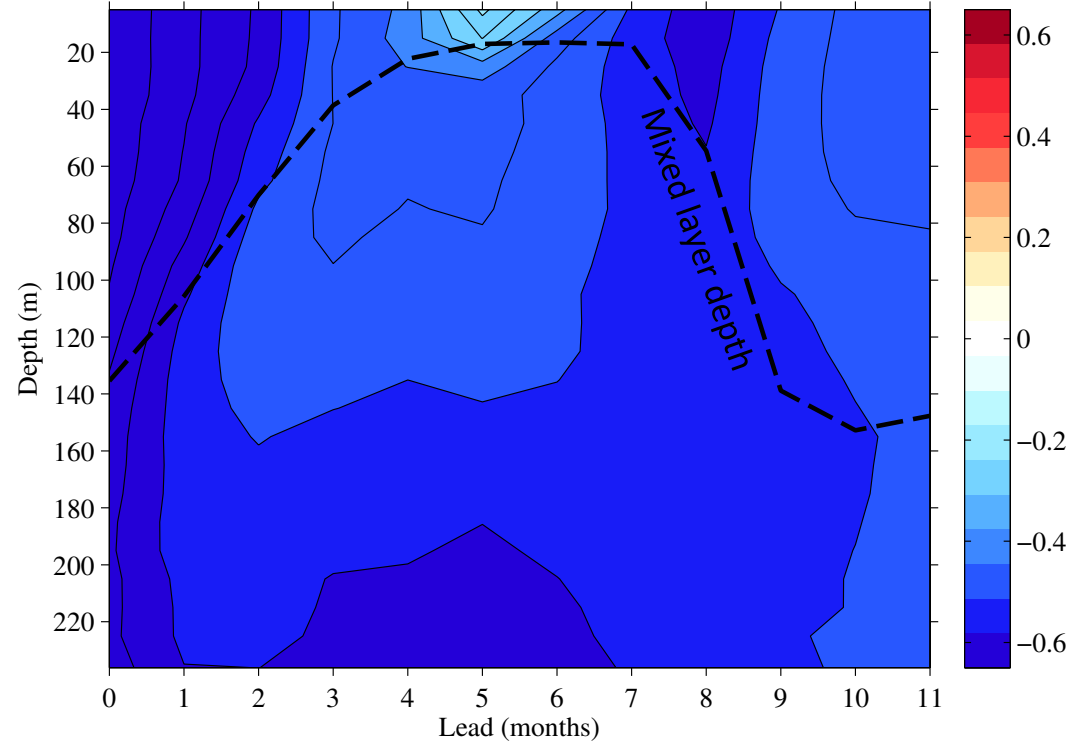
J F M A M J J A S O N D
Target Month

Sources of Winter Prediction Skill: Ocean Temperature Initialization

Barents Sea



$r(\text{Observed Barents SIE}_{\text{Jan}}, \text{Ocean Temperature IC}_{\text{Jan}} - \text{lead})$



- Subsurface ocean temperature initialization provides key source of winter prediction skill
- Important skill improvements associated with assimilation of CTD and SST data

Conclusions

1. In nearly all Arctic regions, there is a large skill gap between perfect model and operational prediction skill
2. Highest regional SIE skill is found for North Atlantic regions; attributable to persistence of subsurface ocean temperatures
3. Summer SIE skill generally lower than winter SIE skill; some summer regions display May prediction skill barrier
4. Skill improvements are possible with improved subsurface ocean initialization and satellite-based sea-ice thickness initialization

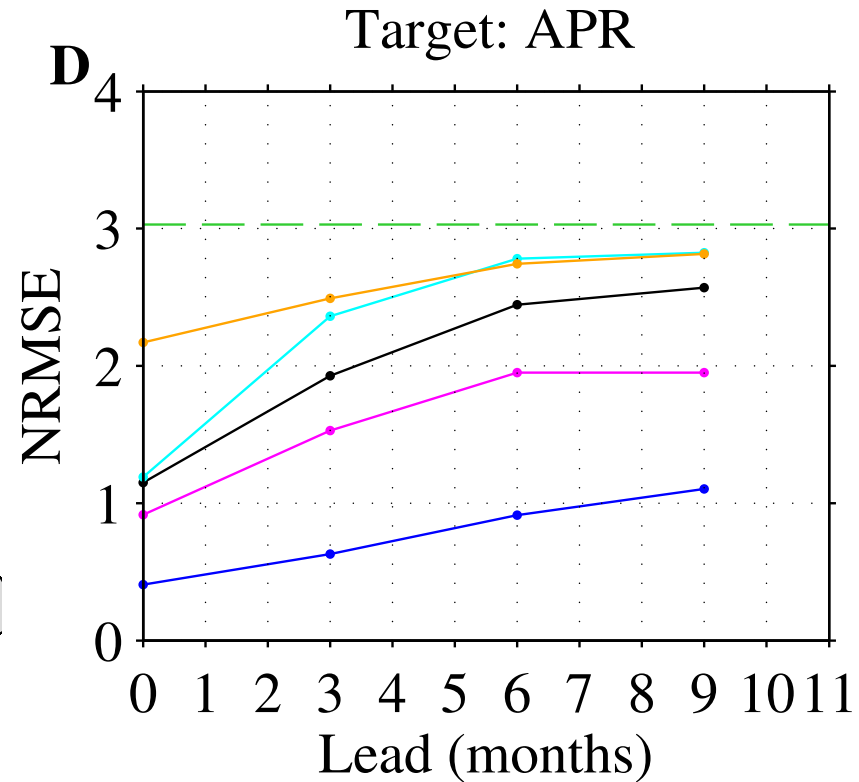
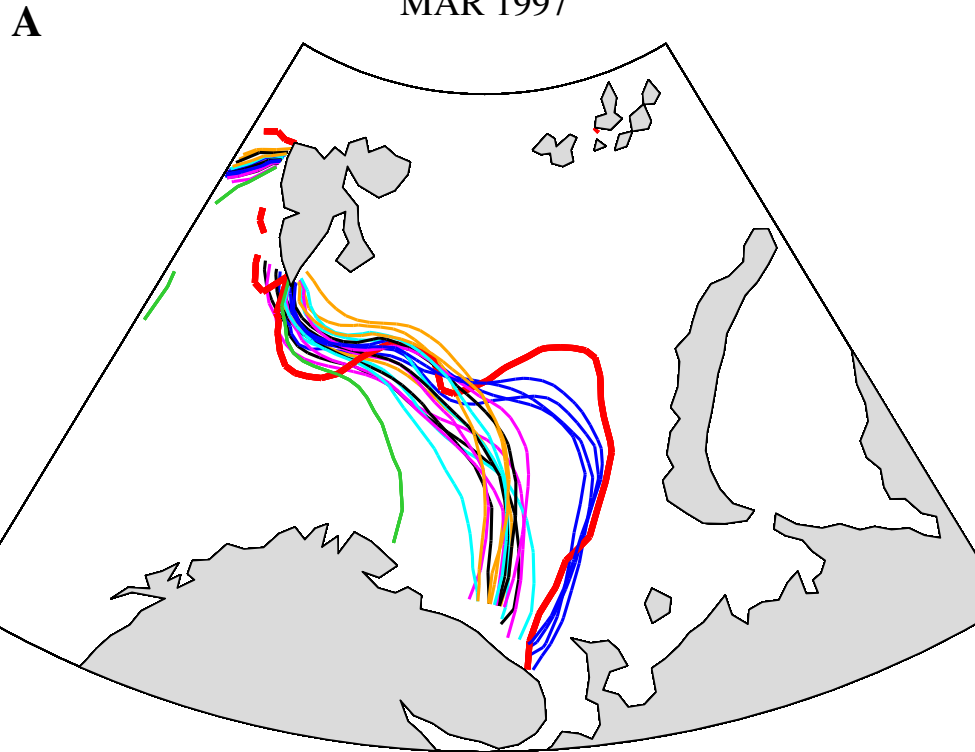
Thank you!

Questions?

Contact me at: Mitchell.Bushuk@noaa.gov

Appendix Slides

Barents Sea Prediction Skill: Surface vs Subsurface Data

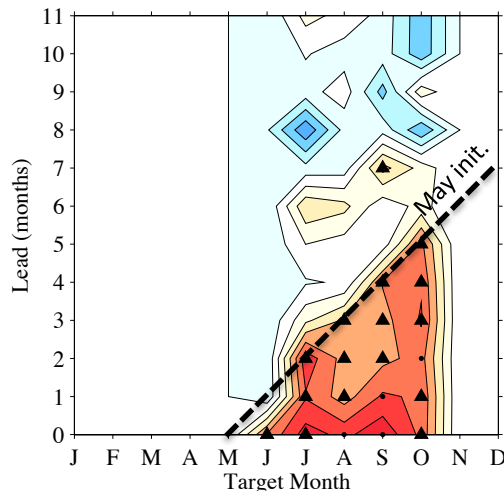


— Obs — Control — No CTD — No Subsurface — SST Only — Atm. Only — Uninit.

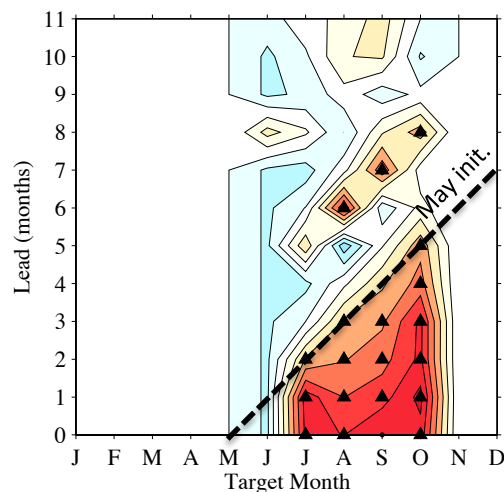
- Observing System Experiments performed over 1995-2016
- Important skill improvements associated with assimilation of CTD and SST data

Sources of Summer Prediction Skill: Sea Ice Thickness Initialization

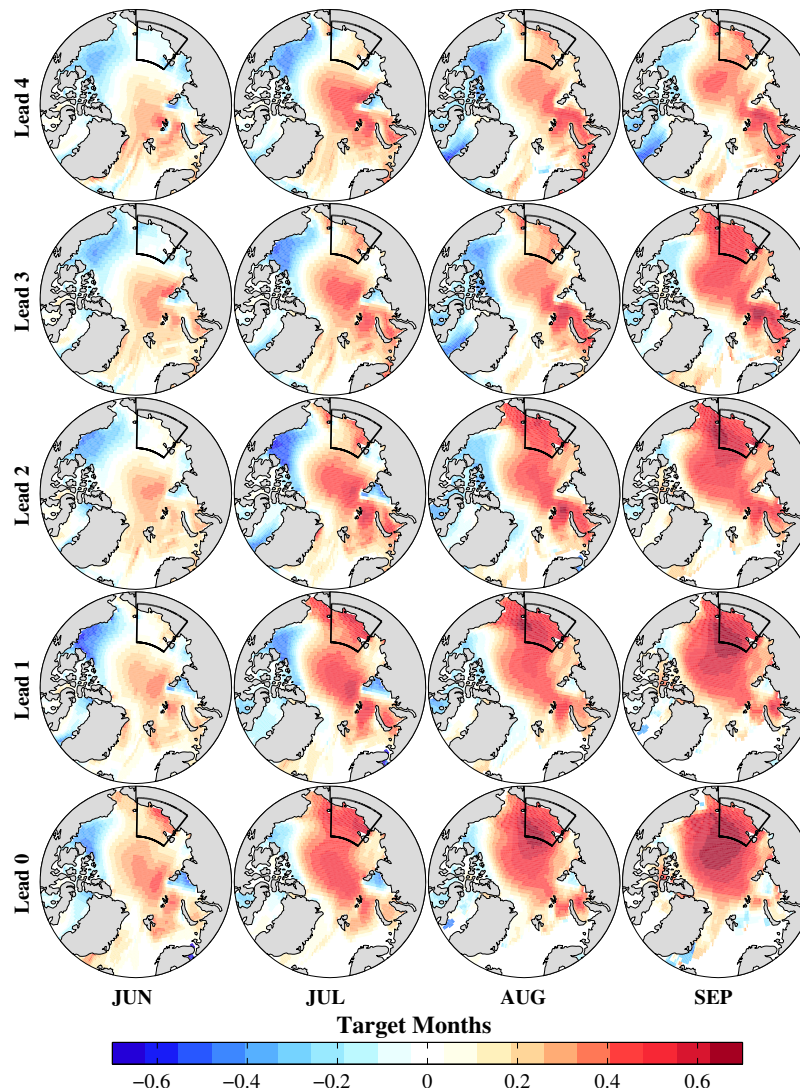
Laptev Sea



East Siberian Sea



$r(\text{Observed East Siberian Sea SIE}_{\text{target month}}, \text{SIT IC}_{\text{target month} - \text{lead}})$

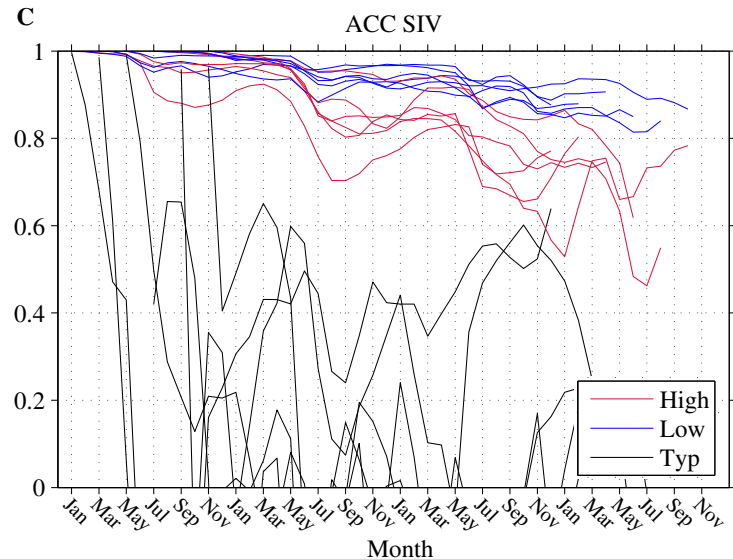


- Laptev and East Siberian Seas have spring prediction skill barrier: Predictions initialized May 1 and later are skillful; those initialized prior to May 1 are not
- Sea ice thickness initialization provides key source of summer prediction skill

Perfect model skill metrics

- Perfect model ACC is state dependent; can be biased by start date sampling

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

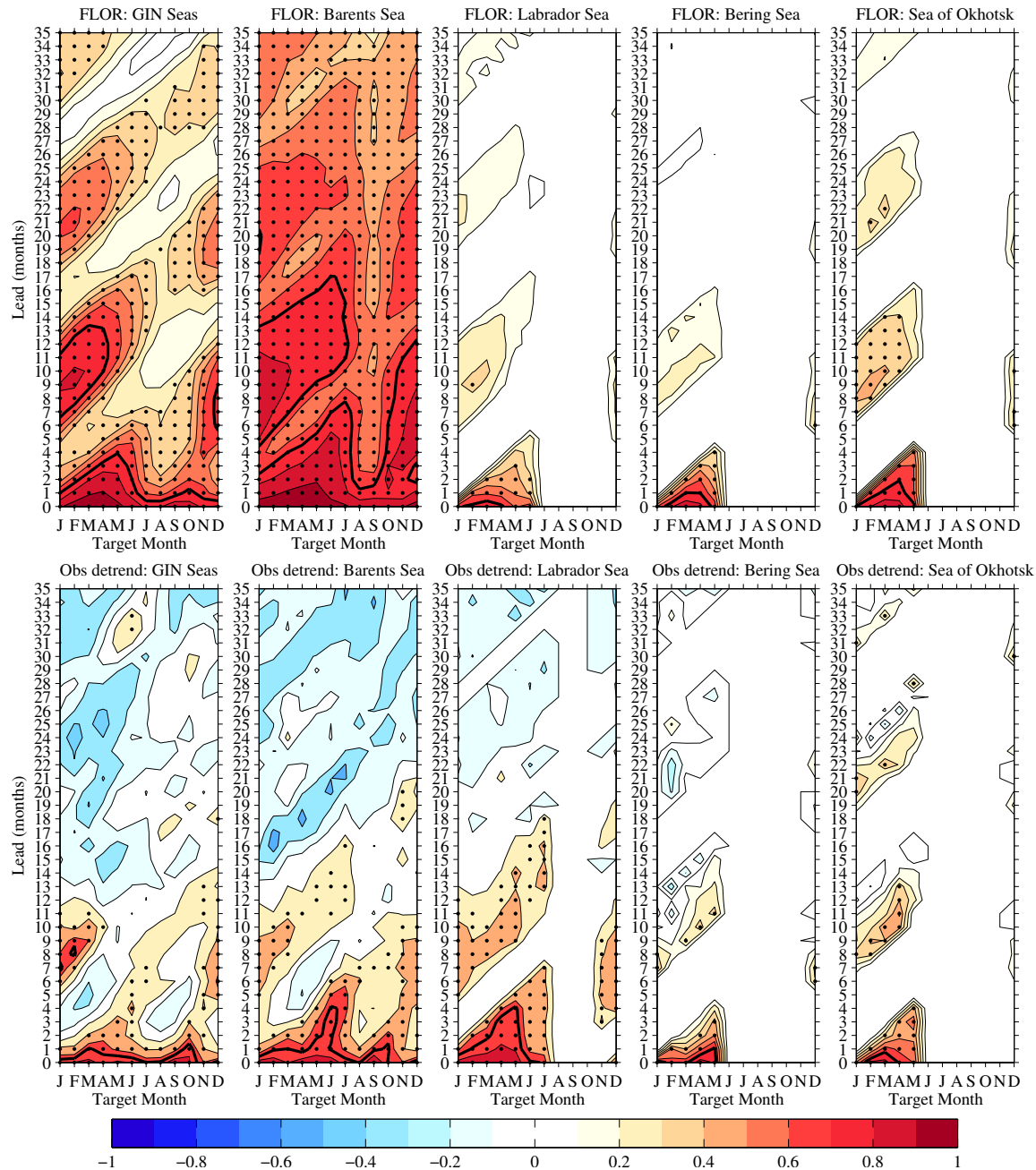


- Perfect model RMSE of Collins et al. (2002) not directly comparable to operational RMSE
- We define RMSE and an “unbiased ACC” which can be directly compared to operational RMSE and ACC.

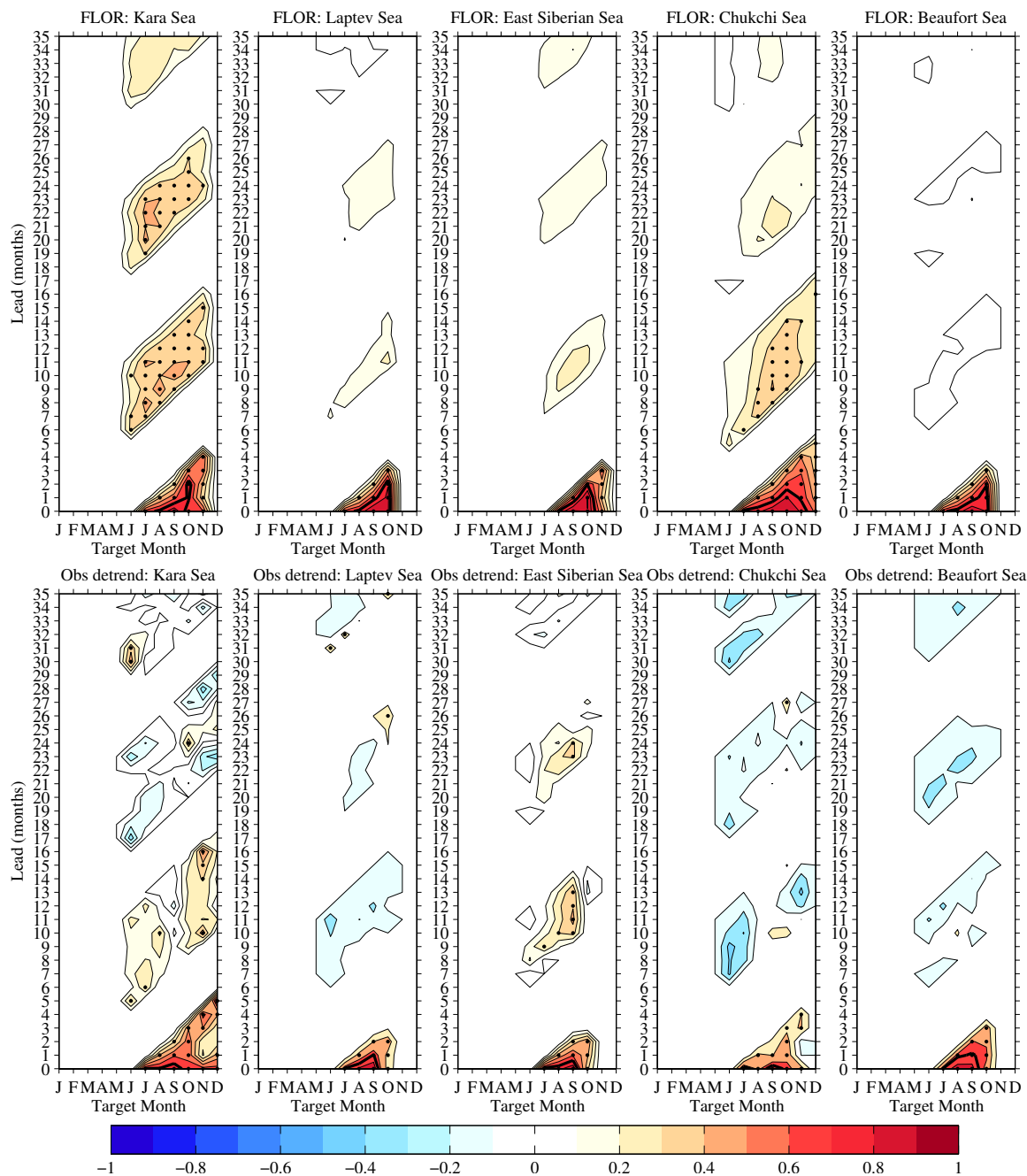
$$RMSE_{PM} = \sqrt{2} RMSE_{OP}$$

$$ACC_U = \sqrt{MSSS}.$$

Comparison of SIE Autocorrelation: Winter SIE regions

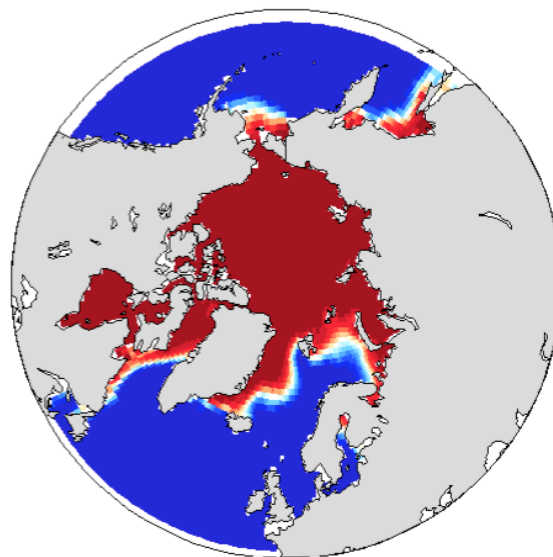


Comparison of SIE Autocorrelation: Summer SIE regions

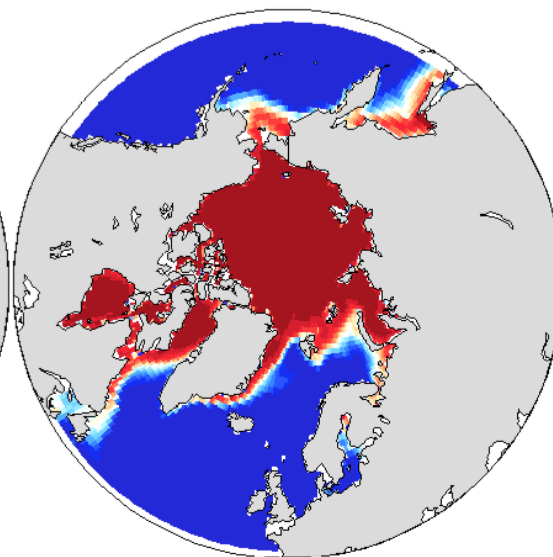


FLOR SIC Climatological Biases

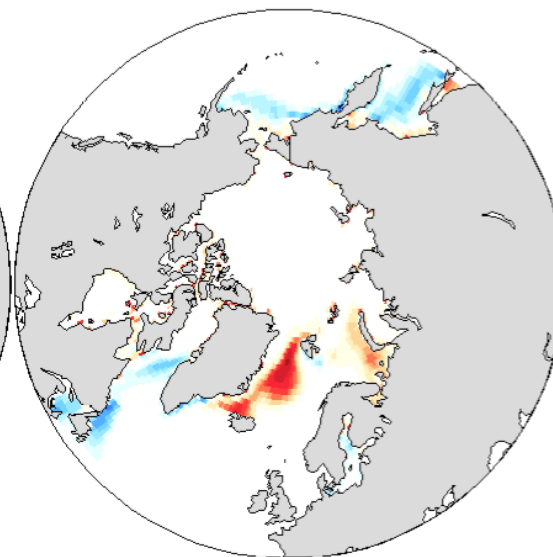
A March SIC FLOR



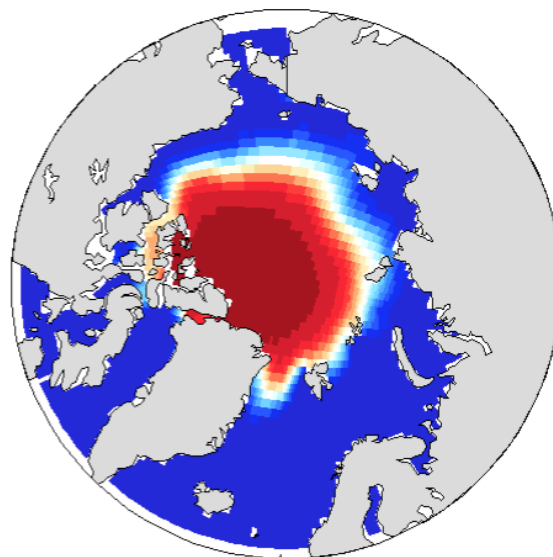
B March SIC NSIDC



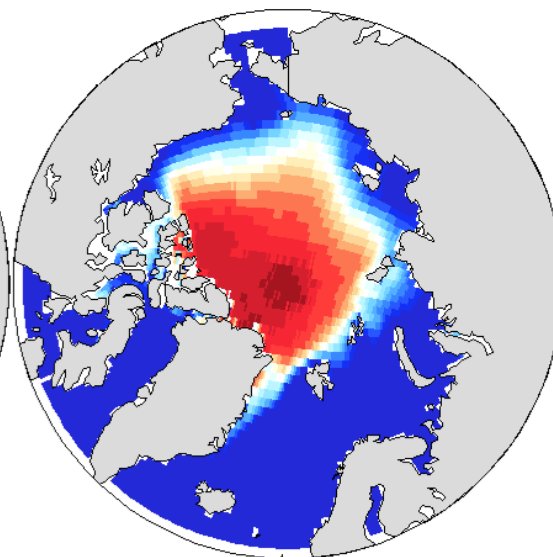
C March SIC bias



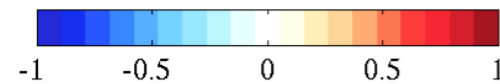
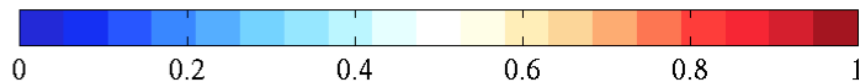
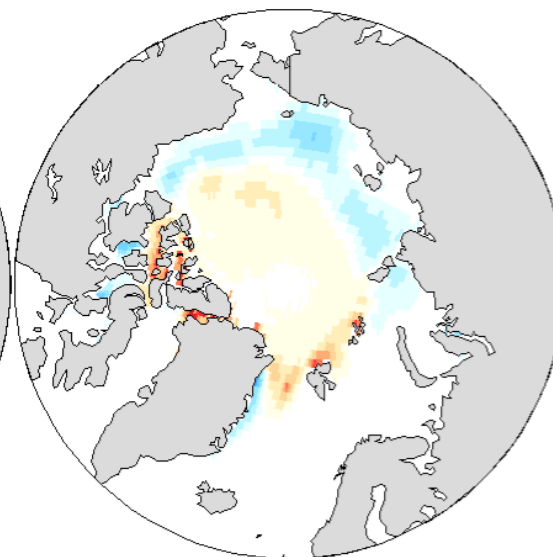
D Sept SIC FLOR



E Sept SIC NSIDC

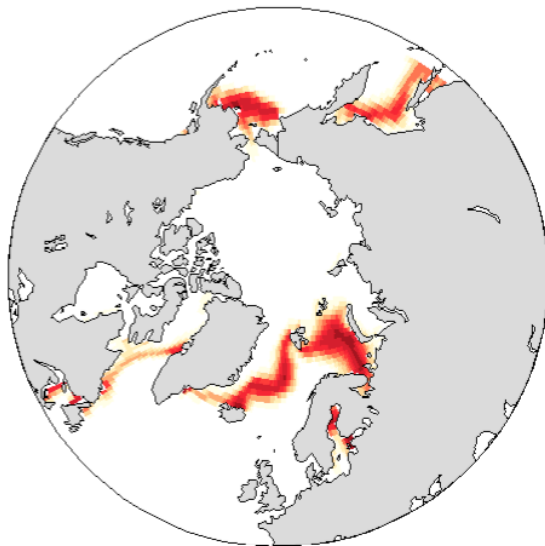


F Sept SIC bias

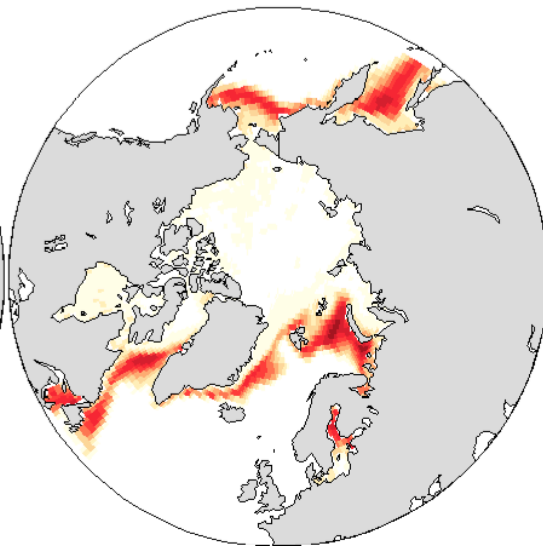


FLOR SIC Variability Biases

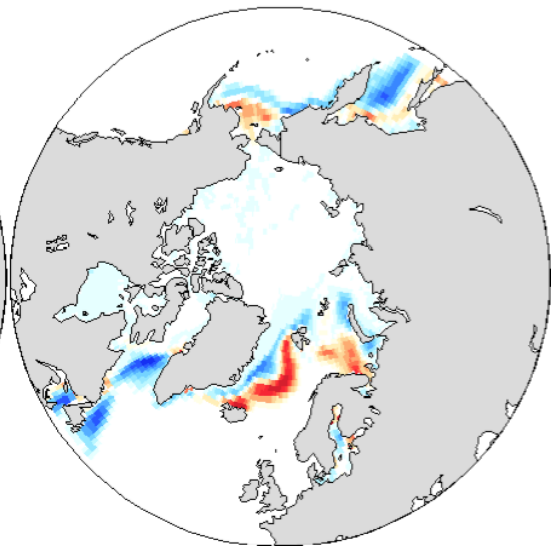
A March SIC σ FLOR



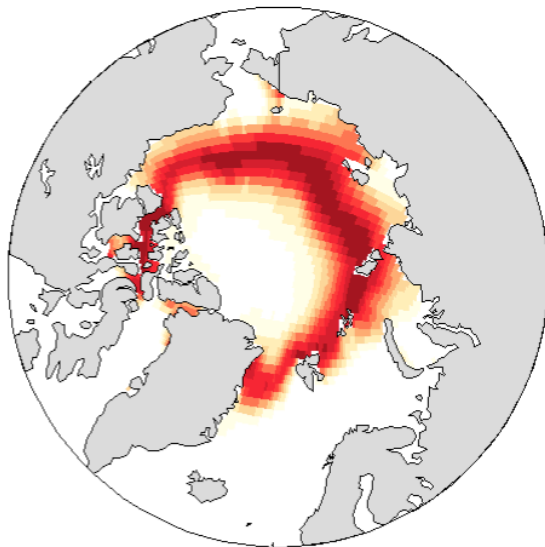
B March SIC σ NSIDC



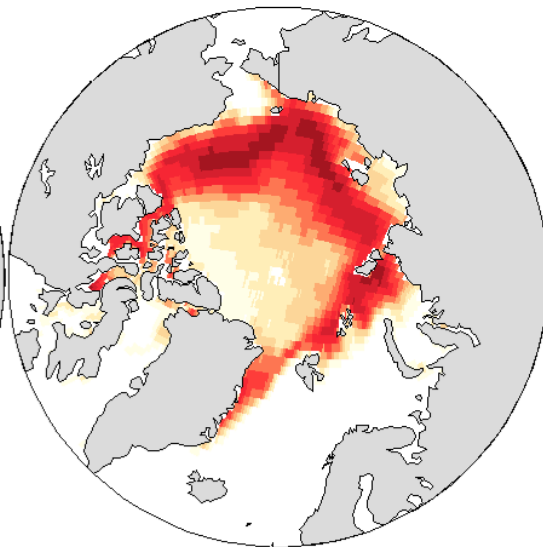
C March SIC σ bias



D Sept SIC σ FLOR



E Sept SIC σ NSIDC



F Sept SIC σ bias

