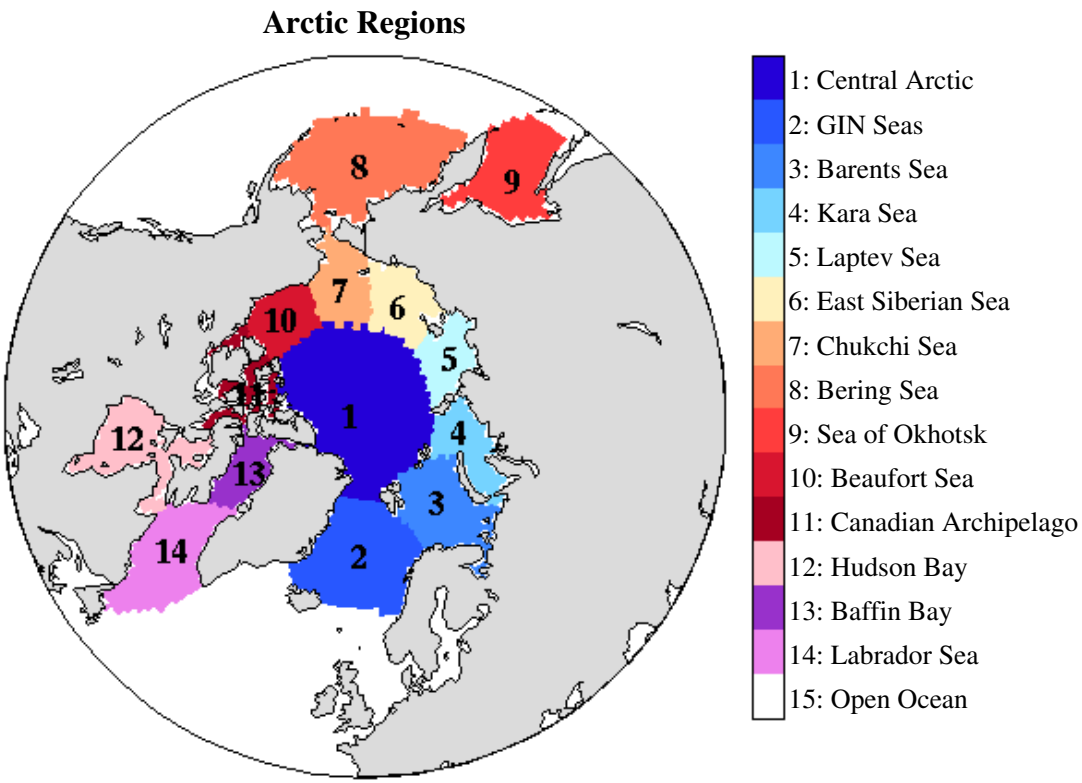
Regional Arctic sea ice prediction: Mechanisms, forecast skill, and future outlook

Mitch Bushuk
GFDL/NOAA

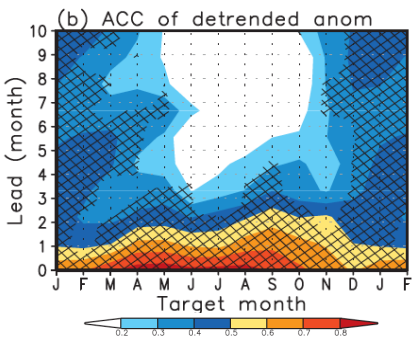
With contributions from:
Rym Msadek, Michael Winton, Gabriel Vecchi, Anthony Rosati, Xiaosong Yang, Rich Gudgel

Arctic Modeling Workshop
June 26, 2017

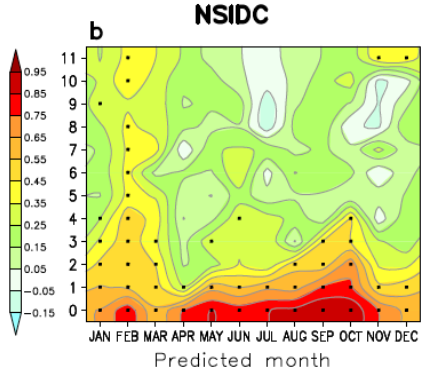


The Arctic Sea-Ice Prediction Gap

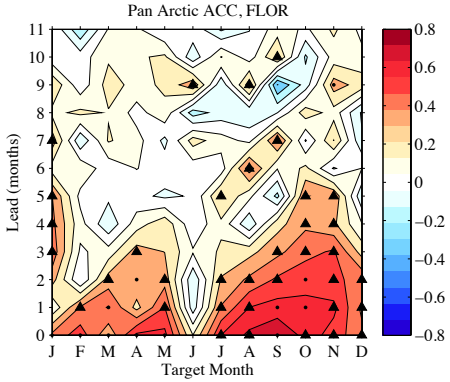
- **GCM-based hindcast skill for detrended SIE: 0-5 months**



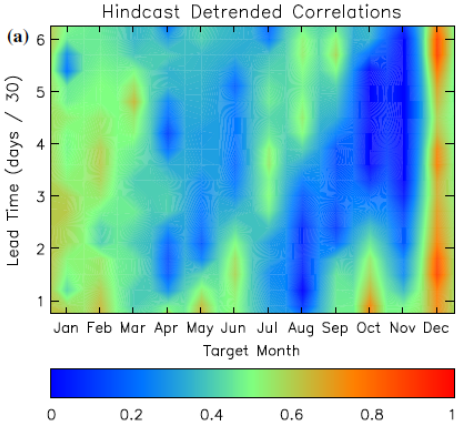
Wang et al. 2013, *Mon. Wea. Rev.*



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

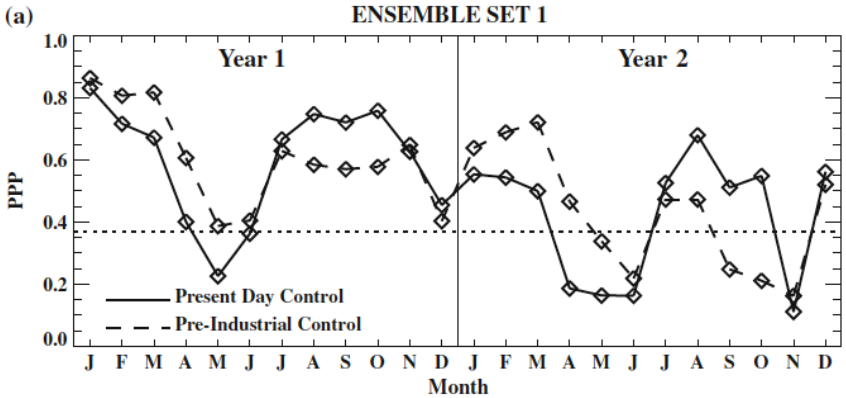


Msadek et al. 2014, *GRL;* Bushuk et al. 2017, *GRL*

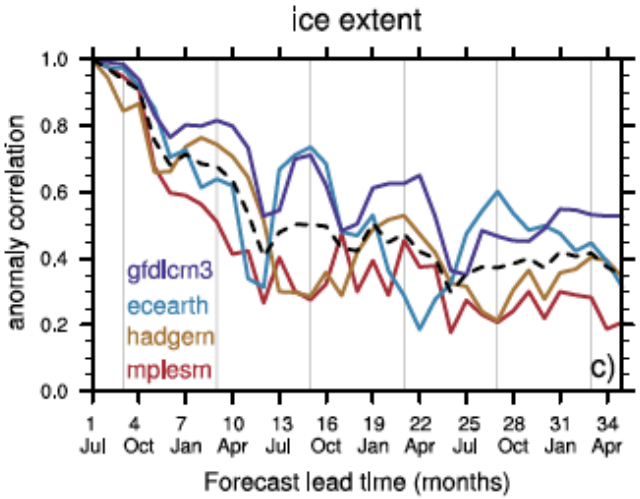


Peterson et al. 2015, *Clim. Dyn.*

- **Perfect model predictability: 12-24 months**



Holland et al. 2010, *Clim. Dyn.;* Blanchard-Wrigglesworth et al. 2011, *GRL*



Tietsche et al. 2014, *GRL*

Motivating Questions

(1) How skillful are regional predictions of Arctic sea ice?

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(2) How skillful could regional predictions be?

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(2) How skillful could regional predictions be?

(3) Why are regional predictions skillful? How do we improve predictions?

The Dynamical Forecast Model

GFDL-FLOR[1]: **F**orecast-oriented **L**ow **O**cean **R**esolution

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

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

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Initialization Procedure

ECDA[2]: **E**nsemble Kalman Filter **C**oupled **D**ata **A**ssimilation

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

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Forecast Experiments

- Forecasts initialized on the first of each month; run for one year
- 12-member ensemble
- Retrospective forecasts spanning 1980-2016

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

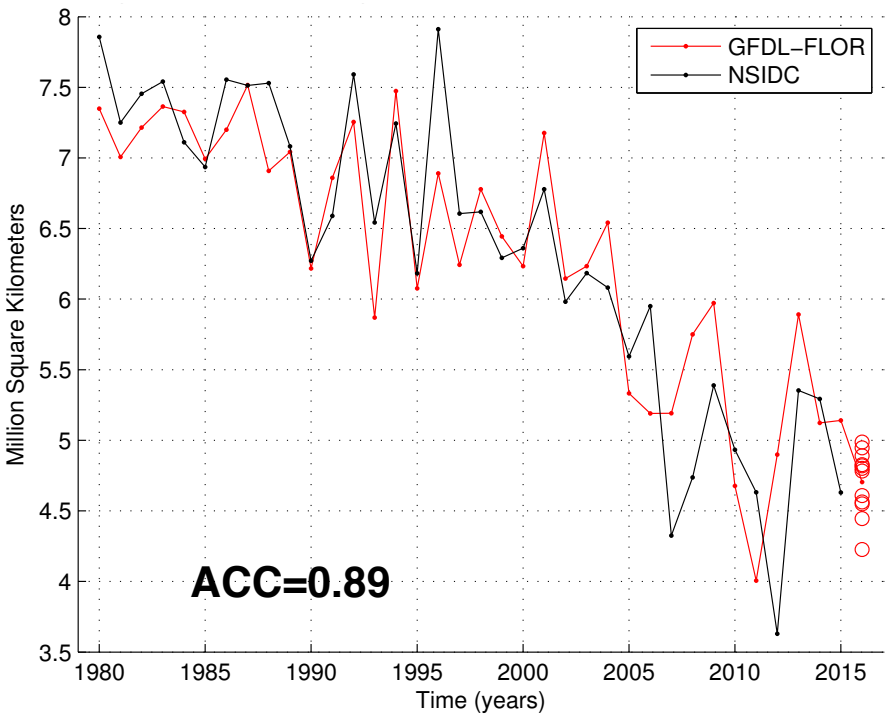
Prediction Skill in Retrospective Forecasts

Target month: Month we are trying to predict

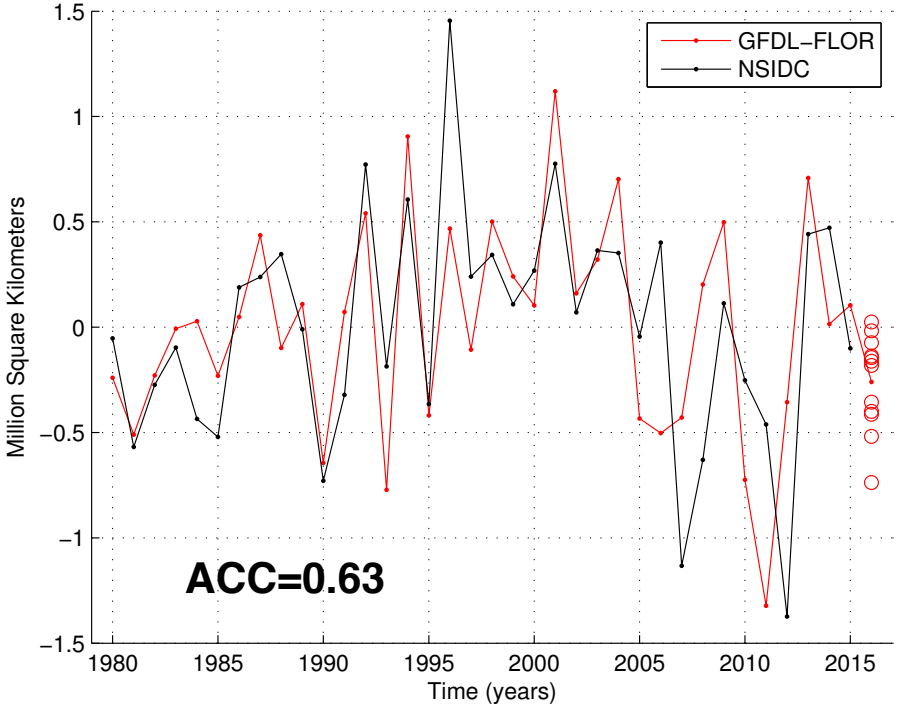
Lead time: Number of months prior to target month that forecast was initialized

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

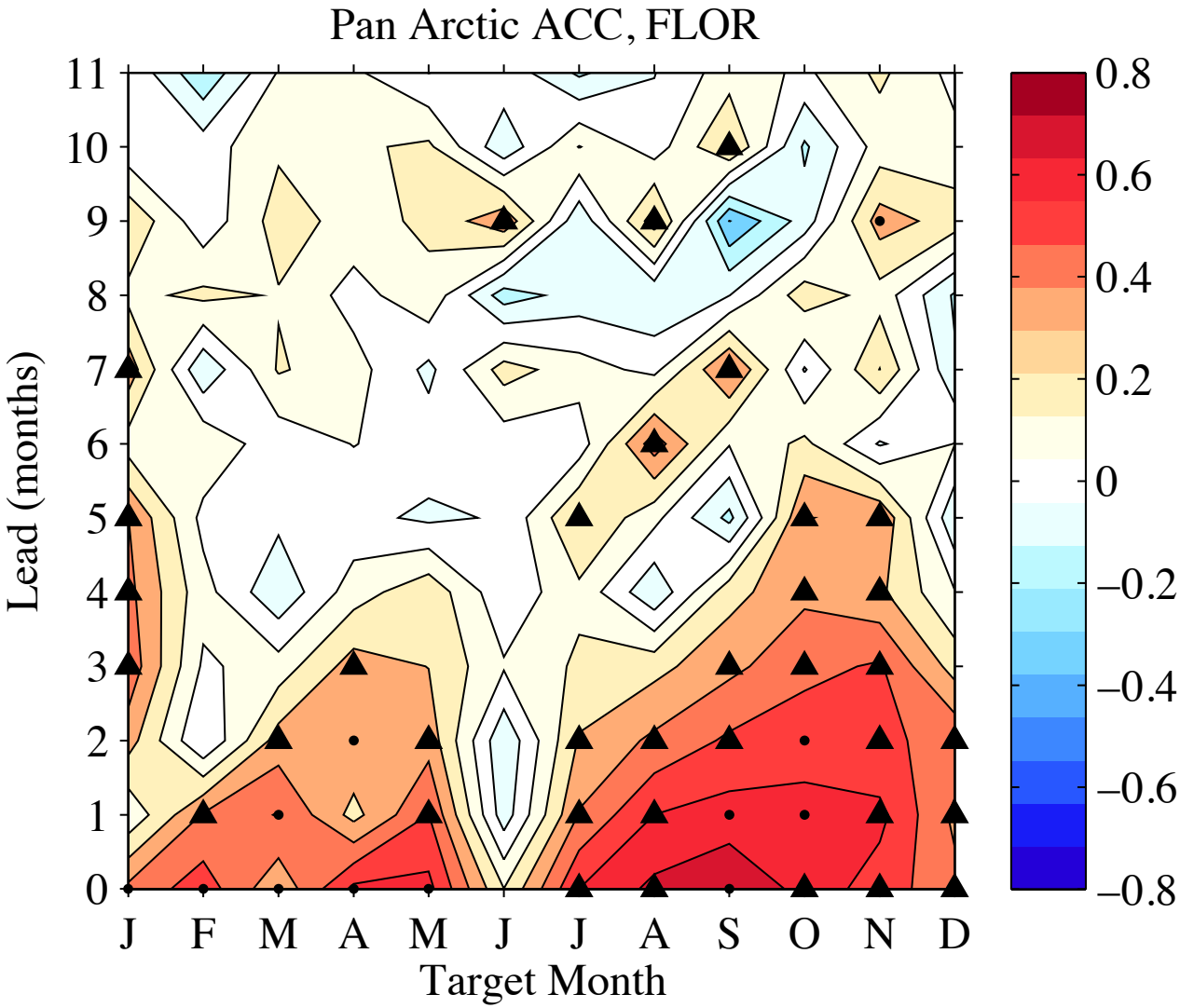
Target: September; Lead: 2



Target: September; Lead: 2; Detrended



Pan-Arctic Prediction Skill: All target months and lead times 0-11 months

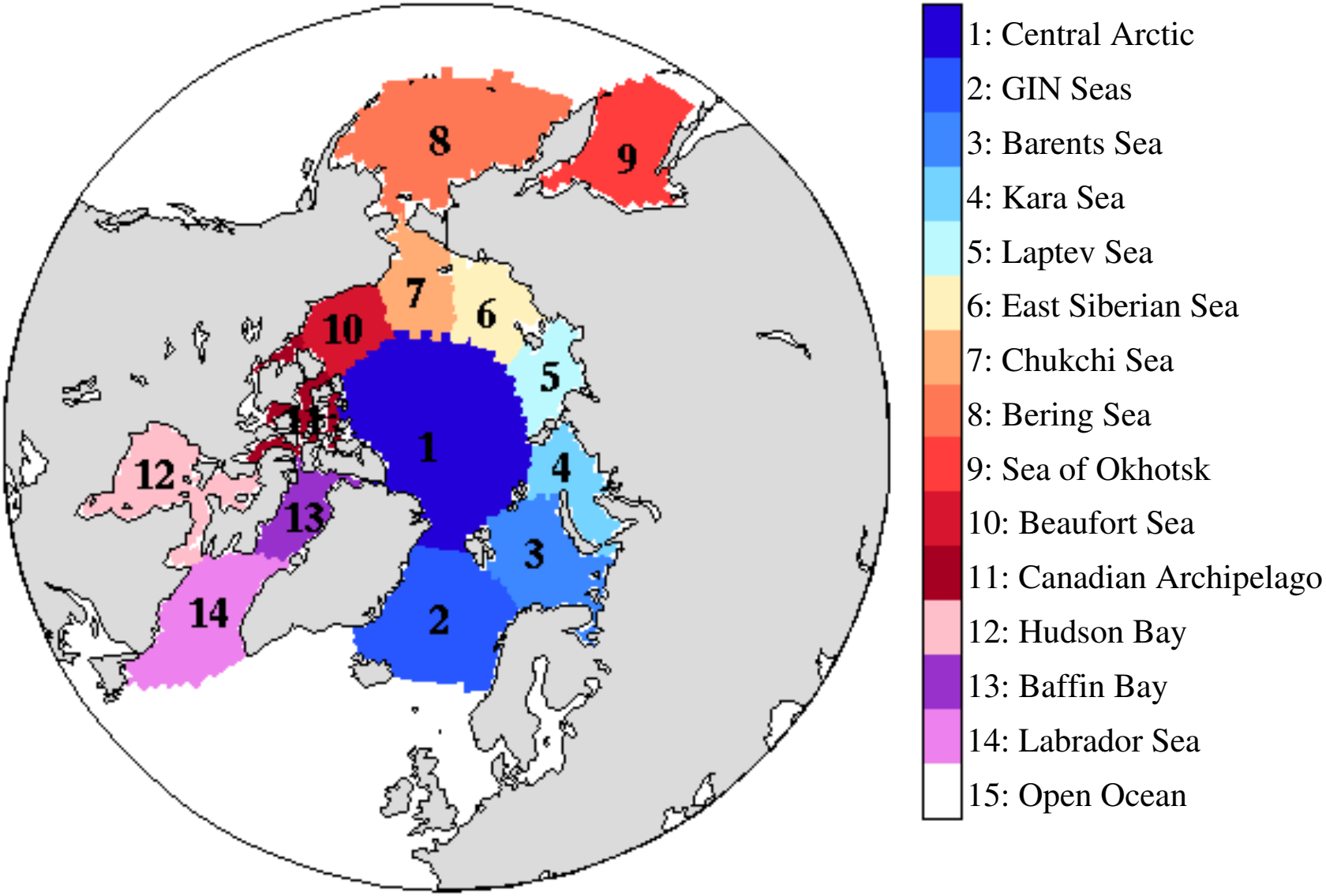


▲: Anomaly correlation coefficient (ACC) exceeds persistence forecast and is significant at 95% level

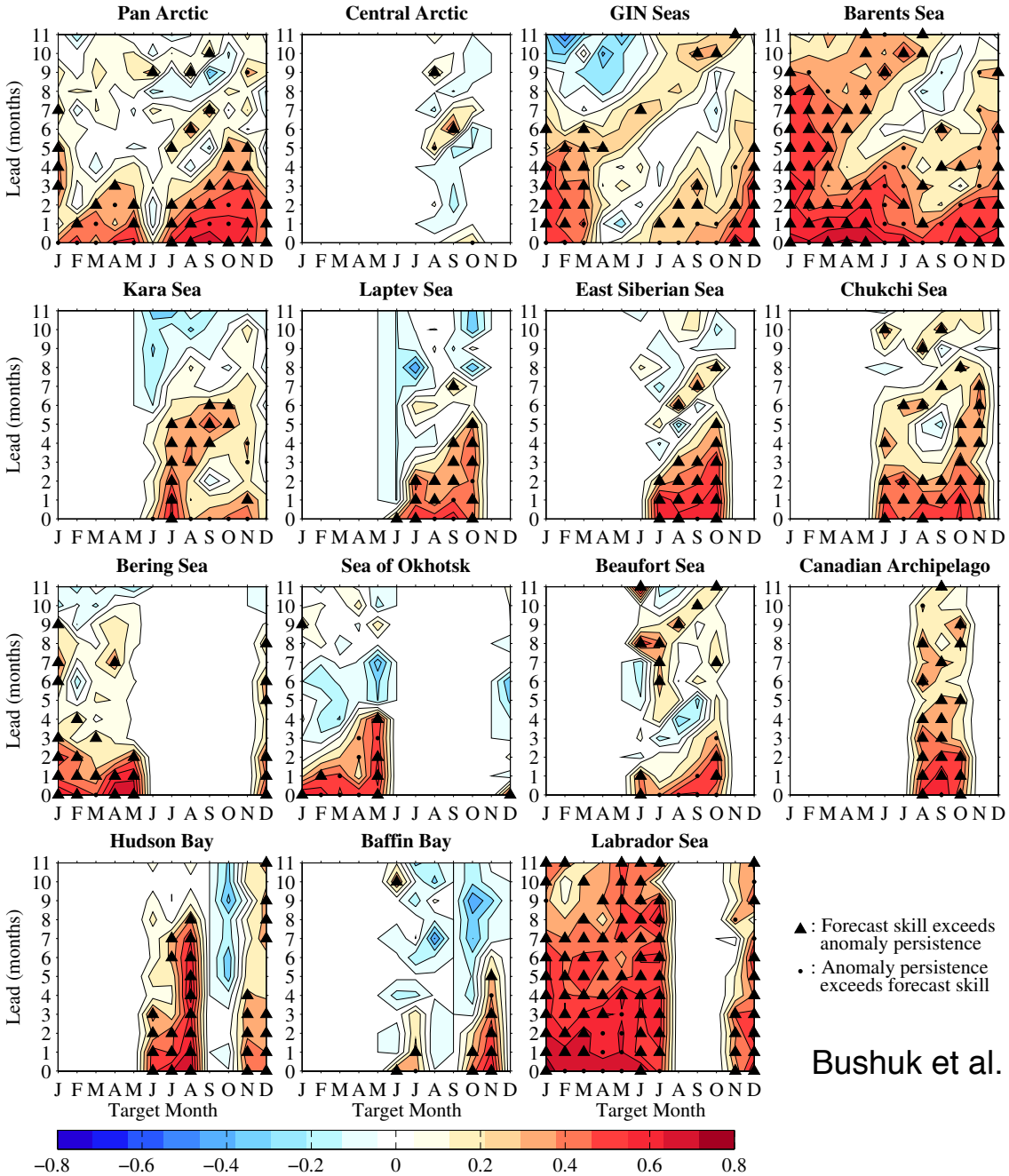
Note: All correlations computed using **linearly detrended** data

Regional Prediction Skill

Arctic Regions



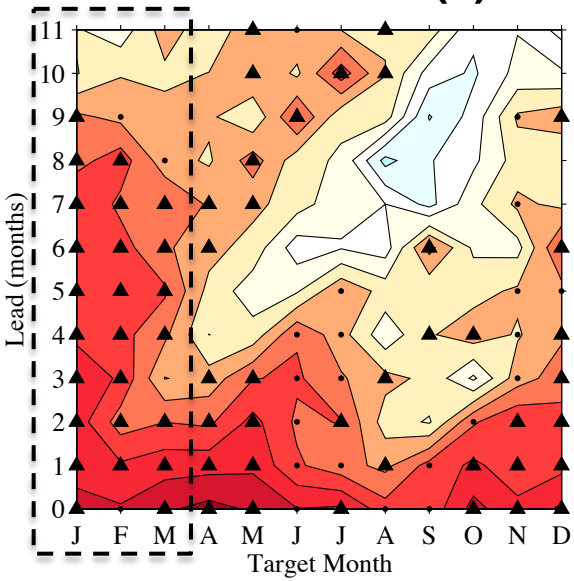
Regional Prediction Skill (ACC) for detrended SIE



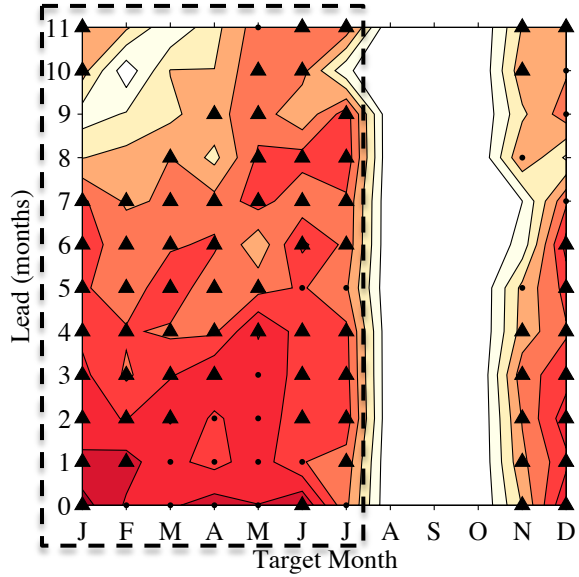
Bushuk et al. 2017, *GRL*

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

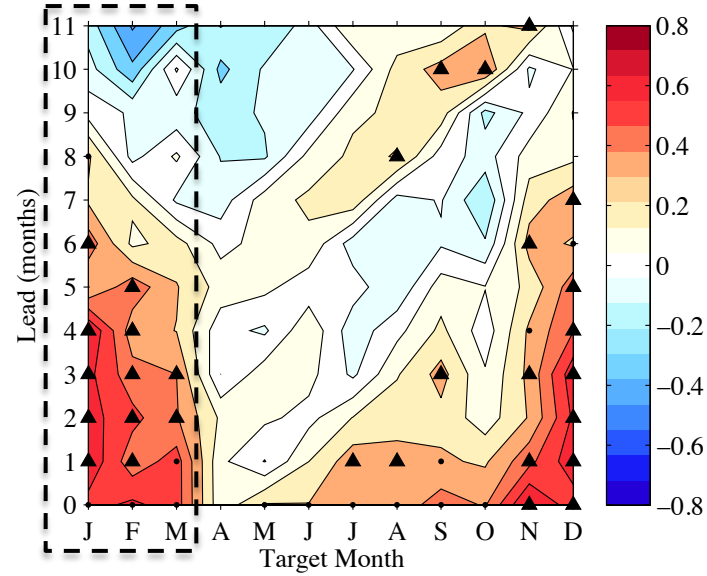
Barents Sea (3)



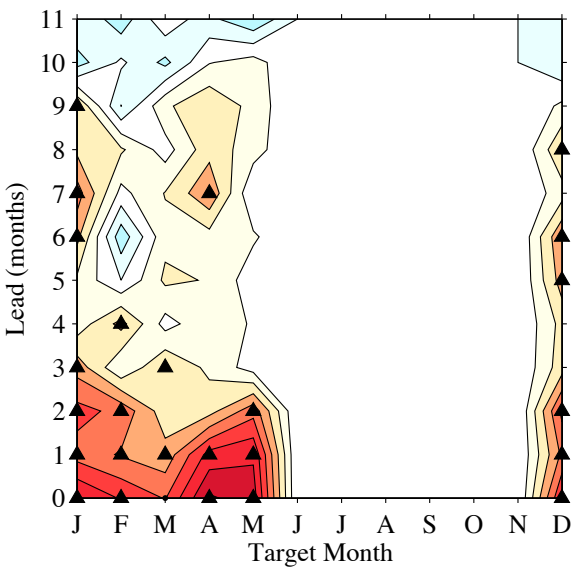
Labrador Sea (14)



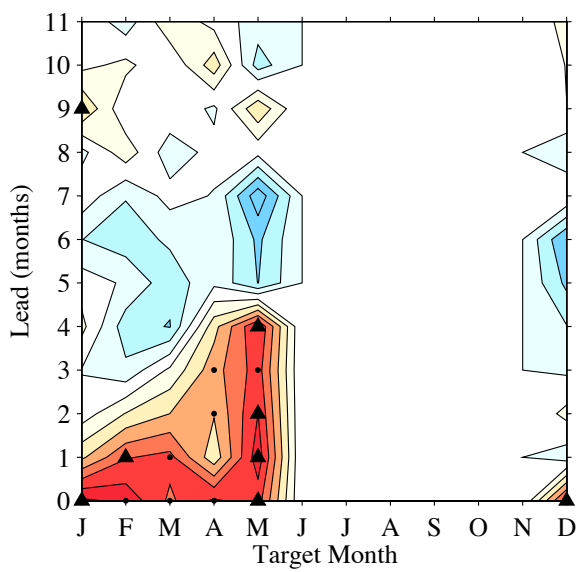
GIN Seas (2)

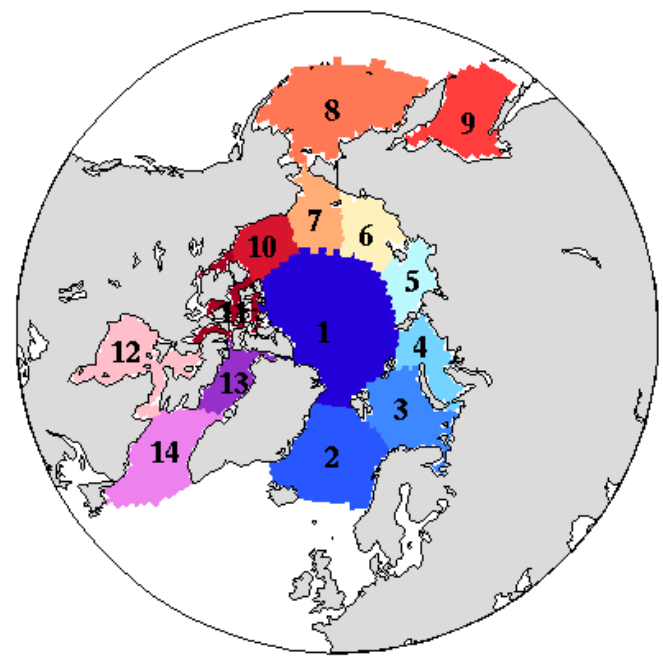


Bering Sea (8)



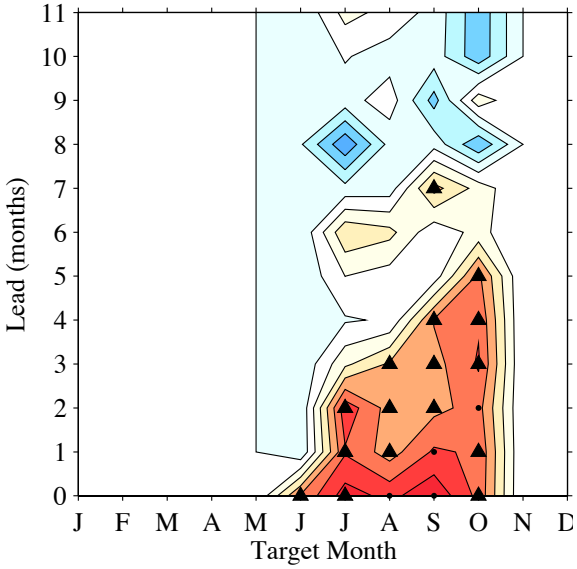
Sea of Okhotsk (9)



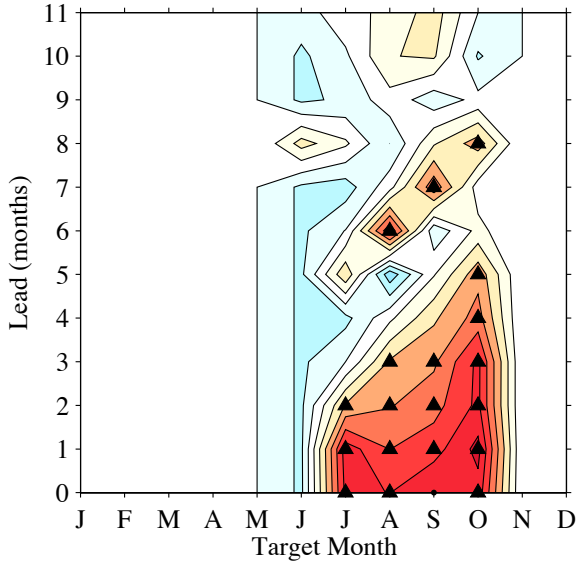


Prediction Skill For Summer Ice Regions (Region # in parentheses)

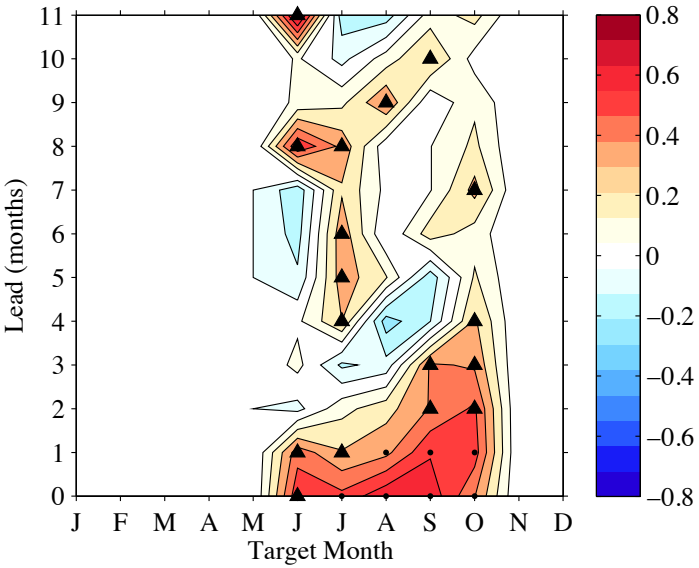
Laptev Sea (5)



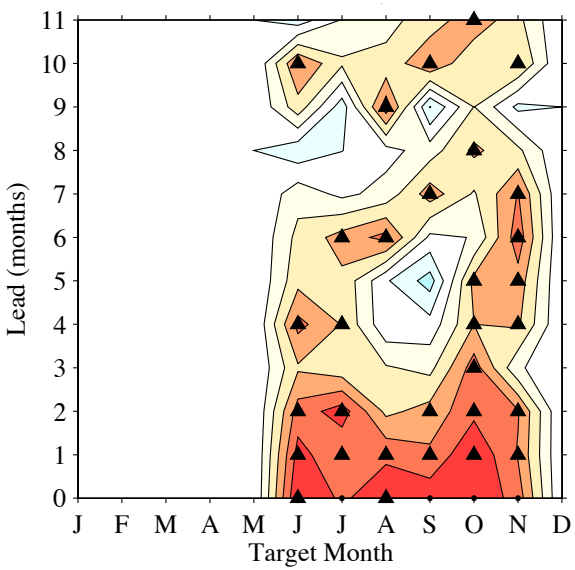
East Siberian Sea (6)



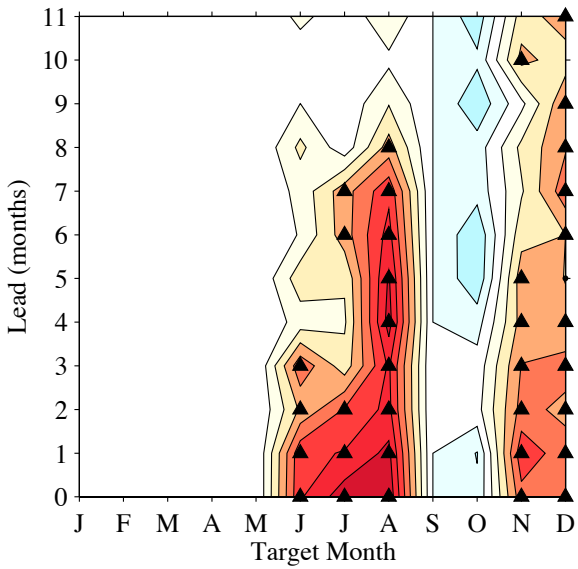
Beaufort Sea (10)

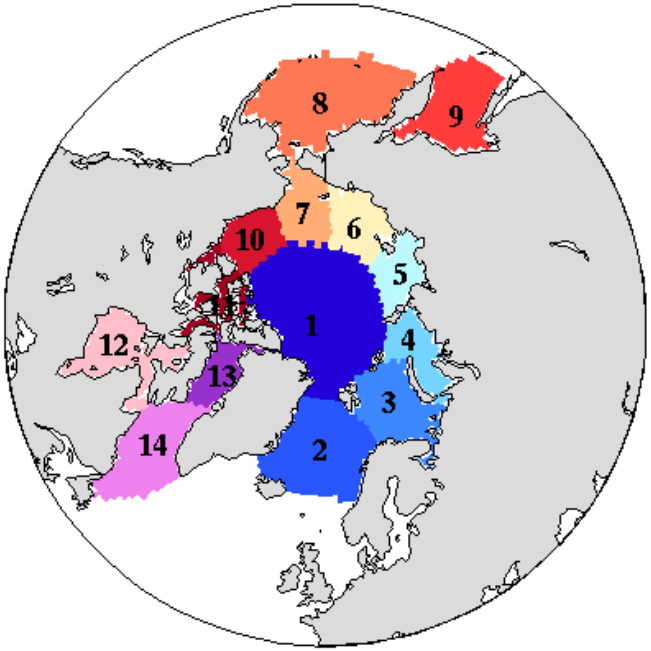


Chukchi Sea (7)



Hudson Bay (12)





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

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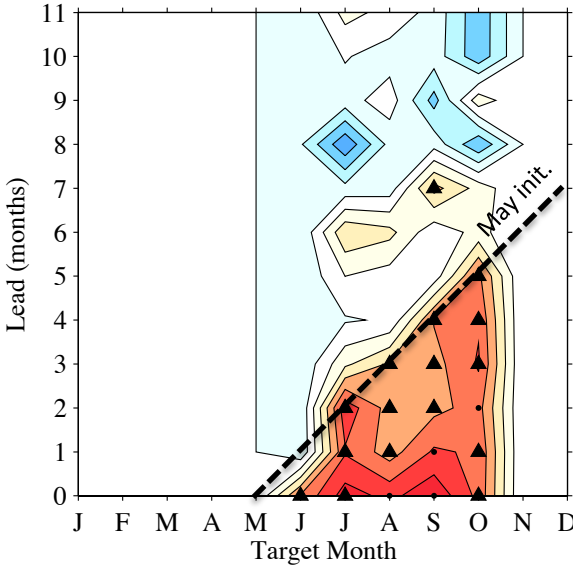

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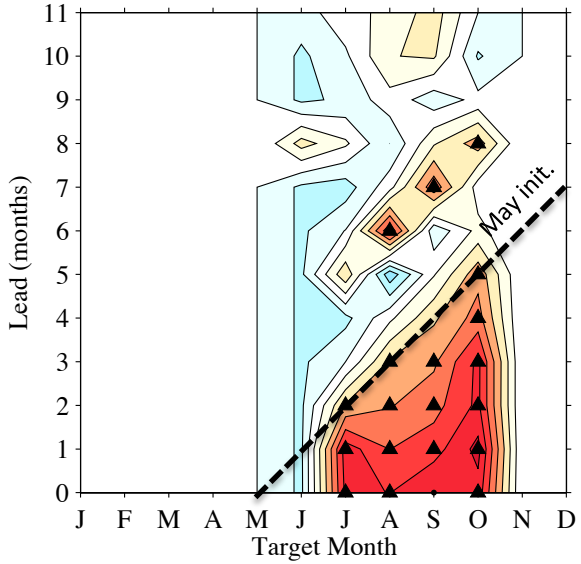

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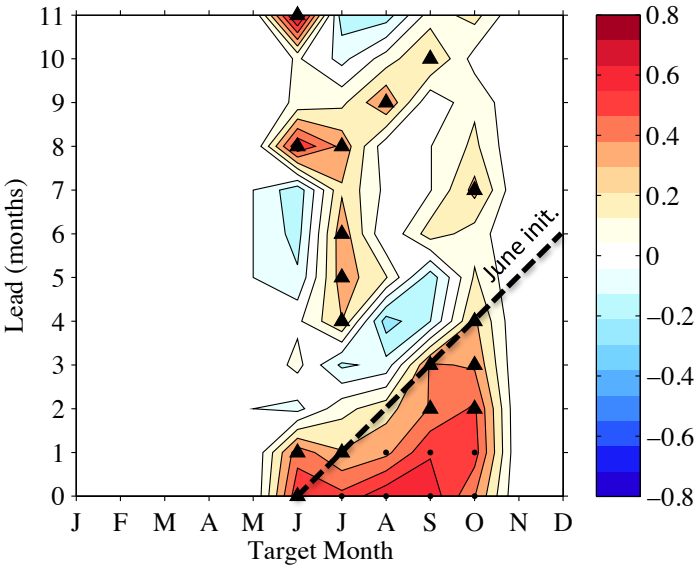

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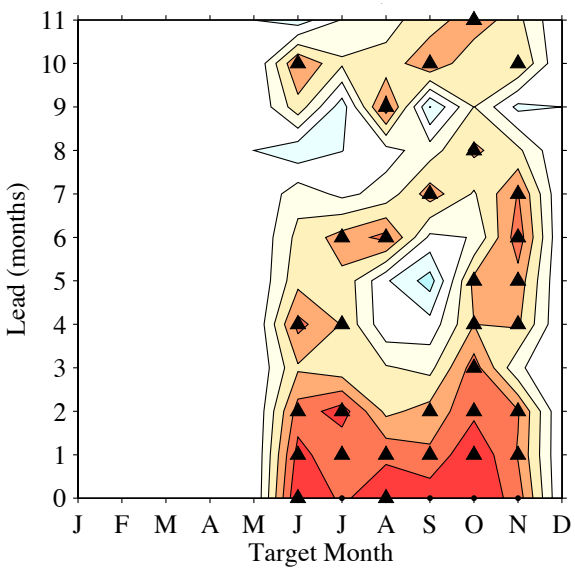

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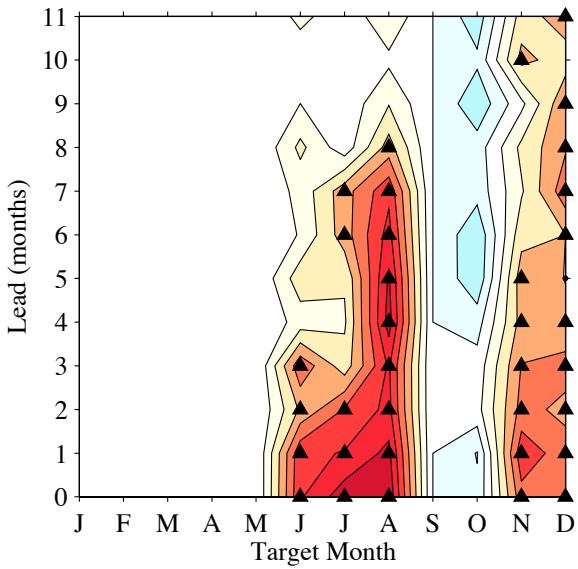

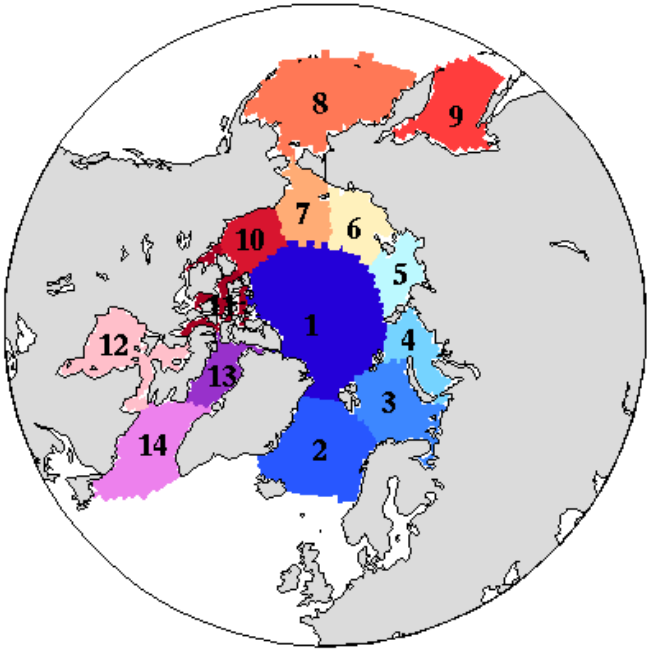

Motivating Questions

(1) How skillful are regional predictions of Arctic sea ice?

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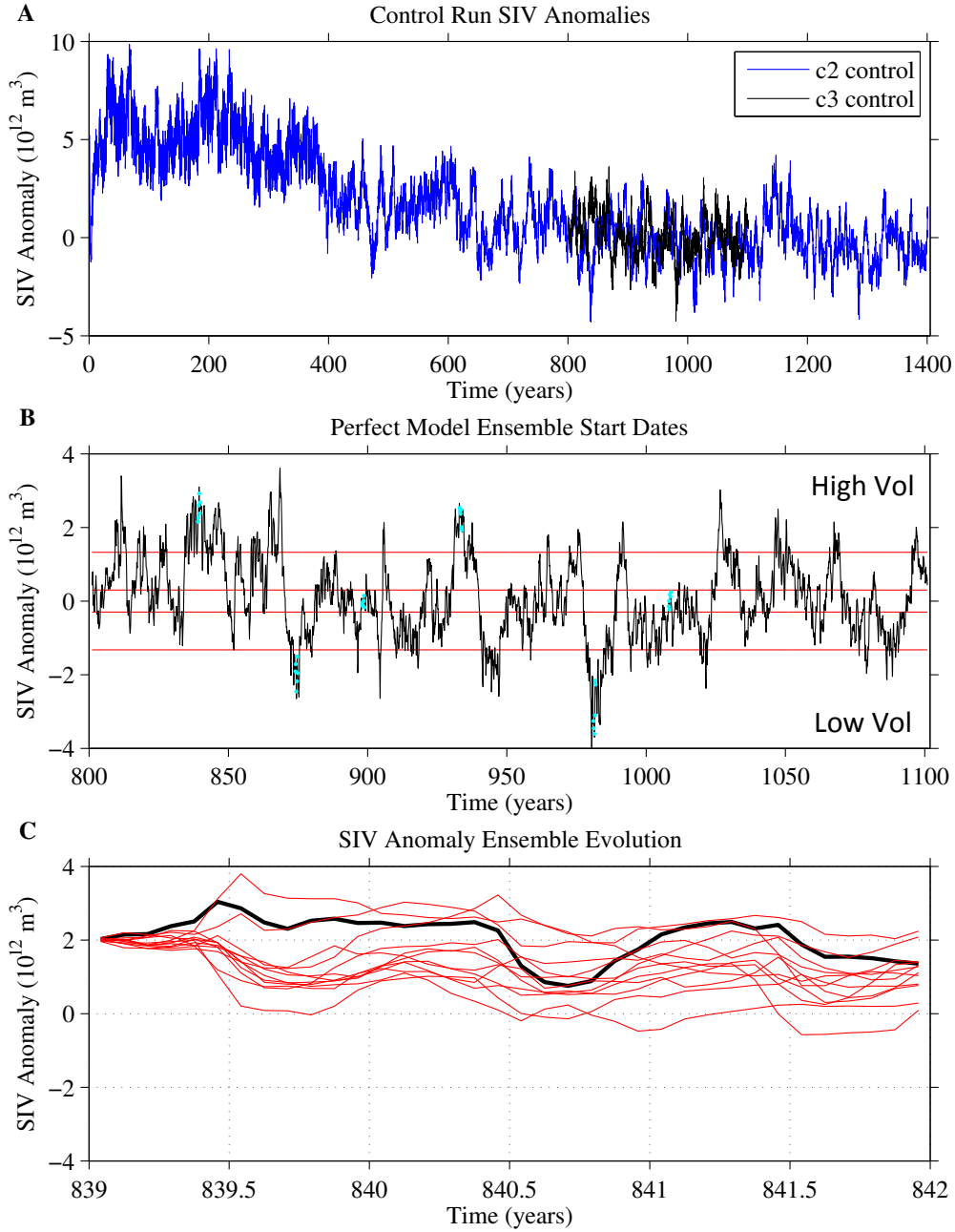
Perfect Model Predictability Experiments with GFDL-FLOR



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

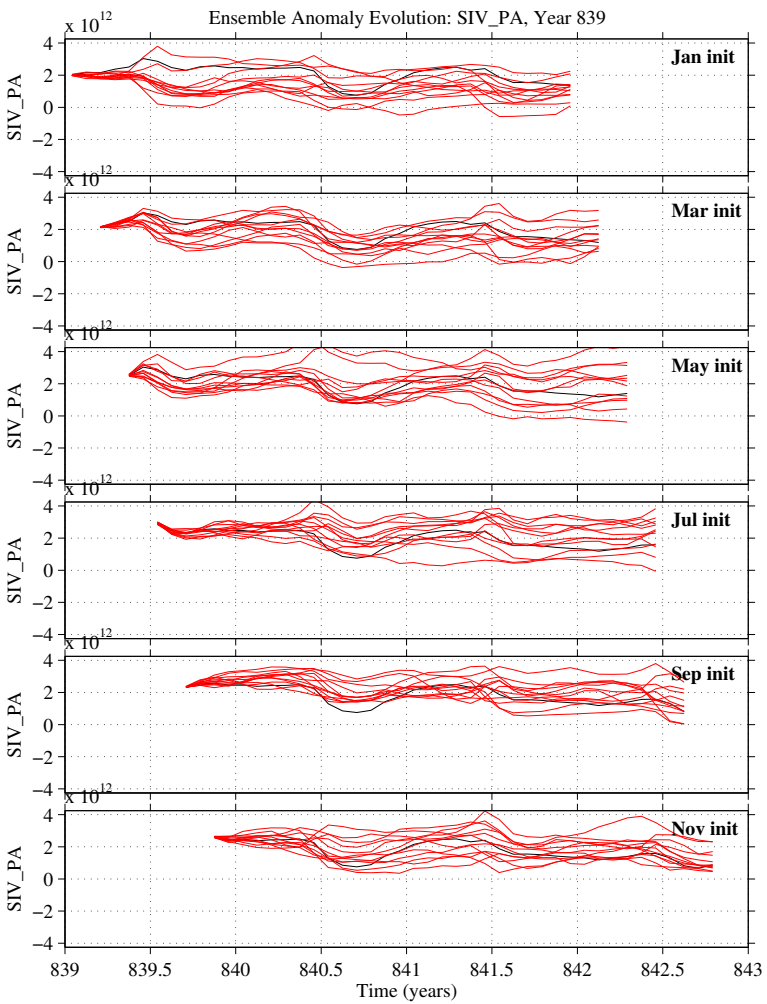
Key Design Aspects

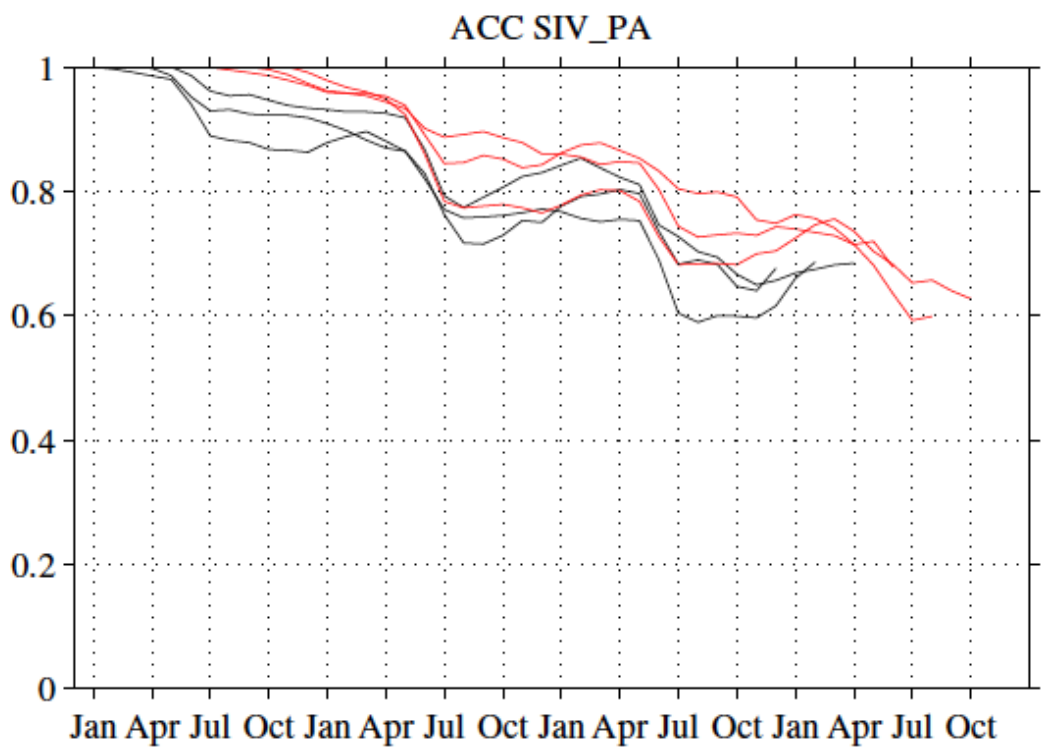
- Experiments run from well equilibrated model state
- Seasonal coverage of start dates allows for study of skill at different lead times
- Performed with same model as seasonal forecast system. Allows for direct comparison of perfect model and “operational” skill

Predictability Metrics: Ensemble Evolution

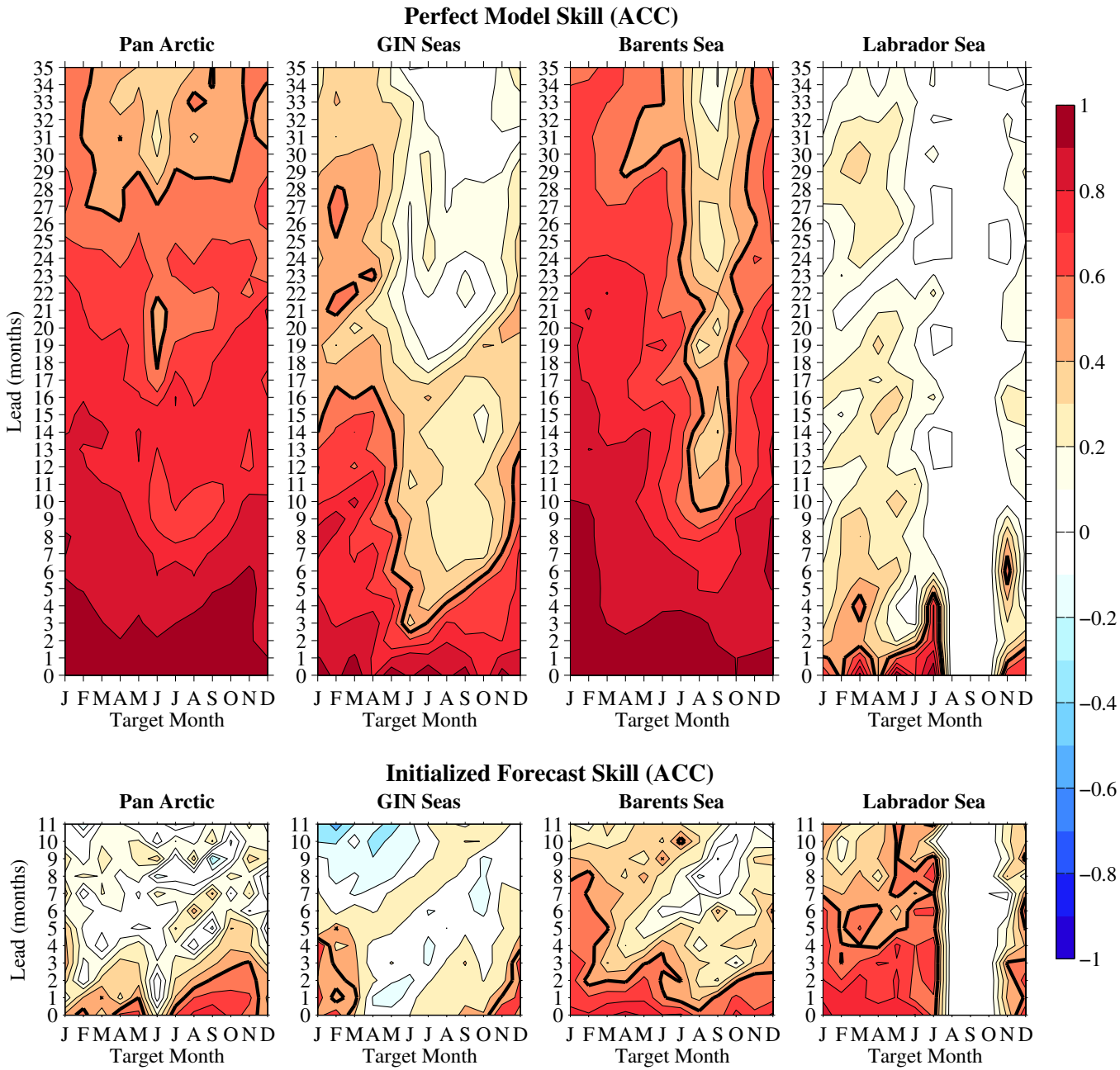
$$ACC(\tau) = \frac{\sum_{j=1}^{M}\sum_{i=1}^{N}\sum_{k\neq i}^{N}(x_{ij}(\tau)-\mu(\tau))(x_{kj}(\tau)-\mu(\tau))}{\sum_{j=1}^{M}\sum_{i=1}^{N}\sum_{k\neq i}^{N}(x_{kj}(\tau)-\mu(\tau))^2}$$

x is the metric of interest
τ is the lead time
i, k ensemble indices
j start date index
μ is the climatological value
M is the number of start years
N is the number of ensemble members



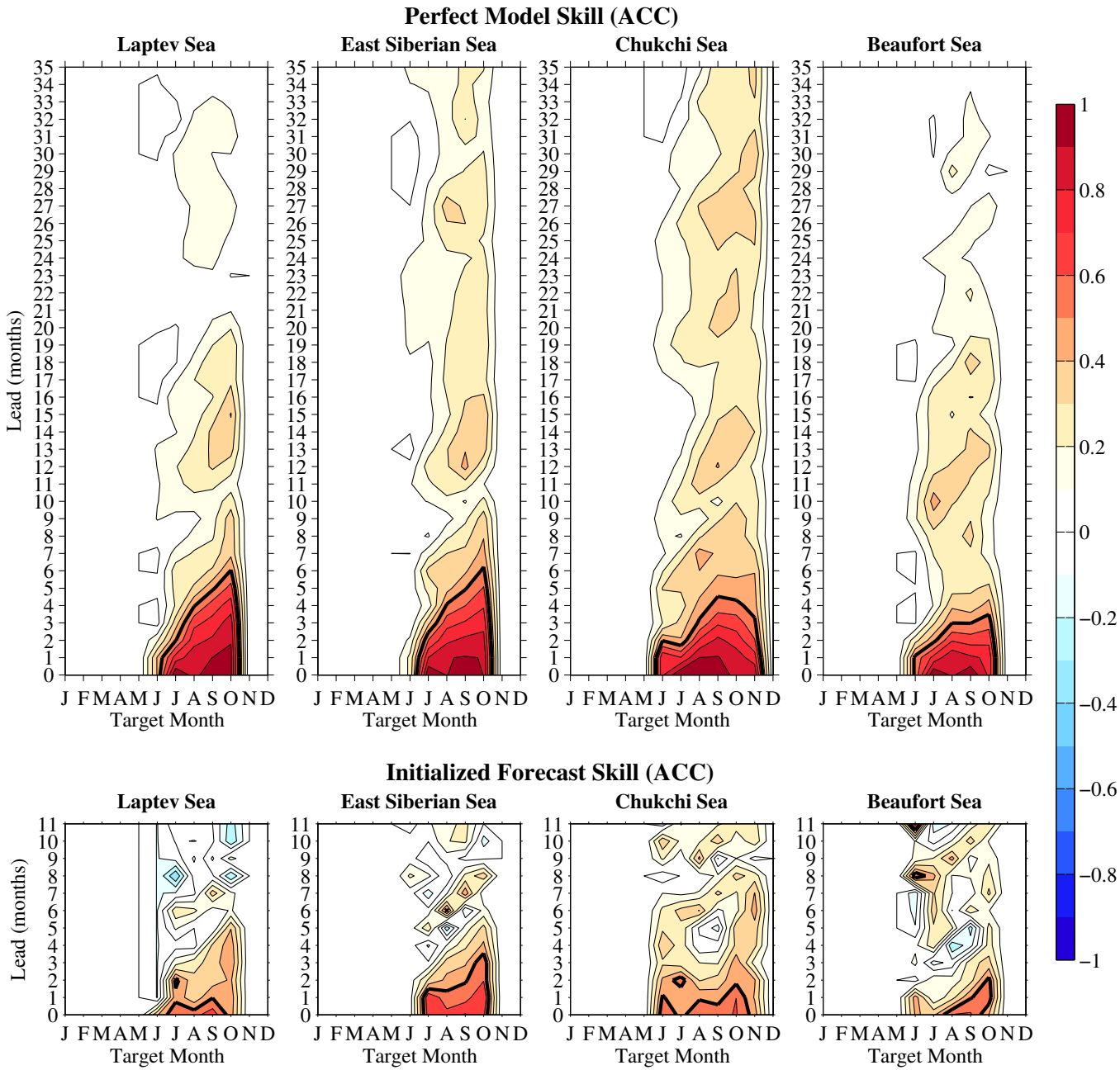


Comparison of Perfect Model and Operational Skill



Black contour: ACC=0.5

Comparison of Perfect Model and Operational Skill: Summer ice regions



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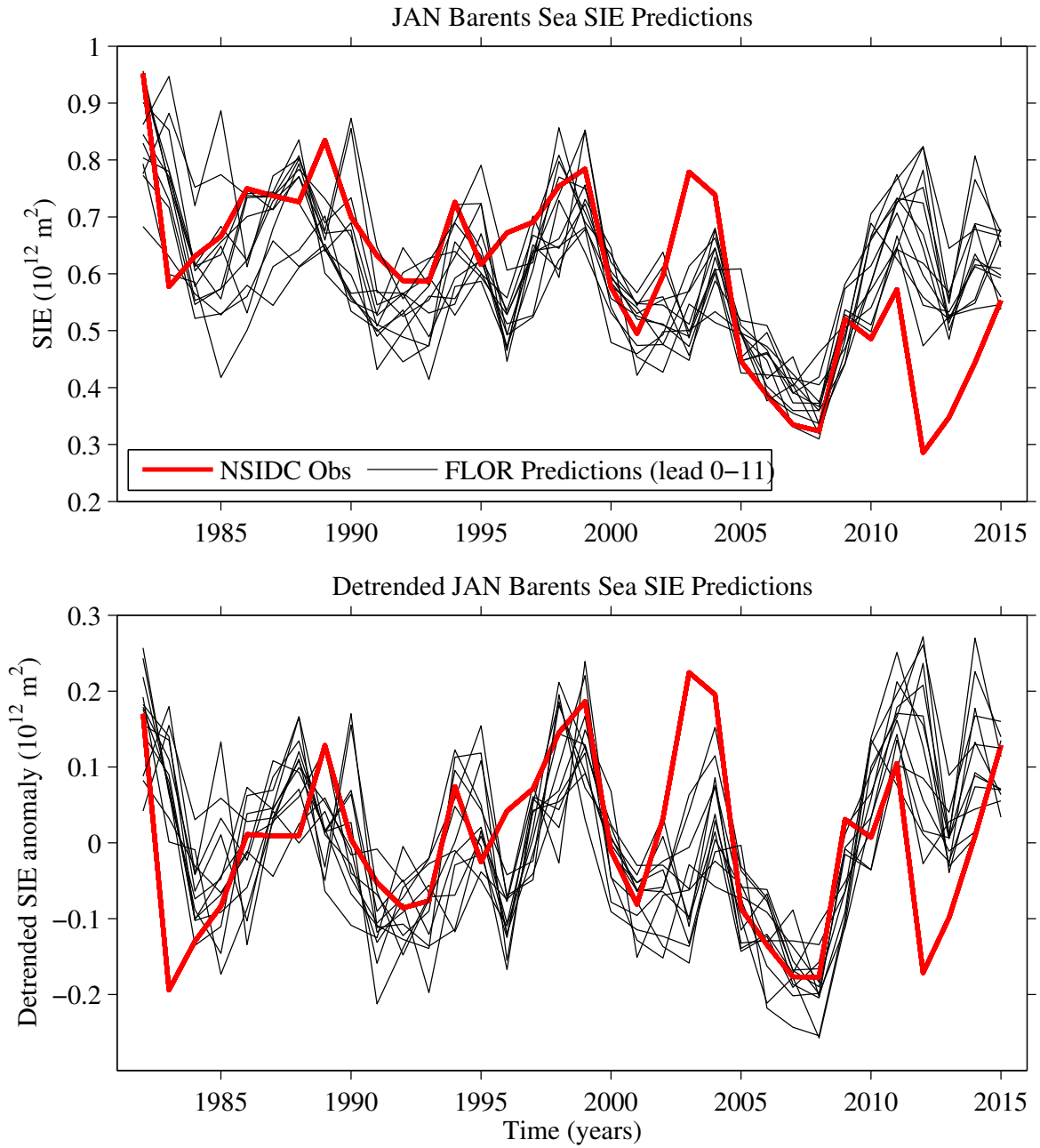
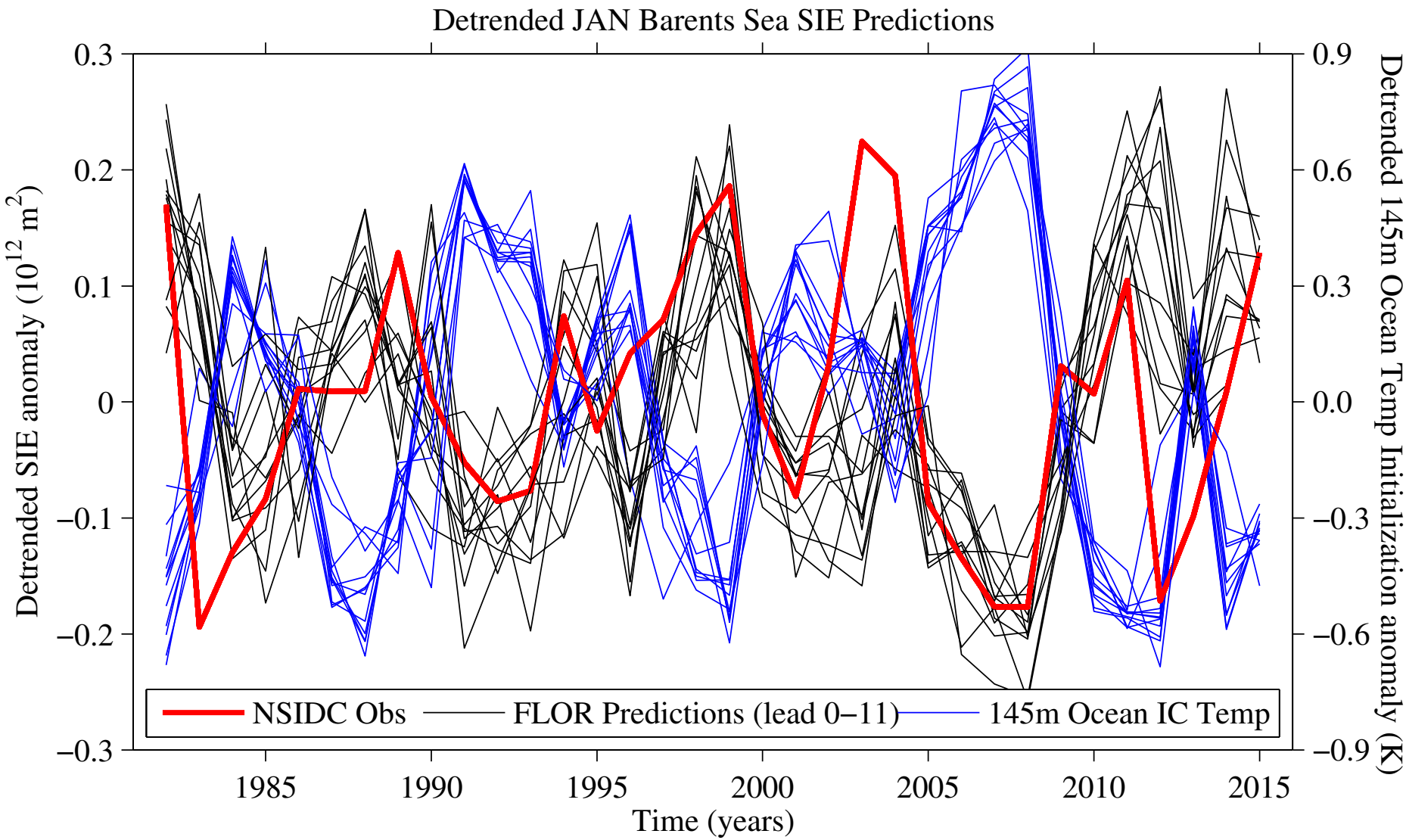
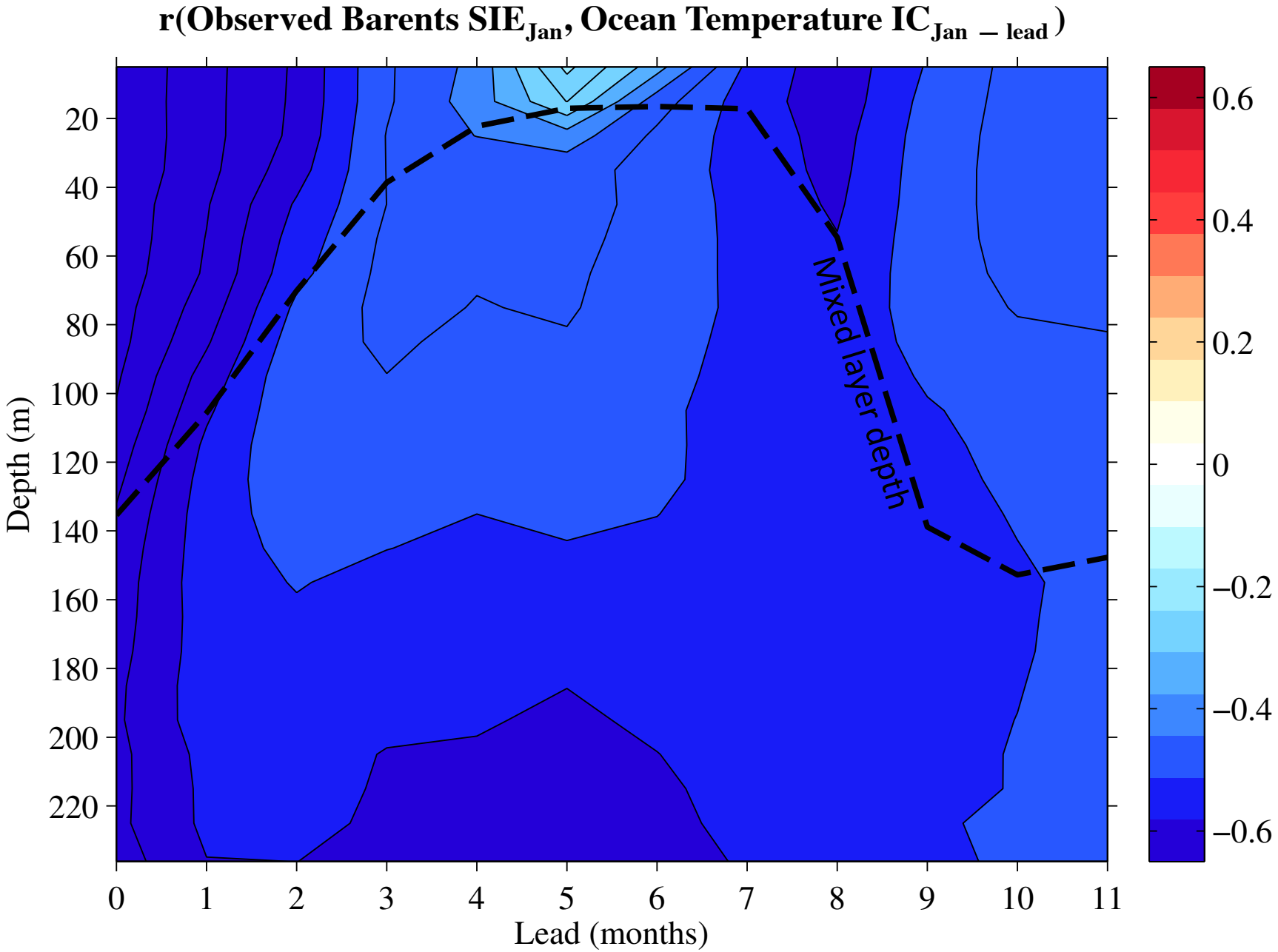
Barents Sea January SIE Predictions



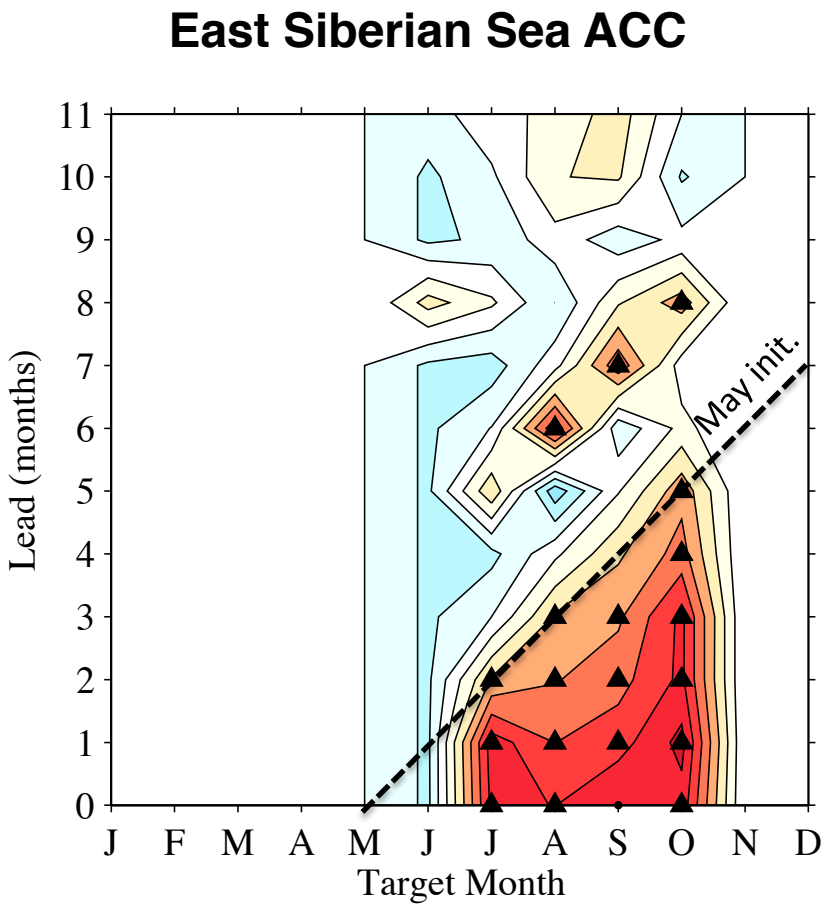
Where is Barents winter skill coming from?

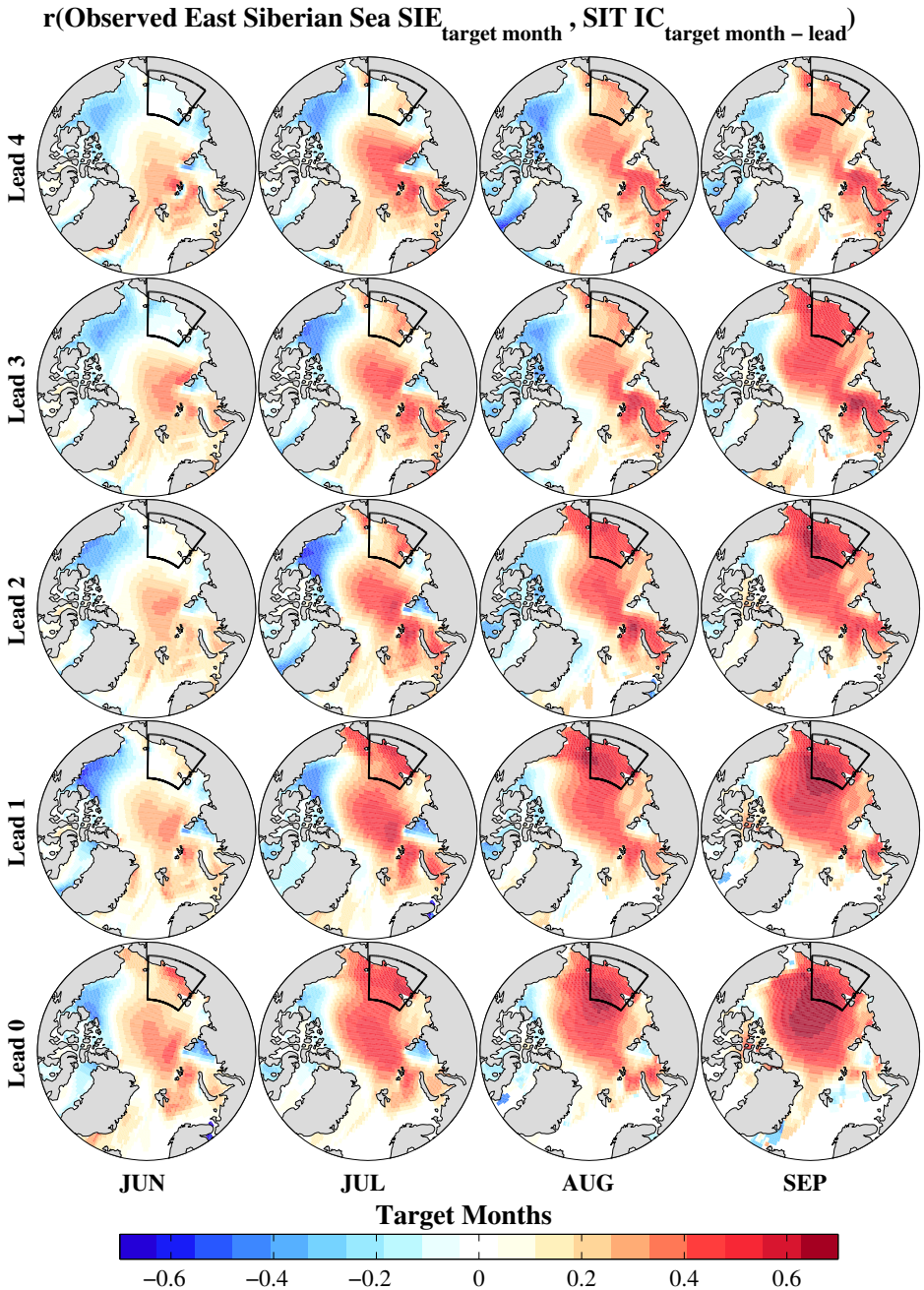


Sources of Winter Prediction Skill: Ocean Temperature Initialization



Sources of Summer Prediction Skill: SIT initialization





Conclusions

1. Regional prediction skill generally exceeds the skill of an anomaly persistence forecast
2. Skill is notably high for winter SIE in the North Atlantic Sector
3. Potential for skill up to 36 months in certain Arctic regions
4. Winter SIE skill is partially attributable to accurate initialization of ocean temperature anomalies
5. Summer SIE skill is partially attributable to initialization of sea-ice thickness anomalies
6. Further skill improvements may be possible with improved subsurface ocean initialization and satellite-based sea-ice thickness initialization

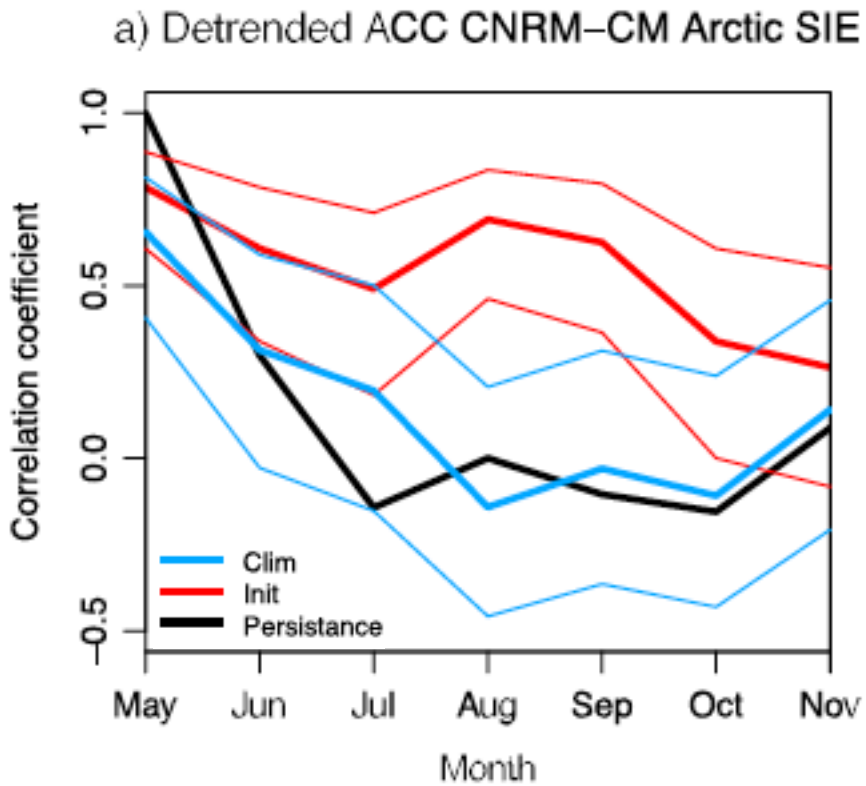
Thank you!
Questions?

Contact me at: mitchell.bushuk@noaa.gov

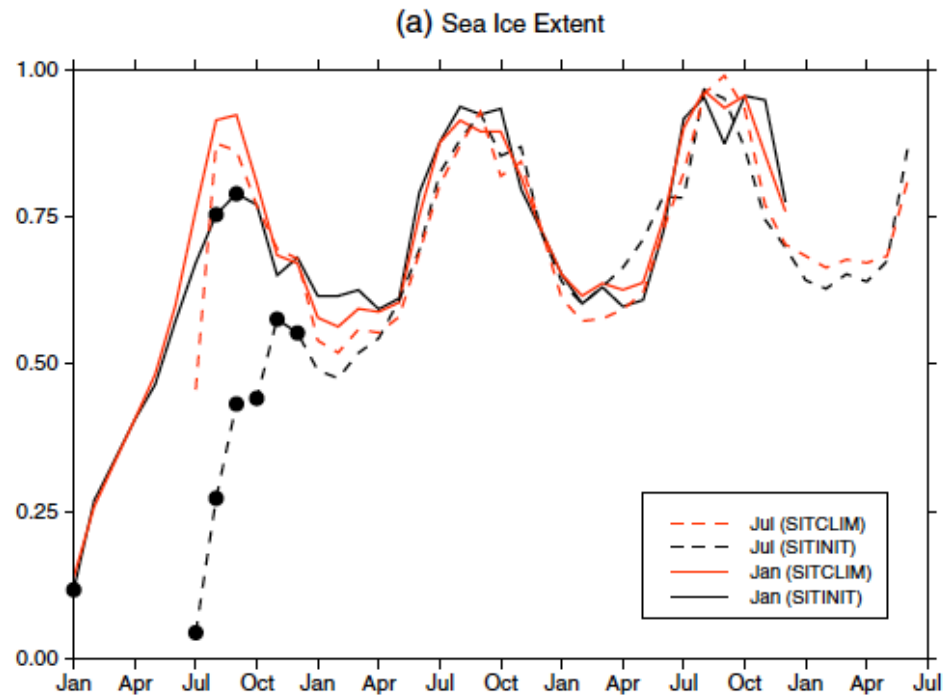
Appendix Slides

Importance of Thickness Initialization

Accurate thickness initial conditions provide improved forecast skill

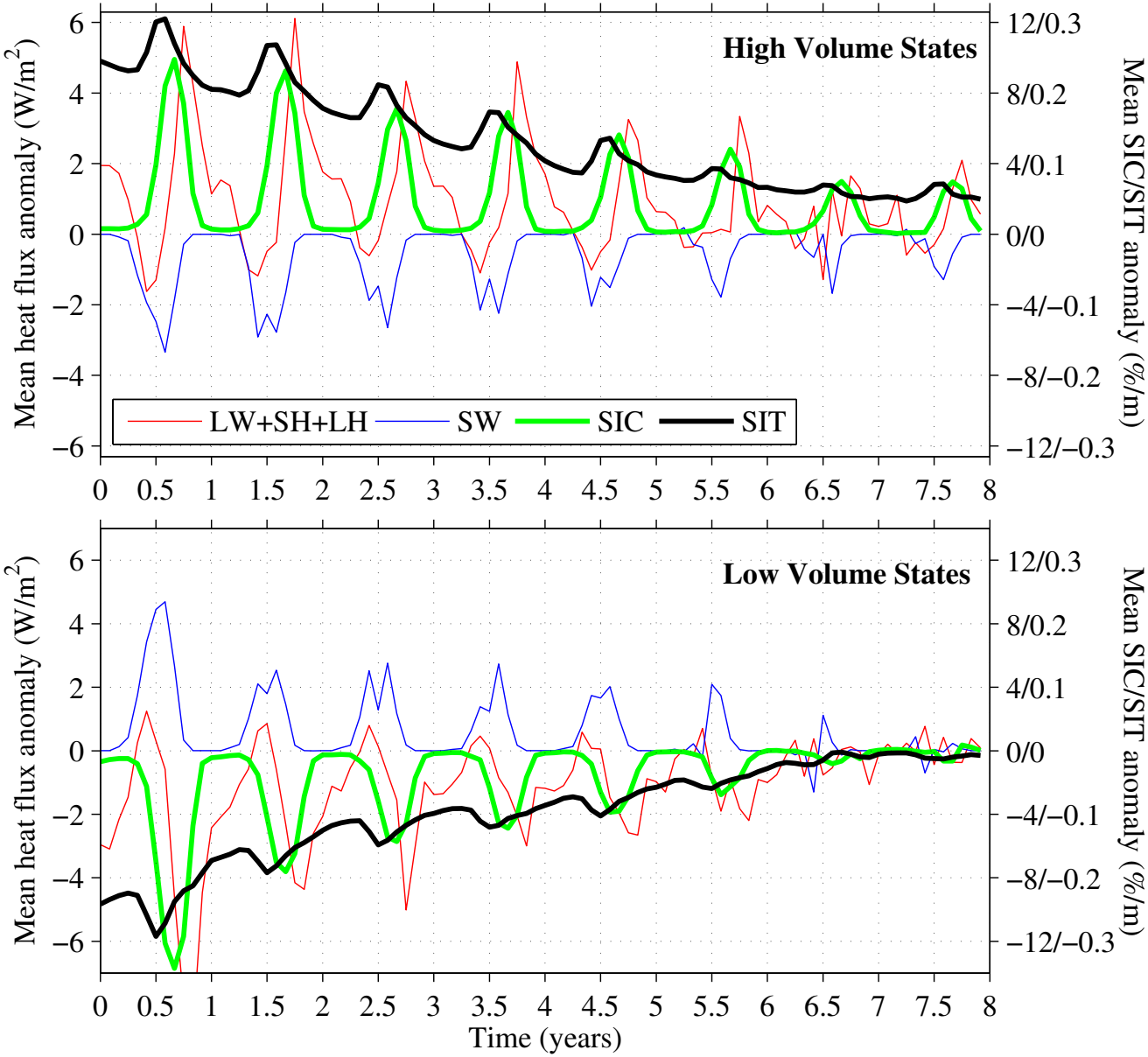


Guemas et al (2016), *GRL*



Day et al (2014), *GRL*

Summer Enhancement of Sea-Ice Volume Anomalies



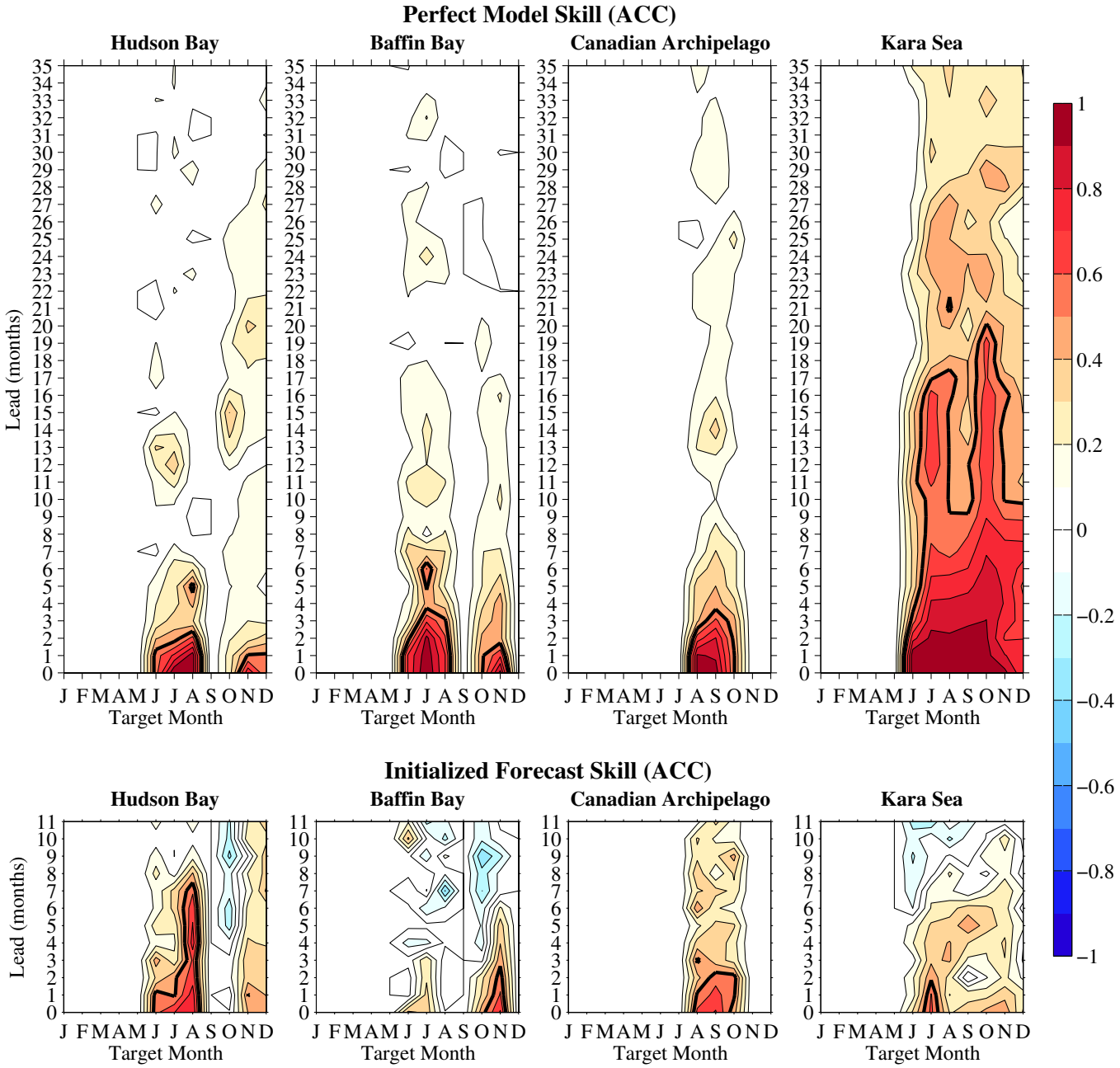
$$F_{\text{sfc}} = SW + LW + SH + LH$$

+ fluxes: Melt ice
- fluxes: Freeze ice

SIT: sea ice thickness
SIC: sea ice concentration
SW: Net shortwave radiation
LW: Net longwave radiation
SH: Sensible heat
LH: Latent heat

Bushuk et al. 2017, *J. Climate*

Comparison of Perfect Model and Operational Skill



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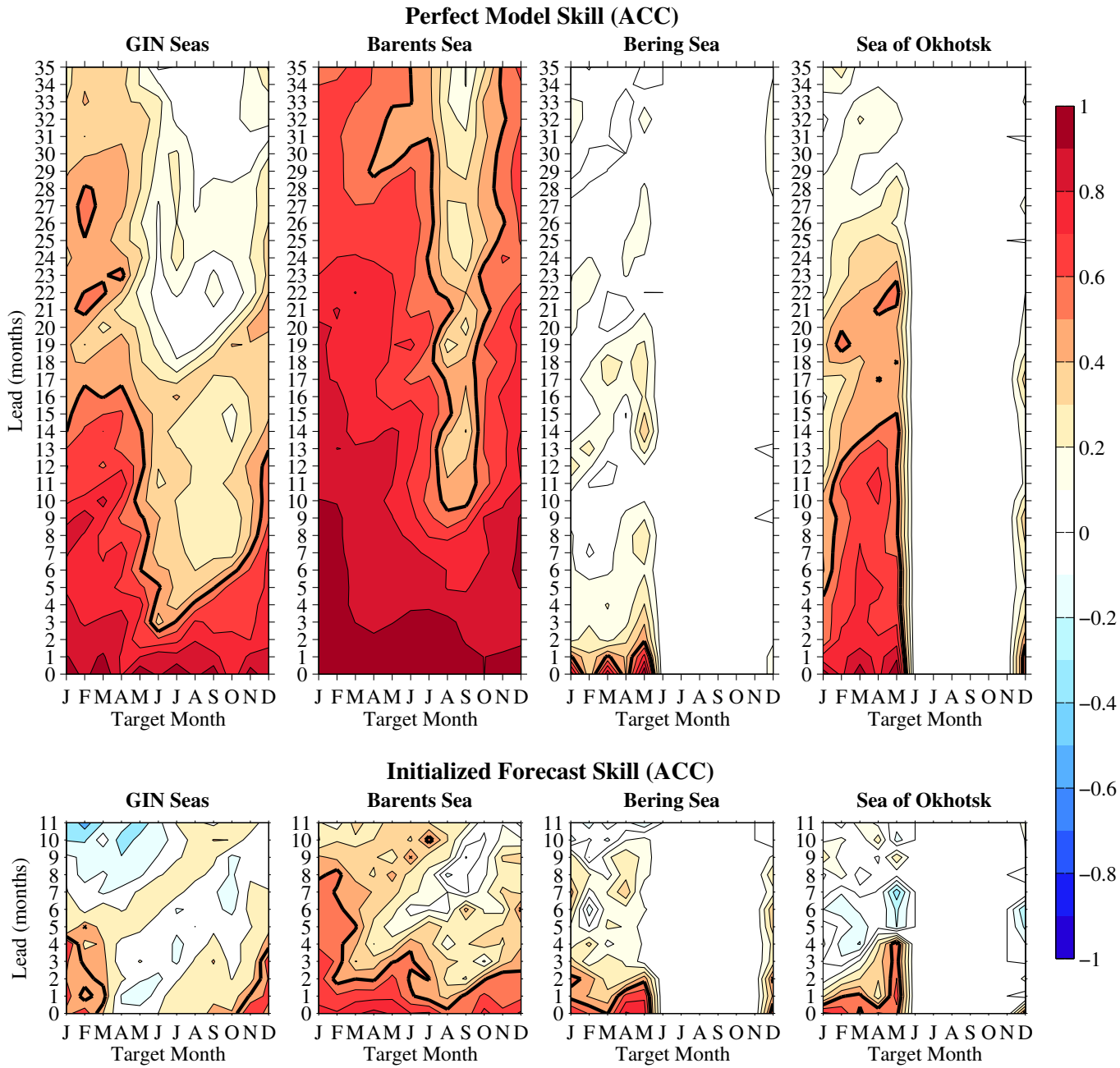
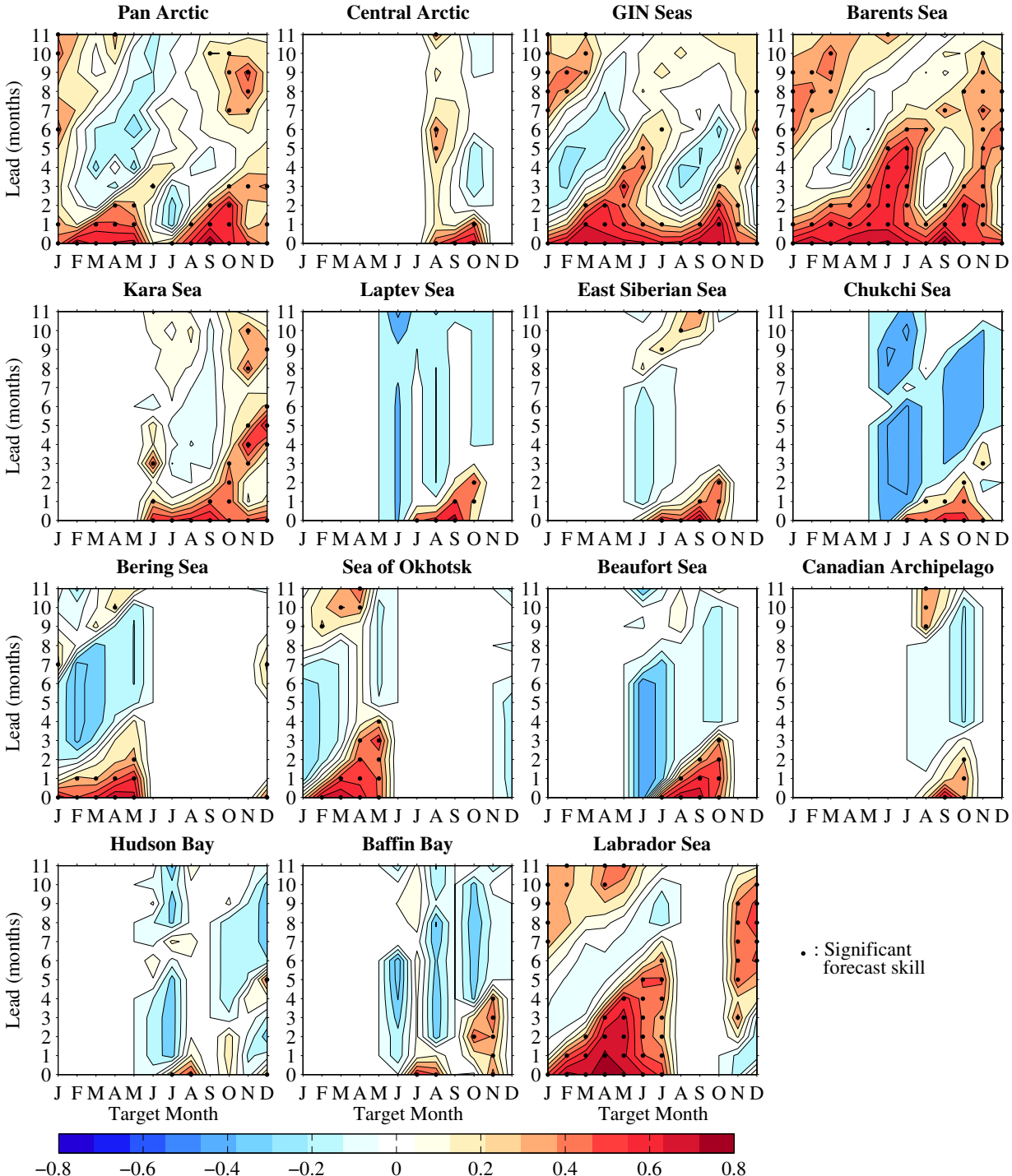
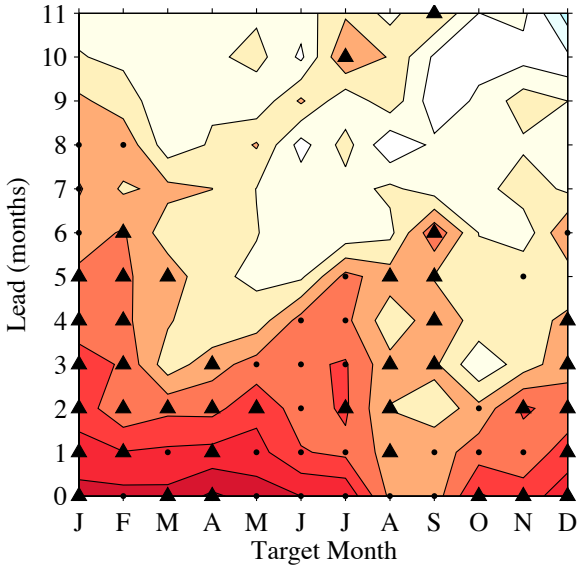




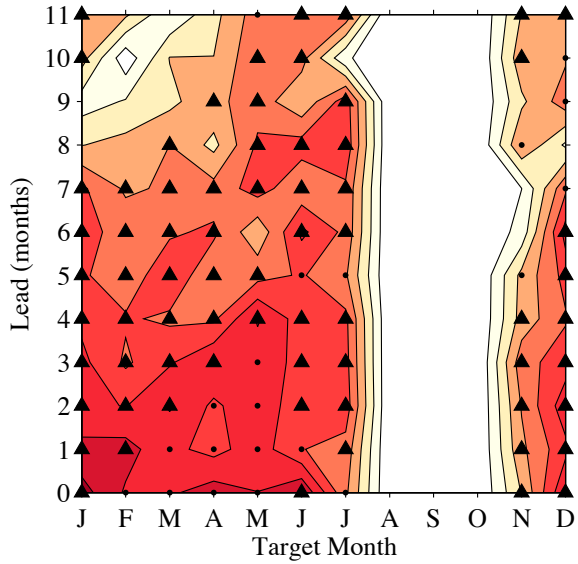
Anomaly persistence forecast

Sources of Winter Prediction Skill

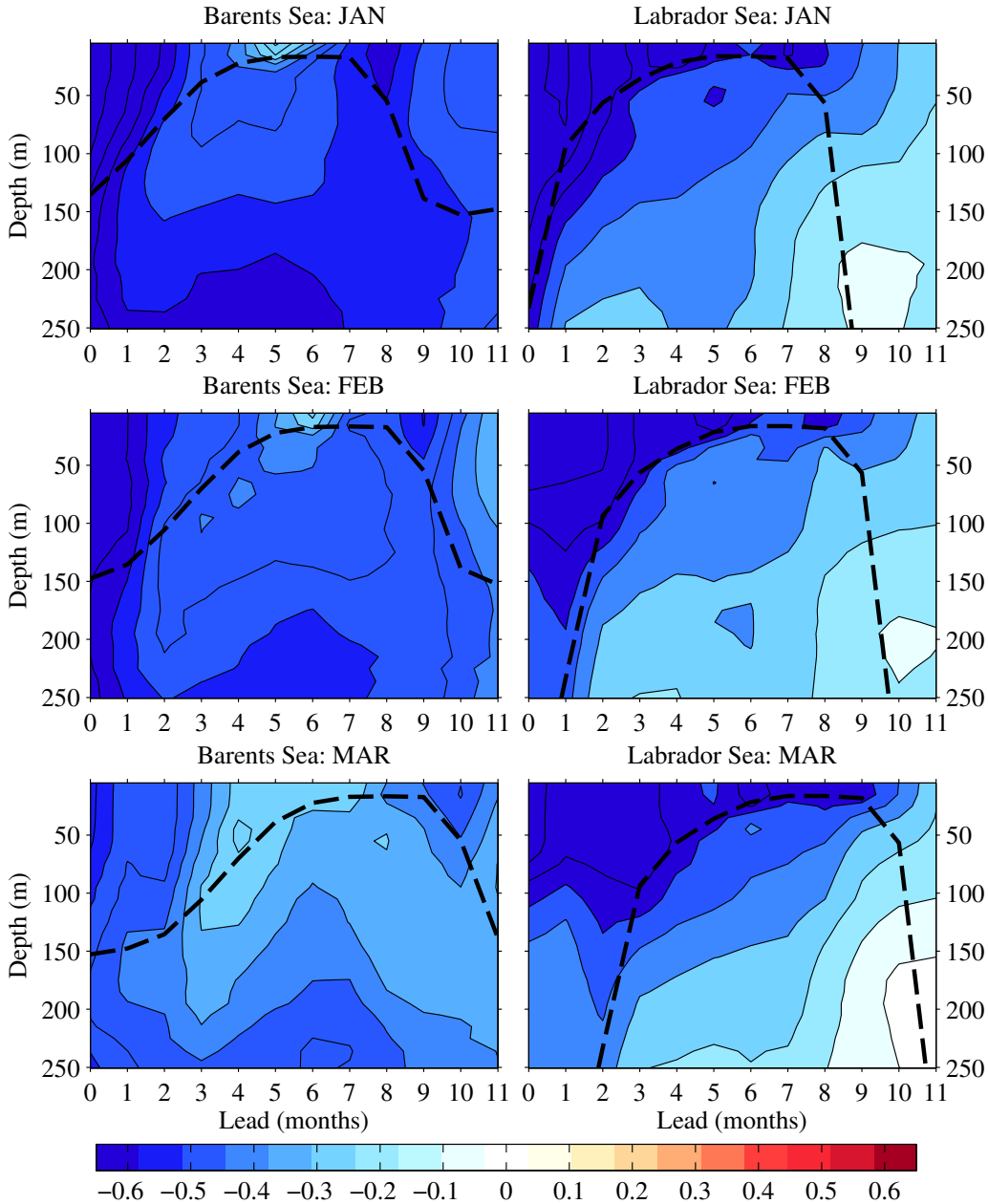
Barents Sea ACC



Labrador Sea ACC



r(Observed Regional SIE$_{\text{target month}}$, Ocean Temperature IC$_{\text{target month – lead}}$)

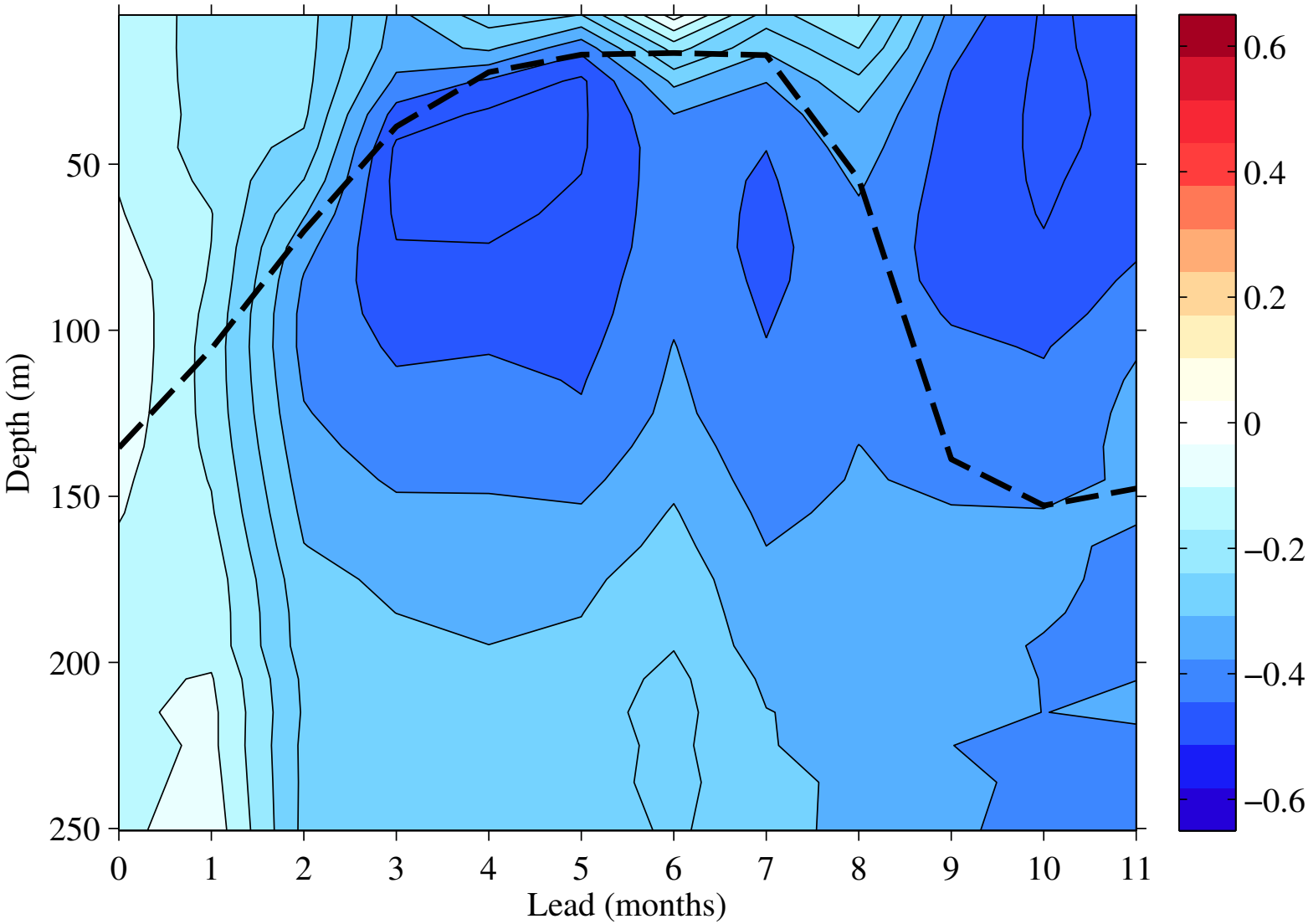


Potential Improvements in Winter Prediction Skill

r(Predicted Barents SIE_{Jan}, Ocean Temperature $IC_{Jan-lead}$)

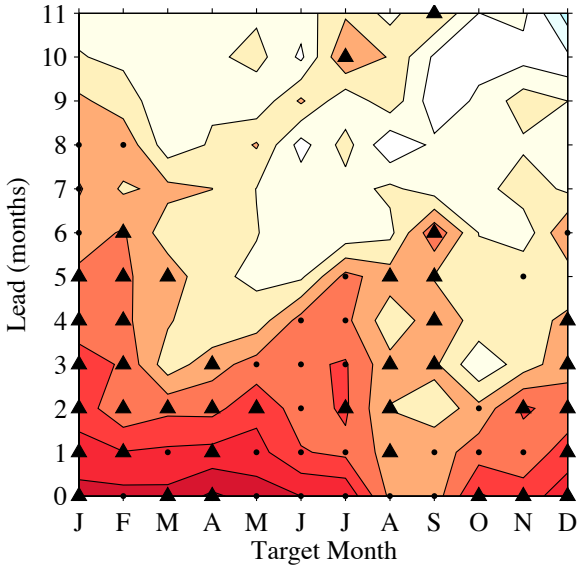
minus

r(Observed Barents SIE_{Jan}, Ocean Temperature $IC_{Jan-lead}$)

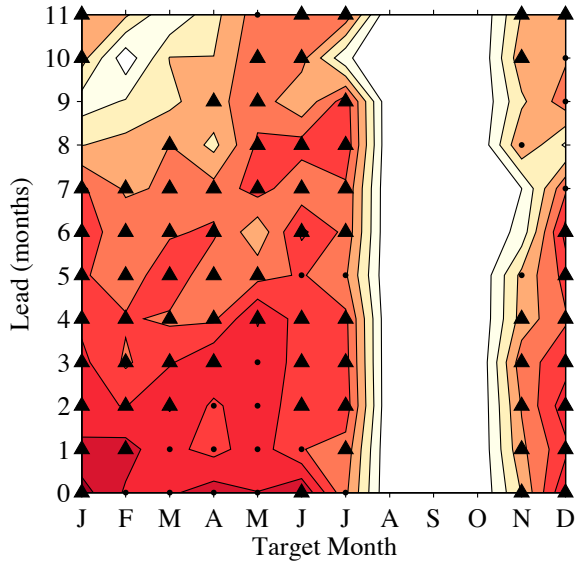


Sources of Winter Prediction Skill

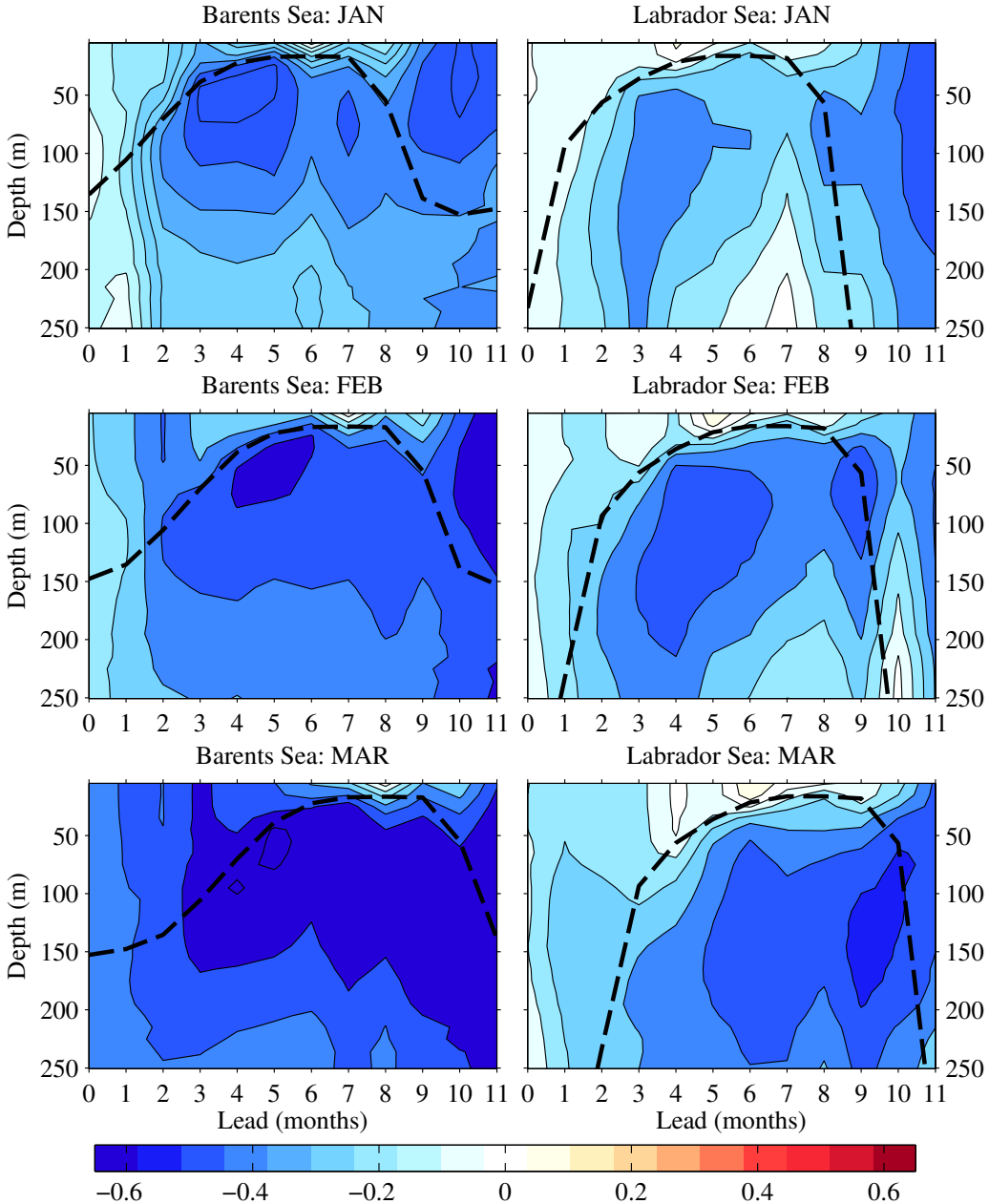
Barents Sea ACC



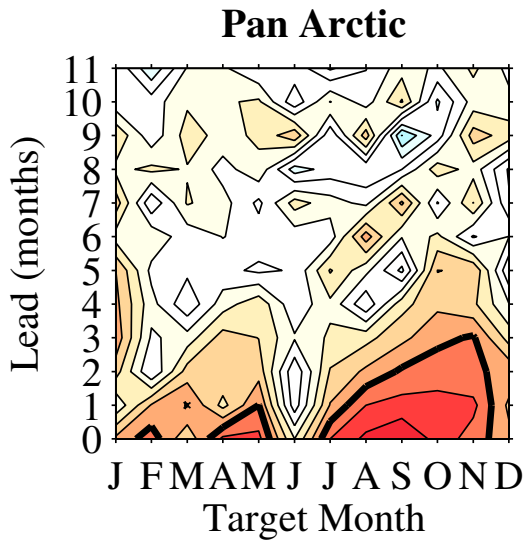
Labrador Sea ACC

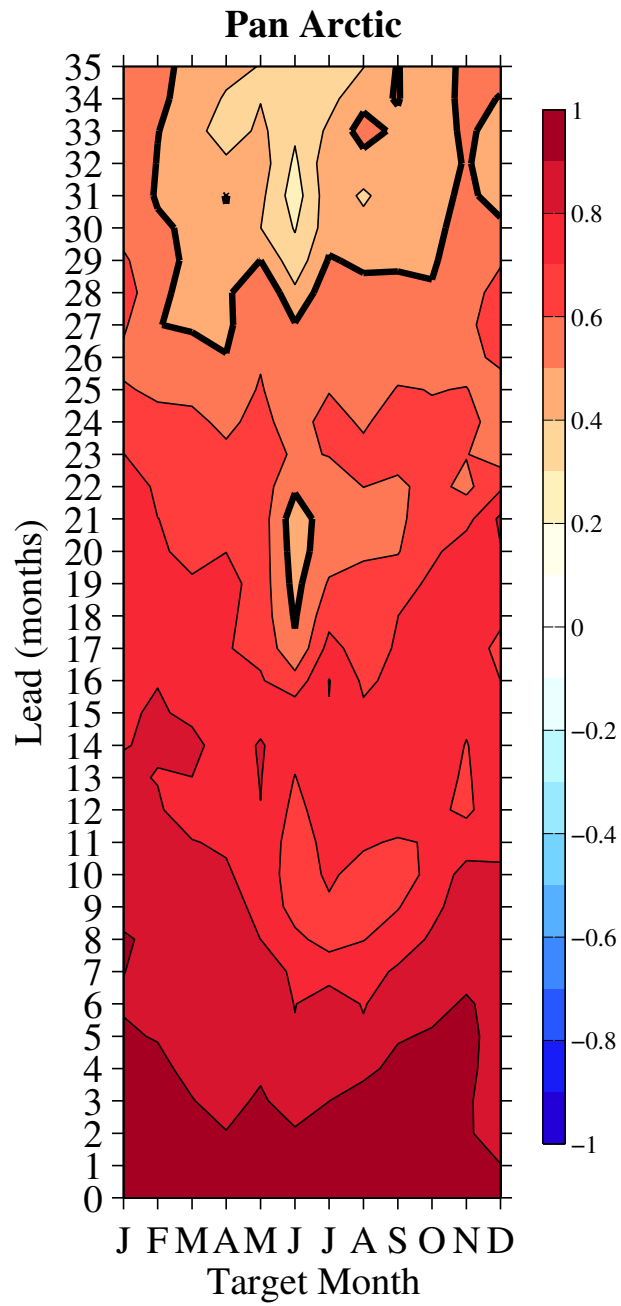


Correlation difference between Predicted and Observed SIE



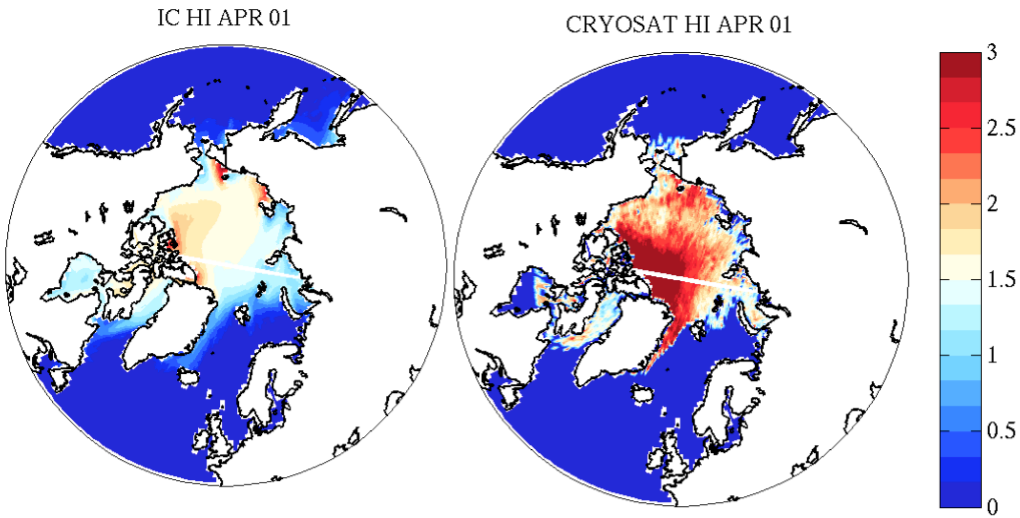
Comparison of Perfect Model and Operational Skill: Pan-Arctic SIE



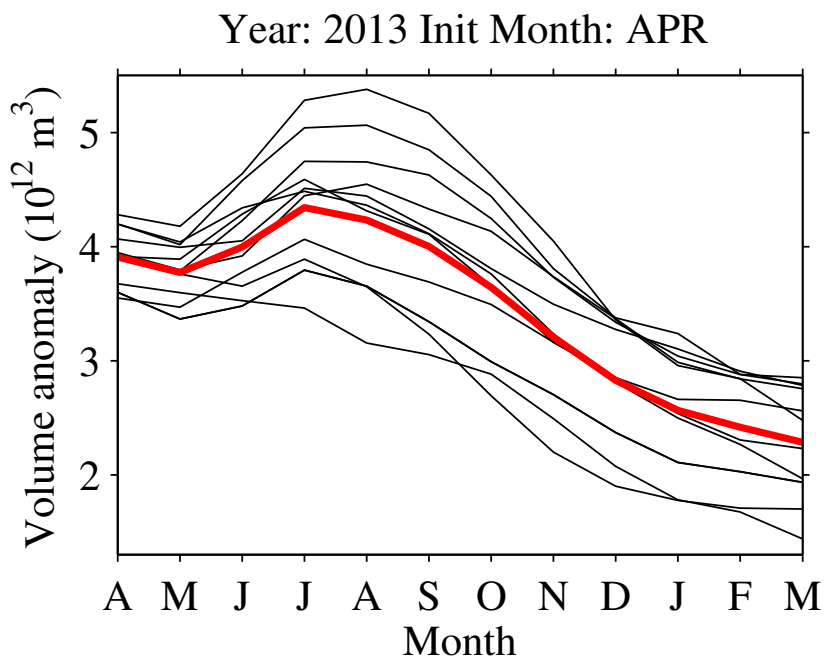


Initialized Forecasts Using CryoSat-2[1] Thickness

Modified ice thickness initial conditions



Volume anomaly evolution

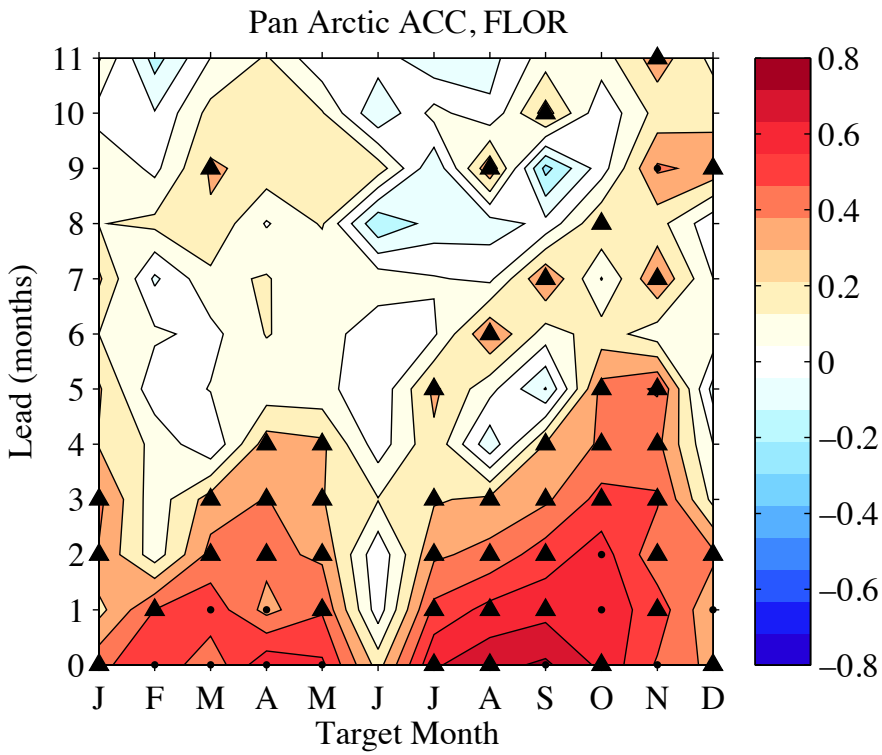


1: Data from CPOM @ UCL; See Tilling et al (2015), *Nat. Geosci.*

The Arctic Sea-Ice Prediction Gap

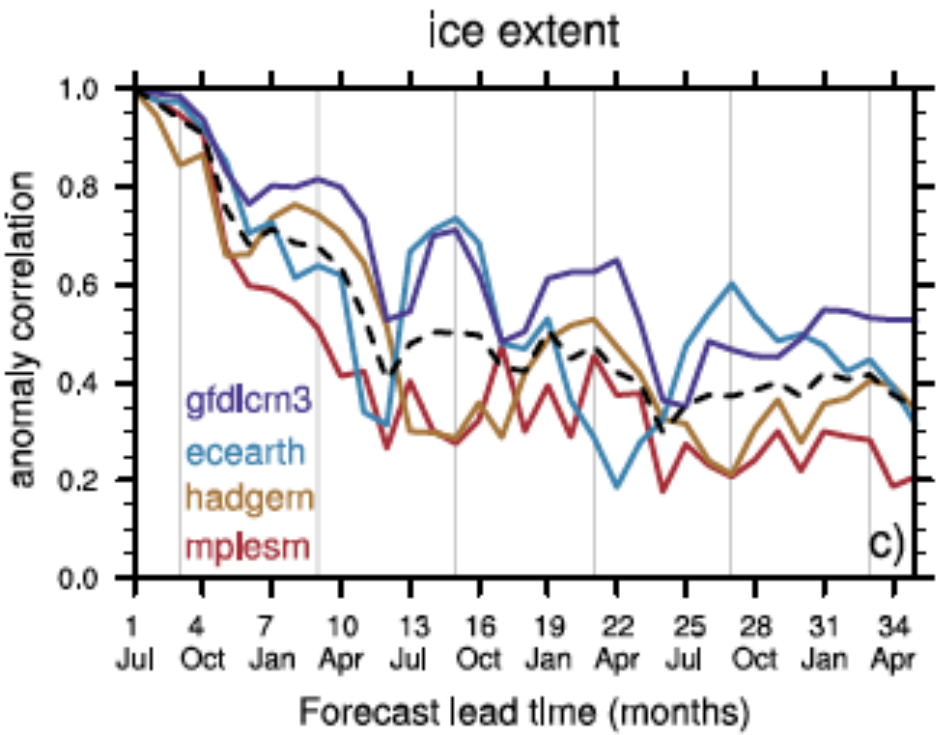
Operational Prediction Skill[1]

0-5 months



Perfect Model Predictability[2]

12-24 months



1: Bushuk et al (2017), *GRL*

2: Tietsche et al (2014), *GRL*