Status of Arctic sea ice forecasting: challenges and opportunities

Ed Blanchard-Wrigglesworth
University of Washington

Outline

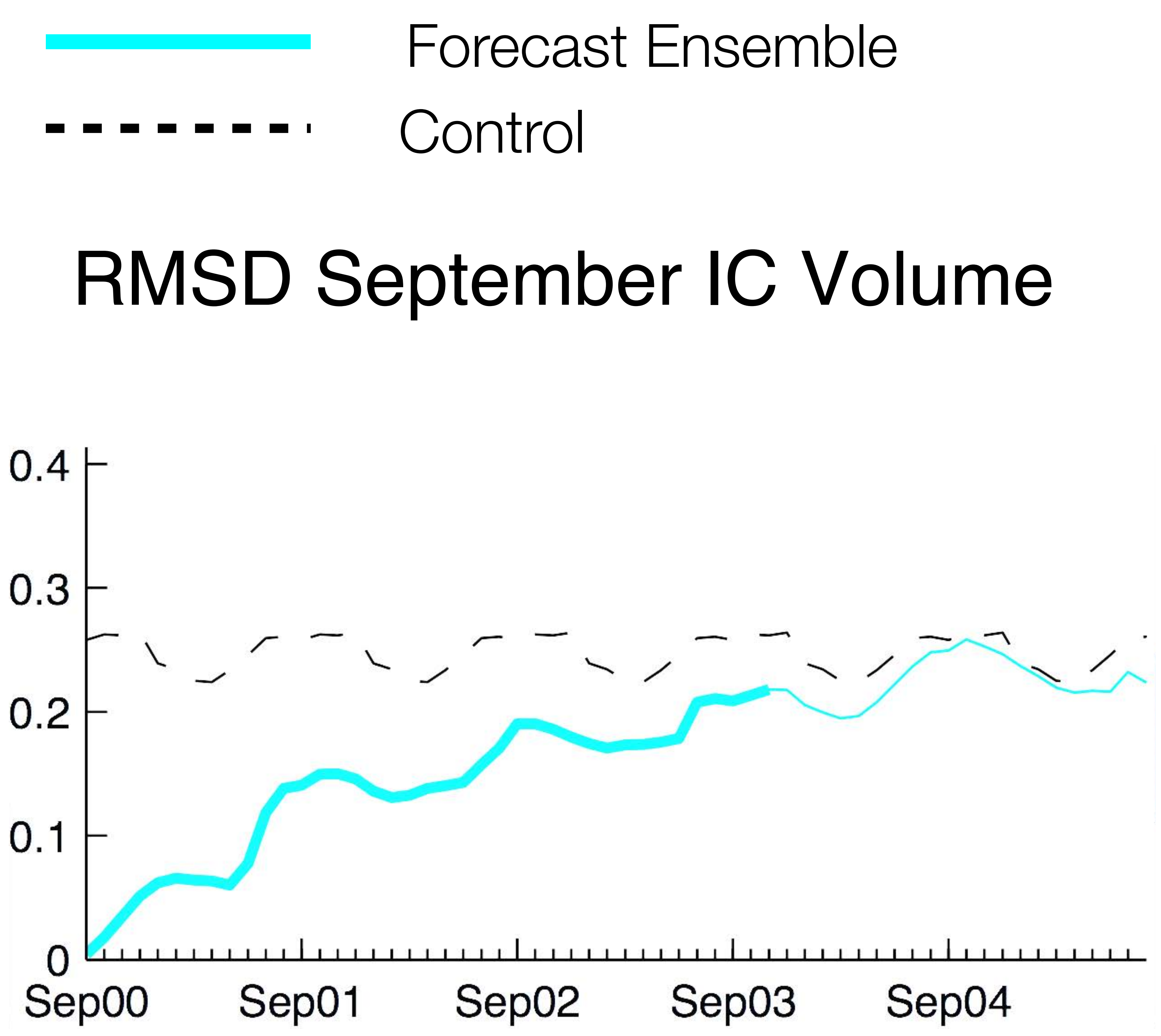
Quantifying Arctic sea ice predictability

- Results from dynamical models (potential predictability)
- Mechanisms (what processes yield forecast skill/error growth)

Real world forecast skill

- Current efforts
- Gap between potential and real world skill: observations or model physics?

Initial Value predictability of Arctic sea ice



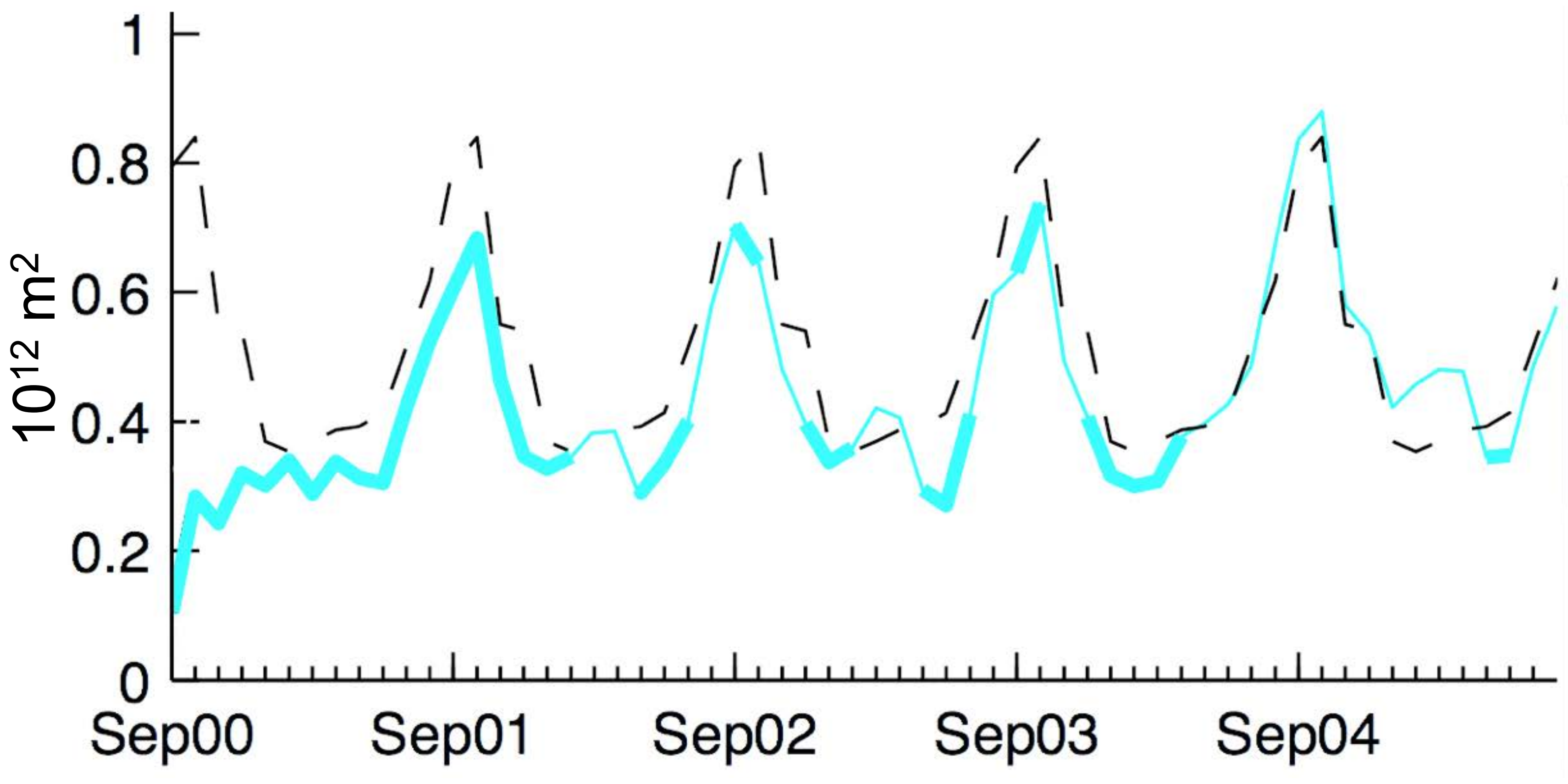
- Volume: continuous predictability for 3-4 years.

- Rapid loss of predictability in June-July (albedo?)

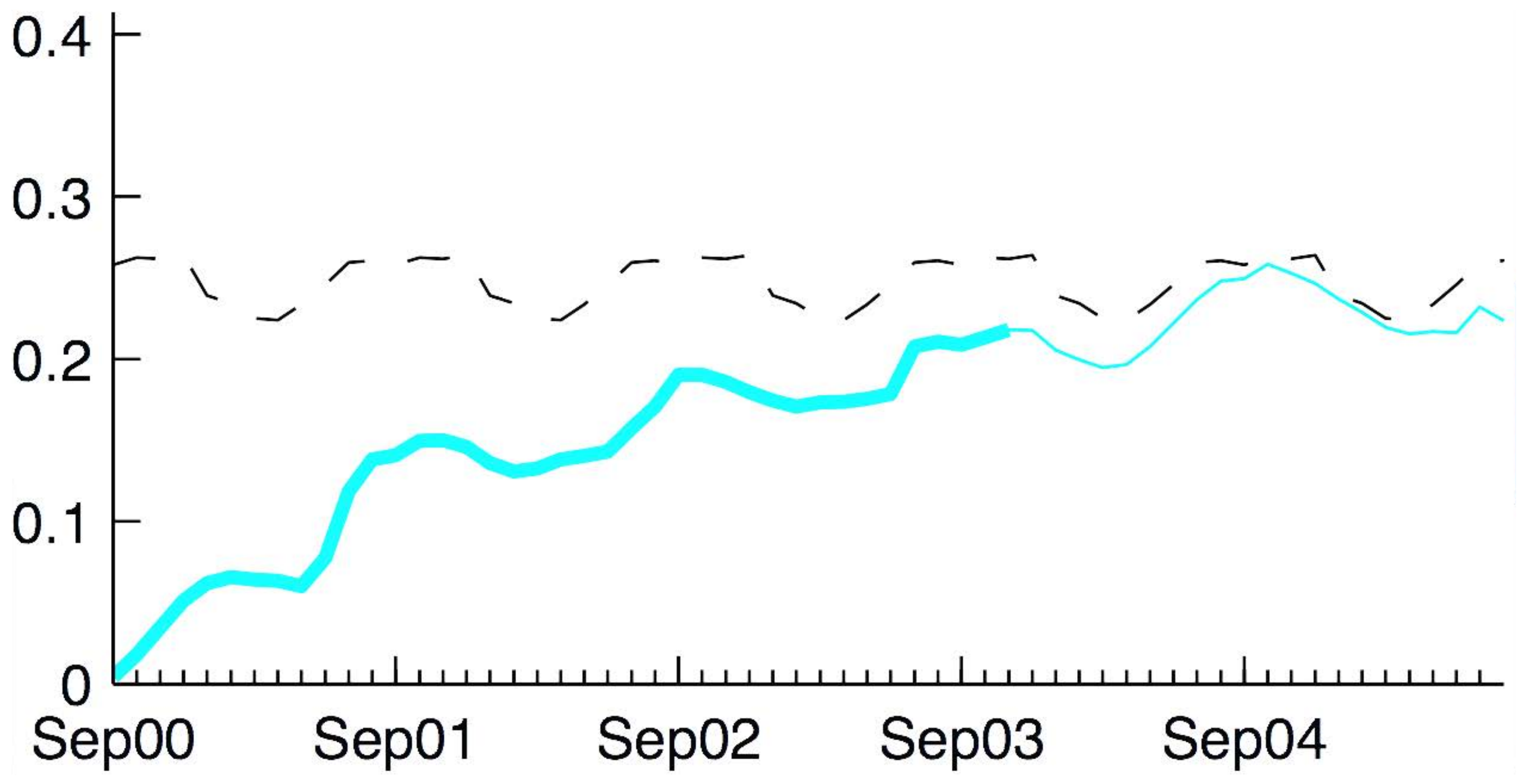
Initial Value predictability of Arctic sea ice

Forecast Ensemble
Control

RMSD September IC Area



RMSD September IC Volume



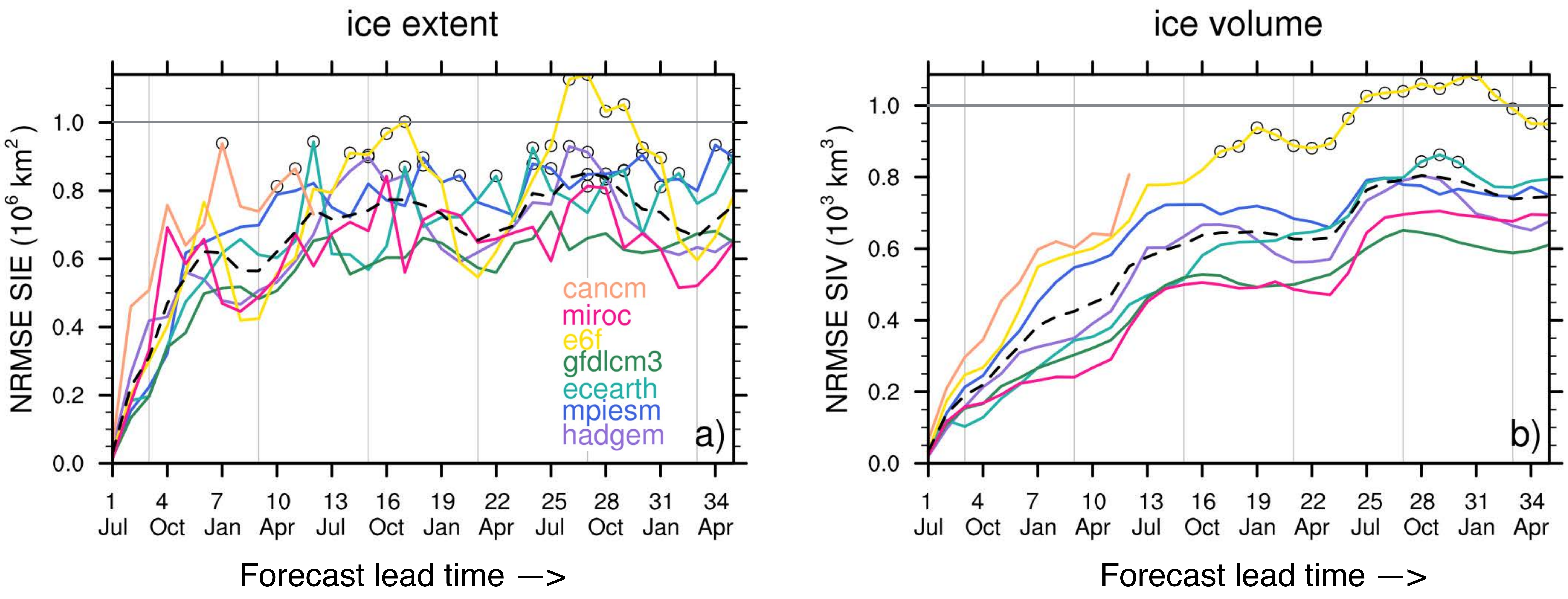
- Lower for area than for volume.
- Area: fast initial decline (first 1-2 seasons), re-emergence weak predictability at times for 1-3 years.

- Volume: continuous predictability for 3-4 years.
- Rapid loss of predictability in June-July (albedo?)

Blanchard-W et al, 2011

Initial Value predictability of Arctic sea ice

normalized RMSE from July 1 IC forecasts



Perfect model predictability shows similar patterns across different GCMs, but also differences in magnitude

Day et al, 2016 & Tietsche et al, 2014

Predictability timescales: perfect model results for Arctic sea ice

forecast lead time:

Day/weekly
Seasonal → Initial value predictability

Annual → Diminishing to none

Decadal → Forced (boundary) predictability

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Day/weekly Seasonal →	Initial value predictability
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Decadal →	Forced (boundary) predictability

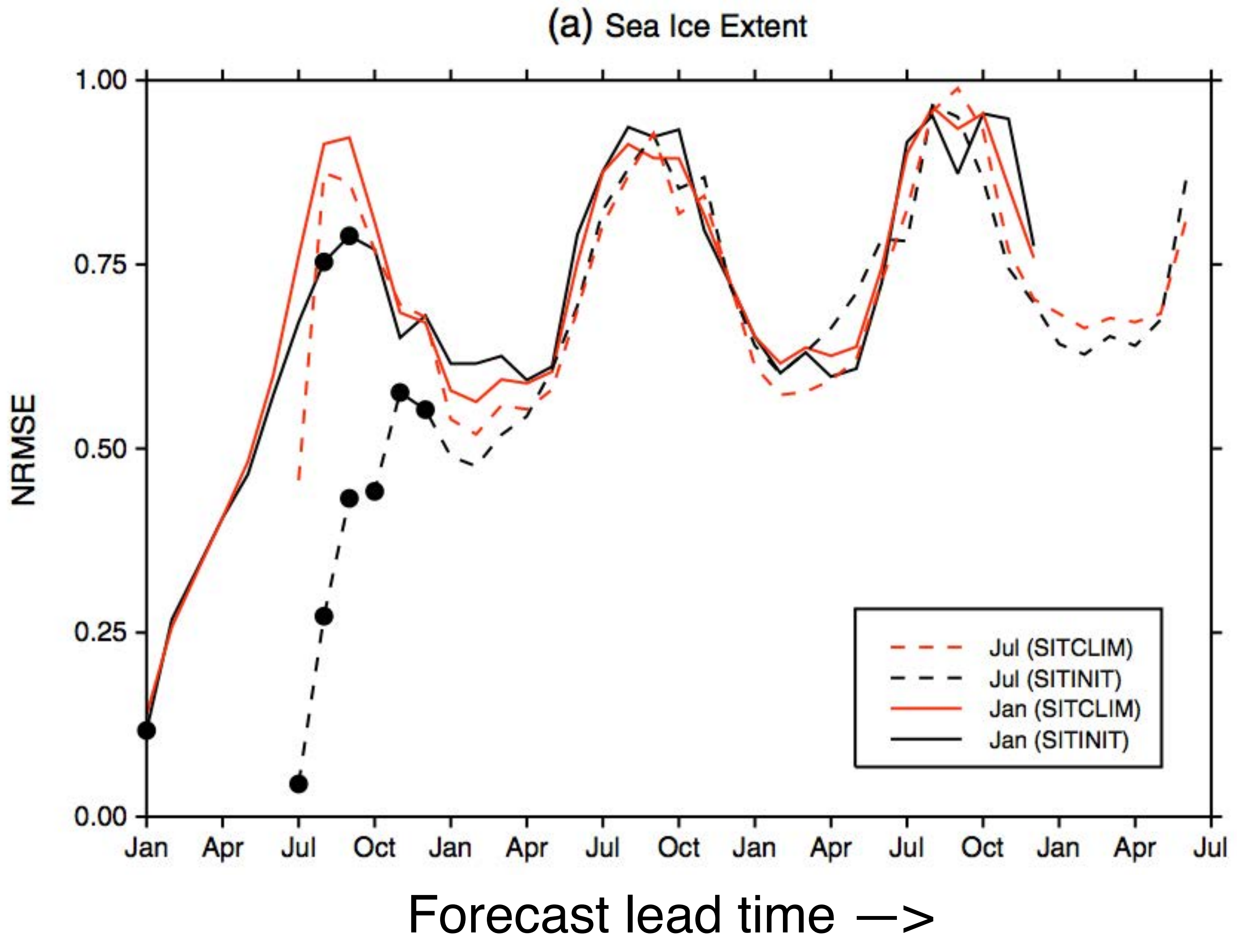
Initial value : forecast skill depends on **quality of initial conditions** (ICs) and **model physics** that simulate evolution of ICs

Forced : forecast skill depends on **how well you simulate future climate change and sea ice response:** right sensitivity to changing boundary conditions, right amount of forcing.

Mechanisms (what actually drives initial value predictability)

Sea ice thickness (especially summer, melt back) and upper ocean heat content/SSTs (especially winter/ freeze up), ocean dynamics.

‘Data-denial experiment’



Day et al, 2014

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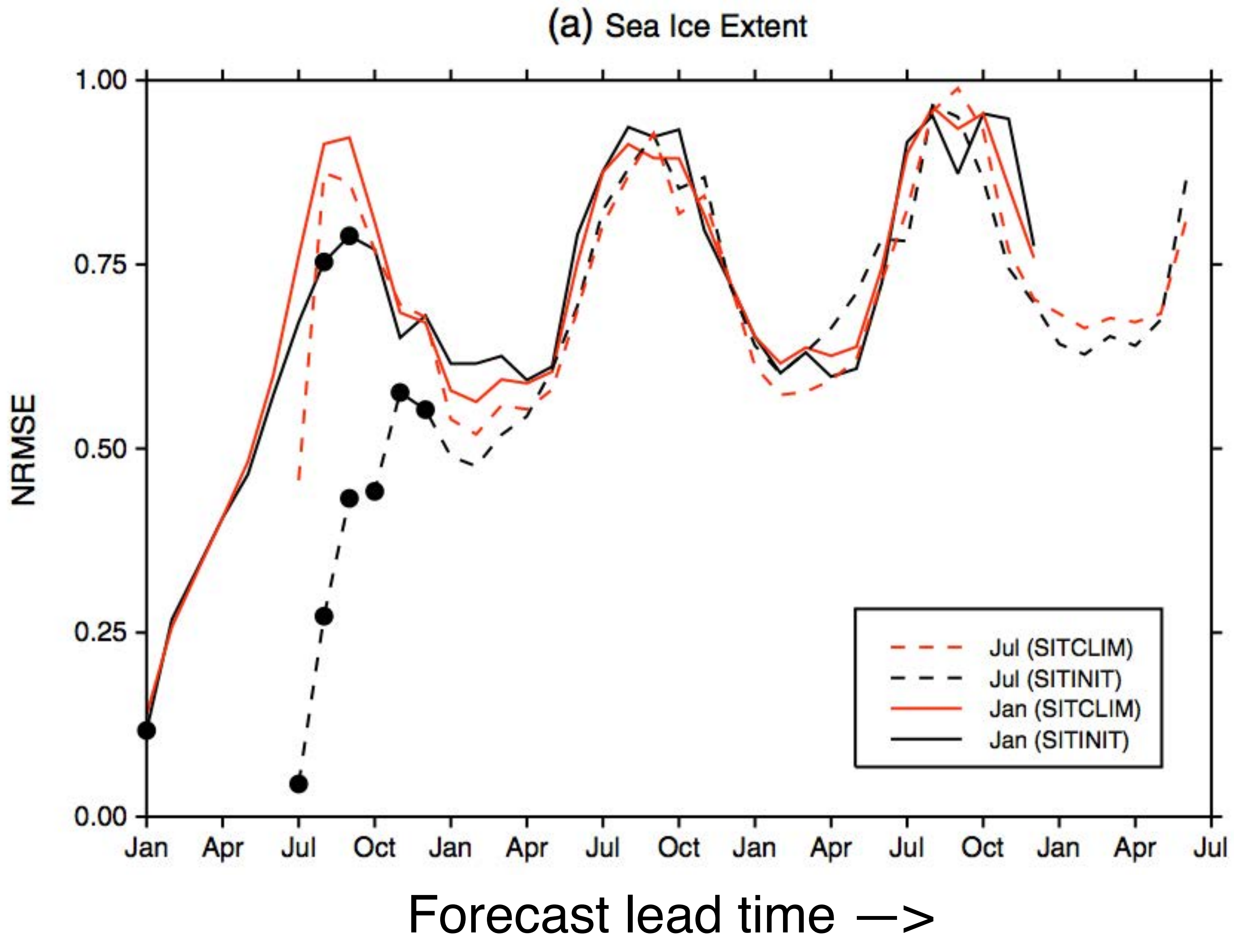

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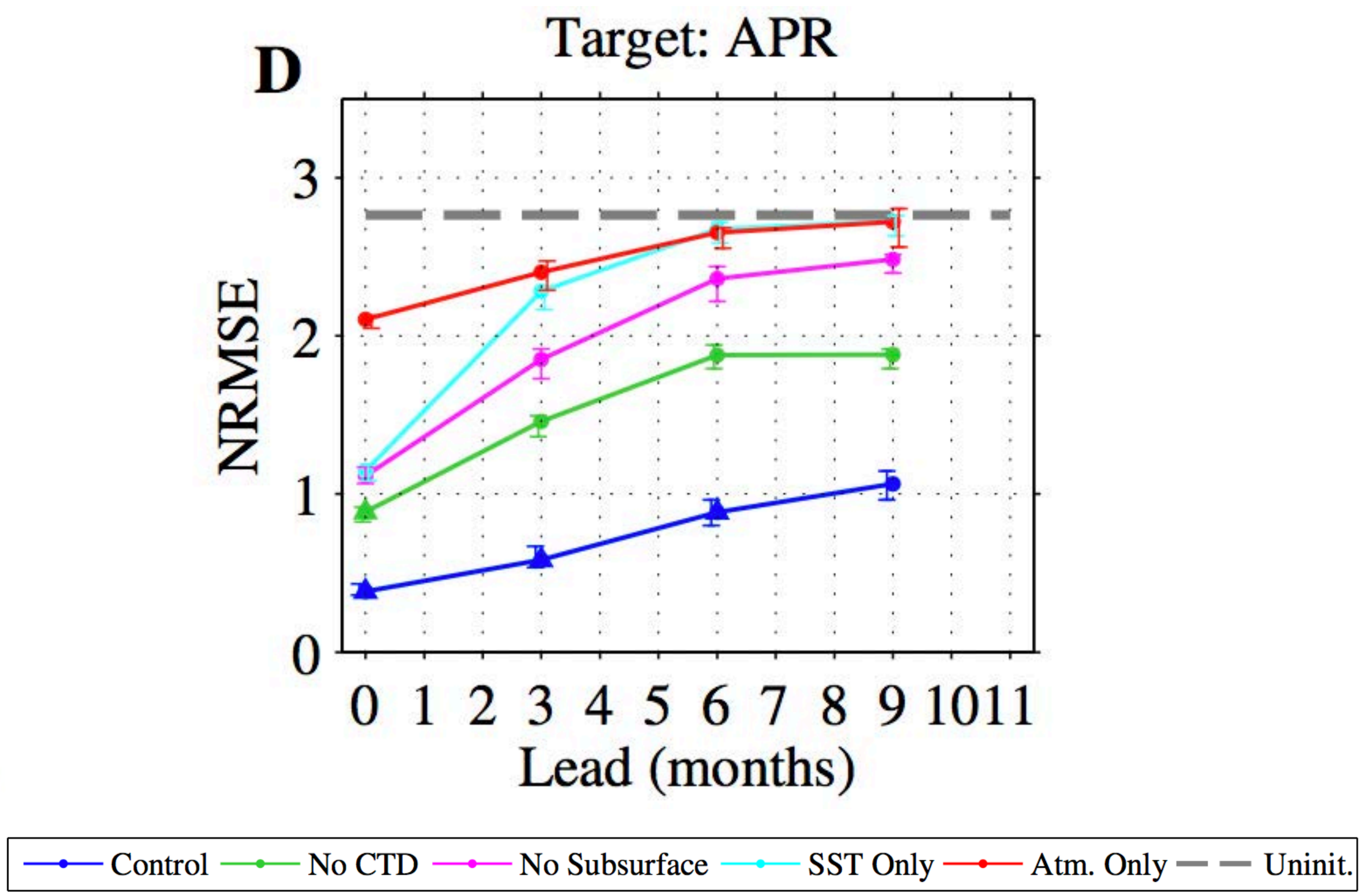

Bushuk et al, 2019

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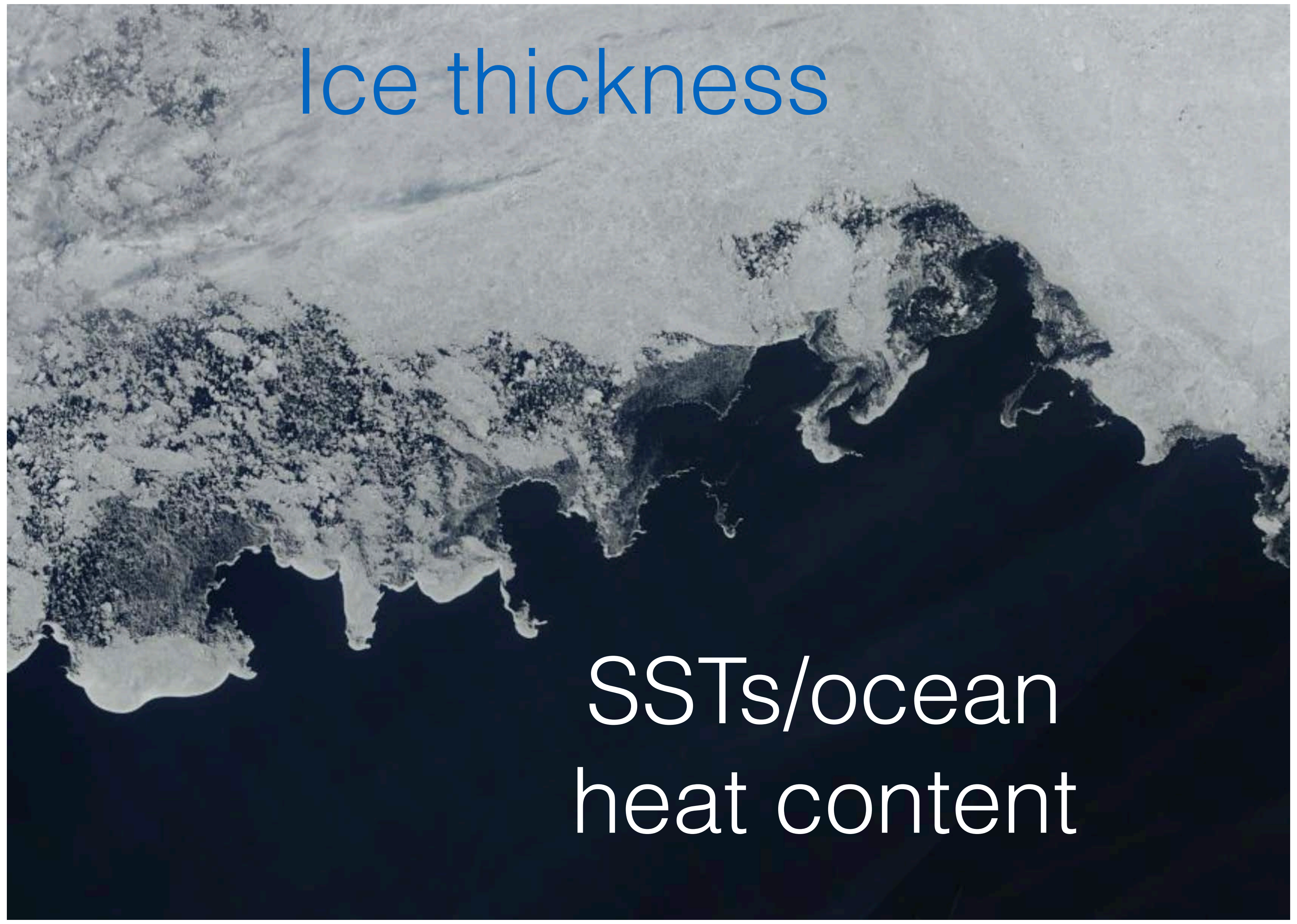
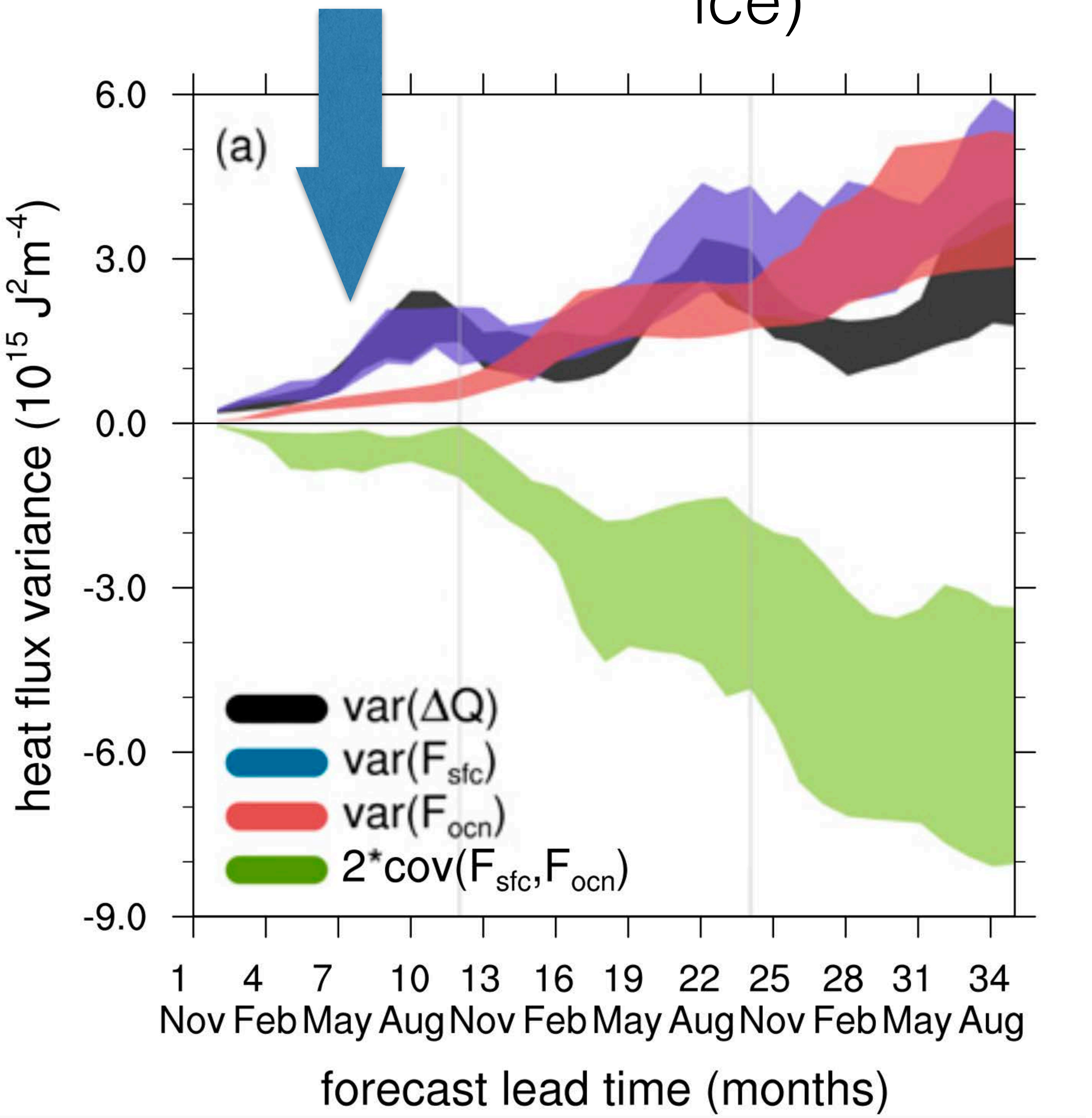
Summer



Winter

Mechanisms (what drives error growth)

The atmosphere (shorter timescales than ocean/sea ice)



Tietsche et al, 2016

Real world skill

Hindcasts (retrospective forecasts)

Several studies in the last few years (Chevallier et al, 2013, Sigmond et al, 2013, Wang et al 2013, Msadek et al, 2014, Peterson et al 2015) study seasonal hindcasts of Arctic sea ice over satellite era.

They all show some level of skill in seasonal forecasts of summer/September sea ice extent

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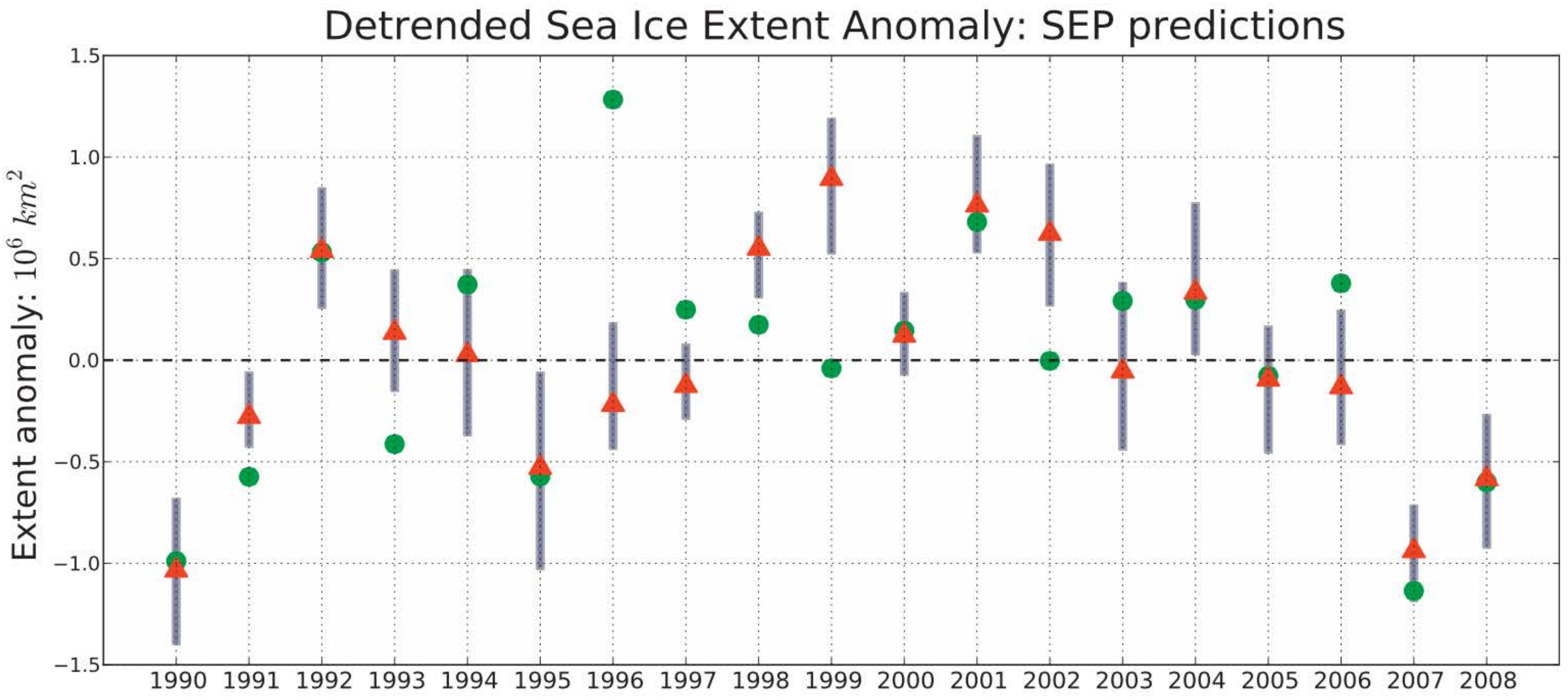

May forecasts of September SIE r=0.6

Chevallier et al, 2013

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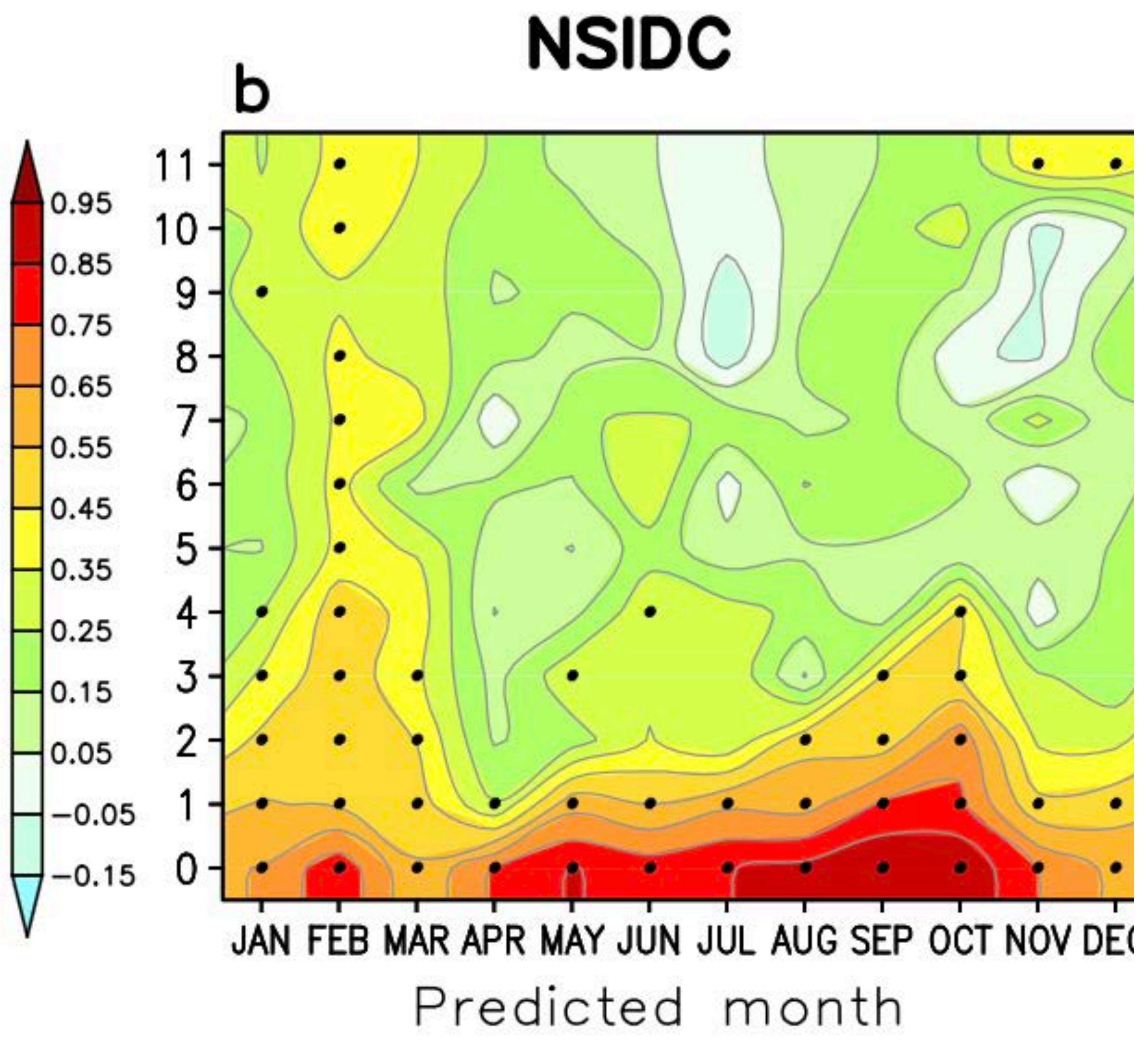
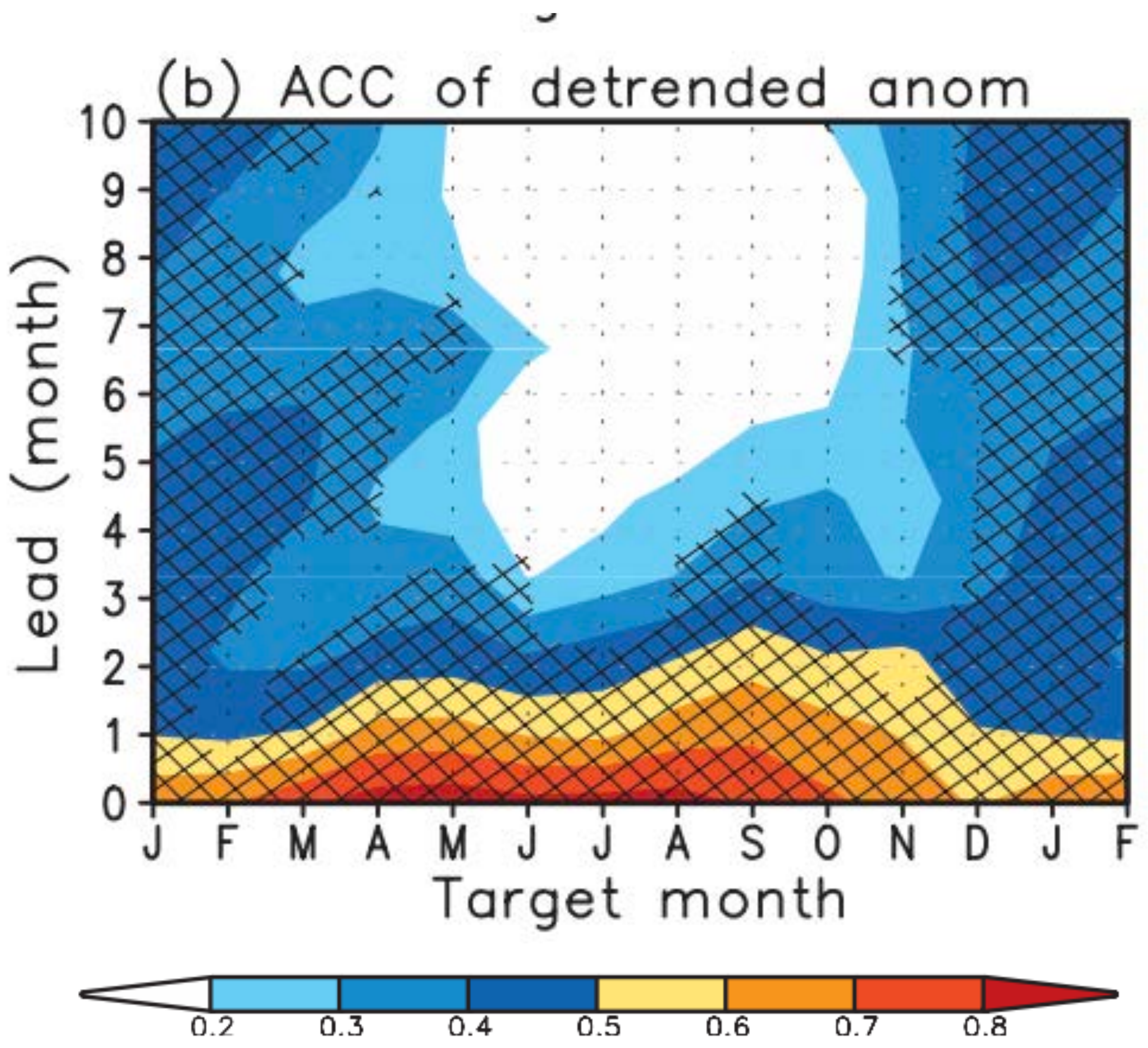
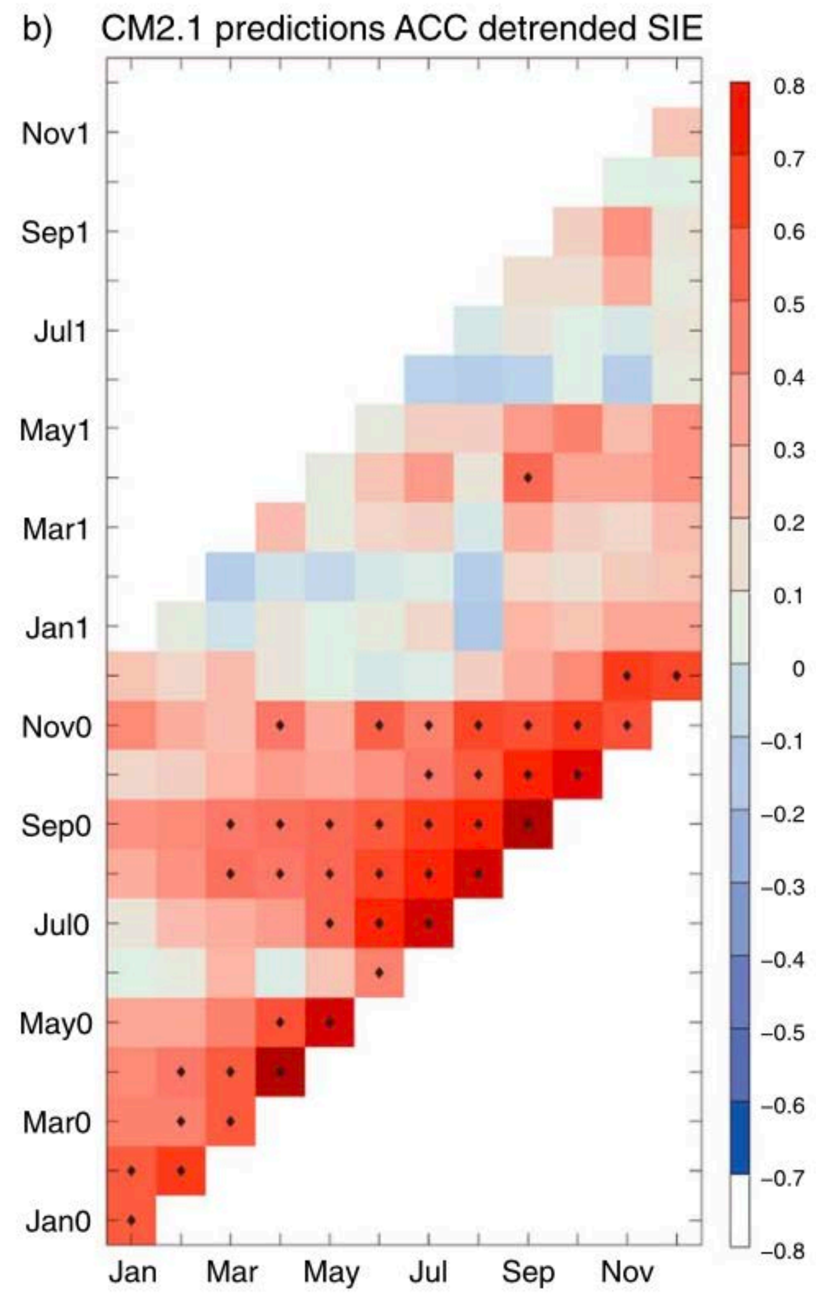


Sigmond et al 2013



Wang et al 2013



Msadek et al 2014

Current efforts in sea ice forecasting: the Sea Ice Outlook

Since 2008, seasonal forecasts of **September sea ice extent** have been collected and analyzed by the **S**ea **I**ce **P**rediction **N**etwork - SIPN - and known as the **S**ea **I**ce **O**utlook (**SIO**).

Each summer, 3 submission calls - early June, early July, early August (i.e., ~**2-4 month lead forecasts**)
All types of forecast techniques welcome: dynamical models, statistical, heuristic, public polls.

https://www.arcus.org/sipn/sea-ice-outlook

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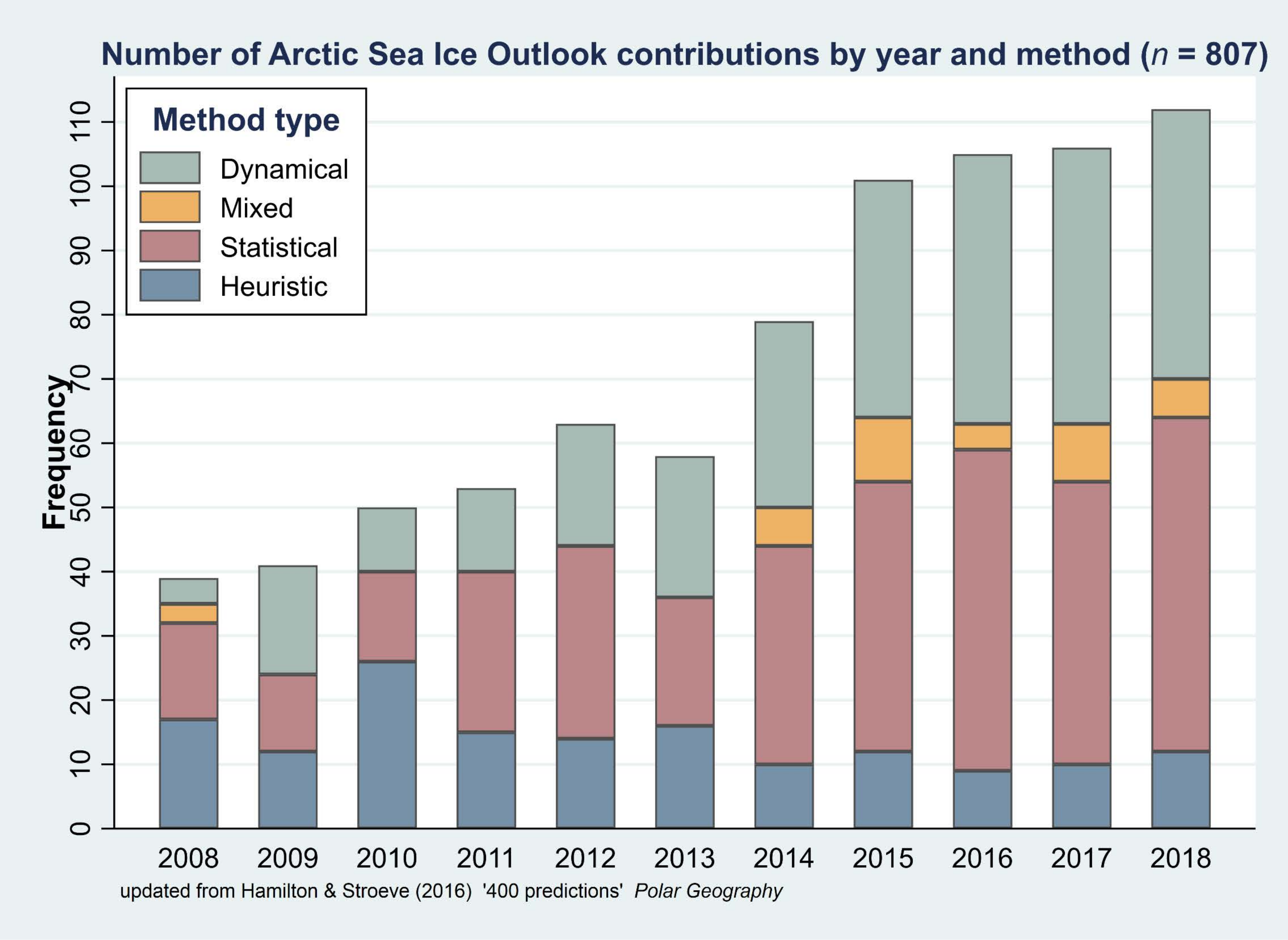

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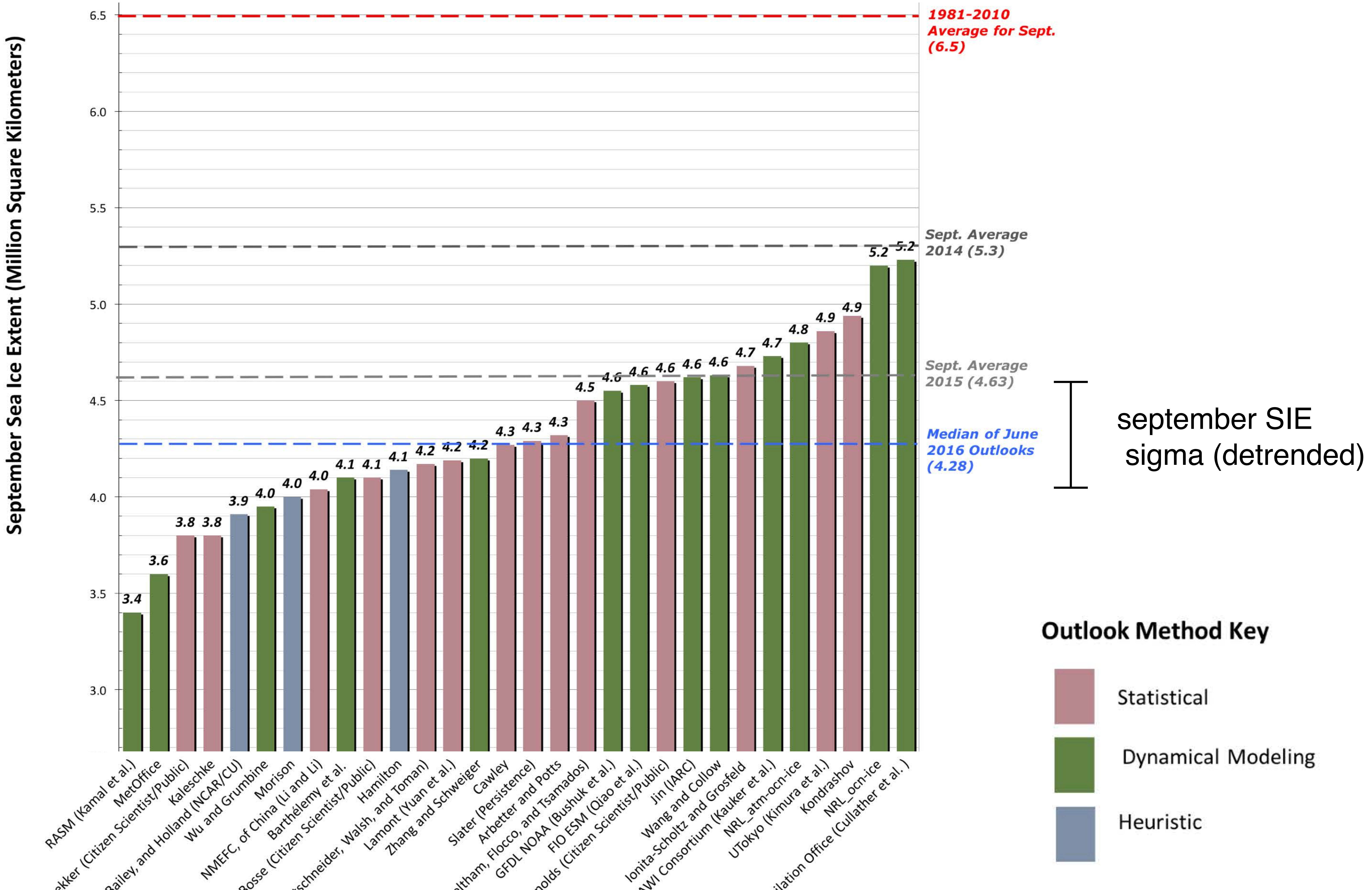

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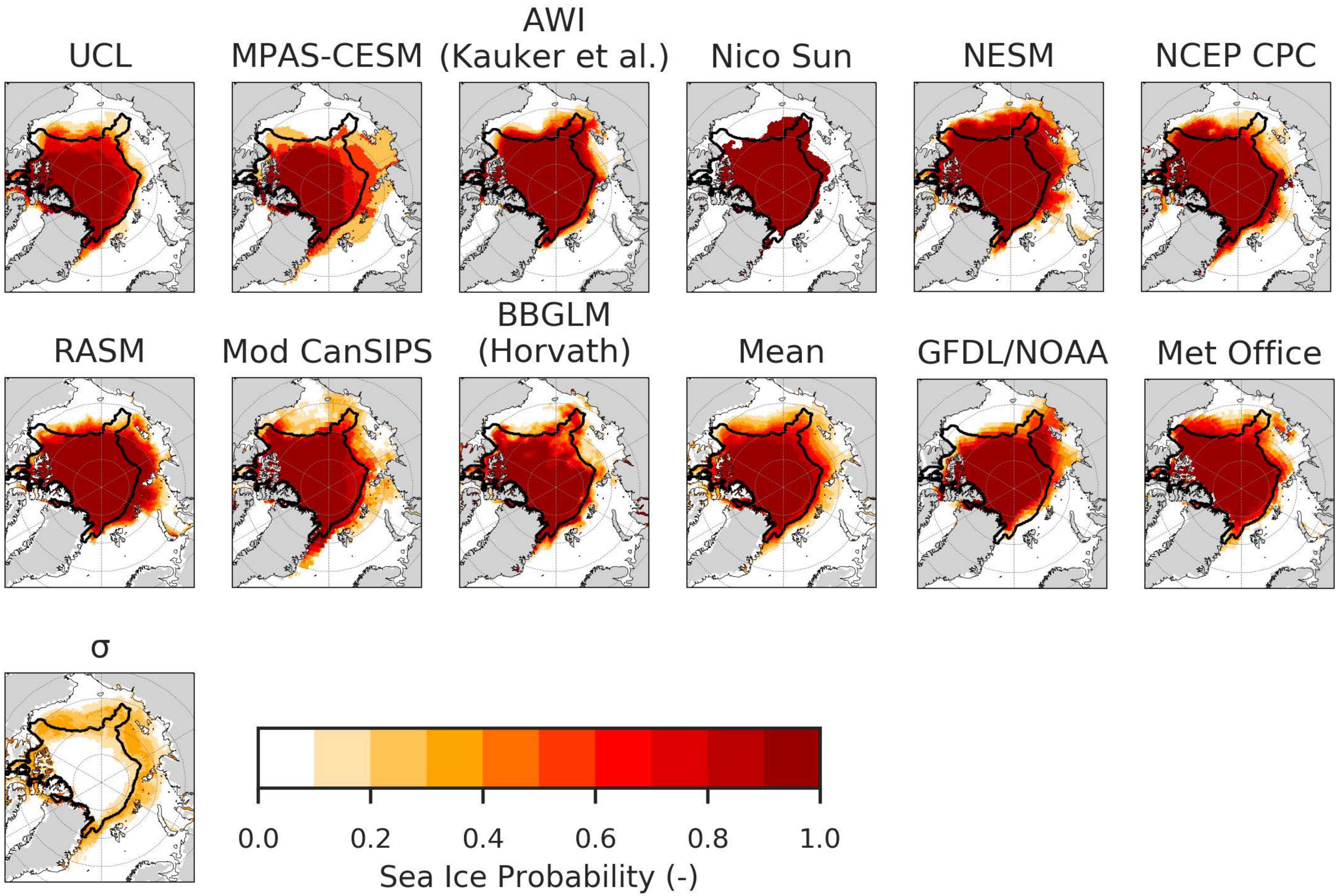
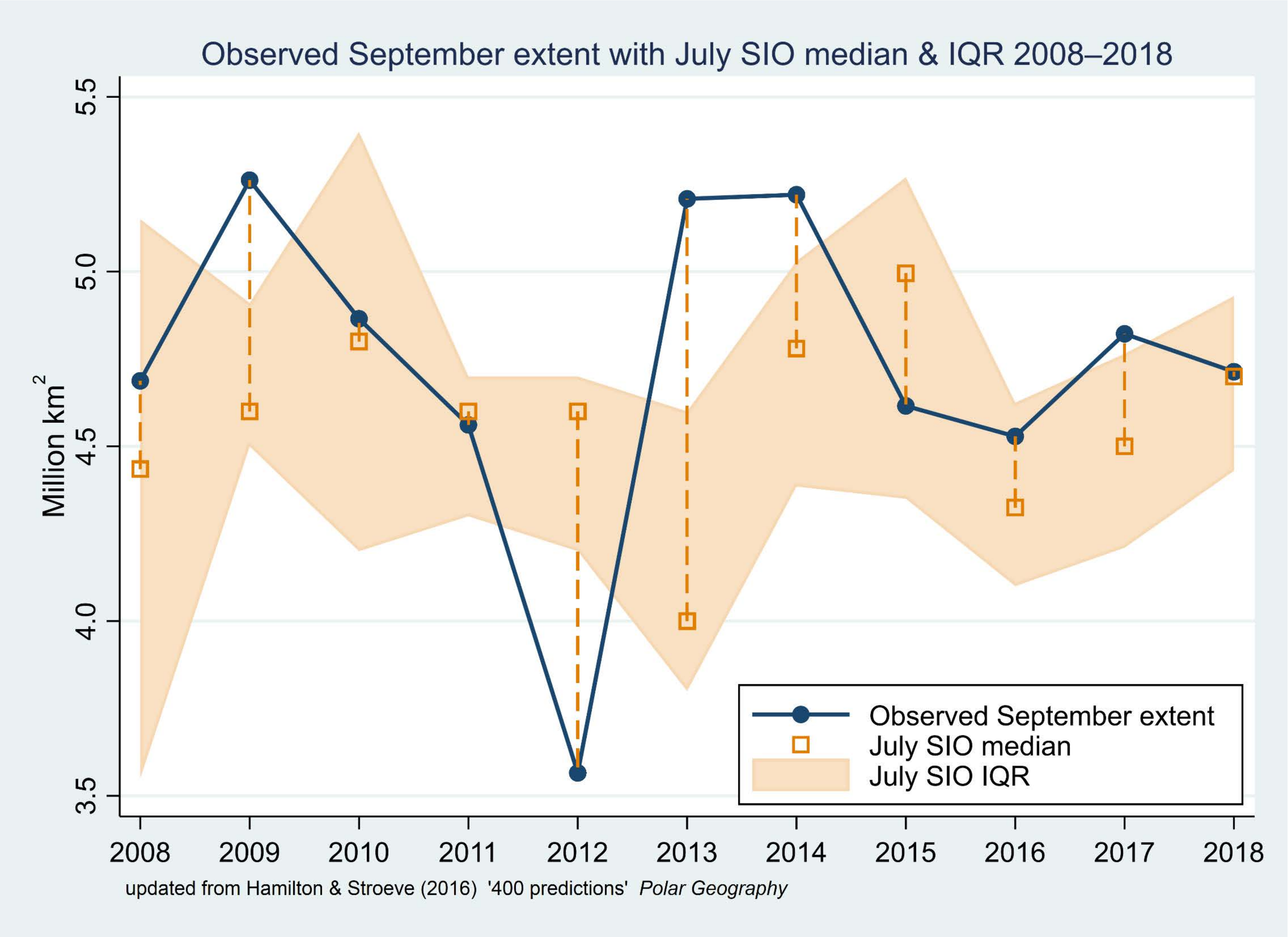
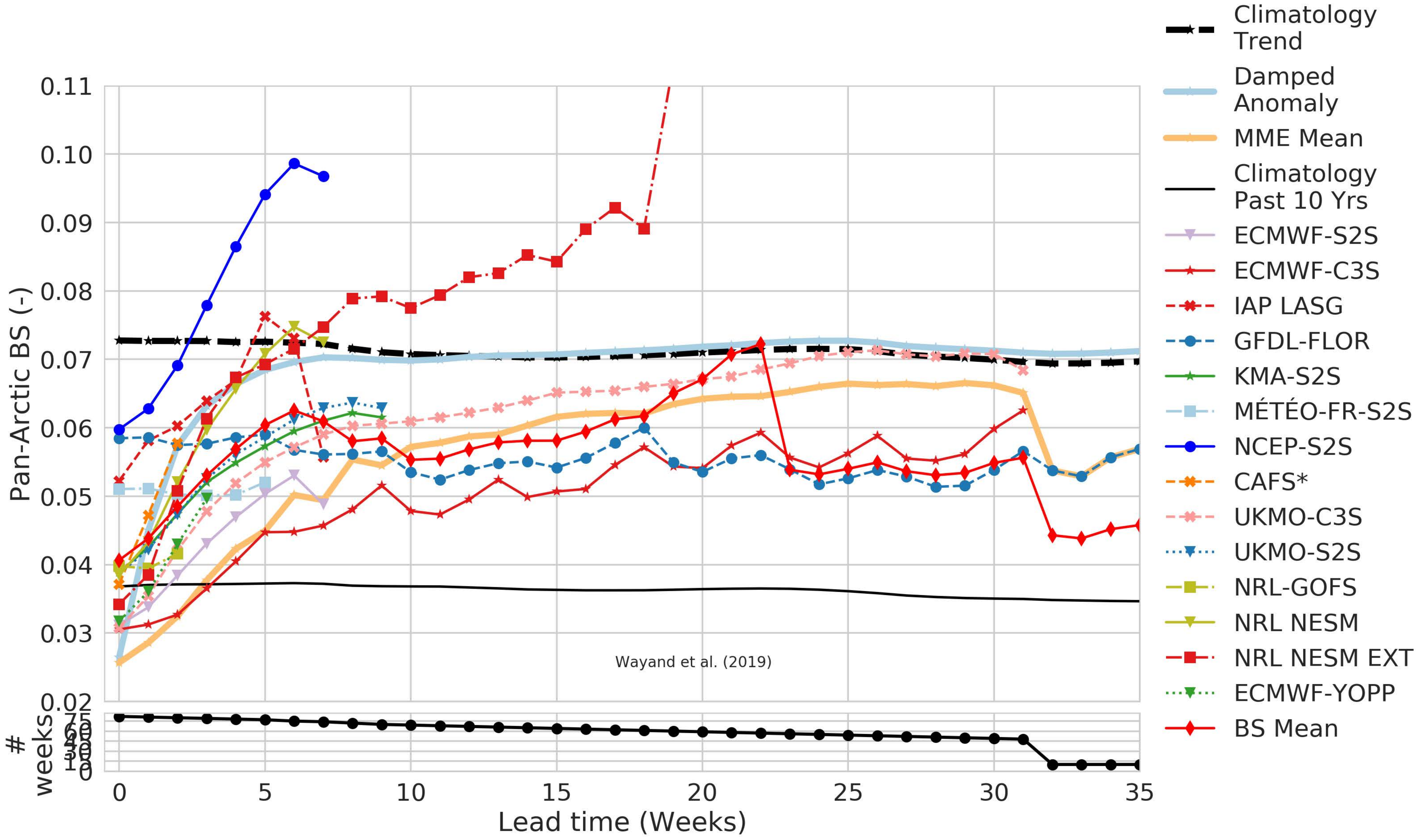


Forecast skill in SIO



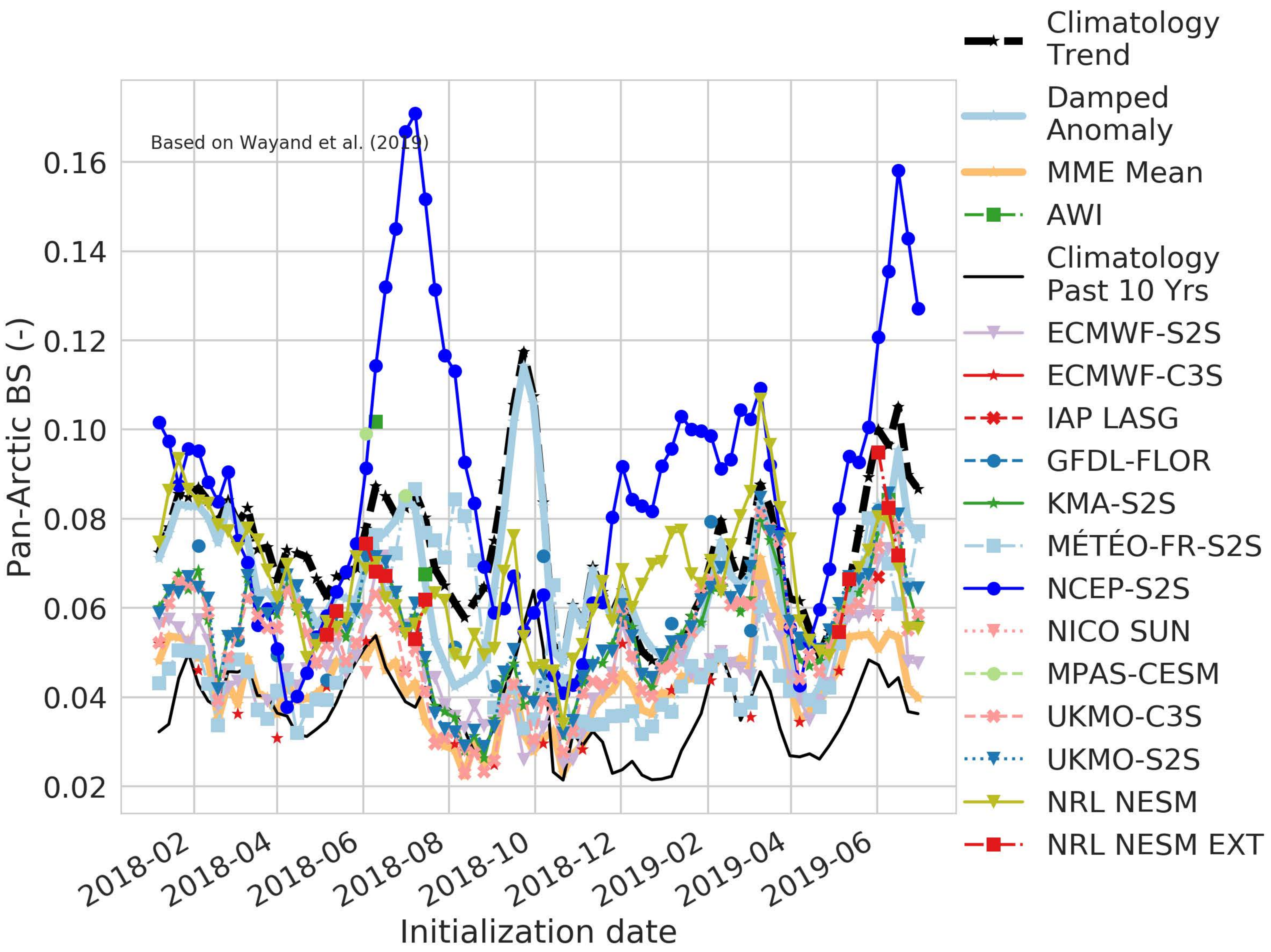
Updated from Hamilton and Stroeve (2016)

Spatial forecast skill



www.atmos.washington.edu/sipn

Spatial forecast skill



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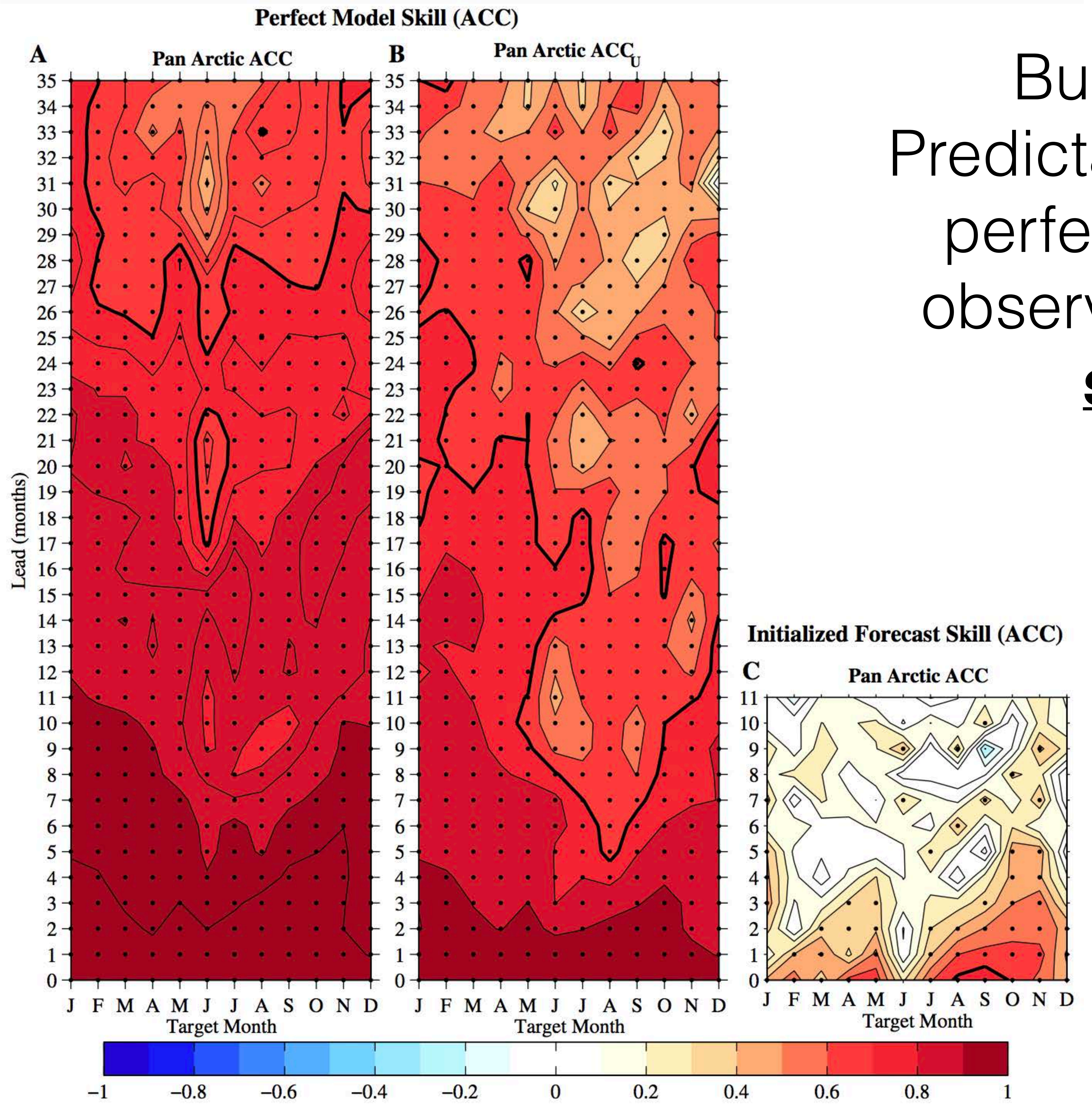
Gap in forecast skill?



Bushuk et al 2018
Predictability gap between perfect model skill and observational skill **using same model**
Why?

The predictability gap between perfect models and the real world (hindcasts/forecasts)

Uncertainty in a forecast arises from **a) unknown initial conditions**, b) **imperfect model physics**, c) growth from infinitesimal errors (chaos)

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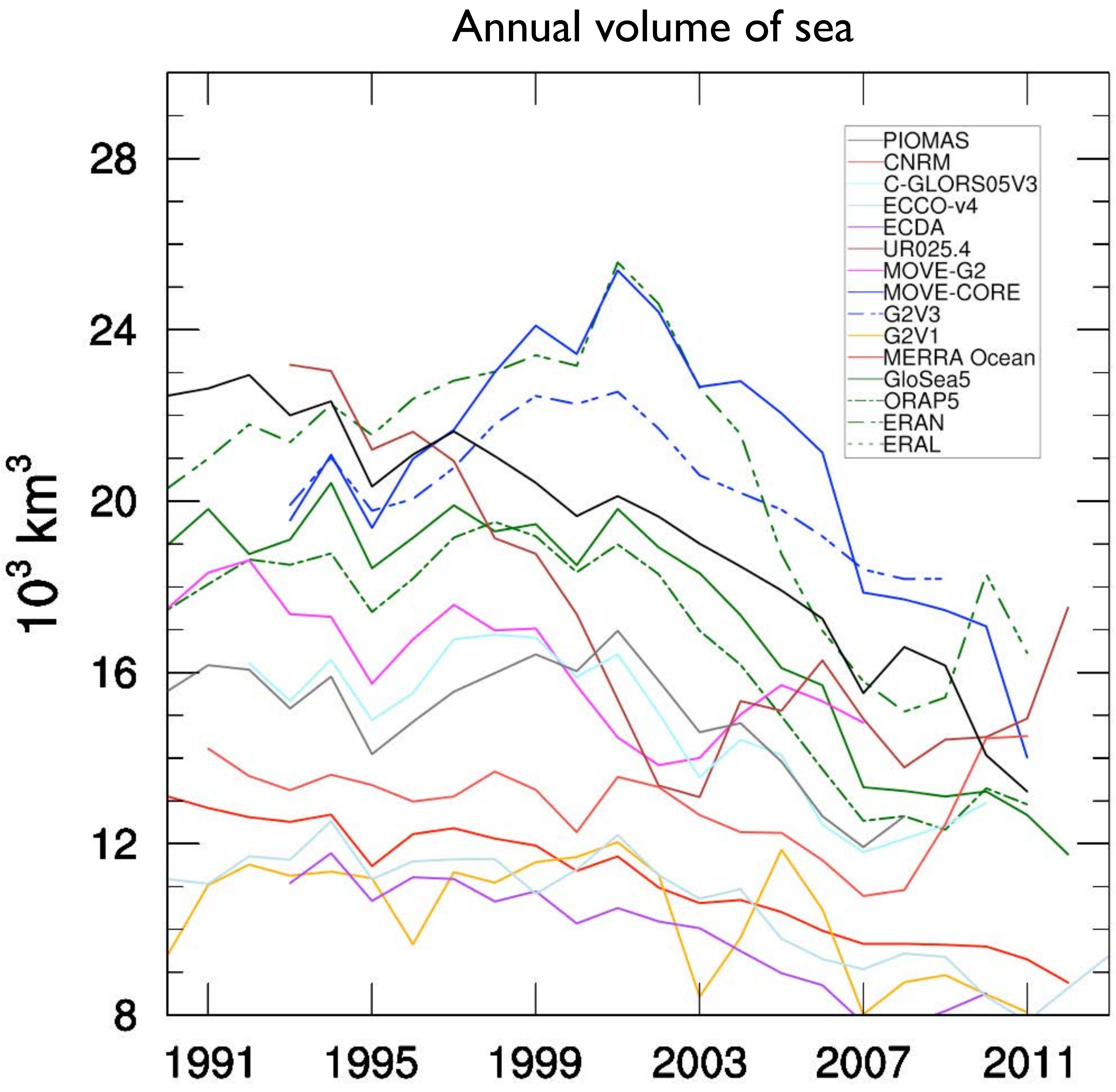
Good models, but poor observations* (i.e., Initial Conditions)

Or poor models, but good observations/ICs?

Or poor models and poor observations/ICs?

*and assimilation techniques to incorporate observations to model

Uncertainty in sea ice reanalysis/reconstruction products (from which initial conditions are taken)



Chevallier et al (2016)

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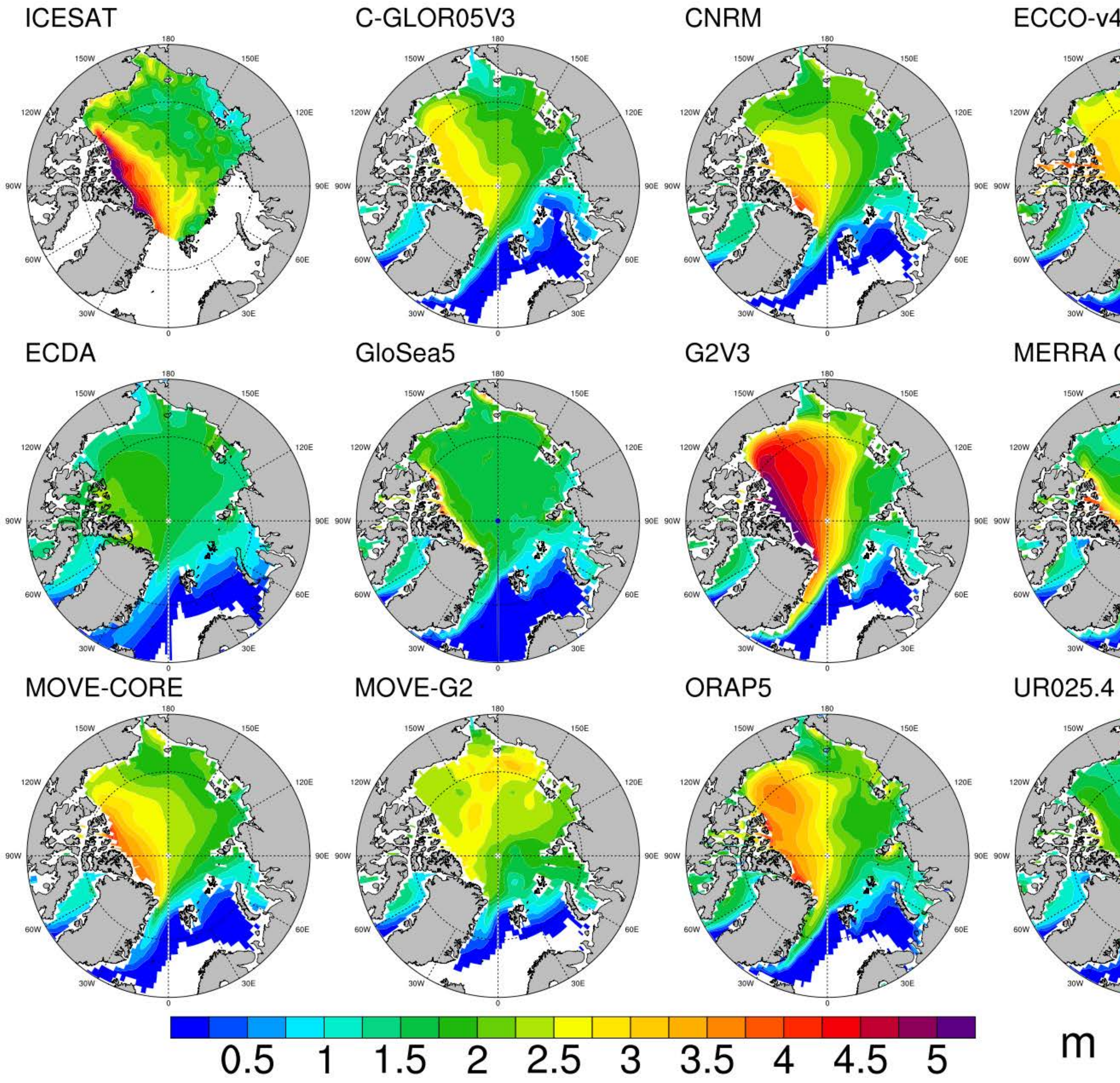
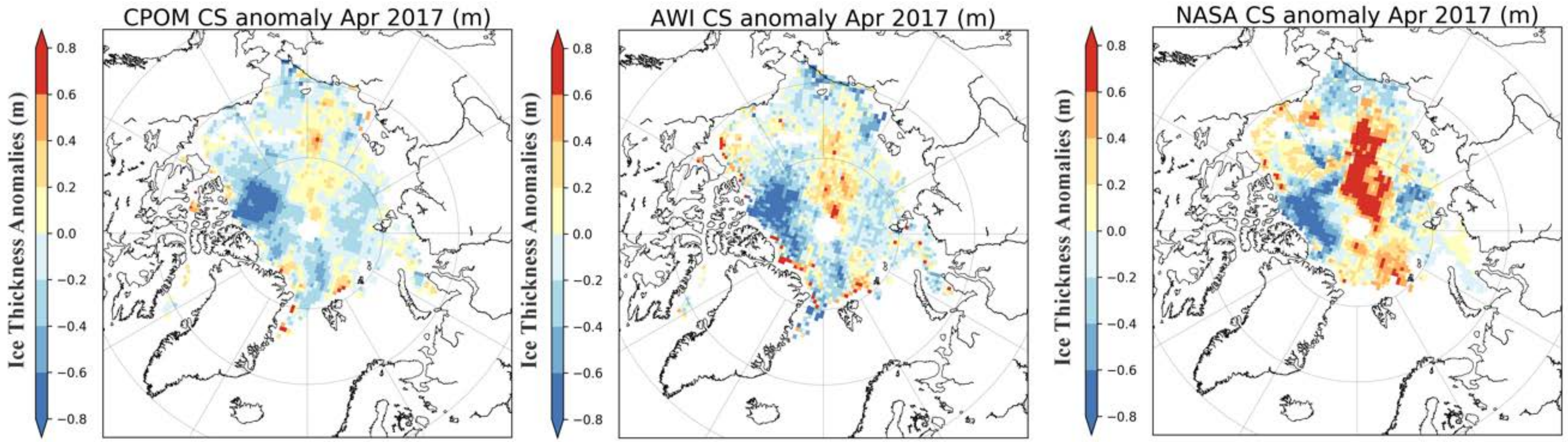


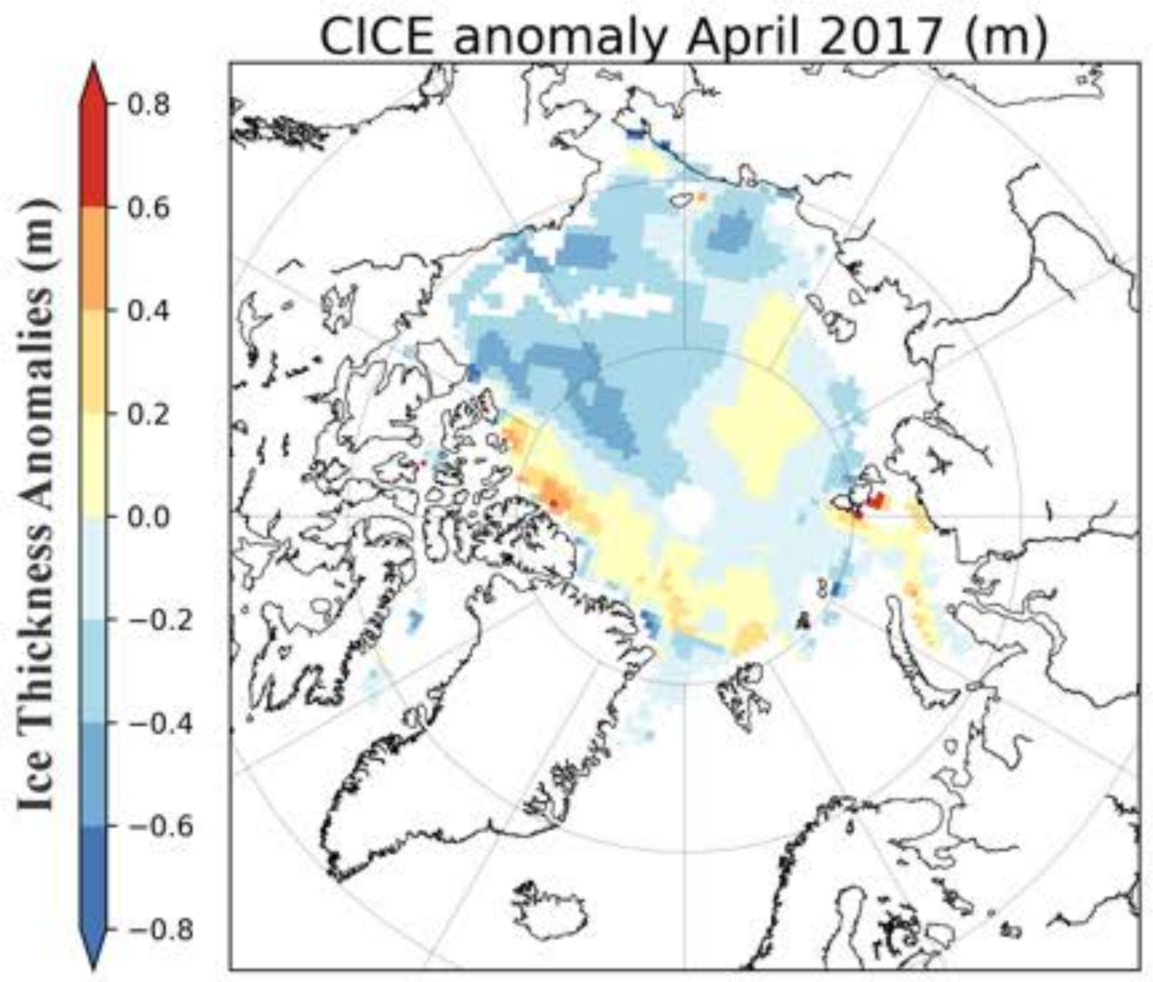
Chevallier et al (2016)

Mean March 2003-2007 Sea Ice Thickness (m) in global ocean-sea ice reanalyses with assimilation of sea ice concentration

(In) Direct observations of sea ice thickness: sparse in time, uncertain

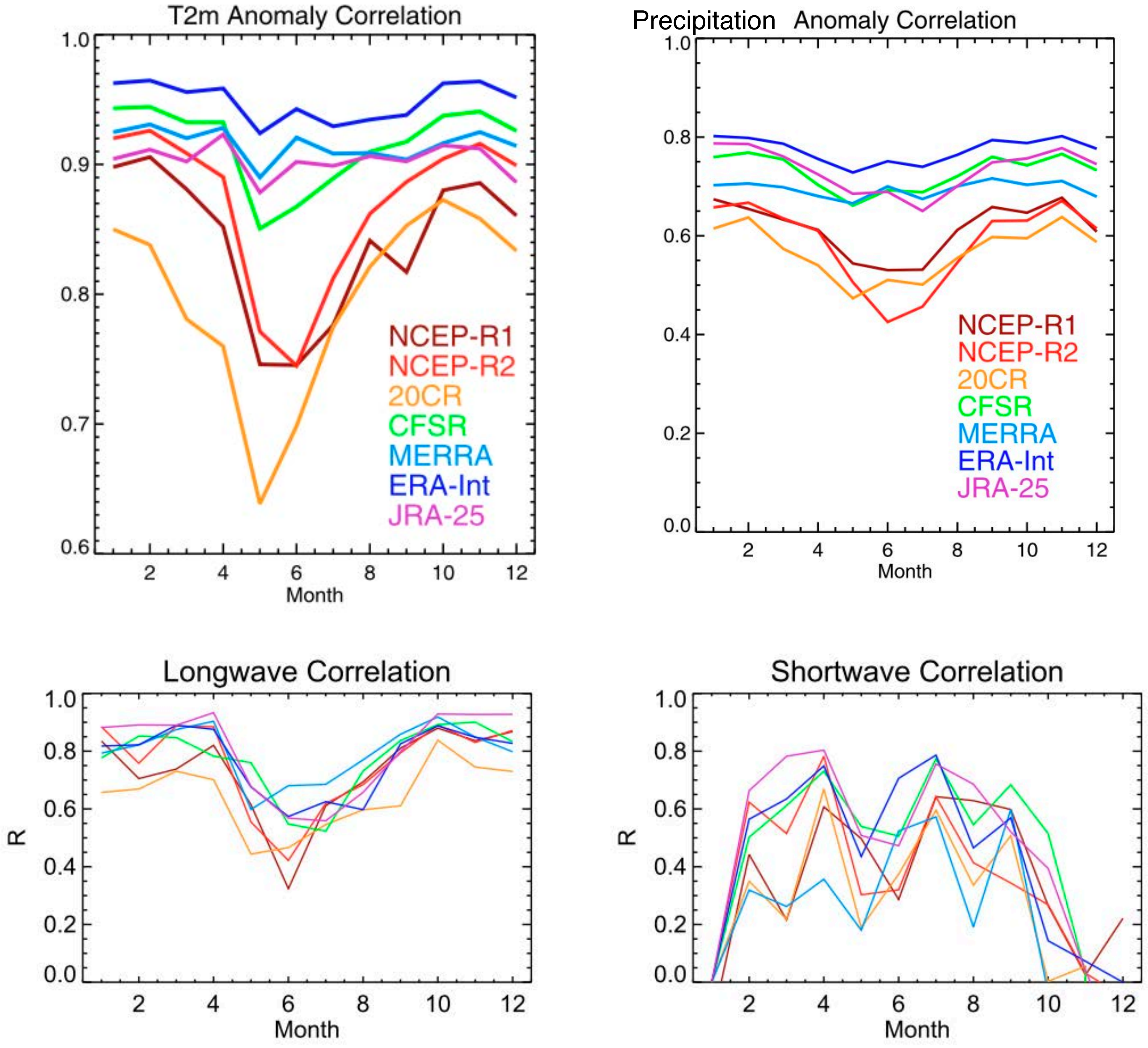


Sea ice thickness anomalies for April 2017 from 3 different algorithms using the same satellite sea ice freeboard retrievals



Sea ice thickness anomalies in CICE for April 2017 (obtained from running CICE with November 2016 CS2 thickness and forcing with NCEP2 reanalysis)

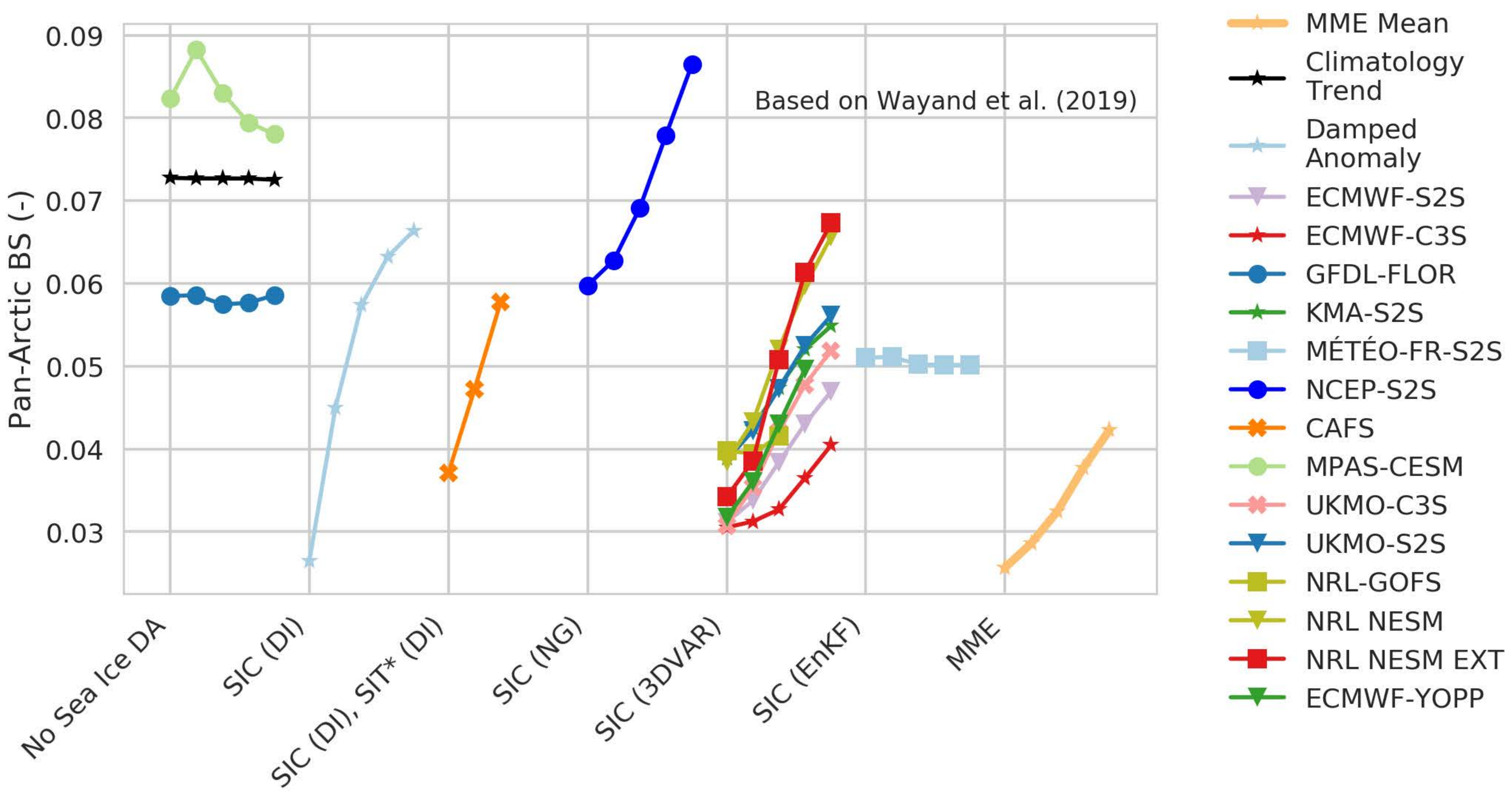
Atmospheric reanalysis in polar regions are known to have less fidelity than in other regions*



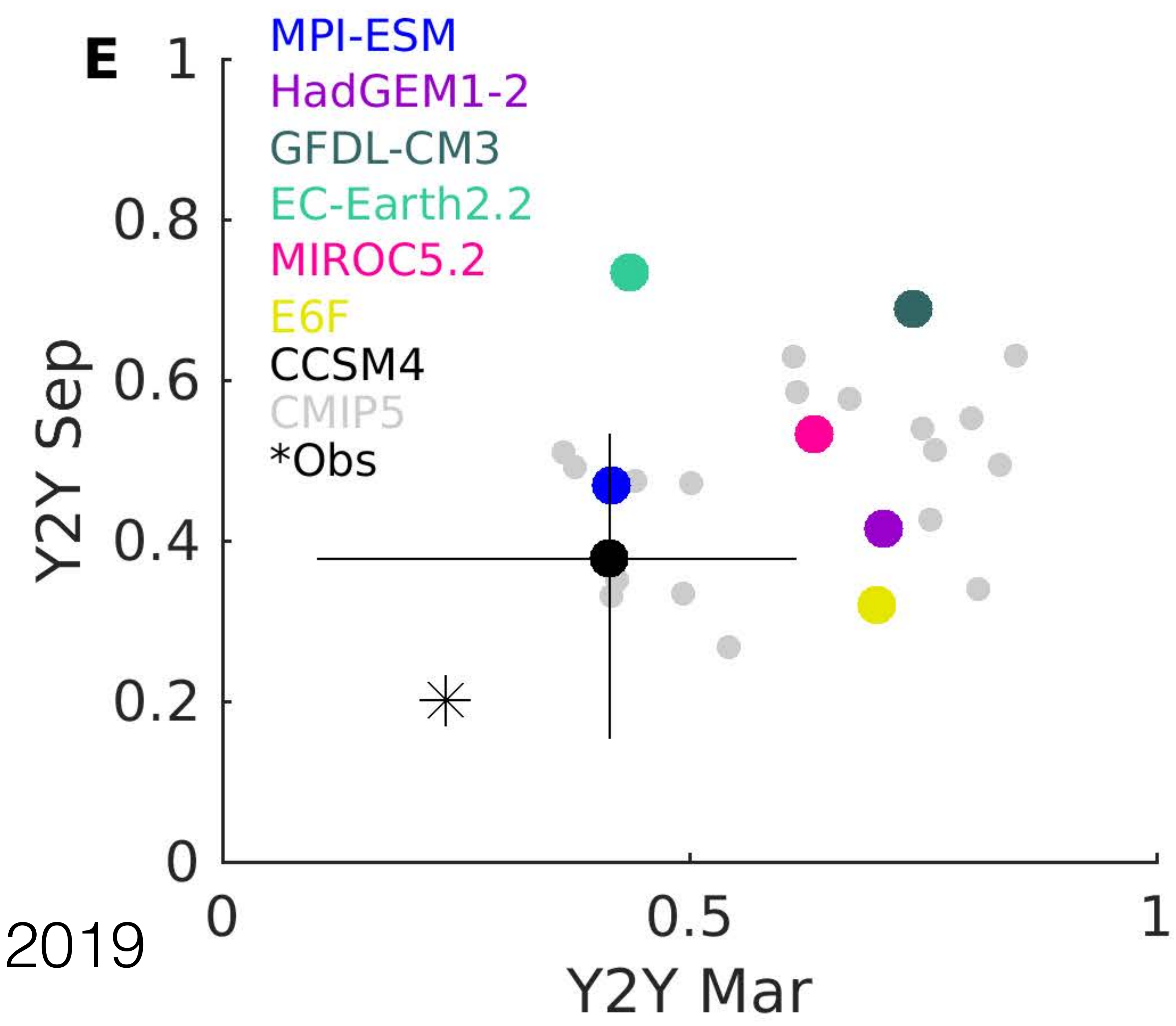
Lindsay et al 2014

*Important because these are used to force ice-ocean models to derive initial conditions

How to optimally use observations for initial conditions?



Role of model bias in assessing predictability



BW and Bushuk, 2019

Y2Y SEP: Year-to-year September autocorrelation

Y2Y MAR: Year-to-year March autocorrelation

GCMs: no link between Y2Y March/Sep

Models more persistent than observations

Are models too persistent ('sluggish'), and therefore too predictable?

Summary/key issues

Initial value perfect model experiments show sea ice area is predictable for at least 1 year, hindcasts and forecasts mostly show skill for a season. Spatial forecasts even less (weeks).

Why the gap? Errors/uncertainty in initial conditions, model physics and forecast bias correction likely all play significant role.

But do models overestimate potential predictability? What physics are missing/ poorly simulated? Coupling between components? Is sea ice in models (GCMs) too persistent? If so why?

What is optimal way to improve forecast skill - focus on initial condition/ observations or model physics?