Introduction to prediction science

(predictability, what is it and how do we measure it)

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What is predictability?

‘consistent repetition of a state, course of action, behavior, or the like, making it possible to know in advance what to expect’

free online dictionary

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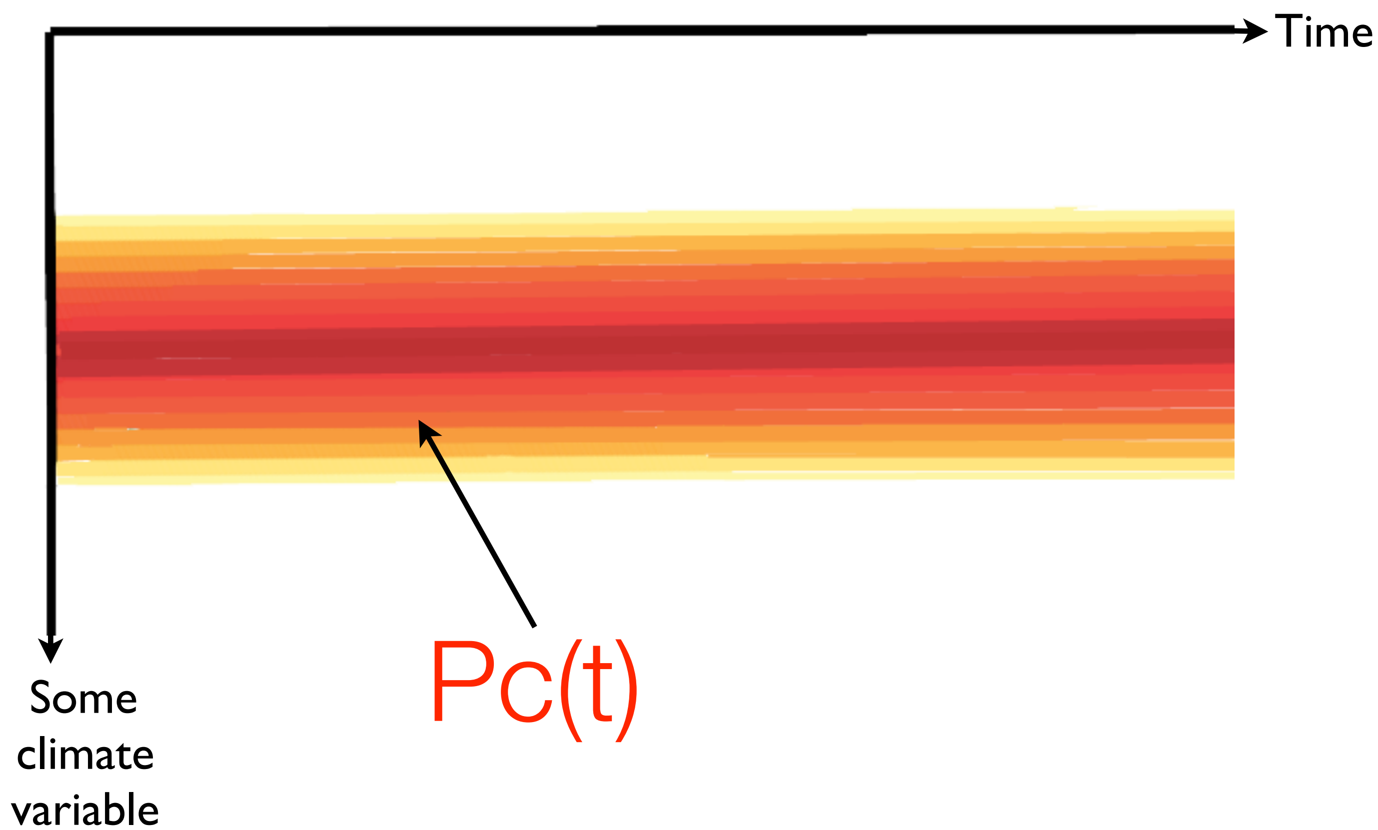
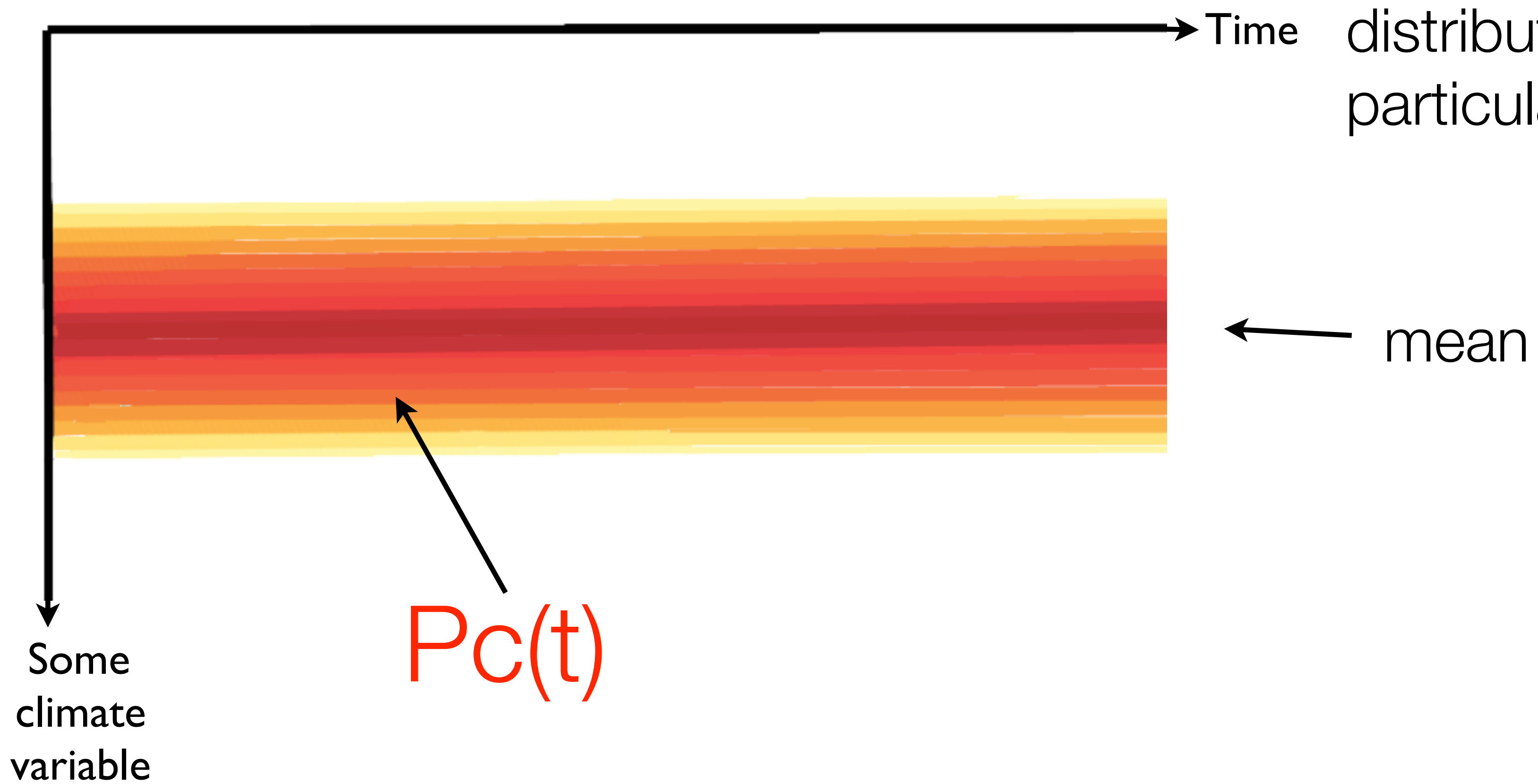
‘a limit to the accuracy with which forecasting is possible’
Lorenz (1969)

On predictability



- Pc(t) represents the control (background) distribution. It is independent of any particular initial state.

On predictability



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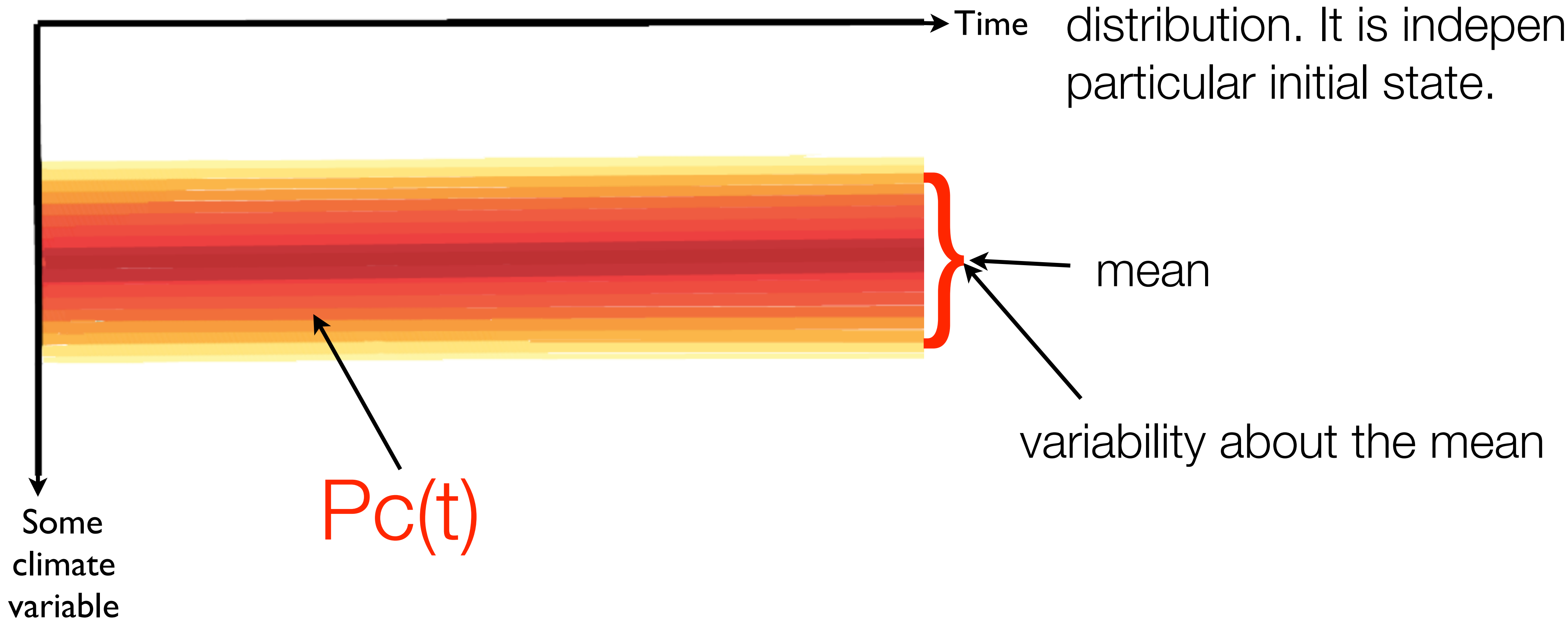

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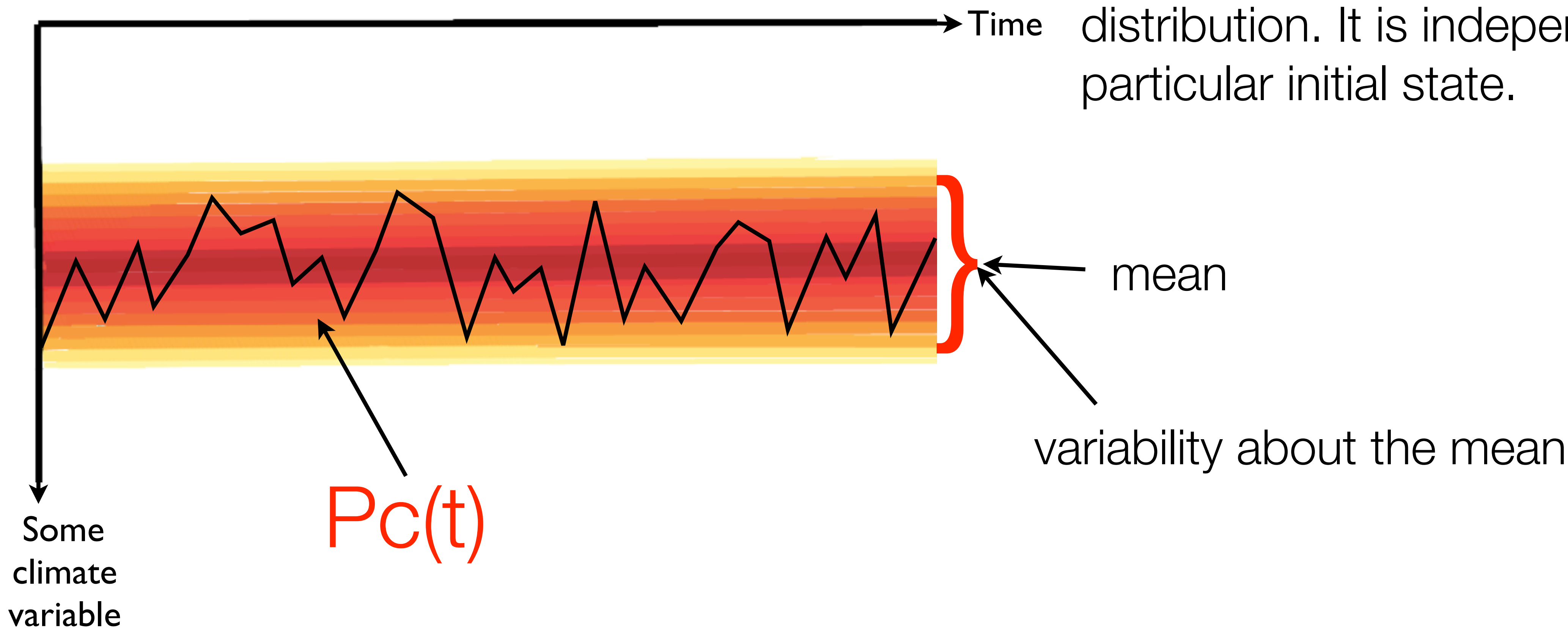

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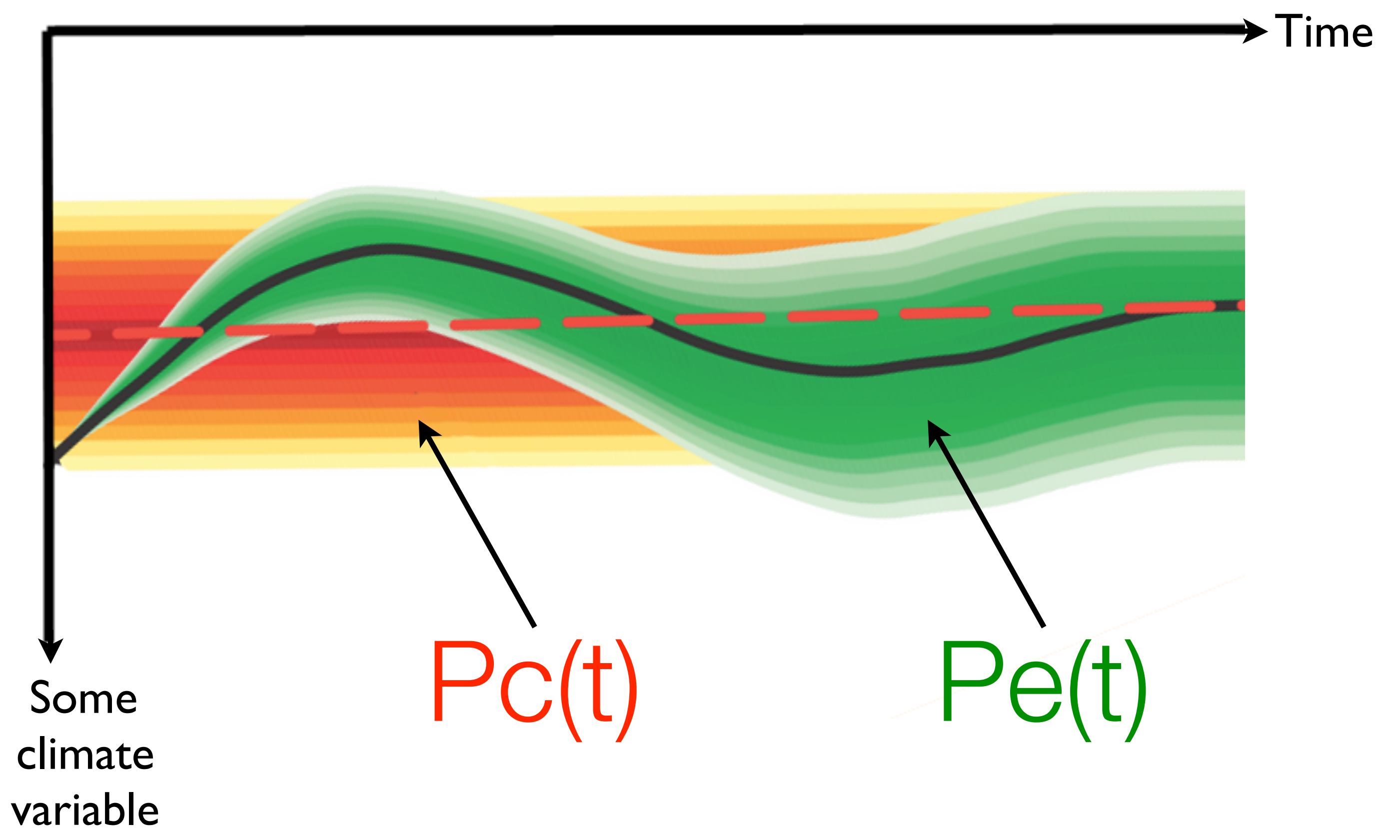

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- Pe(t) is an ensemble of predicted states evolving from a specific tight cluster of initial conditions.

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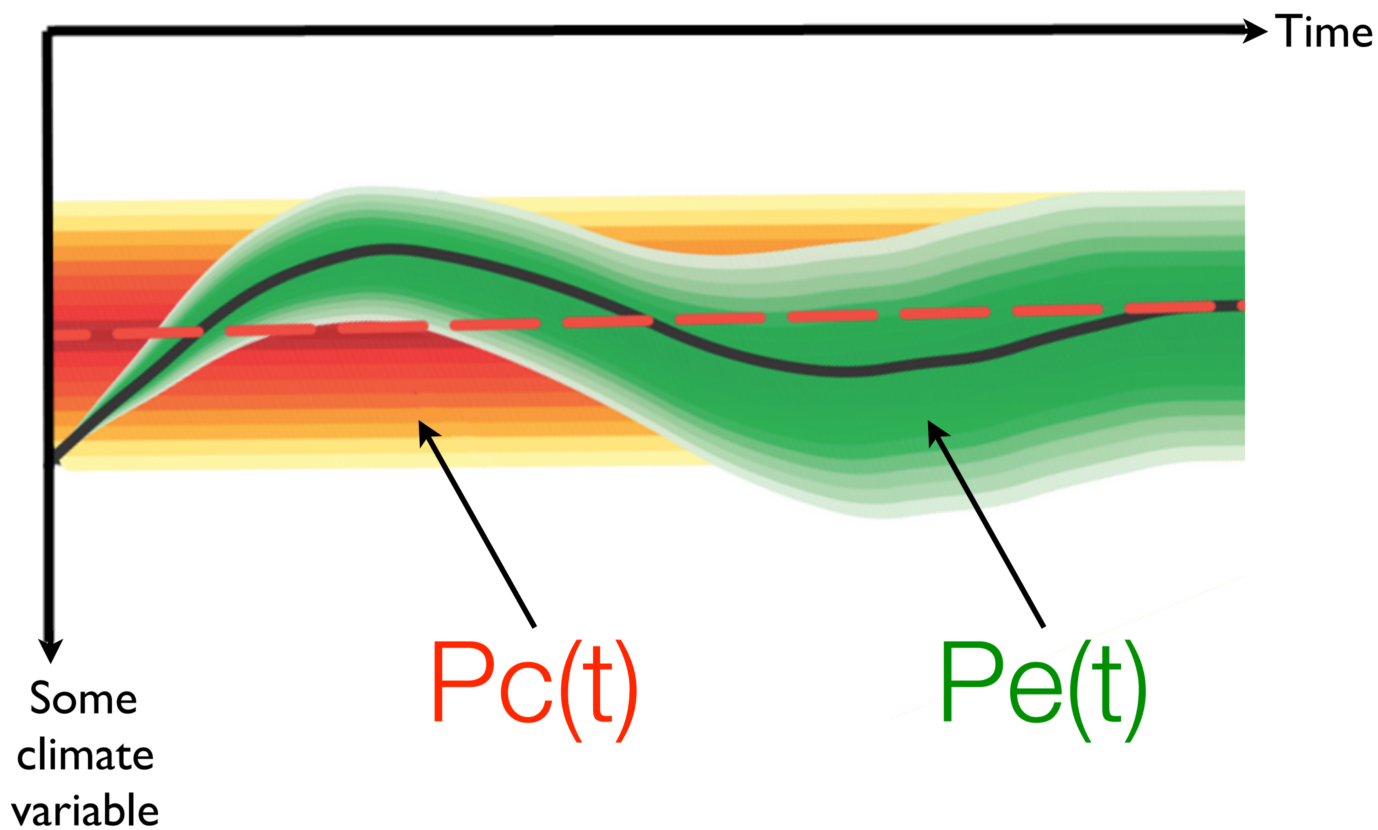
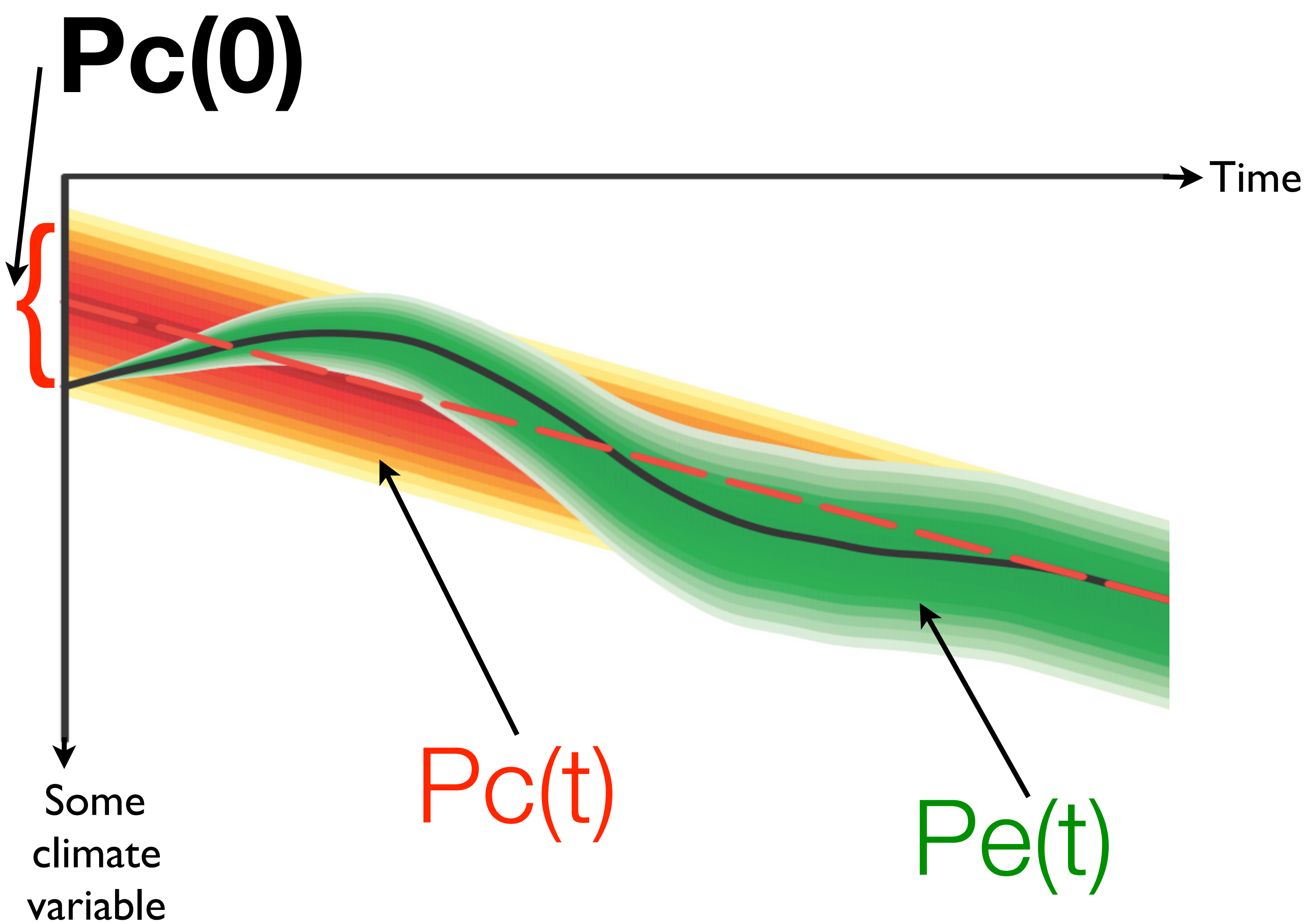


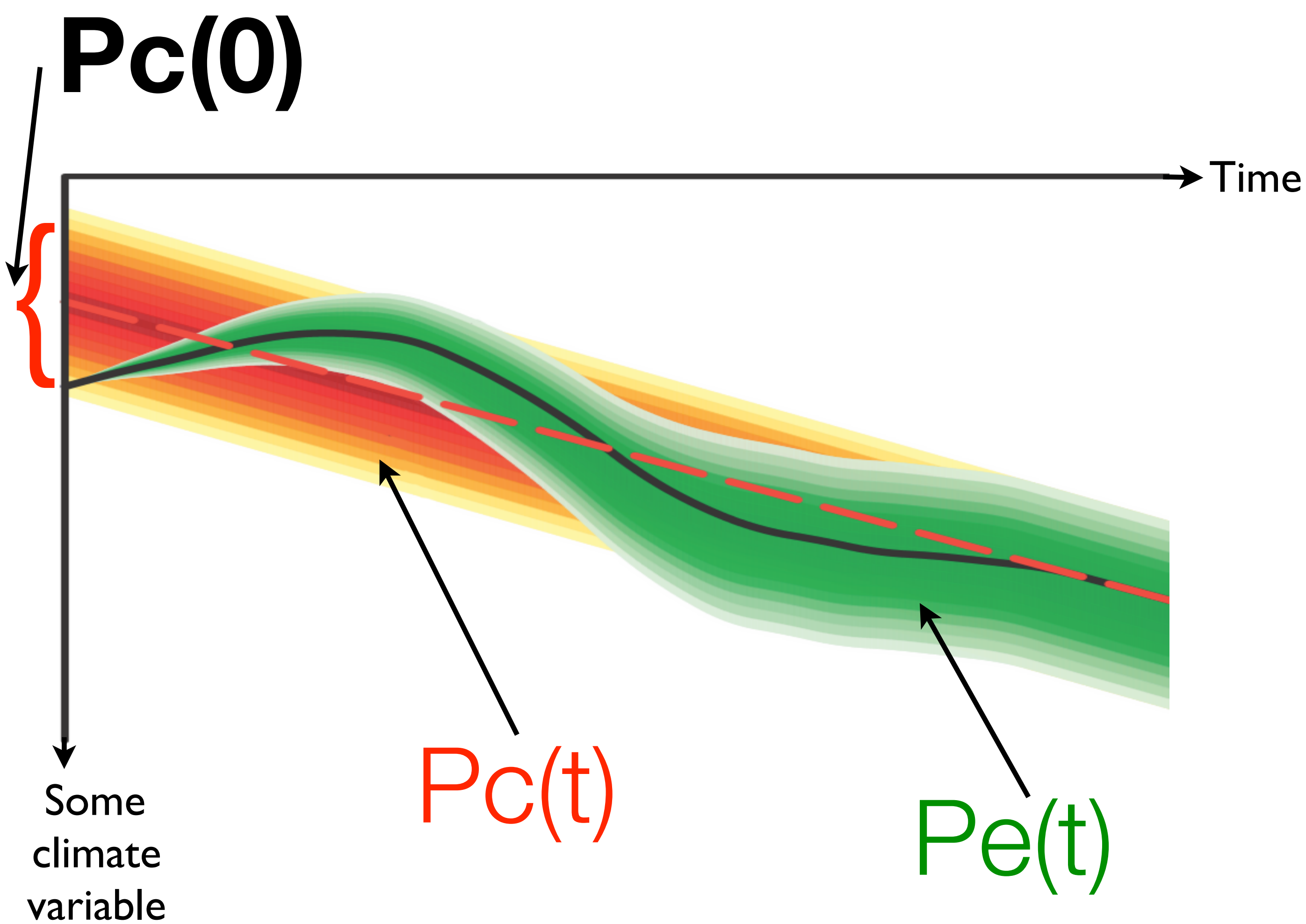
- Pc(t) represents the control (background) distribution. It is independent of any particular initial state.
- Pe(t) is an ensemble of predicted states evolving from a specific tight cluster of initial conditions.
- A comparison of Pe(t) to Pc(t) represents **"initial-value predictability"** (Lorenz 1975). This is what a weather forecast is.

On predictability



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

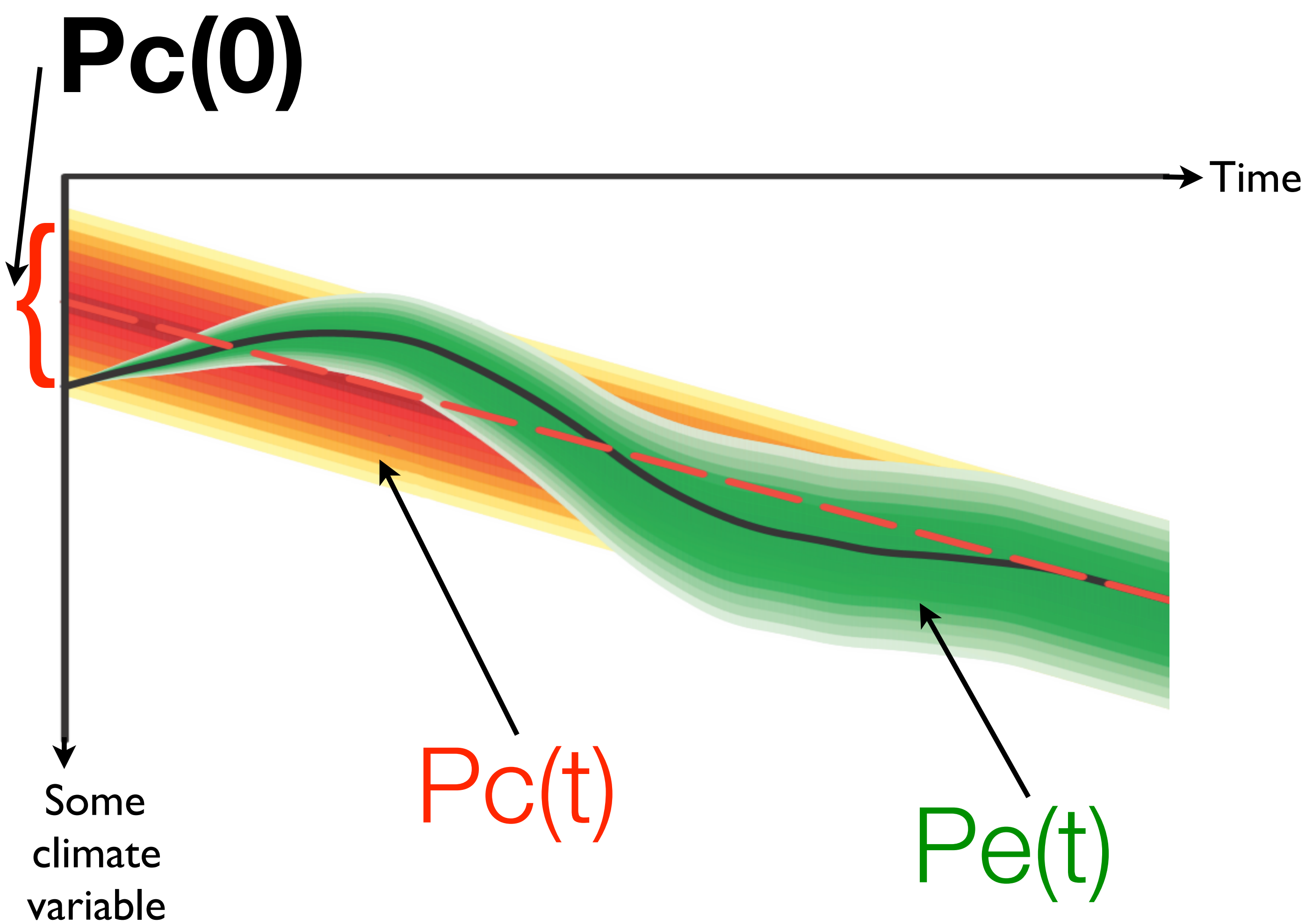
On predictability



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

- a comparison of Pc(t) to **Pc(0)** corresponds to ‘**“forced predictability”** (Lorenz 1975). This is what a climate change prediction is.

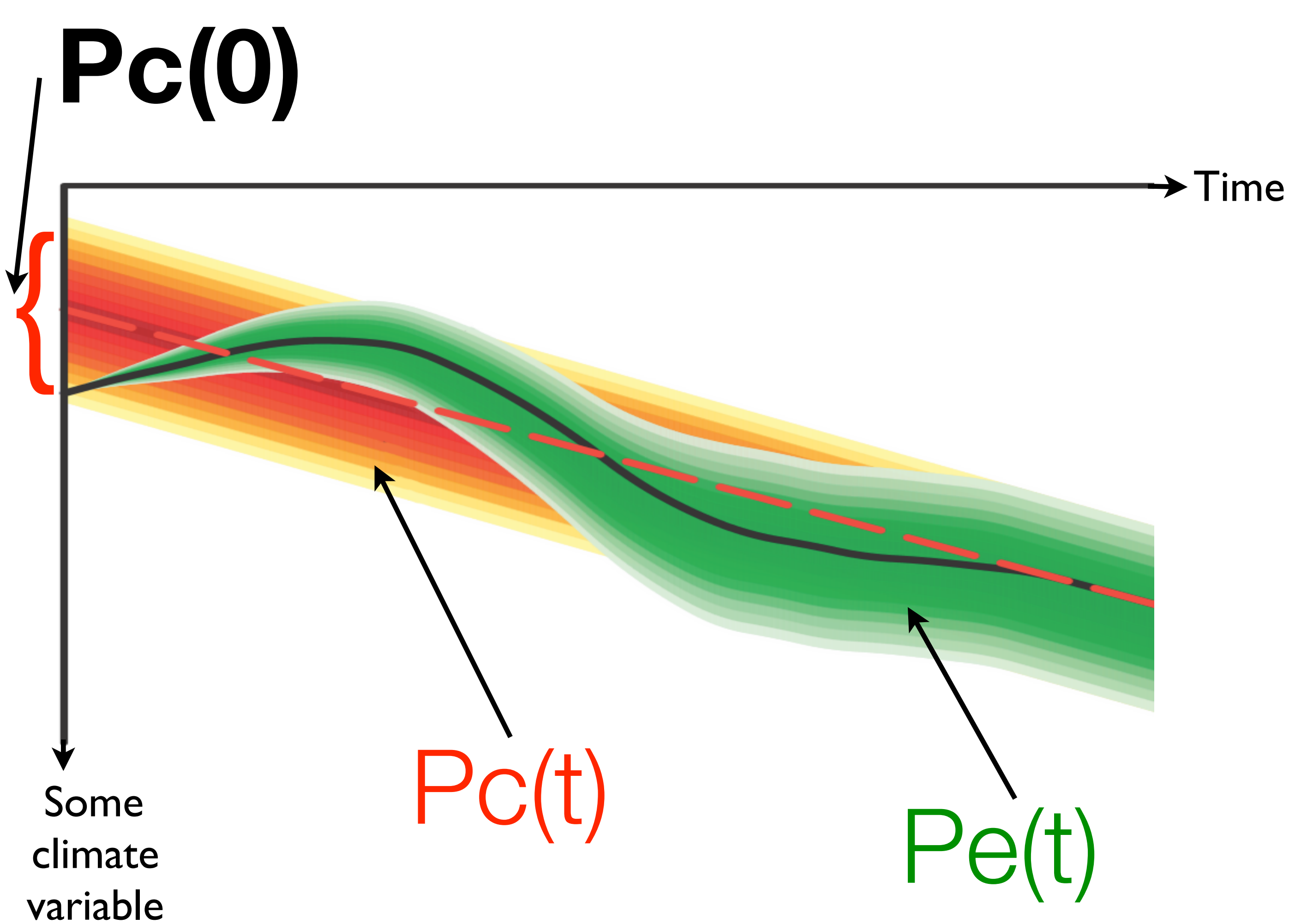
On predictability



•Historically, in seasonal/decadal predictability studies, emphasis has been placed on initial value predictability.

•Forced predictability could be very important for a system whose mean state is rapidly changing, as is the case for Arctic sea ice.

On predictability



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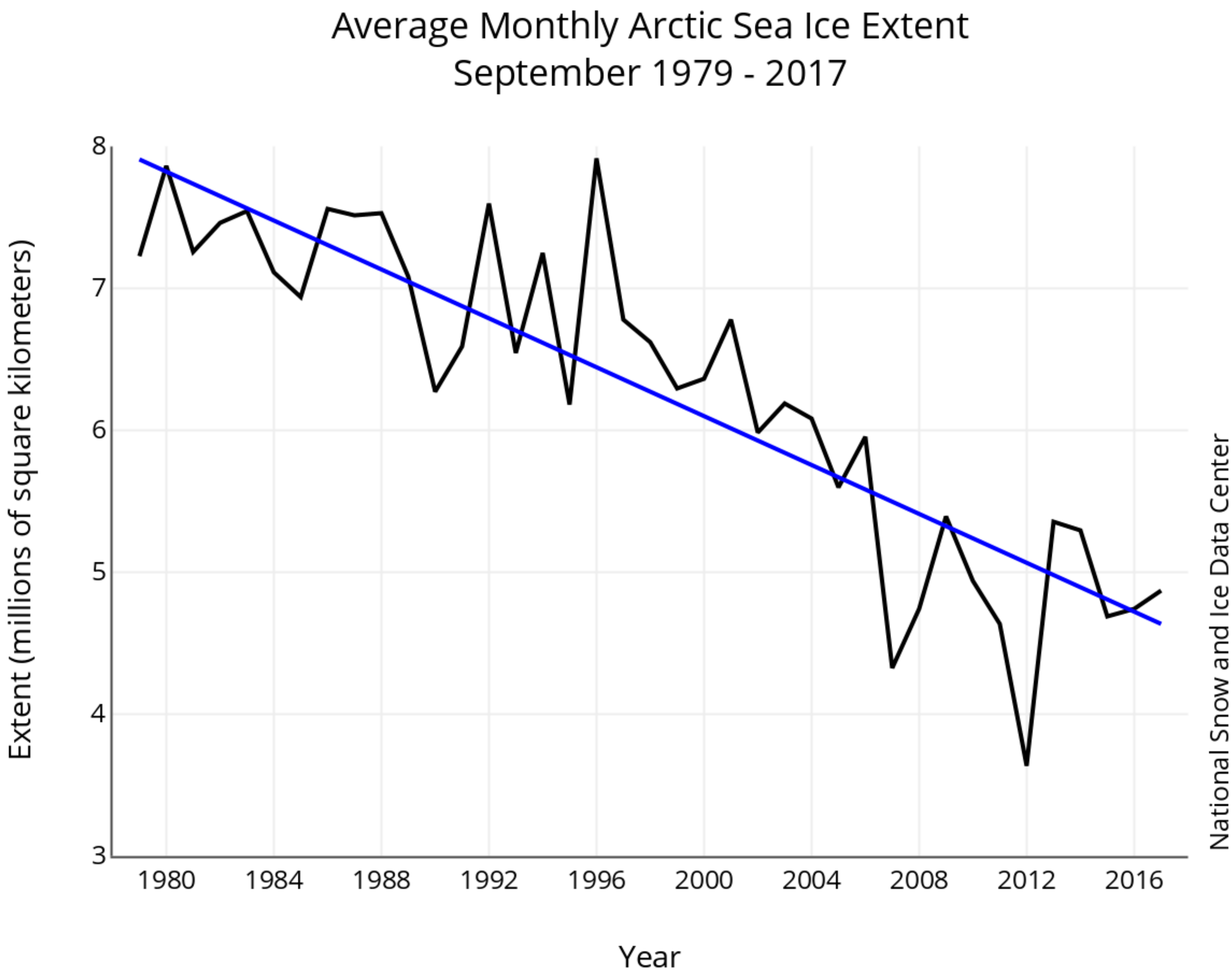
•Forced predictability could be very important for a system whose mean state is rapidly changing, as is the case for Arctic sea ice.

•(note how to compare Pe(t), we need an ensemble of forecast runs. Also allows to make a **probabilistic** forecast.

If only have one forecast run, this is a **deterministic** forecast)

On predictability



How to measure predictability?

Observations:

The observed divergence in time of analogs (i.e., similar observed atmospheric states) provides an estimate of forecast divergence.

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Model:

Can use a model to predict observations, or to predict itself (‘**perfect model**’ experiments).

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

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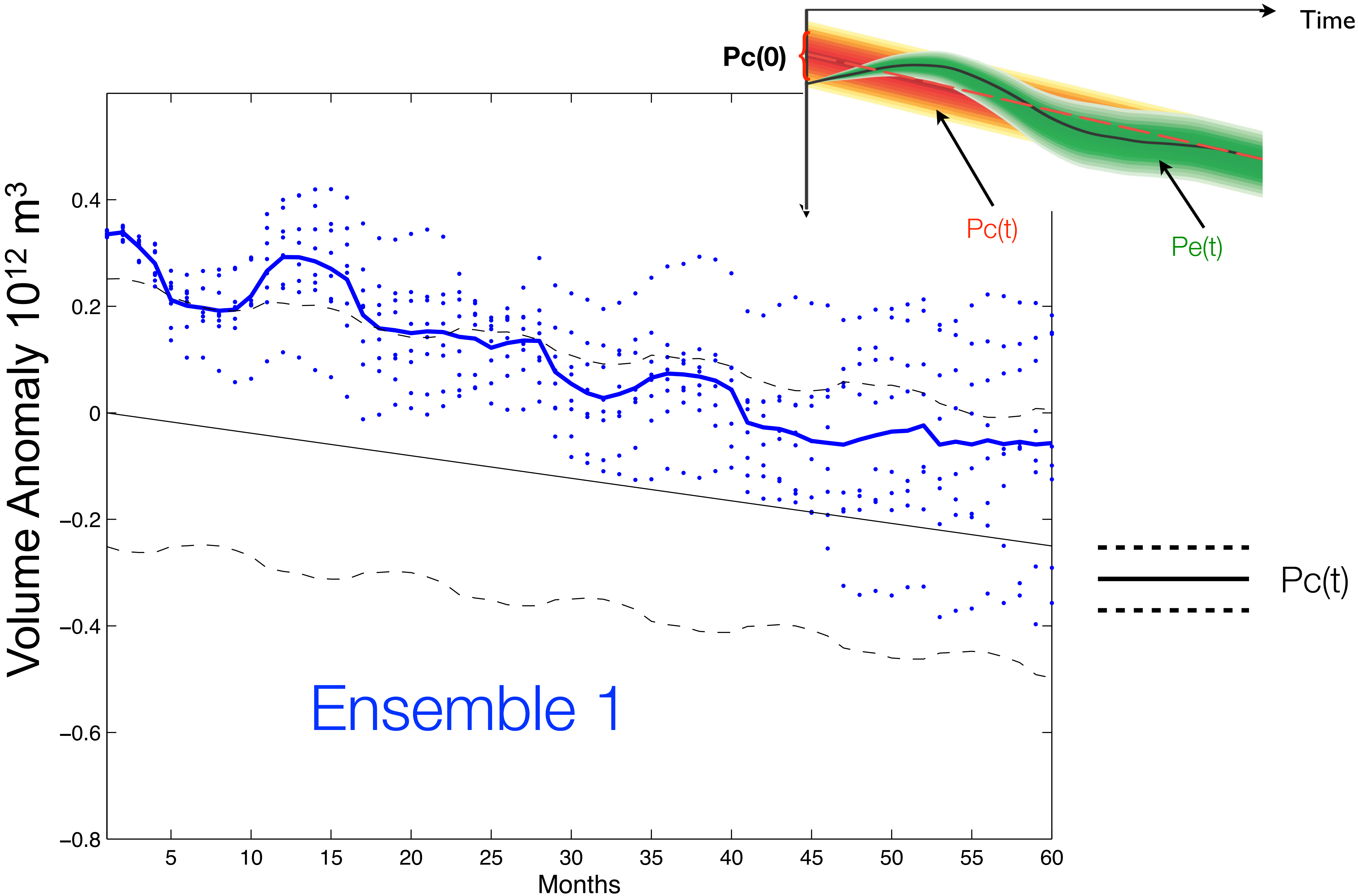
Can also use control runs to examine 'diagnostic predictability' -> generally assess fraction of variance explained by low frequency variability, or persistence characteristics

Predictability studies with a GCM ('Perfect model')



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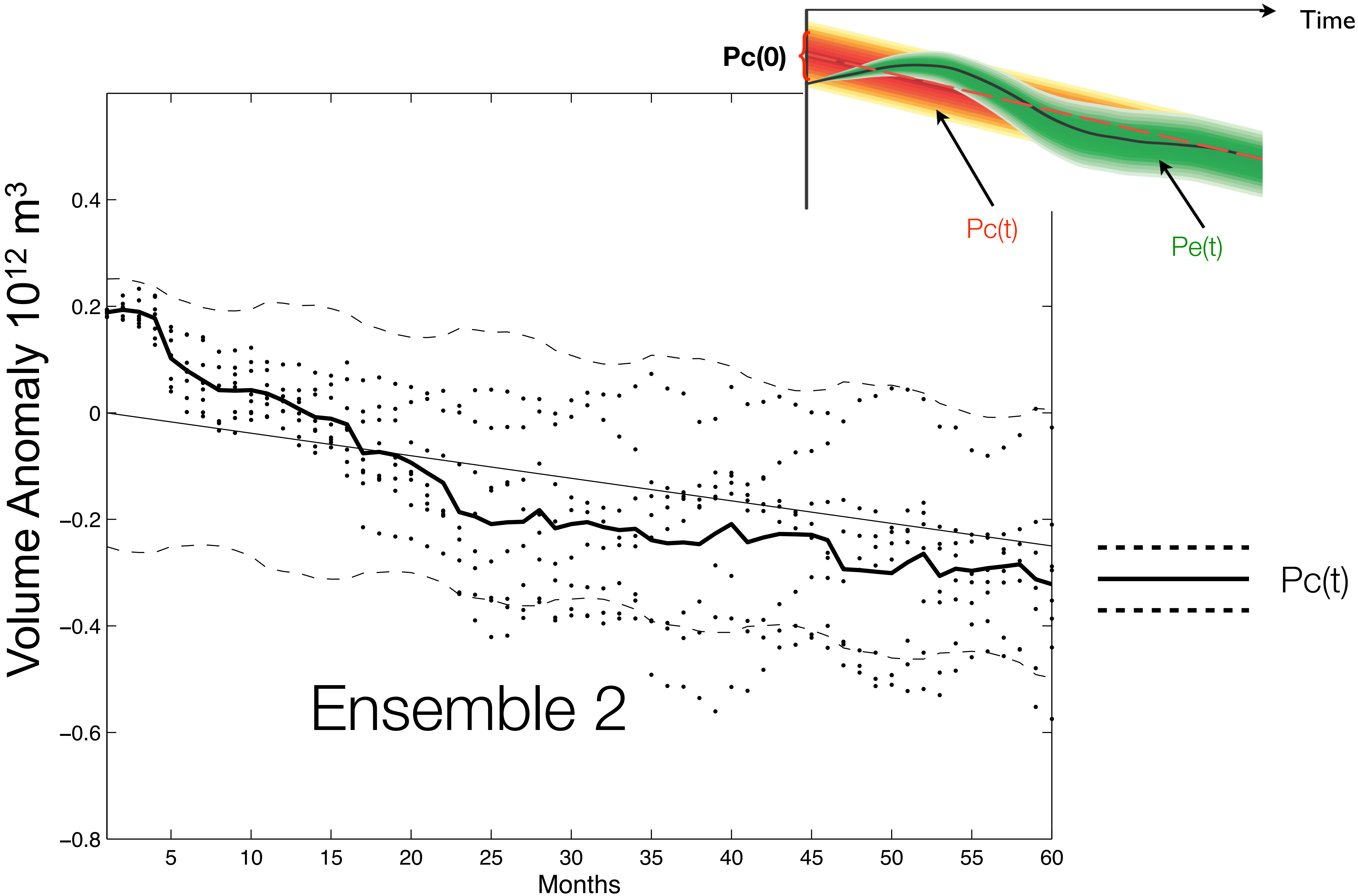

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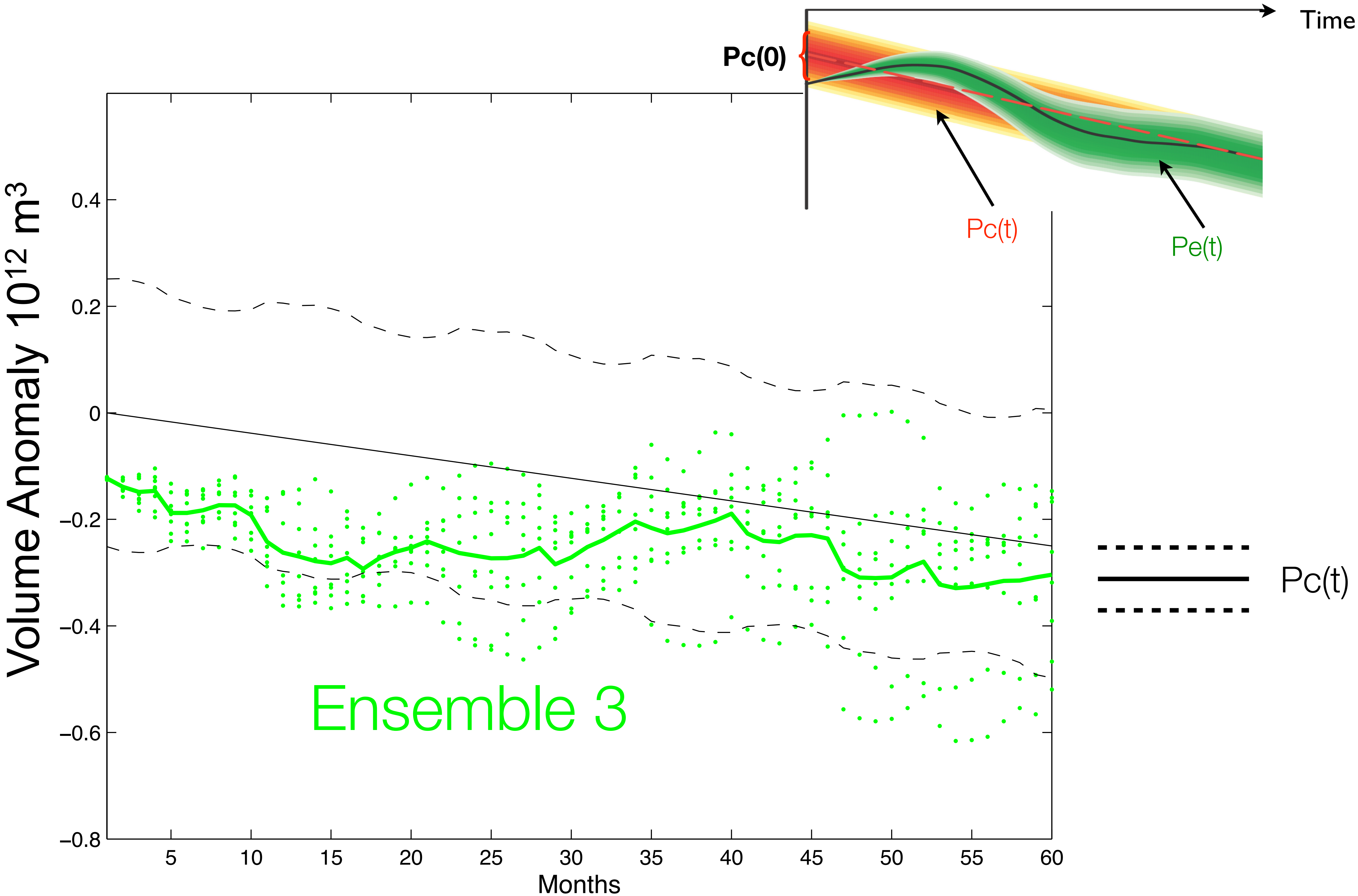

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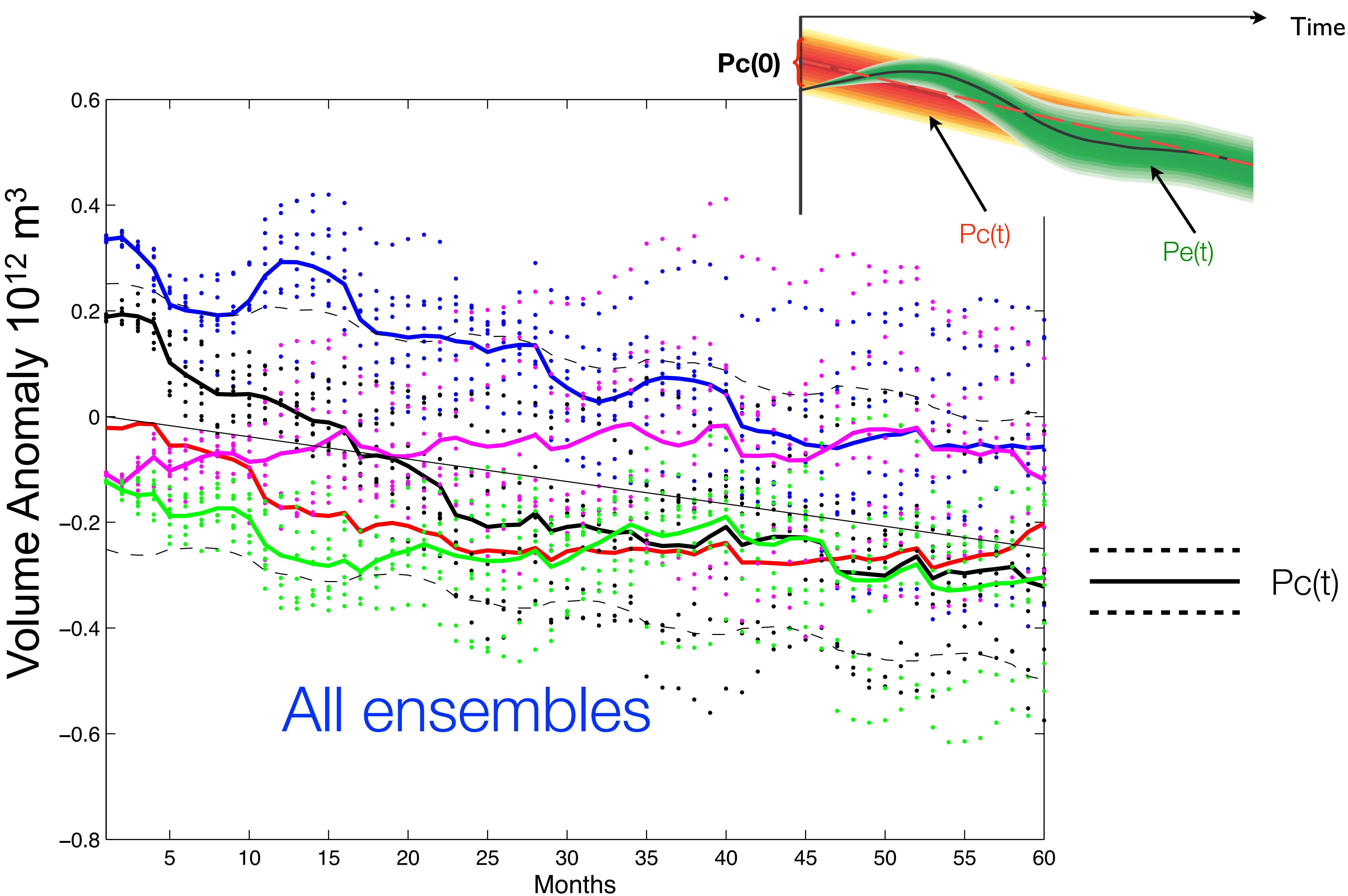

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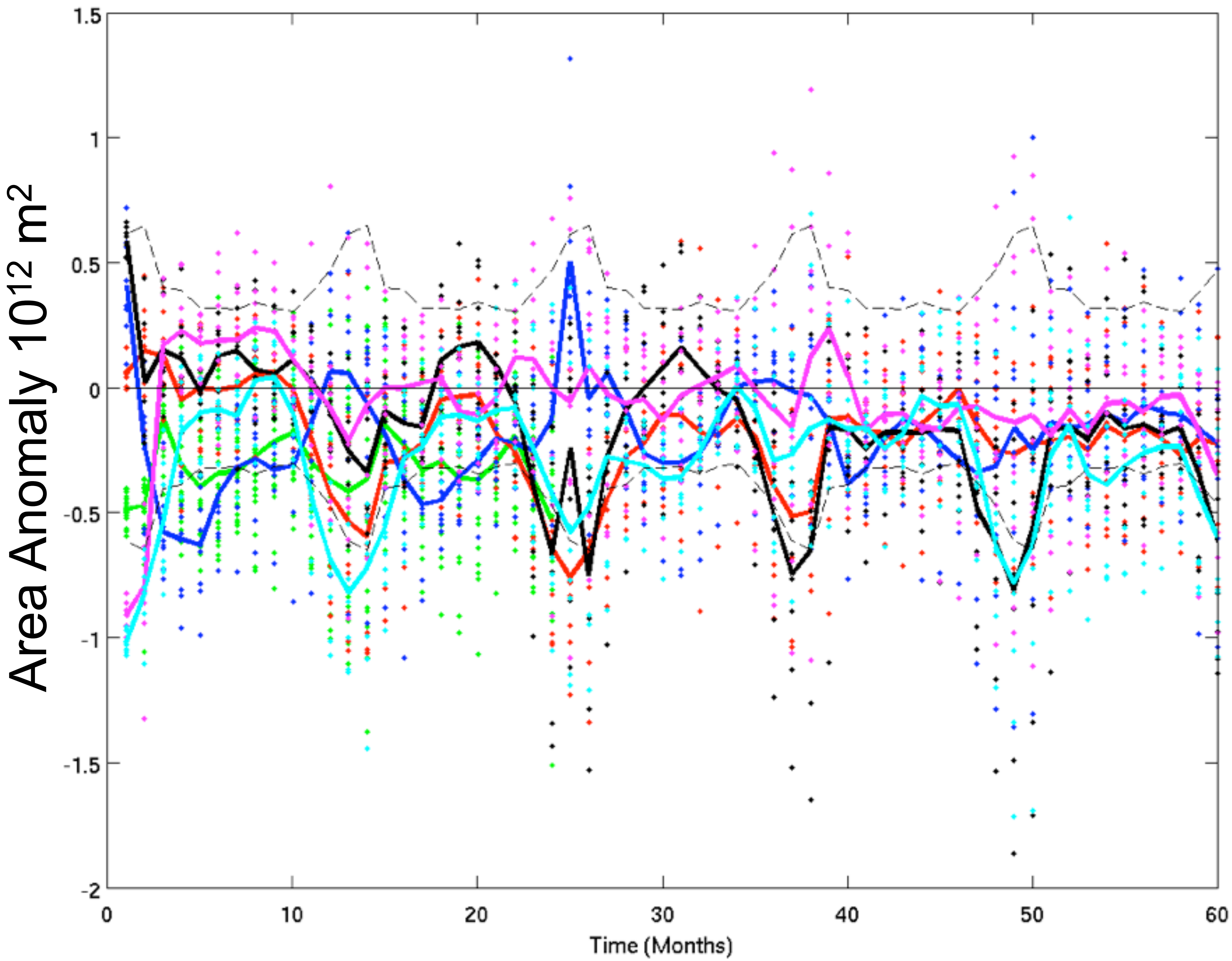
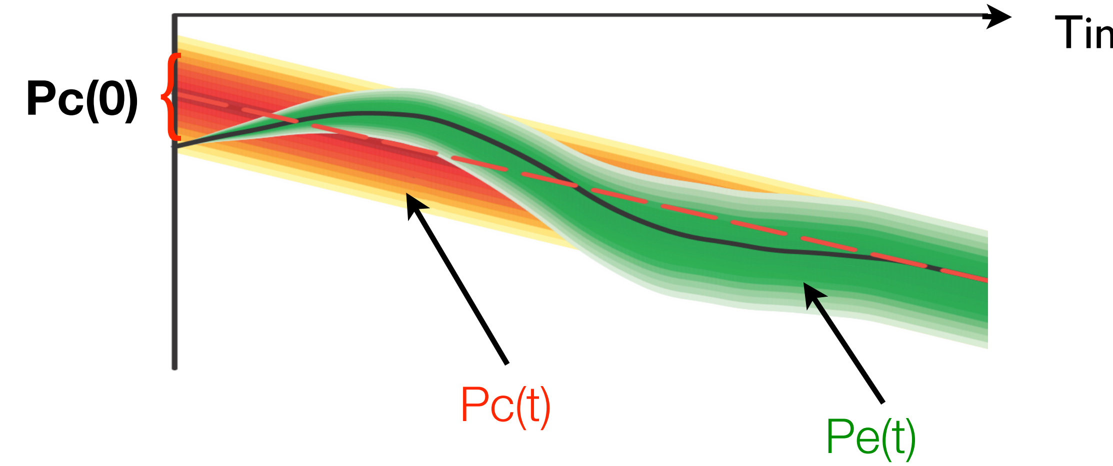




How to quantify predictability?

Metrics:

Two aspects of Pe(t) and Pc(0) to compare to each other: **forecast spread** (its growth), and the **forecast anomaly** (signal). Predictability metrics tend to asses one or the other, in general **good to use more than one.**

Spread:
Root mean square error (RMSE),
or normalized RMSE (RMSE)):

$$\mathrm{NRMSE} = \frac{\sqrt{\left\langle (x_{ij} - x_{kj})^2 \right\rangle_{i,j,k \neq i}}}{\sqrt{2\left\langle \sigma_j^2 \right\rangle_j}}$$

Prognostic Potential Predictability (PPP):

$$PPP(t) = 1 - \frac{\sigma_e^2}{\sigma_c^2}$$

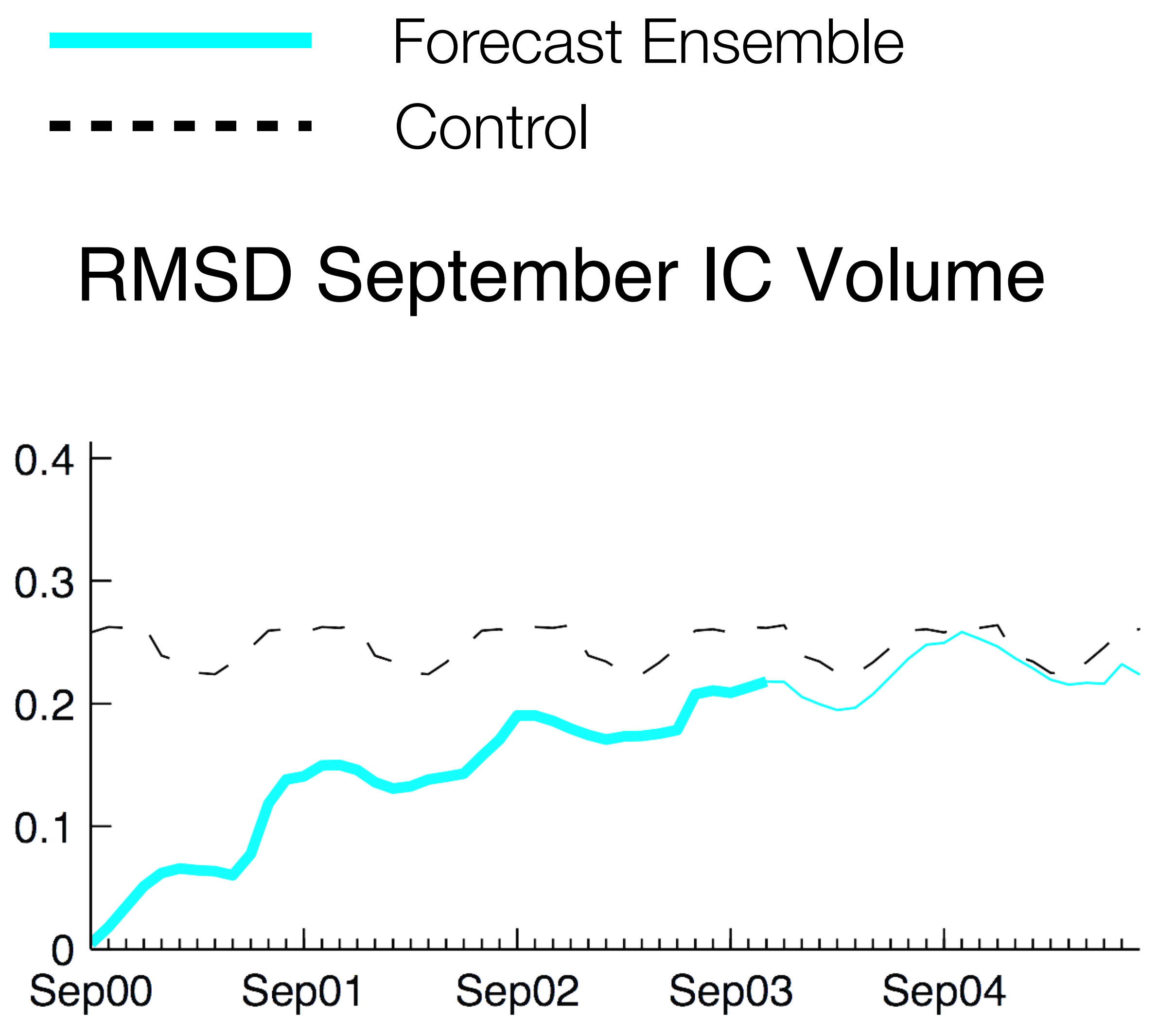
Signal:
Anomaly correlation coefficient (ACC)

$$ACC = \frac{\langle (x_{ij} - \mu_j)(x_{kj} - \mu_j) \rangle_{i,j,k \neq i}}{\langle (x_{ij} - \mu_j) \rangle^2}$$

Both mean and spread
Relative entropy (RE)

$$RE = \frac{1}{2}\left[\ln\left(\frac{\sigma_c^2}{\sigma_e^2}\right) + \frac{\sigma_e^2}{\sigma_c^2} + \frac{(\mu_e - \mu_c)^2}{\sigma_c^2} - 1 \right]$$

Initial Value predictability: Arctic



- Volume: continuous predictability for 3-4 years.

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

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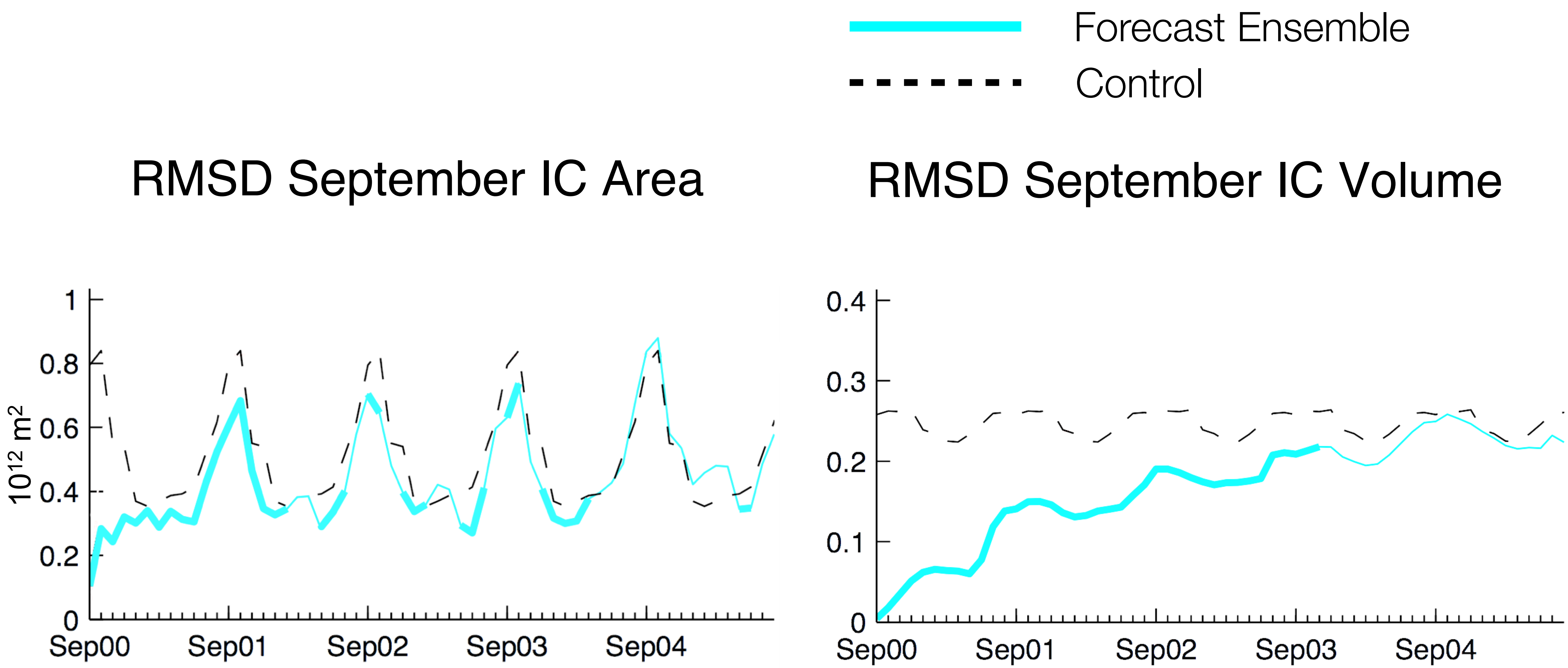
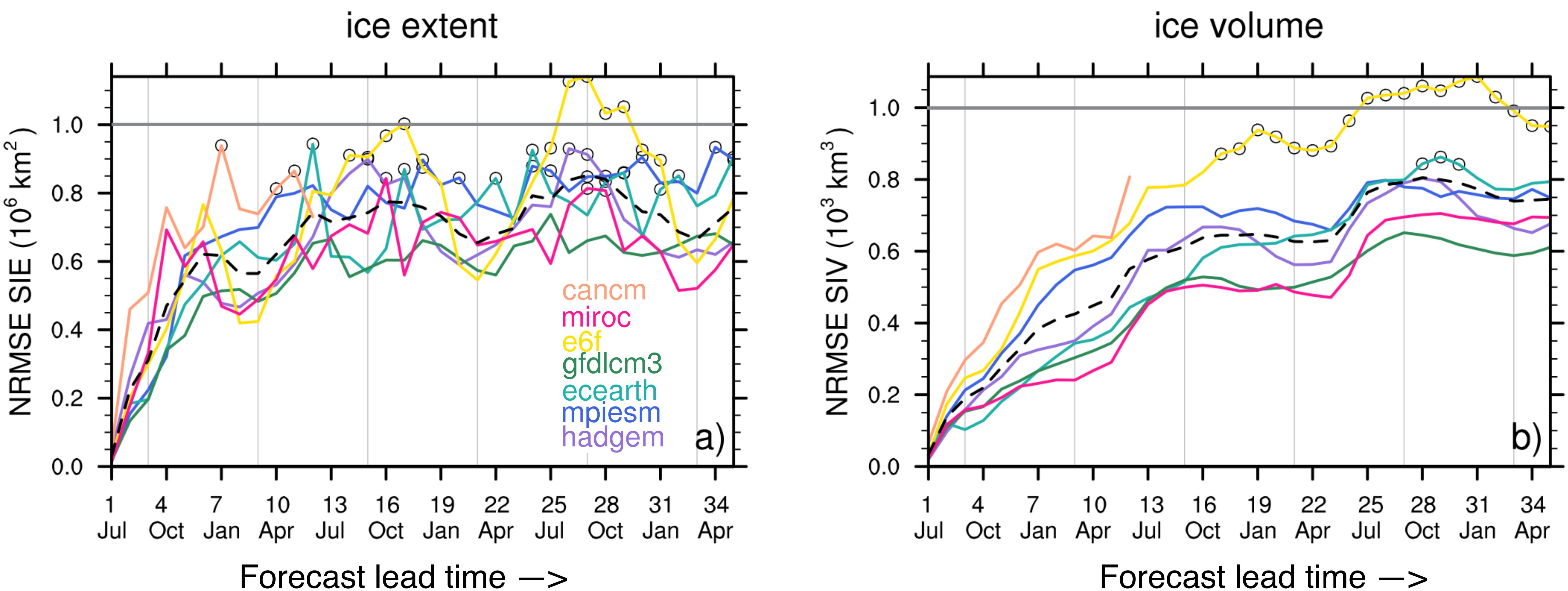


- Lower for area than for volume.
- Area: fast initial decline (first 1-2 seasons), re-emergence weak predictability at times for 1-3 years.
- Volume: continuous predictability for 3-4 years.
- Rapid loss of predictability in June-July (albedo?)

Blanchard-W et al, 2011

Initial Value predictability: Arctic

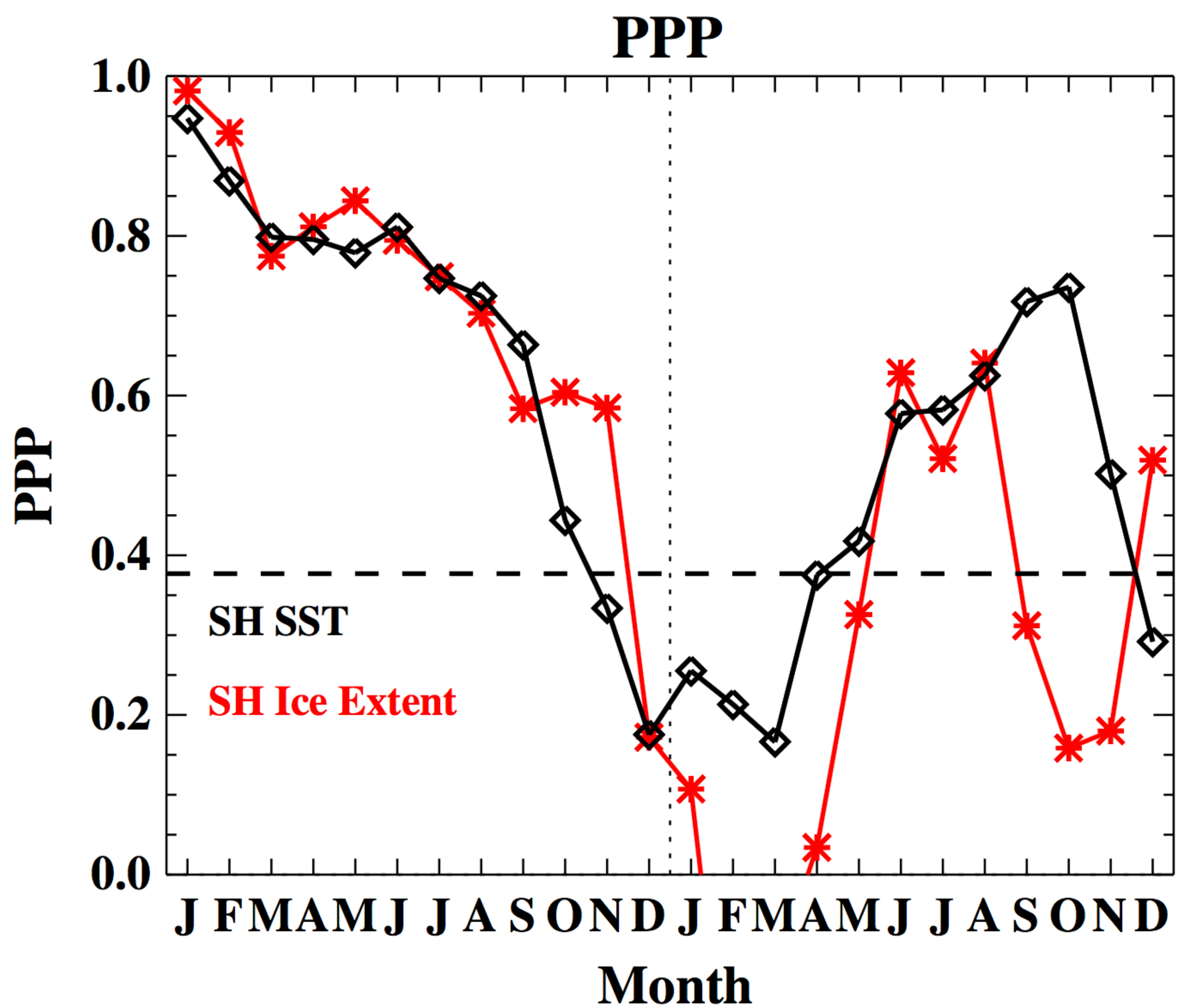
normalized RMSE from July 1 IC forecasts



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

Day et al, 2016 & Tietsche et al, 2014

Initial Value predictability: Antarctica



Forecast lead time —>

$$PPP(t) = 1 - \frac{\sigma_e^2}{\sigma_c^2}$$

Holland et al, 2013

Predictability flavors: perfect model results for polar sea ice/upper ocean

forecast lead time:

Day/weekly

Seasonal

Initial value predictability

Annual

Diminishing to none (mostly)

Decadal

Forced (boundary) predictability

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forecast lead time:

Day/weekly Seasonal	Initial value predictability
Annual	Diminishing to none (mostly)
Decadal	Forced (boundary) predictability

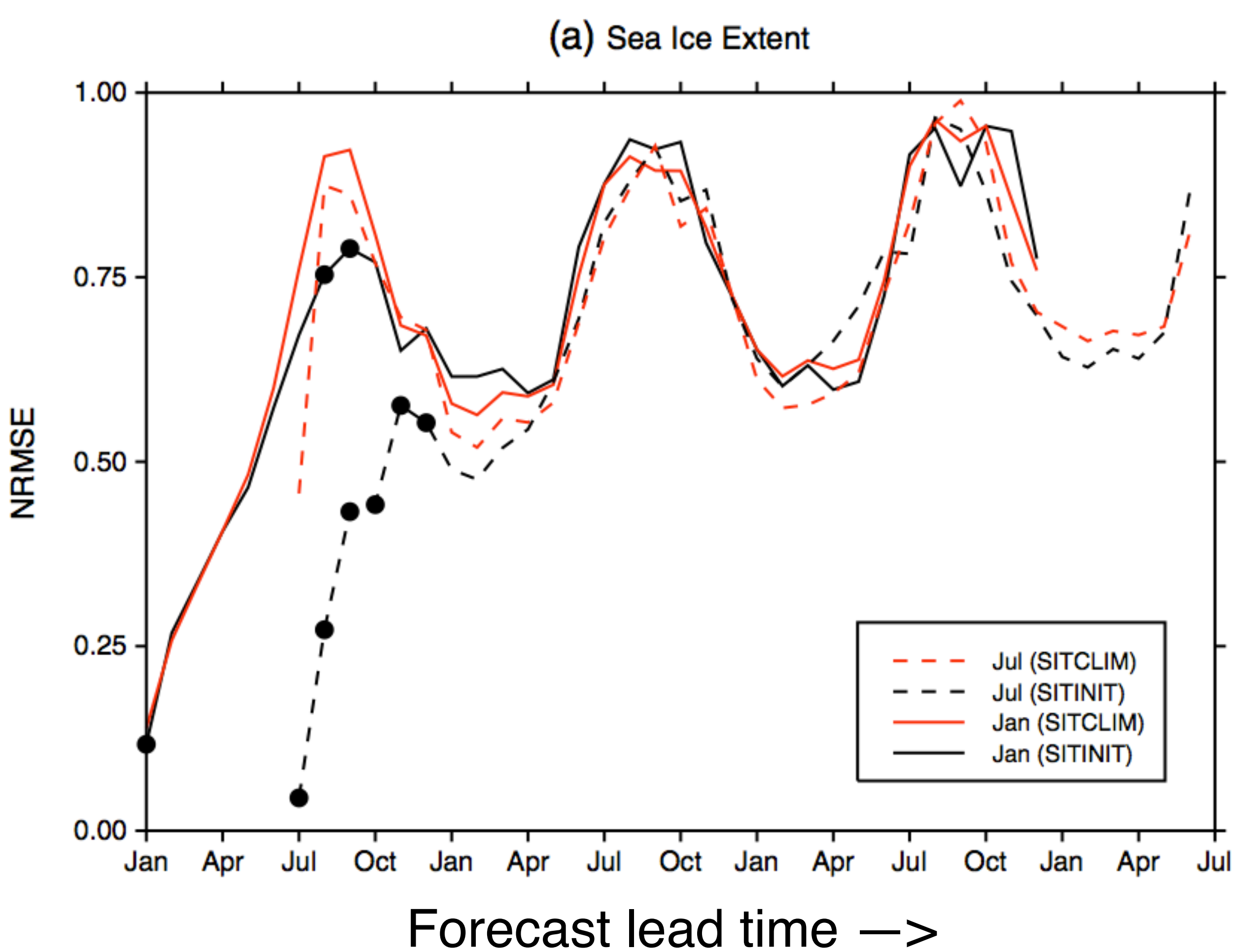
Initial value : forecast skill depends on **quality of initial conditions** (ICs) and **model physics** that simulate evolution of ICs

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

Mechanisms (what actually drives initial value predictability)

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

‘Data-denial experiment’



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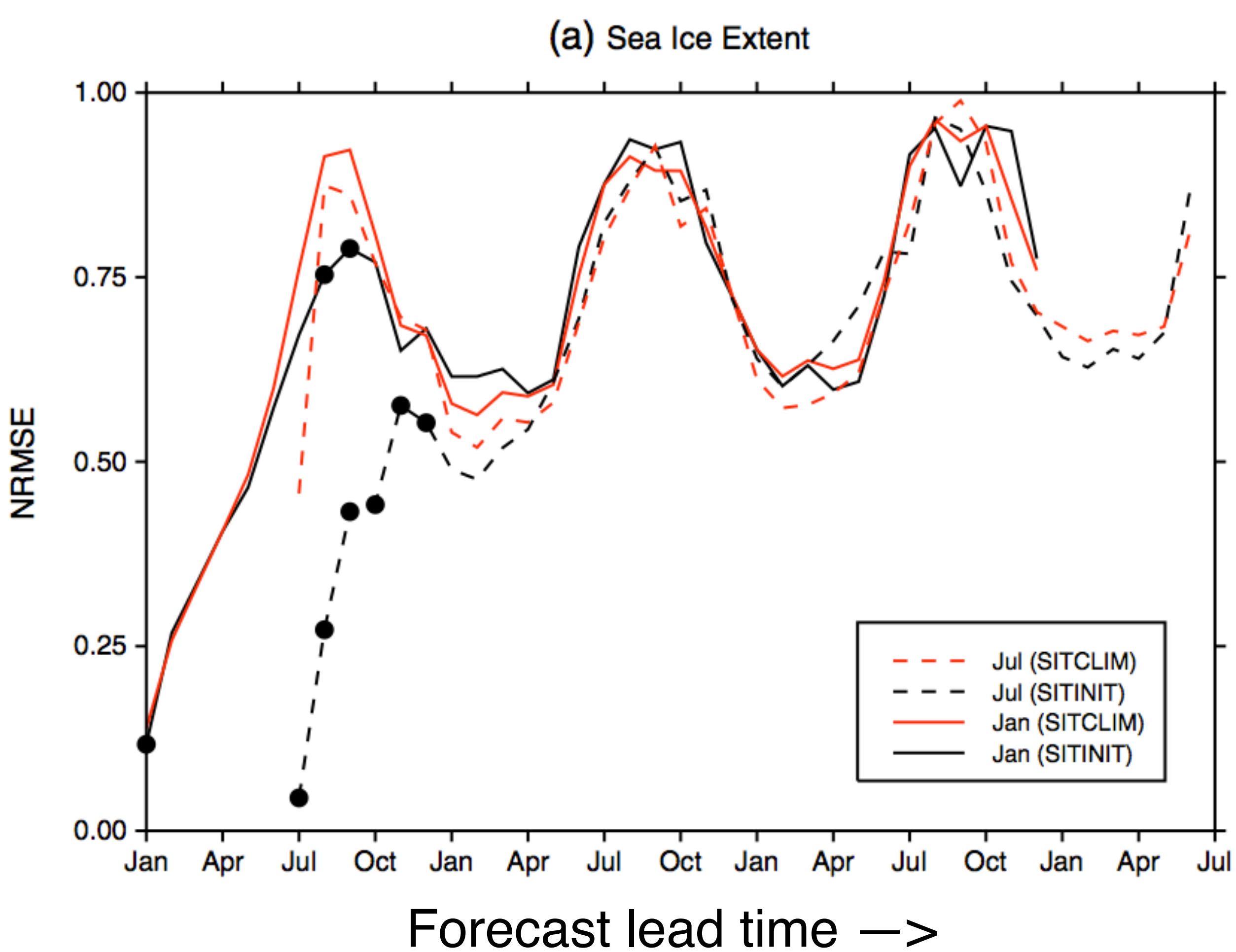

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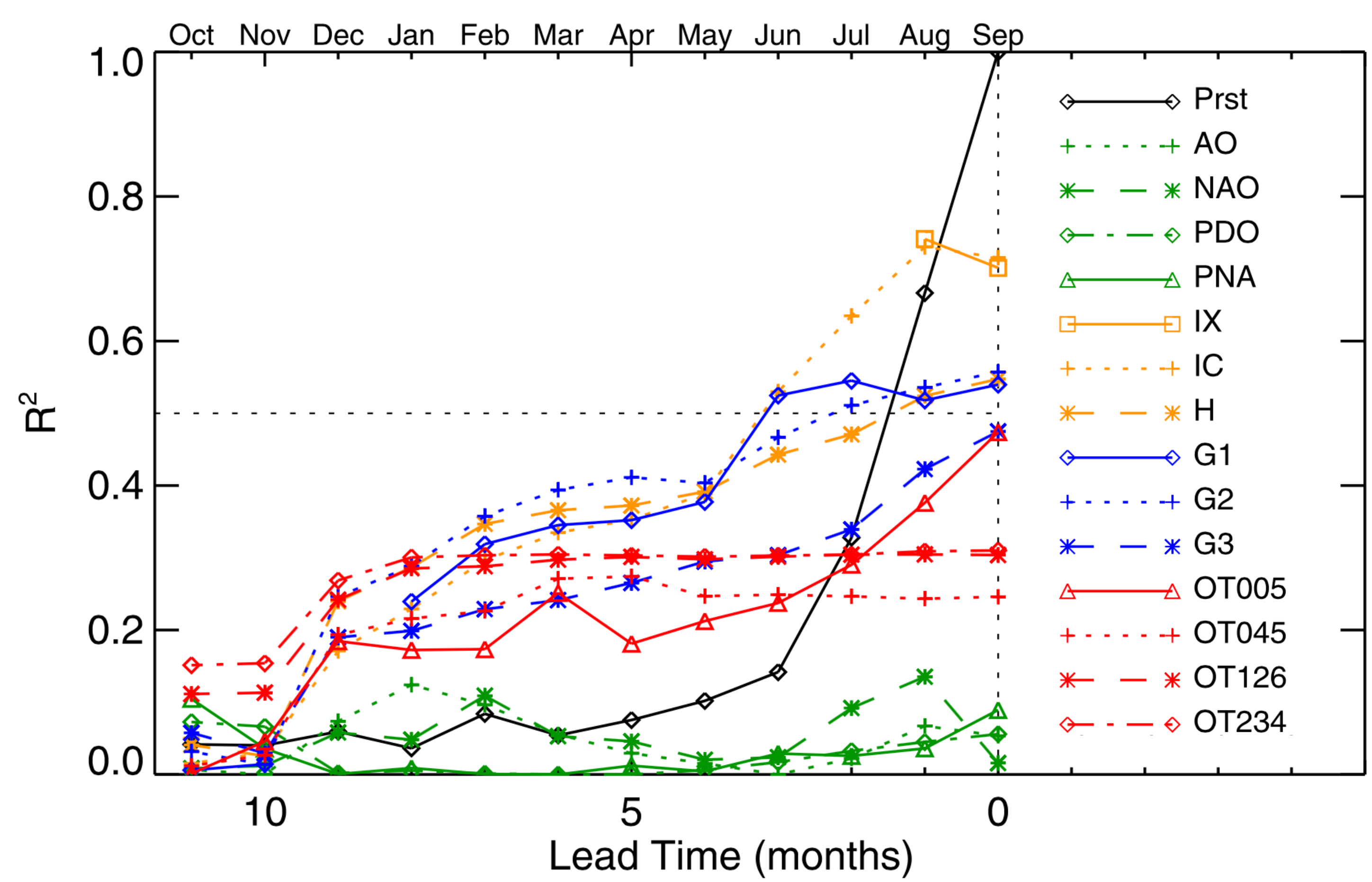

Lindsay et al, 2008

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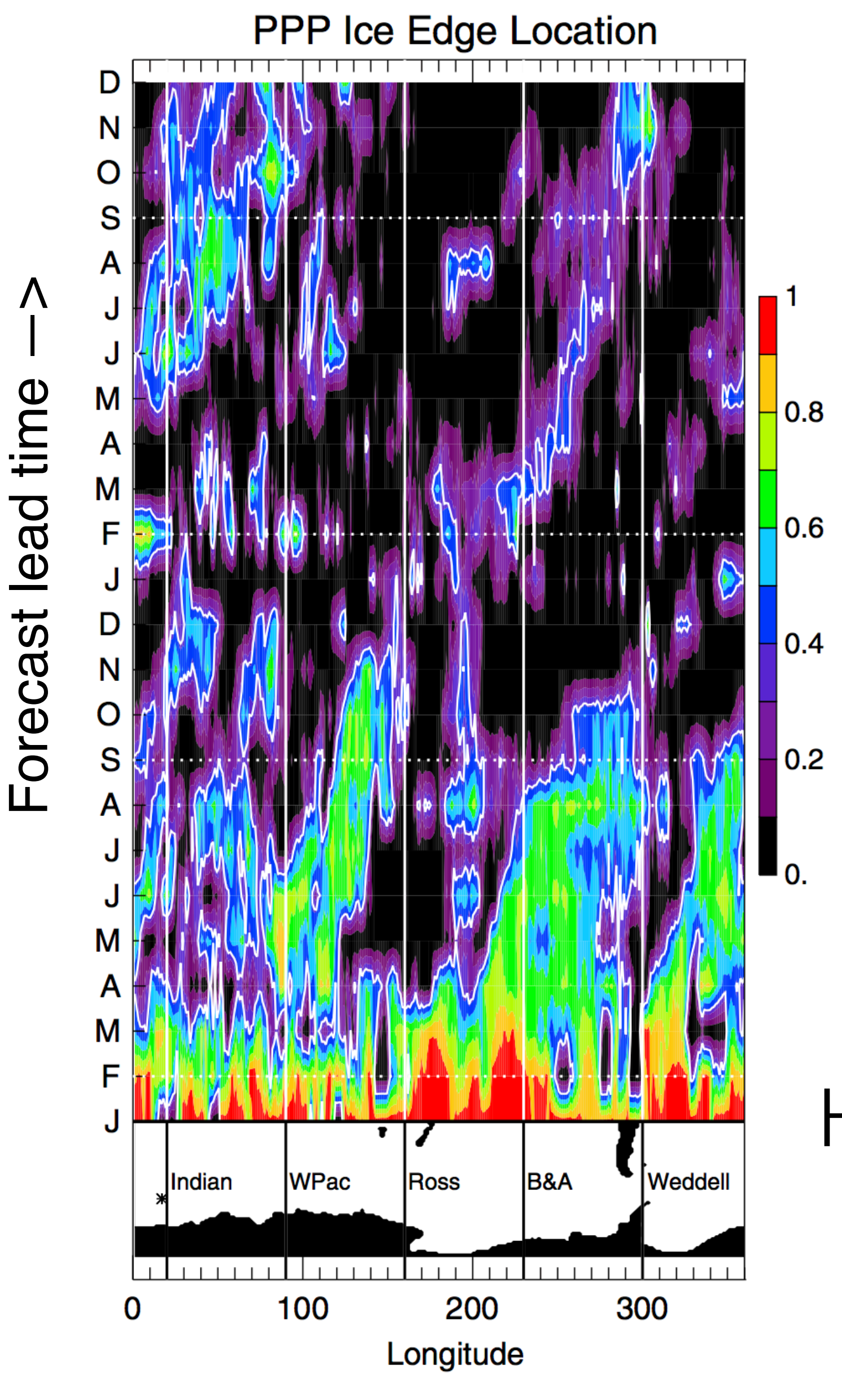

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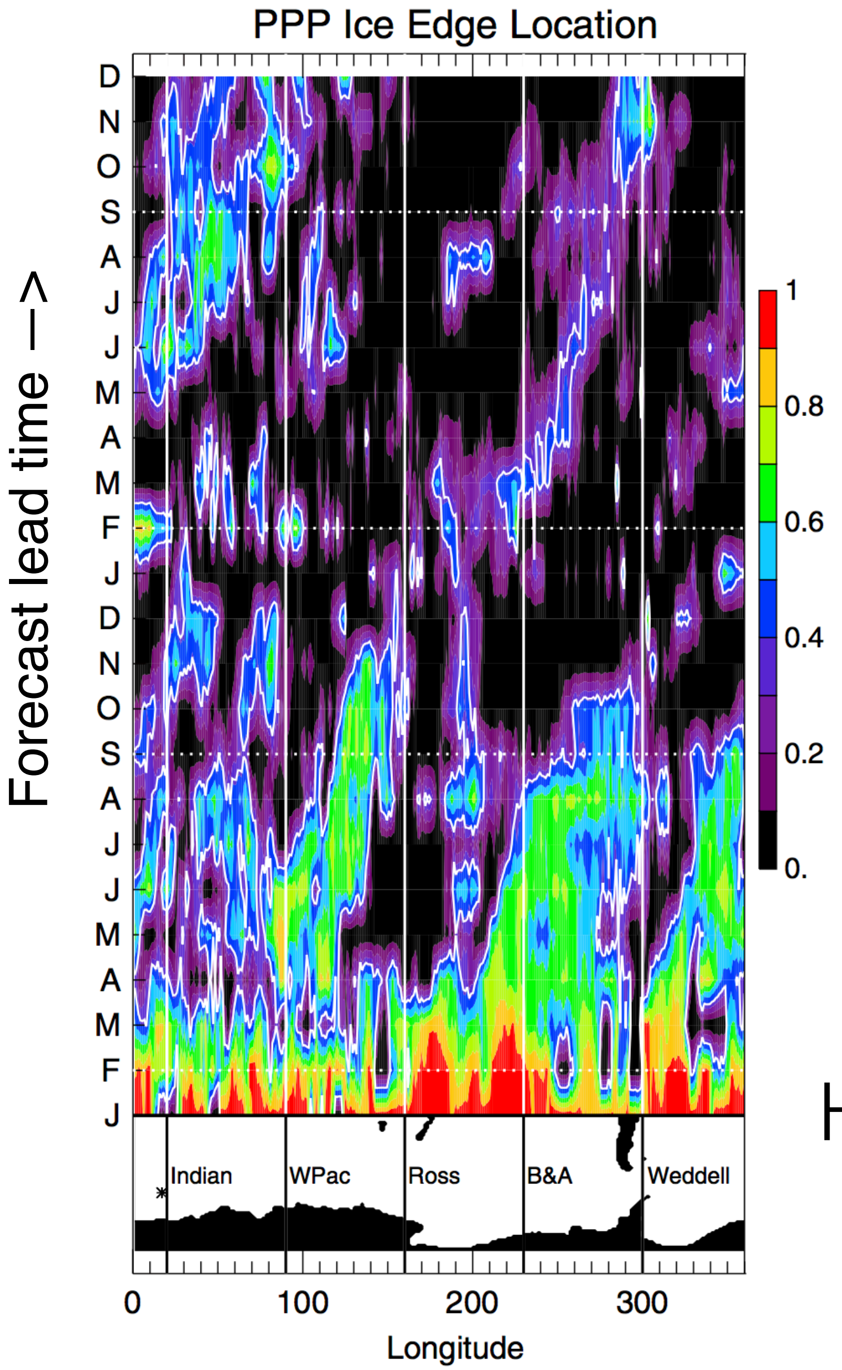

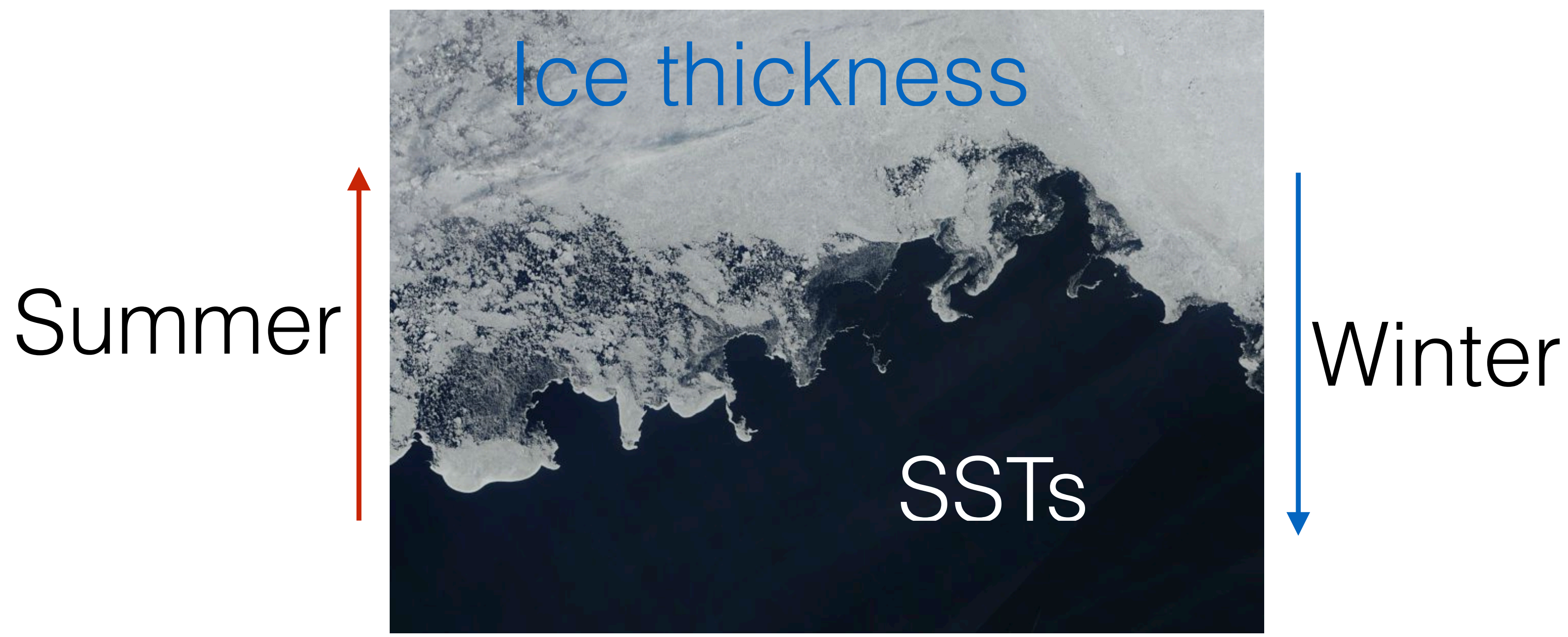

Holland et al, 2013

Antarctica

Models are good and all but… how about the real world?

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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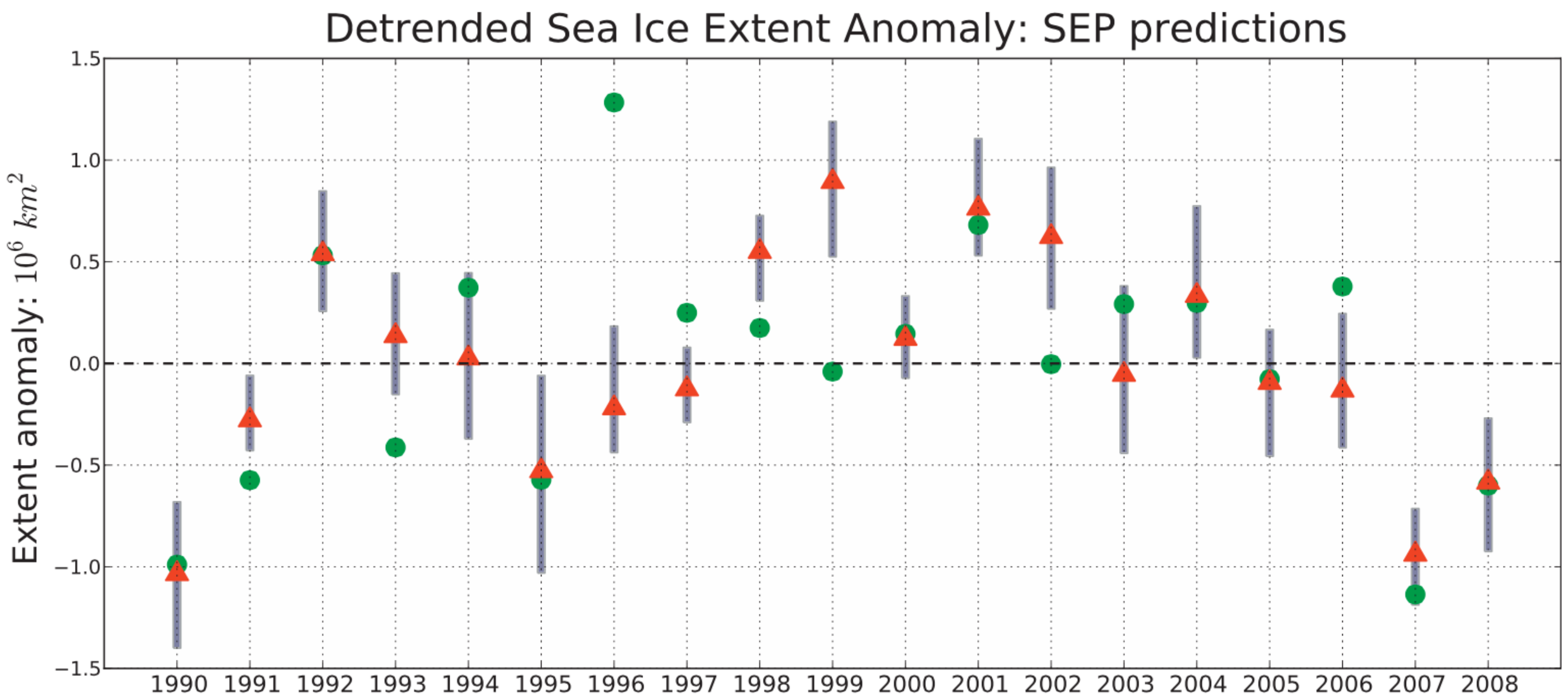

May forecasts of September SIE
r=0.6

Chevallier et al, 2013

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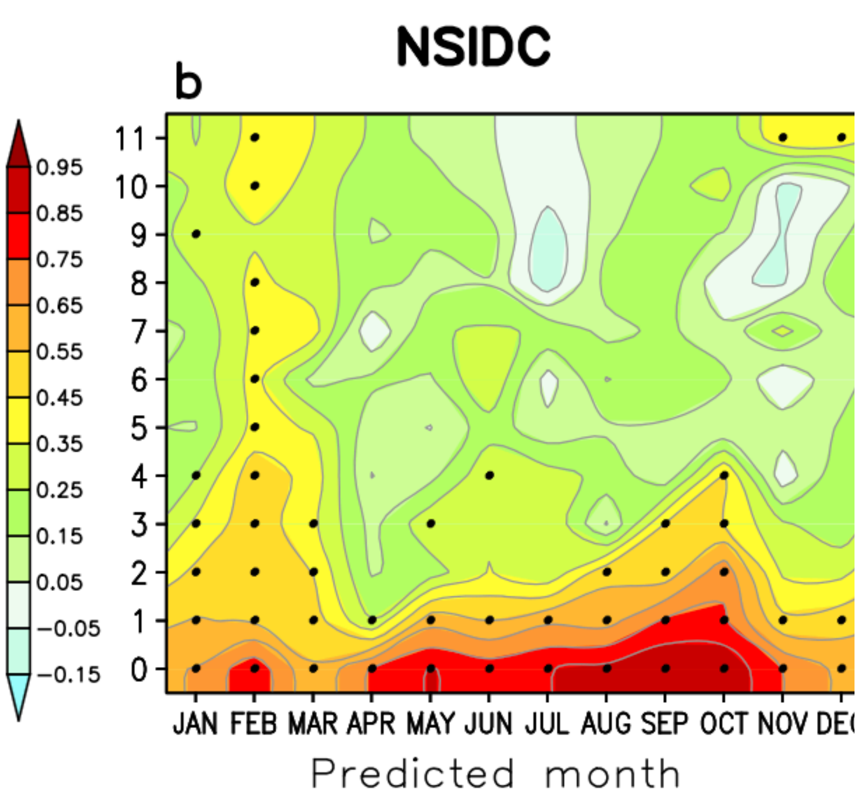
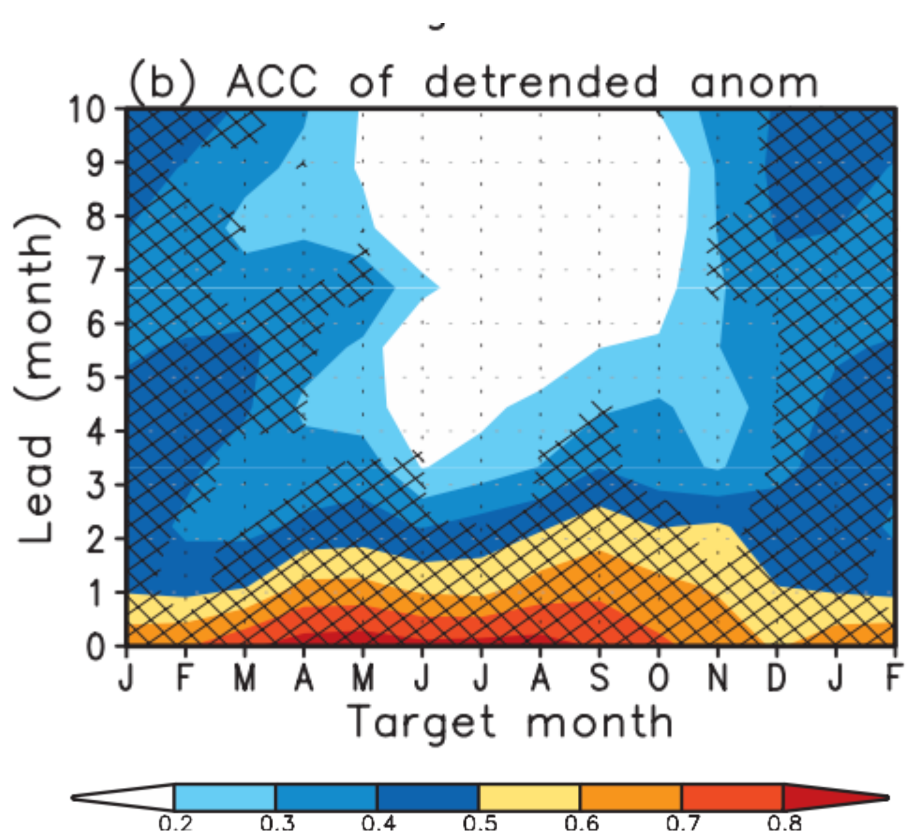
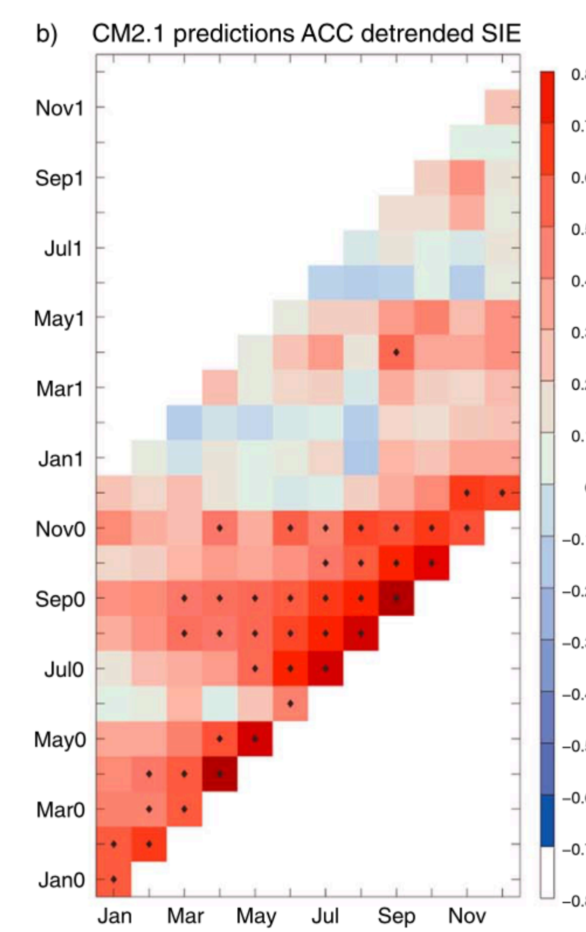


Sigmond et al 2013



Wang et al 2013



Msadek et al 2014

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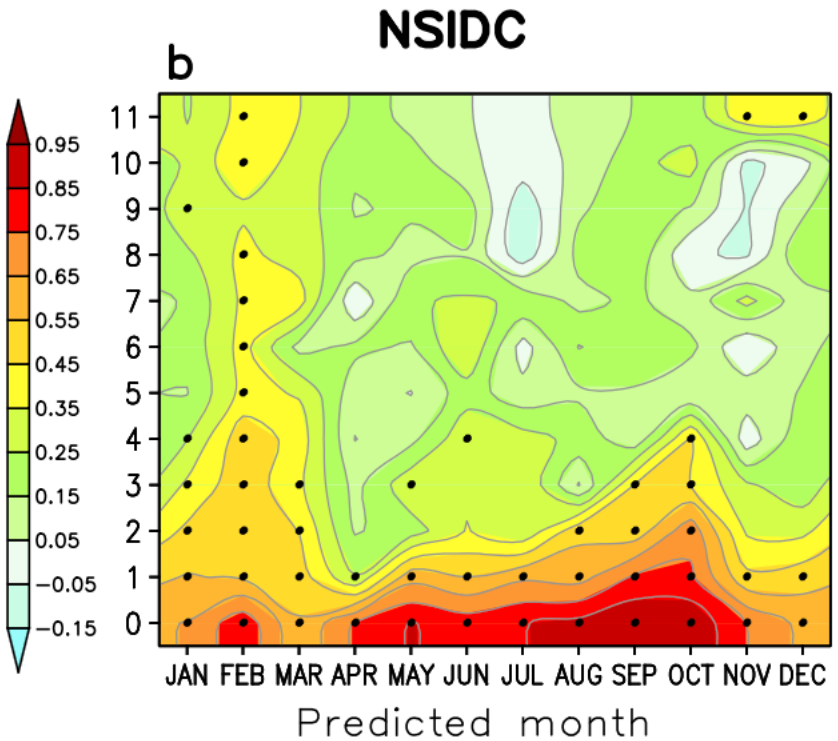

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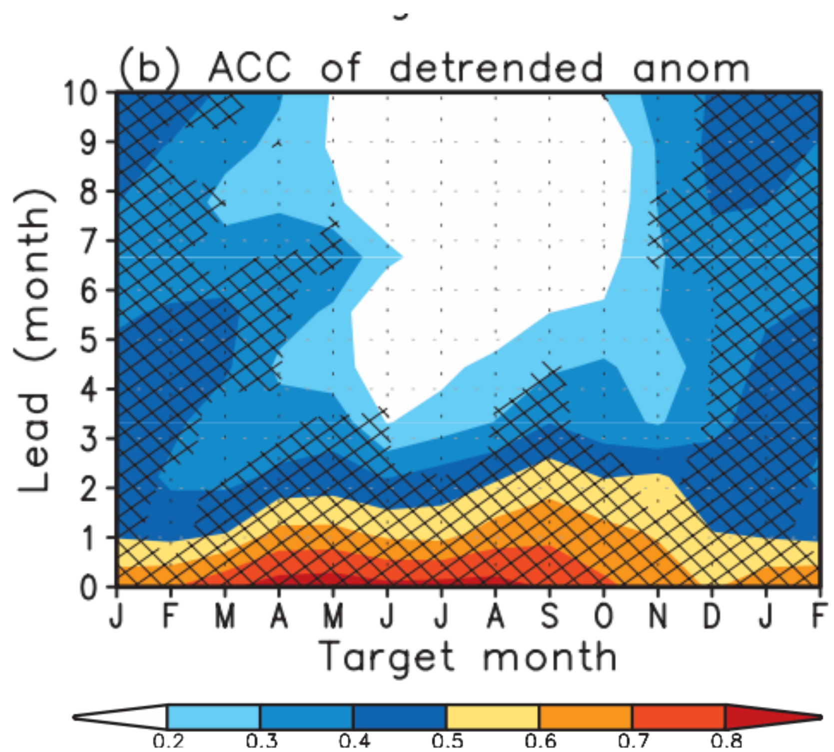

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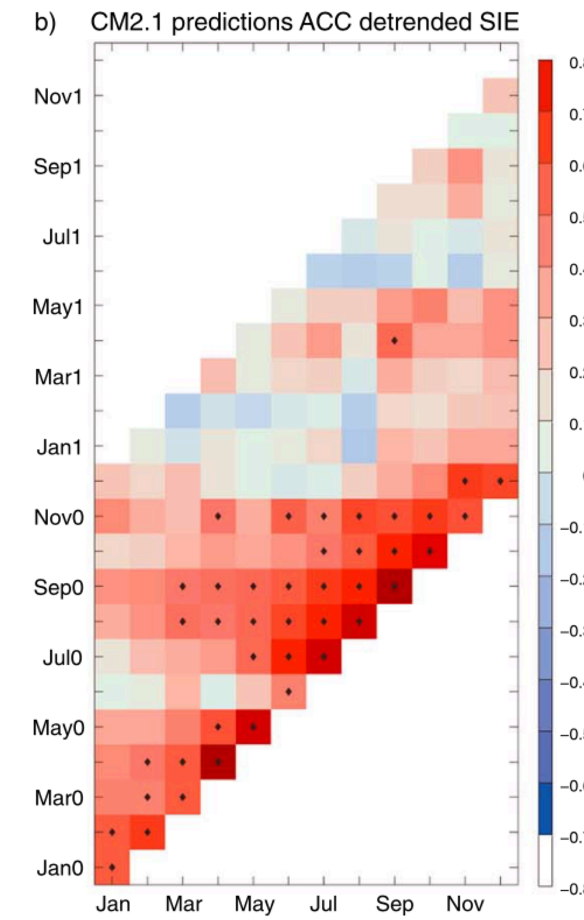

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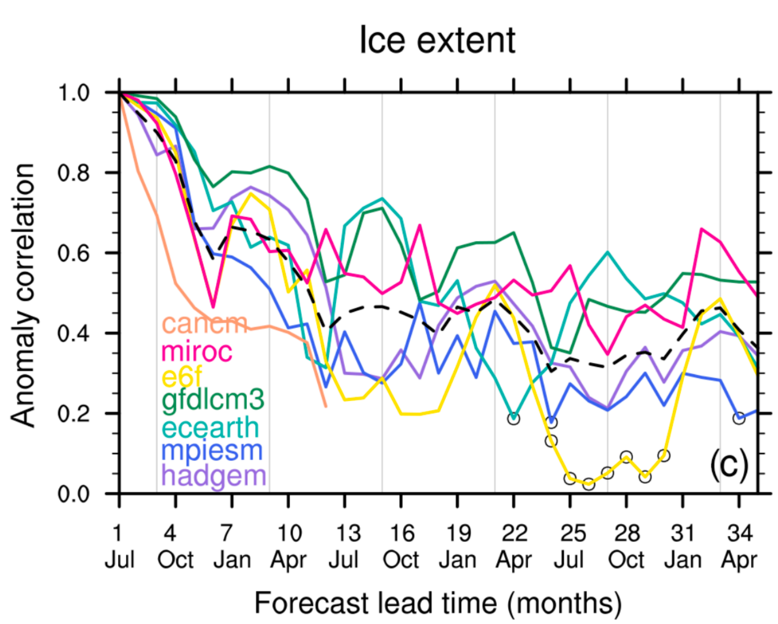


Day et al, 2014

Forecasts of real world sea ice area/extent skillful for a season or two… perfect model shows longer skill

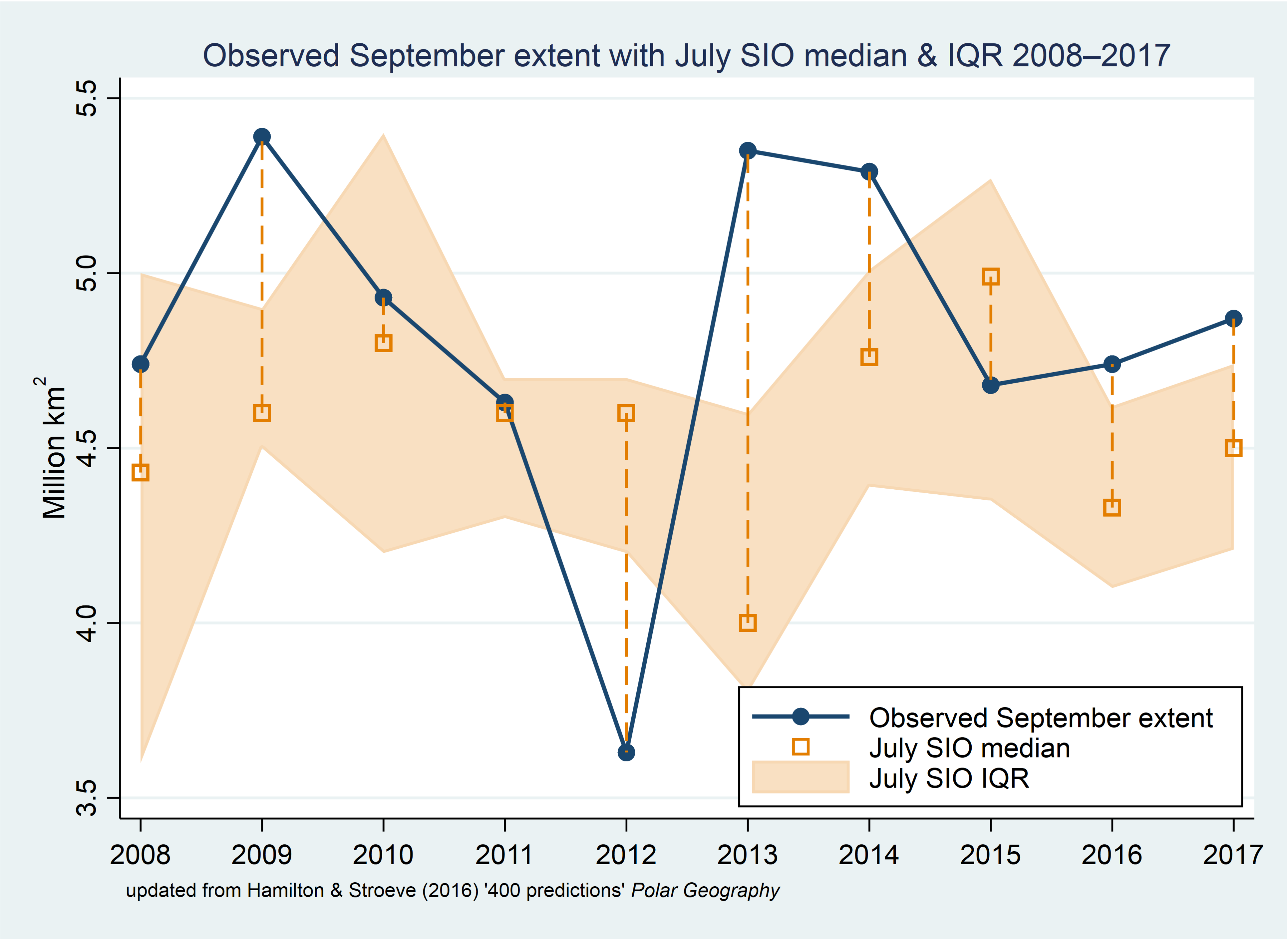
Models are good and all but… how about the real world?

Current forecasts

Seasonal predictability: the Sea Ice Outlook

Observed September extent compared with median and IQR of July SIO predictions, 2008–2016

updated from Hamilton and Stroeve 2016



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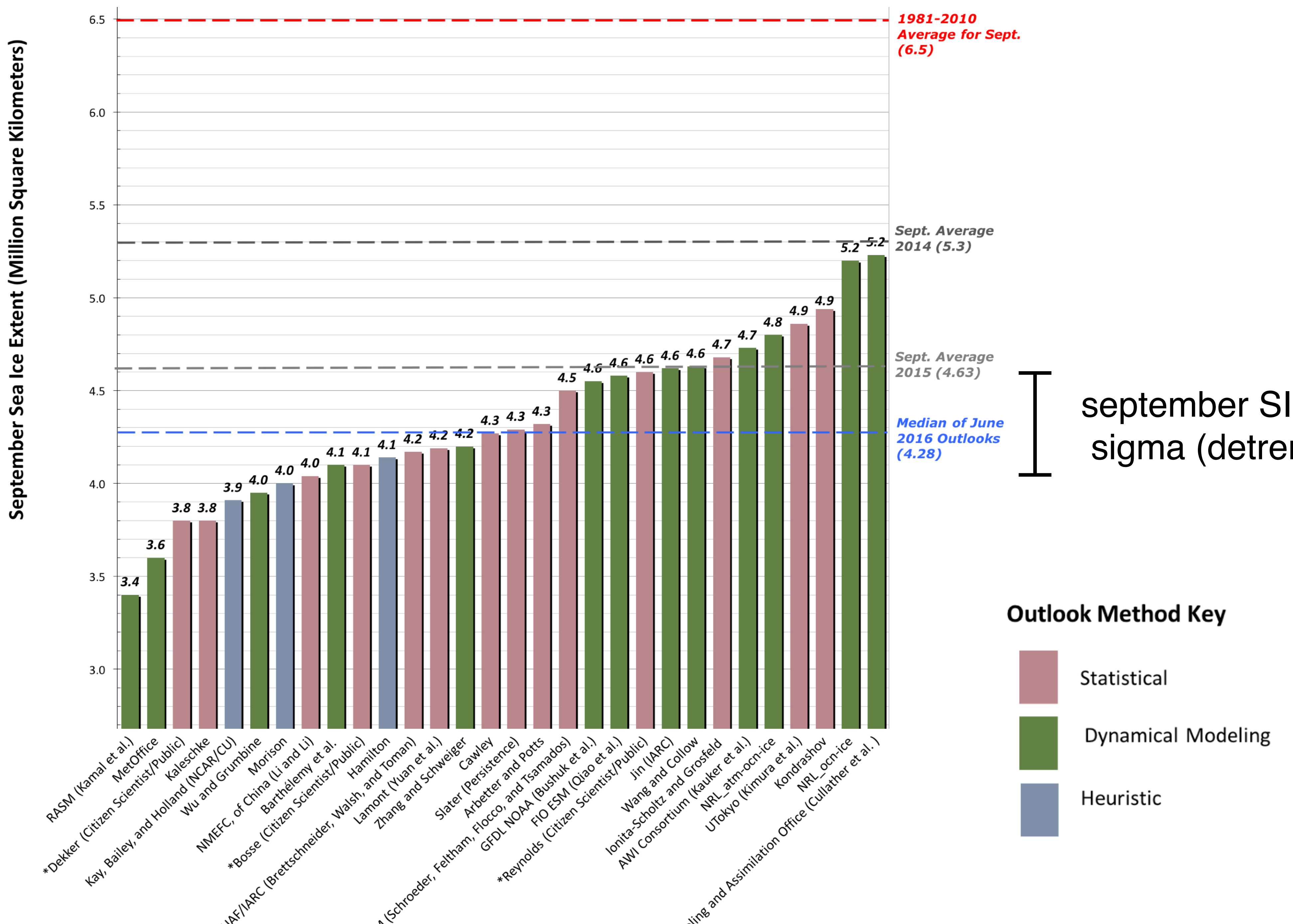

september SIE
sigma (detrended)

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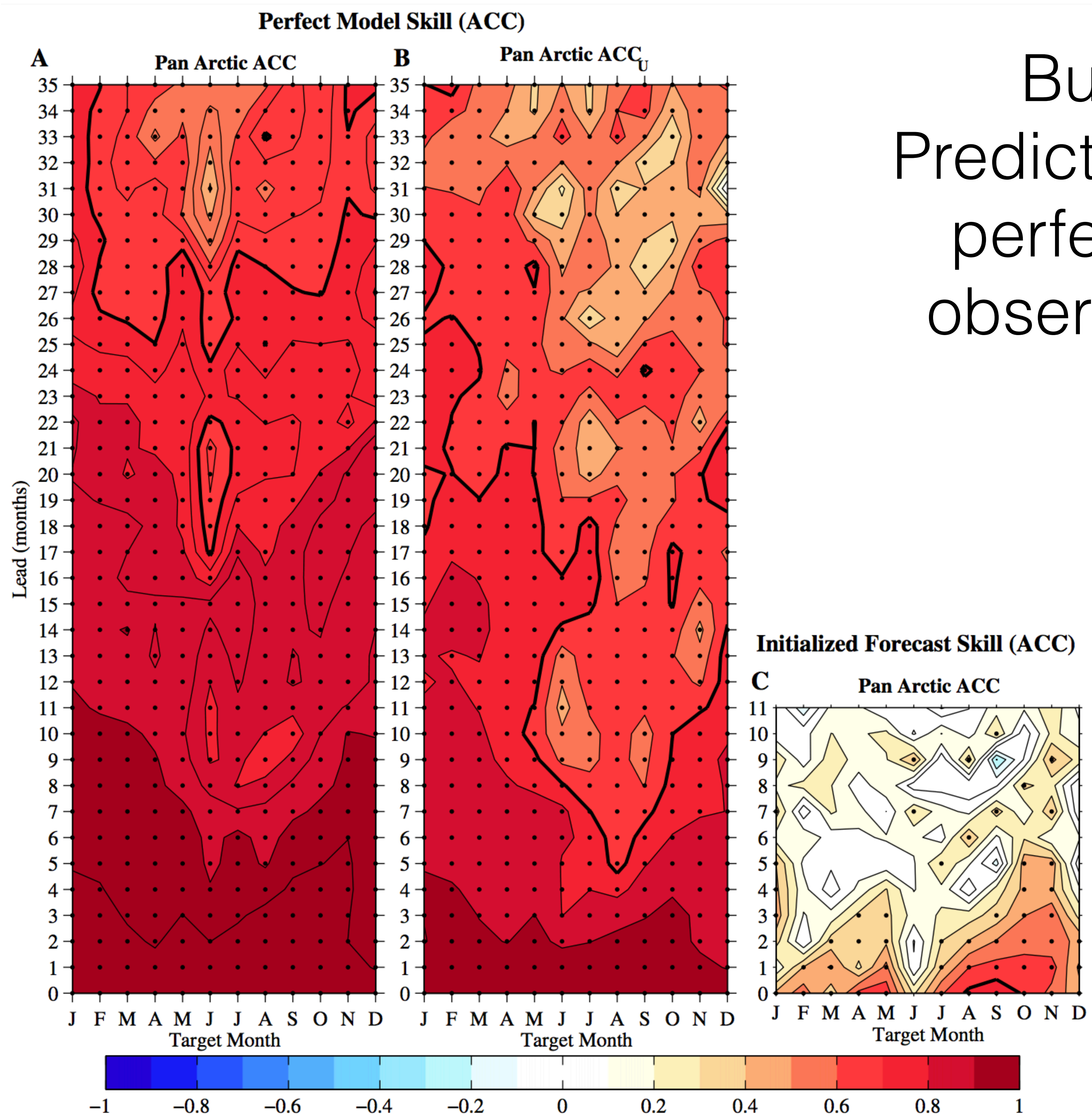

Bushuk et al 2018
Predictability gap between perfect model skill and observational skill **<u>using same model</u>**
Why?

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

Remember…

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

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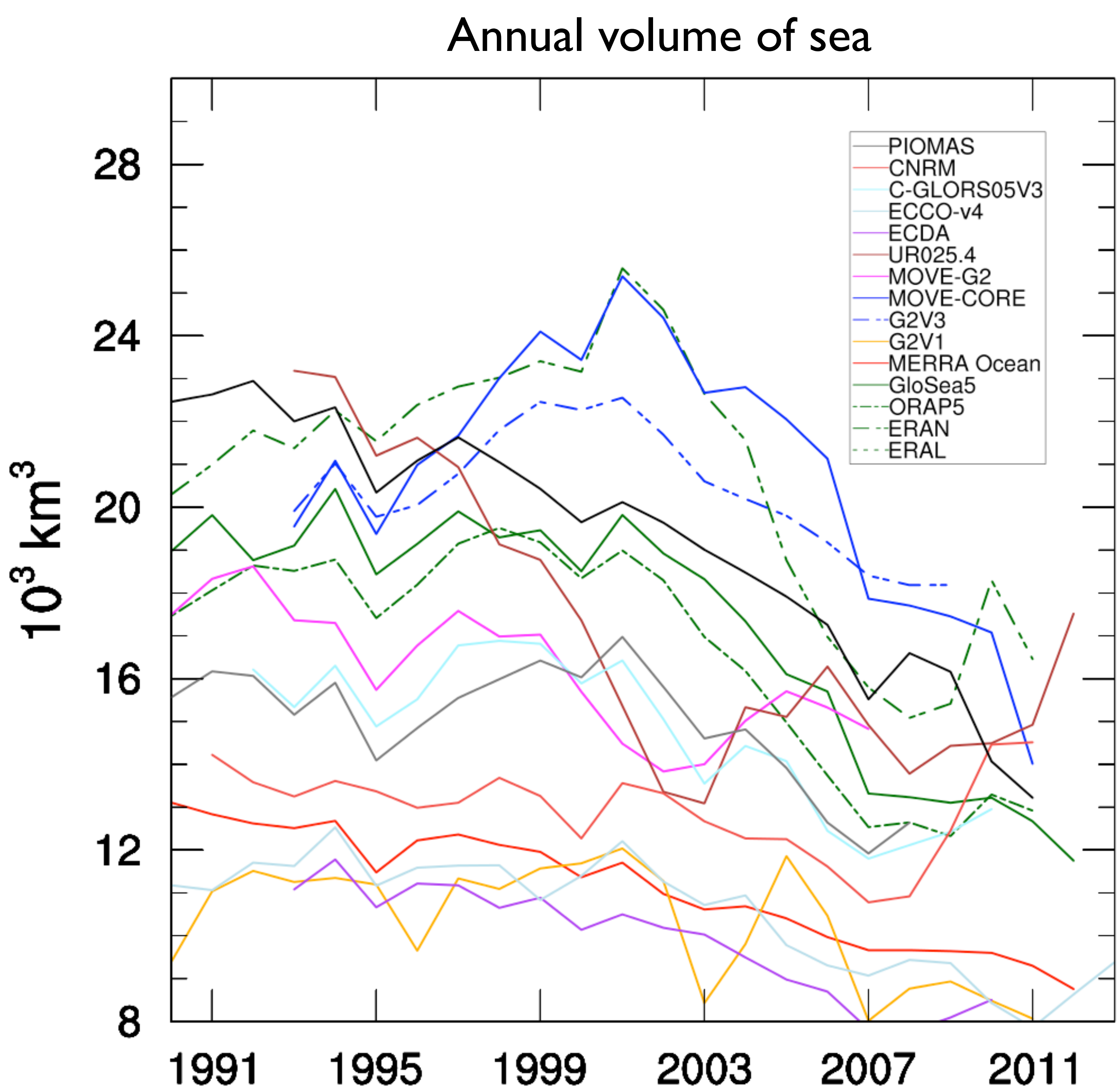
Good models, but poor observations* (i.e., Initial Conditions)

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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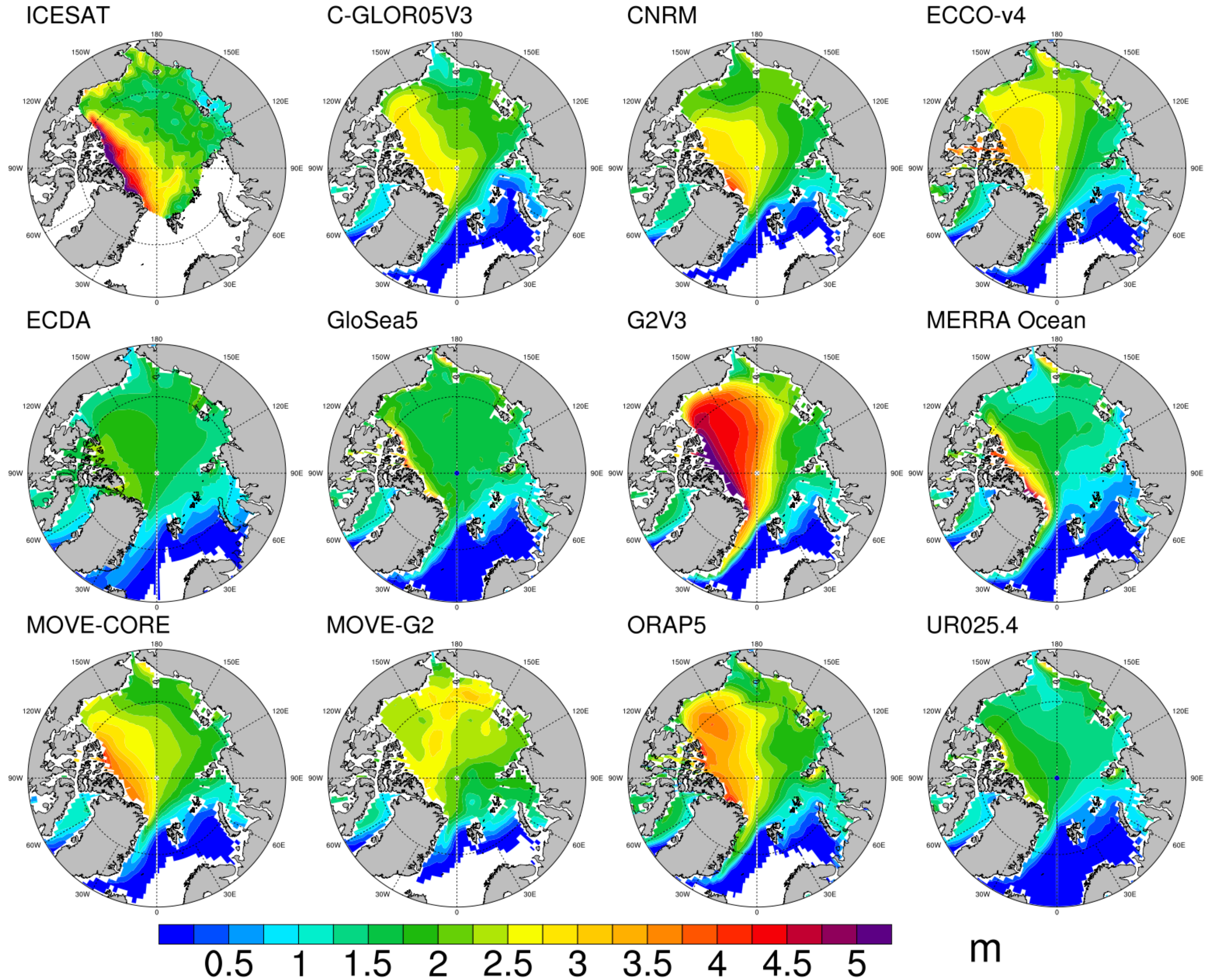
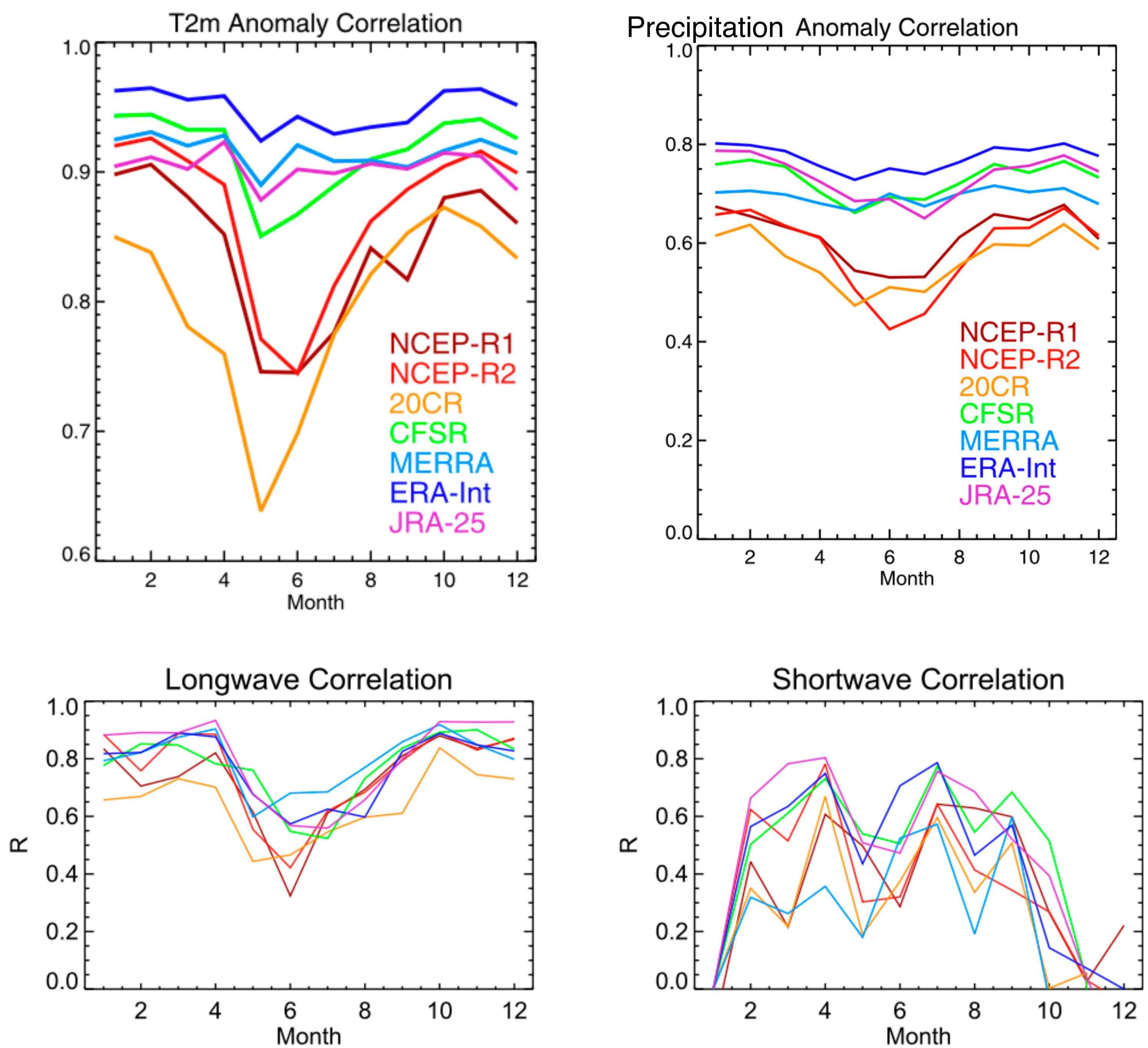


Chevallier et al (2016)

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

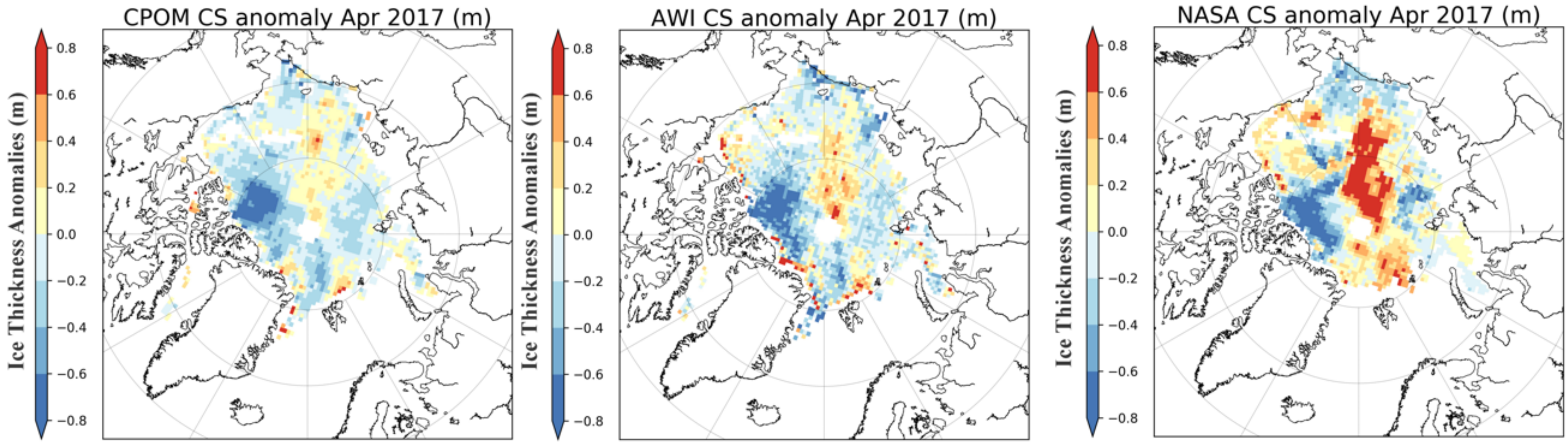
Atmospheric reanalysis in polar regions are known to have less fidelity than in other regions*



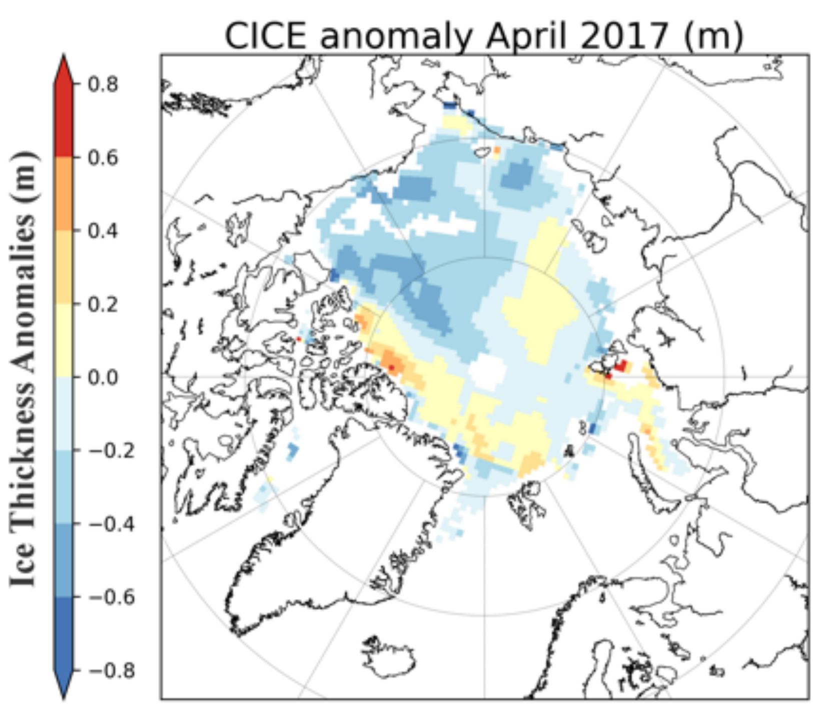
Lindsay et al 2014

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

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



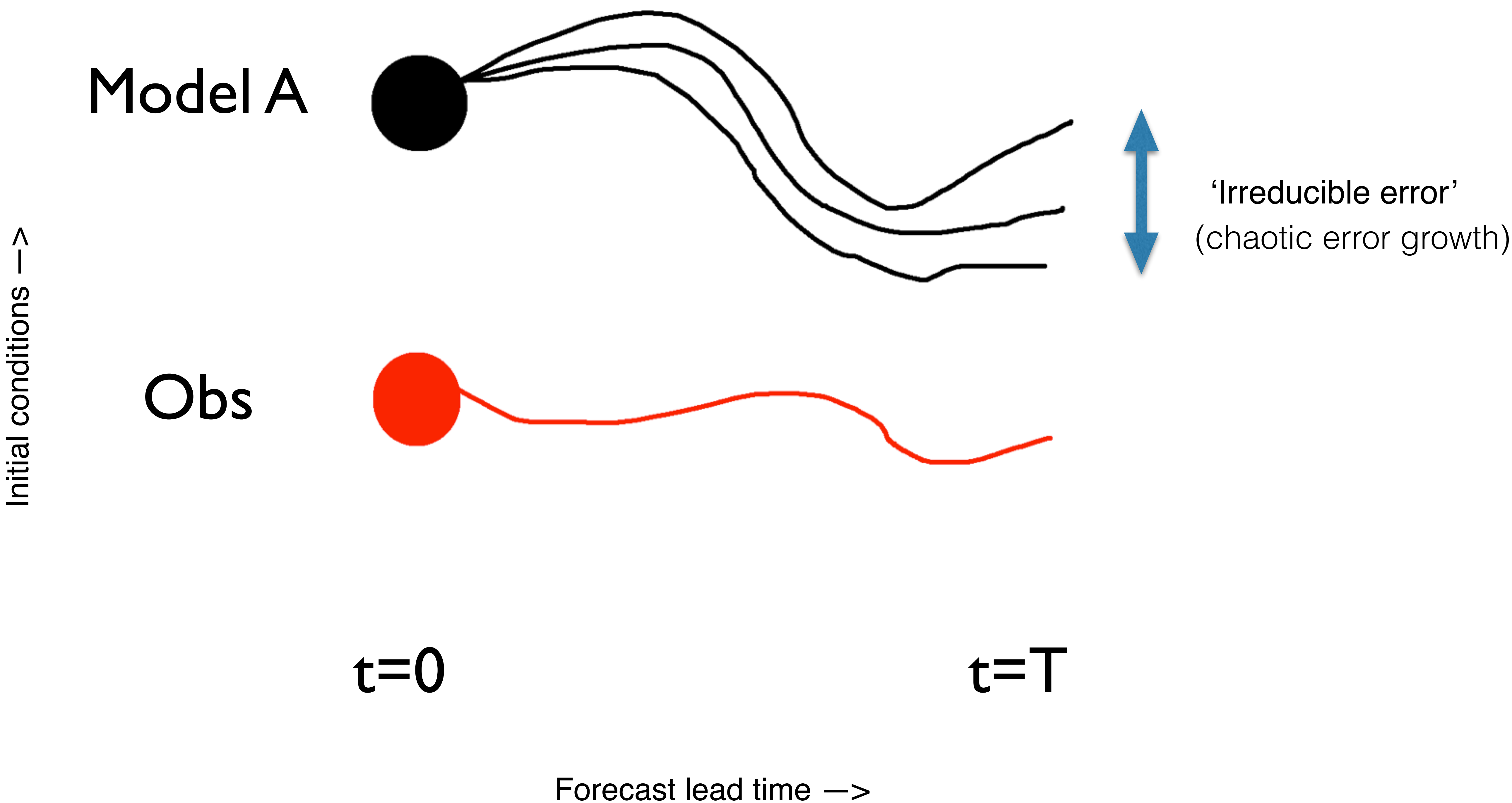
Sea ice thickness anomalies for April 2017 from 3 different algorithms using the same satellite sea ice freeboard retrievals



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

How good are the models?

On forecast uncertainty



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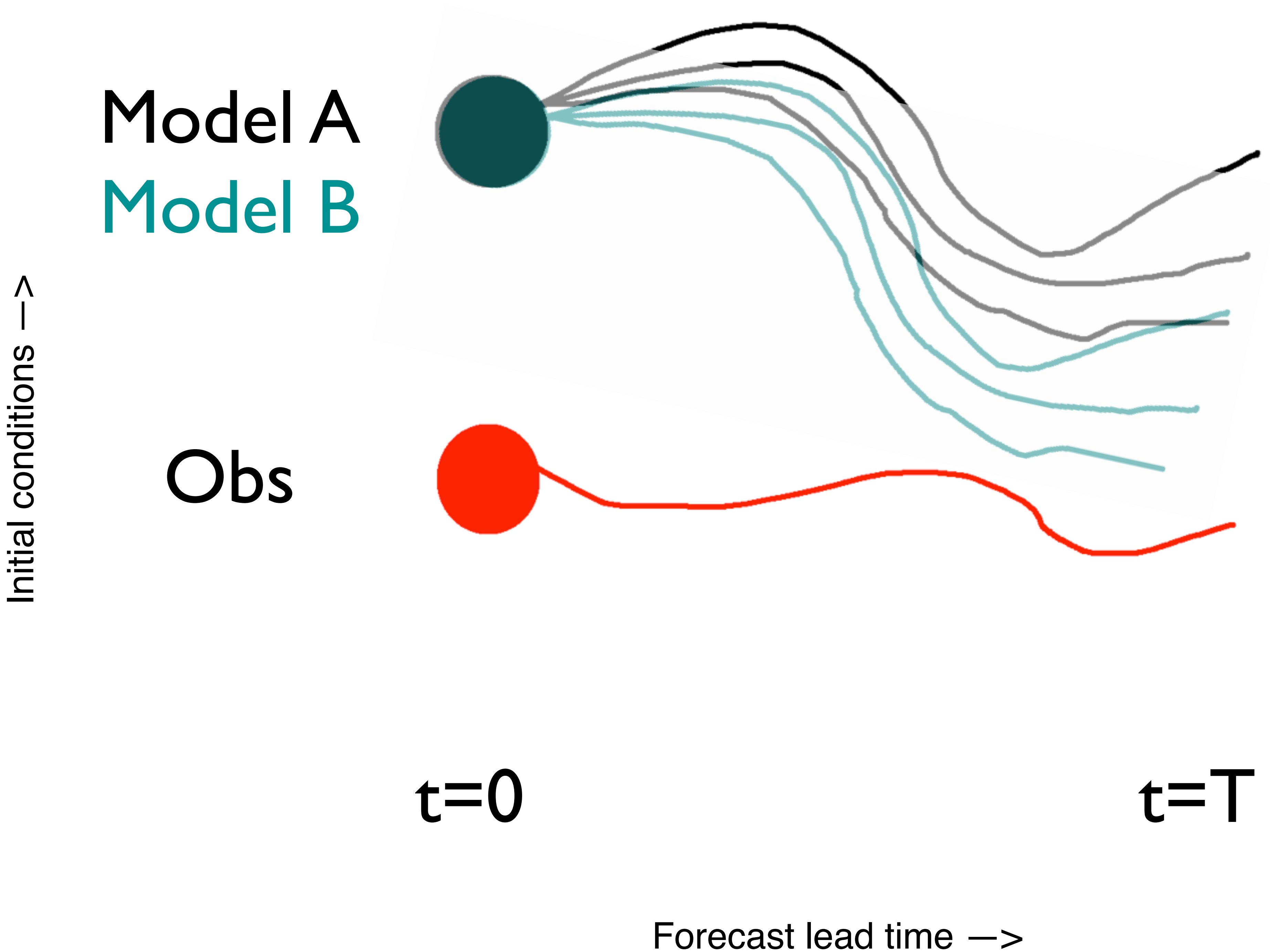

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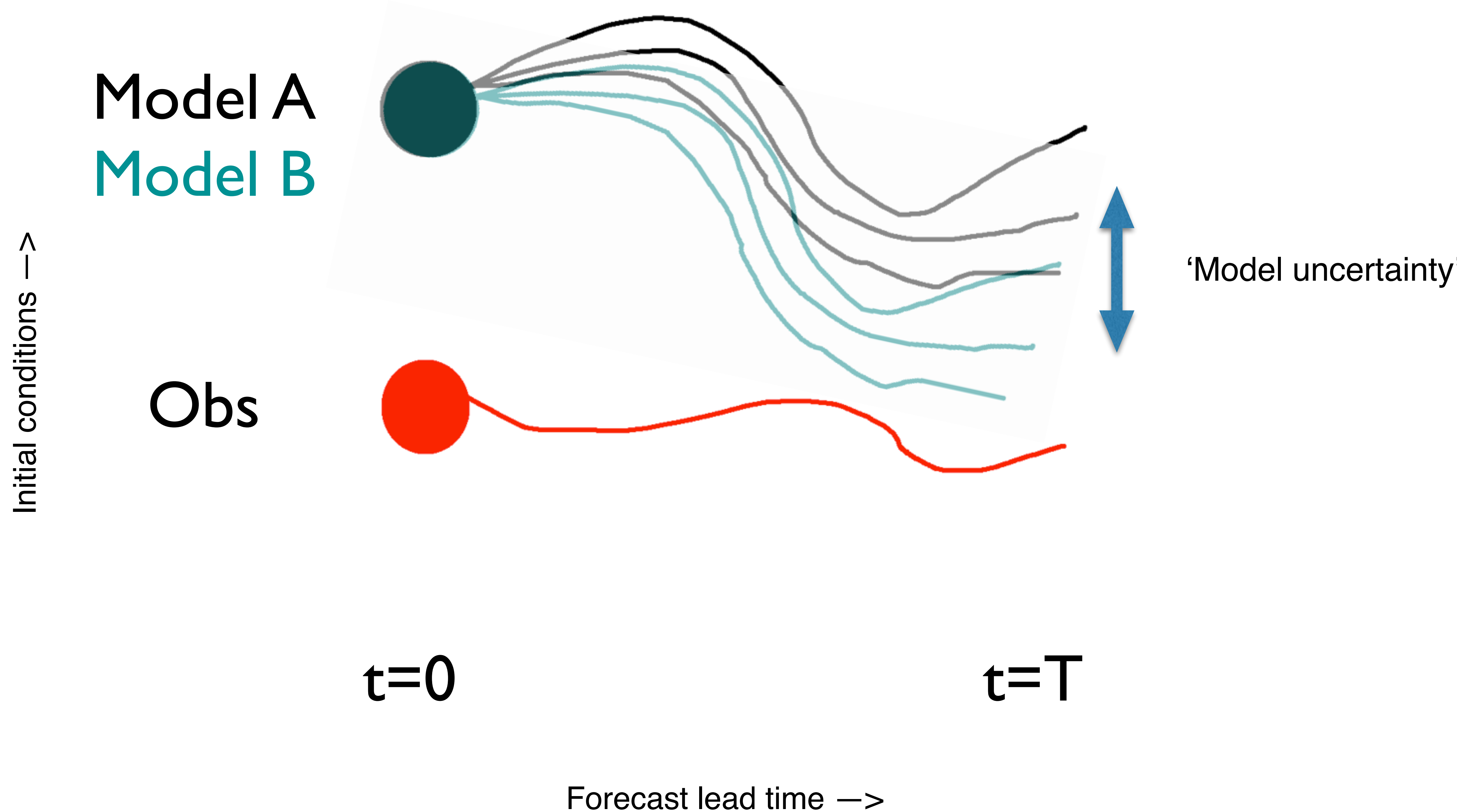

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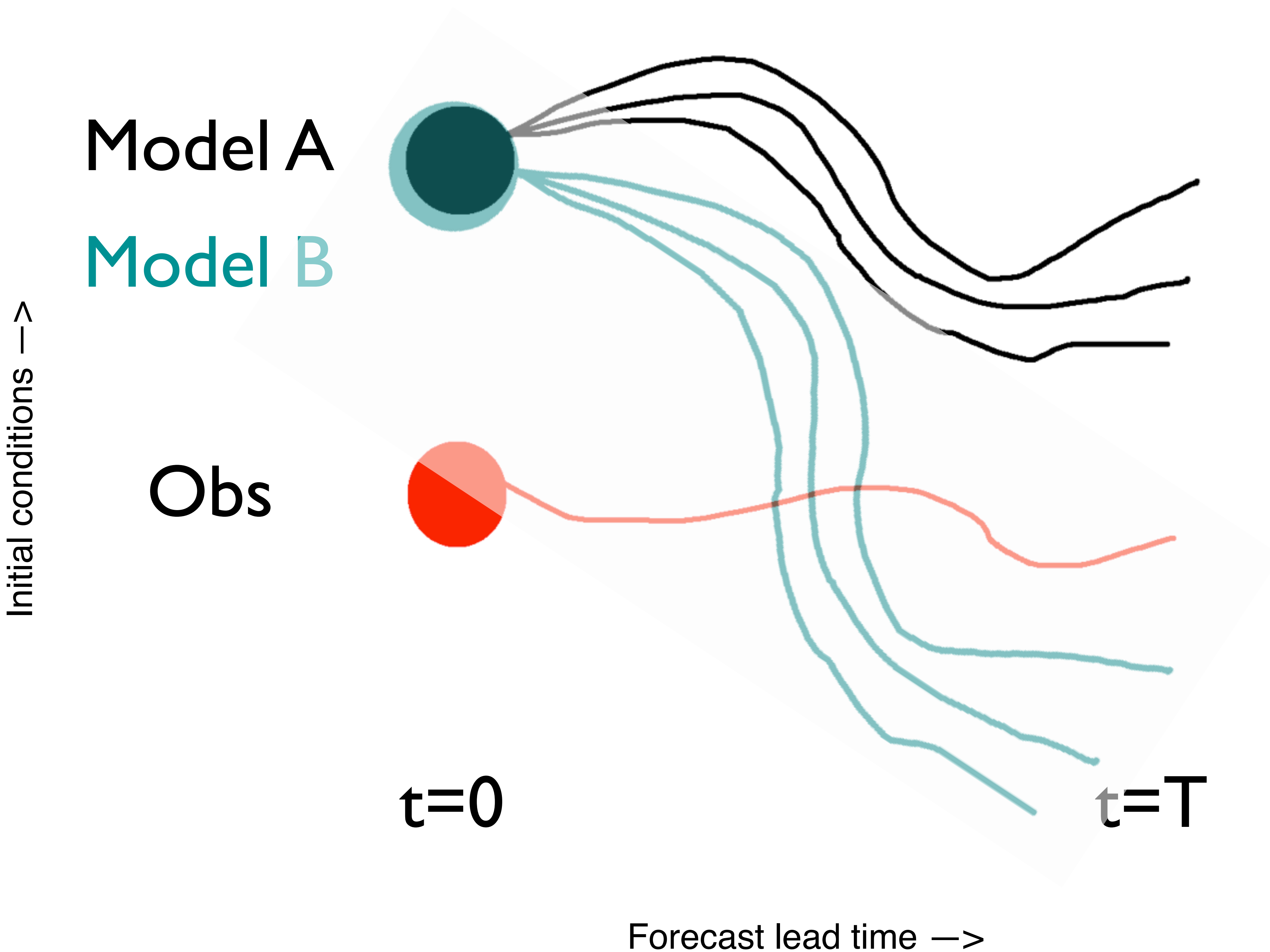
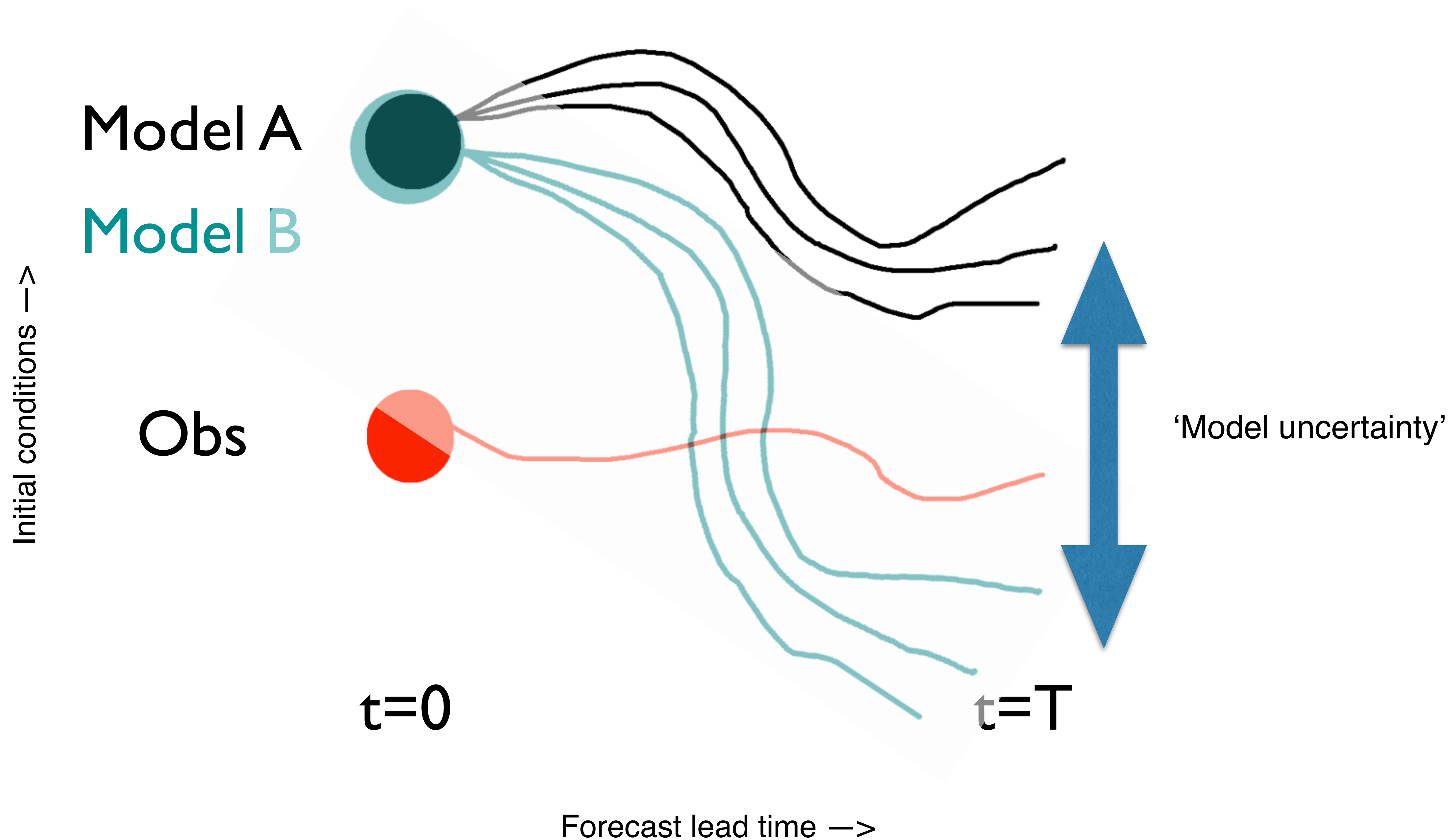


How good are the models?

On forecast uncertainty



Experiment -> Initialize SIO models with same ICs

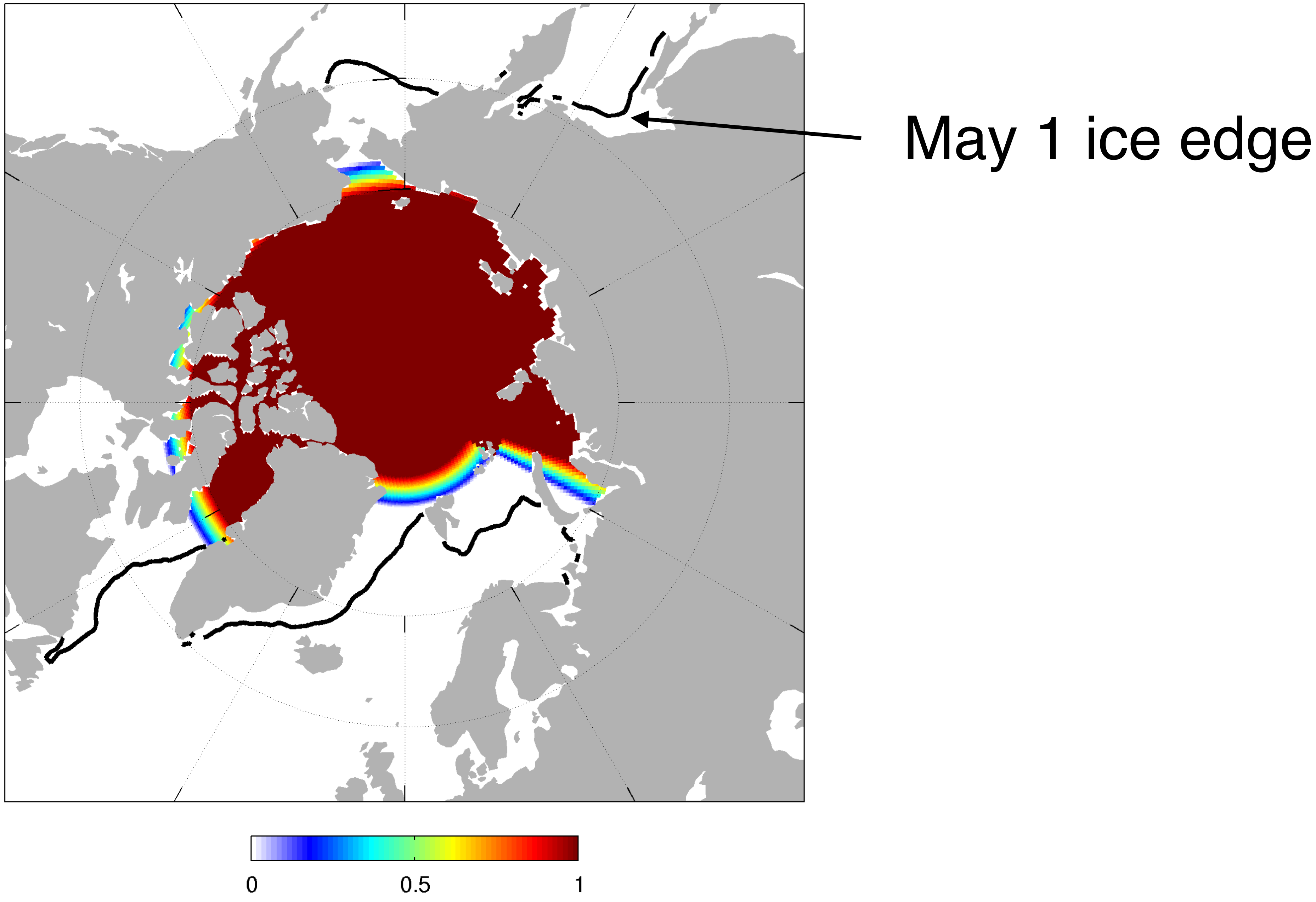
We build a control run, that uses climatological (2007-2014) PIOMAS May 1 sea ice thickness, and an experiment run, that uses 2015 May 1 sea ice thickness.

Model	Model type	Ensemble size
UCL (Barthelemy et al)	Global ice-ocean model forced with past atmosphere reanalysis	7
NRL (Posey et al)		10
PIOMAS (Zhang & Lindsay)	Regional ice-ocean model forced with past atmosphere reanalysis	10
NCAR CCSM4 (BW et al)	Global 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 (Fuckar et al)		20

Blanchard-W et al, 2016

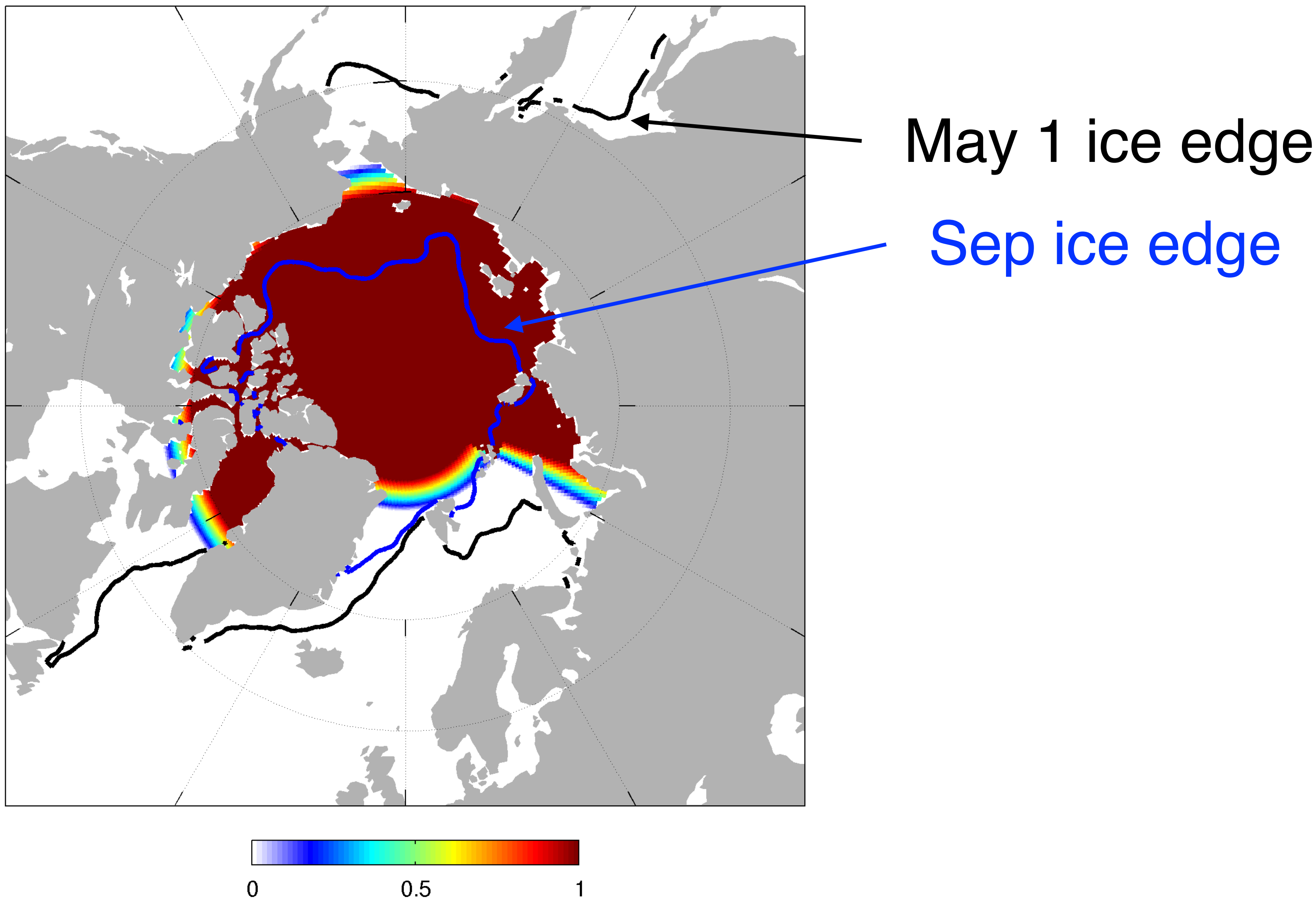
Control: mean May 1 2007-2014 sea ice thickness in Arctic basin

Experiment: May 1 2015 sea ice thickness in Arctic basin



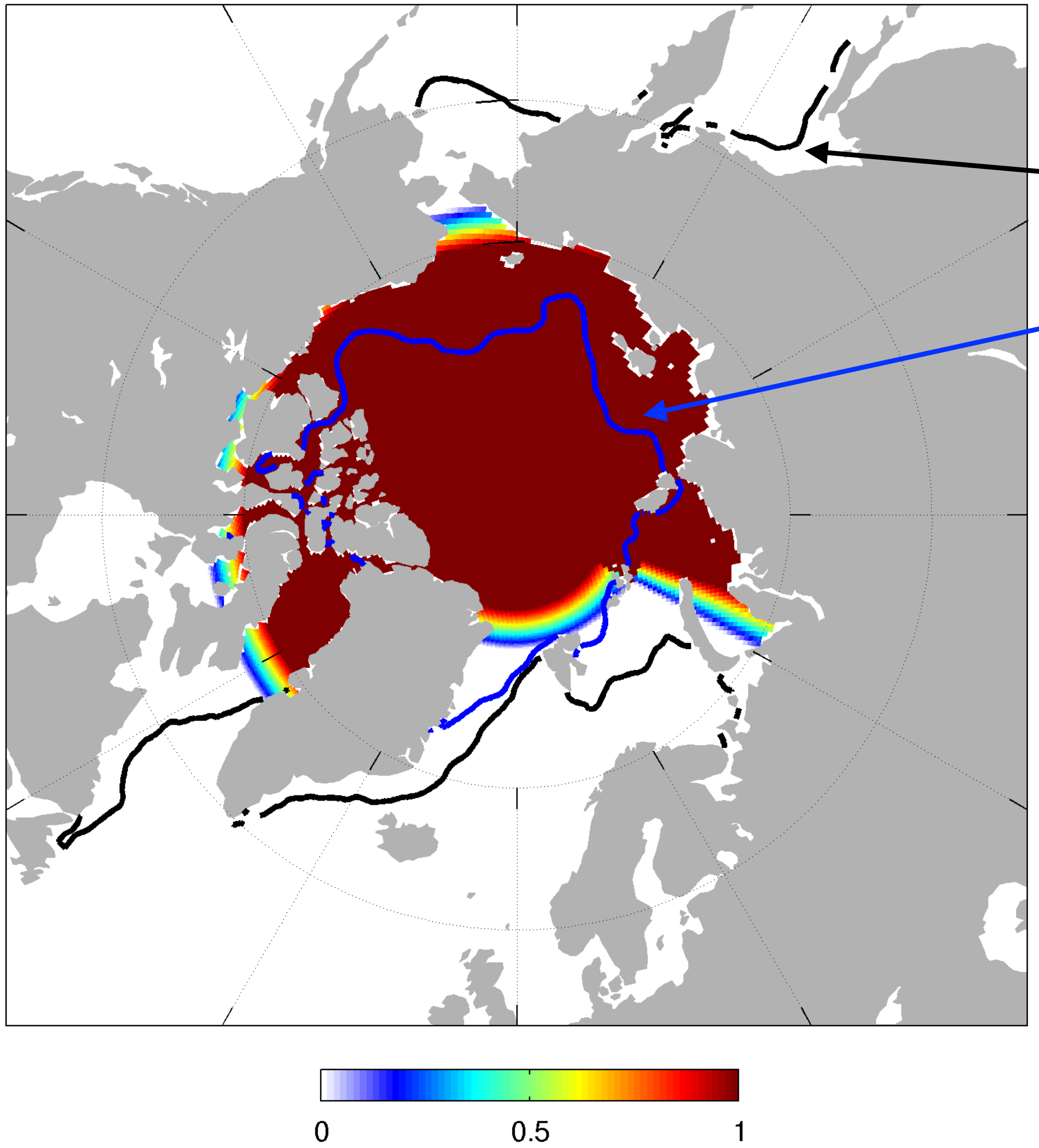
Control: mean May 1 2007-2014 sea ice thickness in Arctic basin

Experiment: May 1 2015 sea ice thickness in Arctic basin



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

Experiment: May 1 2015 sea ice thickness in Arctic basin



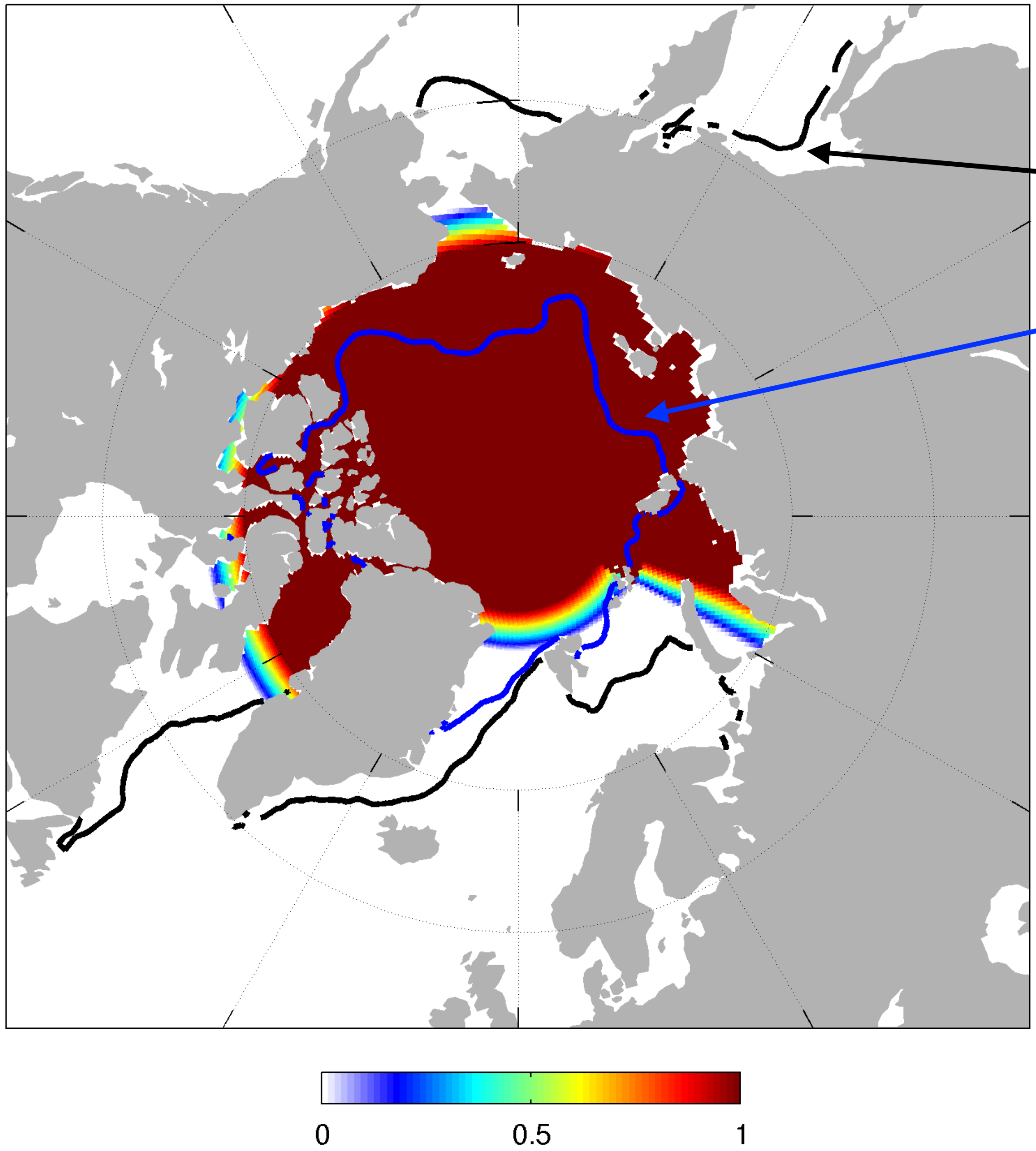
May 1 ice edge

Sep ice edge

No change in sea ice area between experiment & control ICs

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

Experiment: May 1 2015 sea ice thickness in Arctic basin



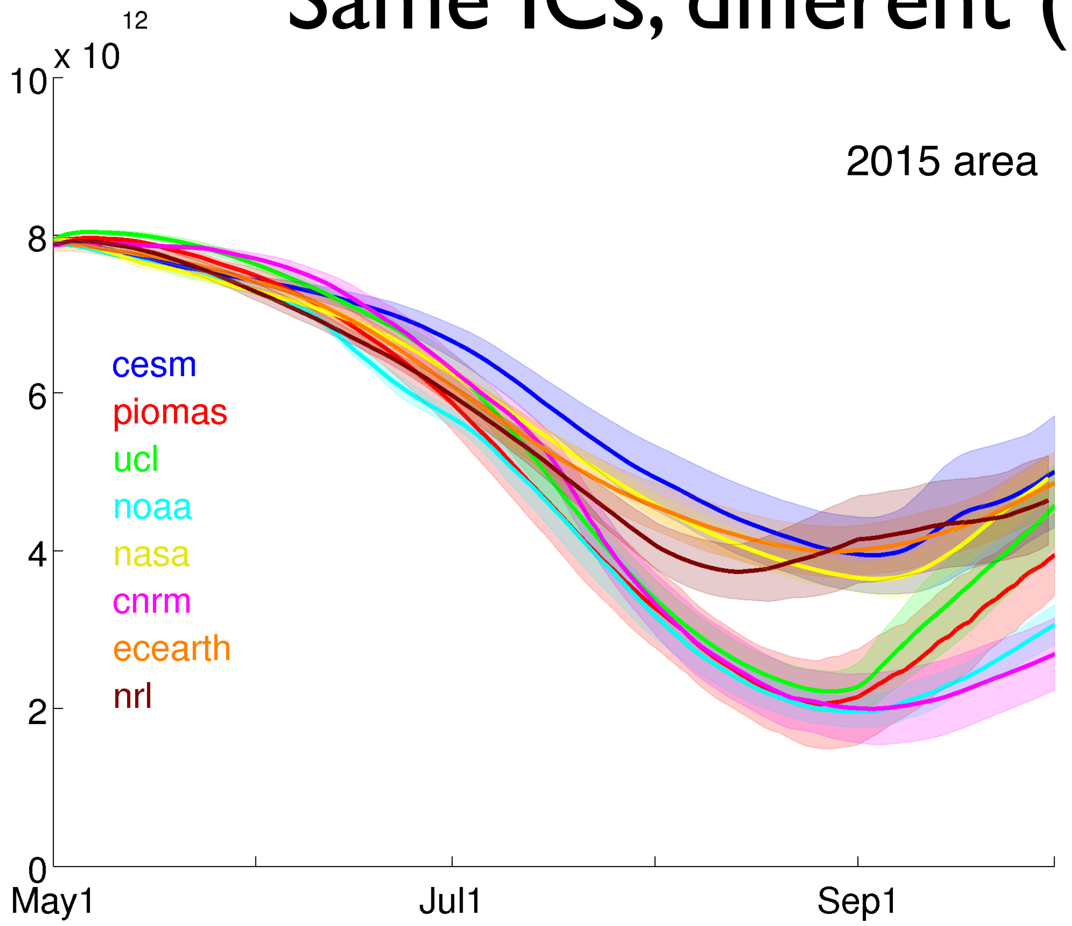
May 1 ice edge

Sep ice edge

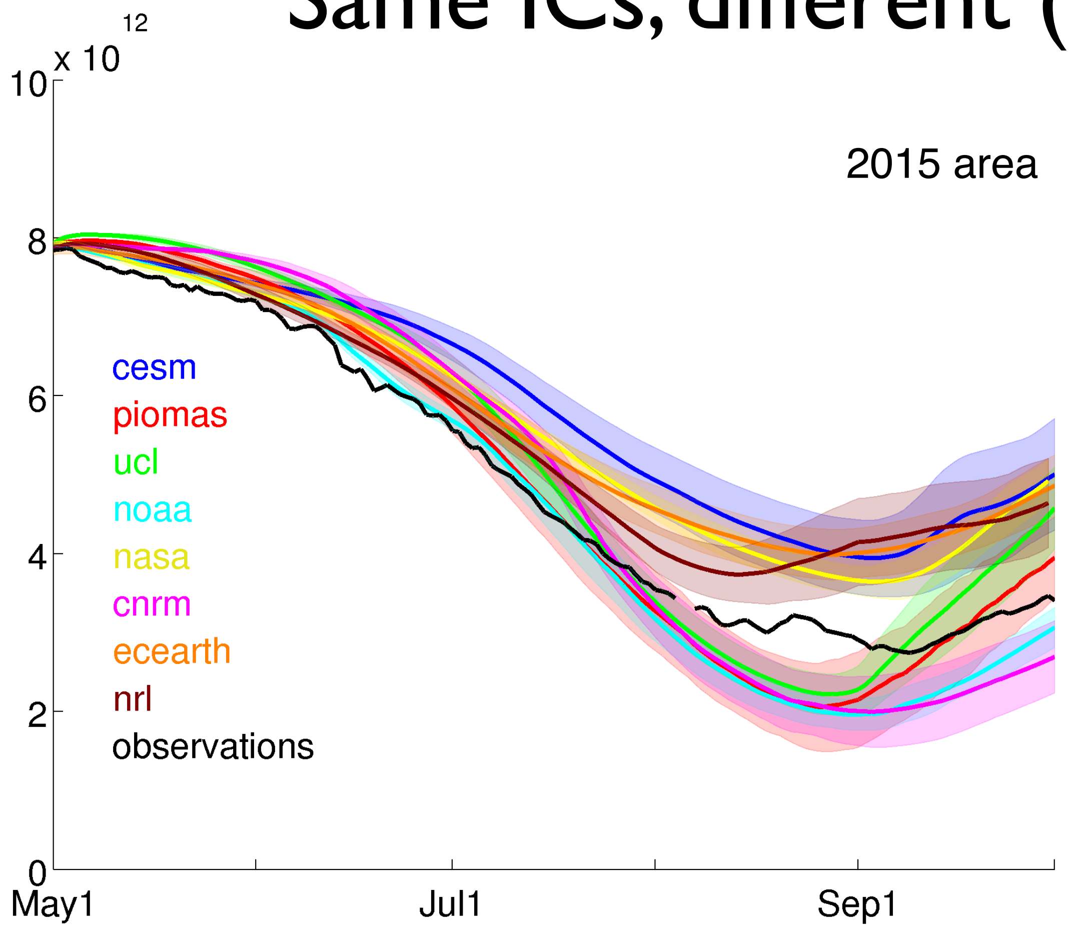
No change in sea ice area between experiment & control ICs

Spring thickness —> summer sea ice area

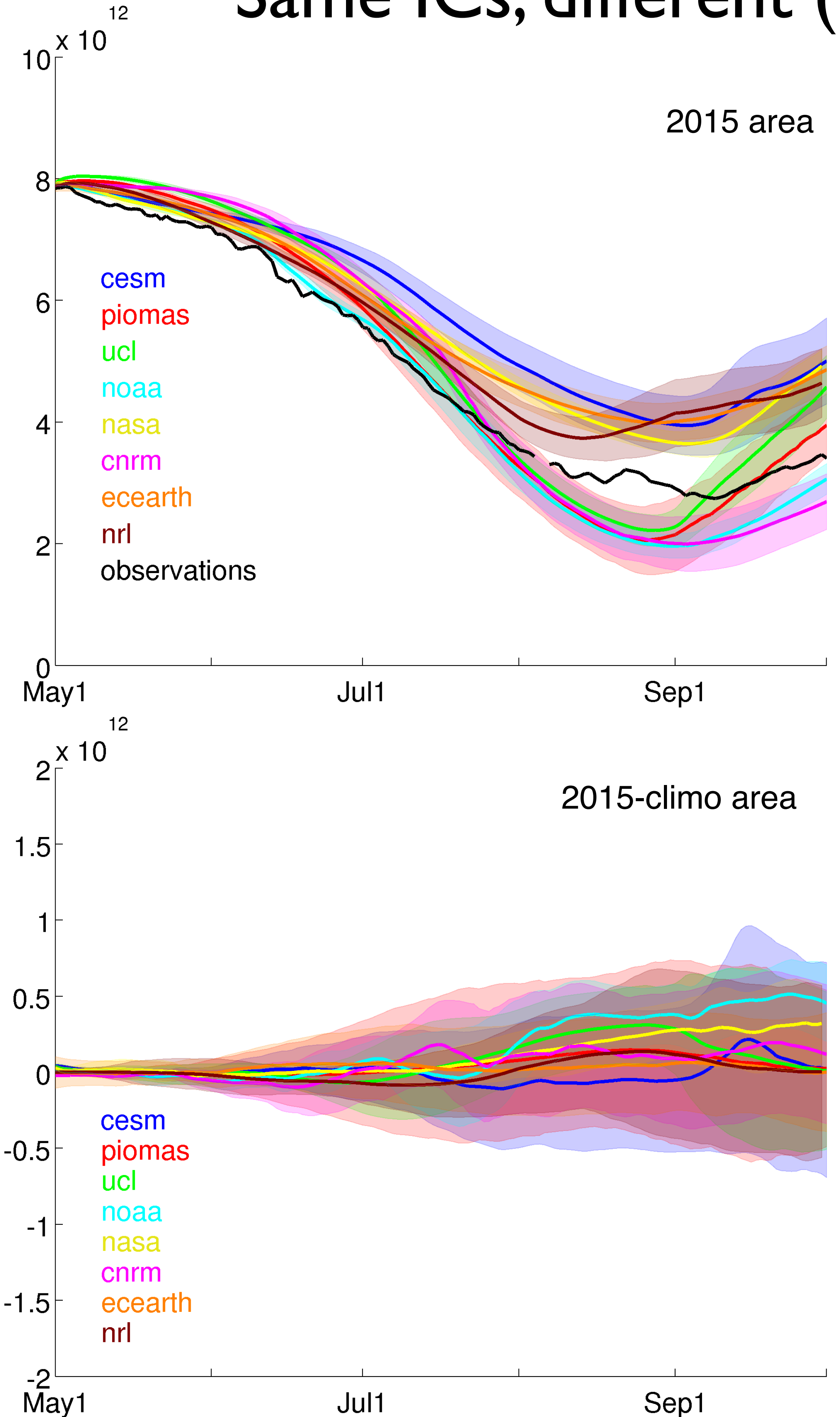
Same ICs, different (uncalibrated) forecasts!



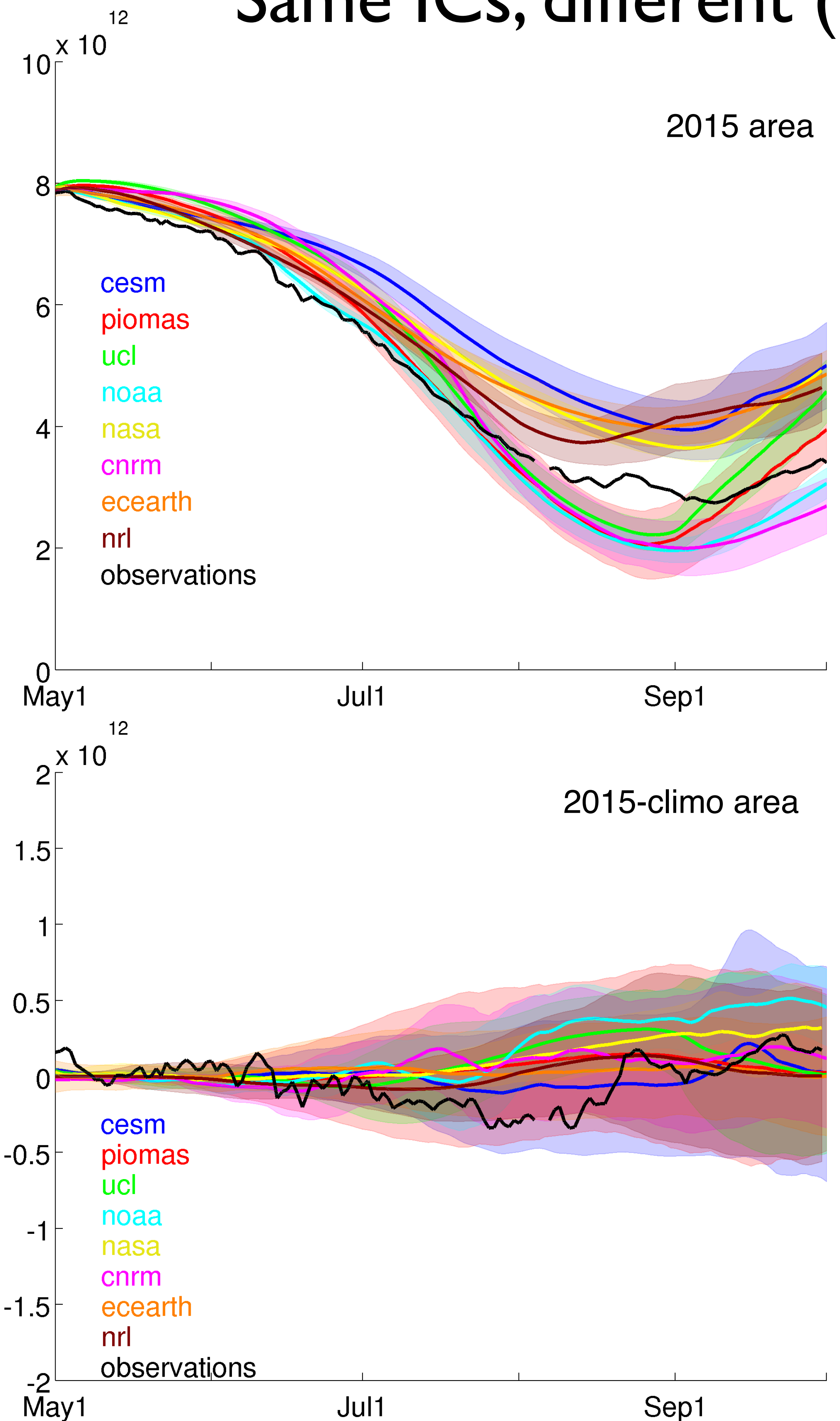
Same ICs, different (uncalibrated) forecasts!



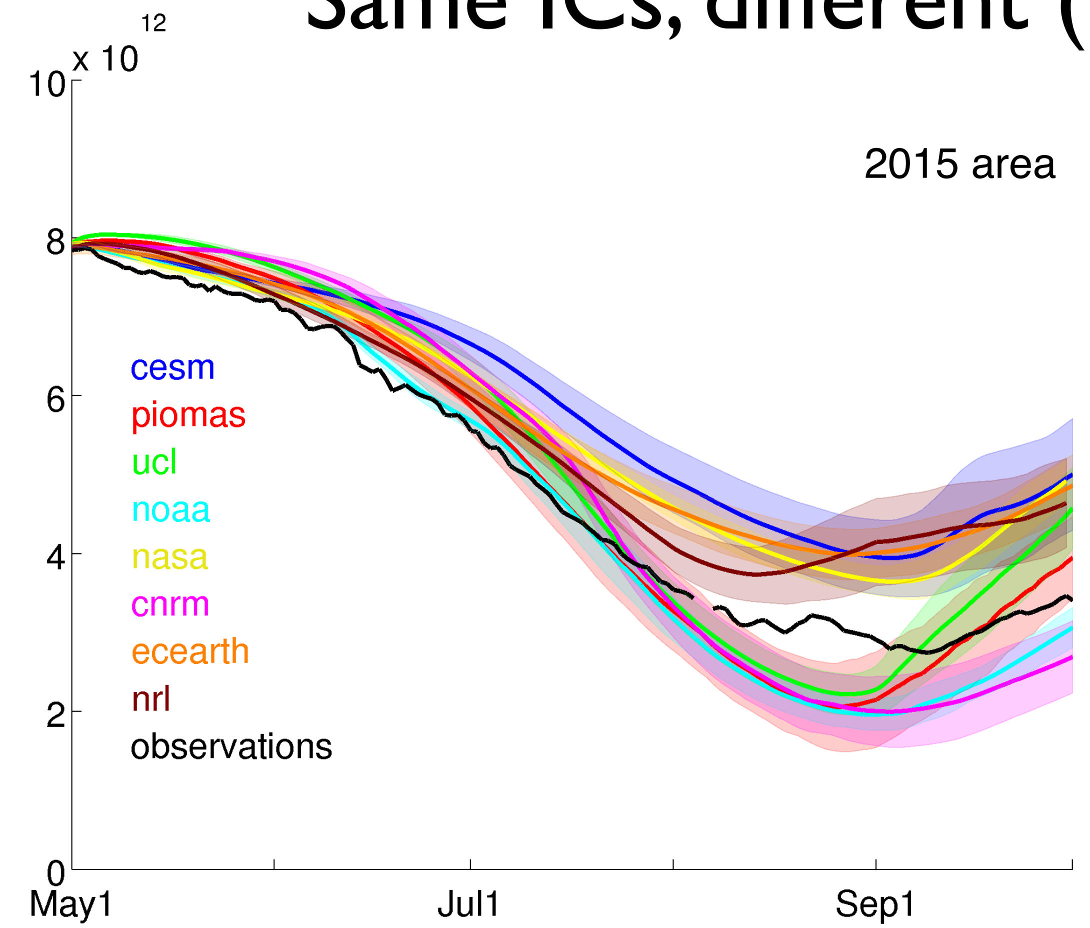
Same ICs, different (uncalibrated) forecasts!

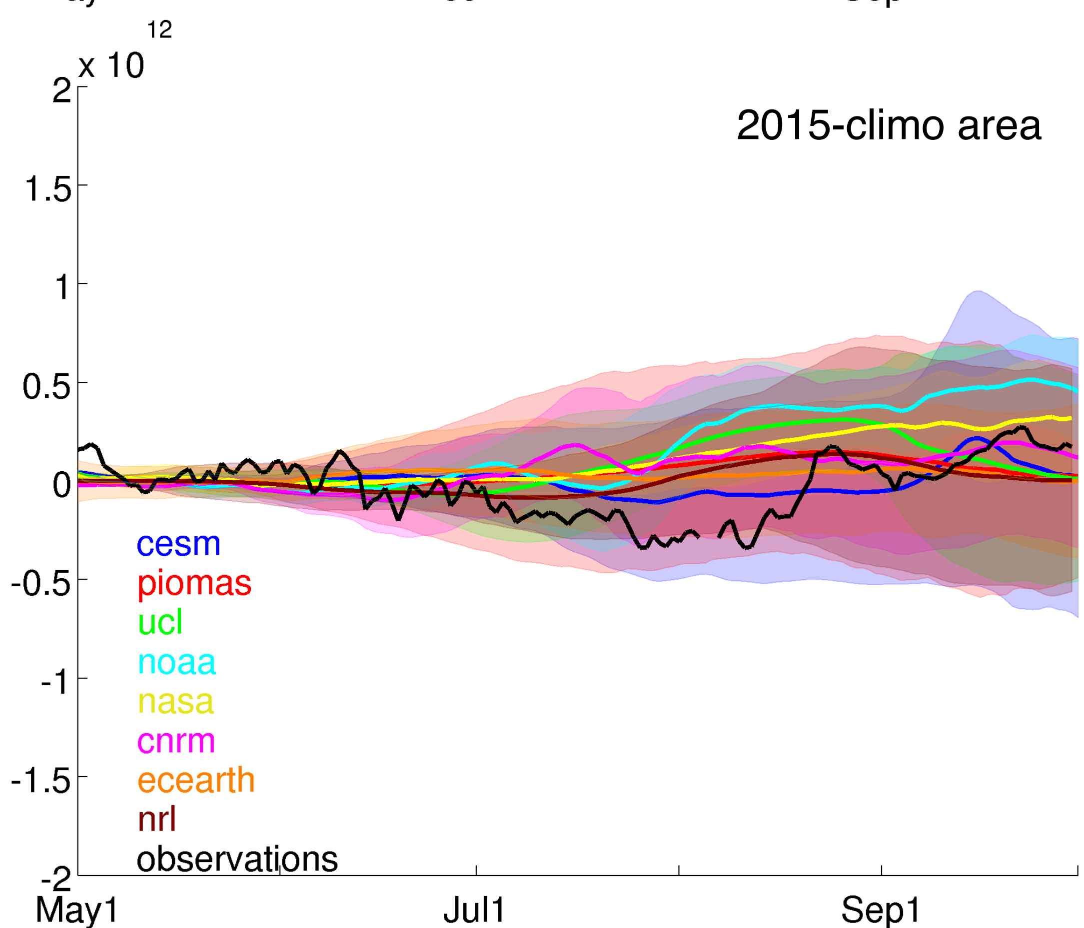


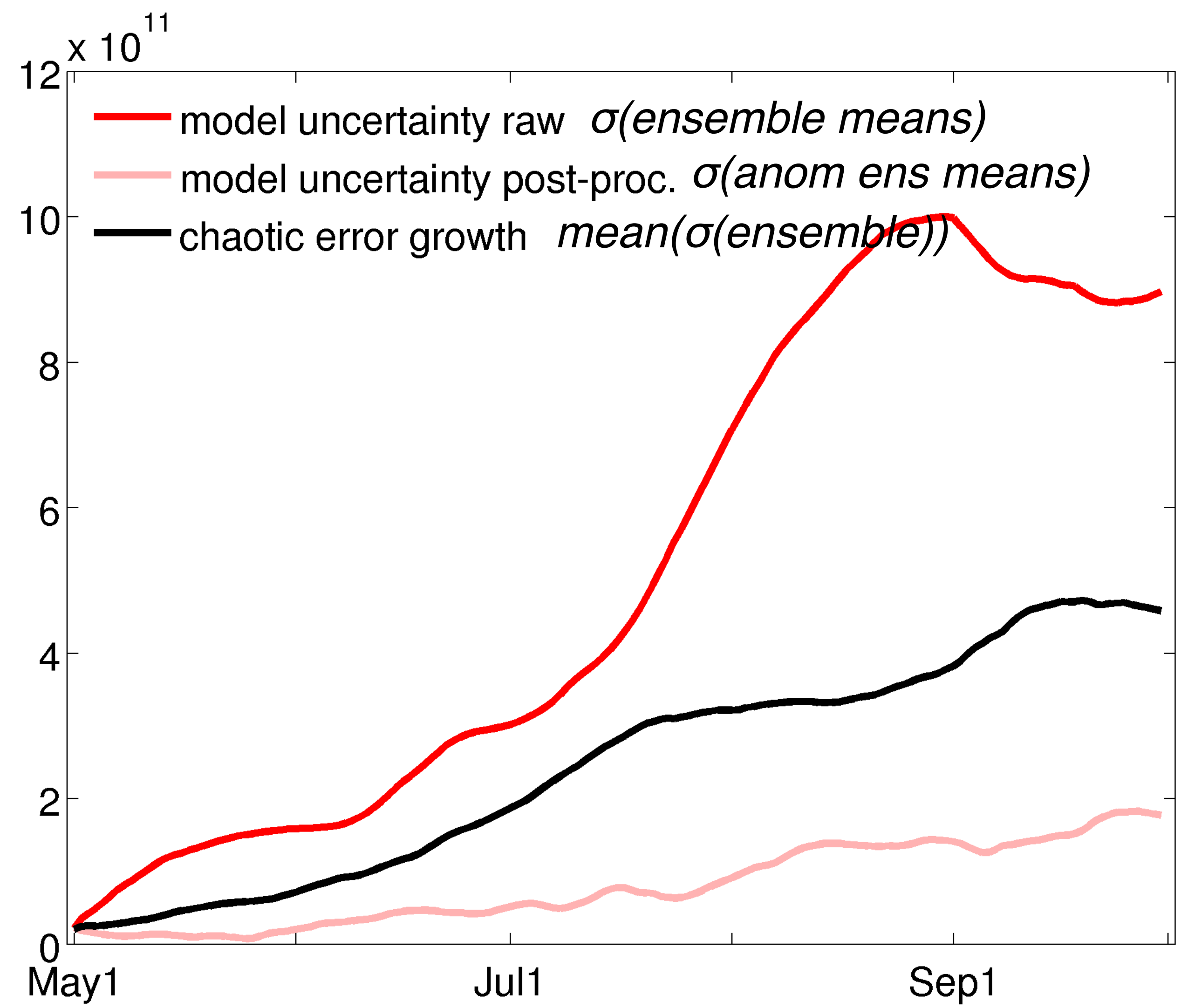
Same ICs, different (uncalibrated) forecasts!



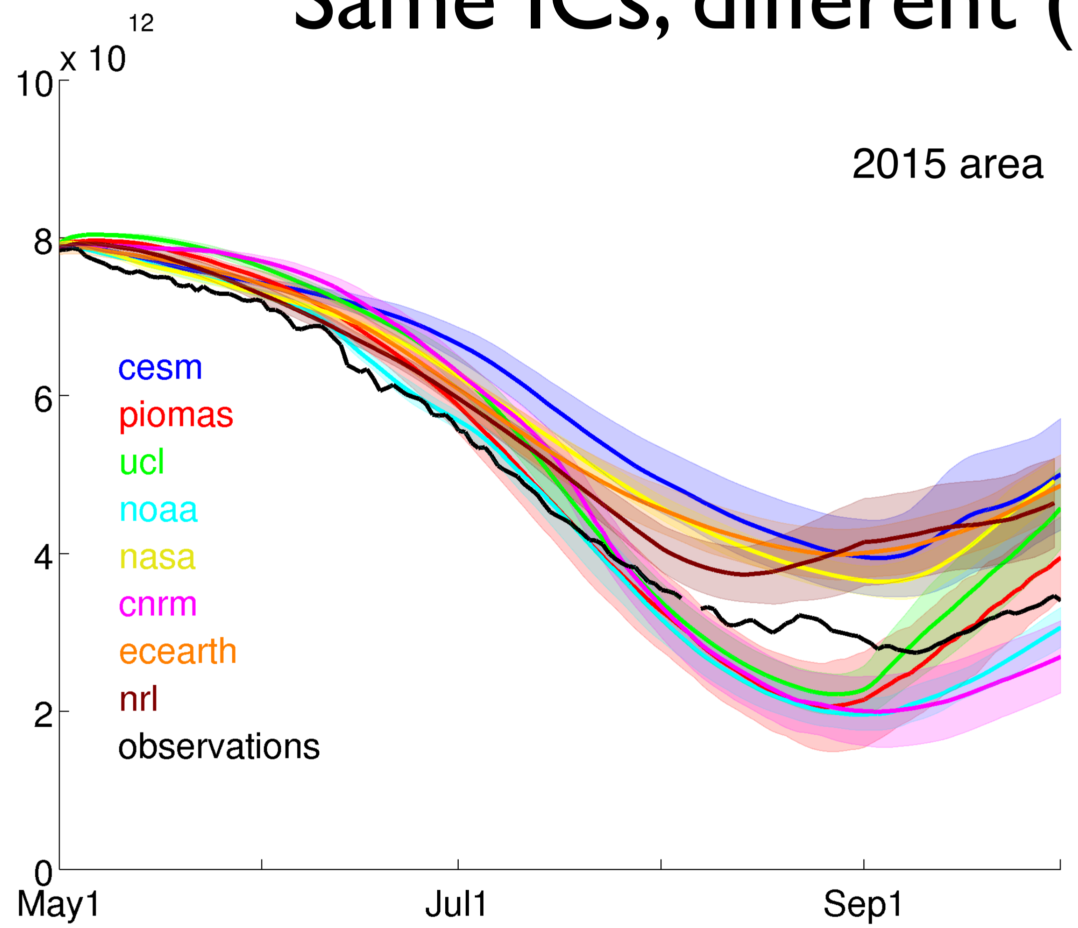
Same ICs, different (uncalibrated) forecasts!

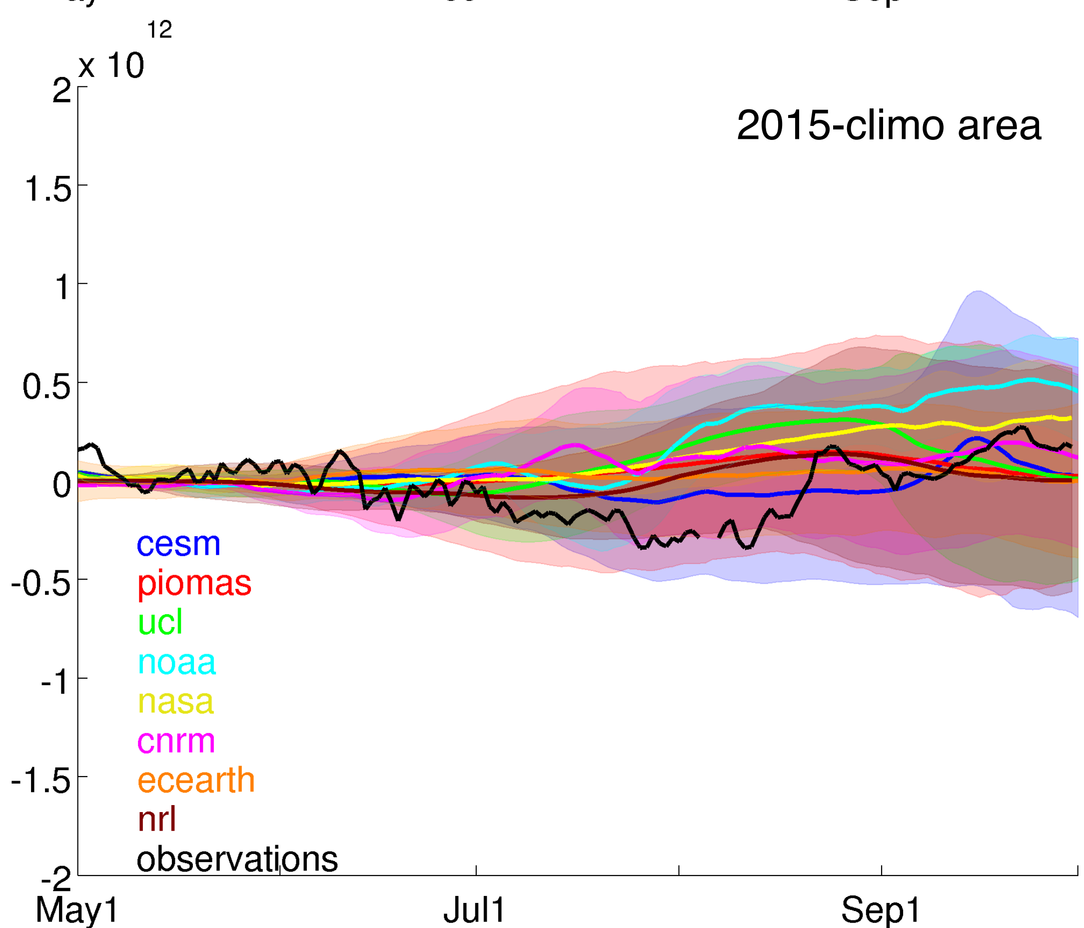


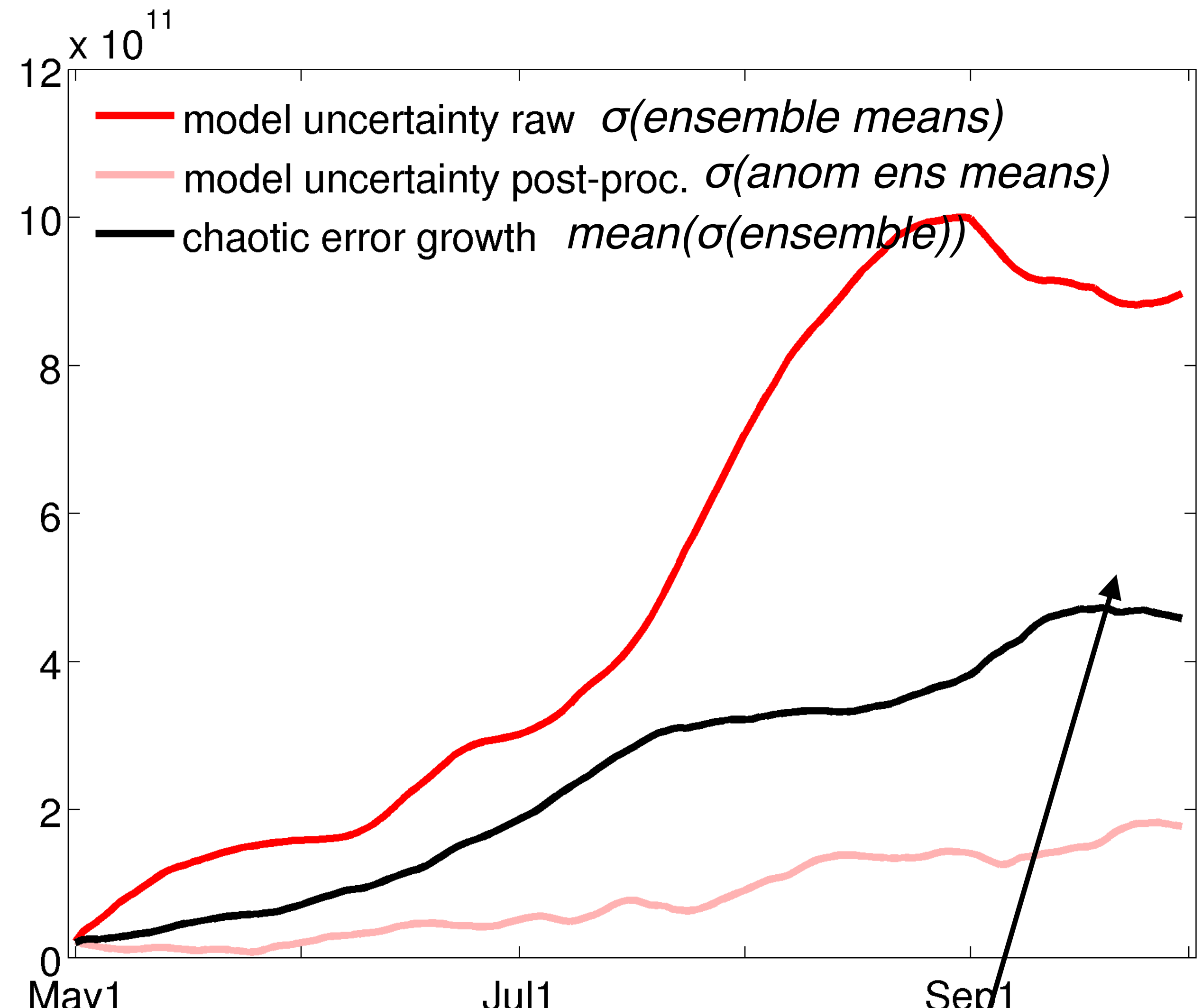




Same ICs, different (uncalibrated) forecasts!

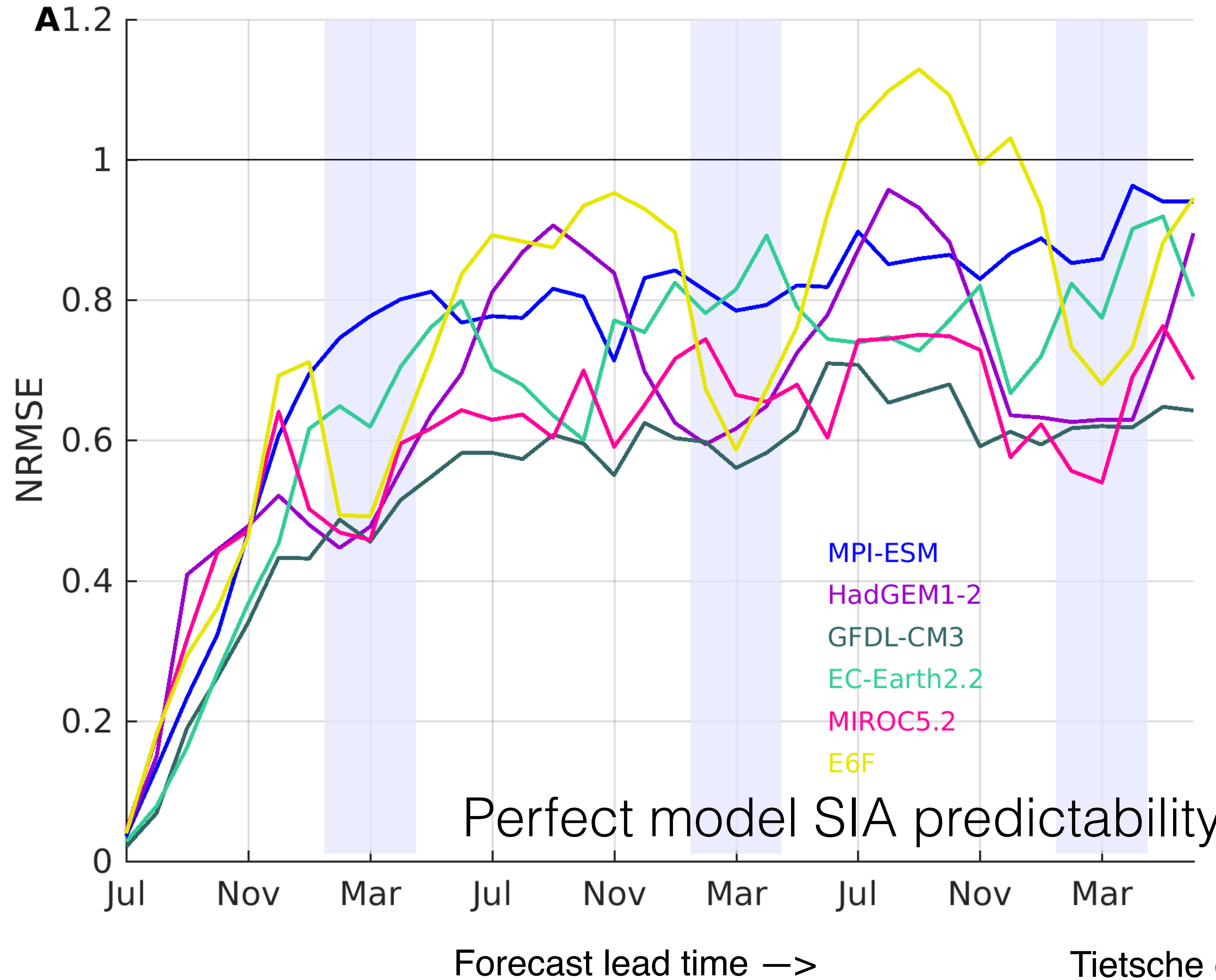






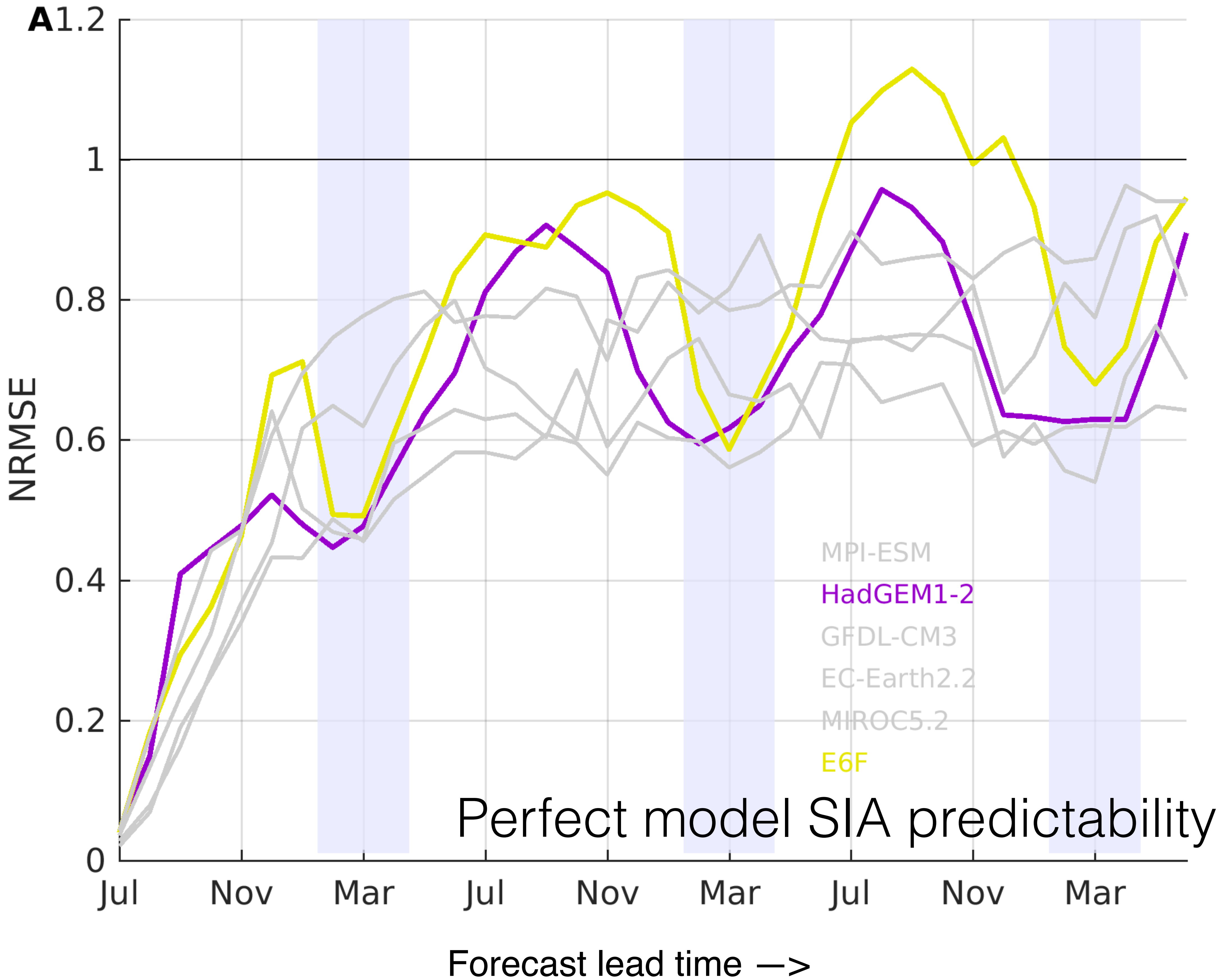
September standard dev. in obs ~5e11

Are the models too predictable?

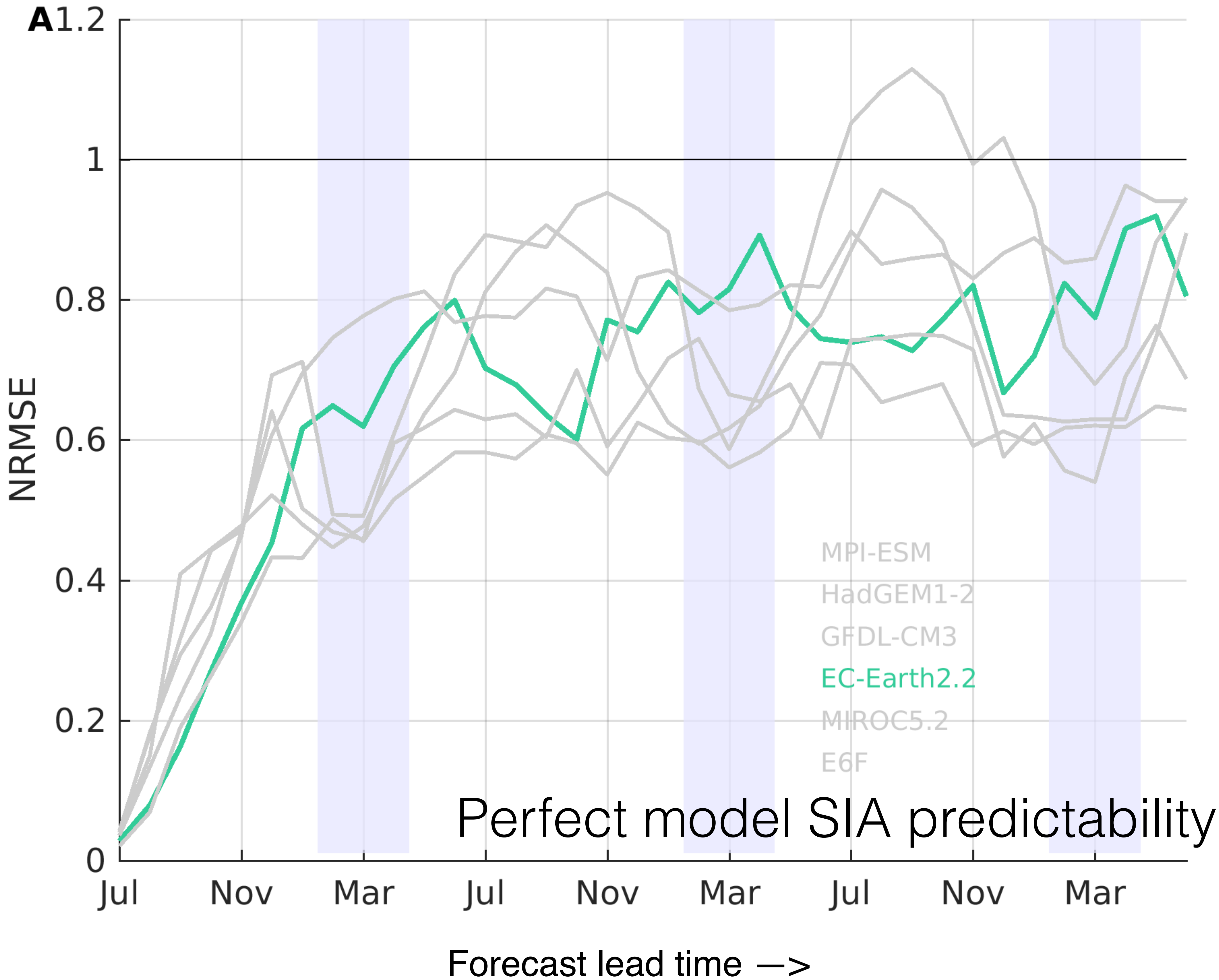


Tietsche et al, 2014;
Day et al 2015

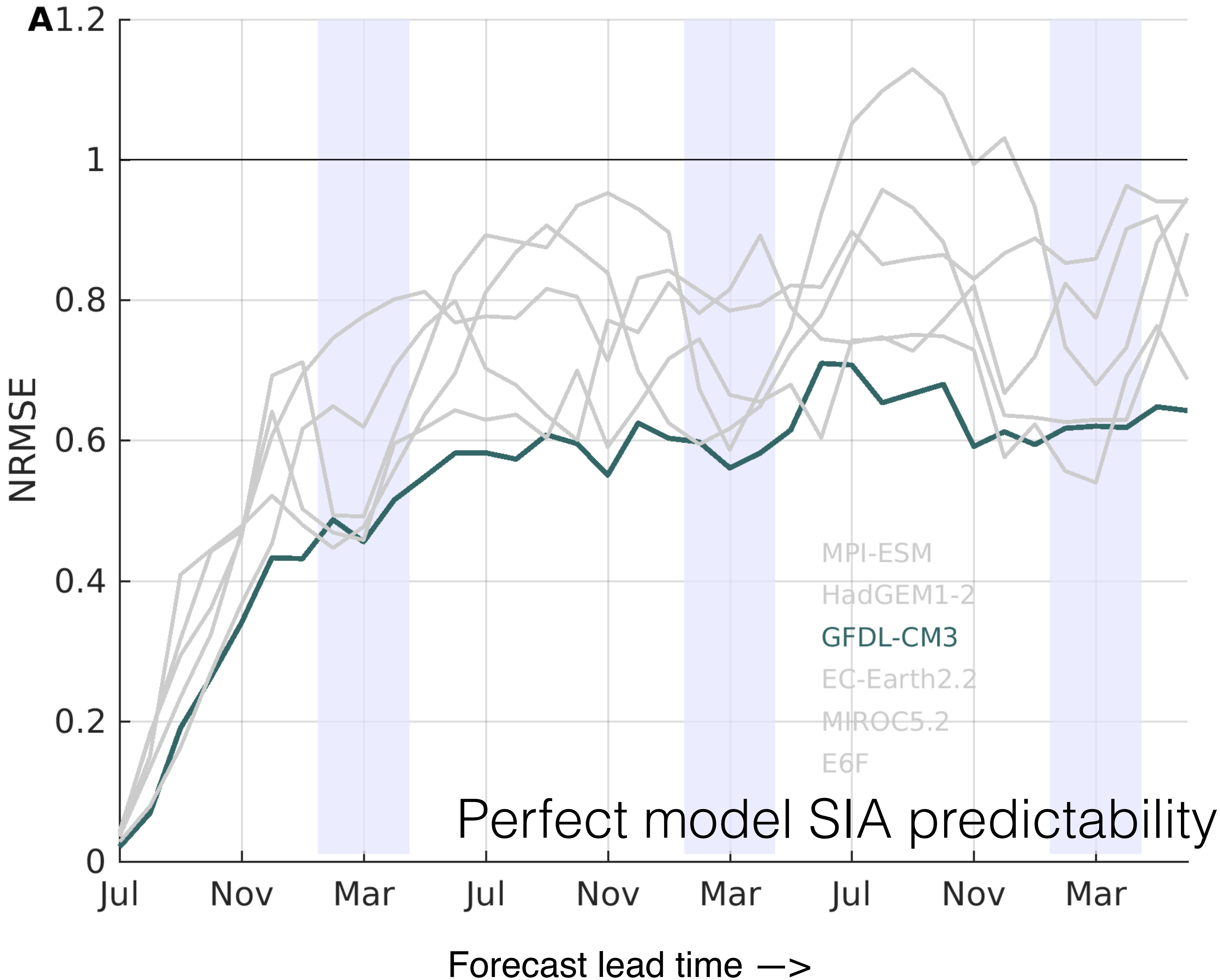
Are the models too predictable?



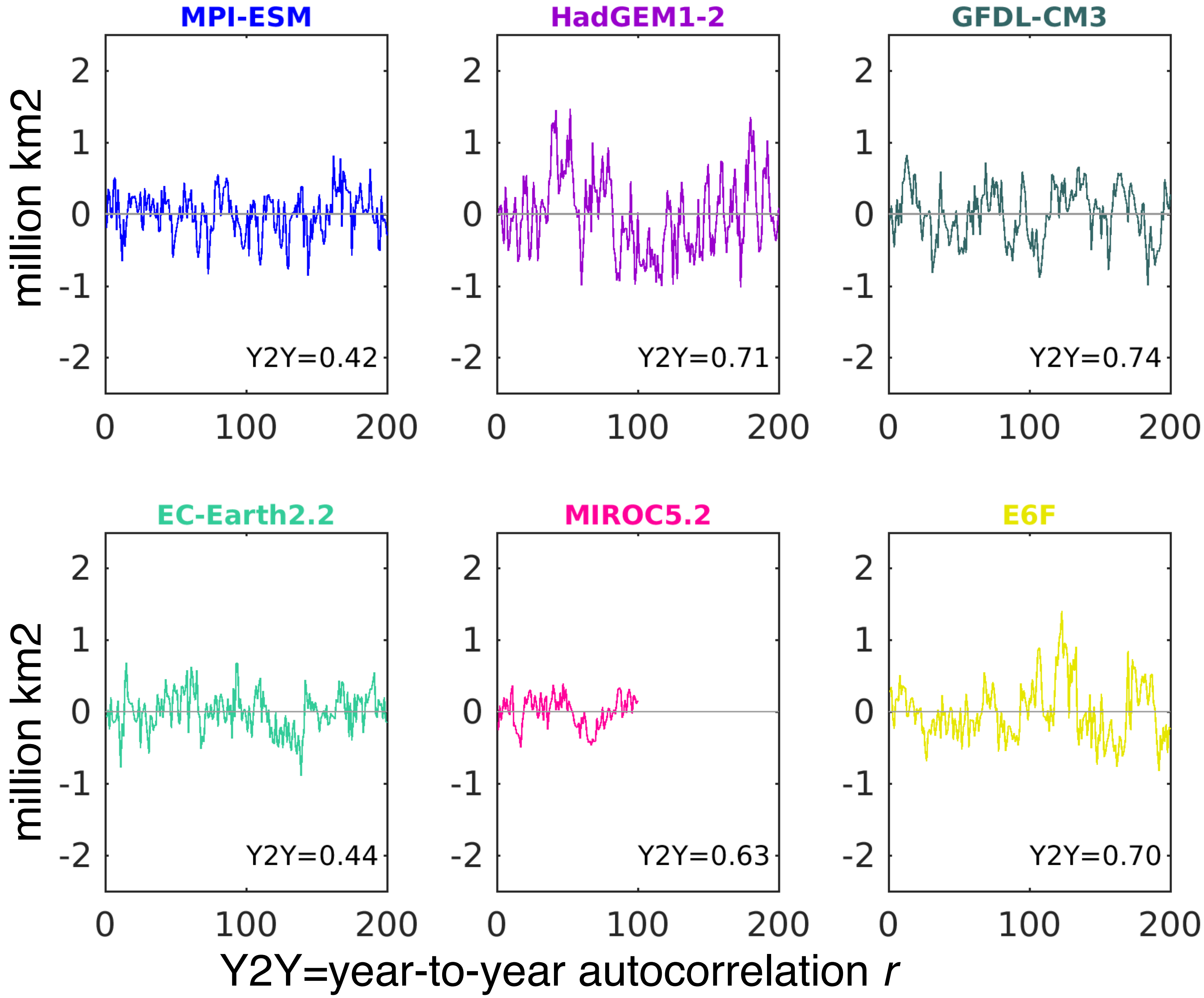
Are the models too predictable?



Are the models too predictable?

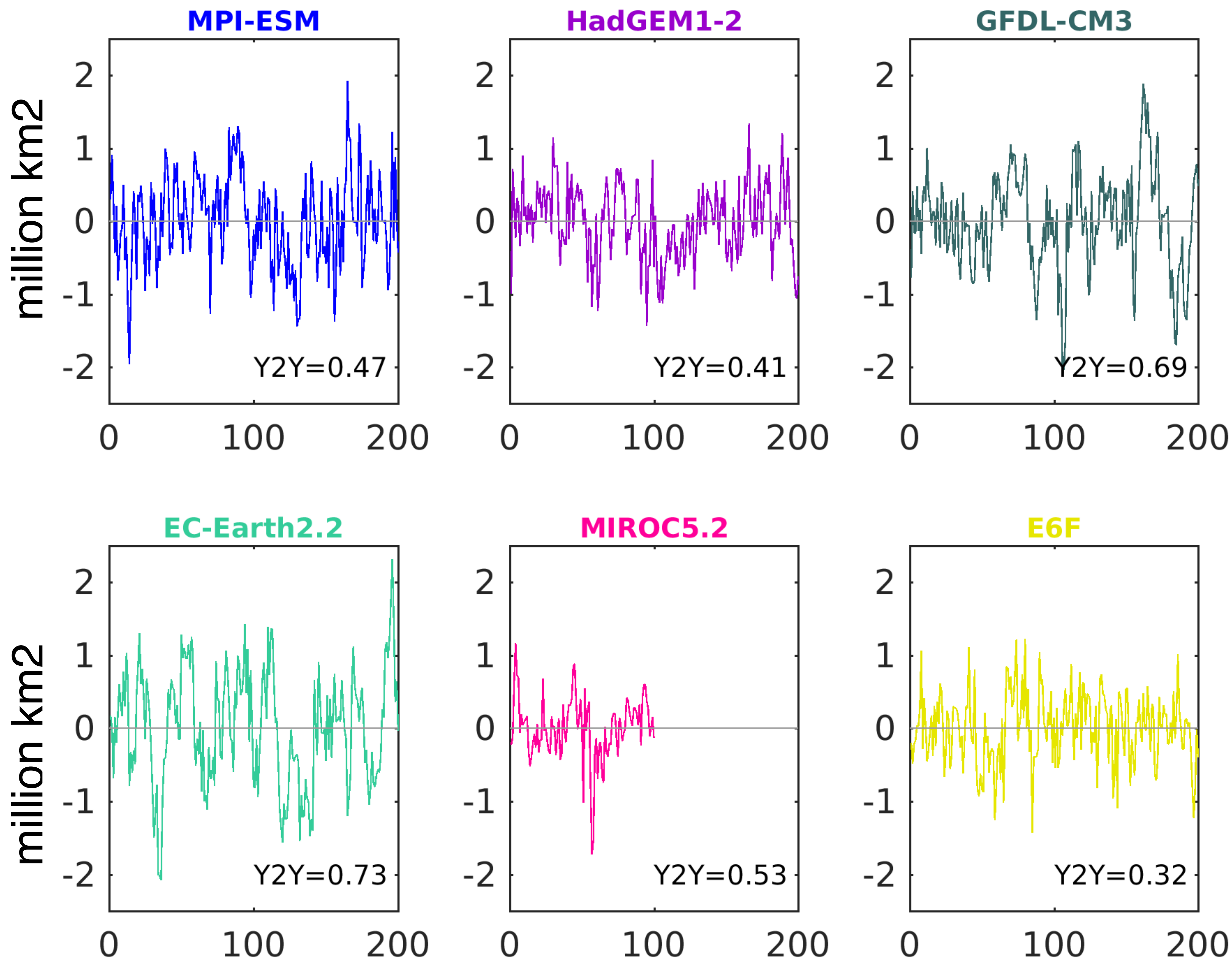


Is there a link between variability (which we can measure in real world) and predictability?



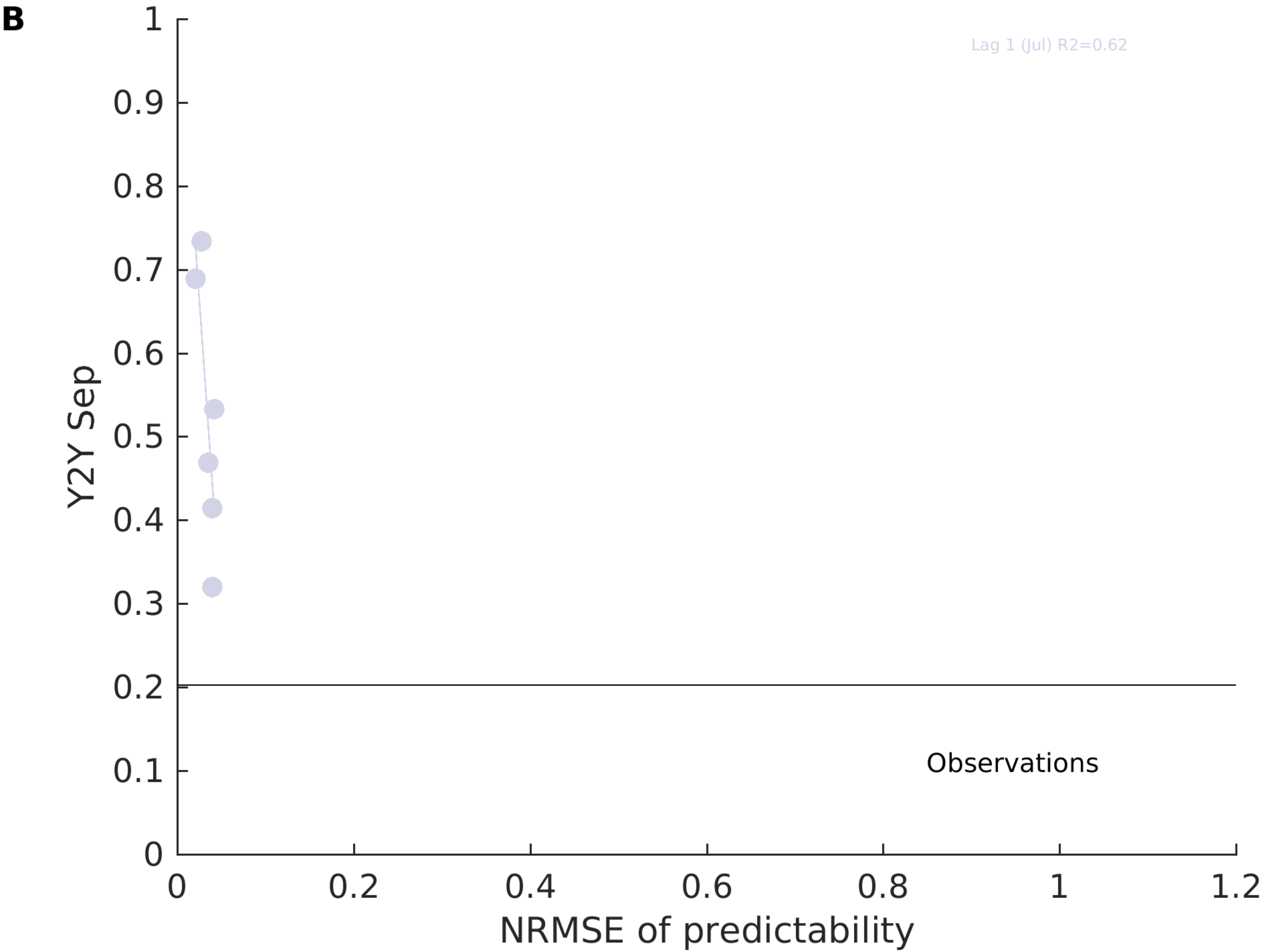
March SIA anomalies from 2000s control

Is there a link between variability (which we can measure in real world) and predictability?

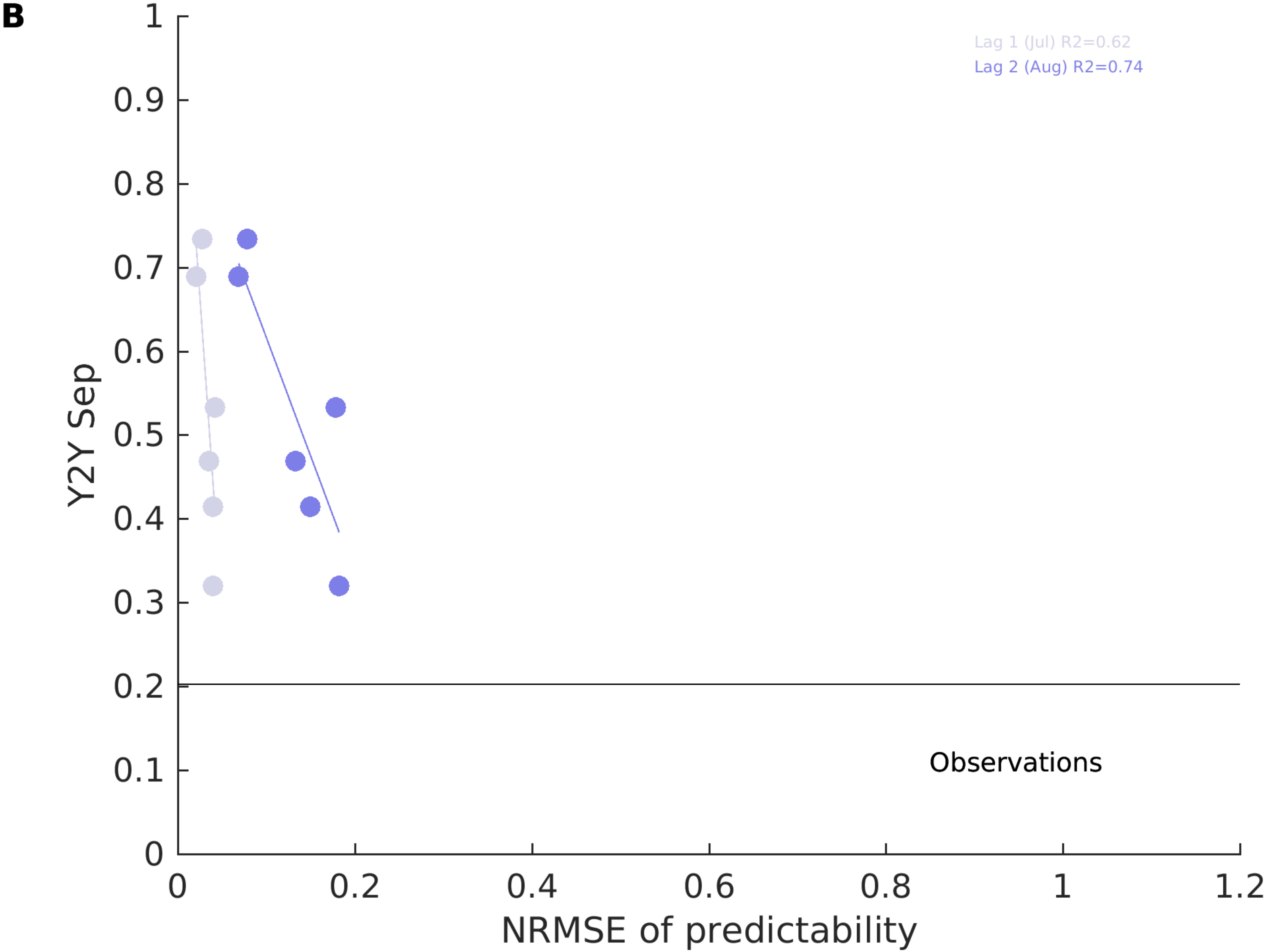


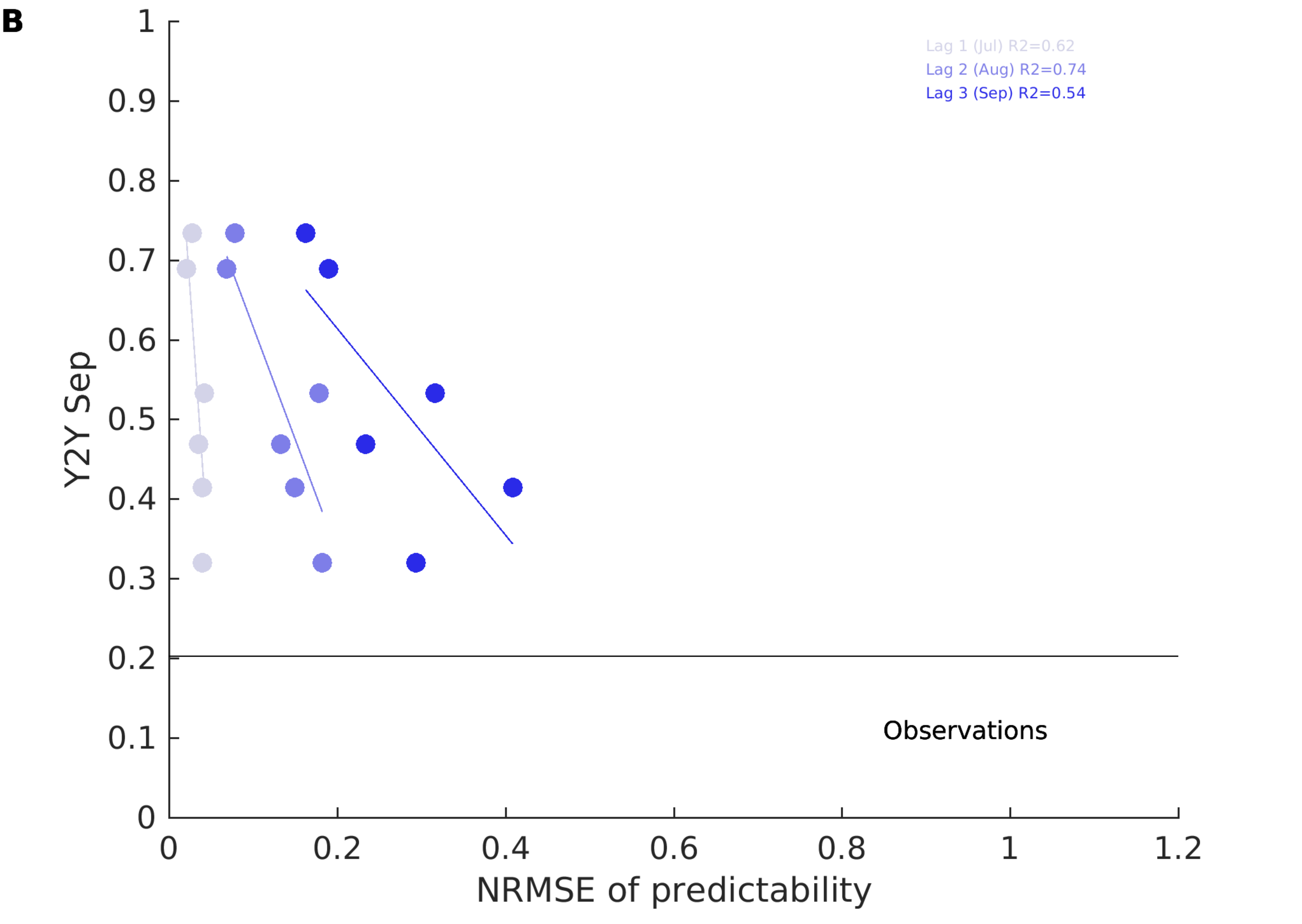
Y2Y=year-to-year autocorrelation *r*

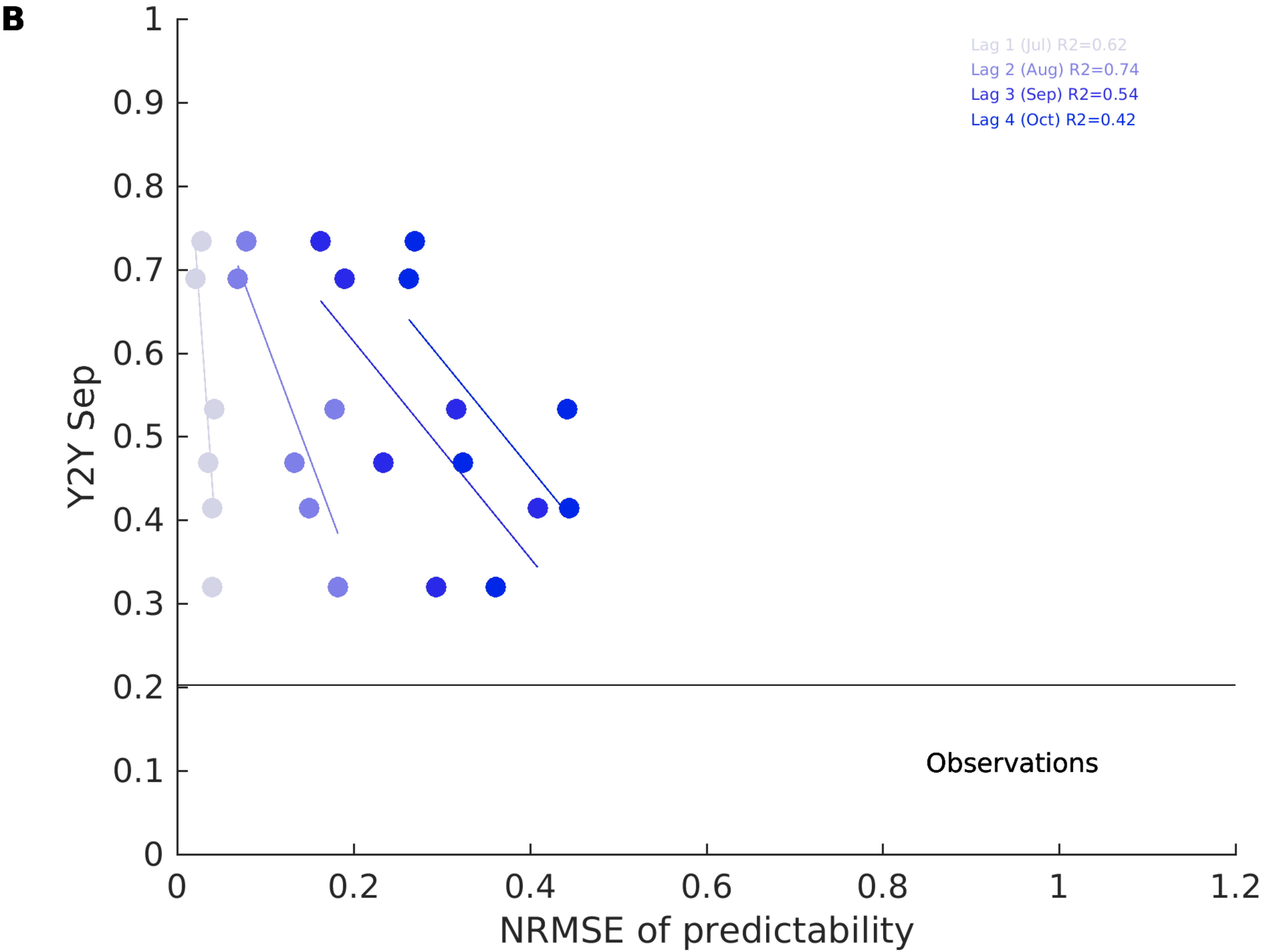
September SIA anomalies from 2000s control

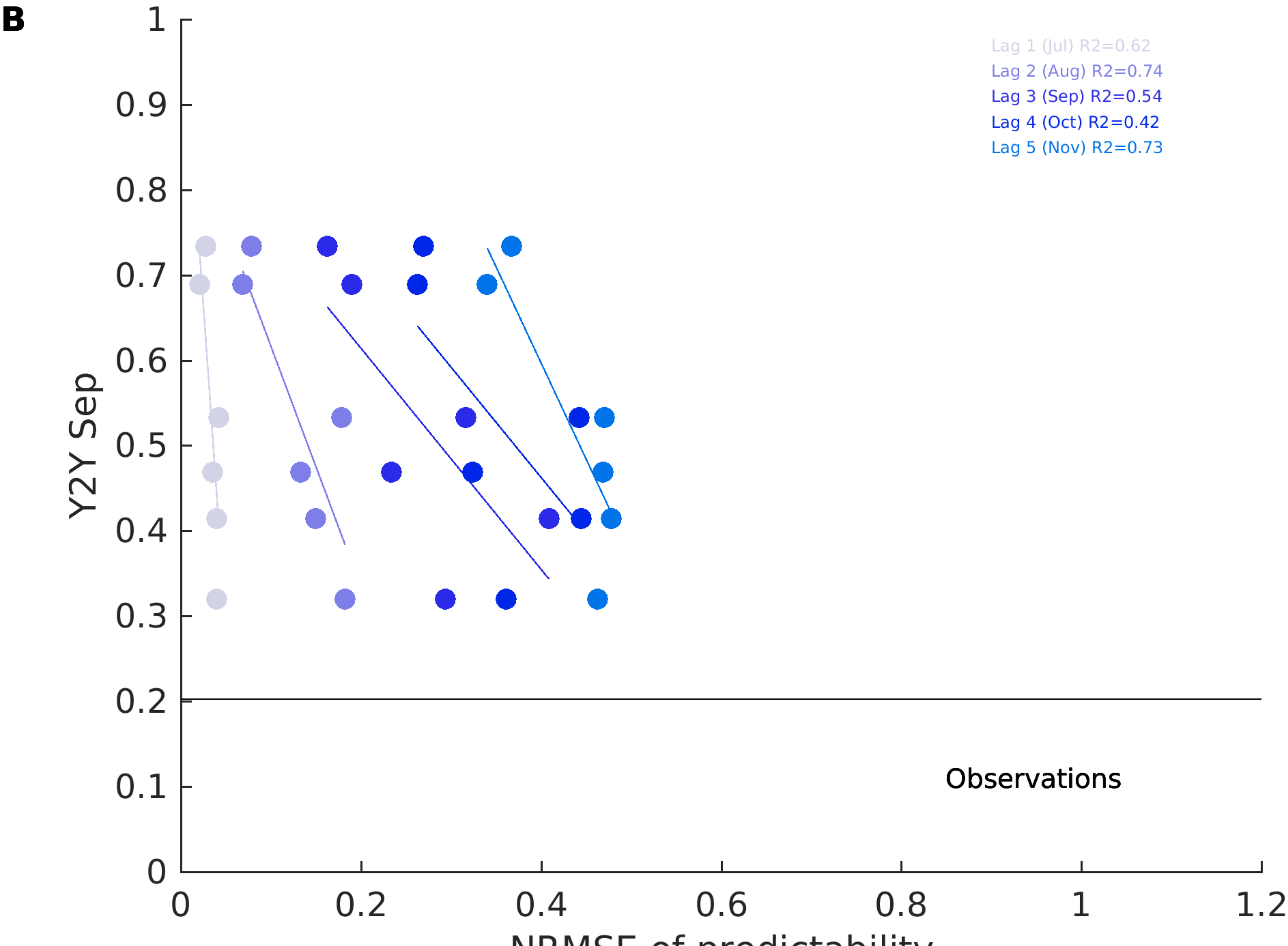


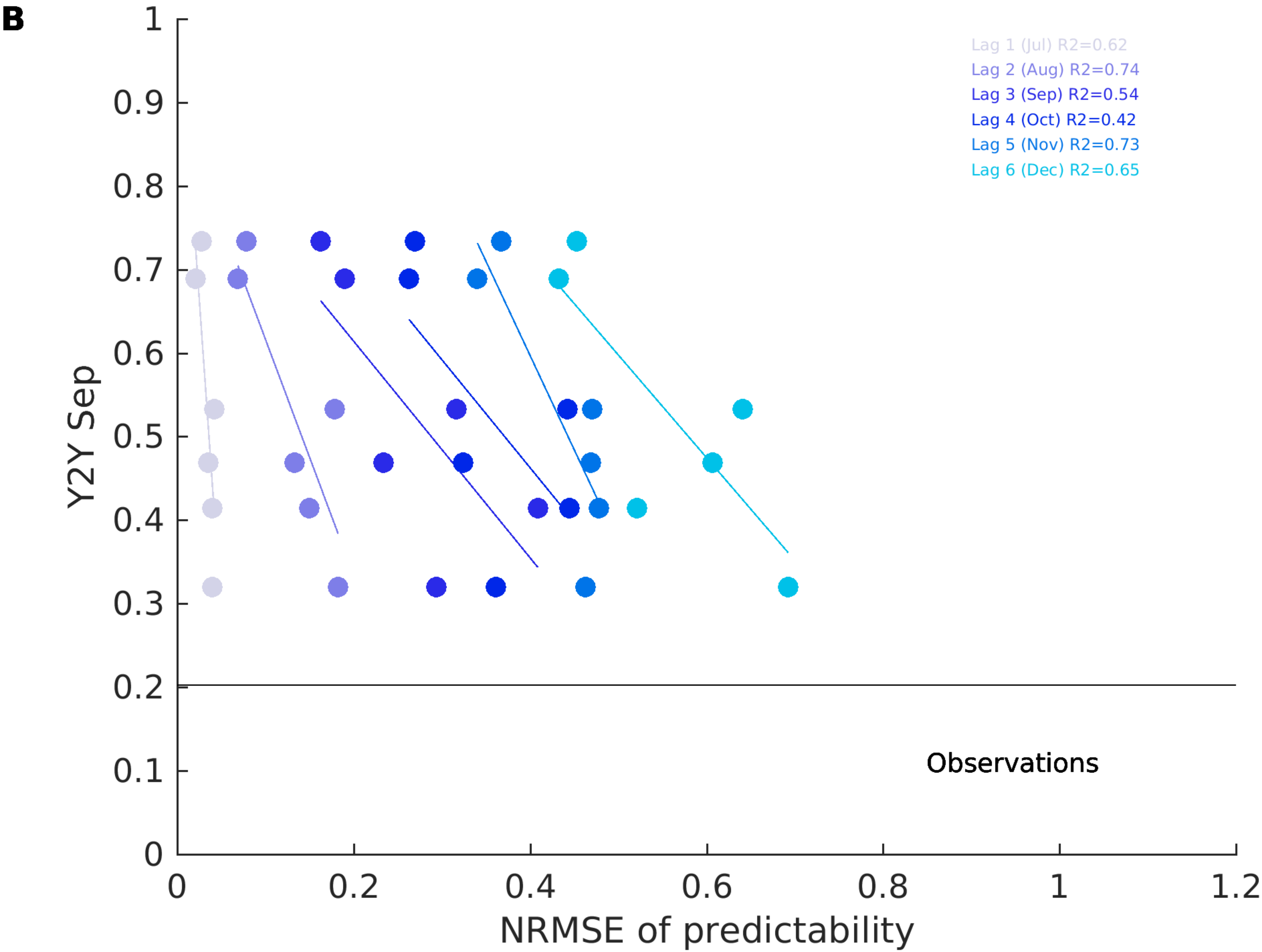
B
Lag 1 (Jul) R2=0.62
Y2Y Sep
Observations
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
1.2


B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Observations
Y2Y Sep
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2

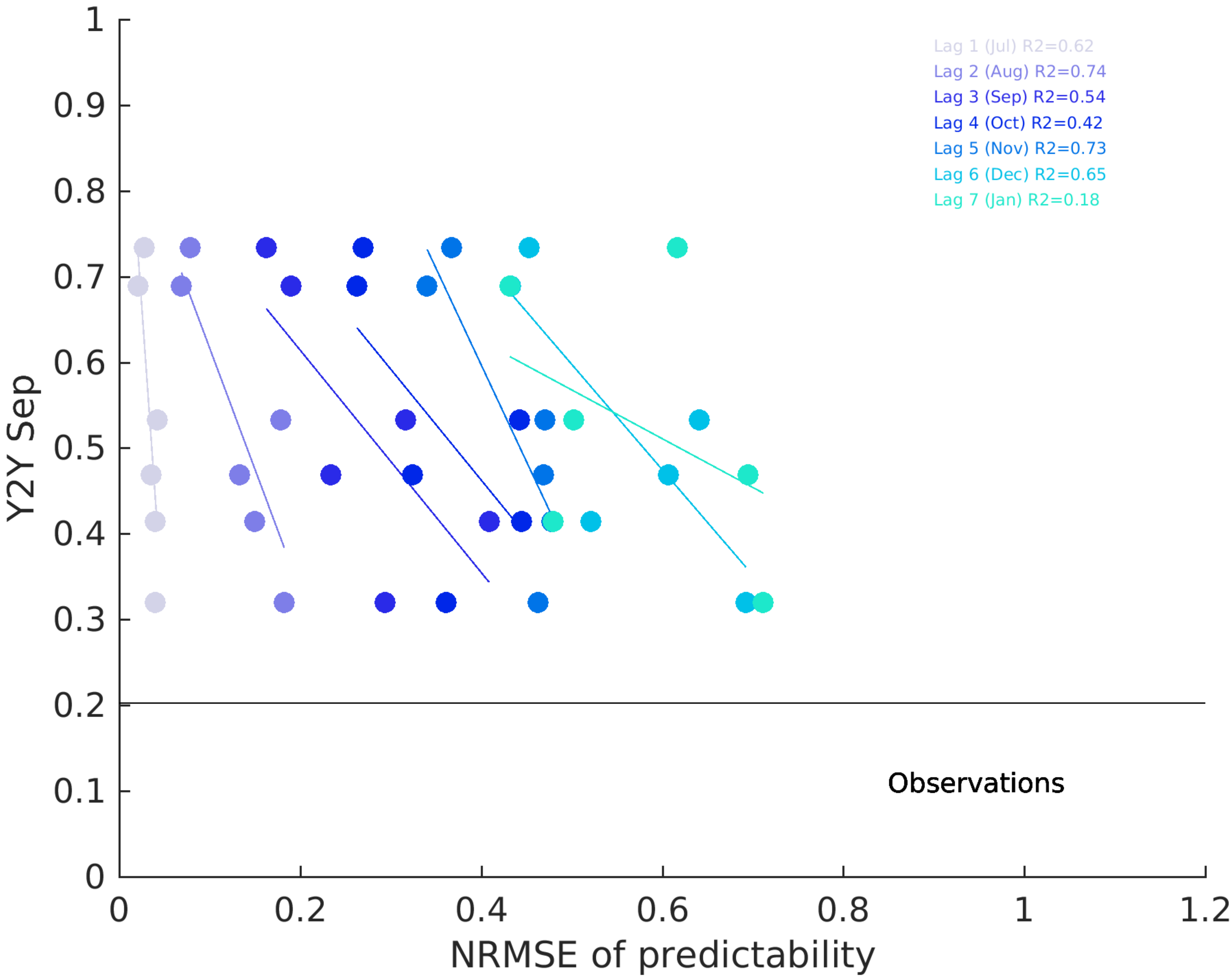

B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Y2Y Sep
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Observations
0
0.2
0.4
0.6
0.8
1
1.2
NRMSE of predictability


B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Y2Y Sep
NRMSE of predictability
Observations
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0.2
0.4
0.6
0.8
1.2

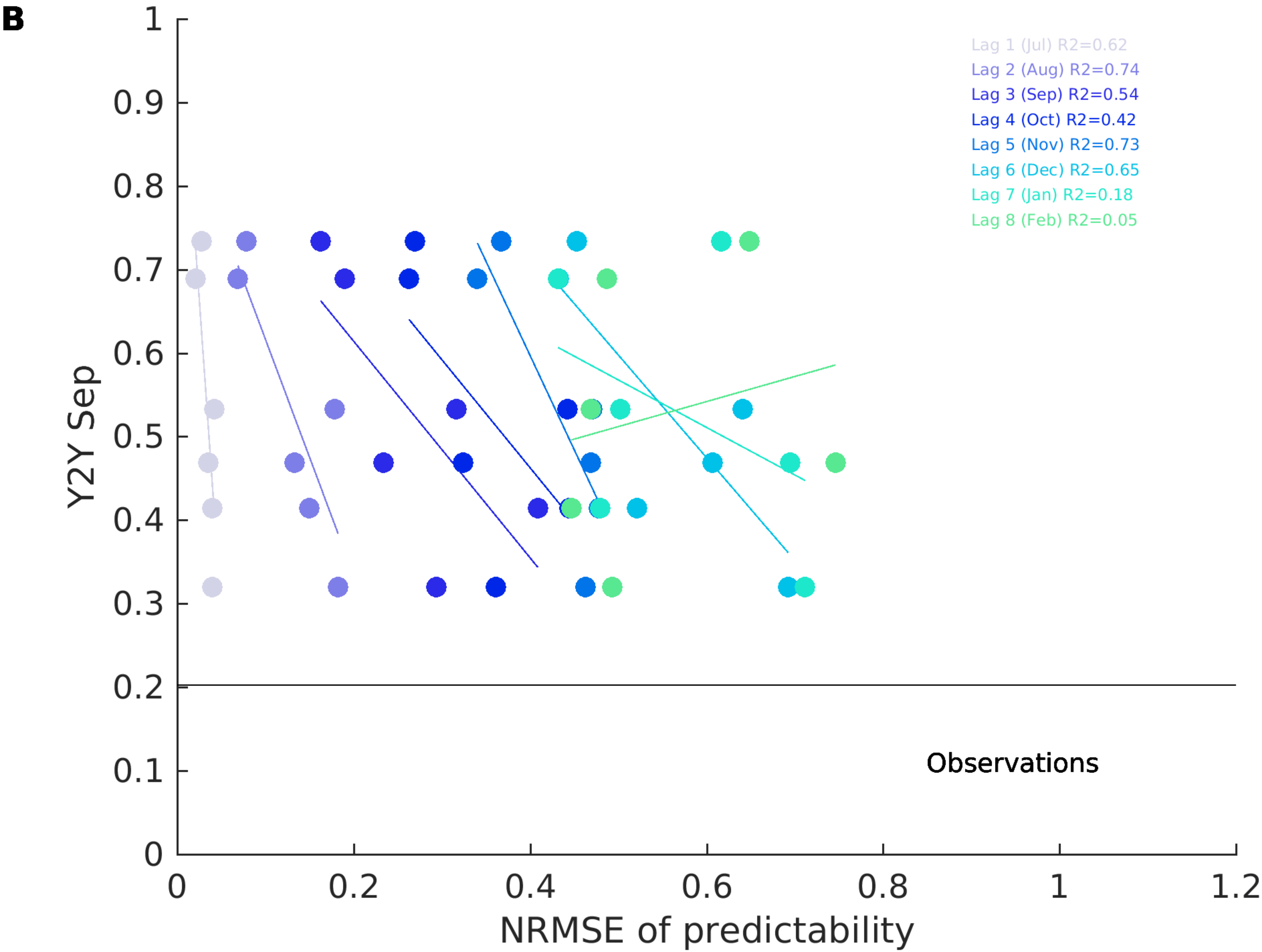

B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Y2Y Sep
Observations
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2


B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Y2Y Sep
Observations
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0.2
0.4
0.6
0.8
1.2

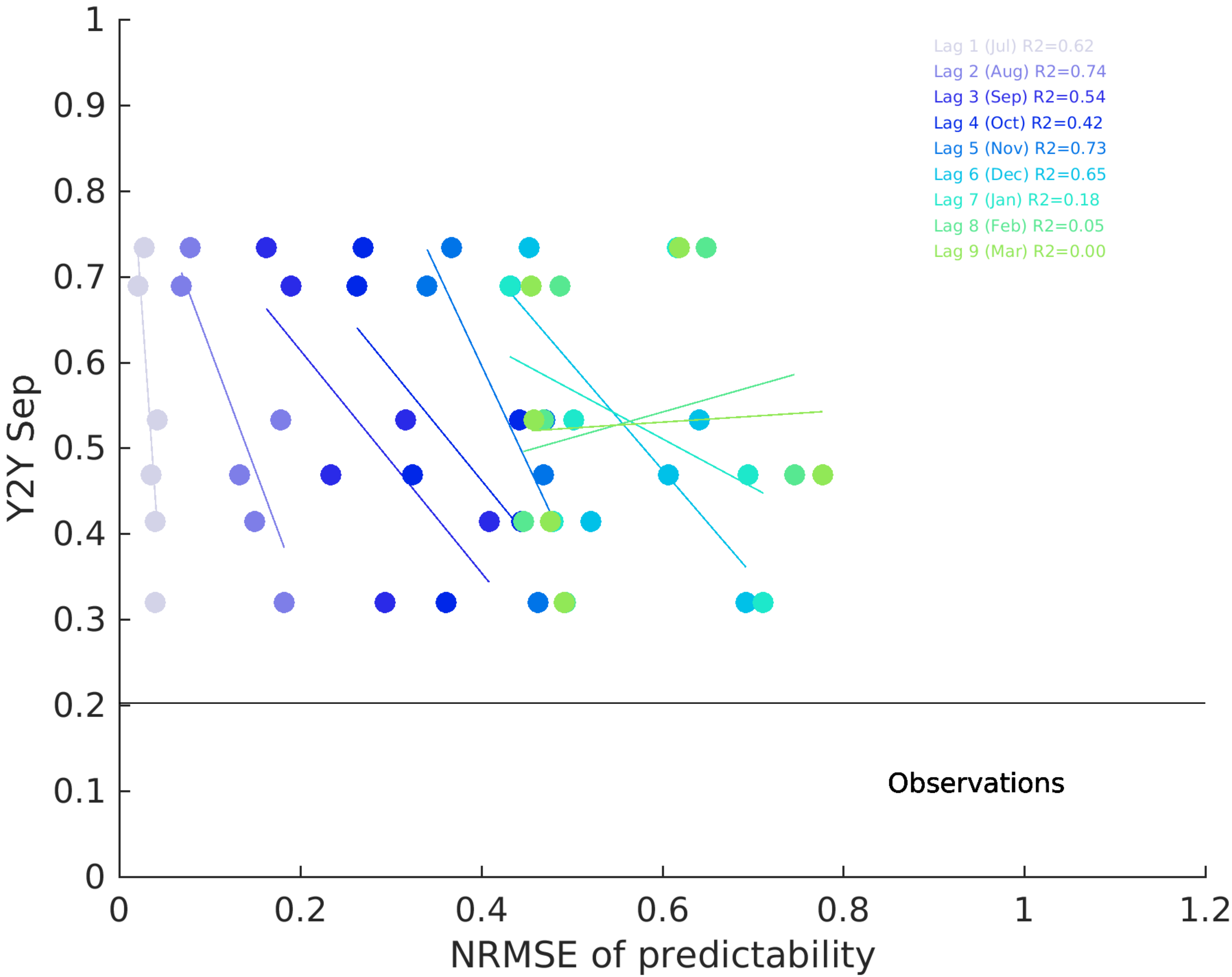
B



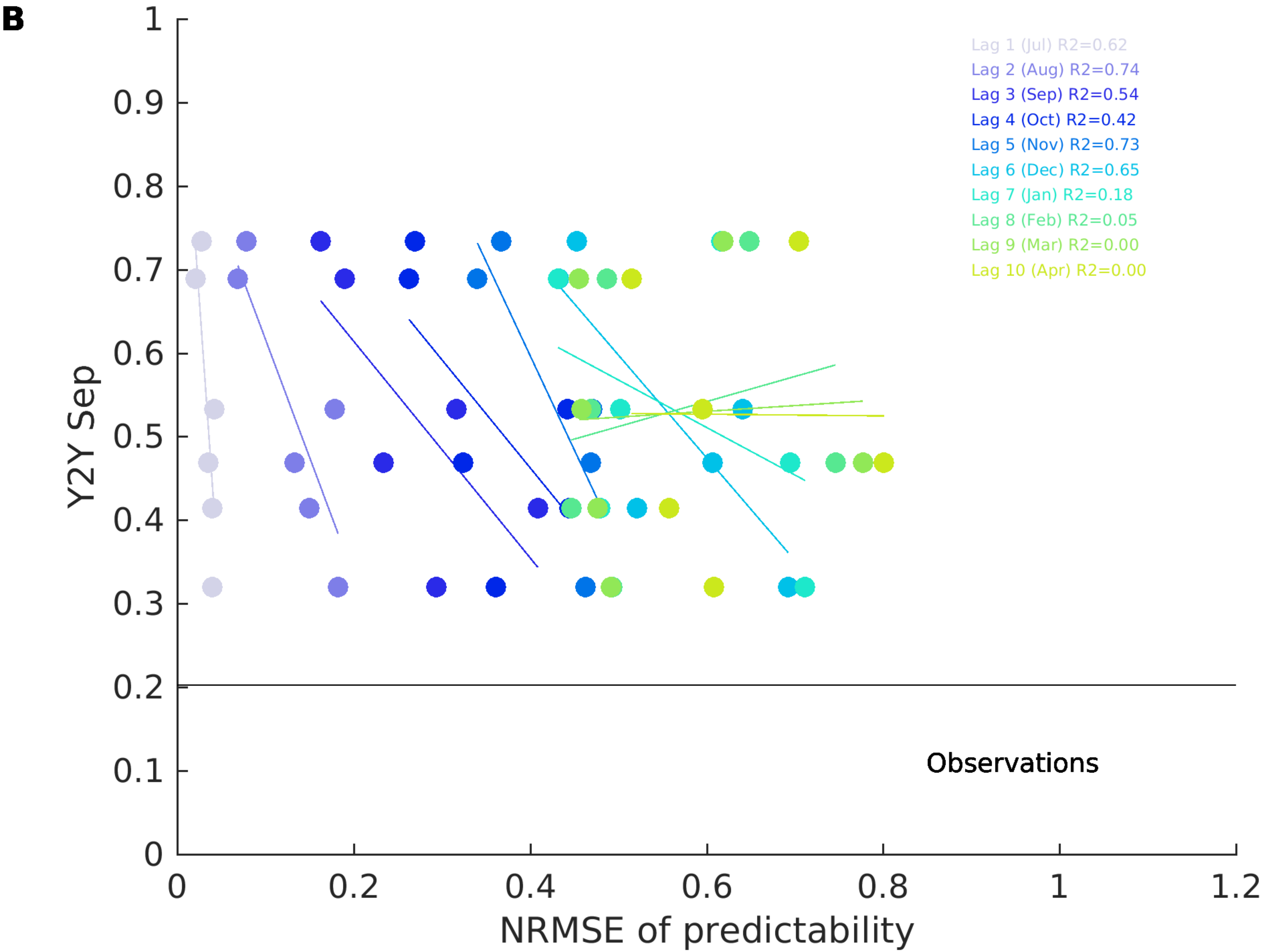
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Observations
Y2Y Sep
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2


B
Y2Y Sep
NRMSE of predictability
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Observations
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2

B

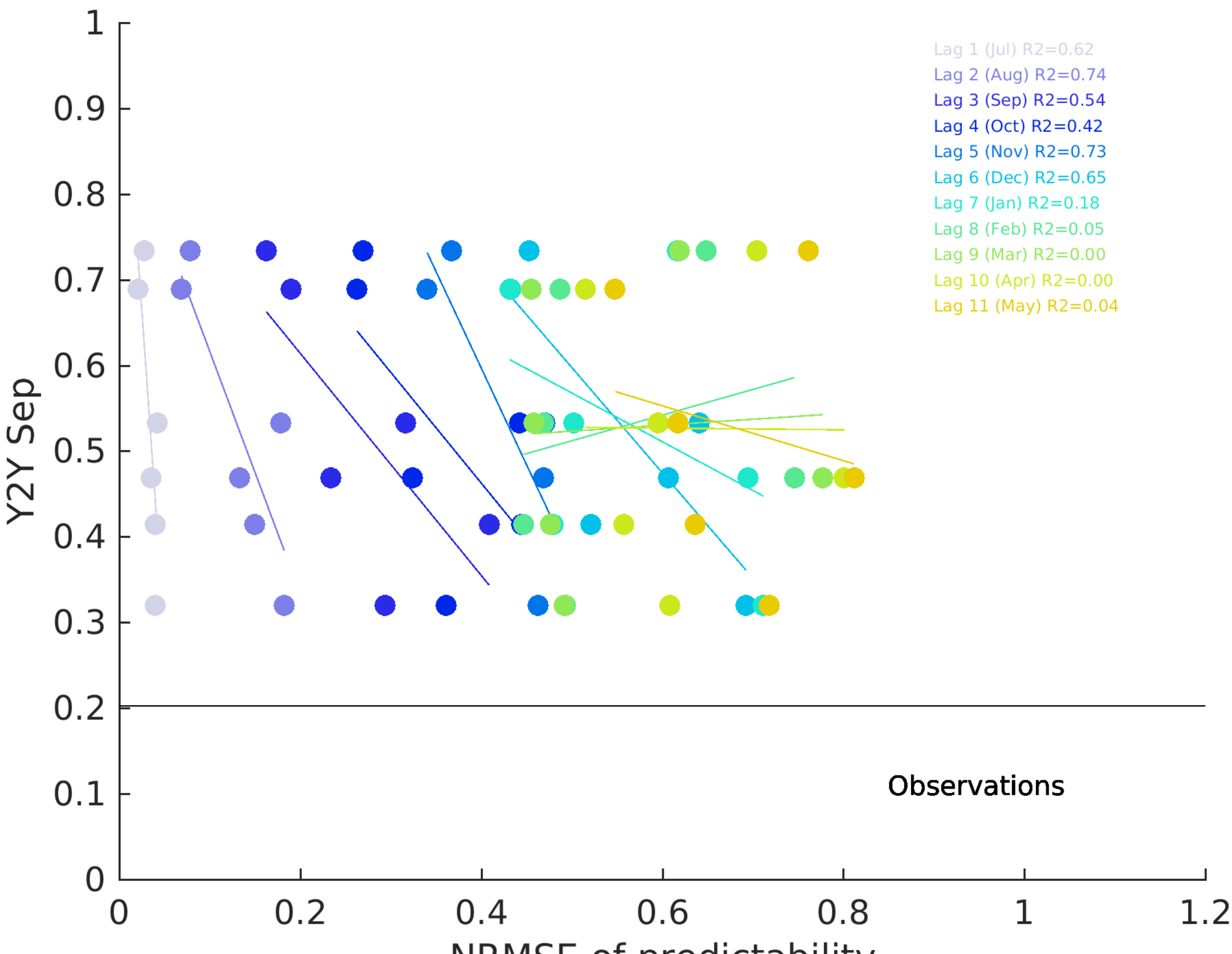


Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Lag 9 (Mar) R2=0.00
Y2Y Sep
NRMSE of predictability
Observations
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2



B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Lag 9 (Mar) R2=0.00
Lag 10 (Apr) R2=0.00
Y2Y Sep
NRMSE of predictability
Observations
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2

B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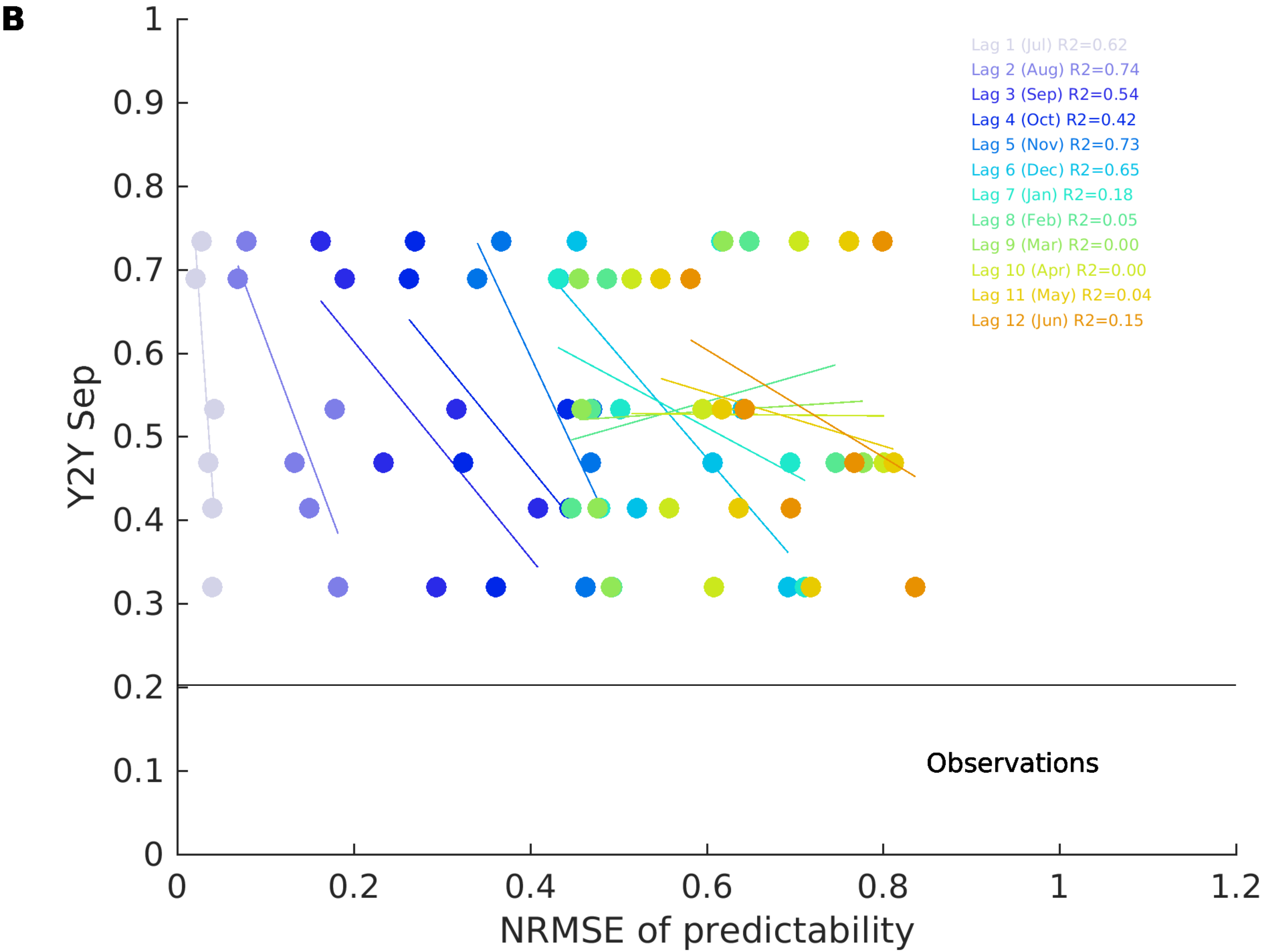
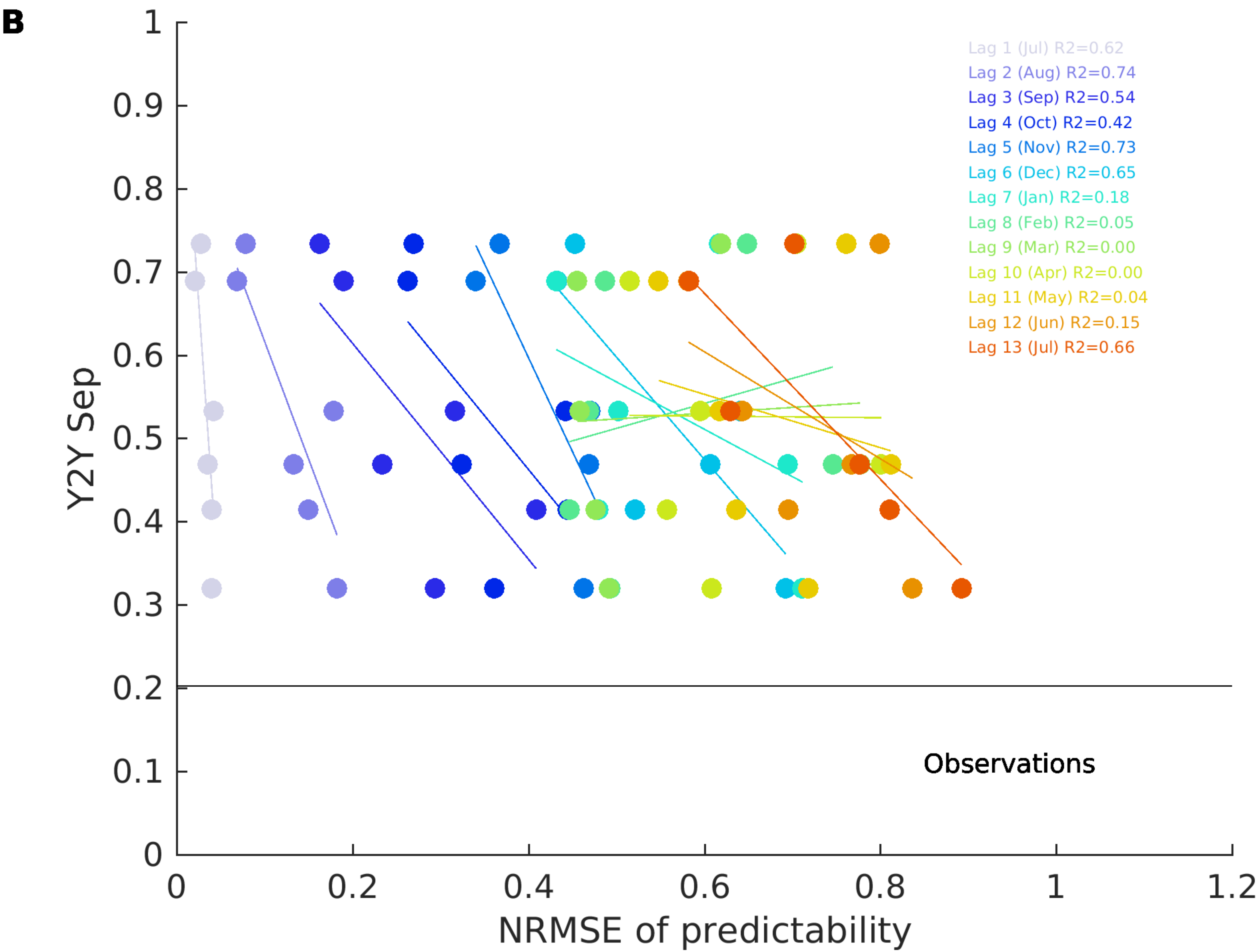
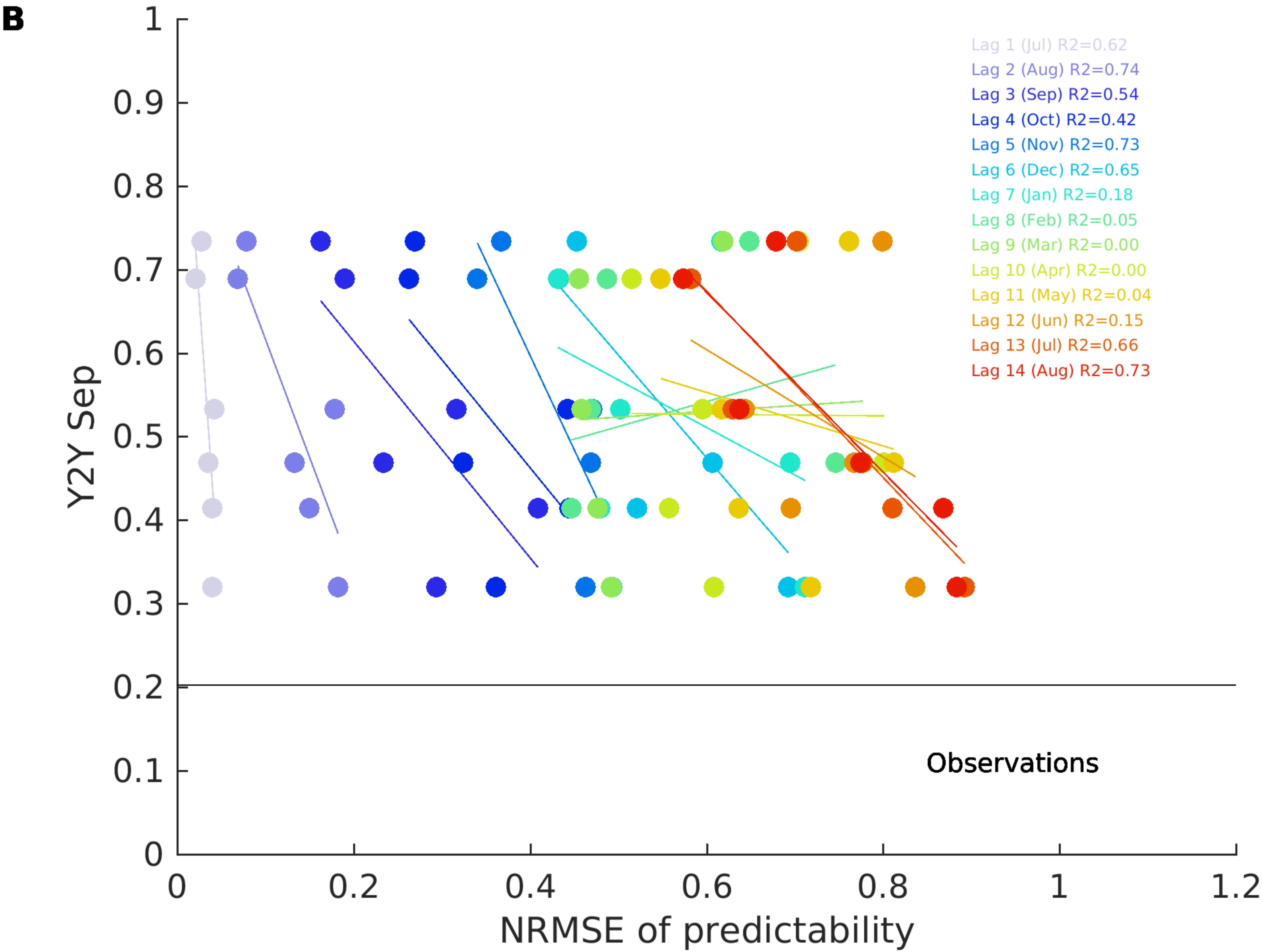
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Lag 9 (Mar) R2=0.00
Lag 10 (Apr) R2=0.00
Lag 11 (May) R2=0.04
Observations
Y2Y Sep
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2



B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Lag 9 (Mar) R2=0.00
Lag 10 (Apr) R2=0.00
Lag 11 (May) R2=0.04
Lag 12 (Jun) R2=0.15
Y2Y Sep
Observations
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0.2
0.4
0.6
0.8
1.2


B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Lag 9 (Mar) R2=0.00
Lag 10 (Apr) R2=0.00
Lag 11 (May) R2=0.04
Lag 12 (Jun) R2=0.15
Lag 13 (Jul) R2=0.66
Observations
Y2Y Sep
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2


B
Y2Y Sep
NRMSE of predictability
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Lag 9 (Mar) R2=0.00
Lag 10 (Apr) R2=0.00
Lag 11 (May) R2=0.04
Lag 12 (Jun) R2=0.15
Lag 13 (Jul) R2=0.66
Lag 14 (Aug) R2=0.73
Observations
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
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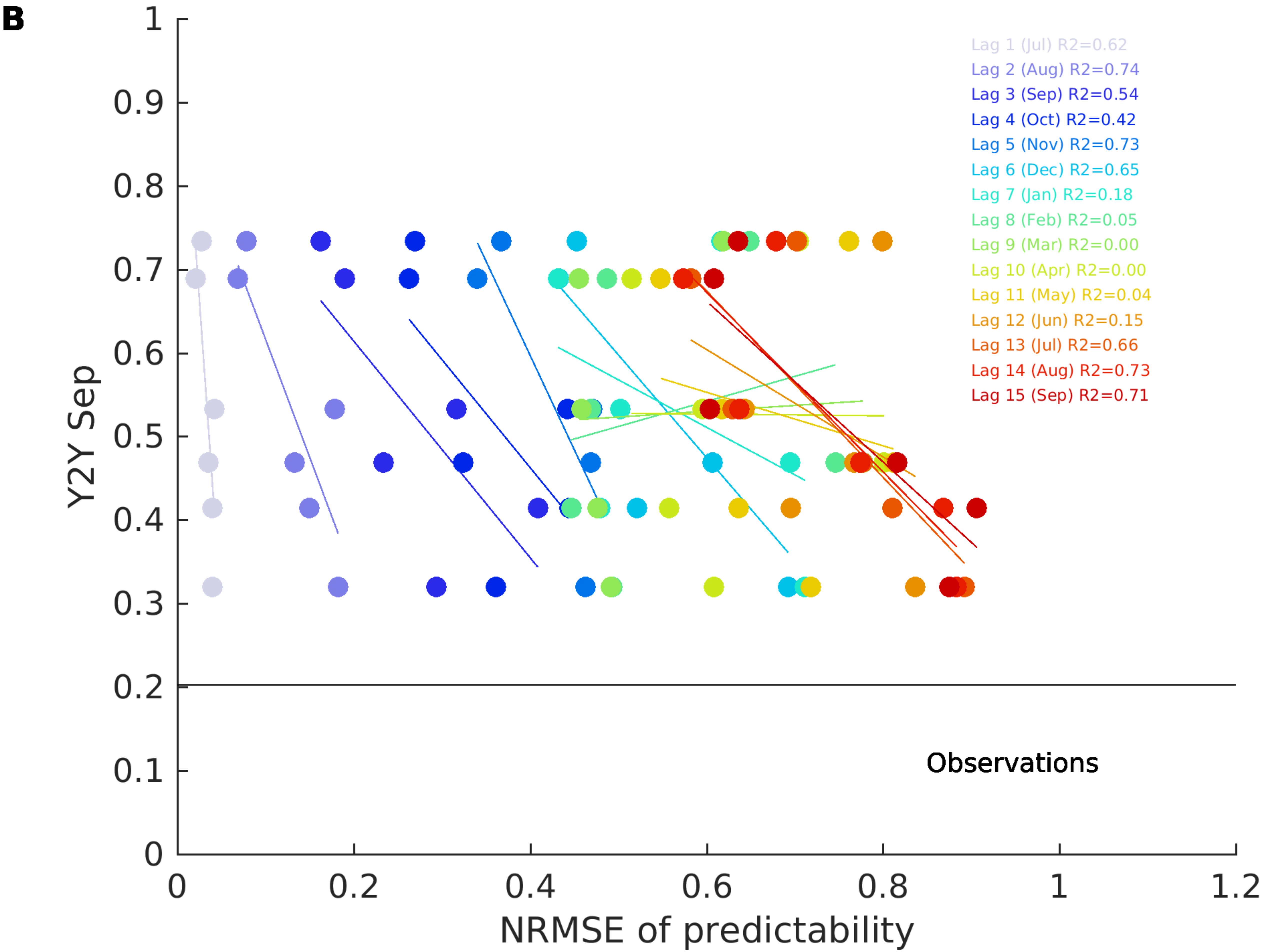
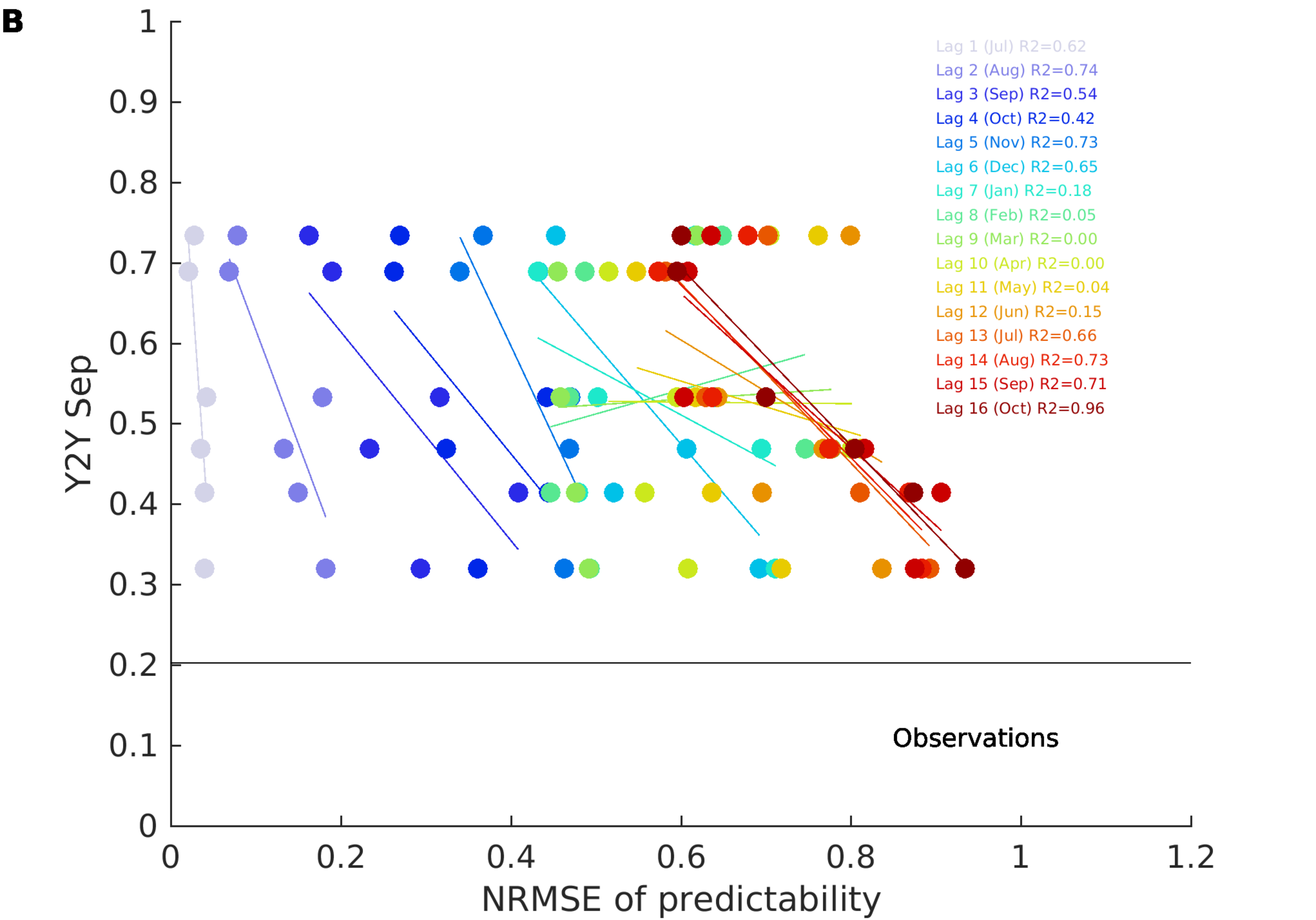
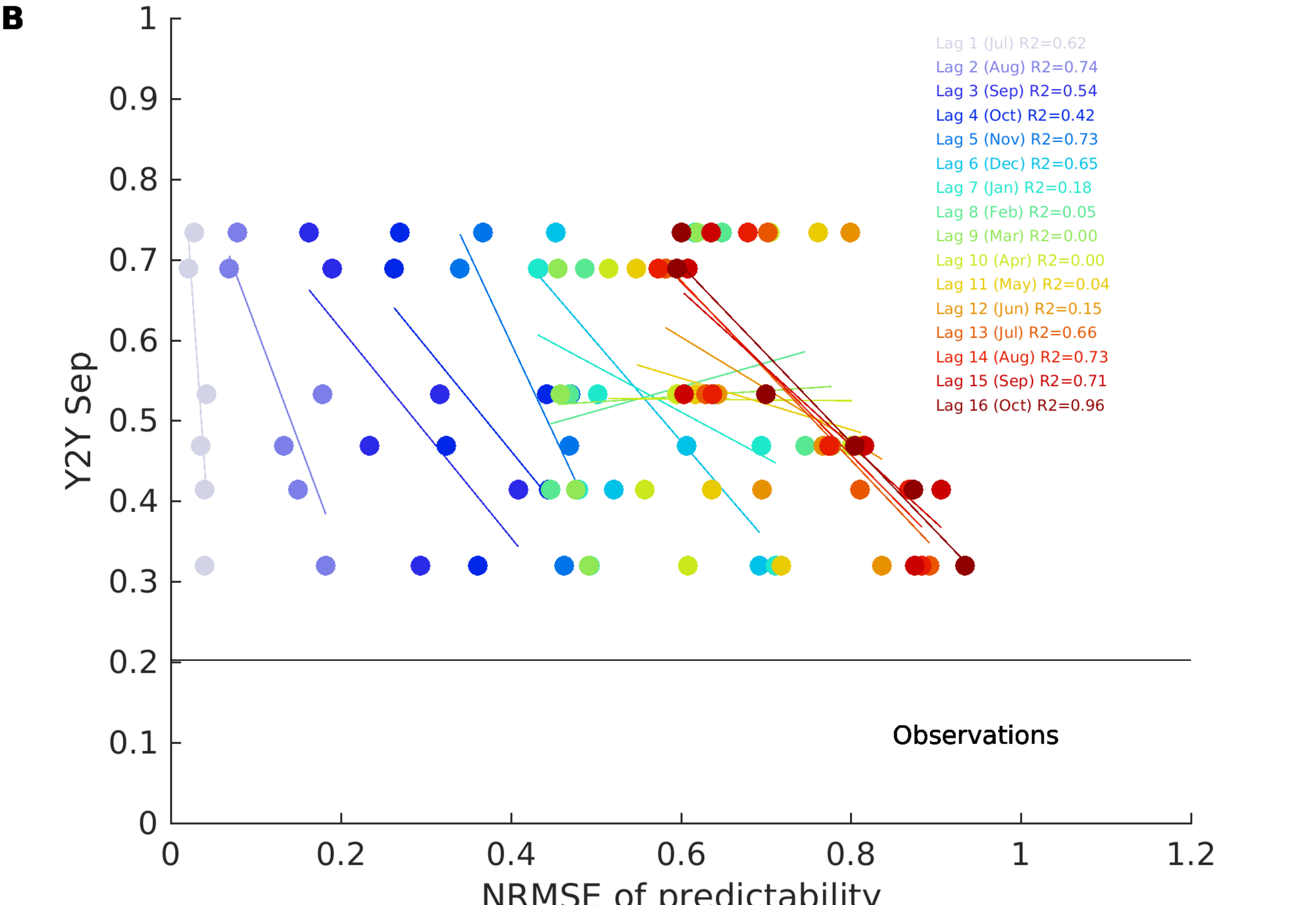
0.8
1
1.2

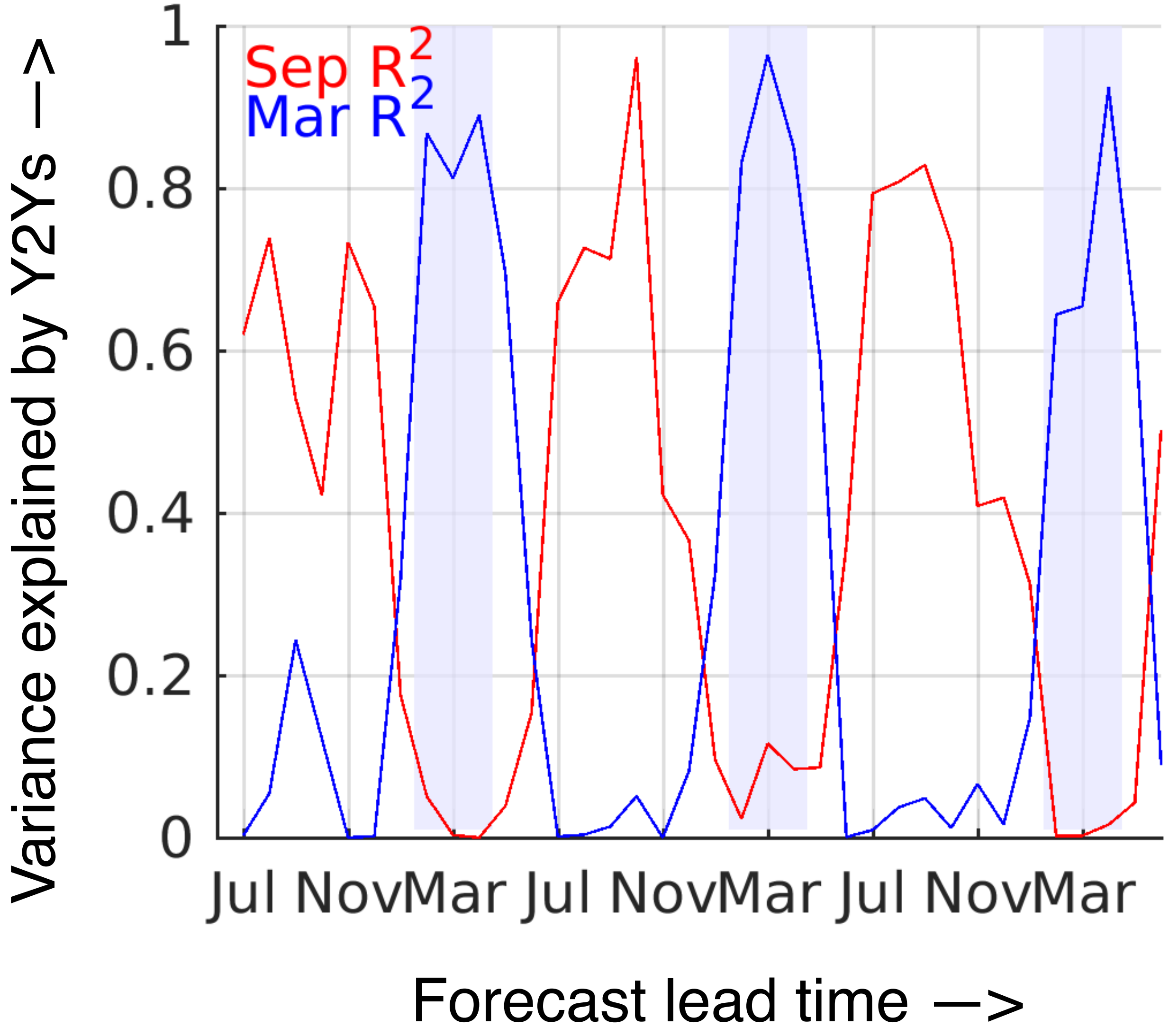

B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Lag 9 (Mar) R2=0.00
Lag 10 (Apr) R2=0.00
Lag 11 (May) R2=0.04
Lag 12 (Jun) R2=0.15
Lag 13 (Jul) R2=0.66
Lag 14 (Aug) R2=0.73
Lag 15 (Sep) R2=0.71
Y2Y Sep
Observations
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2



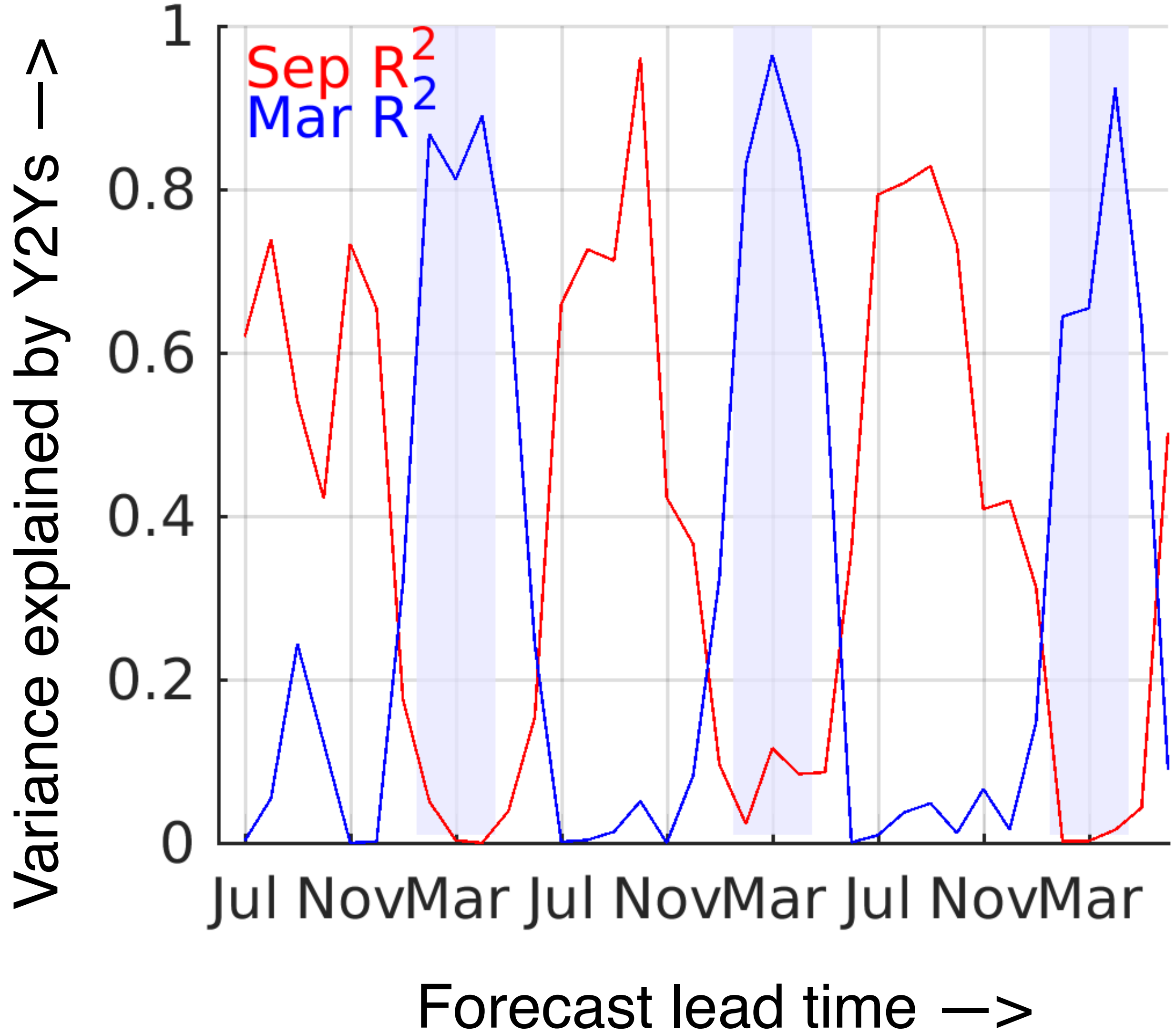
B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Lag 9 (Mar) R2=0.00
Lag 10 (Apr) R2=0.00
Lag 11 (May) R2=0.04
Lag 12 (Jun) R2=0.15
Lag 13 (Jul) R2=0.66
Lag 14 (Aug) R2=0.73
Lag 15 (Sep) R2=0.71
Lag 16 (Oct) R2=0.96
Observations
Y2Y Sep
NRMSE of predictability

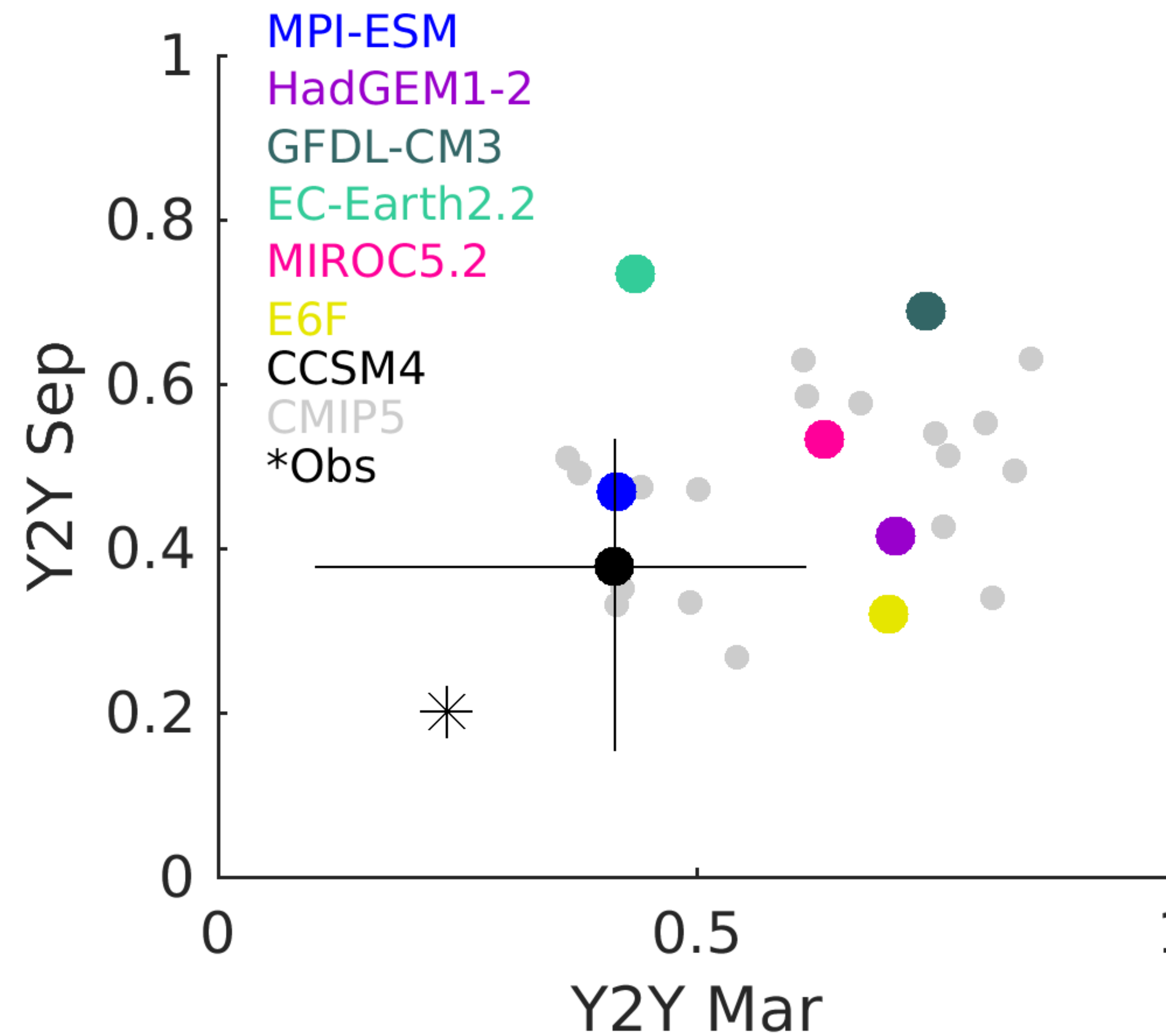


B
Lag 1 (Jul) R2=0.62
Lag 2 (Aug) R2=0.74
Lag 3 (Sep) R2=0.54
Lag 4 (Oct) R2=0.42
Lag 5 (Nov) R2=0.73
Lag 6 (Dec) R2=0.65
Lag 7 (Jan) R2=0.18
Lag 8 (Feb) R2=0.05
Lag 9 (Mar) R2=0.00
Lag 10 (Apr) R2=0.00
Lag 11 (May) R2=0.04
Lag 12 (Jun) R2=0.15
Lag 13 (Jul) R2=0.66
Lag 14 (Aug) R2=0.73
Lag 15 (Sep) R2=0.71
Lag 16 (Oct) R2=0.96
Y2Y Sep
Observations
NRMSE of predictability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
1.2



Sep R^2
Mar R^2
Variance explained by Y2Ys —>
1
0.8
0.6
0.4
0.2
0
Jul Nov Mar Jul Nov Mar Jul Nov Mar
Forecast lead time —>





APPOSITE: Samples CMIP5 Y2Y GCMs: no link between Y2Y March/Sep

Models more persistent than observations

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

Summary

Predictability comes in two flavors: initial value (weather forecast) and forced (climate forecast) predictability.

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 or two.

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

Are models too ‘predictable’, too little high frequency variability? (possibly)
Are observations/ICs good enough? (hmmm)

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Are observations/ICs good enough? (hmmm)

Other things to think about…

Decadal predictability: initial value for winter in North Atlantic
Observations too short to see low frequency variability/predictability?

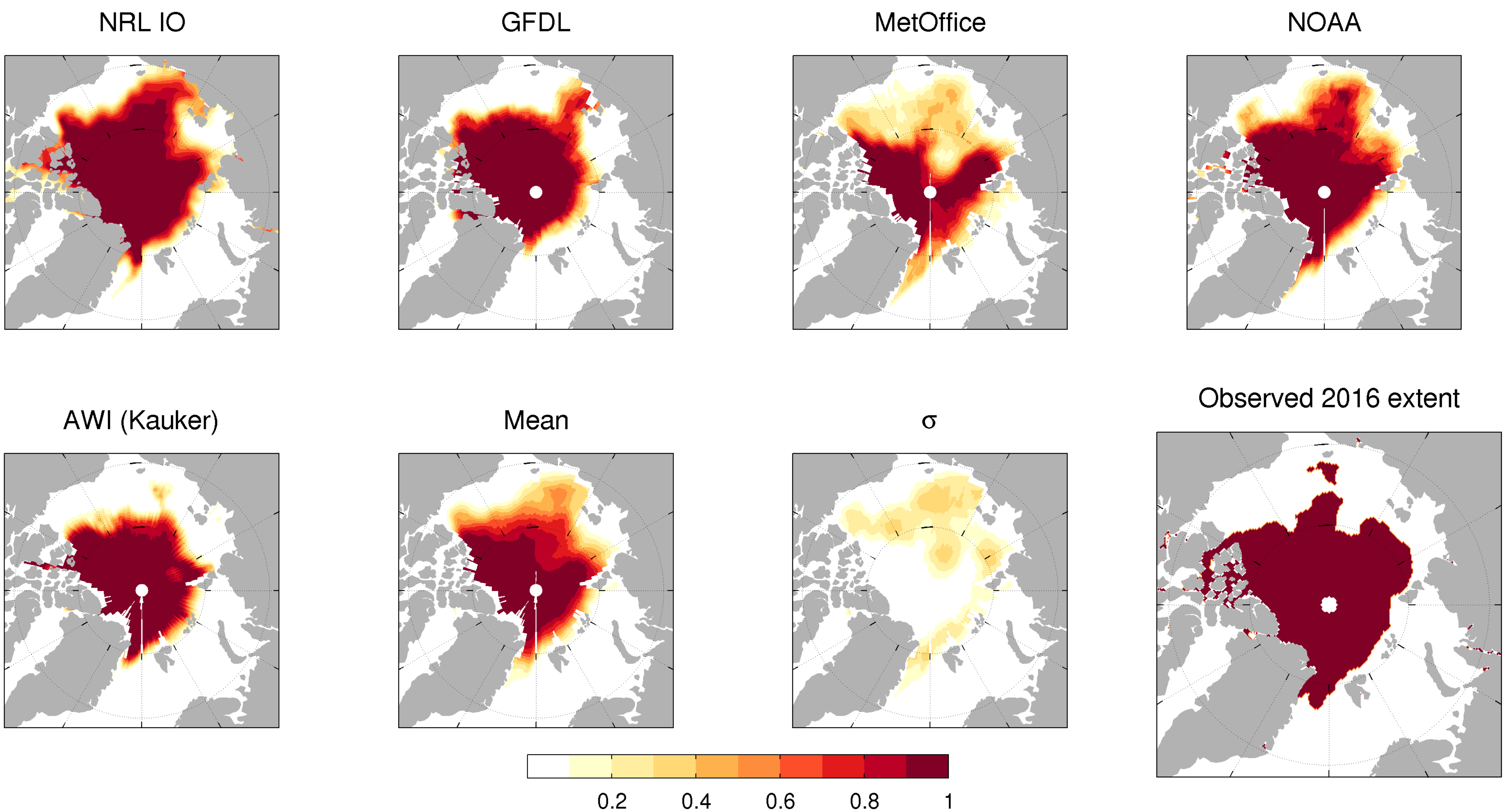
Changes in predictability with changing mean state??

Beyond extent/thickness: Regional predictability? Other climate components?

Extra slides

Beyond sea ice 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 are key.



September Sea ice probability forecast 2016 from August'16

Decadal predictability

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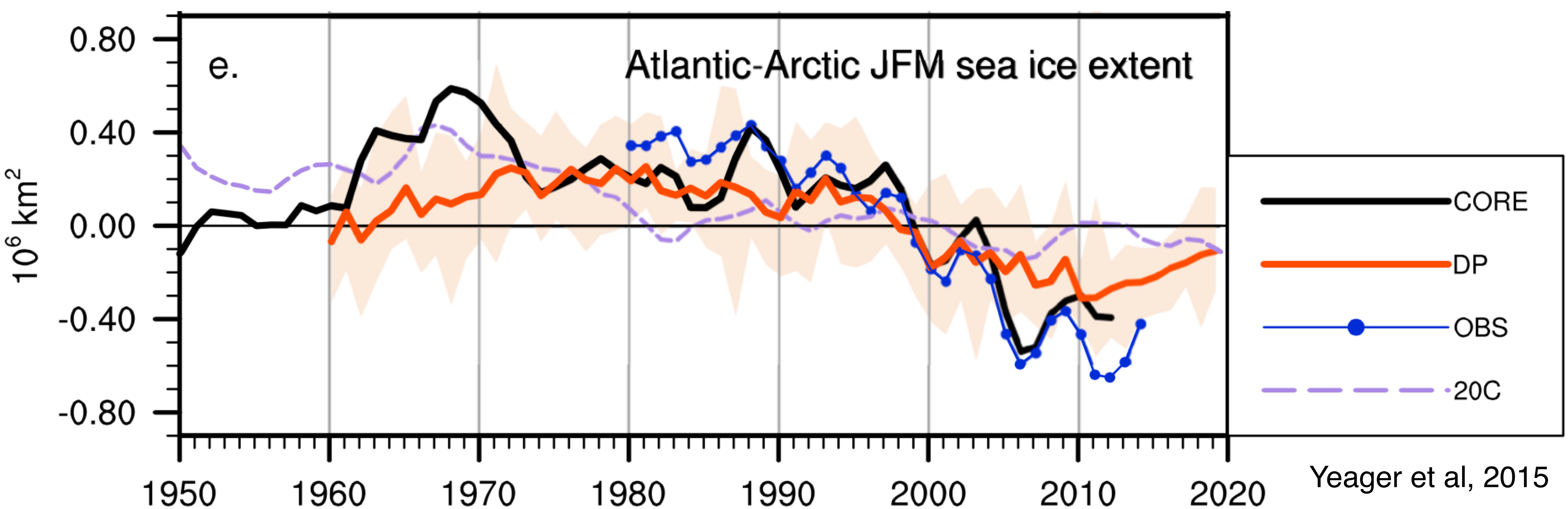
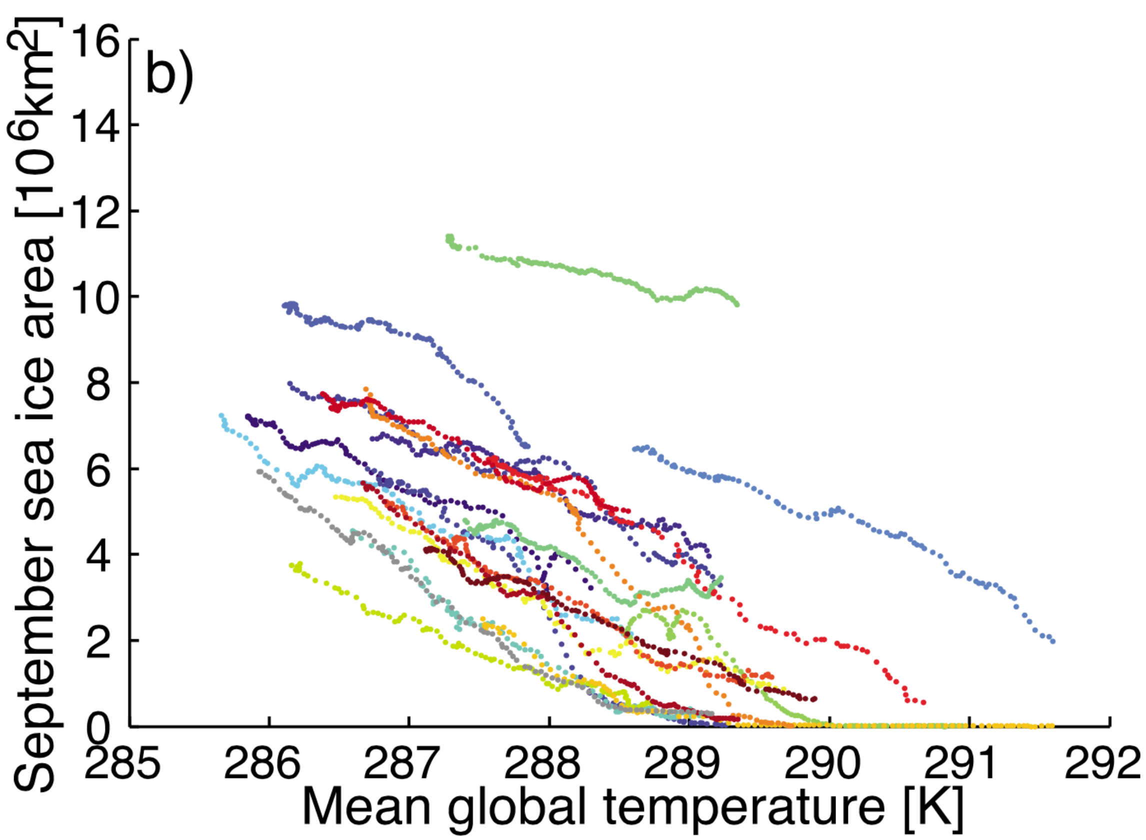
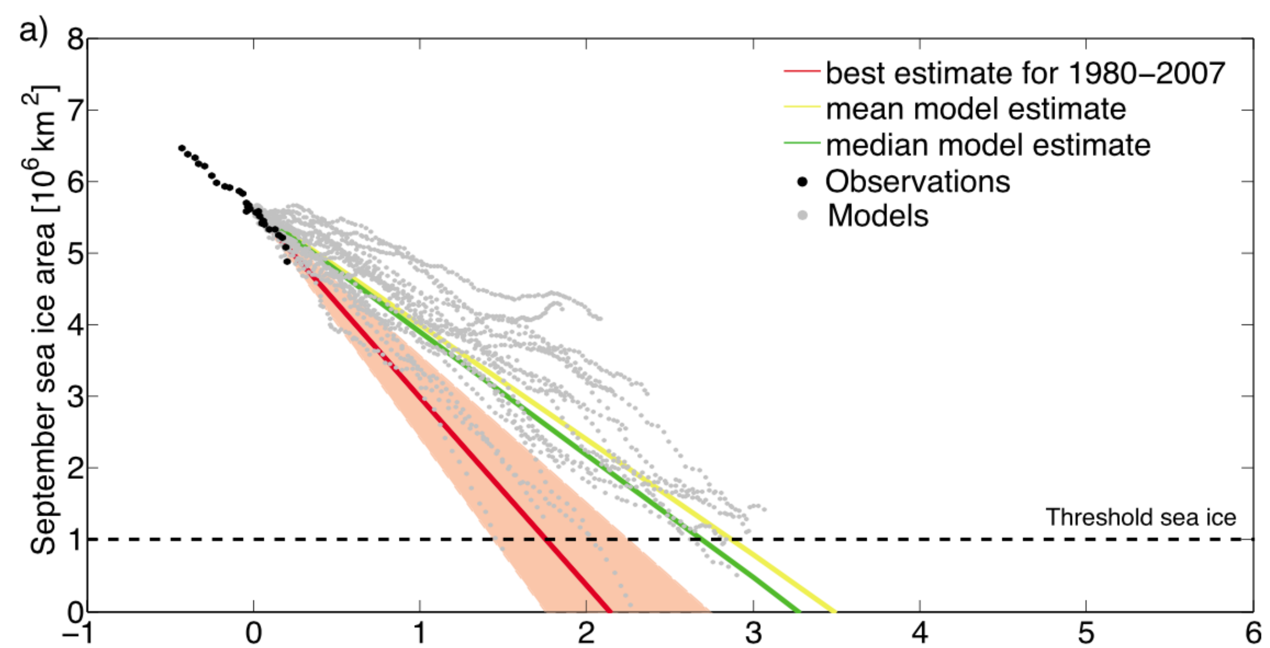


Yeager et al, 2015

Decadal predictability

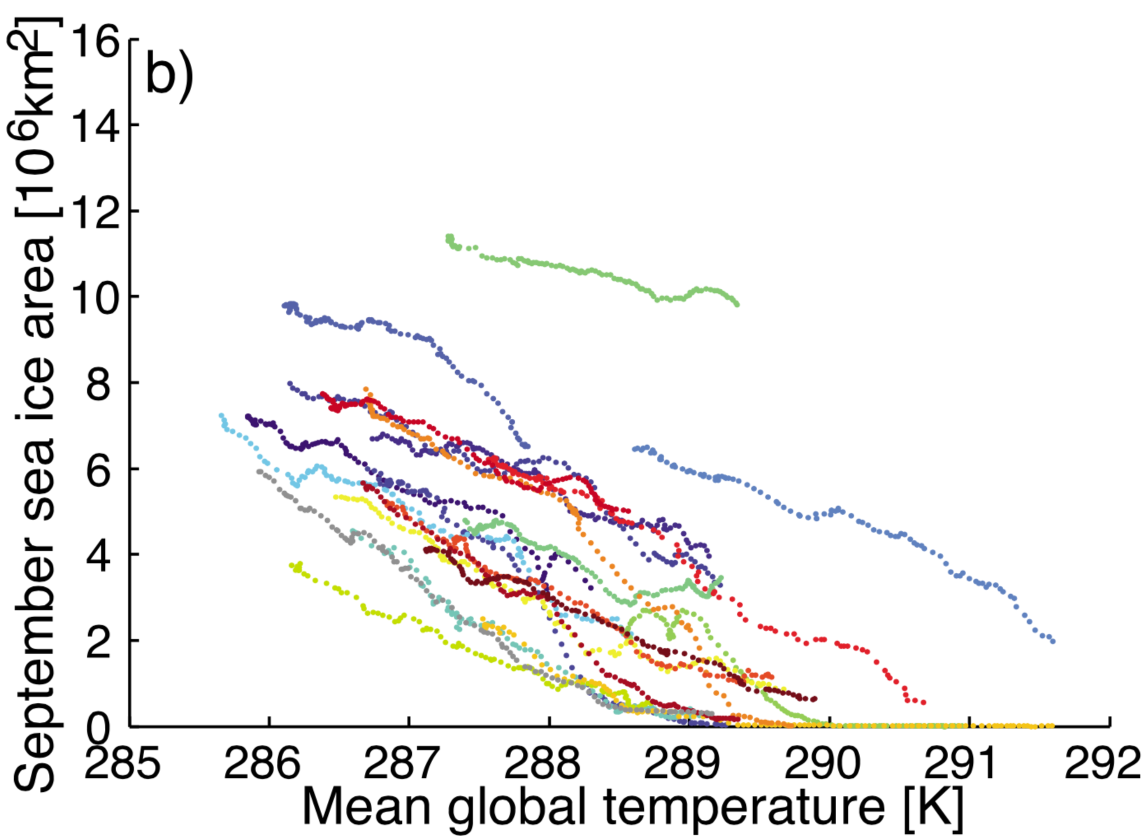


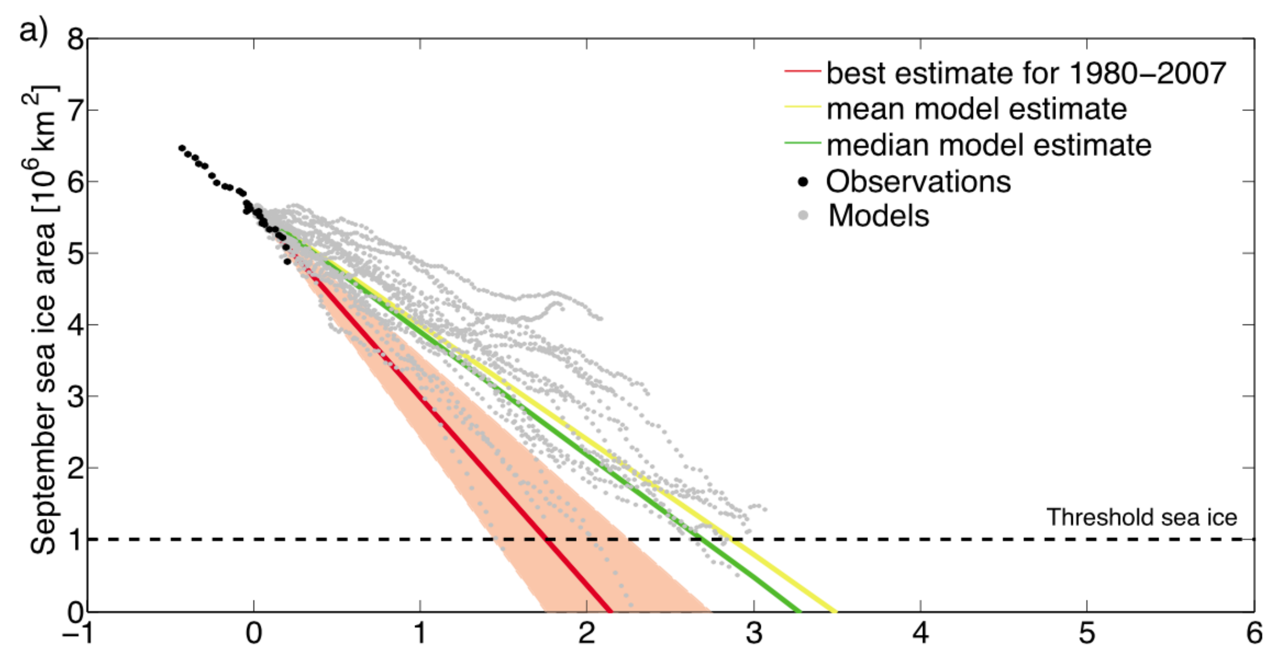


Mahlstein and Knutti, 2012

Decadal predictability

What about sea-ice free summers?





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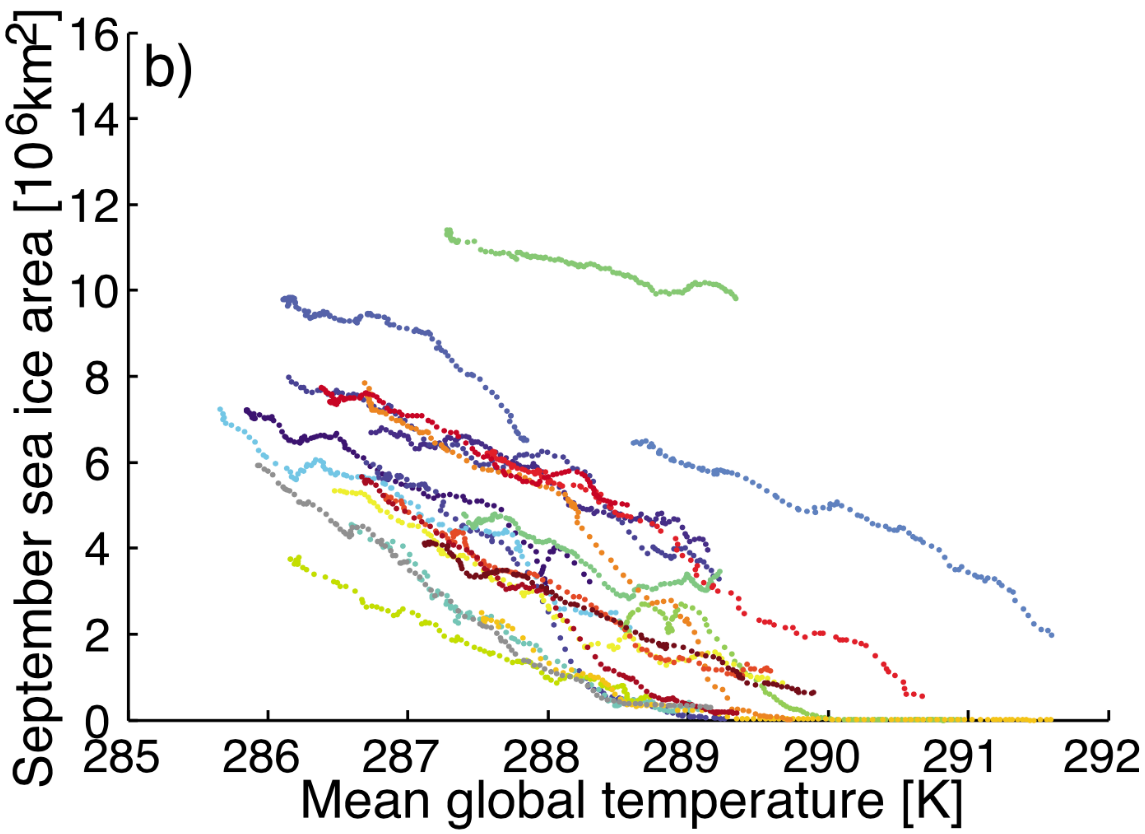

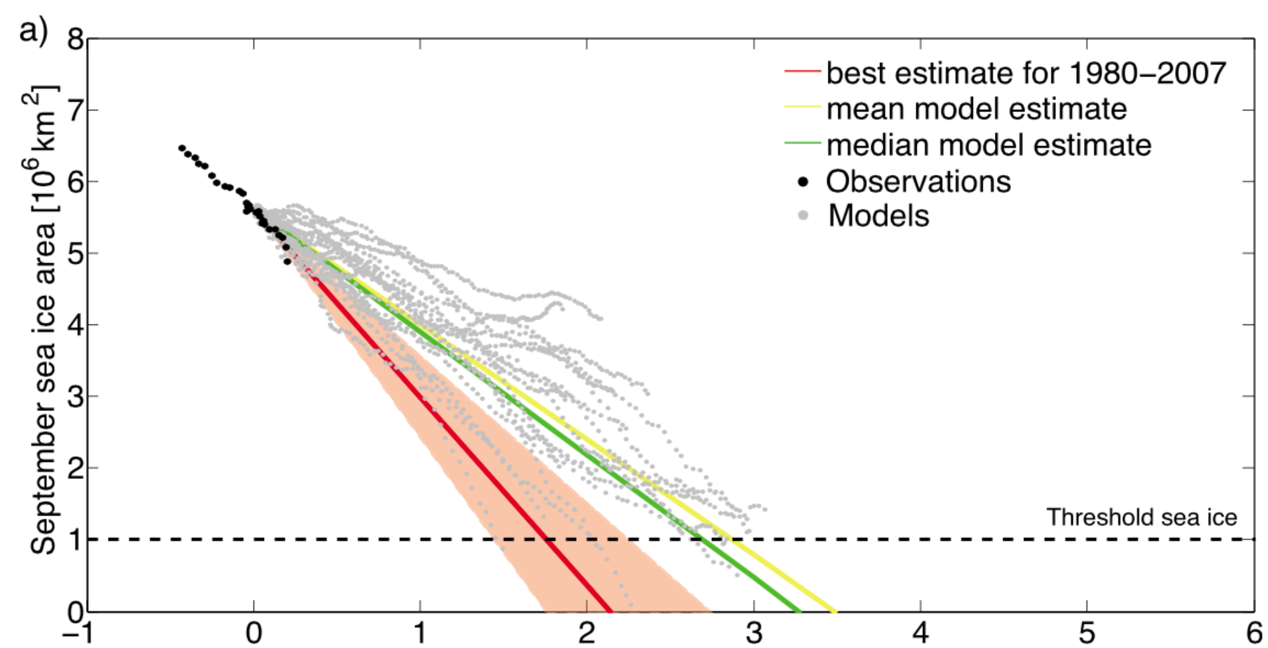

Mahlstein and Knutti, 2012

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