Seasonal predictions of Arctic sea ice

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Workshop on Sea Ice in the Earth System meeting
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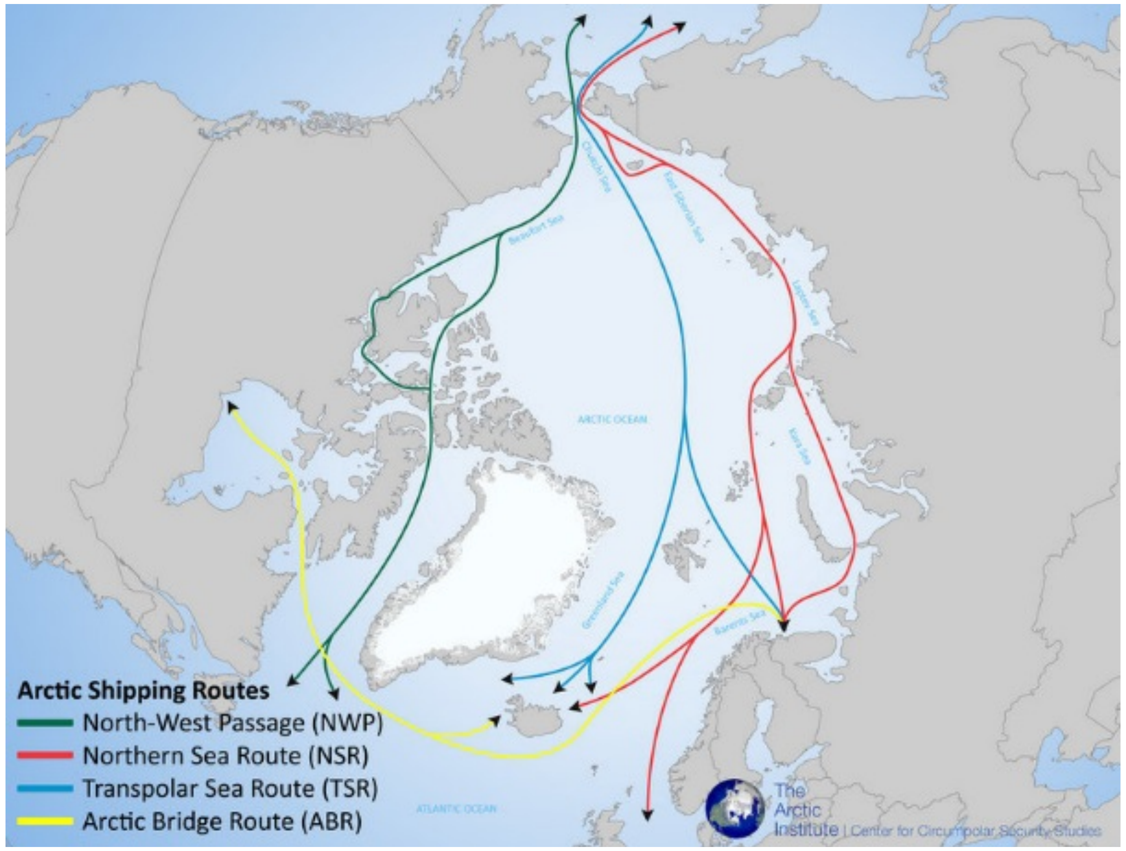
Motivation: Why predicting seasonal changes in Arctic sea ice?

Growing demand of stakeholders in seasonal sea ice forecasts

New routes to access the Arctic Ocean

- Fishing, commercial shipping, tourism, oil and mineral extraction
- Summer **and** winter sea ice predictions.



Arctic sea ice: a source of climate predictability?

Impact on ocean/atmosphere

- Influence of sea ice decline on cold eurasian and European winters ?
- Control of subpolar primary production ?

Predictions of summer sea ice cover

- September 2007 and 2012 record-lows SIE raised high interest in summer sea ice predictions

- Sea ice outlooks (SIO) established in 2008 with open contributions of Pan-Arctic SIE. Contribution of GFDL since 2013 *(Msadek et al., Bushuk et al.)*

- Skill shows room for improvement for all models *(Stroeve et al. 2014)*
    - Models do barely better than trend or anomaly persistence forecast
    - Hindcasts better than actual forecasts
    - Perfect models suggest we could do better

Outline

- Skill of GFDL-CM2.1 in seasonal forecasts of:
    - Pan-Arctic sea ice extent
    - Regional sea ice extent
- Predictive skill vs. predictability
- Insights into physical processes:
    - Role of sea ice thickness
    - Role of the ocean
- Conclusions

The dynamical forecast system

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°)

Operational Predictions

Initialized from ECDA[2]:
Ensemble Kalman Filter **C**oupled **D**ata **A**ssimilation

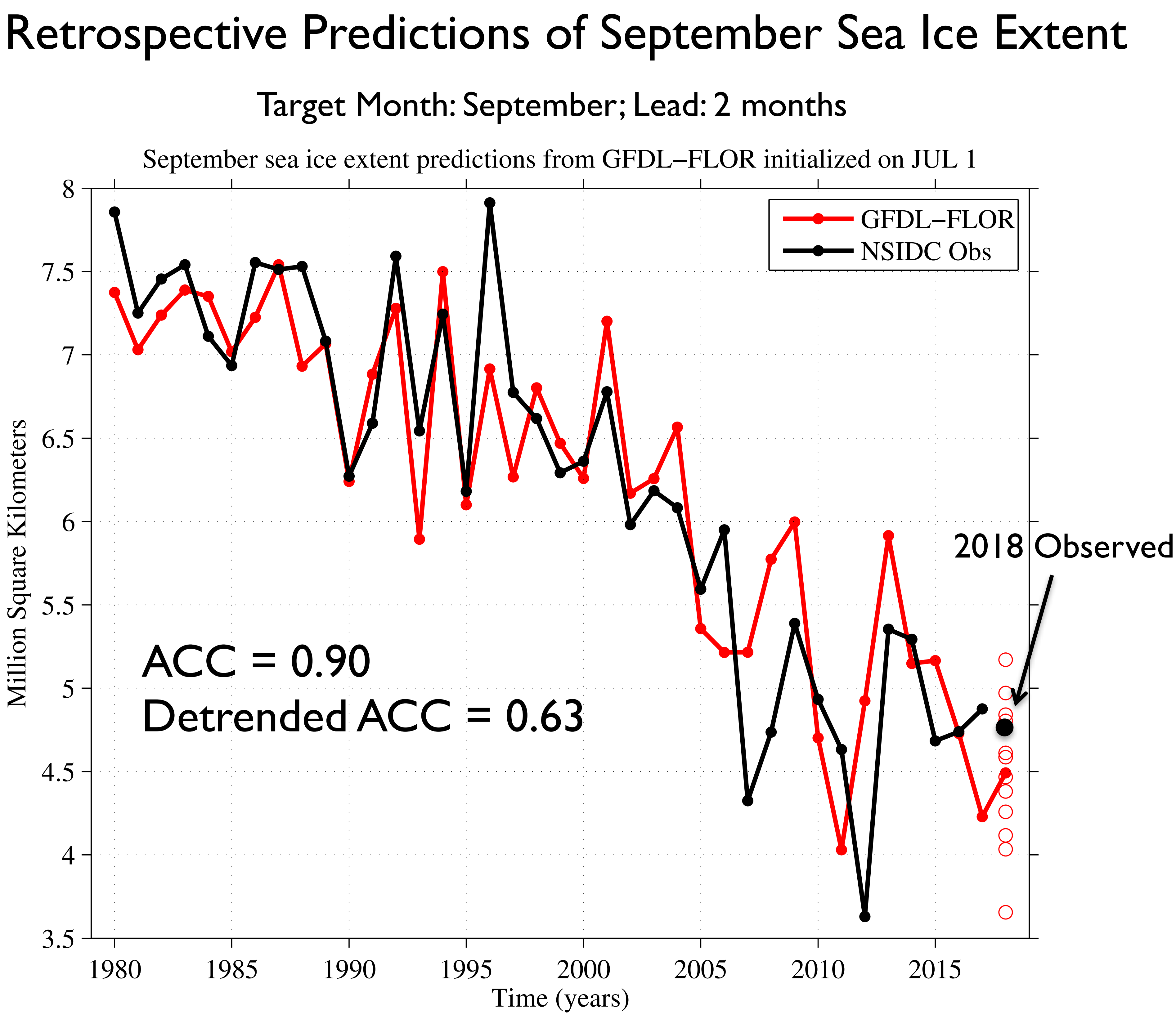
- Ocean assimilates satellite SST, ARGO, CTD, XBT, other WOD profiles
- Atmosphere assimilates NCEP-2 reanalysis
- No assimilation of sea ice data

Retrospective Forecasts

- Forecasts initialized on the first of each month; run for one year
- 12-member ensemble
- Retrospective forecasts spanning 1980-2018

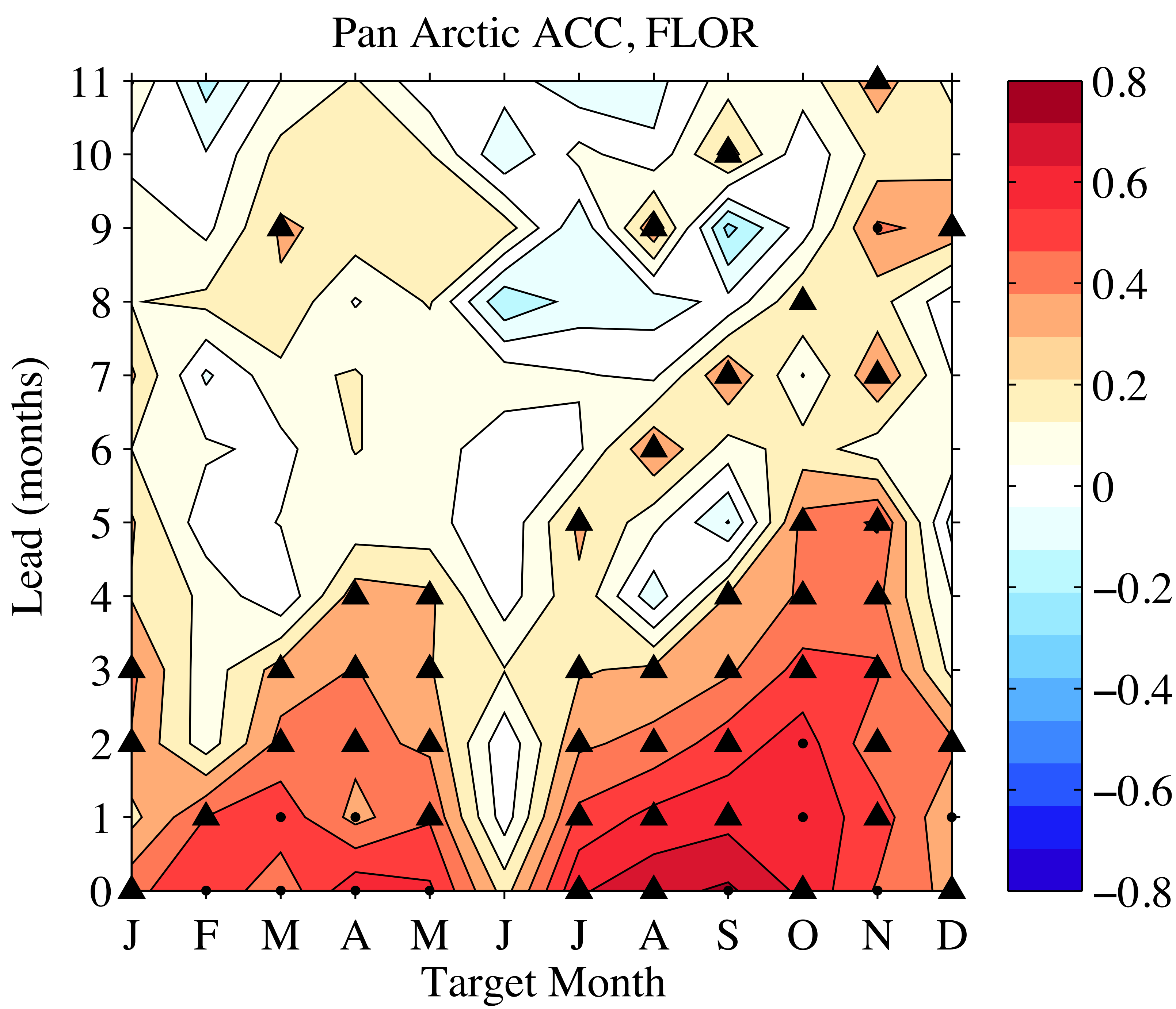
1: Vecchi et al. 2014, *J. Climate*; 2: Zhang et al. 2007 *Mon. Wea. Rev.*

Predictions of Pan-Arctic sea ice extent in the GFDL model



Predictions of Pan-Arctic sea ice extent in the GFDL model

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



Msadek et al. (2014)
Bushuk et al. (2017)

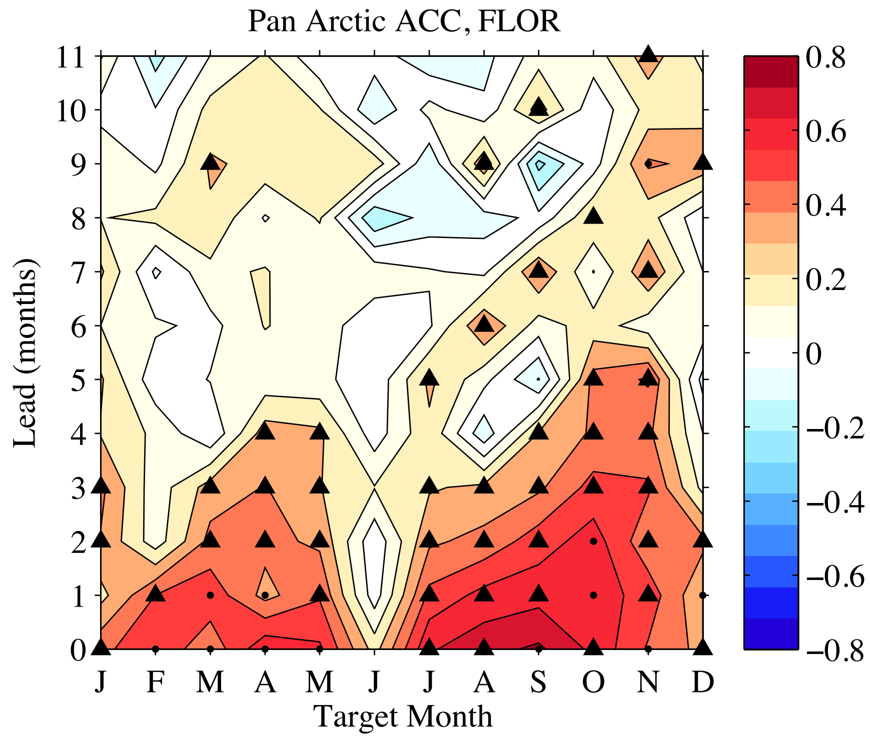
▲: Anomaly correlation coefficient (ACC) exceeds persistence forecast and is significant at 95% level

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

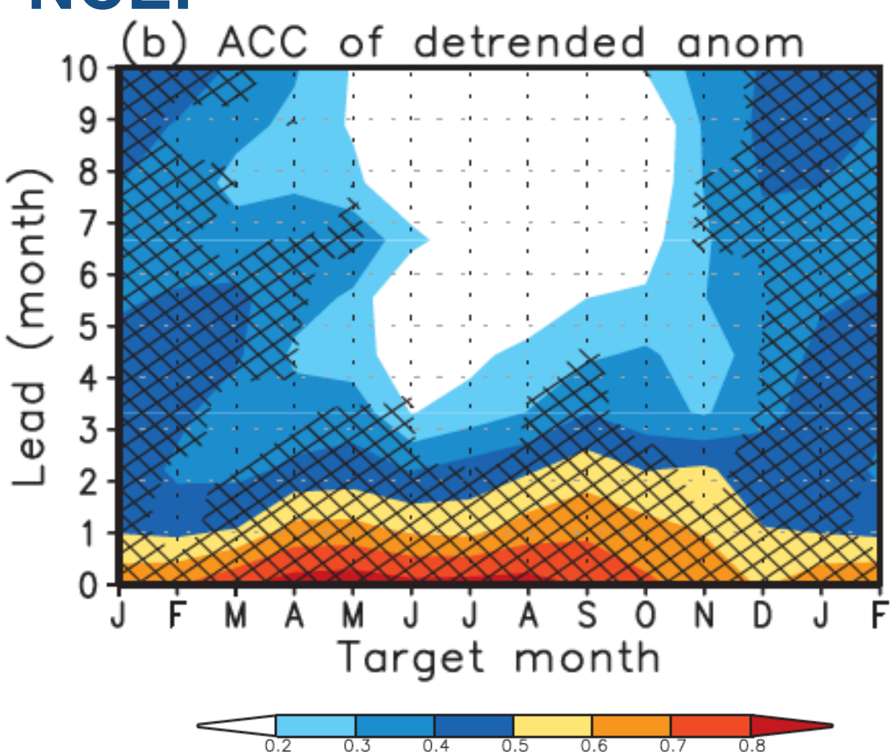
Predictions of Pan-Arctic sea ice extent in other models

- **3**-6 months depending on the month and the target month
- Largest skill in early winter

GFDL

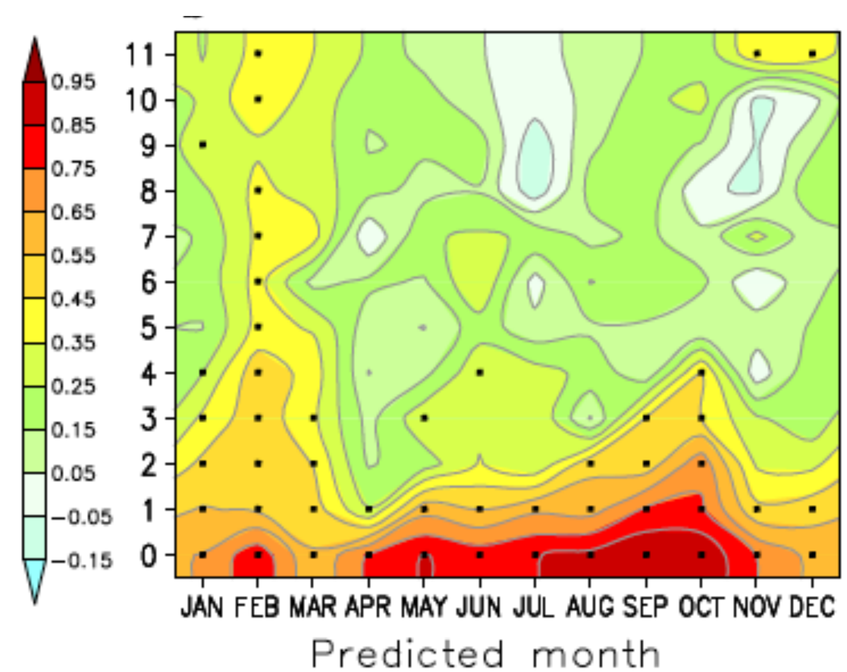


NCEP



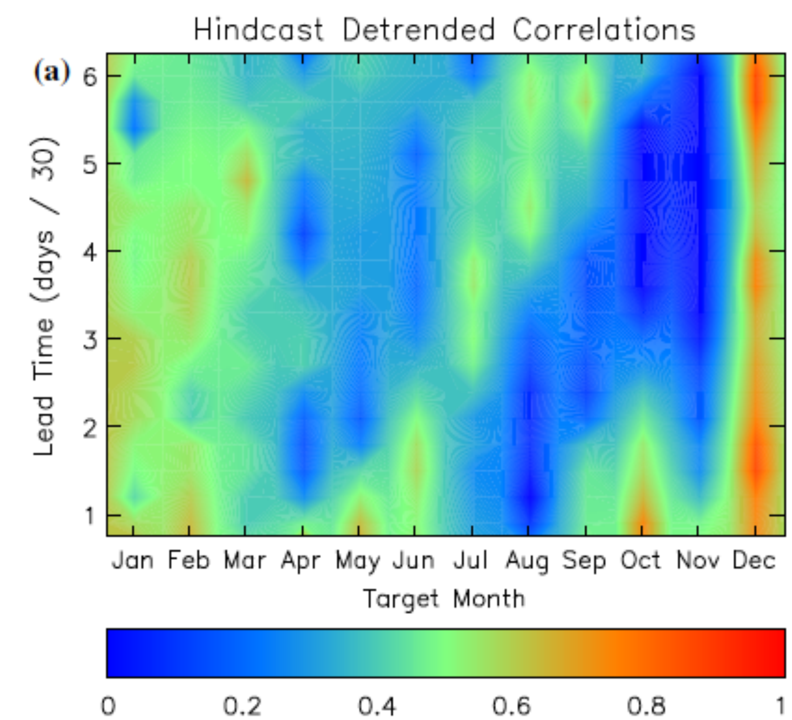
Wang et al. 2013, *Mon. Wea. Rev.*

Canadian model



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

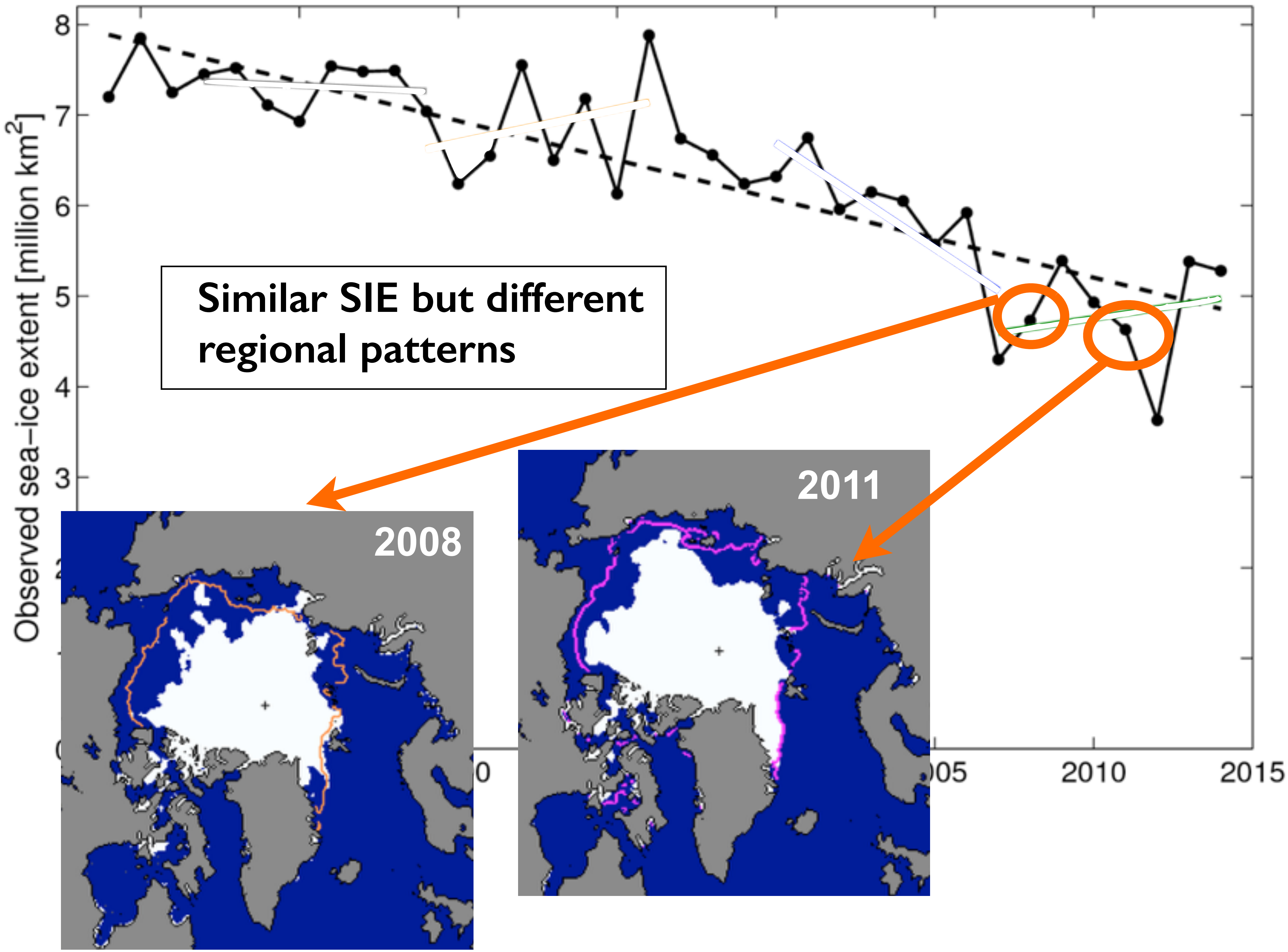
MetOffice



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

See also Chevallier et al. (2013)

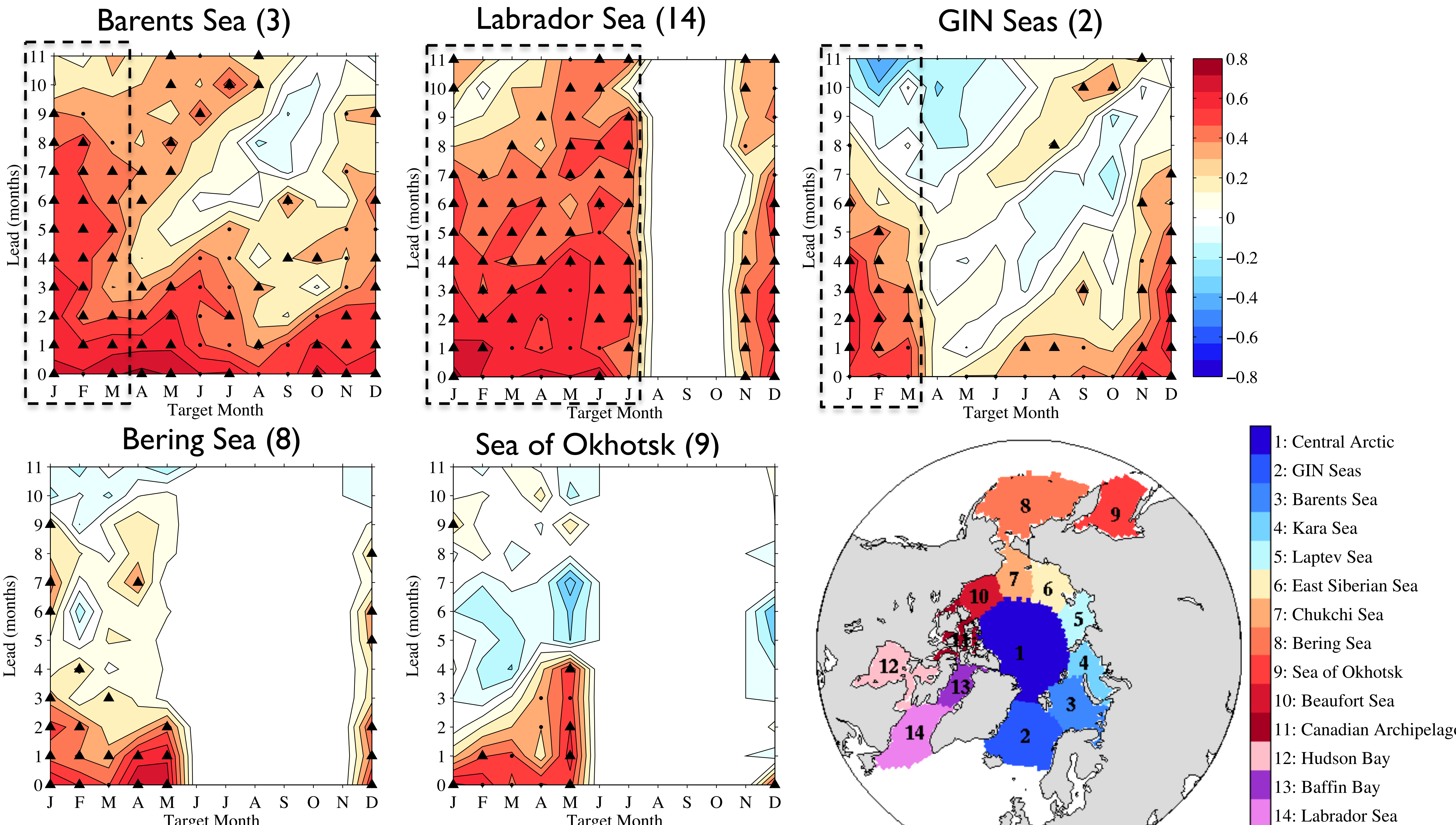
Importance of regional assessment



Source: NSIDC

Predictions of regional Arctic sea ice extent in the GFDL model

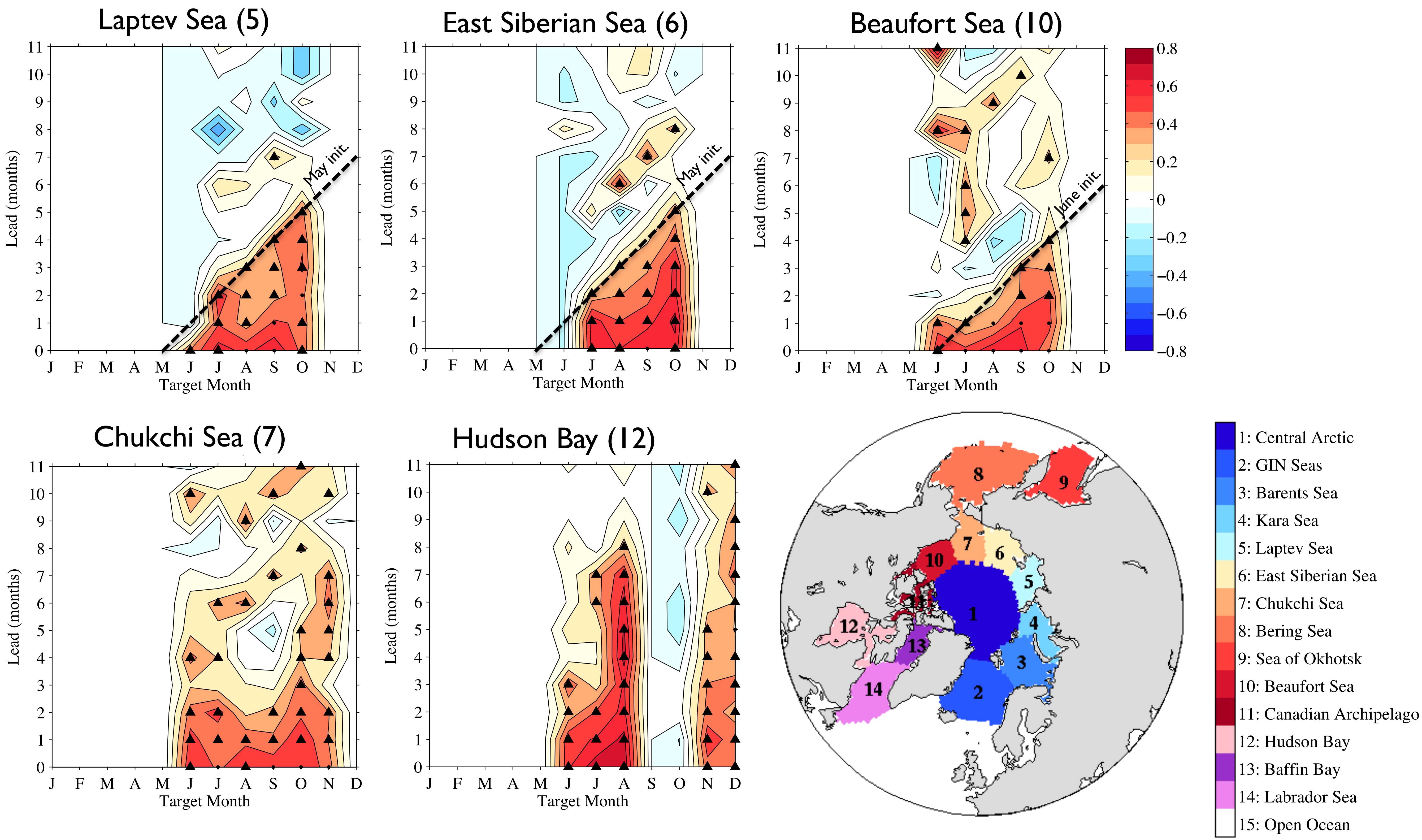
Operational Prediction Skill For Winter Ice Regions (Region # in parentheses)



Bushuk et al. (2017), *GRL*

Predictions of regional Arctic sea ice extent in the GFDL model

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

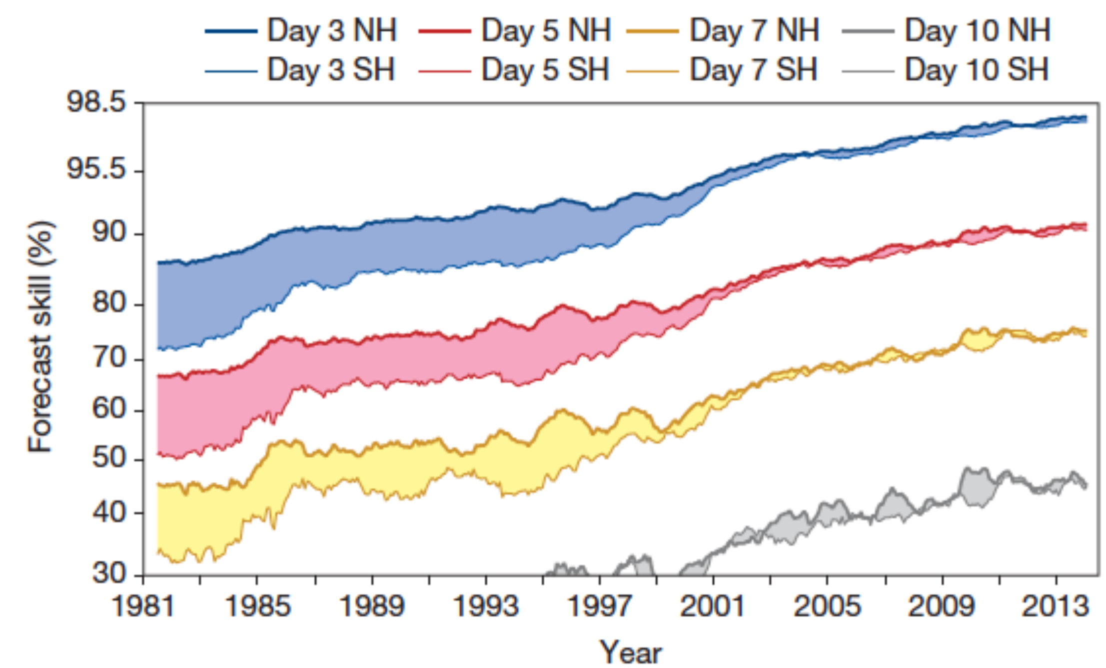


Can we expect higher skill?

Prediction skill ≠ Predictability

Prediction skill: The accuracy of a forecast relative to observations

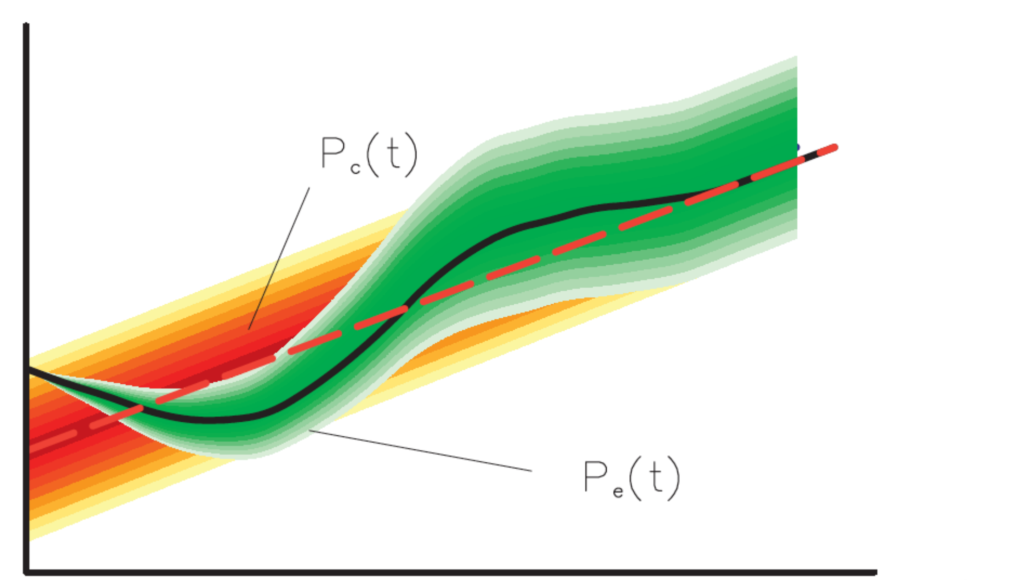
- Depends on quality of model physics and initial conditions
- E.g. current numerical weather forecasts have skill at lead times of roughly 7 days
- Metrics: Anomaly correlation coefficient; Root mean square error



Bauer et al. (2015), *Nature*

Predictability: The degree to which the future state of a dynamical system can be predicted

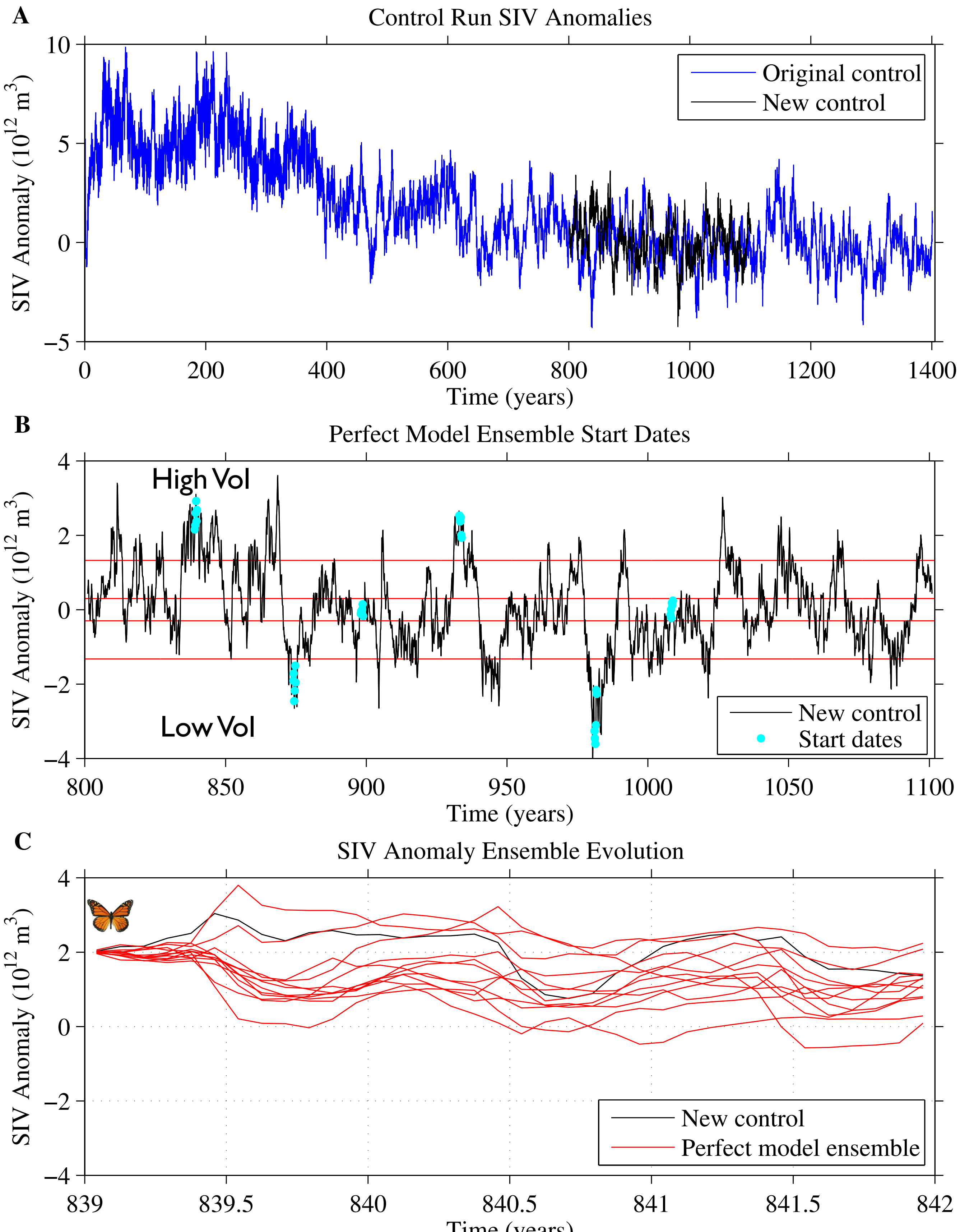
- Fundamental property of the dynamical system, related to chaotic error growth of infinitesimal errors.
- E.g. weather is potentially predictable up to lead times of 14 days
- Imposes an upper limit on prediction skill that is potentially achievable



Branstator and Teng (2010), *J. Climate*

Perfect model assessment

Perfect Model Predictions with GFDL-FLOR



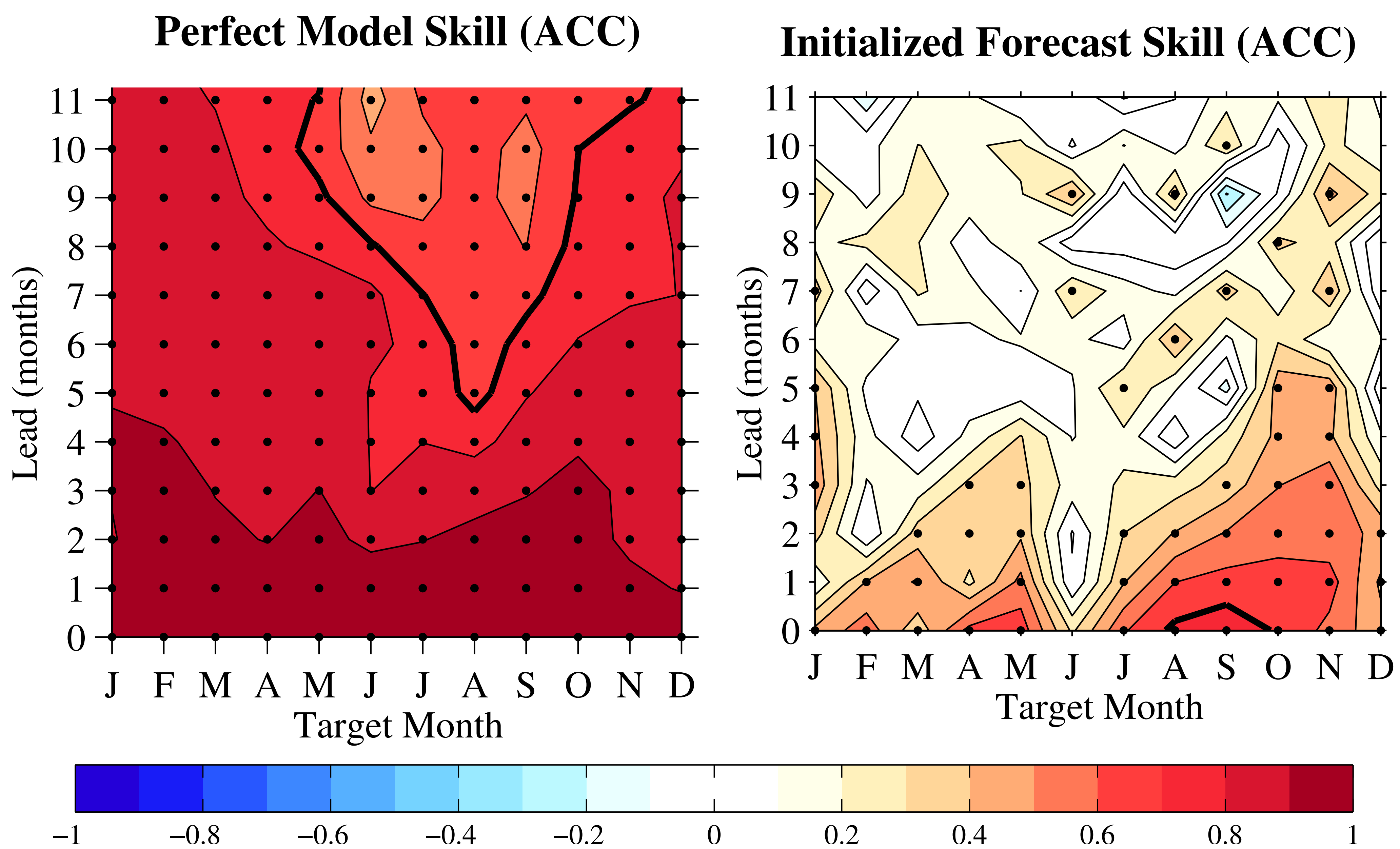
- **Start Months**
  Jan, Mar, May, Jul, Sep, Nov
- **Start Years**
  839, 874, 898, 933, 981, 1008
- **Ensemble members**
  12
- **Integration time**
  3 years

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.*

Comparison of perfect model and operational skill for Pan-Arctic SIE



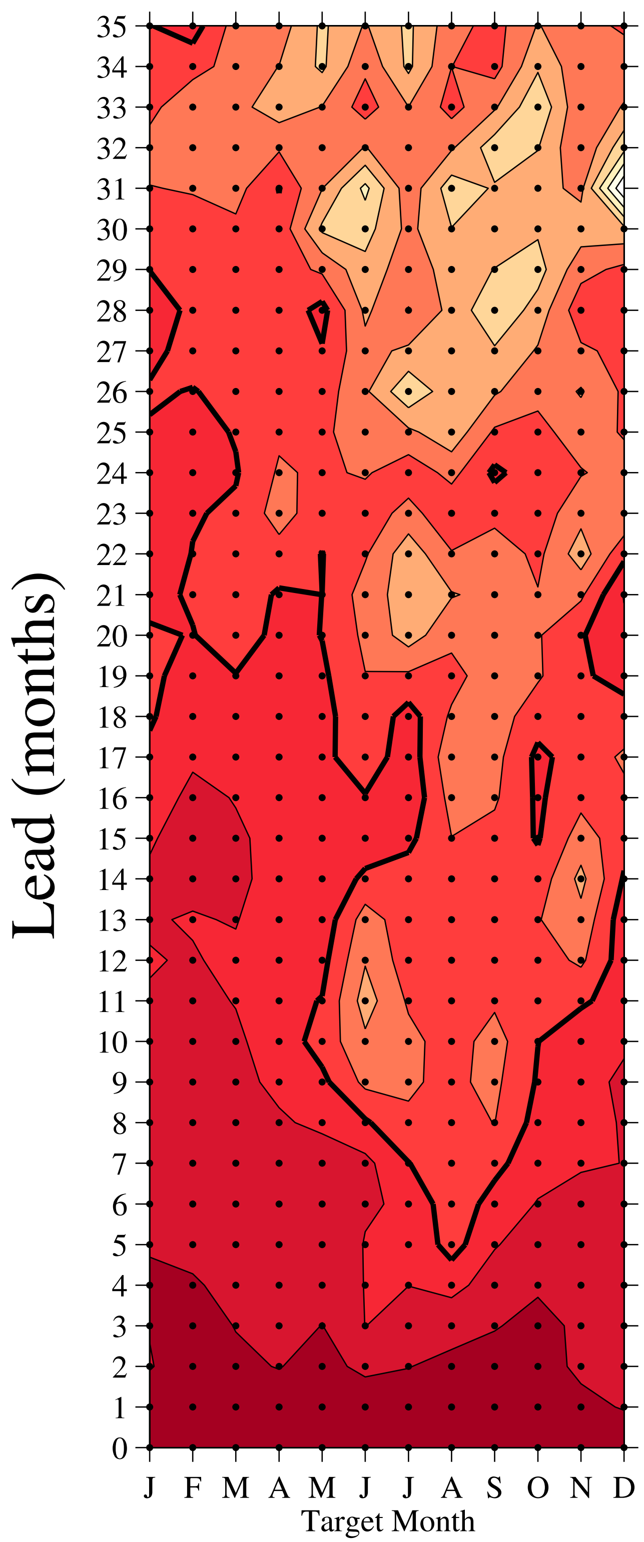
● : Statisically significant prediction skill

Bushuk et al. (2018)

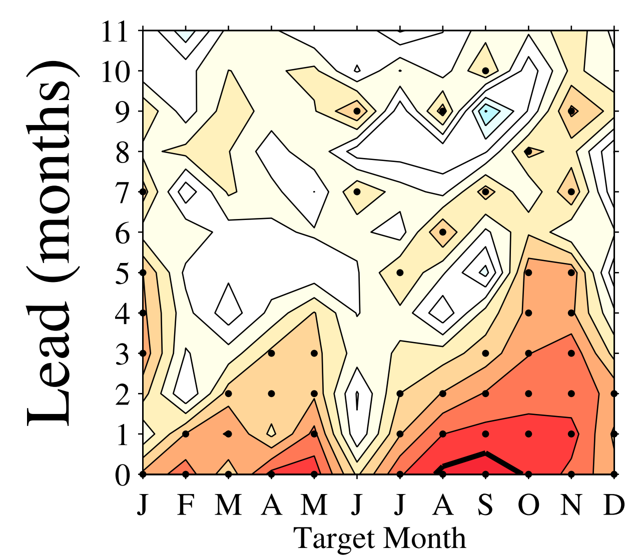
Comparison of perfect model and operational skill for Pan-Arctic SIE

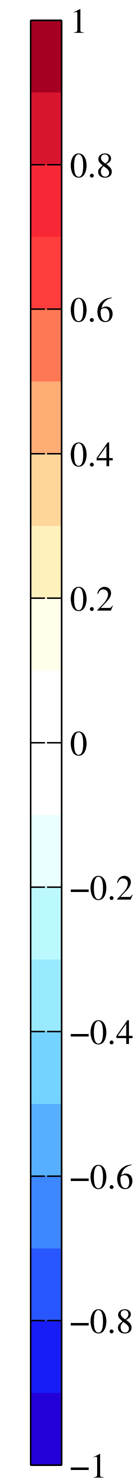
The Prediction Skill Gap: Pan-Arctic SIE

Perfect Model Skill (ACC)



Initialized Forecast Skill (ACC)



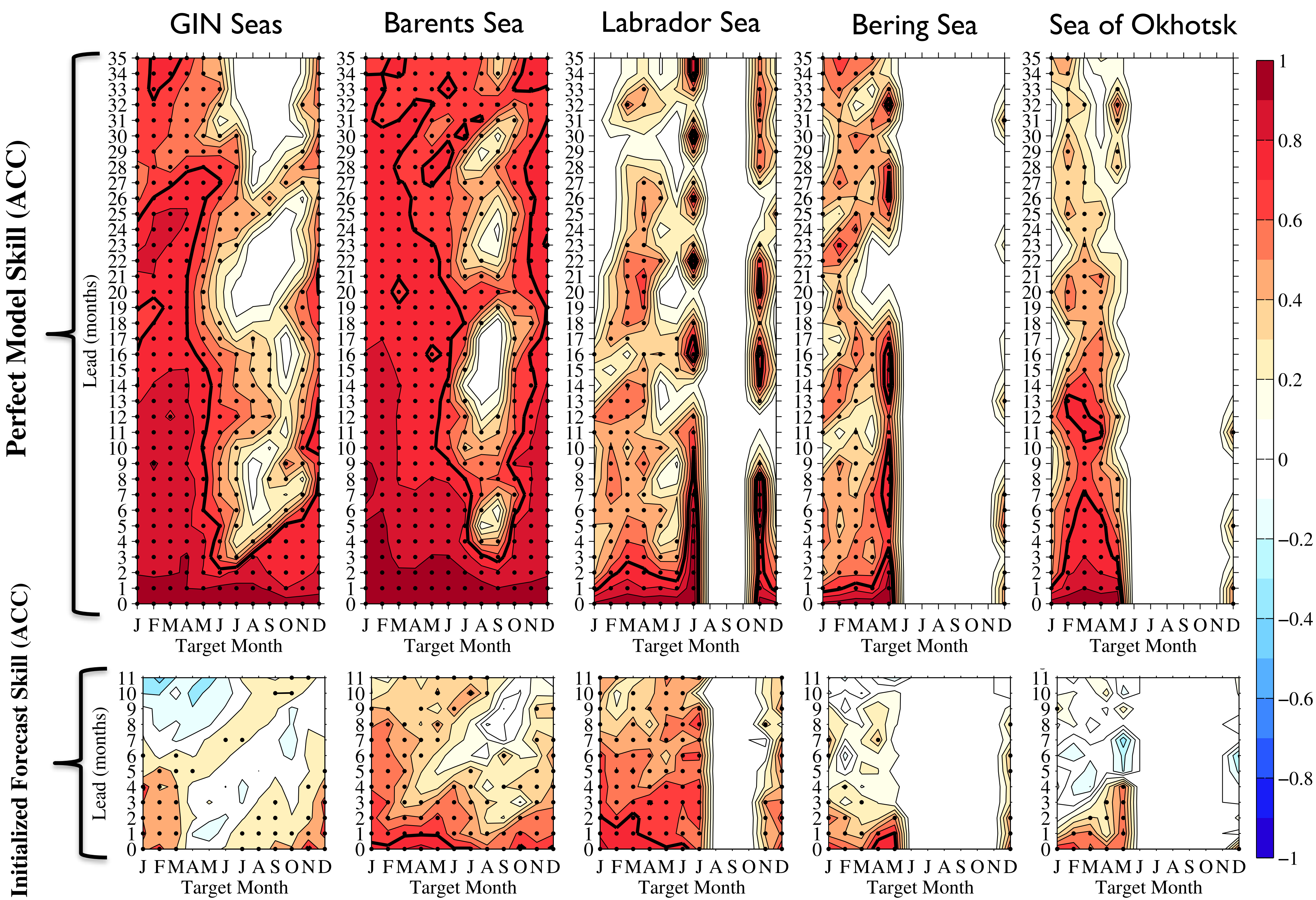


Black contour:
ACC=0.7

Bushuk et al. (2018)

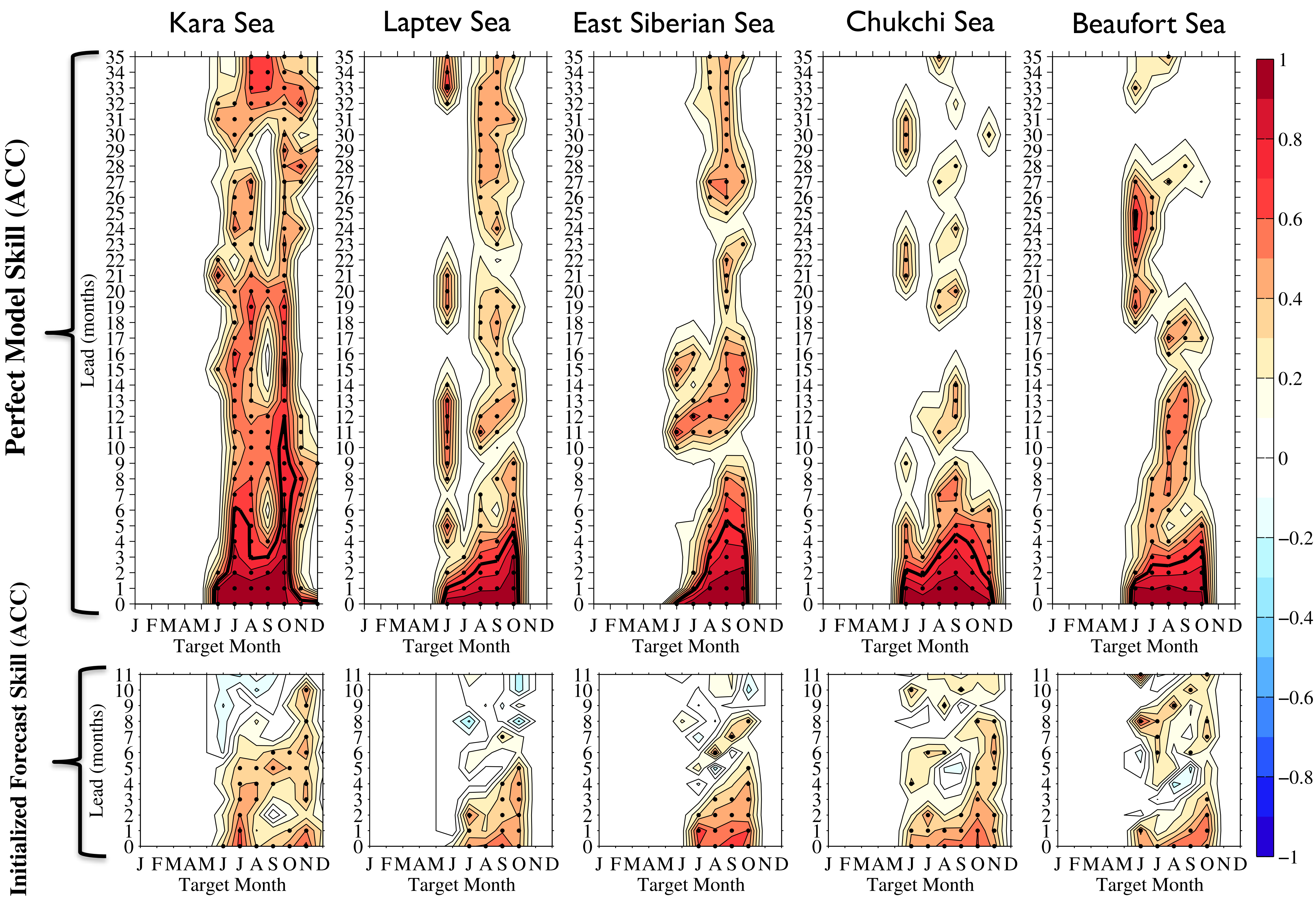
Comparison of perfect model and operational skill for regional Arctic SIE

The Prediction Skill Gap: Regional Winter SIE



Comparison of perfect model and operational skill for regional Arctic SIE

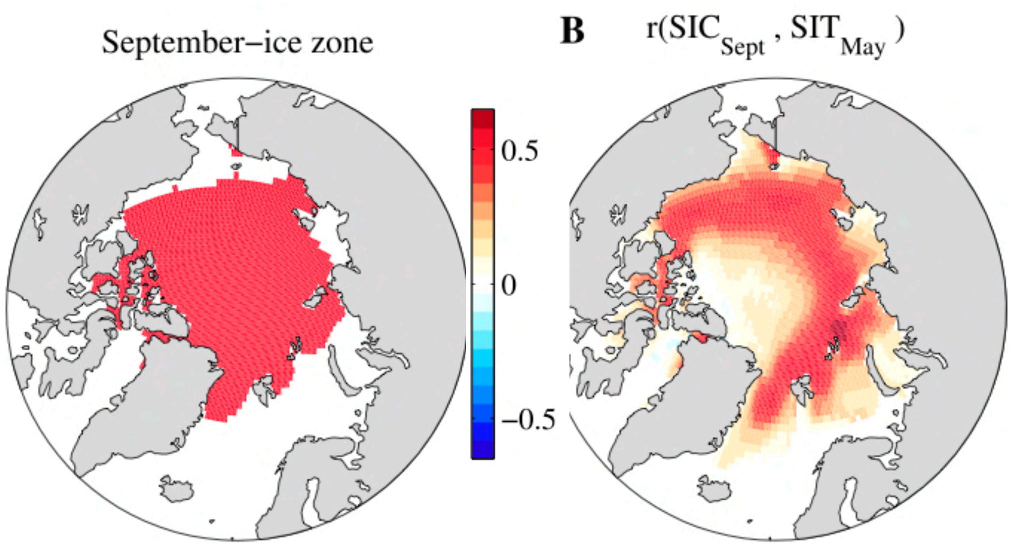
The Prediction Skill Gap: Regional Summer SIE



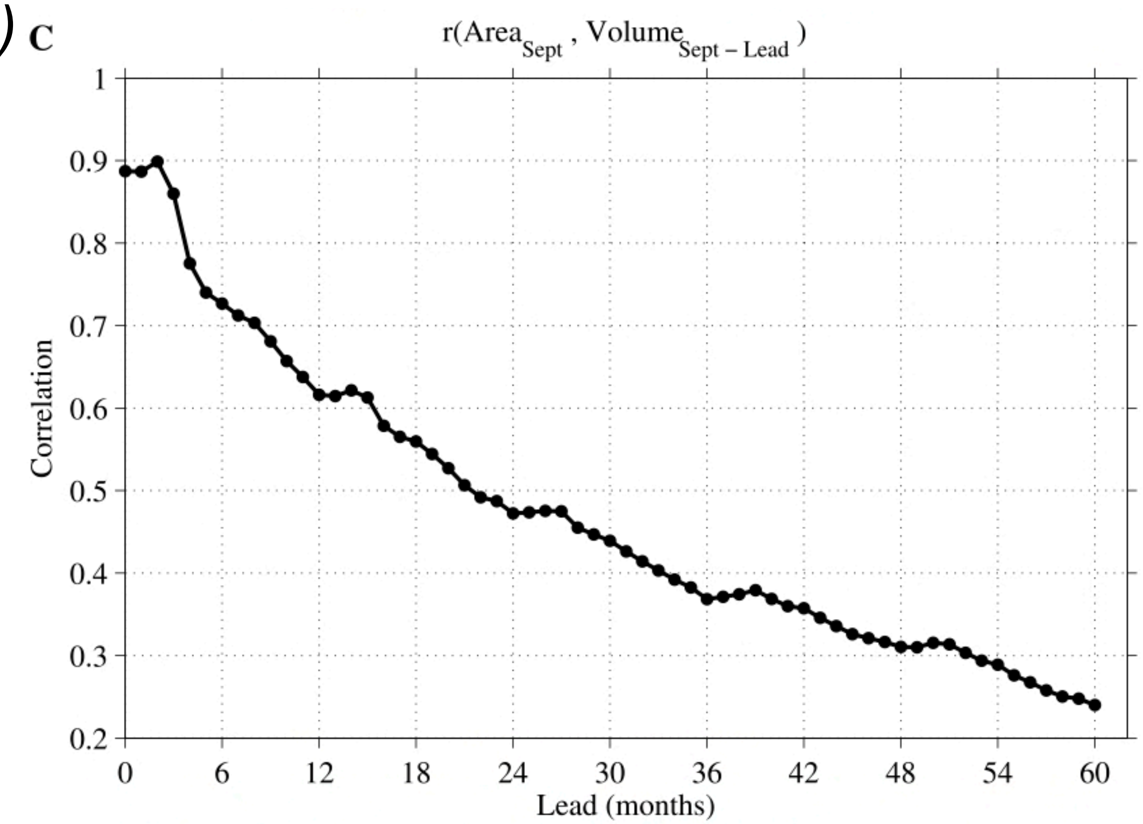
Mechanisms: where does the predictability come from?

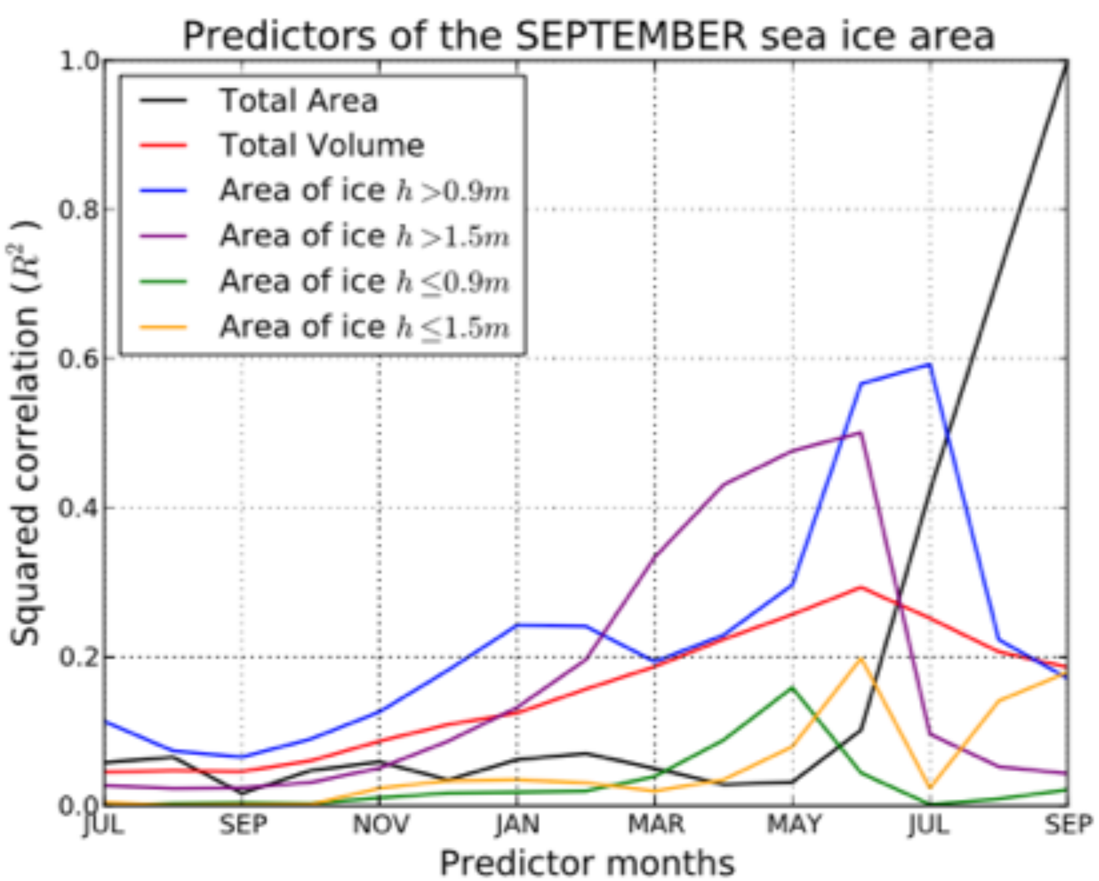
- Role of sea ice thickness in predicting sea ice extent/area in **summer**

Day et al.(2014), Blanchard-Wrigglesworth and Bitz (2014)



Bushuk et al. (2017)



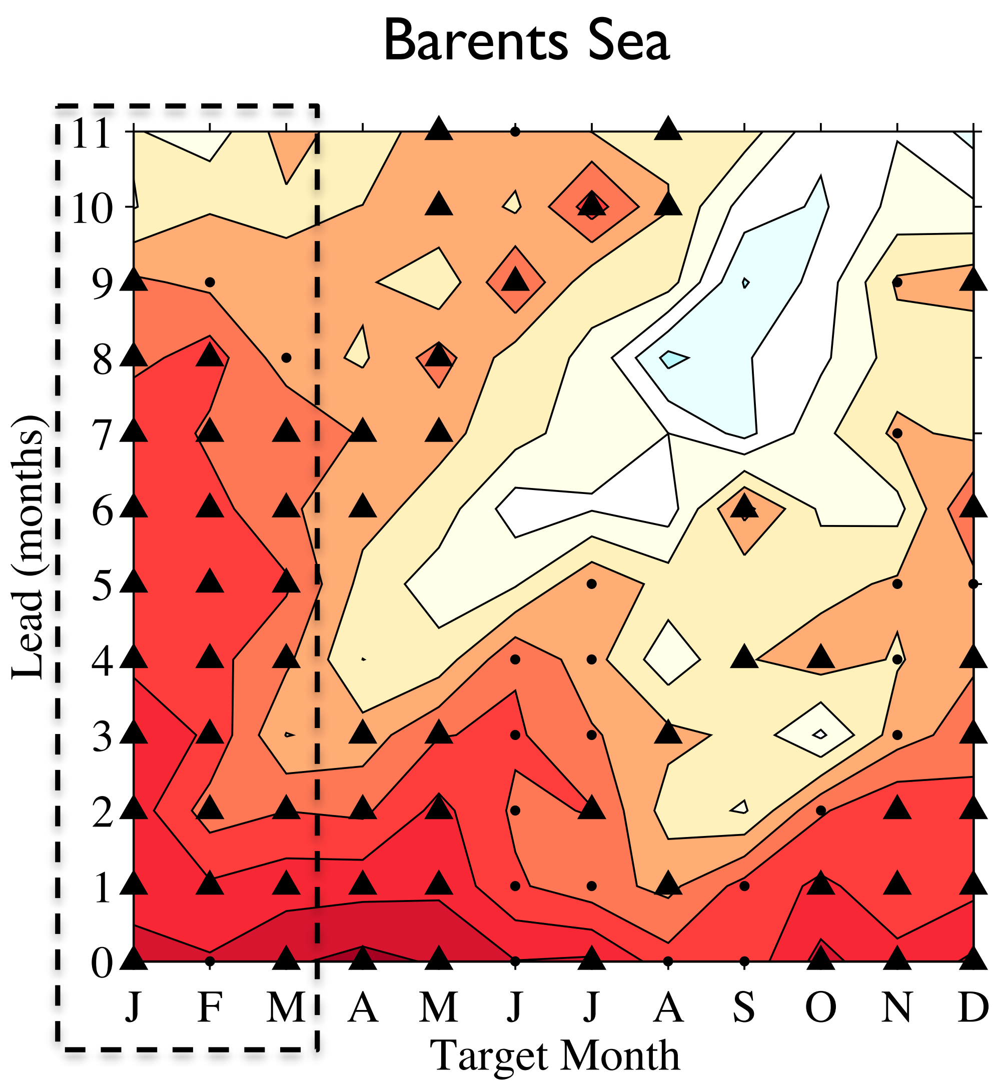


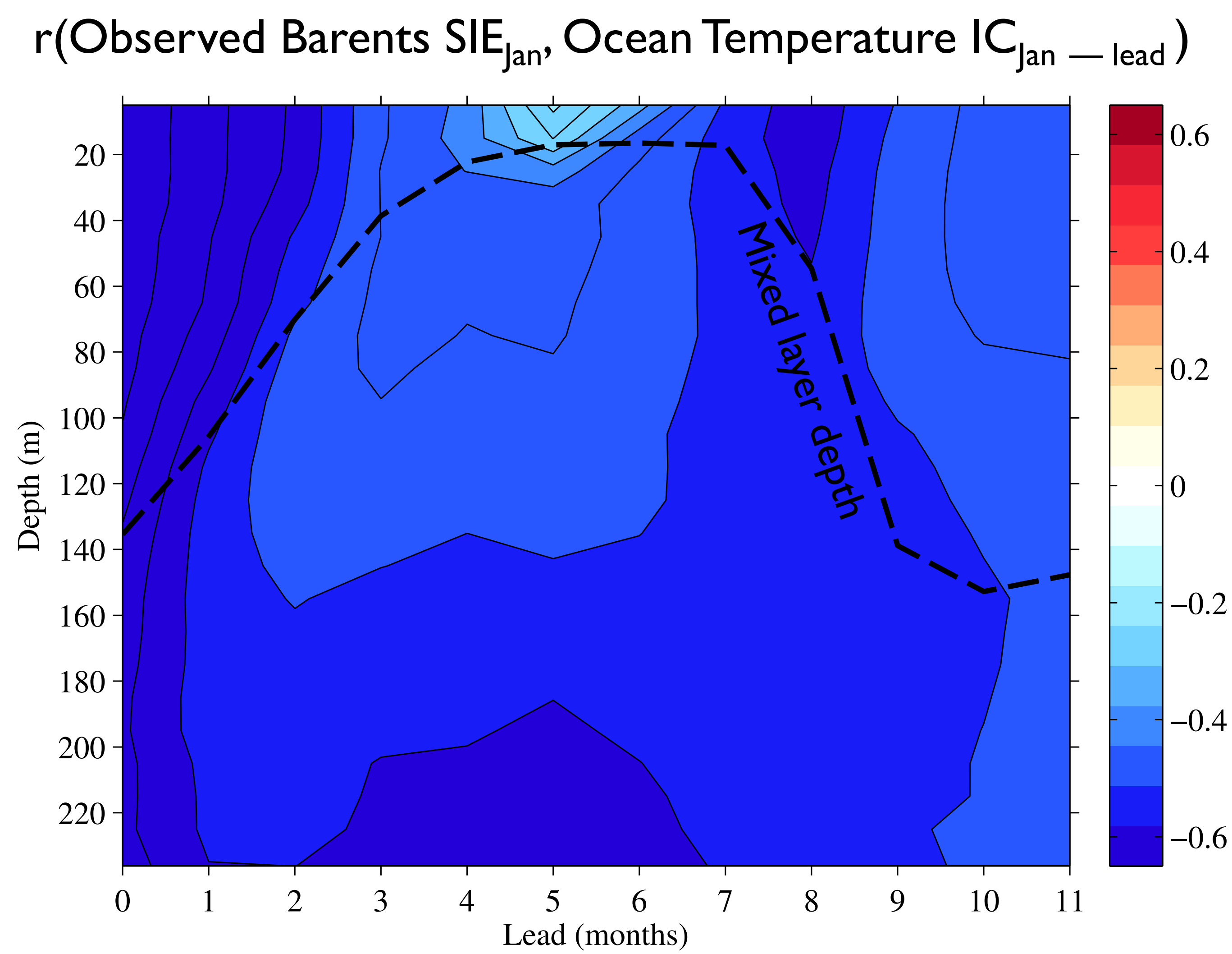
=> Role of March-May thick ice (h>0.8m) for September SIE

Chevallier and Salas y Mélia (2012)

Mechanisms: where does the predictability come from?

- Role of the ocean in predicting sea ice extent/area in **winter** *(Bitz et al. (2005), Schlichtholz 2011)*
  - Role of ocean heat advection in the MIZ (Barents Sea, GIN seas, Bering sea)
  - Link between summer temperature of AW in the BSO and winter SIE in the GIN Seas





Bushuk et al. (2019)

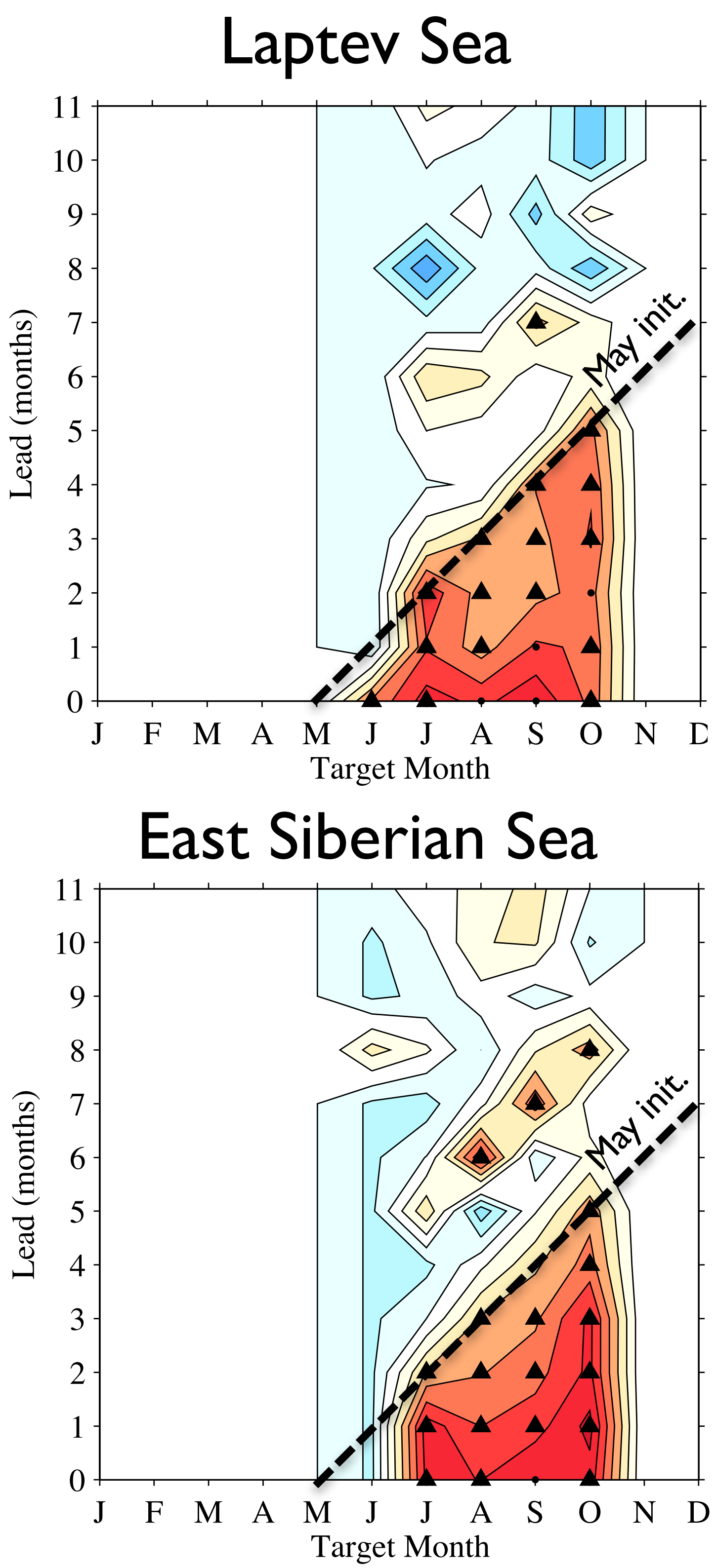
Subsurface ocean temperature initialization provides key source of winter prediction skill

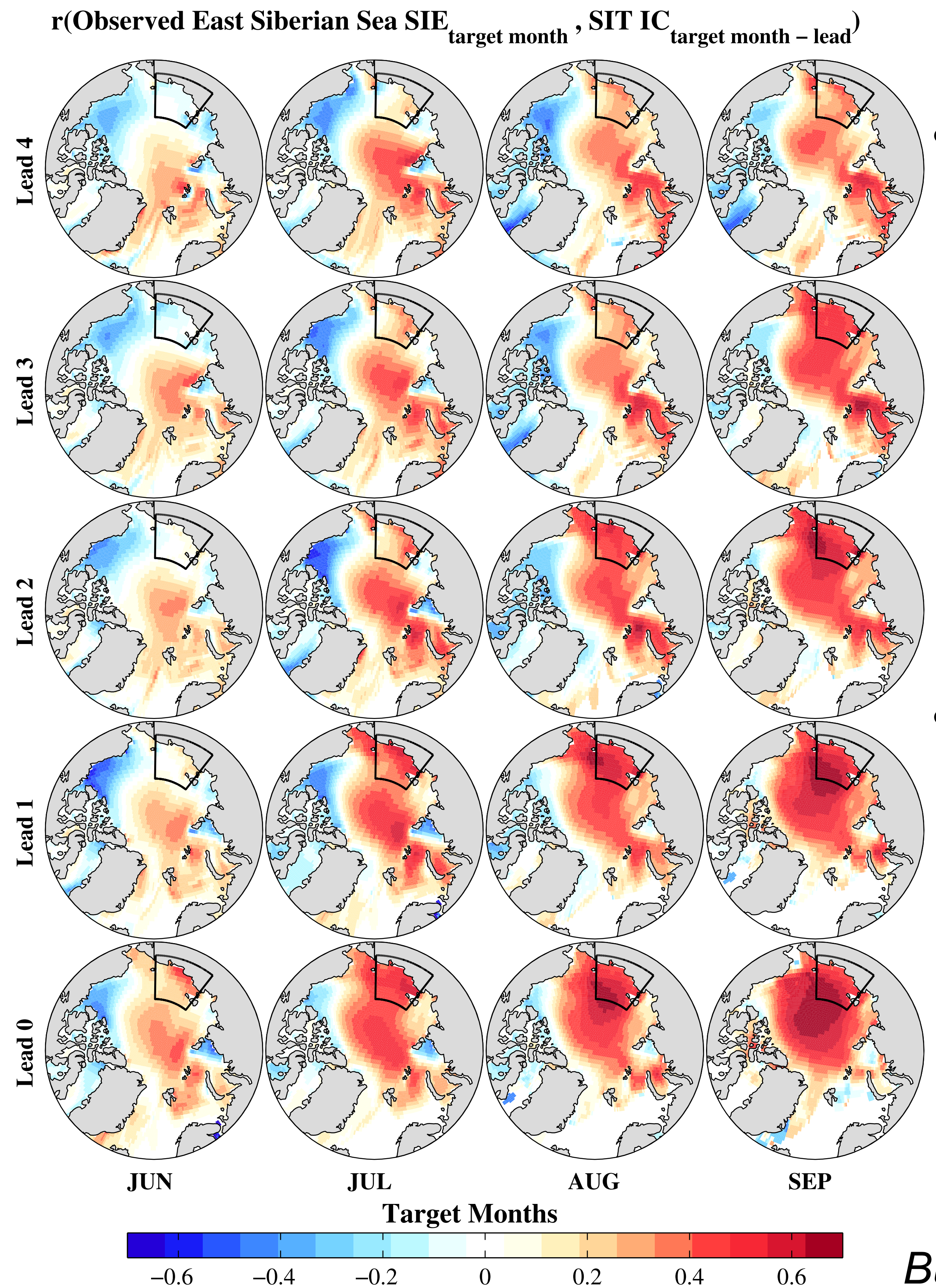
Improved ocean and sea ice initial conditions

$\Downarrow$?

Improved sea ice predictions

Sources of summer prediction skill: SIT initialization

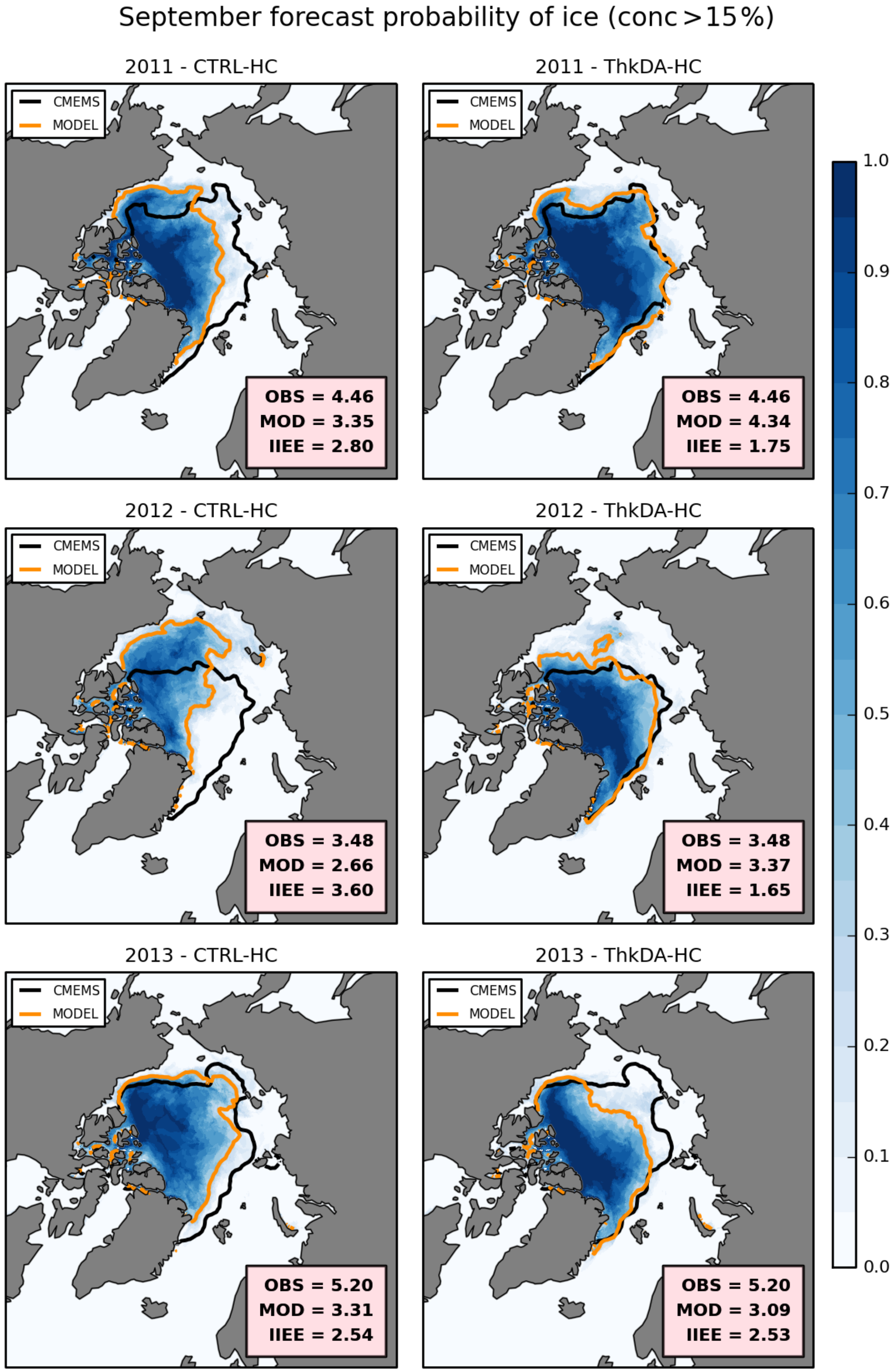




- Laptev and East Siberian Seas have spring prediction skill barrier: Predictions initialized May 1 and later are skillful; those initialized prior to May 1 are not
- Sea ice thickness initialization provides key source of summer prediction skill

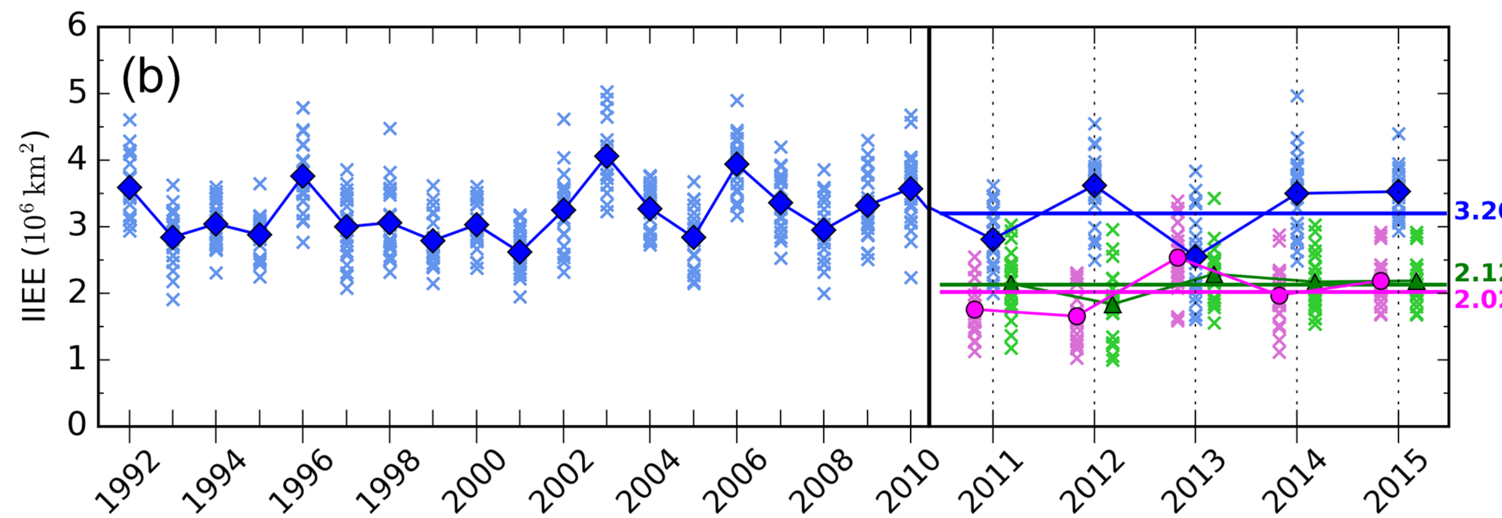
Bushuk et al. (2017)

Improvement of summer predictions due to initialization of sea ice thickness



Sea ice edge predictions: general reduction in edge error (37% less for 5yr total)

Integrated sea ice edge error *(Goessling et al. 2016)* vs OSI-SAF



Blockley and Peterson (2018)

SIT initialization shows promising results

See also Guemas et al. (2016)

ThKDA=initialising FOAM with CryoSat-2 sea ice thickness

Improvement of winter predictions due to initialization of the ocean

Observing System Experiment (OSE) Hierarchy

- Data assimilation runs spanning 1995-2016

Experiment Name	Atmo. 3-D Temp	SST	CTD	Other Subsurface
1. Control	✓	✓	✓	✓
2. No CTD	✓	✓	×	✓
3. No Subsurface	✓	✓	×	×
4. SST Only	×	✓	×	×
5. Atmosphere Only	✓	×	×	×
6. Uninitialized	×	×	×	×

- For each assimilation run, we perform retrospective ensemble predictions with CM2.1 initialized Jan 1, April 1, July 1, Oct 1, and spanning 1995-2016.
- 10-member ensemble, run for one year

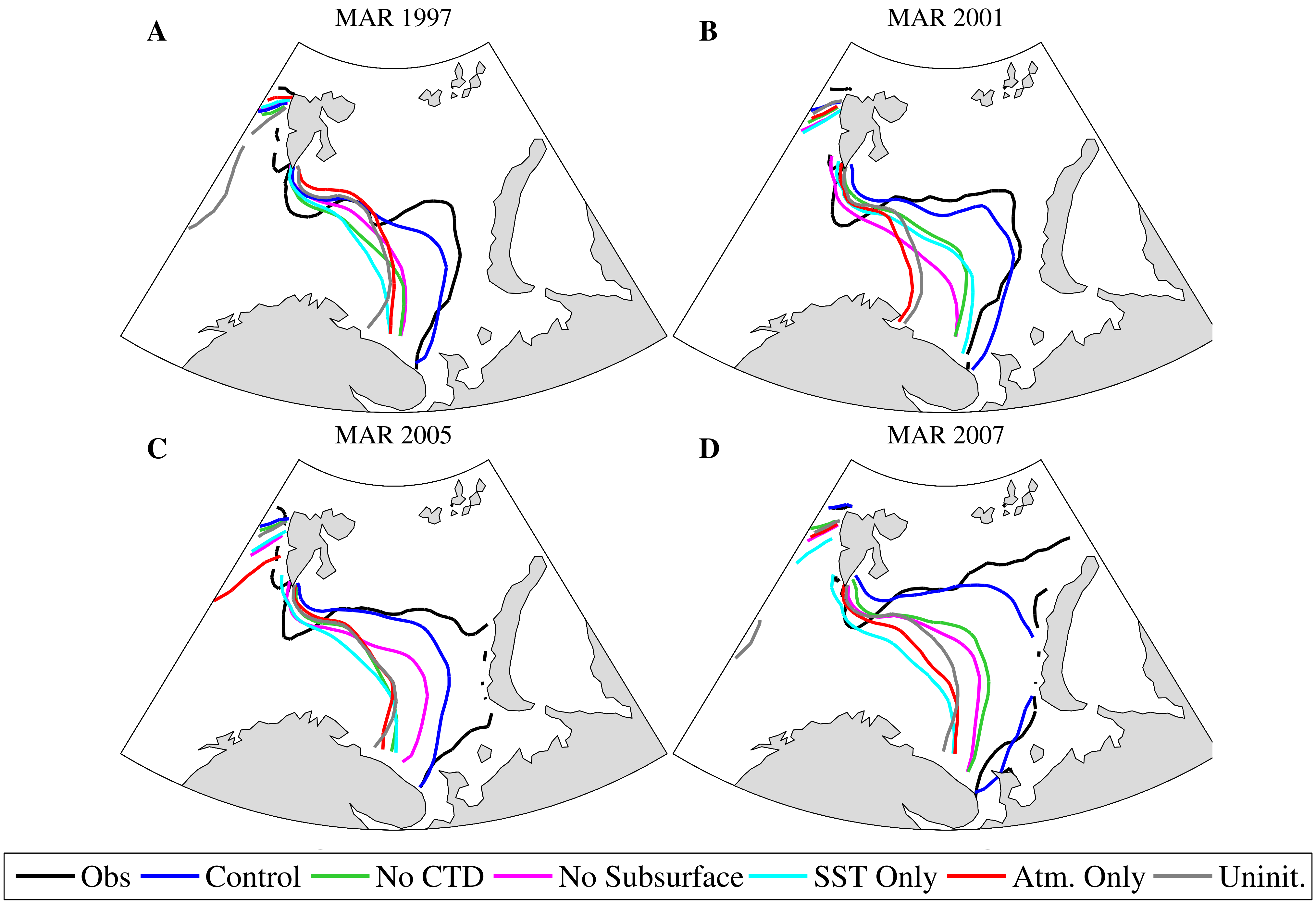
Bushuk et al. (2019)

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

- 95% confidence intervals computed via bootstrapping

Improvement of winter predictions due to initialization of the ocean

March Barents sea ice edge predictions: Lead 8 months



- **Improved sea ice edge prediction**
- **Improved RMSE and ACC of regional SIE**

Bushuk et al. (2019)

Conclusions

- **GFDL-FLOR seasonal predictions skillfully predict pan-Arctic and regional sea ice extent at lead times of 0-11 months depending on region and target month**
- **Perfect model experiments suggest substantial skill improvements are possible in most regions**
- **Assimilation of sea ice thickness improves seasonal predictions of summer sea ice edge but there is a spring barrier in most regions**
- **Assimilation surface and subsurface ocean observations improves seasonal predictions of winter sea ice, in particular in the Barents Sea**

=> Where do we focus our efforts? What are the crucial mechanisms?
Our work suggest sea ice thickness and subsurface ocean

Credit: M. Vancoppenolle