

# Arctic sea ice forecasting: an update from the trenches

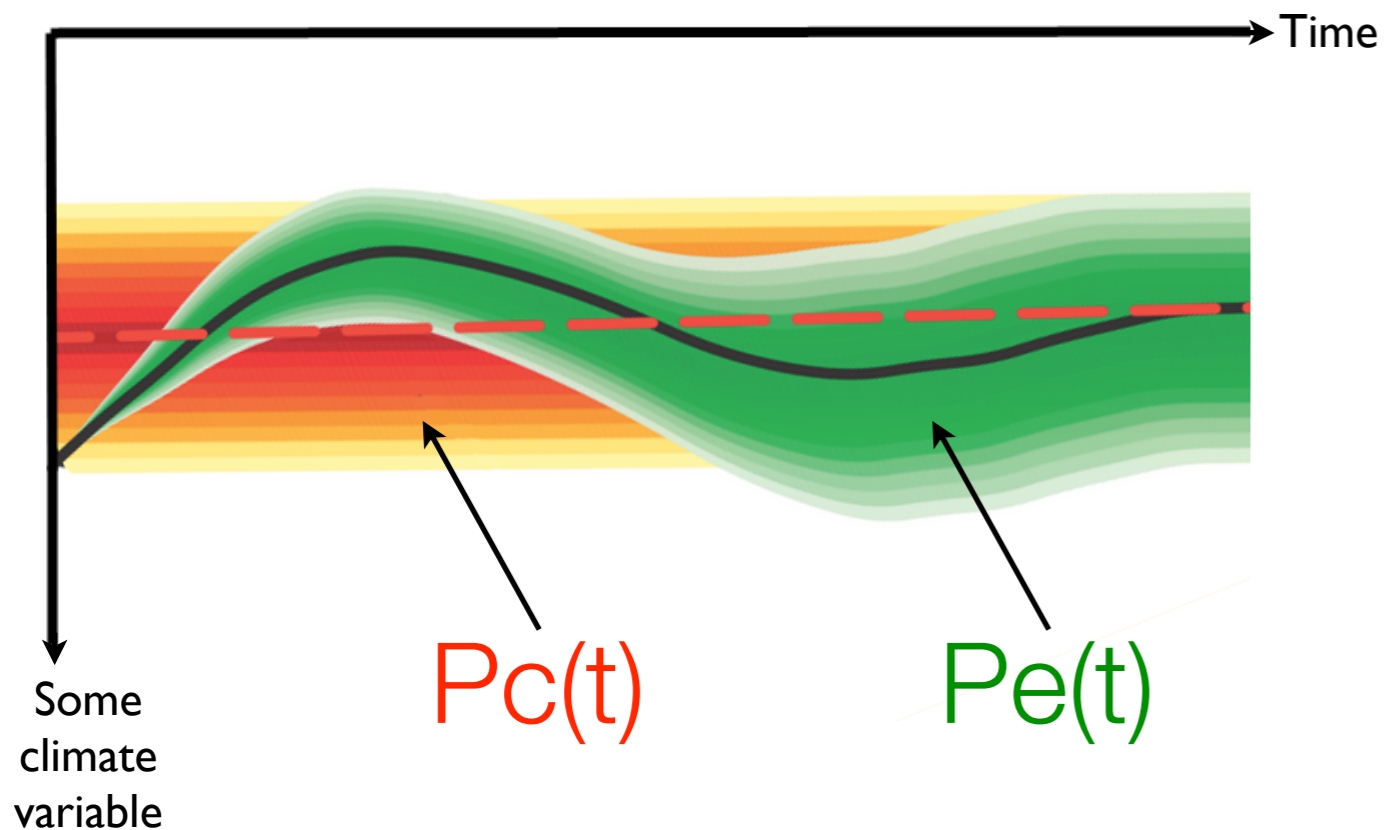
Ed Blanchard-Wrigglesworth  
University of Washington

with Cecilia Bitz (UW), Richard Cullather (NASA), Wanqiu Wang (NOAA), Jinlun Zhang (UW), Francois Massonnet (IC3&UCL), Neven Fuckar (IC3), Pamela Posey (NRL), Matthieu Chevallier (MeteoFrance), and many others



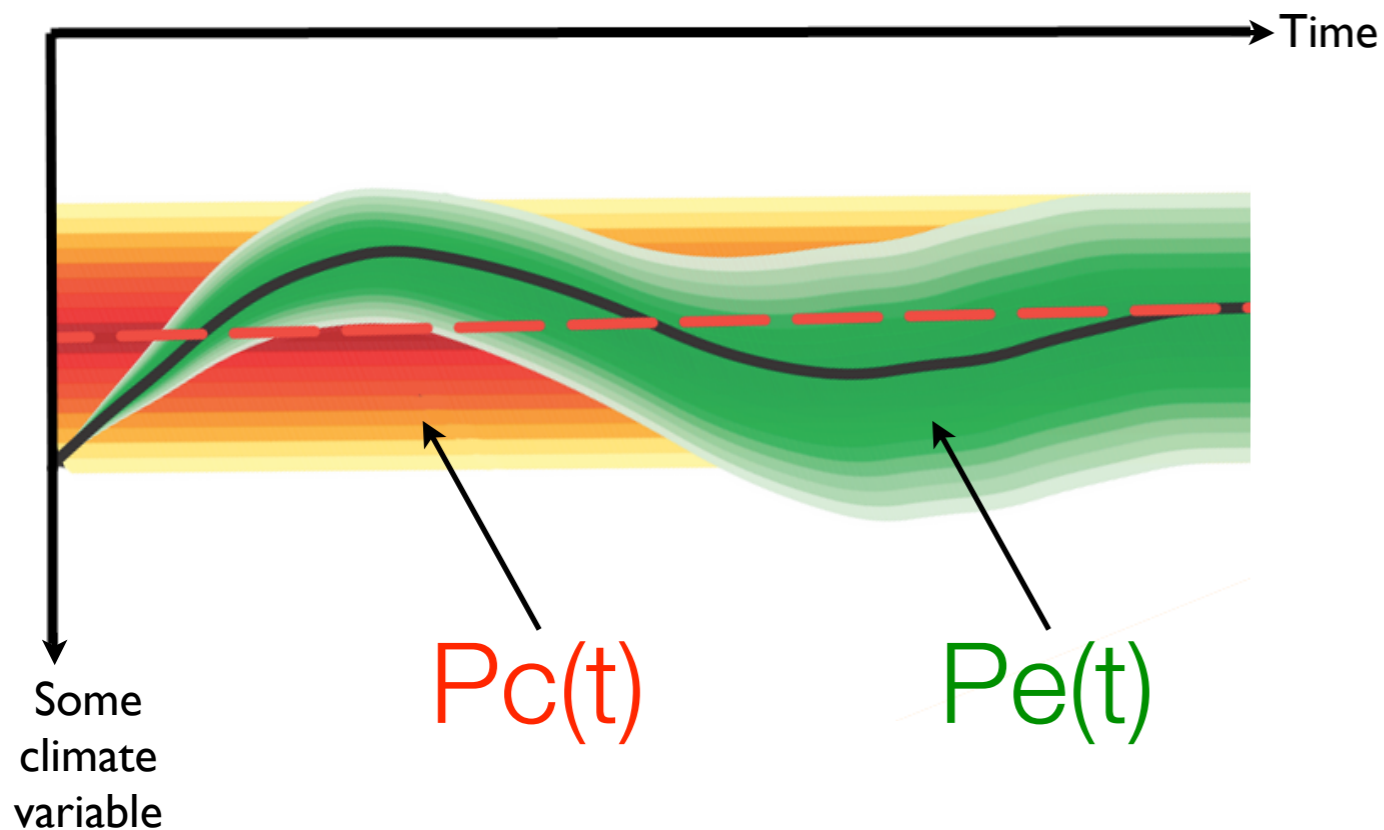
# On predictability

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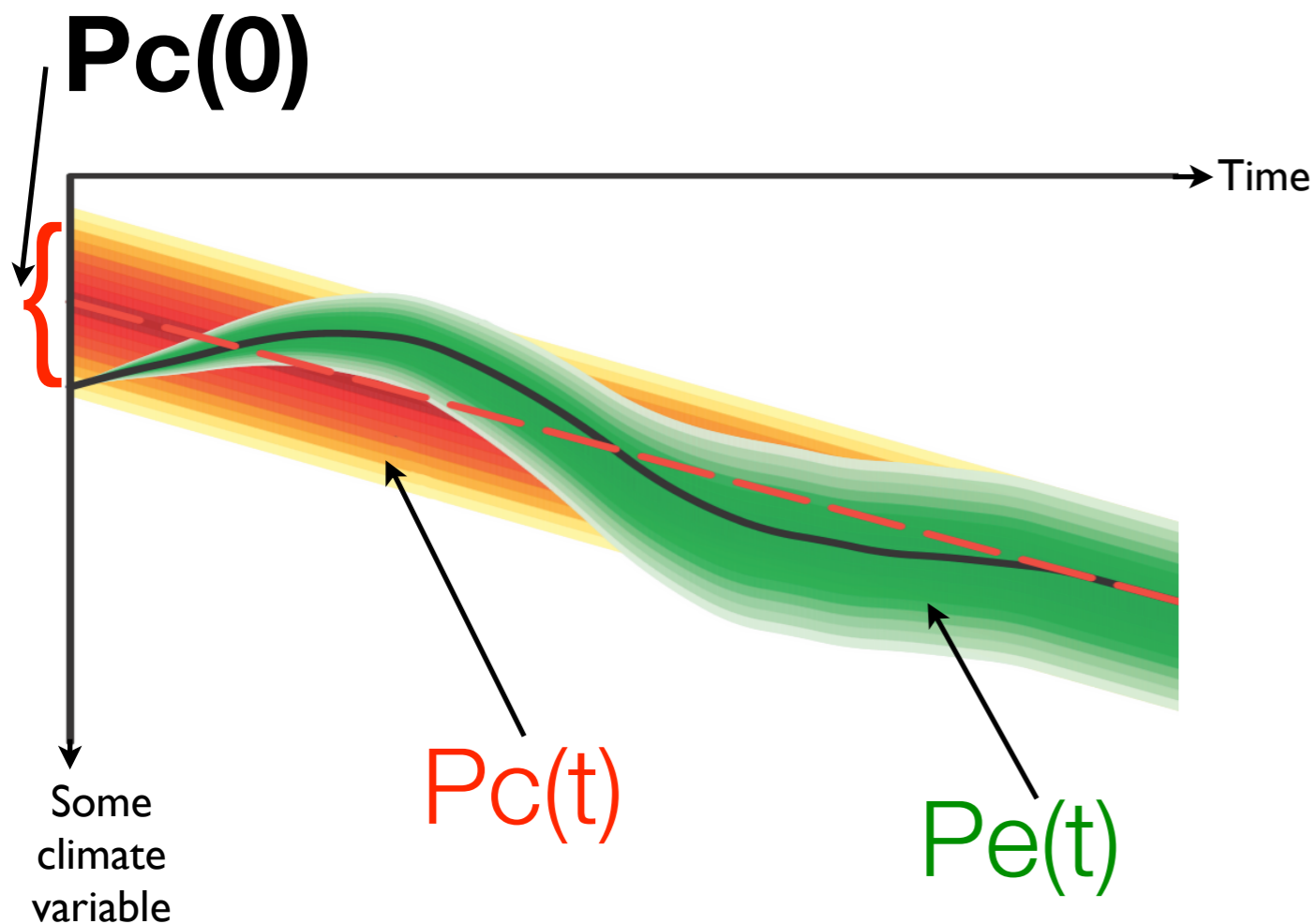
- $P_c(t)$  represents the climatological distribution. It is independent of any particular initial state.
- $P_e(t)$  is an ensemble of predicted states evolving from a specific tight cluster of initial conditions.
- Eventually,  $P_e(t)$  converges to  $P_c(t)$  as the influence of the particular initial conditions is lost (*i.e. we lose predictability*).

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- $P_e(t)$  is an ensemble of predicted states evolving from a specific tight cluster of initial conditions.
- Eventually,  $P_e(t)$  converges to  $P_c(t)$  as the influence of the particular initial conditions is lost (*i.e. we lose predictability*).
- A comparison of  $P_e(t)$  to  $P_c(t)$  represents “initial-value predictability”, or predictability of the “first kind” (Lorenz 1975). This is what a weather forecast is.

# On predictability



- What if  $P_c(t)$  changes with time due to changing boundary conditions?

- In this case,  $P_c(t)$  will diverge from  $P_c(0)$ , the initial 'climate'.

- a comparison of  $P_c(t)$  to  $P_c(0)$  corresponds to "forced predictability", or predictability of "second kind" (Lorenz 1975).

# On predictability

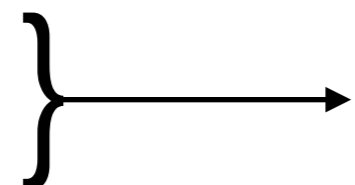
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forecast flavors

Day/weekly

Seasonal

Decadal



Initial value predictability



Forced (boundary) predictability (or  
so we thought...)

# On predictability

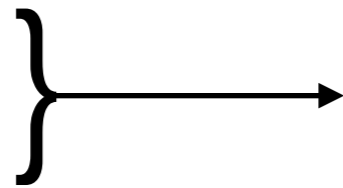
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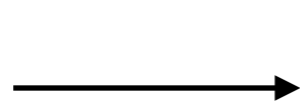
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Initial value predictability



Forced (boundary) predictability (or so we thought...)

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

Forced : forecast skill depends on how well you simulate future climate change i.e., right sensitivity to changing boundary conditions

# Seasonal predictability: the Sea Ice Outlook

Since 2008, seasonal forecasts of **September sea ice extent** have been collected by the Study of Environmental Arctic Change (SEARCH). Since 2013, hosted by the **Sea Ice Prediction Network - SIPN** - and known as the **Sea Ice Outlook (SIO)**.

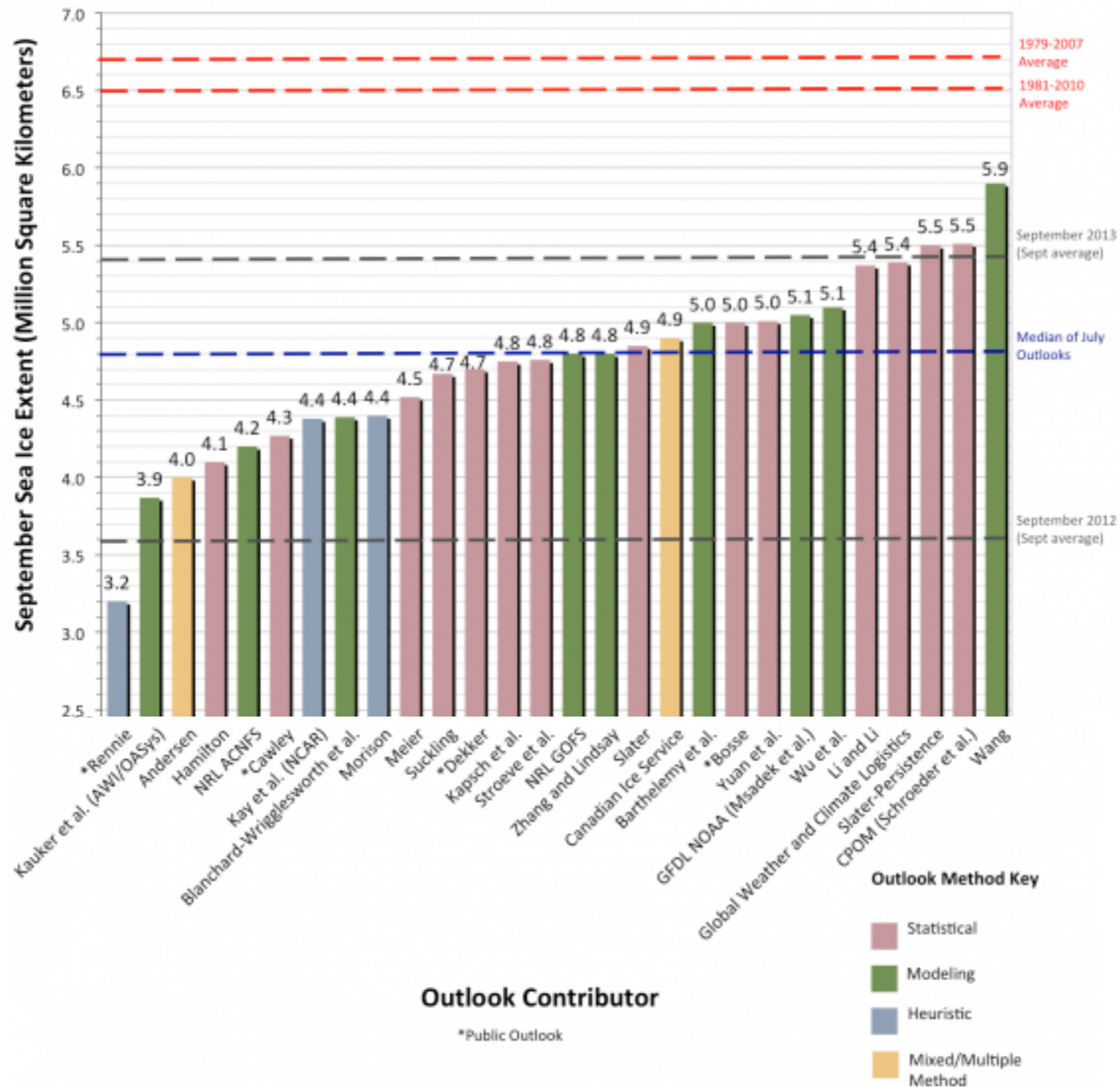
Each summer, 3 submission calls - early June, early July, early August  
(i.e., ~**2-4 month lead forecasts**)

All types of forecast techniques welcome: dynamical models, statistical, heuristic, public polls.

2008 - 2015: 8 years, 24 submission calls, 400+ submissions. **149 from dynamical models.**

# Seasonal predictability: the Sea Ice Outlook

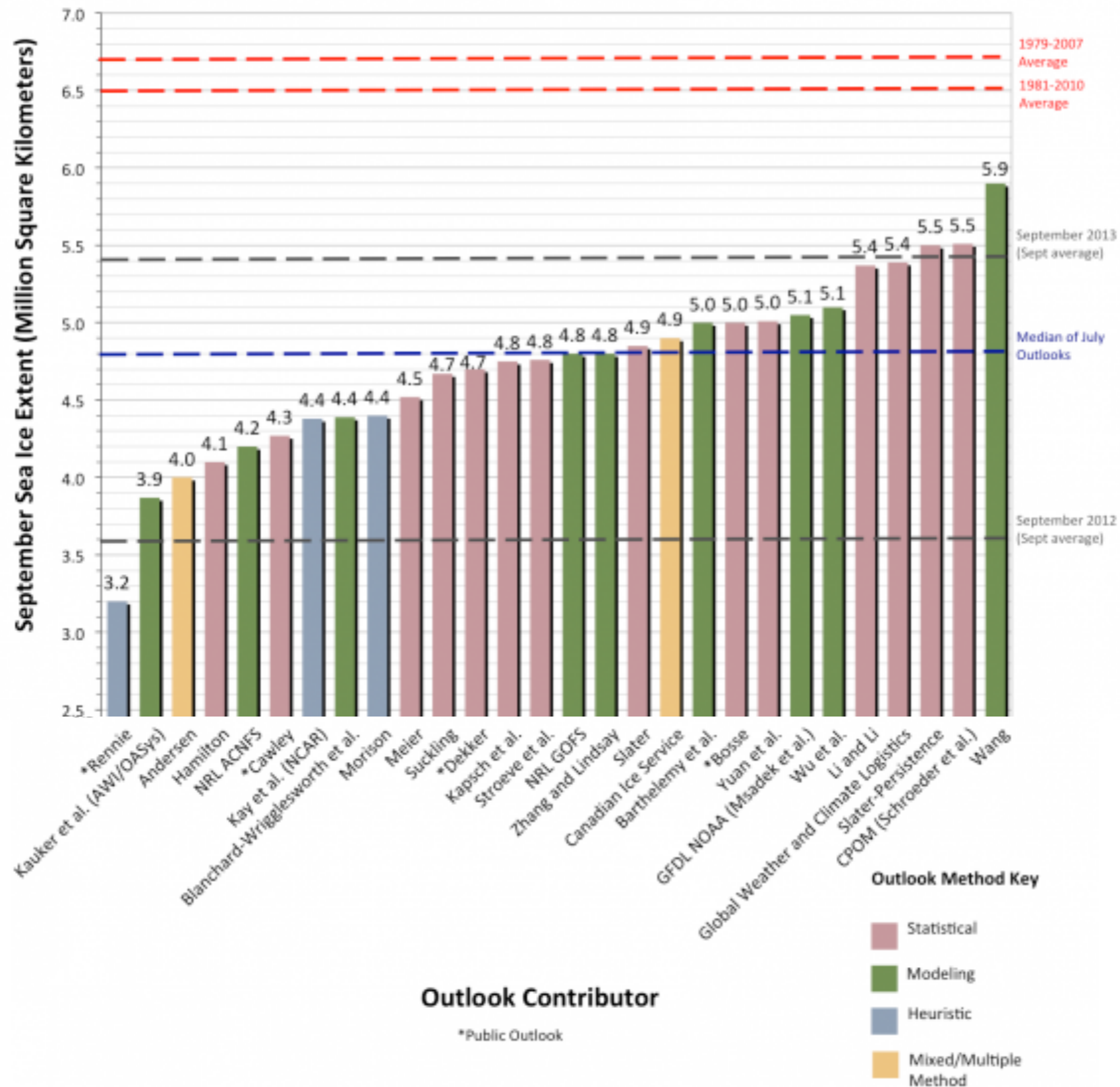
## 2014 Sea Ice Outlook: July Report





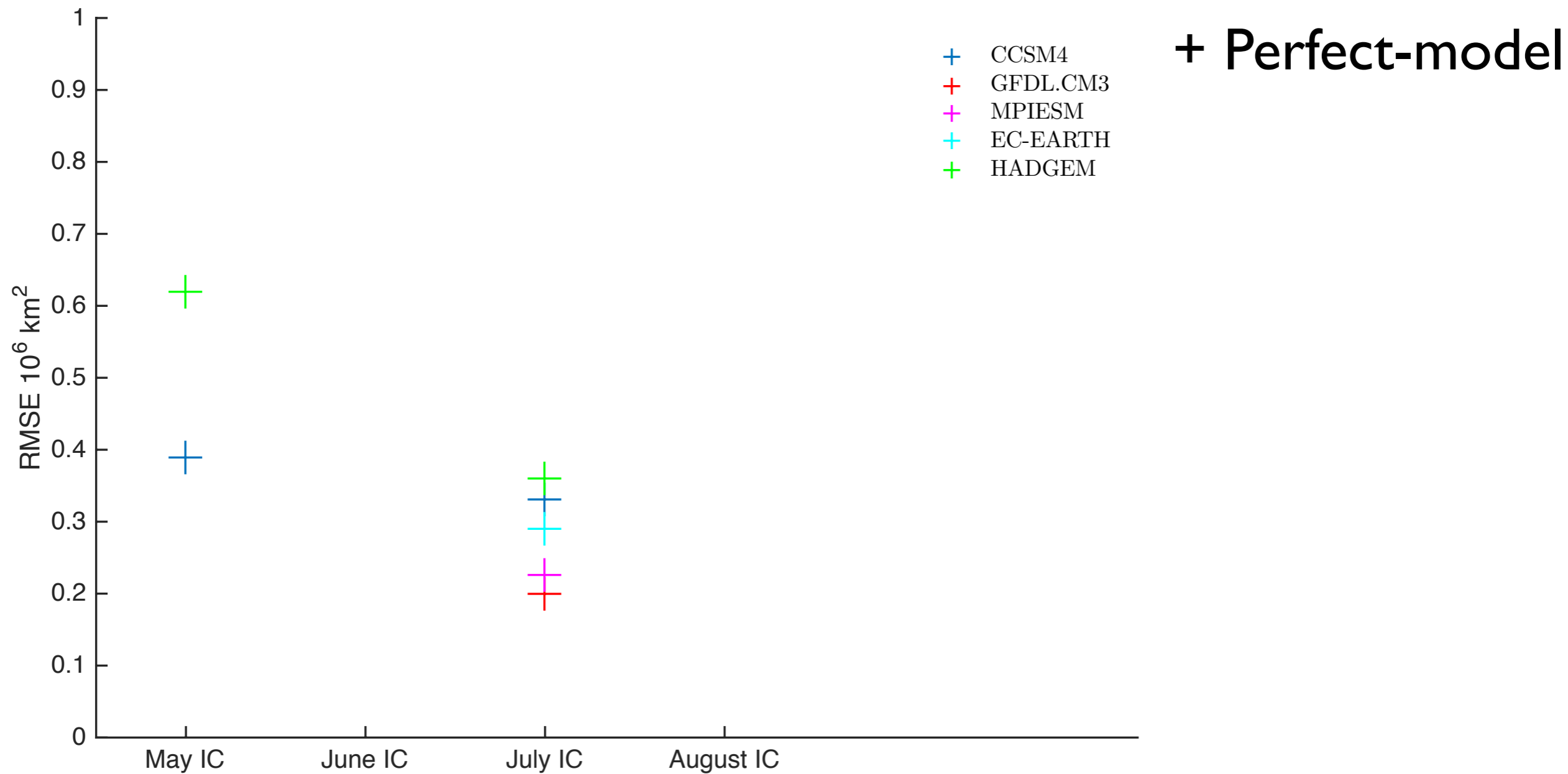
# Seasonal predictability: the Sea Ice Outlook

## 2014 Sea Ice Outlook: July Report

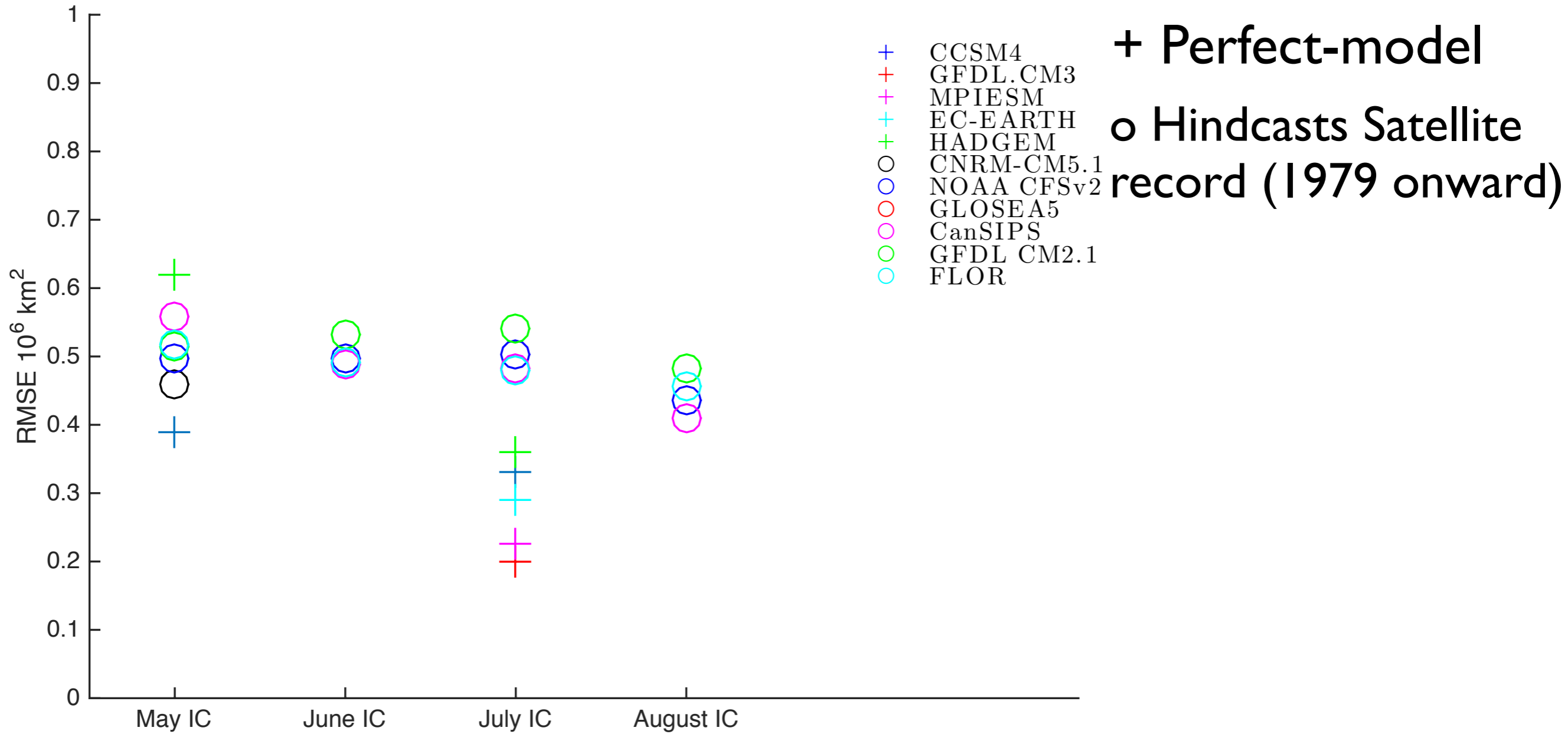


(+/- sigma)

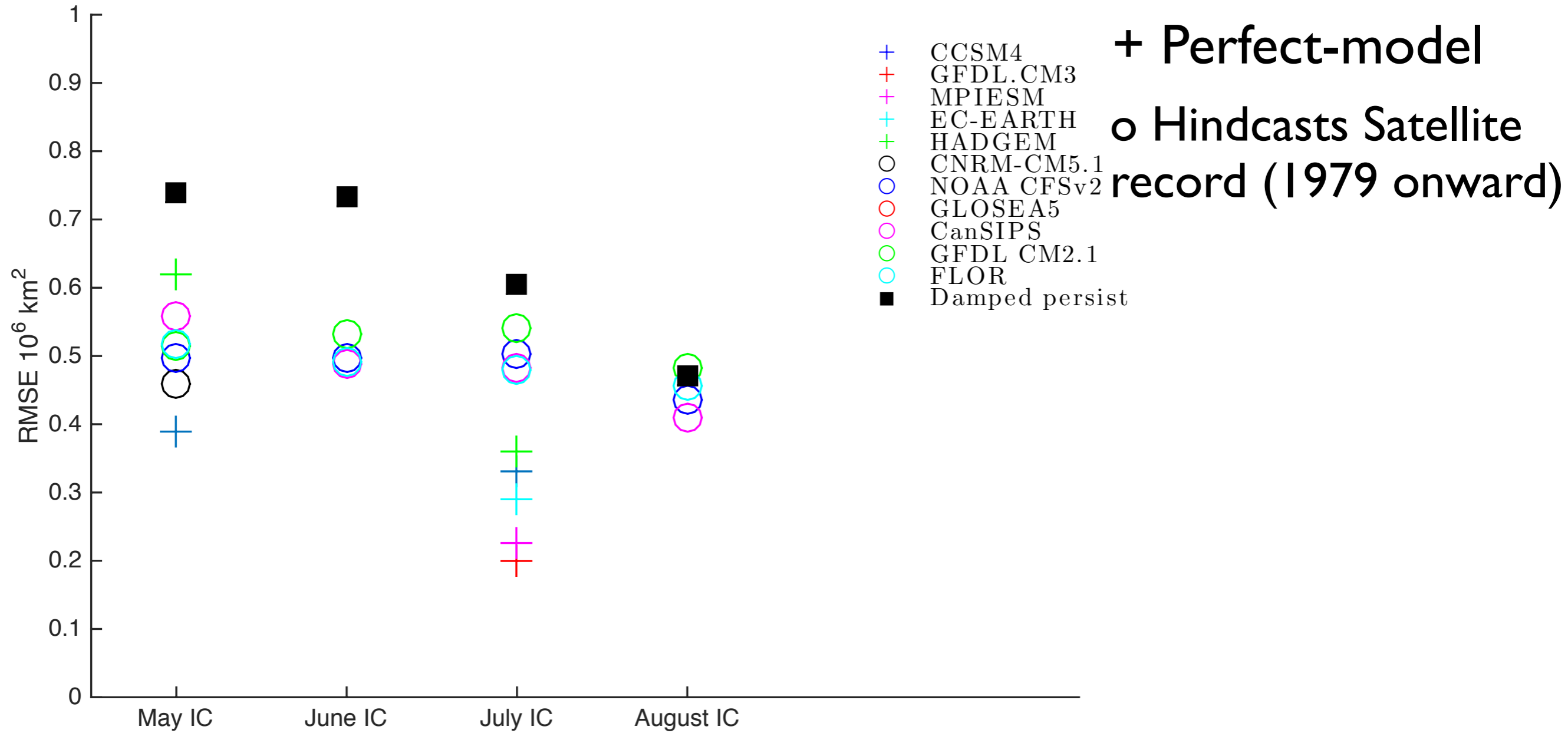
# Forecast skill of September sea ice extent



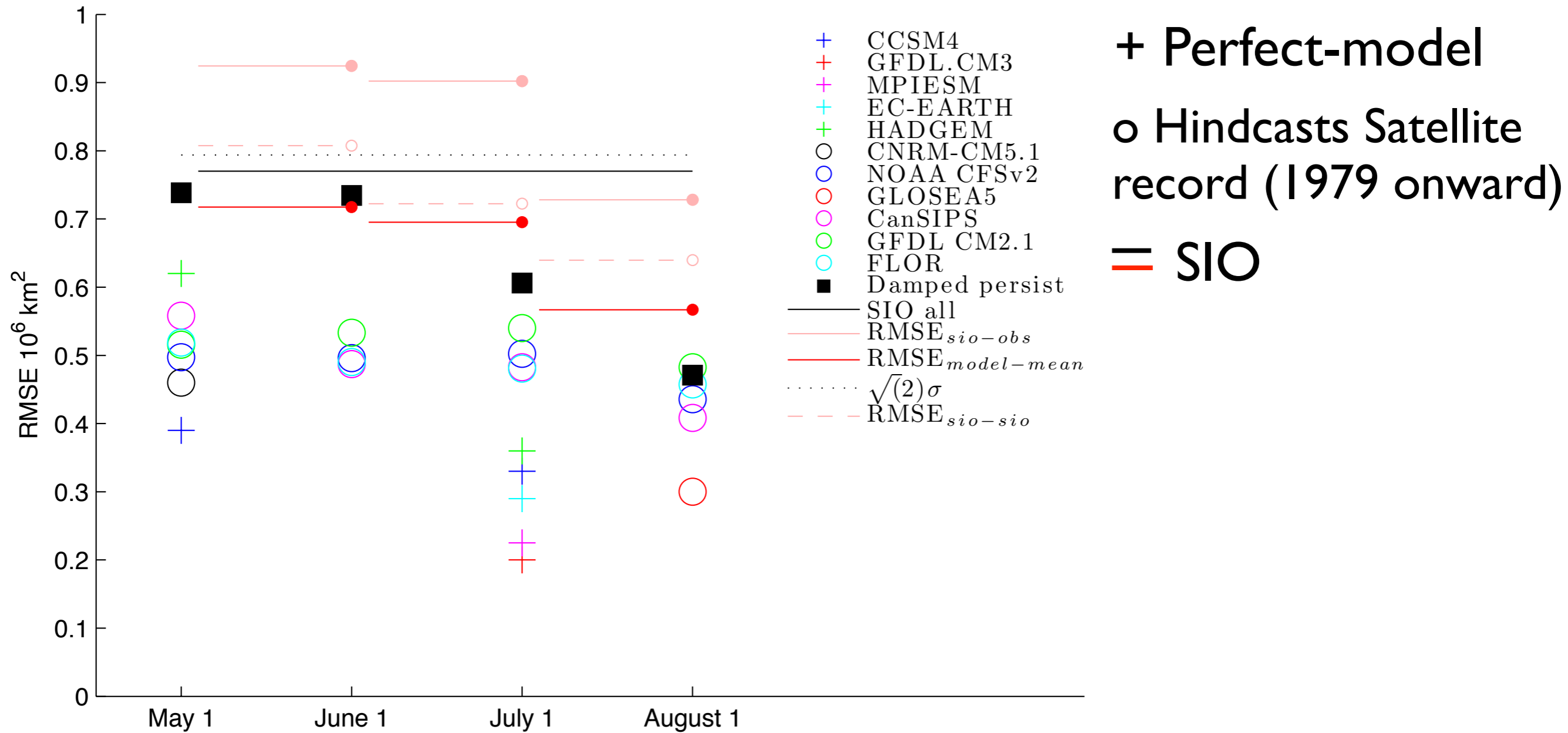
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# Should we expect seasonal skill?

Results from perfect-model experiments, hindcasts, and studies of persistence timescales of sea ice say yes.

SIO models do not even beat damped persistence forecast.

Why is skill so much lower than hindcasts? Some of the models in SIO have performed hindcasts over historical period, found much higher skill.

**Has recent period been inherently more unpredictable than earlier decades?**

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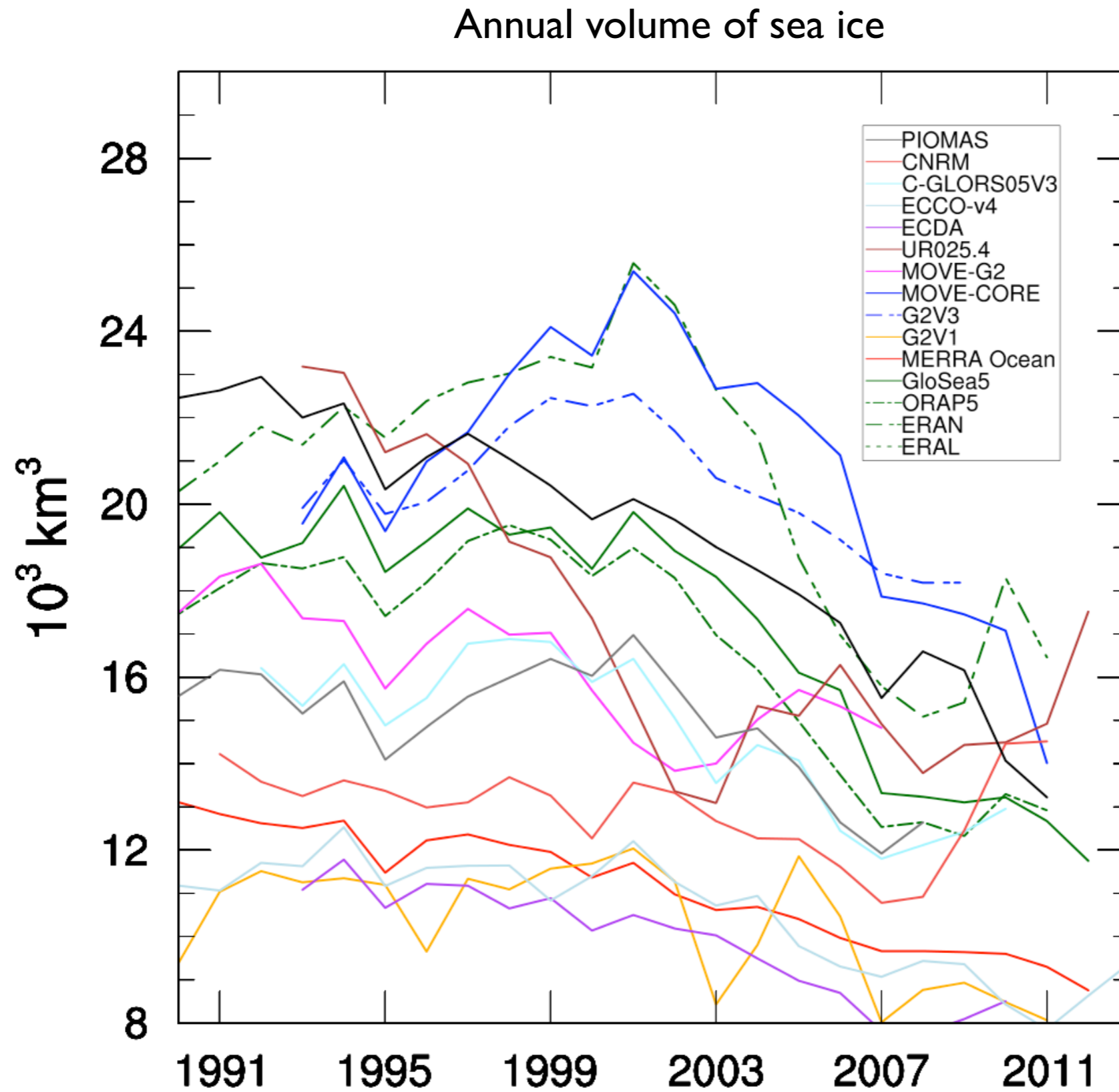
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NOAA CFSV2: hindcast RMSE (1981-2007) 0.5 -> 0.45 million km  
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METOFFICE GLOSEA5: hindcast RMSE (1996-2009): 0.3 million km  
SIO RMSE (7 forecasts): 1 million km

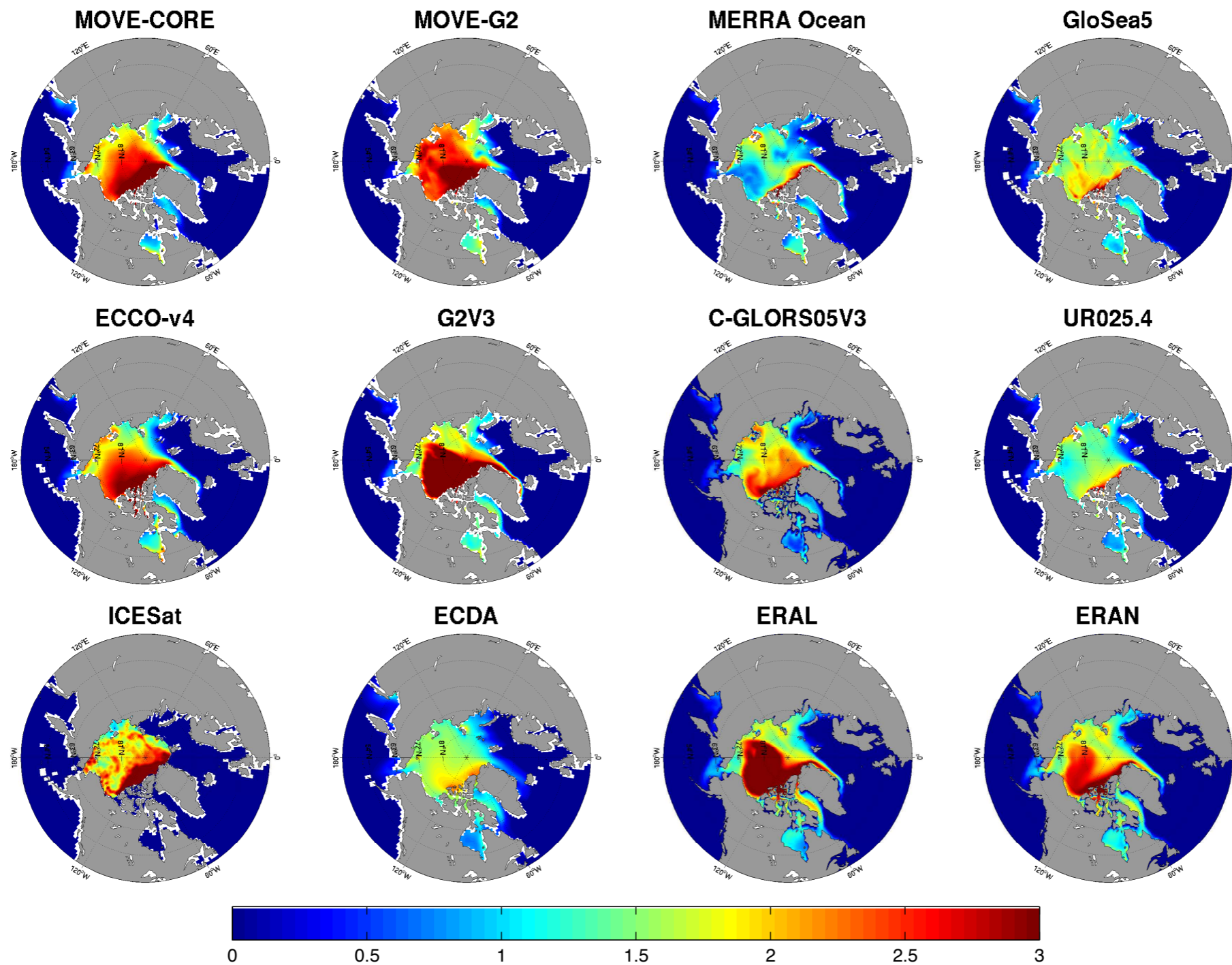


# Errors in reanalysis/reconstruction (from which ICs are taken)



Chevallier et al (in review)

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

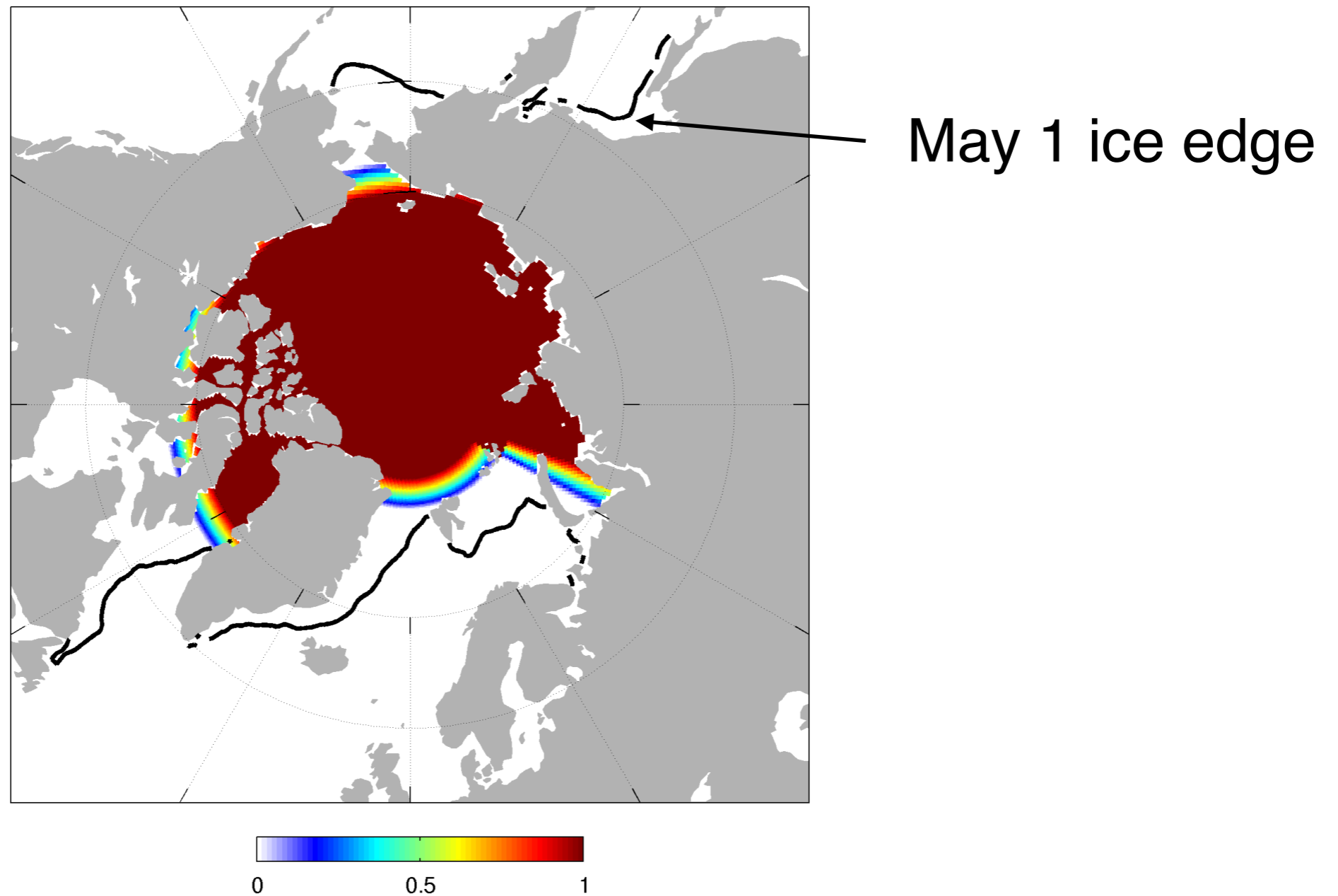
Chevallier et al (in review)

In 2015, we expanded our model experiment effort to 8 participating models. We have built a control run, that uses climatological (2007-2014) PIOMAS May 1 sea ice thickness, and an experiment run, that uses 2015 May 1 sea ice thickness.

Model	Model type	Ensemble size
PIOMAS (Zhang & Lindsay)	Regional ice-ocean model forced with past atmosphere reanalysis	7
NRL (Posey et al)		10
UCL (Barthelemy et al)	Global ice-ocean model forced with past atmosphere reanalysis	10
NCAR CCSM4 (BW et al)	Seasonal forecasting systems/fully coupled models	9
NASA GMAO (Cullather et al)		10
NOAA CFSv2 (Wang et al)		16
CNRM (Chevallier et al)		15
Ec-EARTH (Fuekar et al)		20

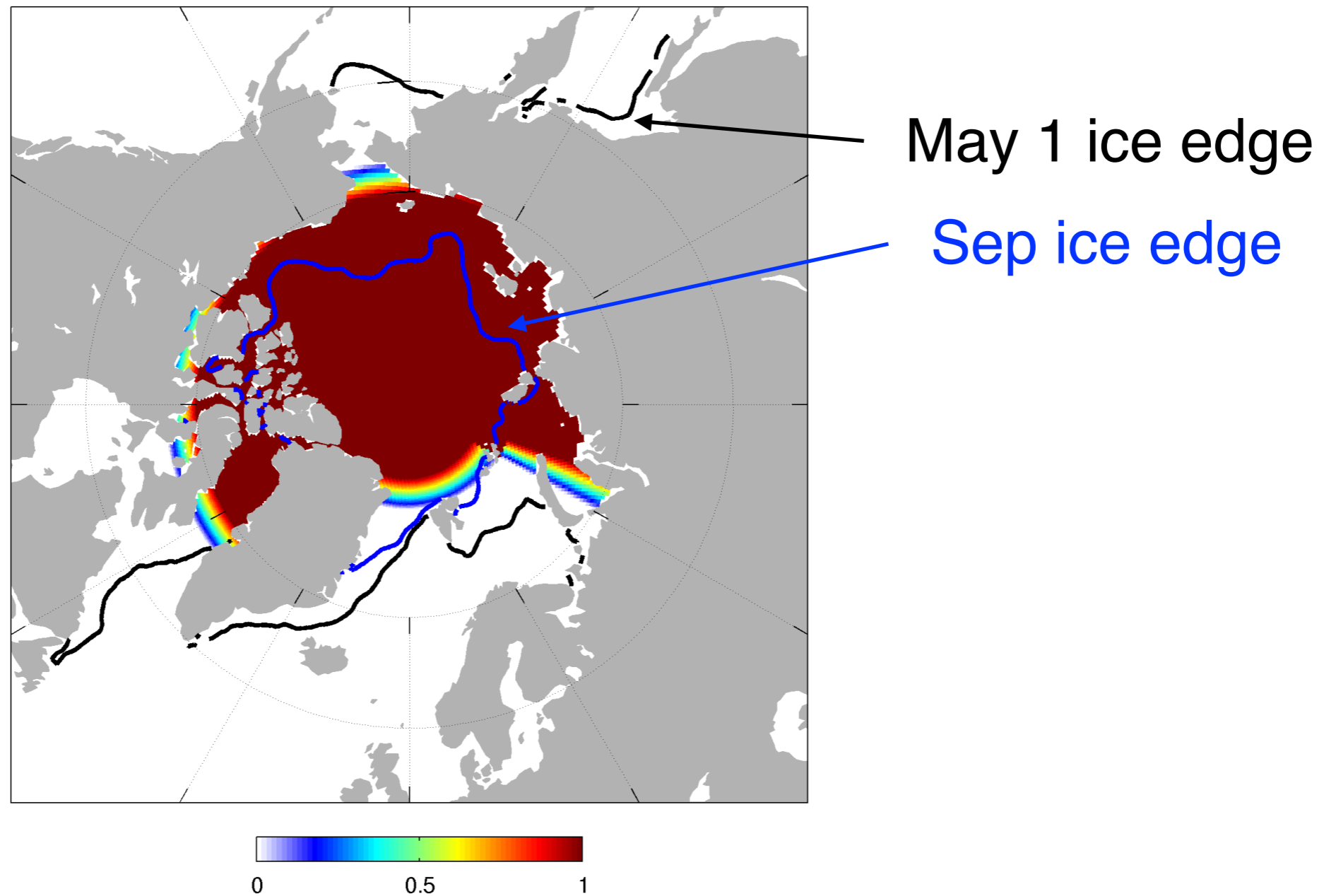
Control: mean May 1 2007-2014 sea ice thickness in Arctic basin

Experiment: May 1 2015 sea ice thickness in Arctic basin



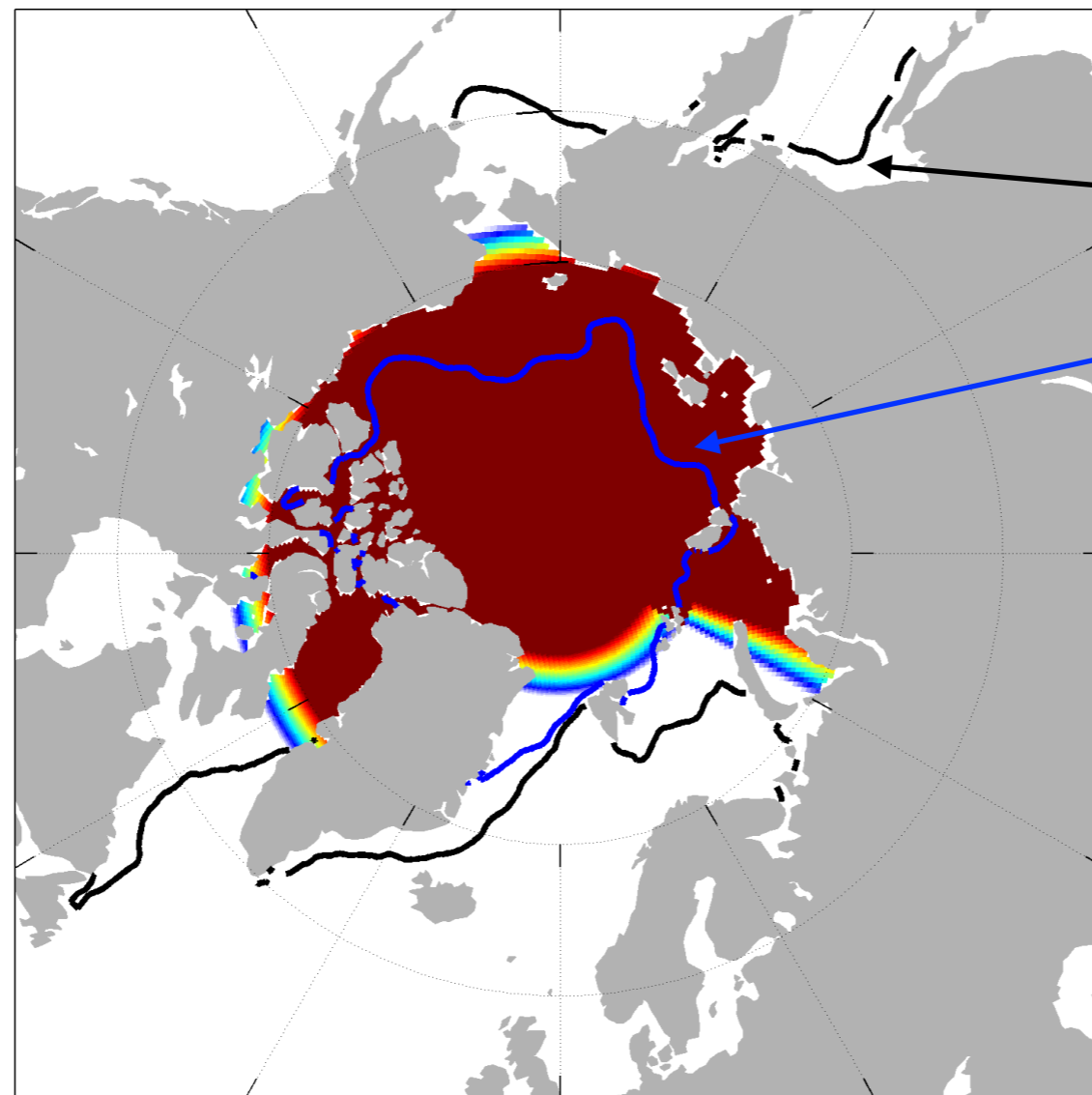
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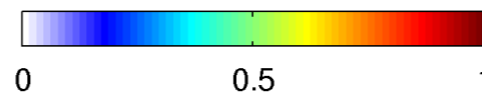
Experiment: May 1 2015 sea ice thickness in Arctic basin



May 1 ice edge

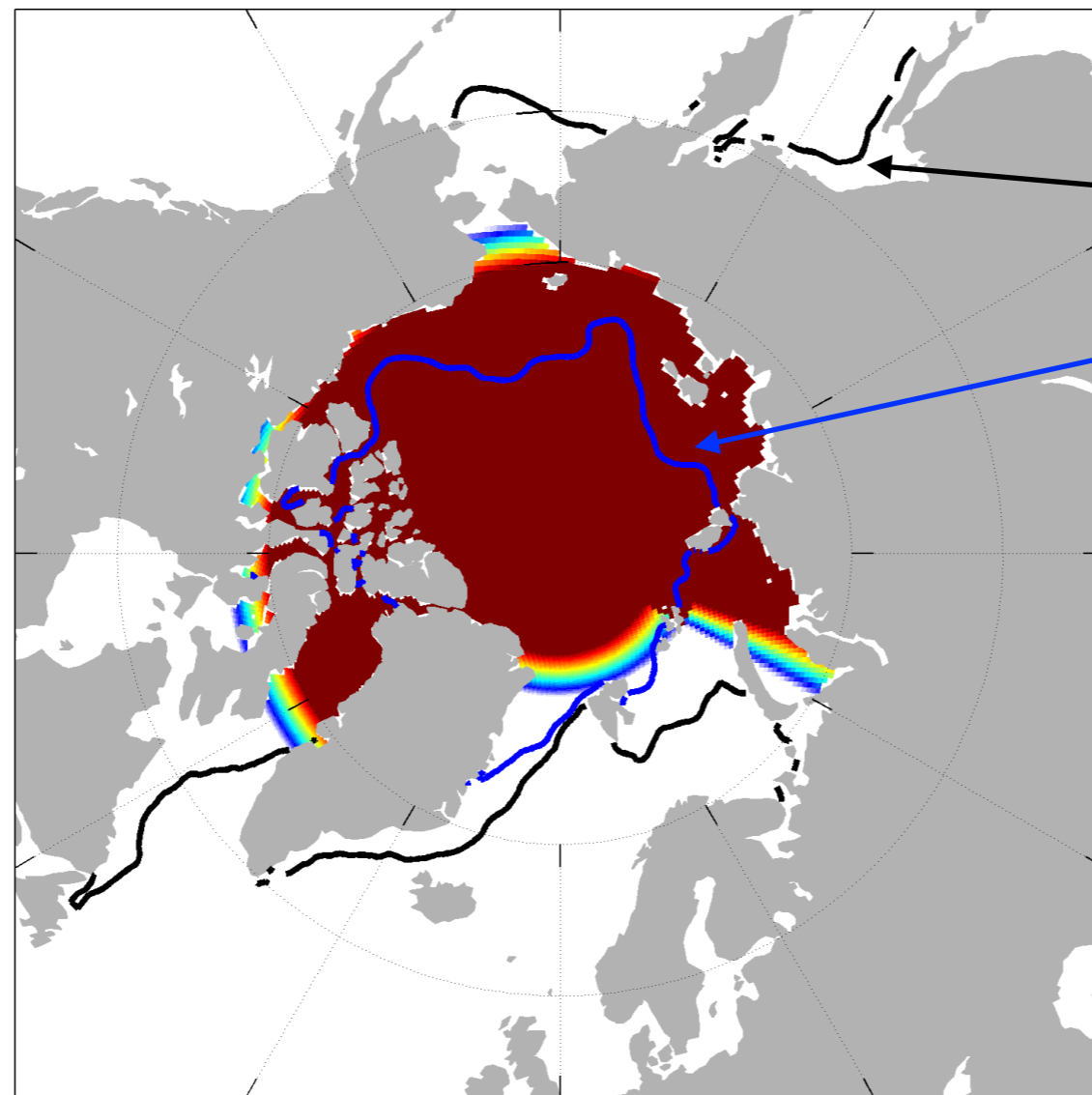
Sep ice edge

No change in sea ice area between experiment & control ICs



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Experiment: May 1 2015 sea ice thickness in Arctic basin

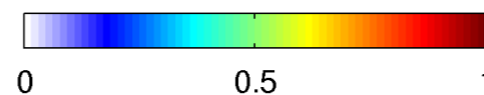


May 1 ice edge

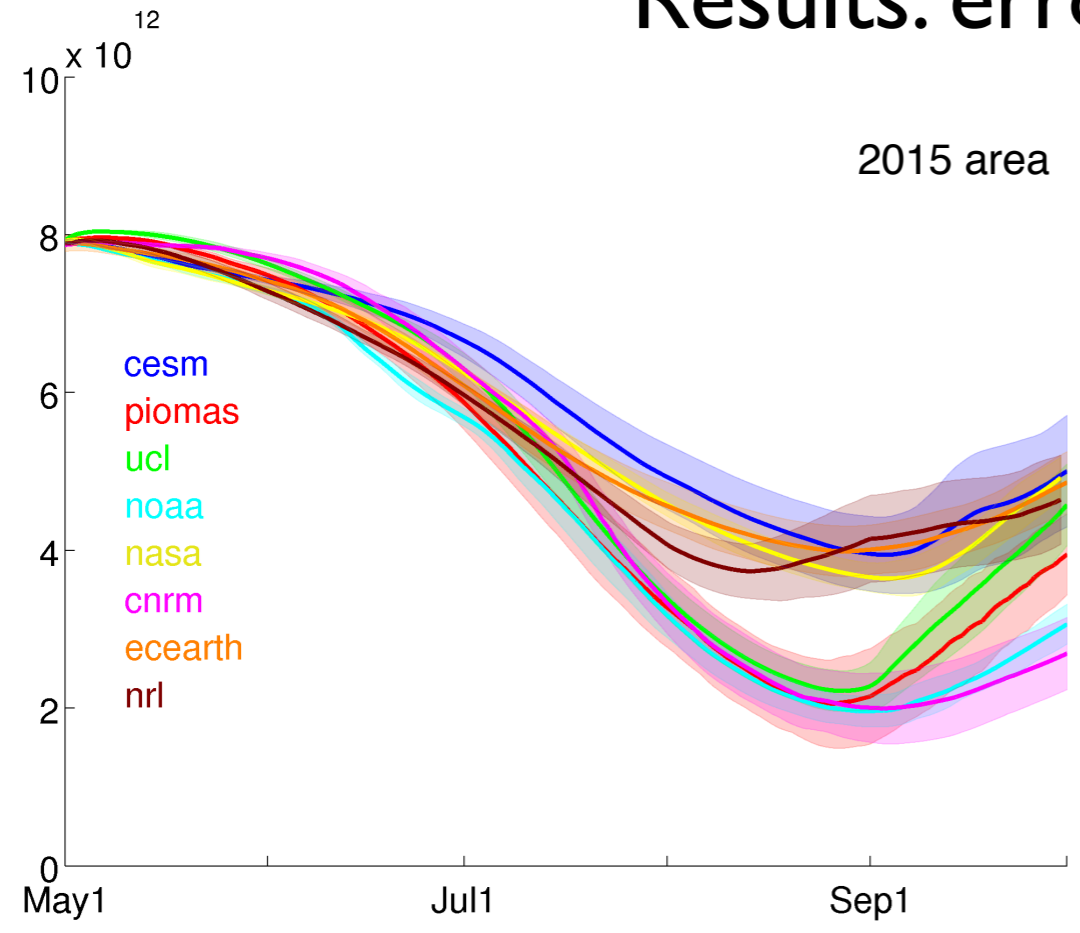
Sep ice edge

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Spring thickness  
—> summer sea ice area



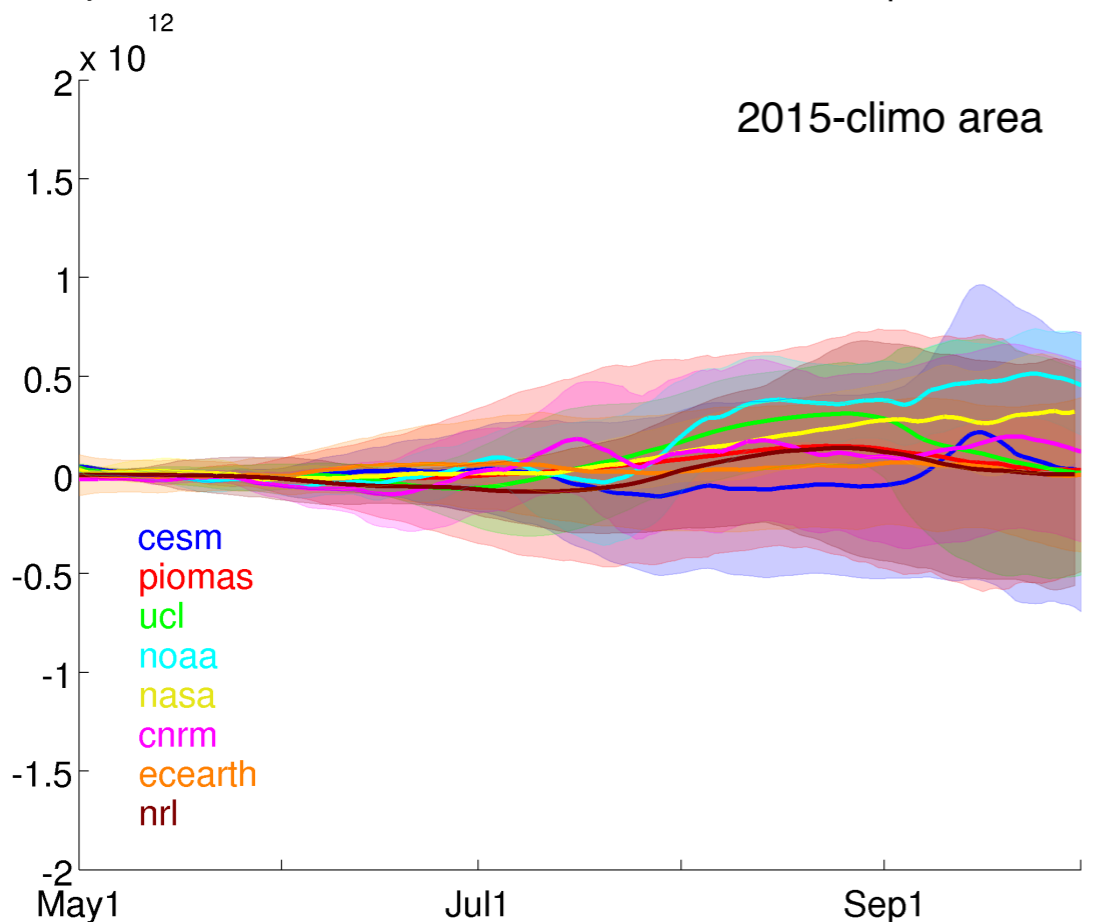
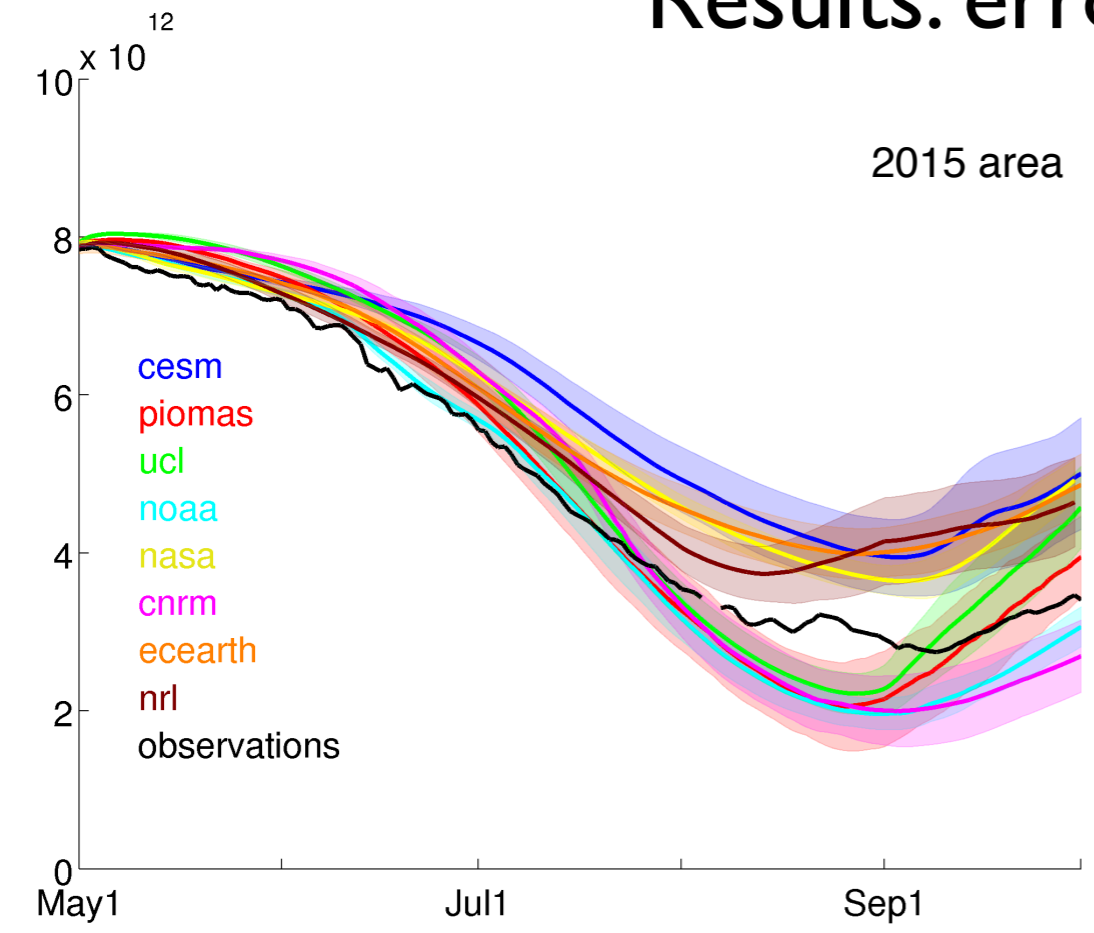
# Results: error growth area



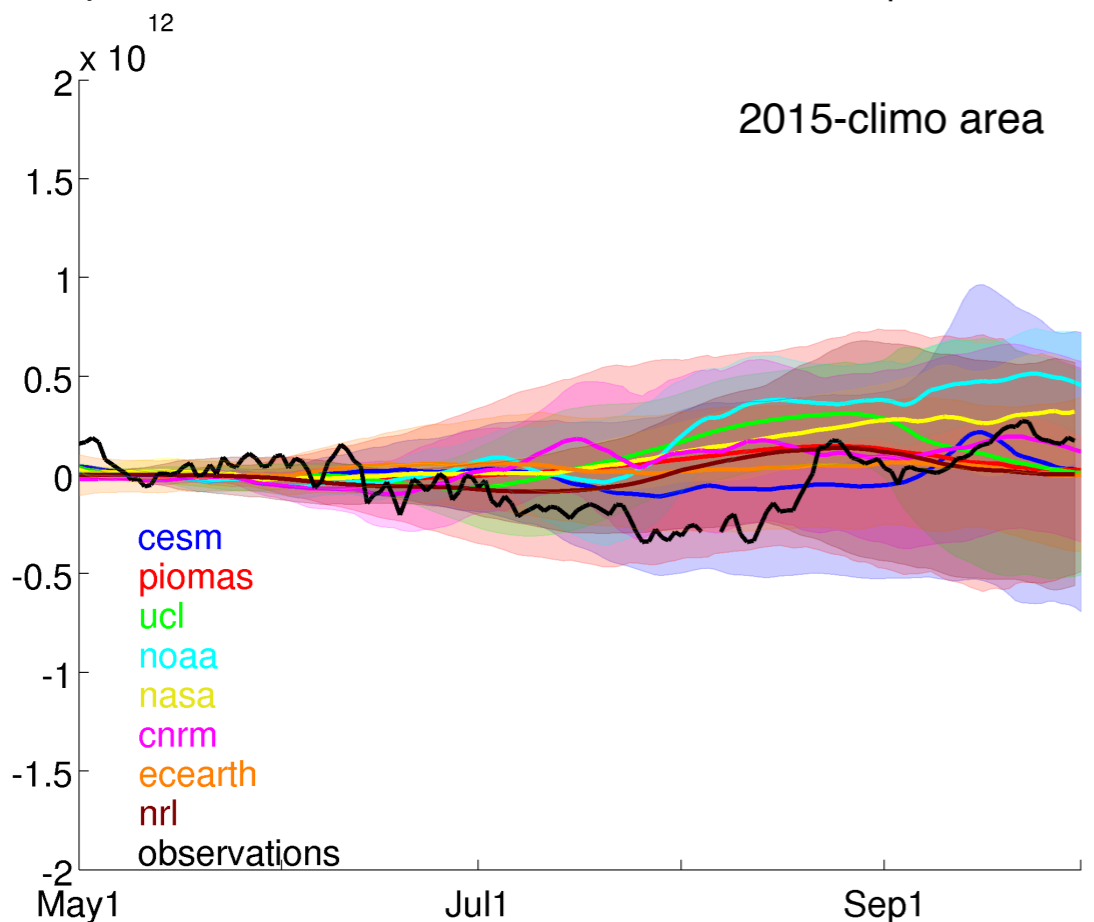
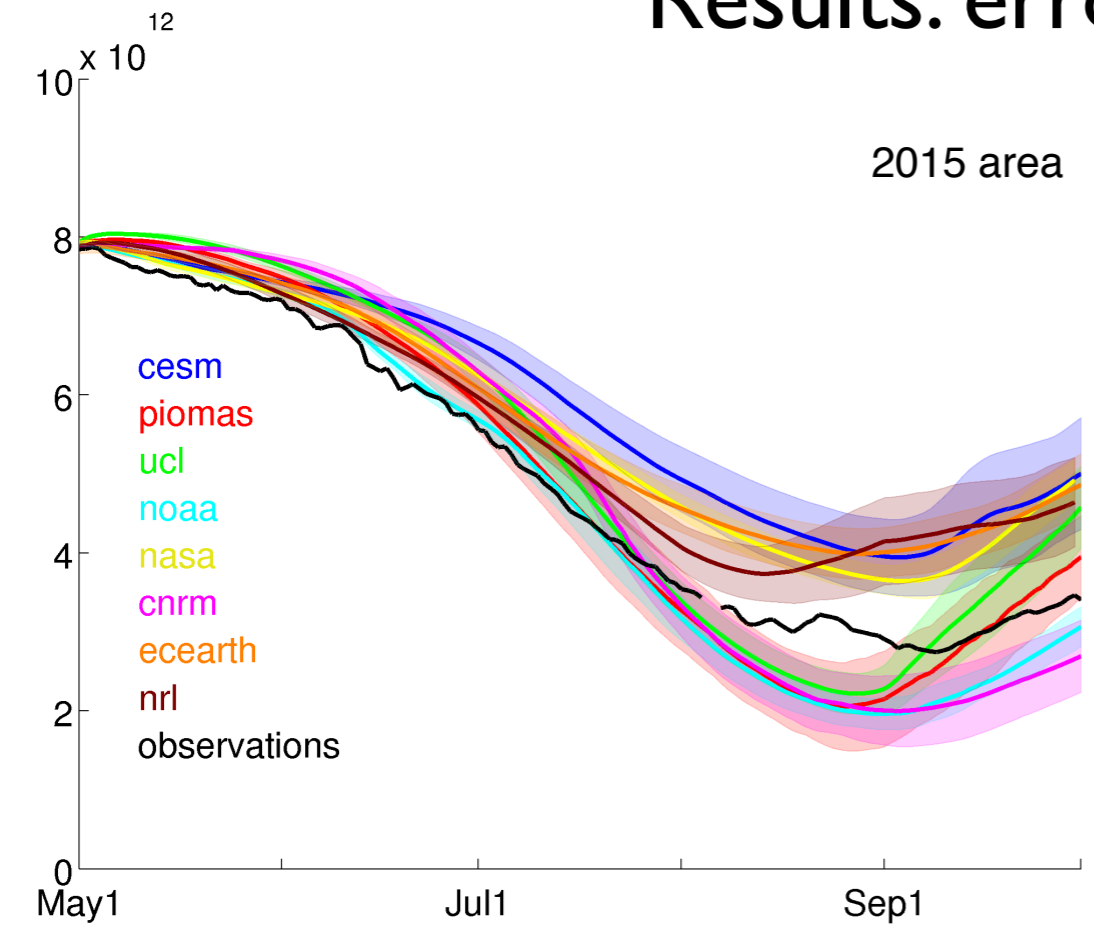




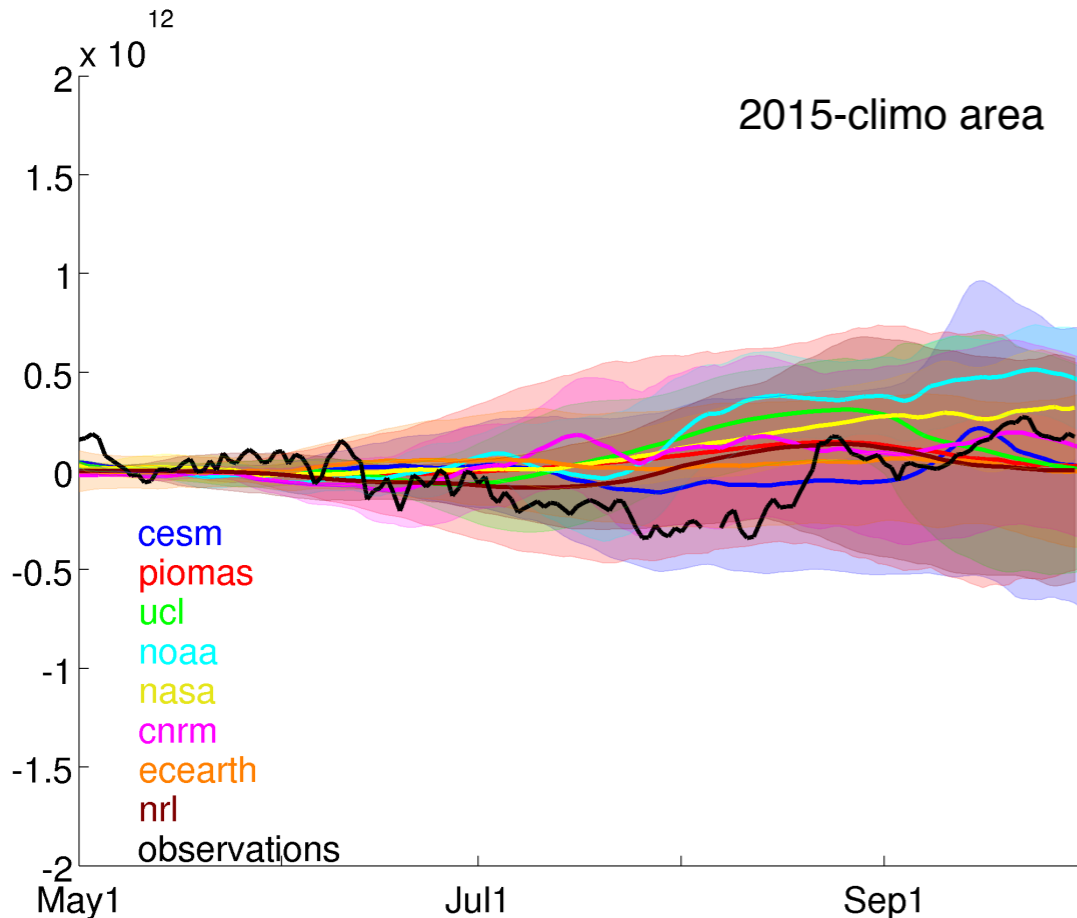
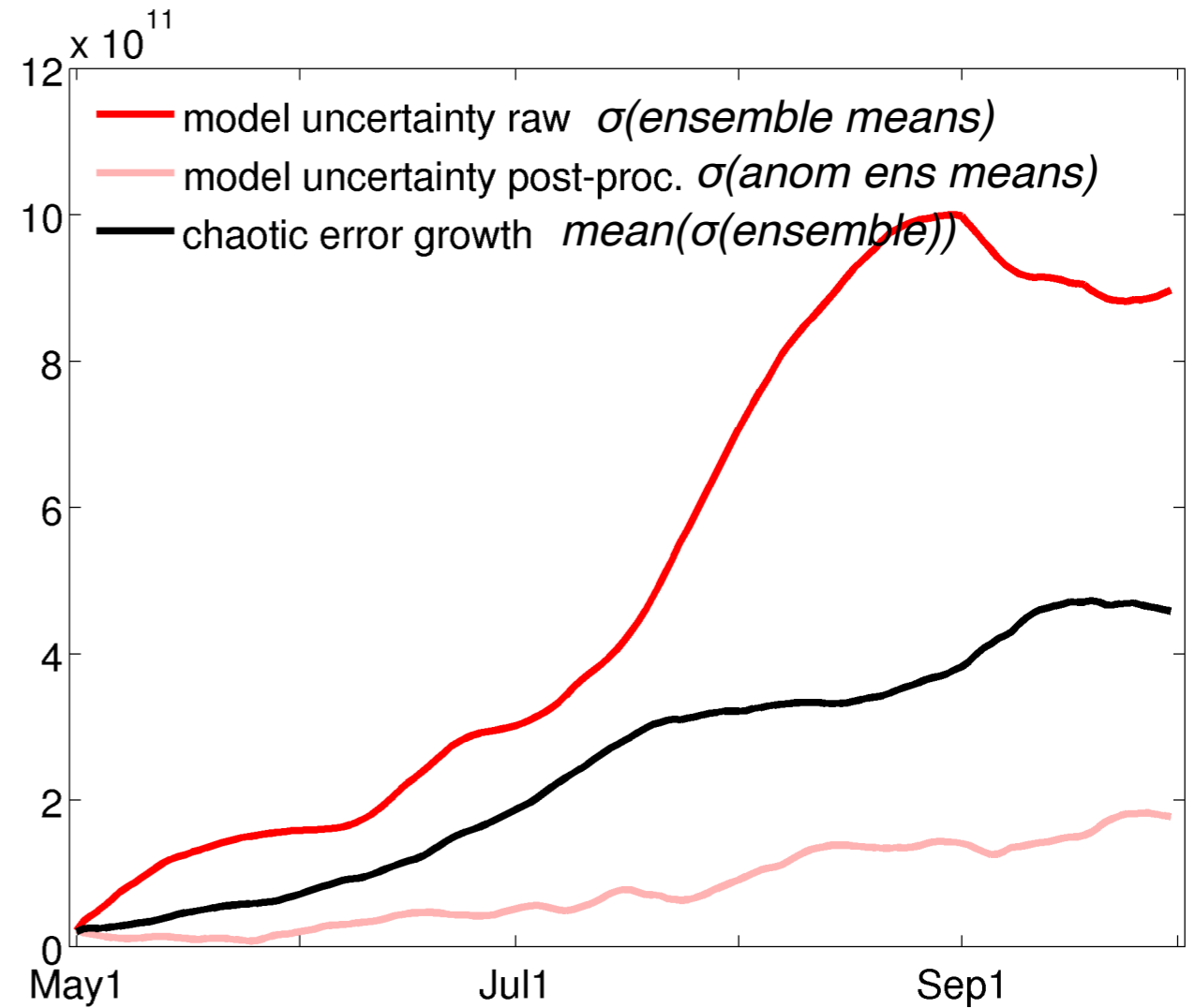
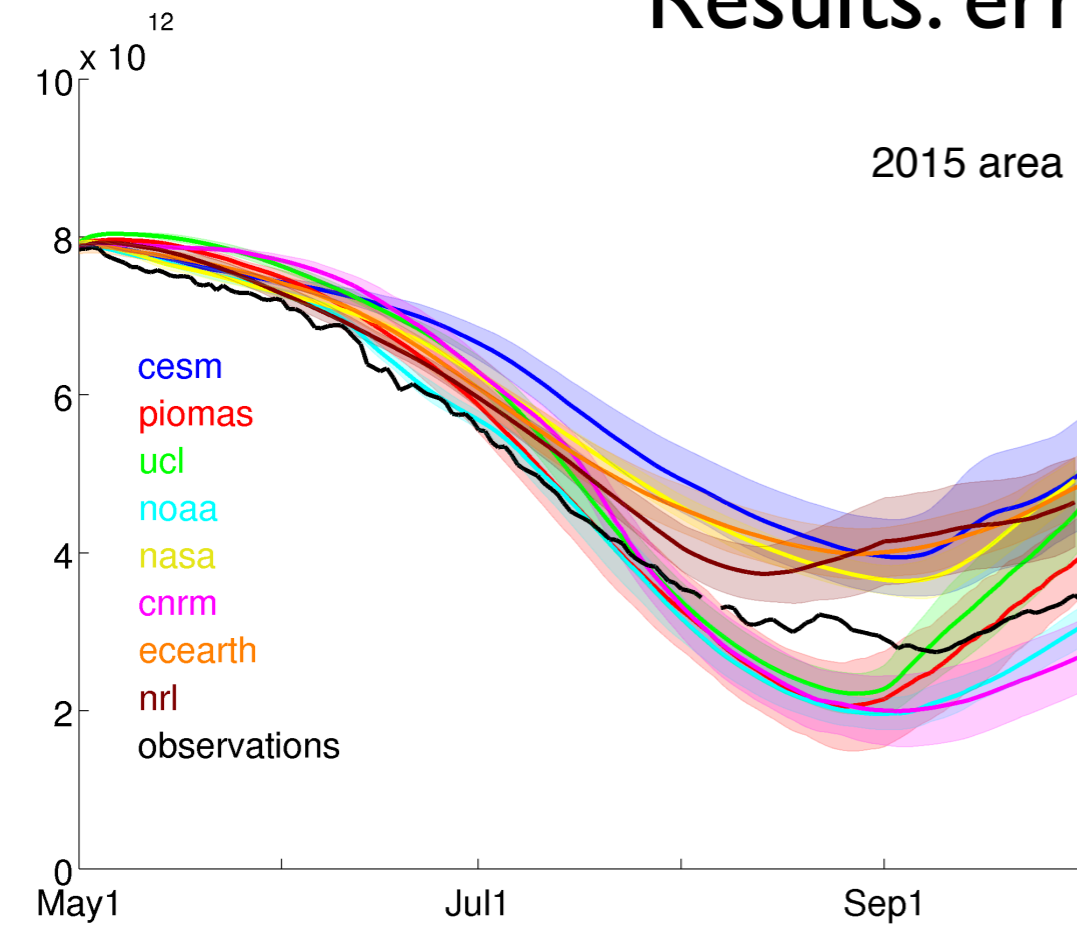
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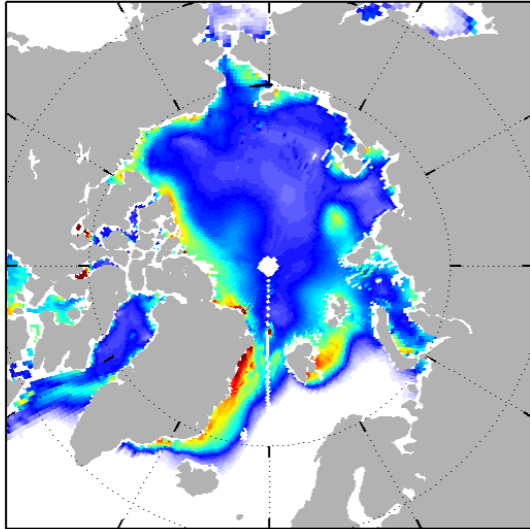


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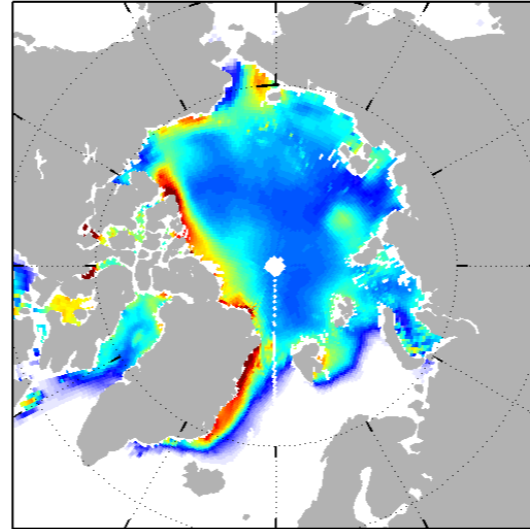


# Results: error growth regional thickness

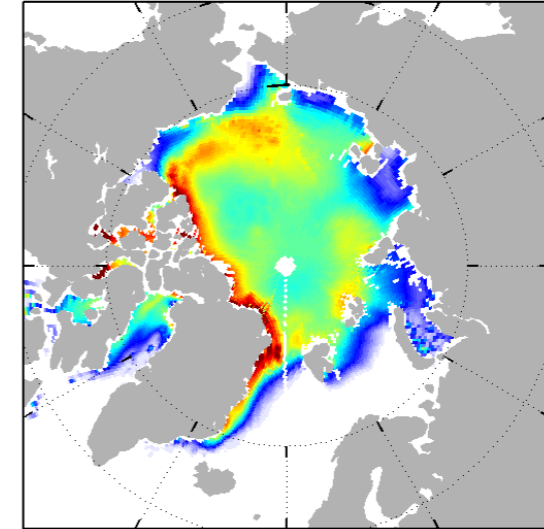
Model uncertainty  $\sigma(\textit{ensemble means})$



Forecast Day 30 (June 1)

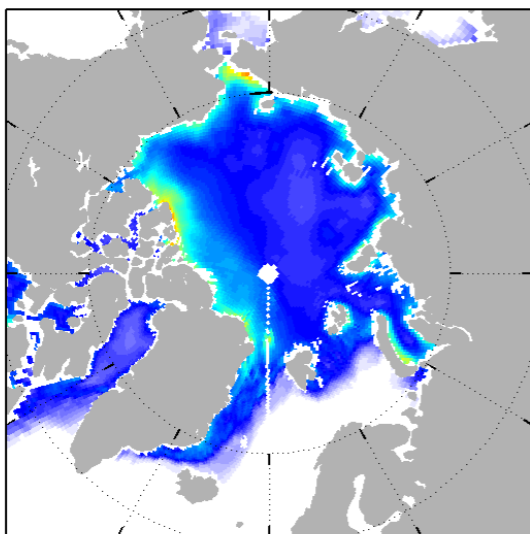


Day 60 (July 1)

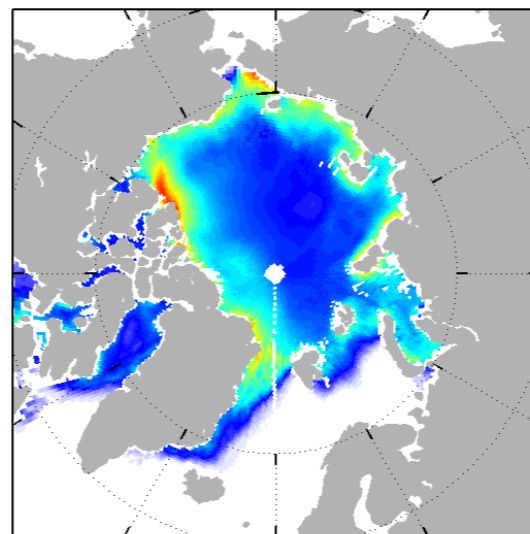


Day 90 (Aug 1)

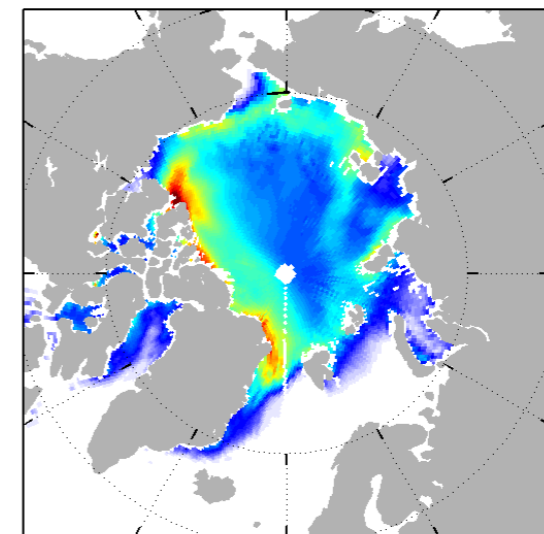
Chaos uncertainty  $\textit{mean}(\sigma(\textit{ensemble}))$



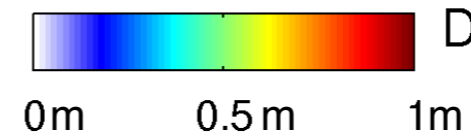
Forecast Day 30



Day 60

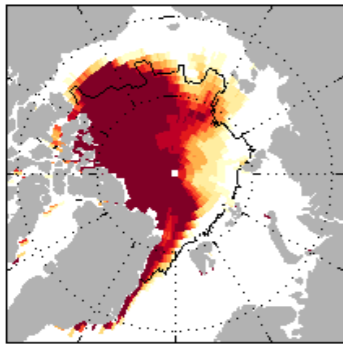


Day 90

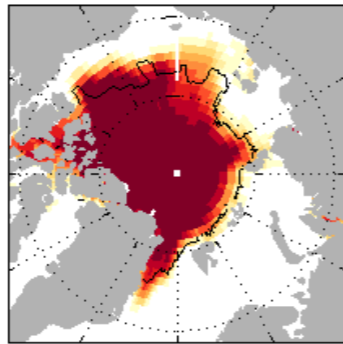


# Beyond extent

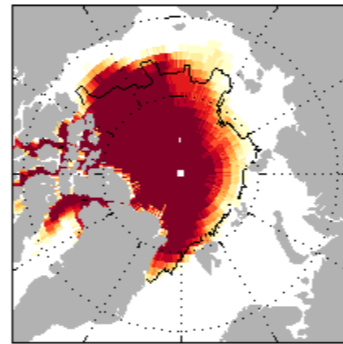
NASA (May/Jun)



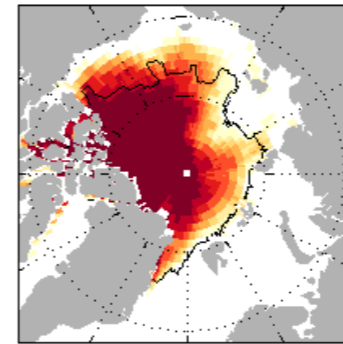
NRL (May/Jun)



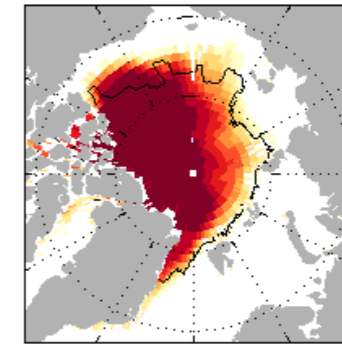
UCL(May/Jun)



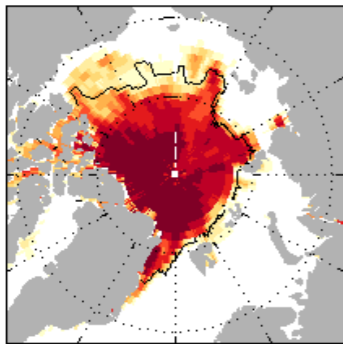
MetOffice(May/Jun)



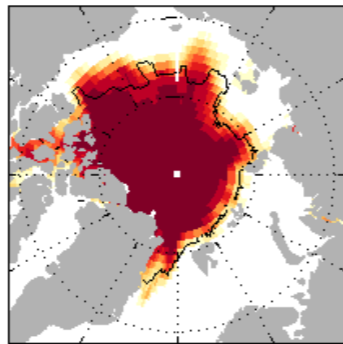
Model mean (May/Jun)



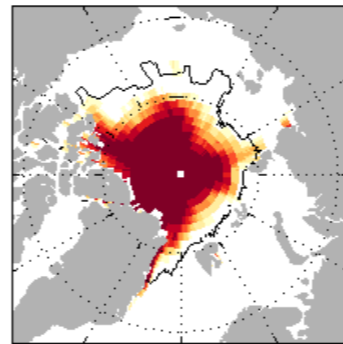
SLATER (Jul/Aug)



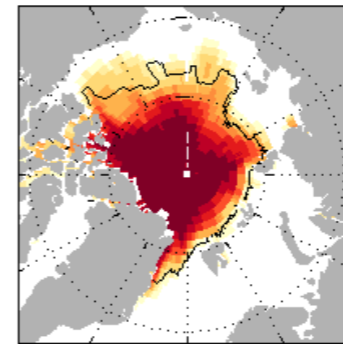
NRL(Jul/Aug)



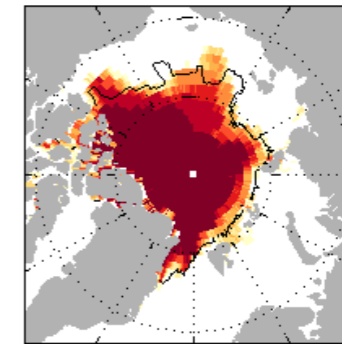
MetOffice(Jul/Aug)



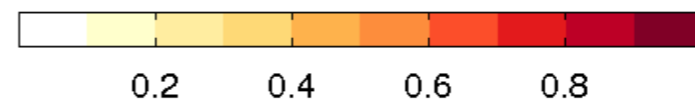
Model Mean(Jul/Aug)



Linear forecast



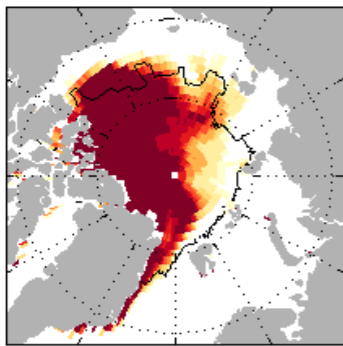
September Sea ice probability  
forecast 2015



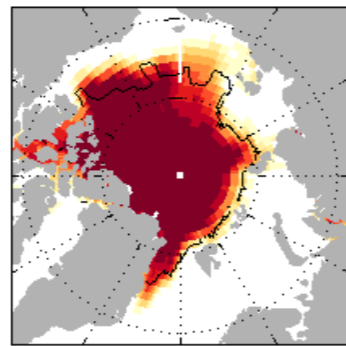
# Beyond extent

Extent is not very practical for most (all?) stakeholders: instead regional metrics such as sea ice probability, ice edge location, ice melt dates, ice freeze-up dates

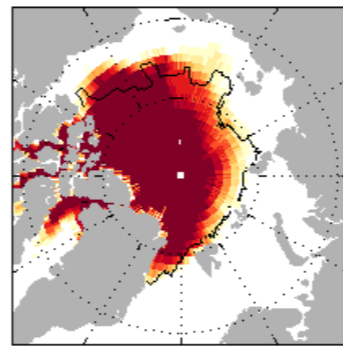
NASA (May/Jun)



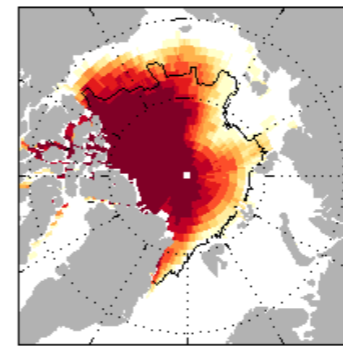
NRL (May/Jun)



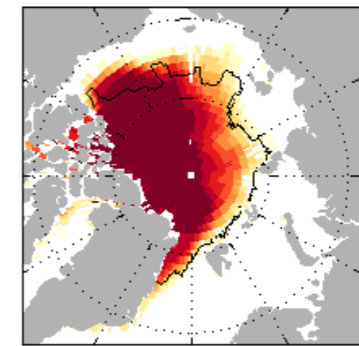
UCL(May/Jun)



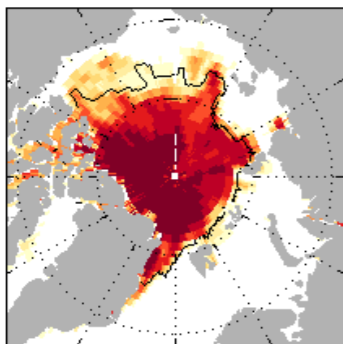
MetOffice(May/Jun)



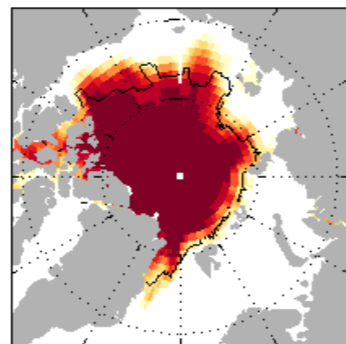
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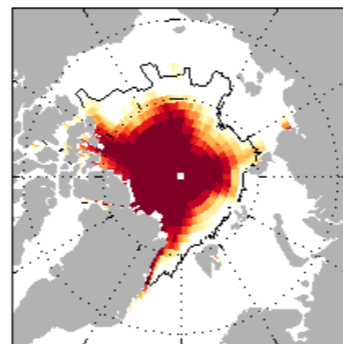
SLATER (Jul/Aug)



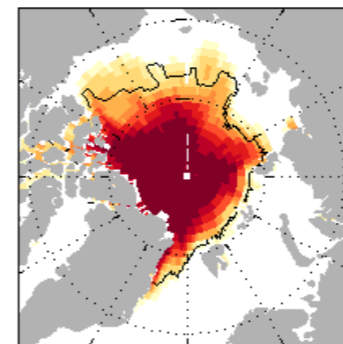
NRL(Jul/Aug)



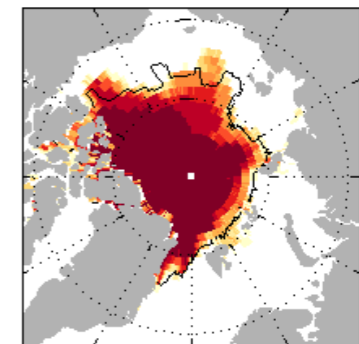
MetOffice(Jul/Aug)



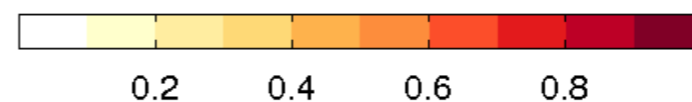
Model Mean(Jul/Aug)



Linear forecast



September Sea ice probability  
forecast 2015



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... and forecasting beyond September: formalize year-round forecasts.

# Decadal predictability

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# Decadal predictability

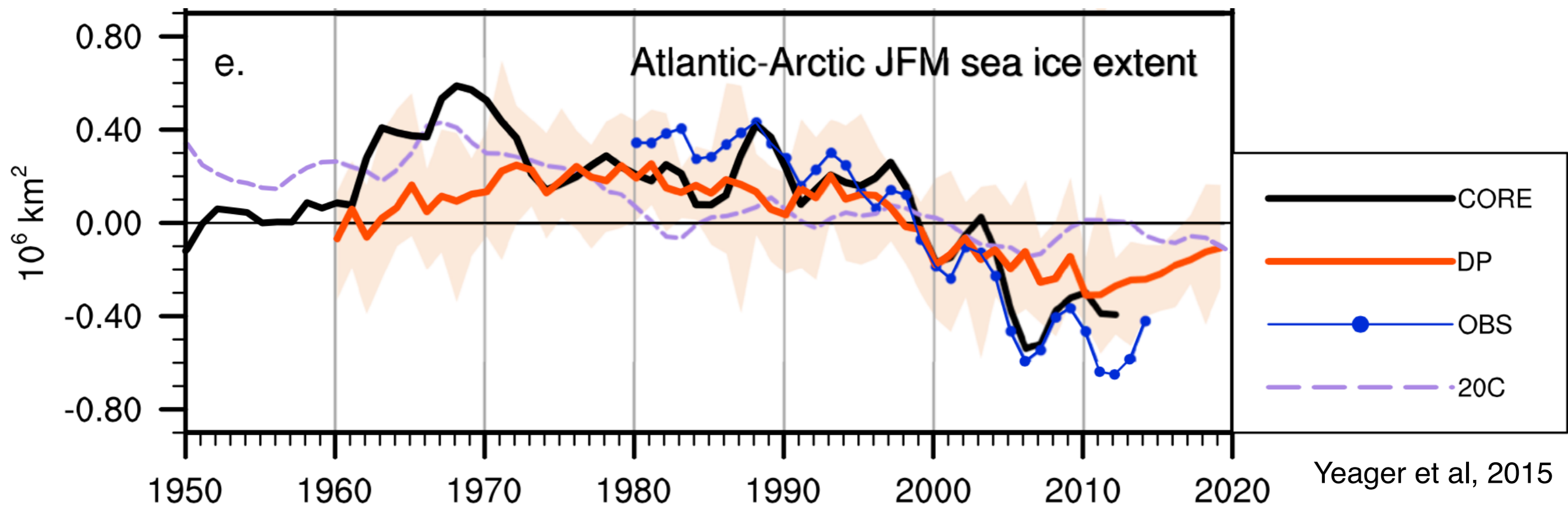
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Recent studies have shown initial value decadal predictability, notably Yeager et al 2015 (for winter North Atlantic sea ice in observations) and Germe et al 2014 (mainly winter, also North Atlantic in perfect-model framework). Also in Antarctica (Zunz et al, 2015)

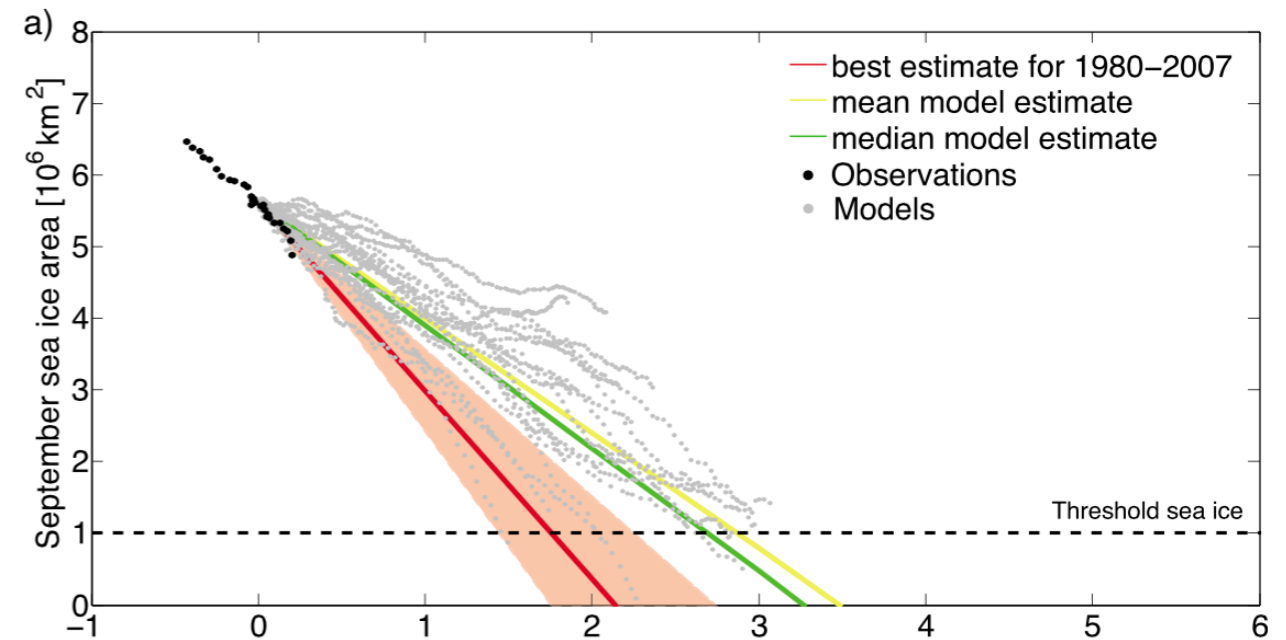
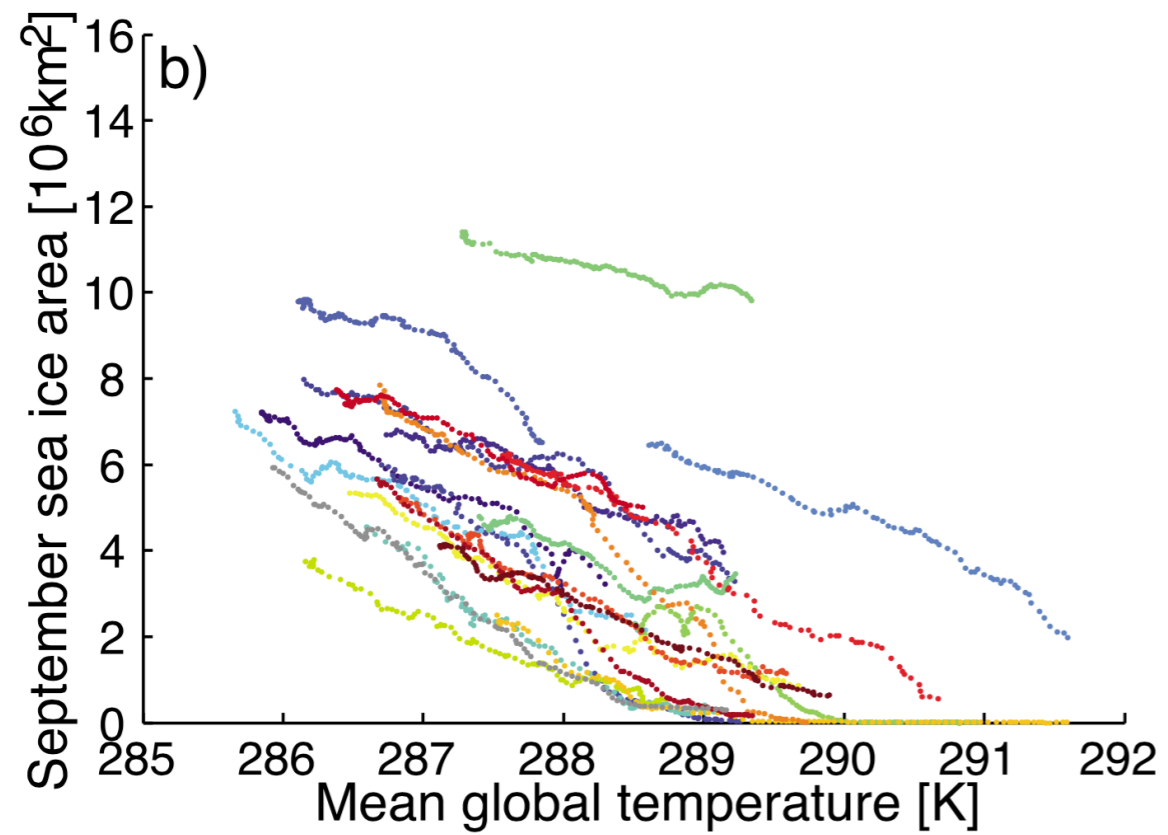
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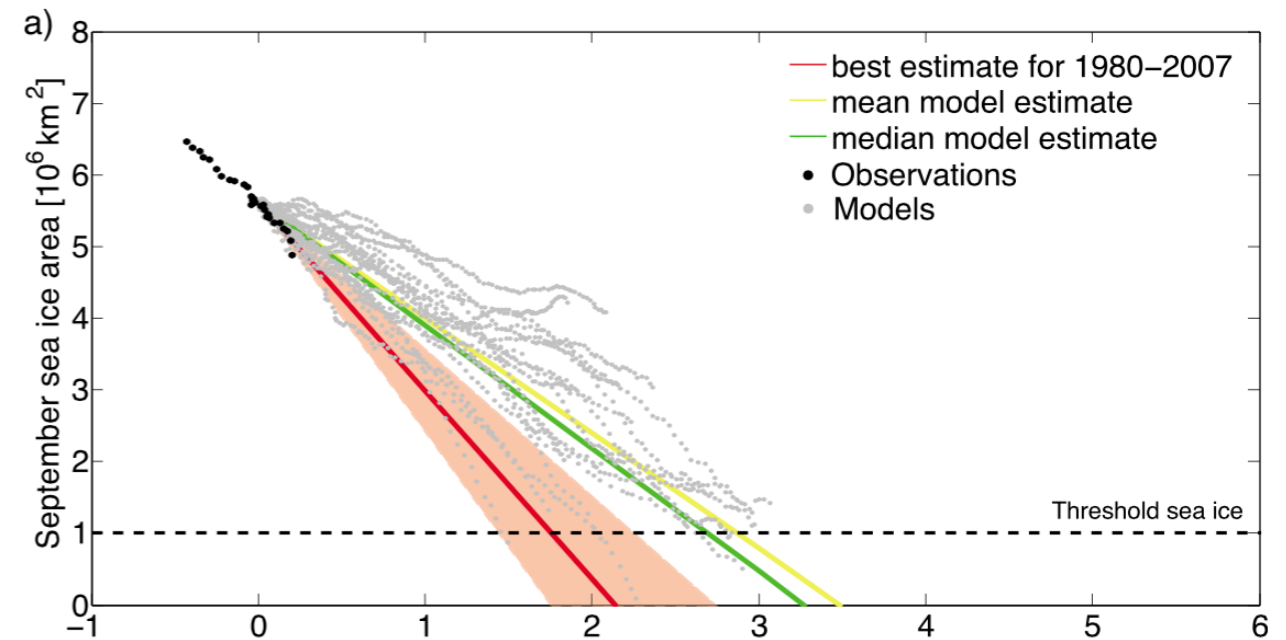
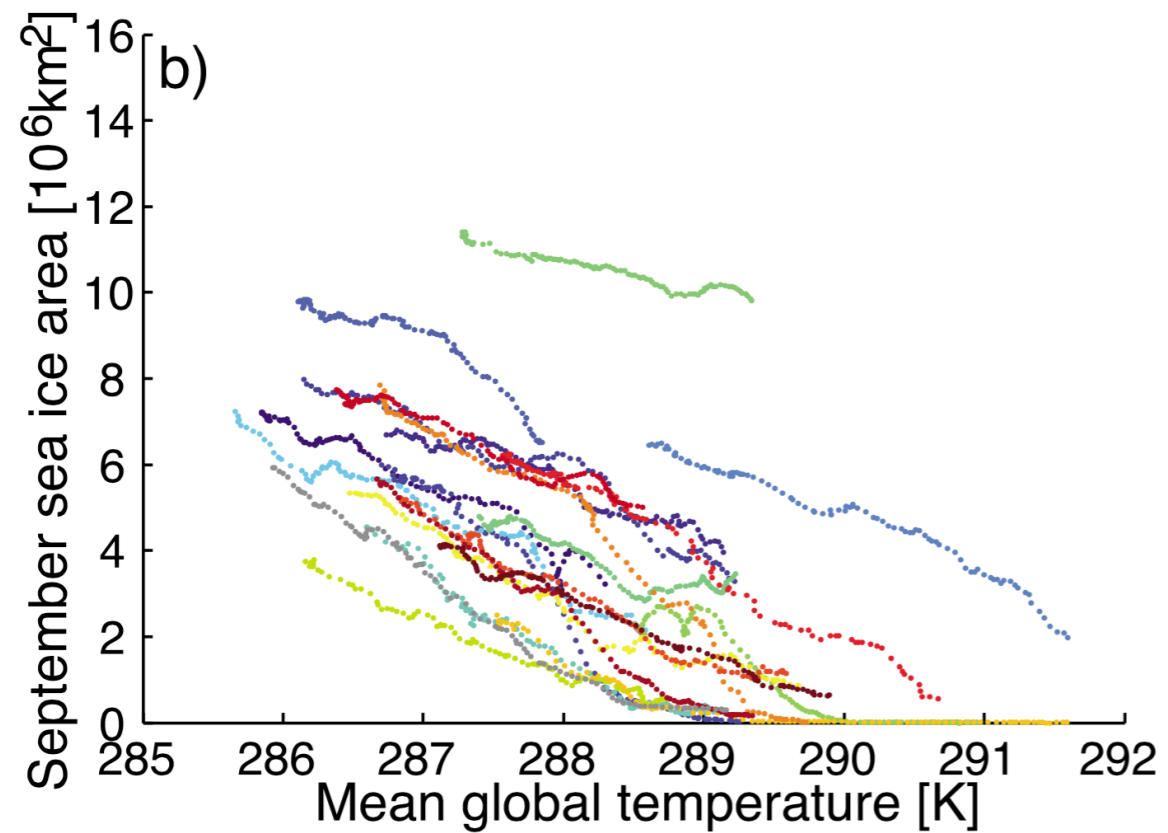
# Decadal predictability



Mahlstein and Knutti, 2012

# Decadal predictability

What about sea-ice free summers?

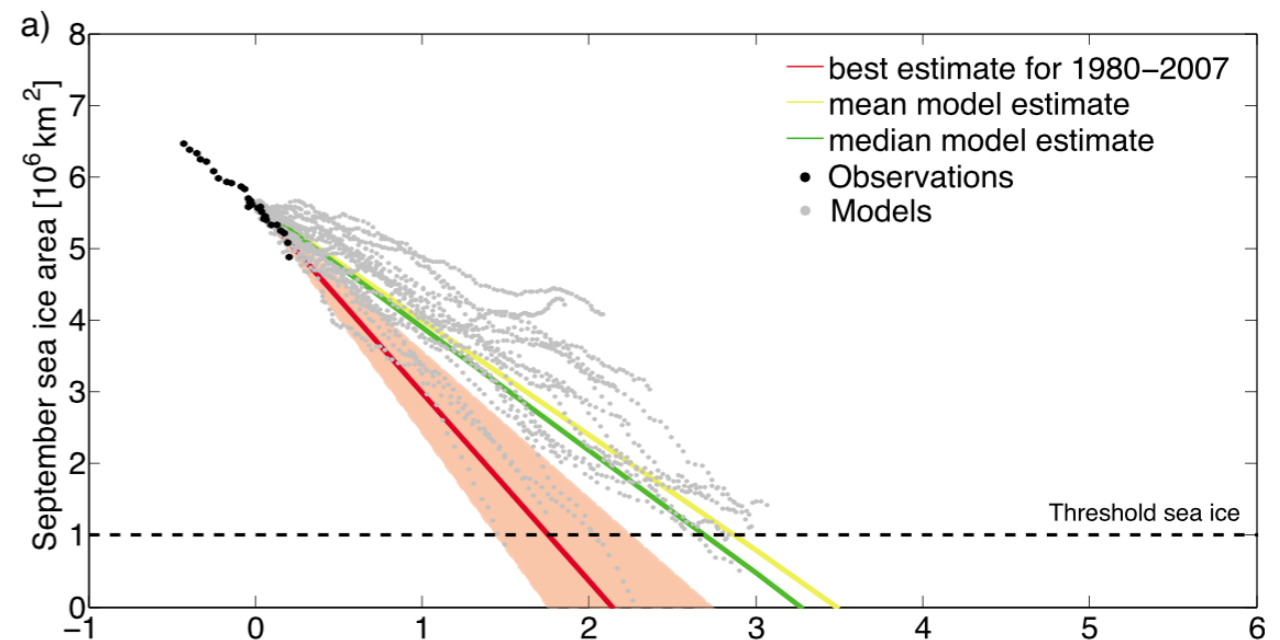
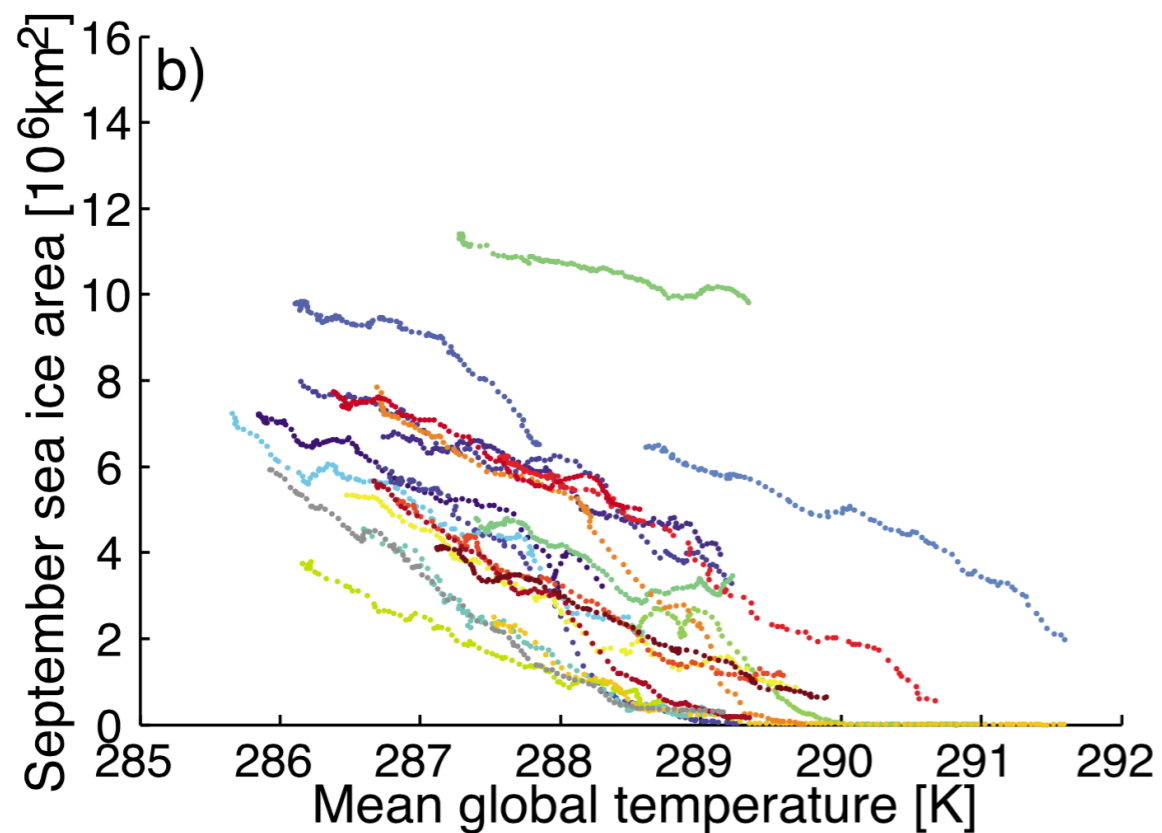


Mahlstein and Knutti, 2012



# Decadal predictability

What about sea-ice free summers?



Mahlstein and Knutti, 2012

How much of observed trend is forced v natural?  
Could intrinsic sensitivity to warming be significantly higher in observations?

# Final thoughts

Perfect model and hindcasts shows that seasonal forecasts of summer sea ice should be skillful (winter perhaps even more so). Recent SIO period (2008-2015) shows lower skill.

While recent period may have been inherently less predictable, difference in initial conditions and/or model uncertainties likely play a role.

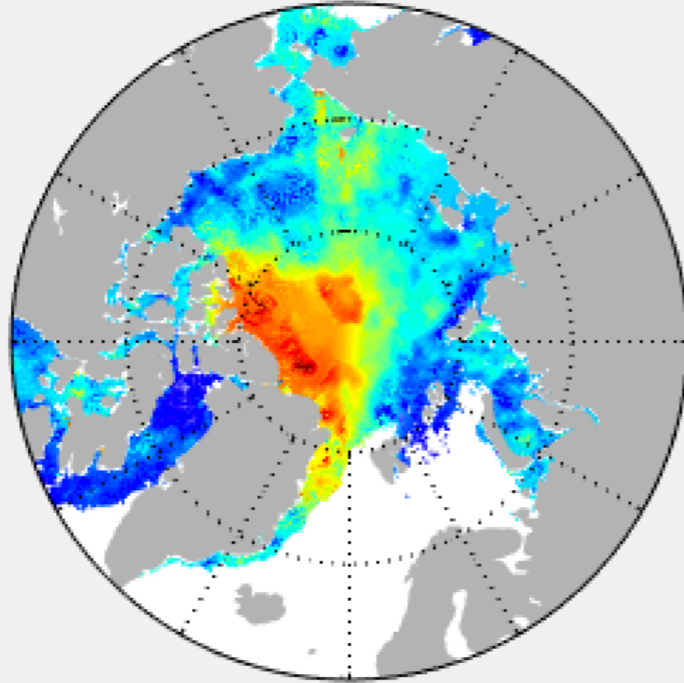
Consistent post-processing (bias correction) of forecasts could offer promise: very large trend demands this! Not seen in other seasonal prediction problems (e.g., ENSO)

Decadal predictability: initial value for winter in North Atlantic

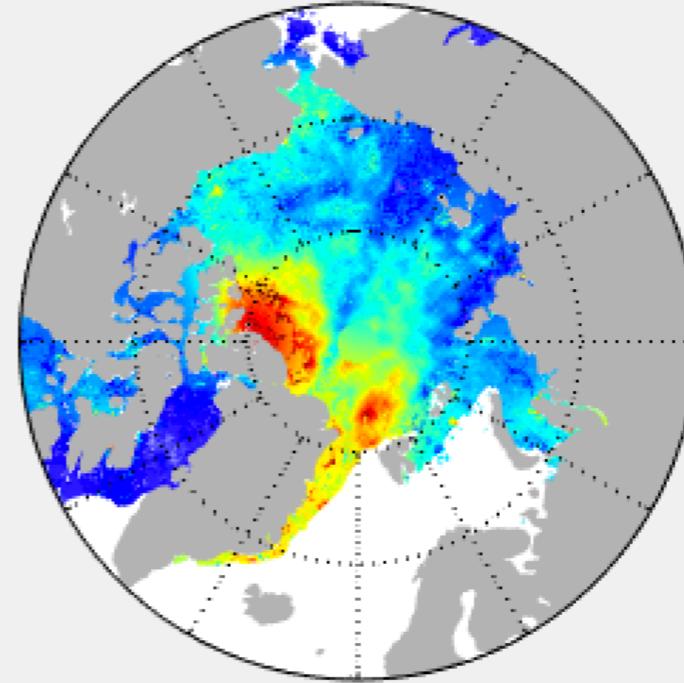
Sea-ice free summer problem: role of natural v forced trend. What is sensitivity?

So..... how about 2015?

Cryosat March 2014

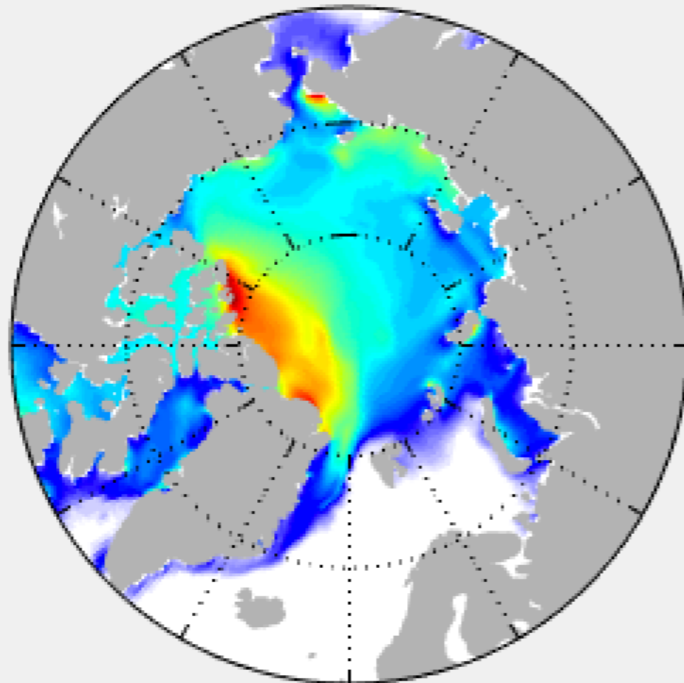


Cryosat March 2015

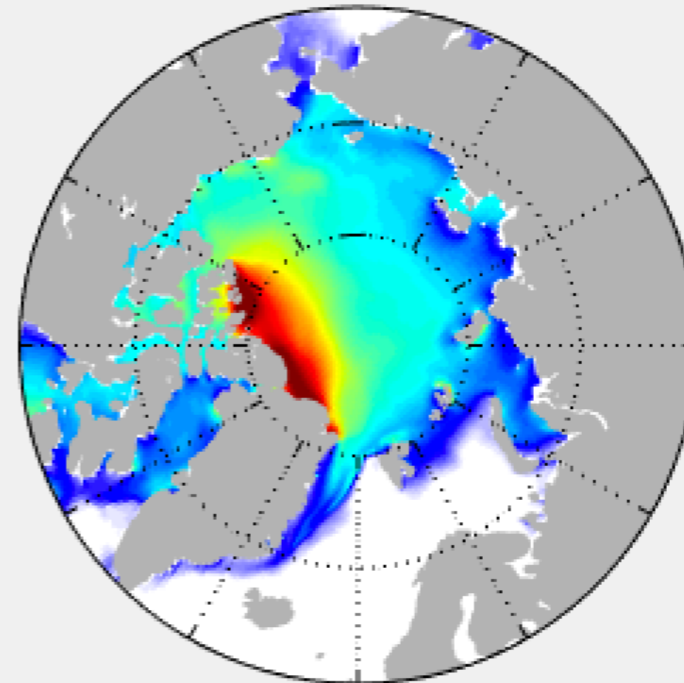


satellite ice  
thickness

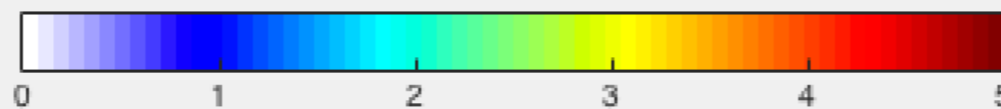
PIOMAS March 2014



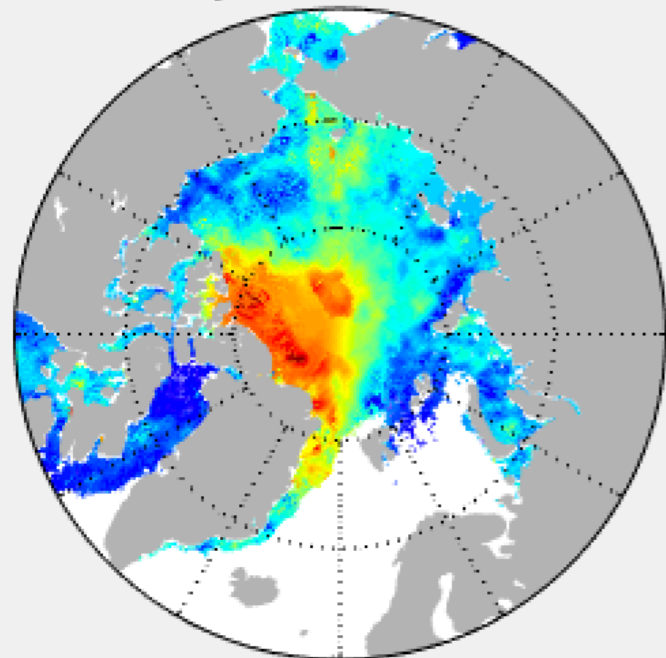
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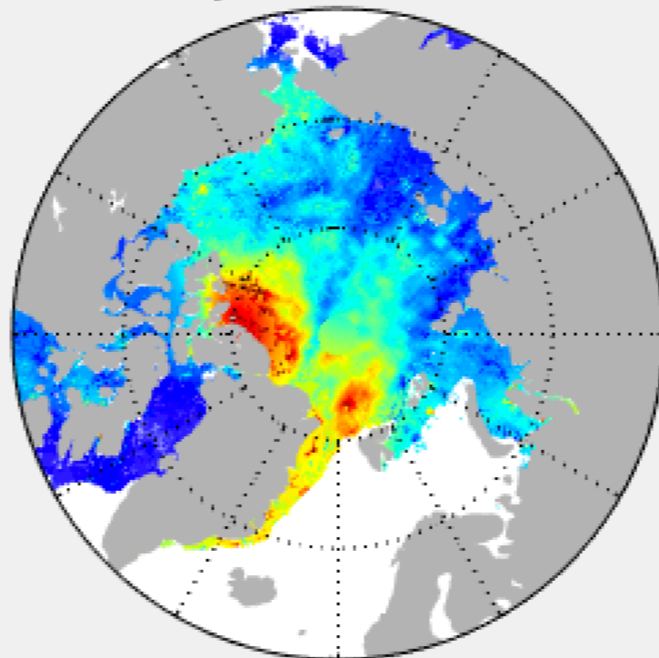
recon ice  
thickness



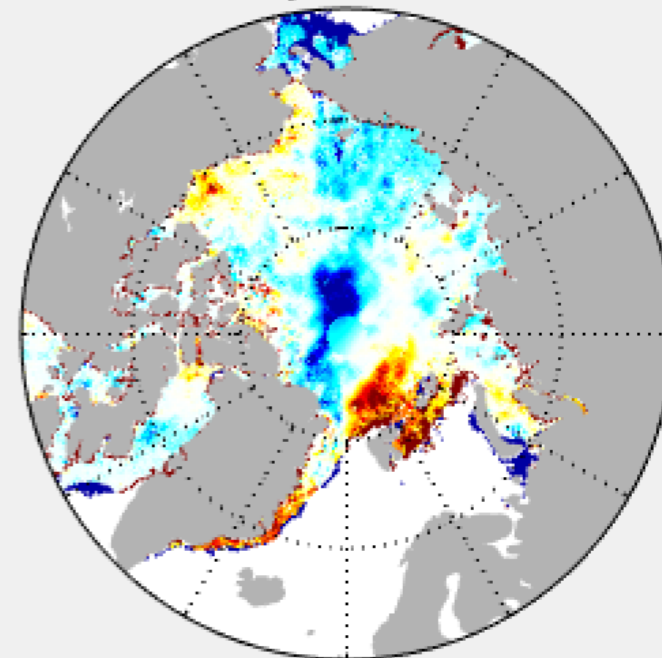
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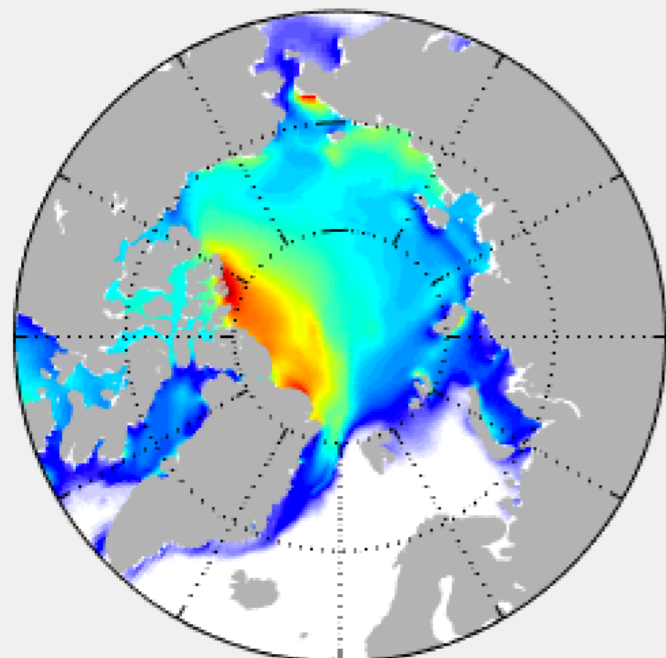
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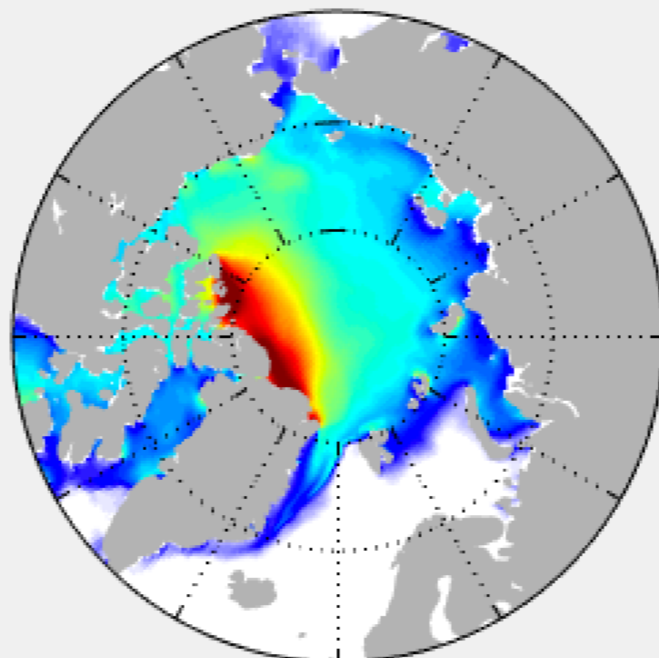
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PIOMAS March 2014



PIOMAS March 2015



PIOMAS Diff

