Which Predictability Estimates are most Realistic?

Kathy Pegion[1,2], Tim Delsole[1,]
Emily Becker[3], Teresa Cicerone[1]

[1]Dept of Atmospheric, Oceanic and Earth Science, George Mason University
[2]Center for Ocean-Land-Atmosphere Studies
[3]NOAA/Climate Prediction Center

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What is Predictability & Why do we care?

- Inherent property of the climate system
- Upper limit of prediction
- Goal of prediction system
- Do not know exactly- have to estimate
- Signal to noise problem
- Important for relaying to users what information we have a scientific basis for accurately predicting

How do we estimate Predictability?

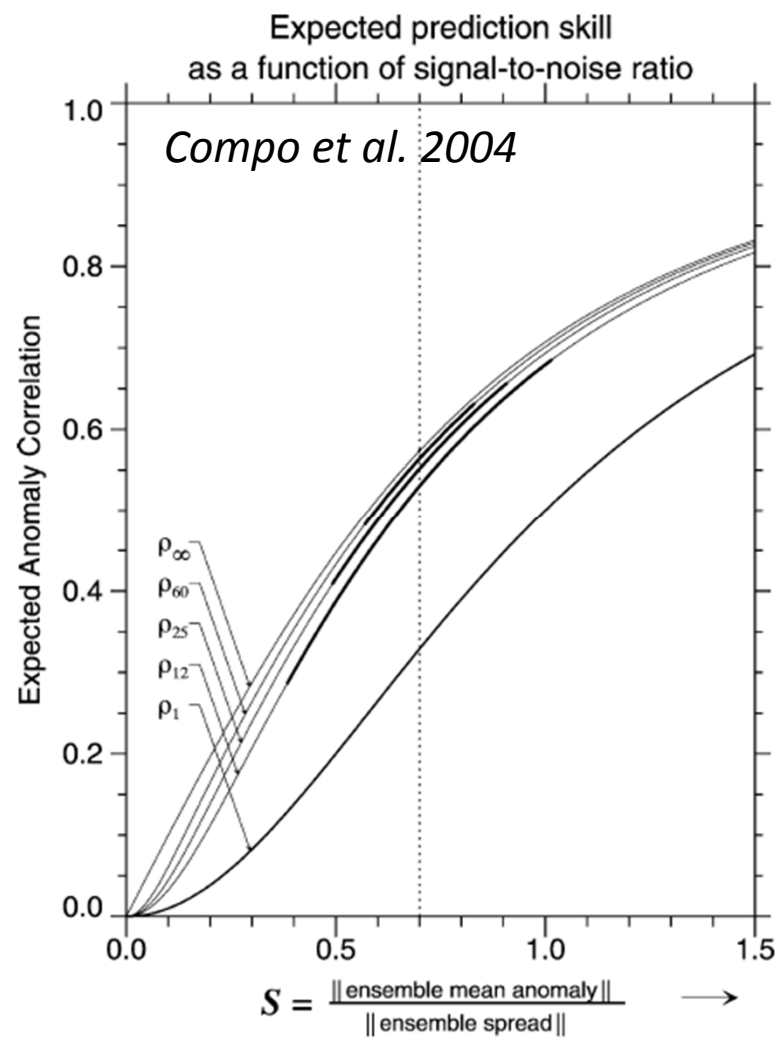
Signal to Noise

$$\sigma^2_{Total}=\sigma^2_{Signal}+\sigma^2_{Noise}$$

$$S^2=\sigma^2_{Signal}/\sigma^2_{Noise}$$

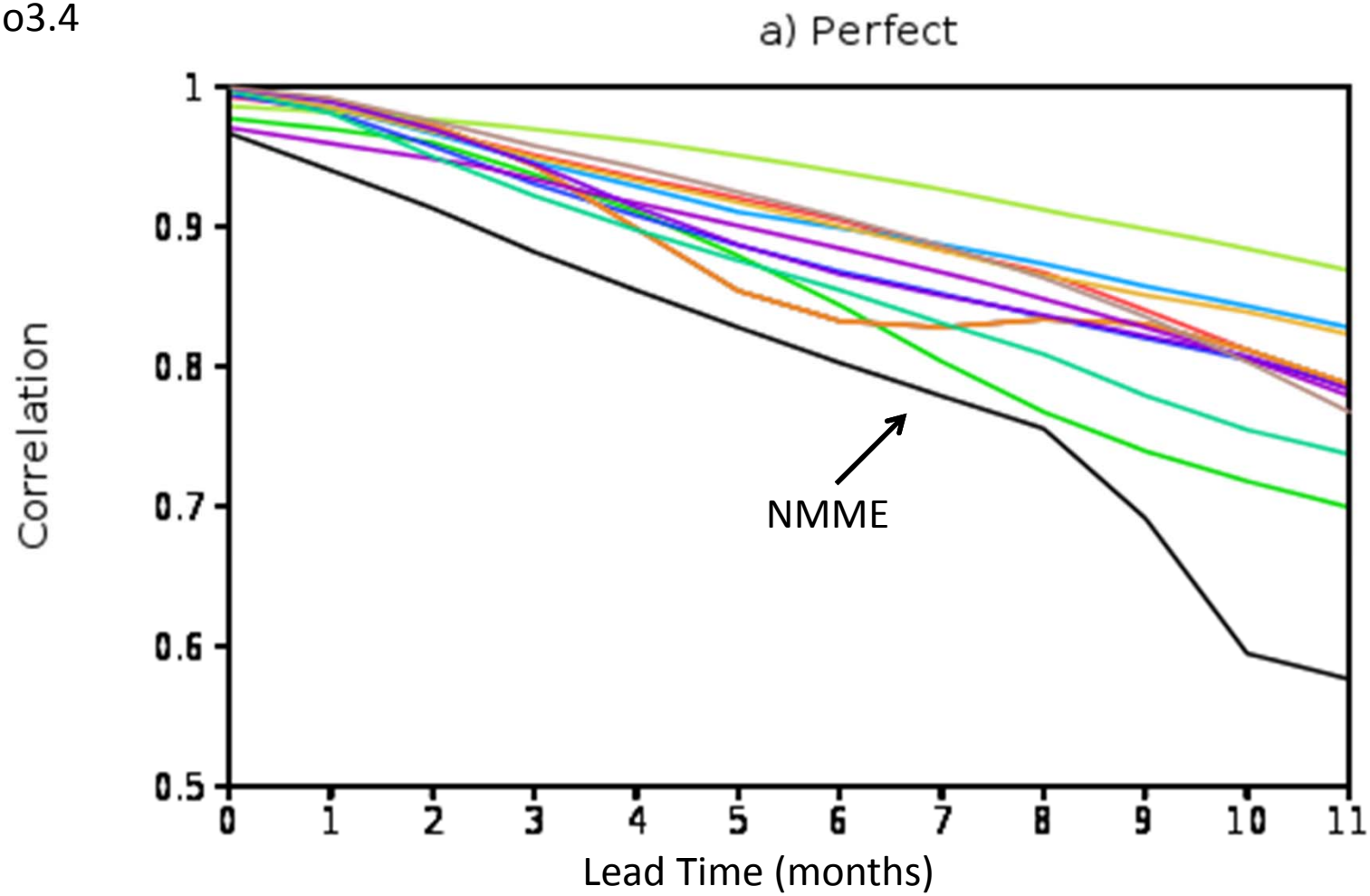
Perfect model correlation skill

$$\rho_n = \frac{S^2}{\left[\left(S^2+1\right)\left(S^2+\frac{1}{n}\right)\right]^{\frac{1}{2}}}$$

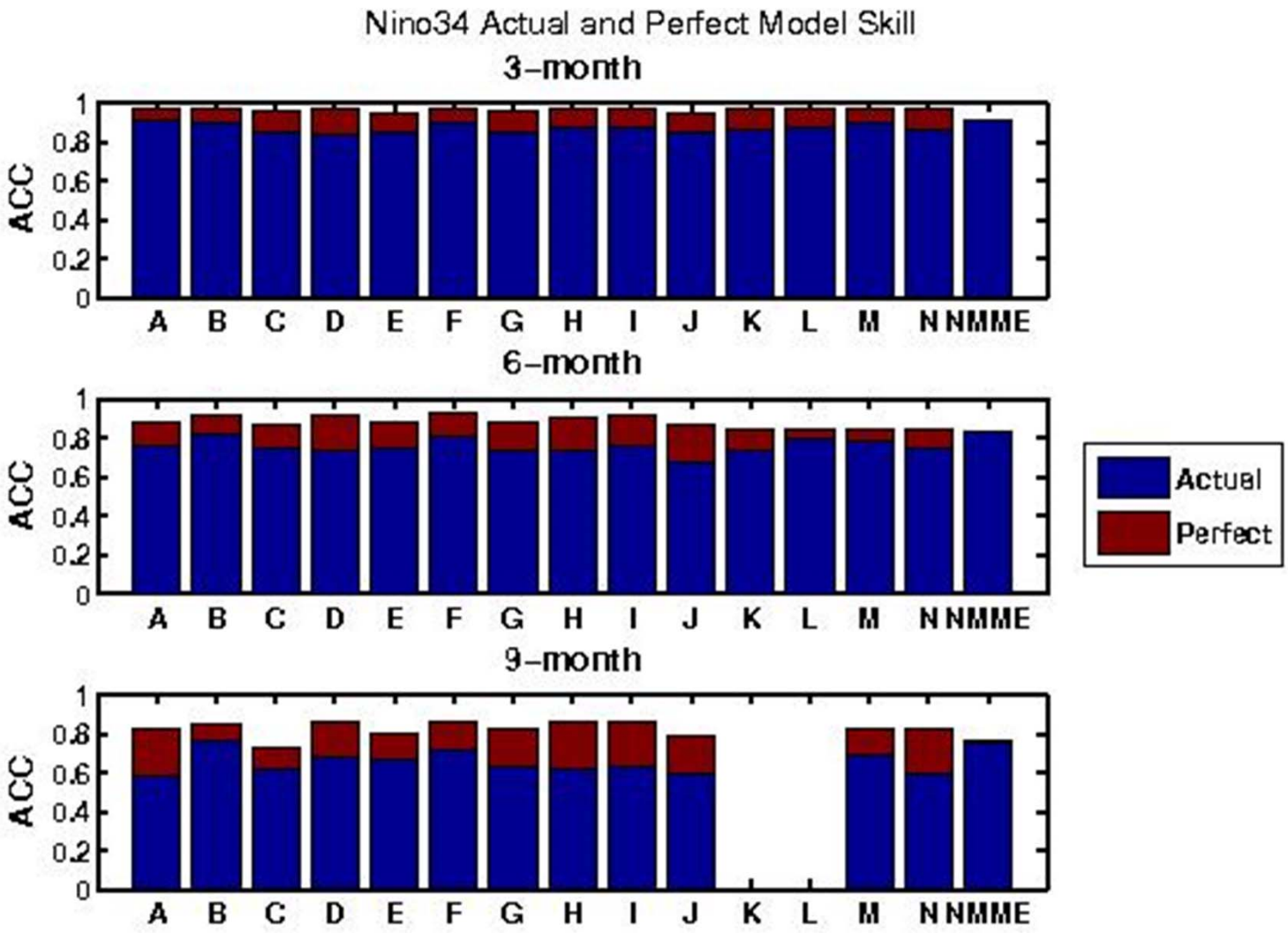


…by calculating how well a model predicts itself

Nino3.4



Which predictability estimate is most representative of the true predictability of the climate system?



How much skill is left to be realized?

Challenge

Nature is 1 ensemble member, so we do not know the true signal, noise, or predictability

Metrics for assessing fidelity of predictability estimates

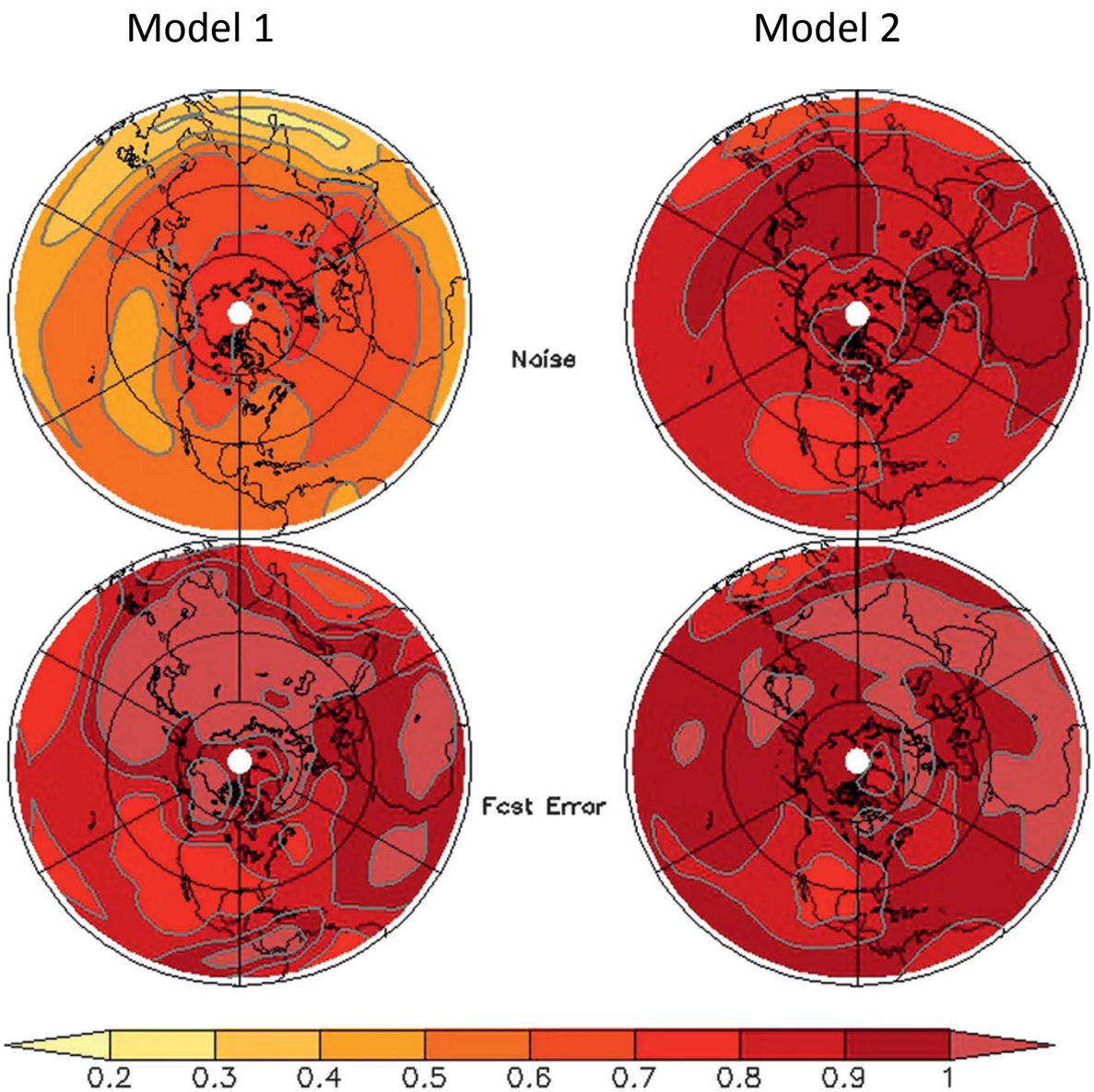
Pegion and Sardeshmukh 2011

- spread/error relationship
- Autocorrelation

Kumar et al 2014

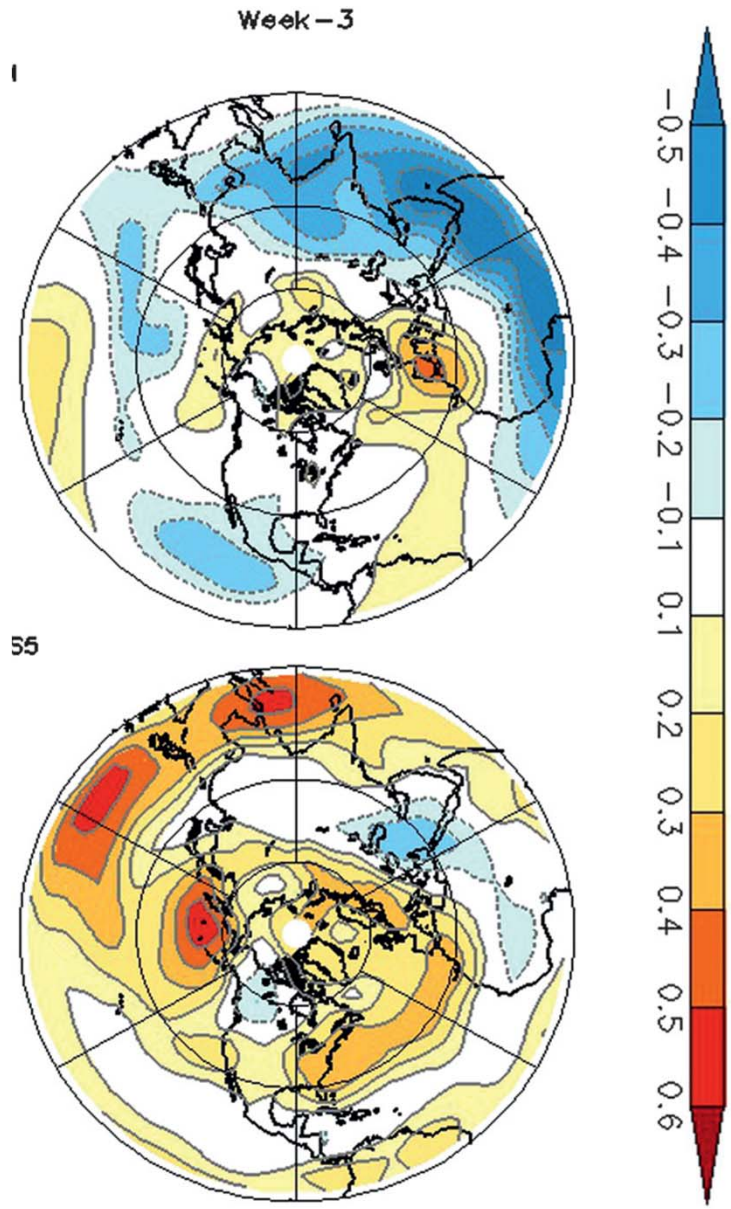
- Autocorrelation
- Actual RMSE v Perfect RMSE (equivalent to Spread/Error)

Week-3 850hPa Streamfunction



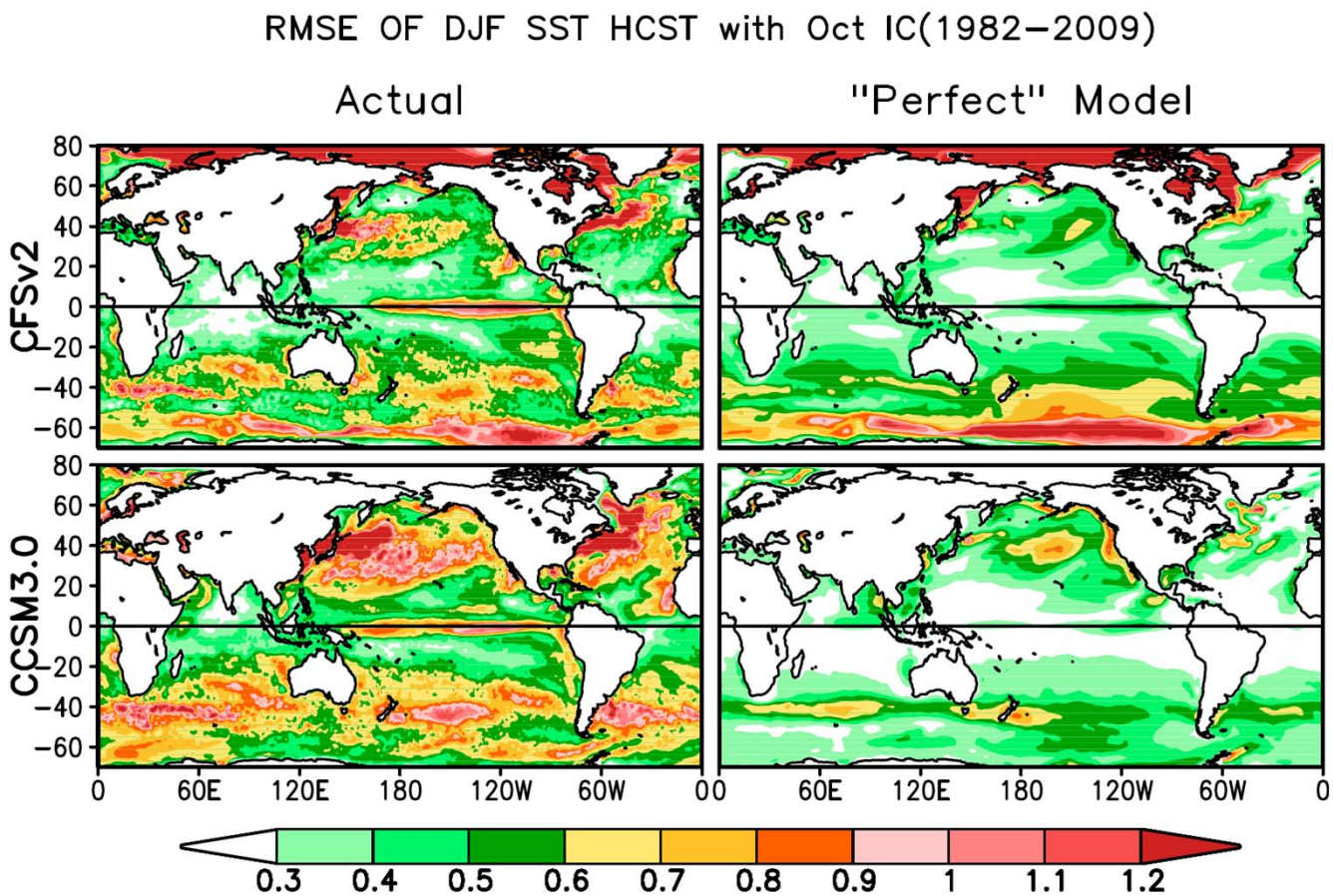
Pegion and Sardeshmukh 2011

Model minus observed autocorrelation 850 hPa streamfunction



Pegion and Sardeshmukh 2011

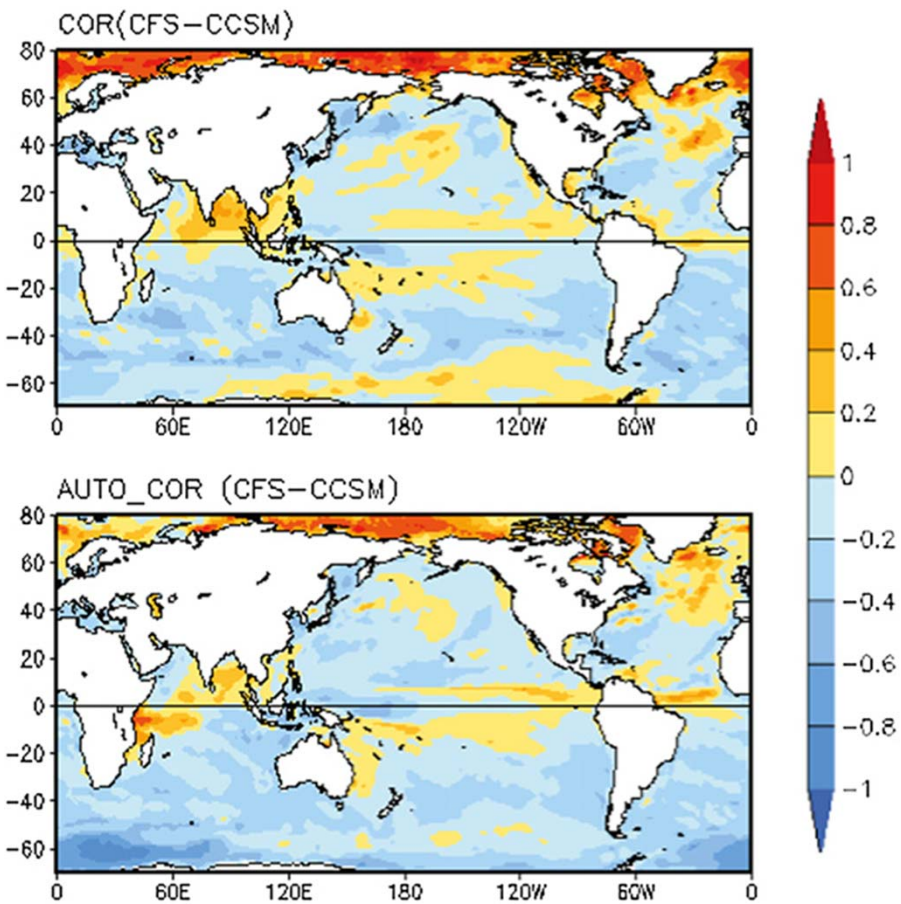
Perfect and actual RMSE should be similar for unbiased model – perfect RMSE < actual RMSE for an underdispersive system

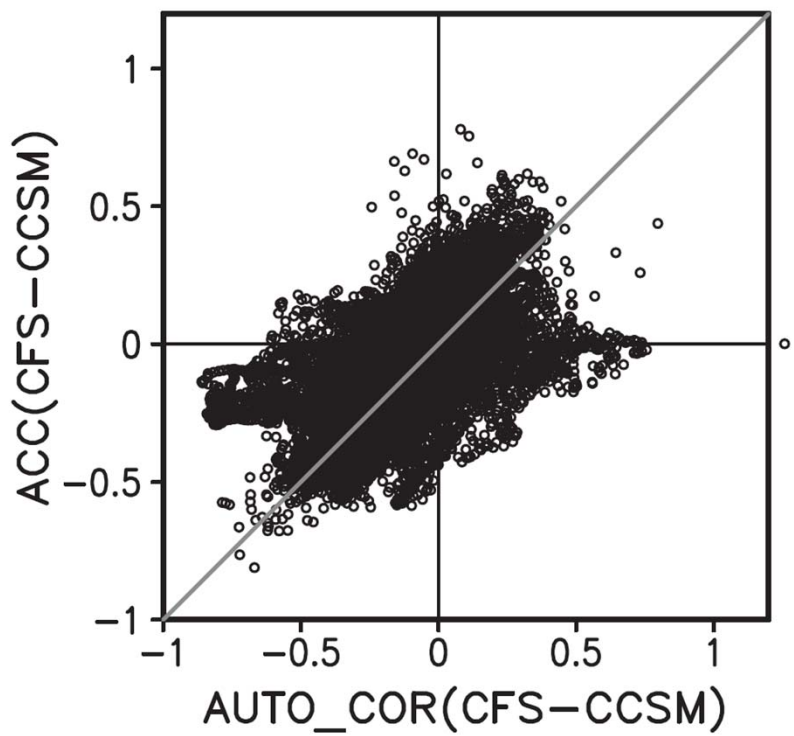


Kumar et al. 2014

Metrics for assessing realism of perfect model skill

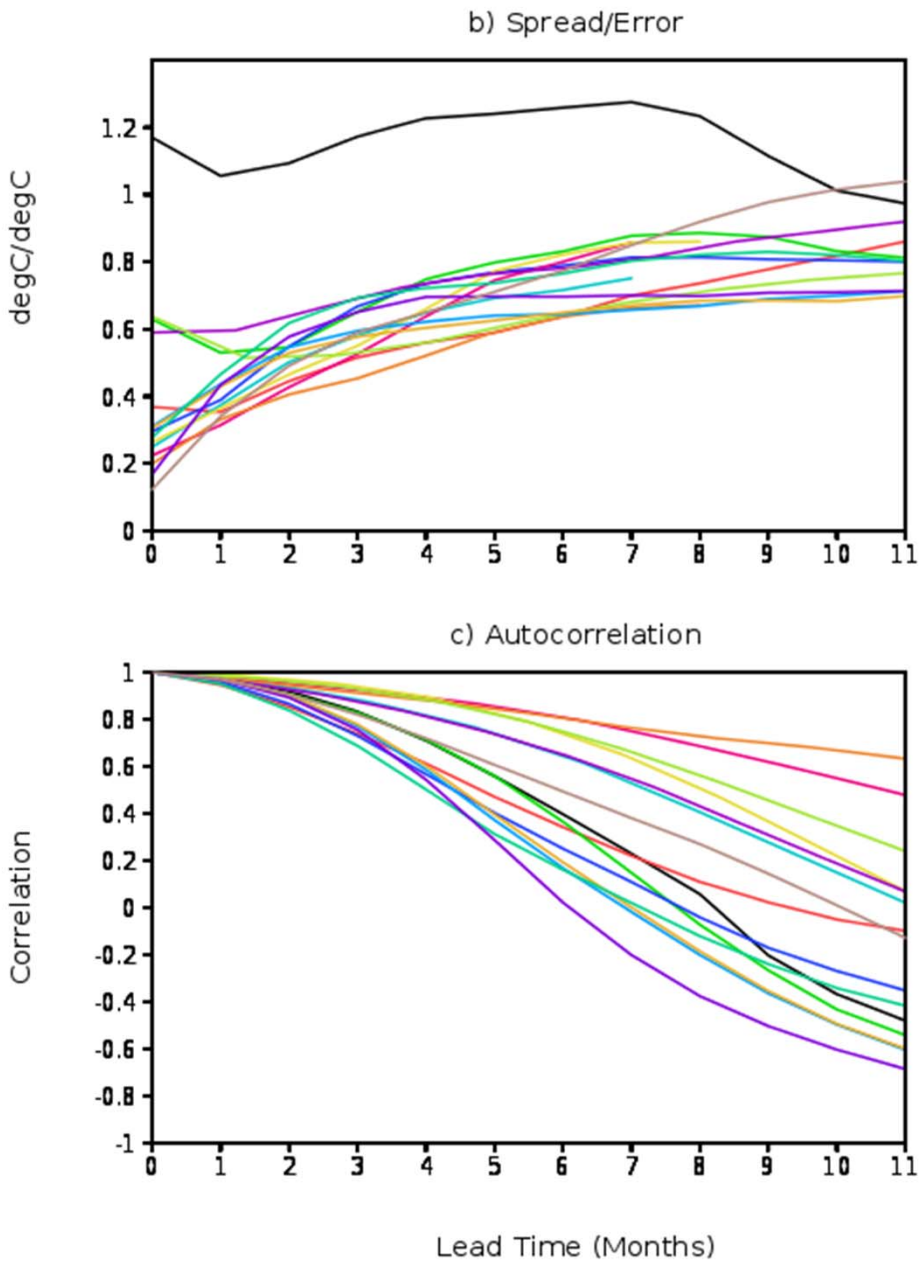
Autocorrelation as a measure of persistence – related to signal and noise, so high autocorrelation = high S2N = high predictability and vice versa





Kumar et al. 2014

Nino34


b) Spread/Error
degC/degC
1.2
1
0.8
0.6
0.4
0.2
0
0 1 2 3 4 5 6 7 8 9 10 11
c) Autocorrelation
Correlation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
0 1 2 3 4 5 6 7 8 9 10 11
Lead Time (Months)

Do Spread/Error and Autocorrelation tell us about the fidelity of predictability estimates?

1. Use the full NMME as the “truth” with a known signal, noise, and predictability

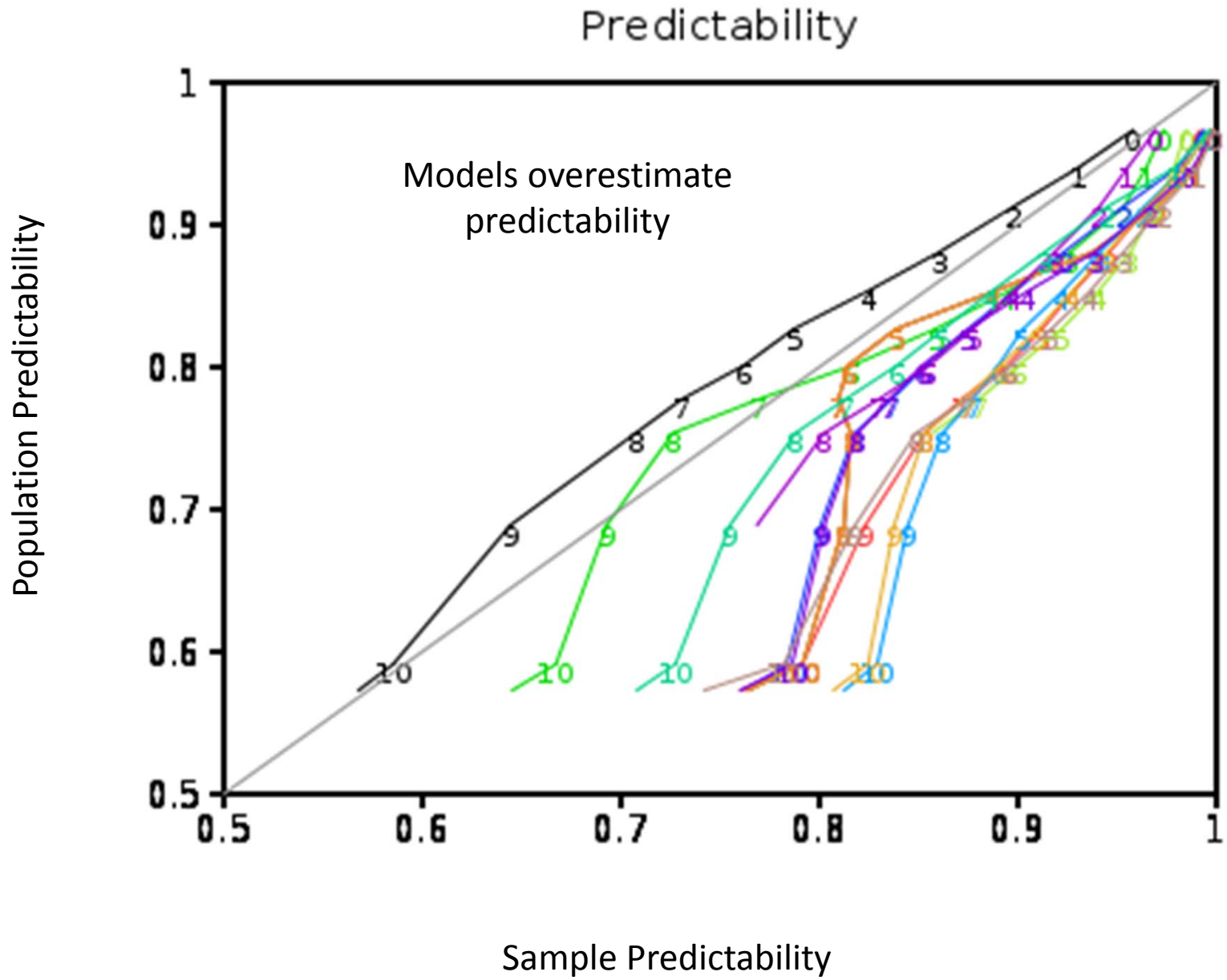
1. Sample estimates of the signal, noise, and predictability using each individual model

1. Test whether these metrics tell us anything about a model’s ability to represent the signal, noise, and predictability properly

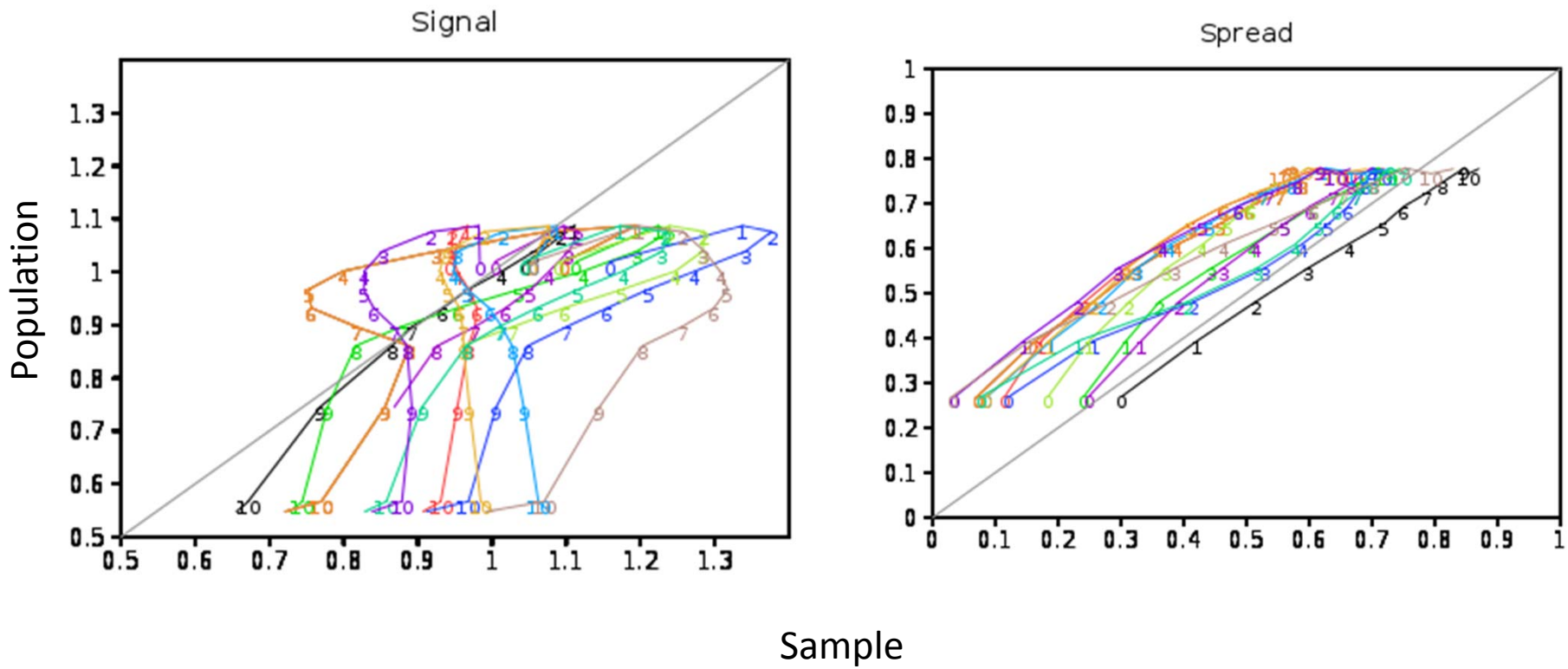
Model	Hindcast Period	No. of Members	Arrangement of Members	Lead (month)	Model resolution (atmos)	Model resolution (ocean)	Reference
Active							
NCEP/CFSv2	1982-2010	24 (28)	4 members (0, 6, 12, 18z) every 5th day	0-9	T126L64	MOM4L40 .25deg Eq	Saha et al (2010)
GFDL/CM2.1	1982-2010	10	All 1st of the month 0Z	0-11	2x2.5degL24	MOM4L50 .3deg Eq	Delworth (2006)
GFDL/CM2.5 (FLOR)	1982-present	24	All 1st of the month 0Z	0-11	C18L32 (50km)	MOM5 L50 0.30 deg Eq 1degPolar1.5	Vecchi et al (2014)
CMC1-CanCM3	1981-2010	10	All 1st of the month 0Z	0-11	CanAM3 T63L31	CanOM4L40 .94deg Eq	Merryfield et al (2013)
CMC1-CanCM4	1981-2010	10	All 1st of the month 0Z	0-11	CanAM4 T63L35	CanOM4L40 .94deg Eq	Merryfield et al (2013)
NCAR/CCSM4	1982-2010	10	All 1st of the month 0Z	0-11	0.9x1.25degL26	POPL60 .25deg Eq	Kirtman et al. (in prep)
NASA/GEOS5	1981-2010	11	4 mems every 5 days; 7 mems on last day of last month	0-9	1x1.25 deg L72	MOM4L40 .25deg Eq	Vernieres et al (2012)
Retired							
NCEP/CFSv1	1982-2009	15	1st 0Z +/-2 days, 21st 0z +/-2d, 11th 0z +/-2d	0-8	T62L64	MOM3L40 0.30 deq Eq	Saha et al (2006)
NCAR/CCSM3	1982-2010	6	All 1st of the month 0Z	0-11	T85L26	POPL42 0.3deg Eq	Kirtman and Min2009)
IRI-ECHAM4f	1982-2010	12	All 1st of the month 0Z	0-7	T42L19	MOM3L25(1.5x0.5)	DeWitt (2005)
IRI-ECHAM4a	1982-2010	12	All 1st of the month 0Z	0-7	T42L19	MOM3L25 (1.5x0.5)	DeWitt (2005)

http://www.cpc.ncep.noaa.gov/products/NMME/Phase1models.png

Nino34


Predictability
Models overestimate predictability
Population Predictability
Sample Predictability
0.5
0.6
0.7
0.8
0.9
1

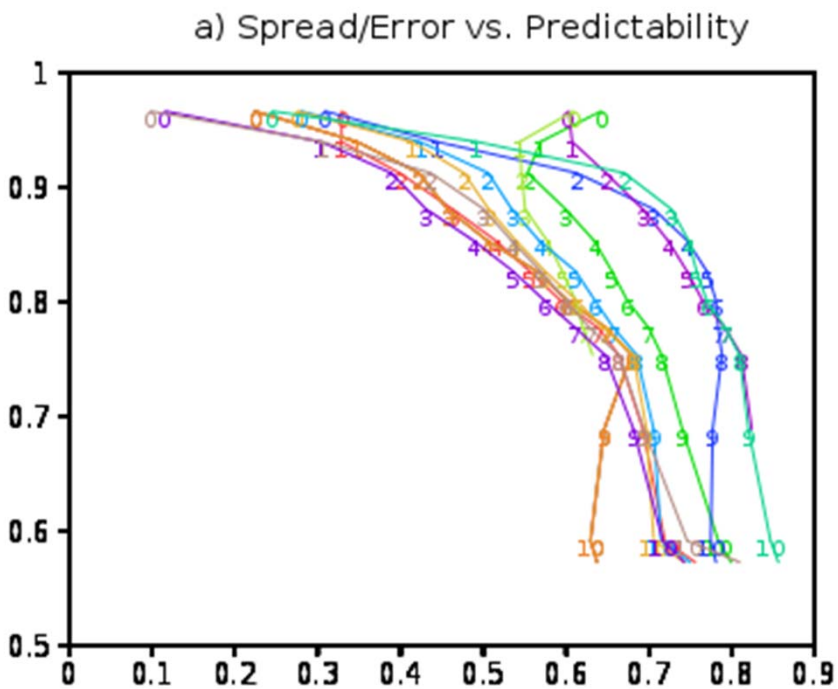
Nino34

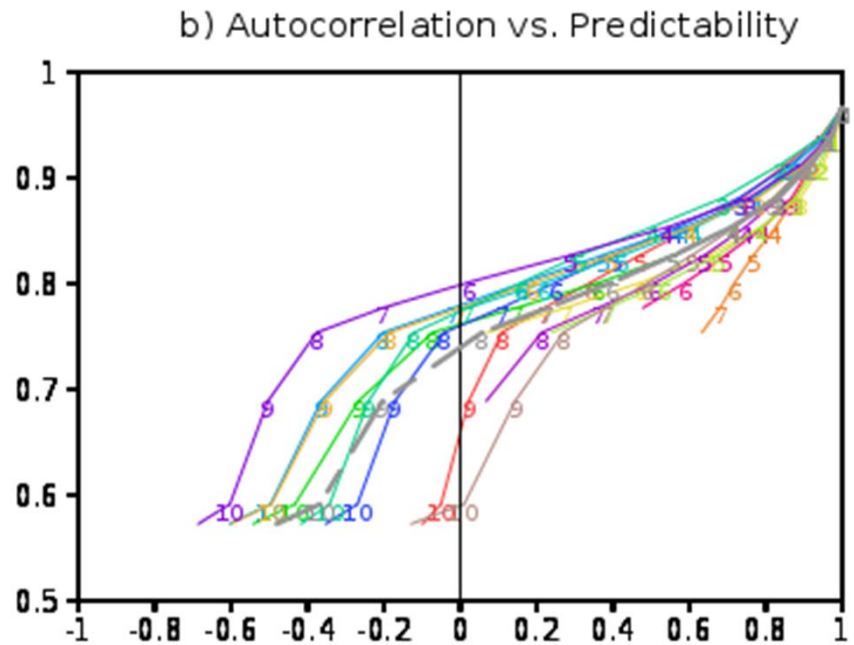


Most individual models over estimate signal

Individual models underestimate the noise

How are the metrics related to predictability?

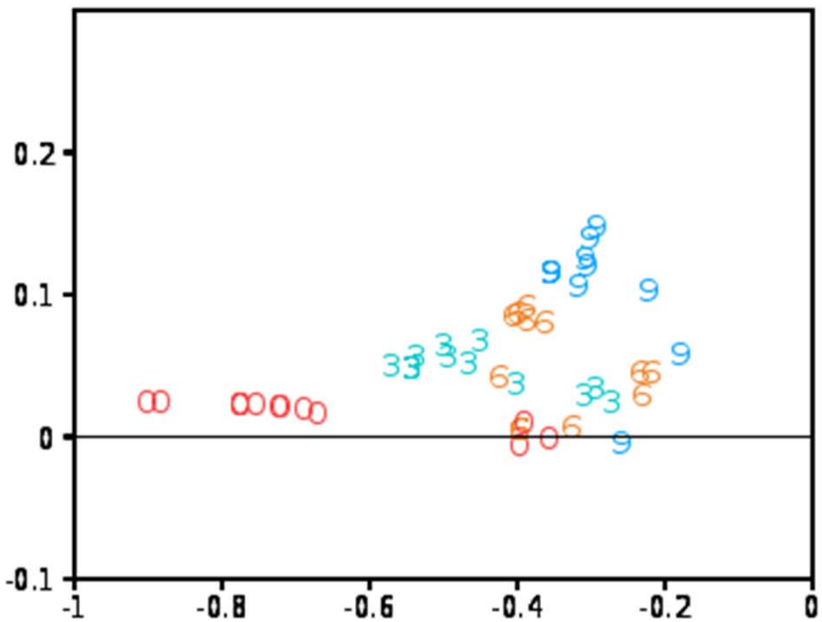




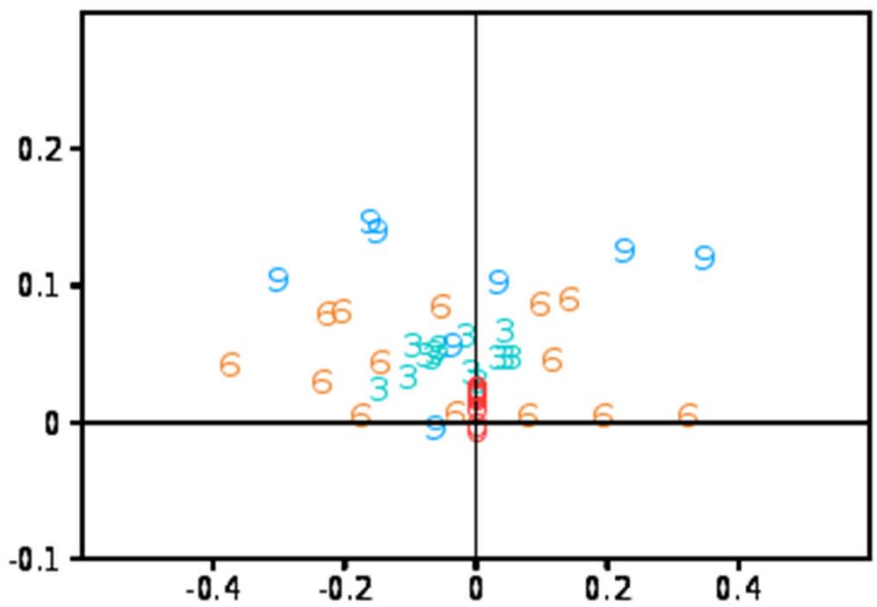
Are errors in these metrics related to errors in estimating predictability?

Nino34

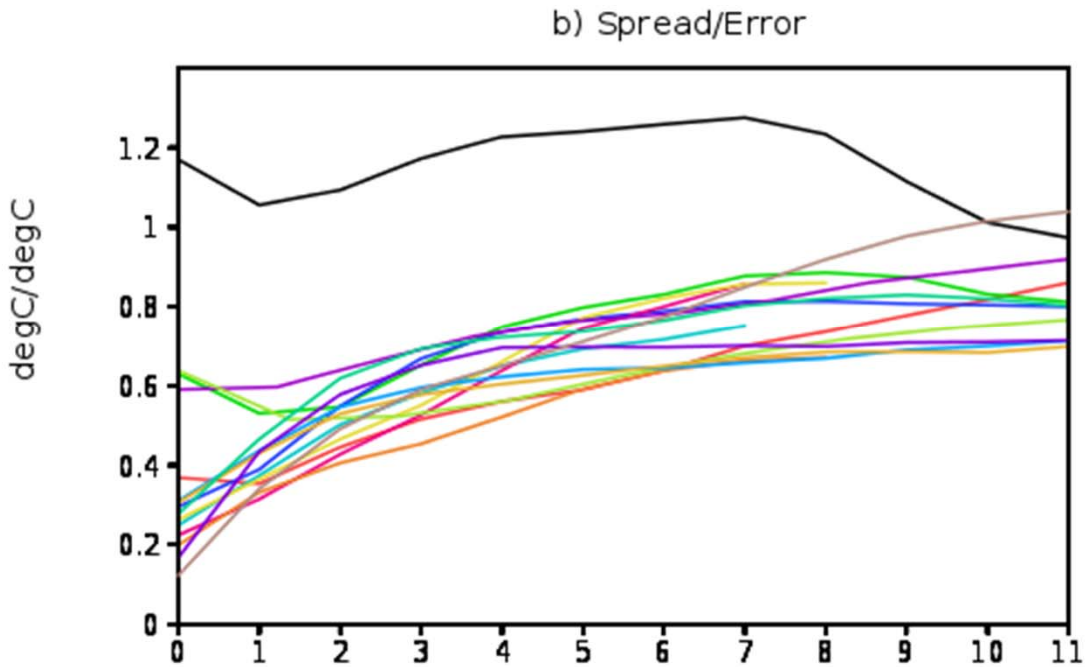
Delta Spread/Error vs. Delta Predictability

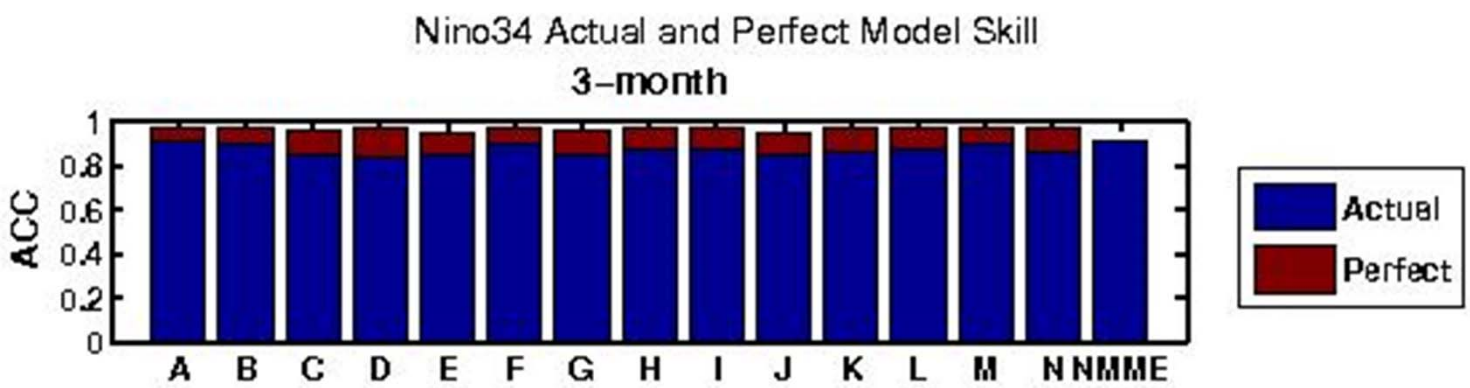


Delta Autocorr vs. Delta Predictability



Nino34





We have already reached the limit of Nino34 skill at 3-months

How does this apply to other regions and variables?

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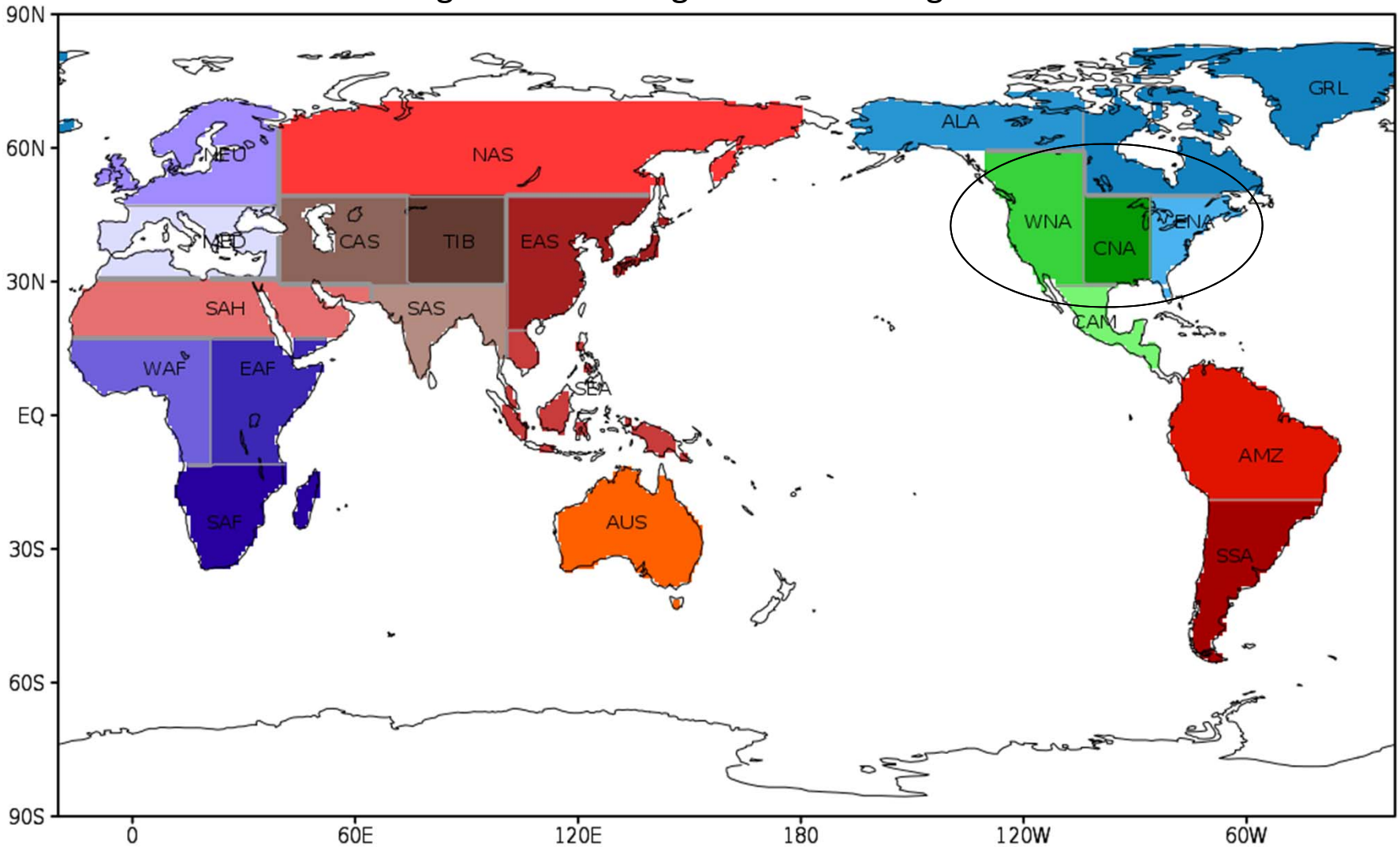
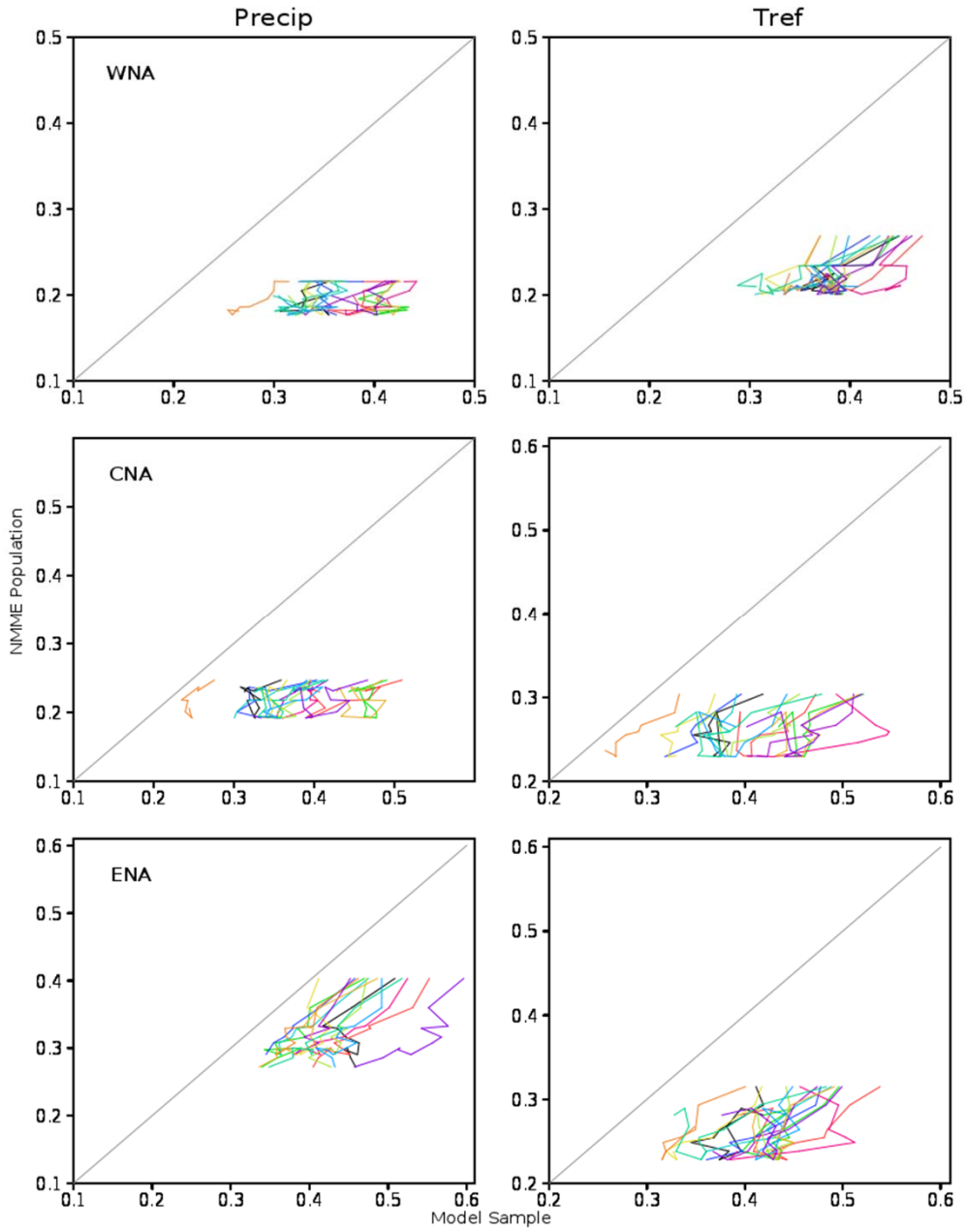
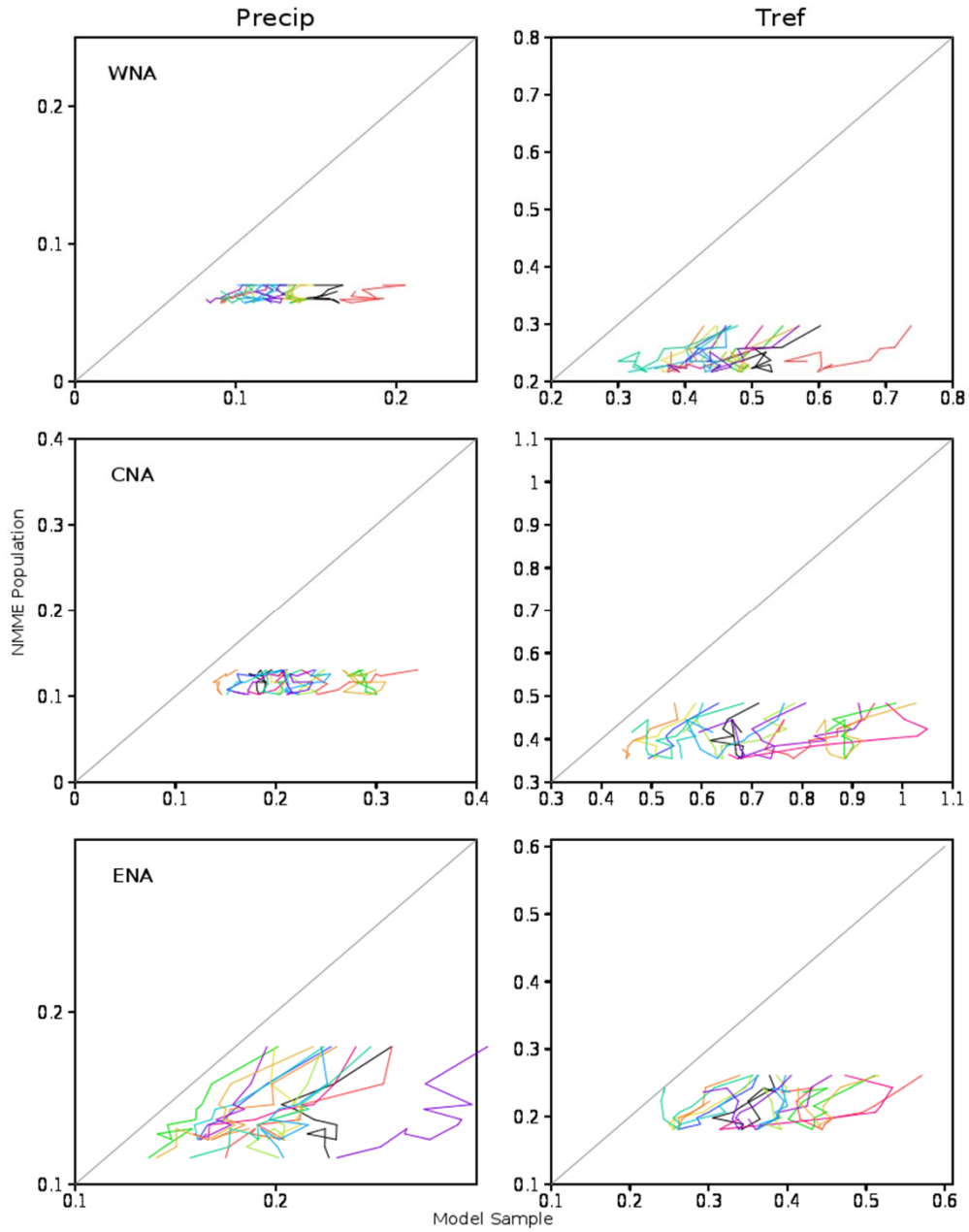
Giorgi et al 2000 Regions on NMME grid



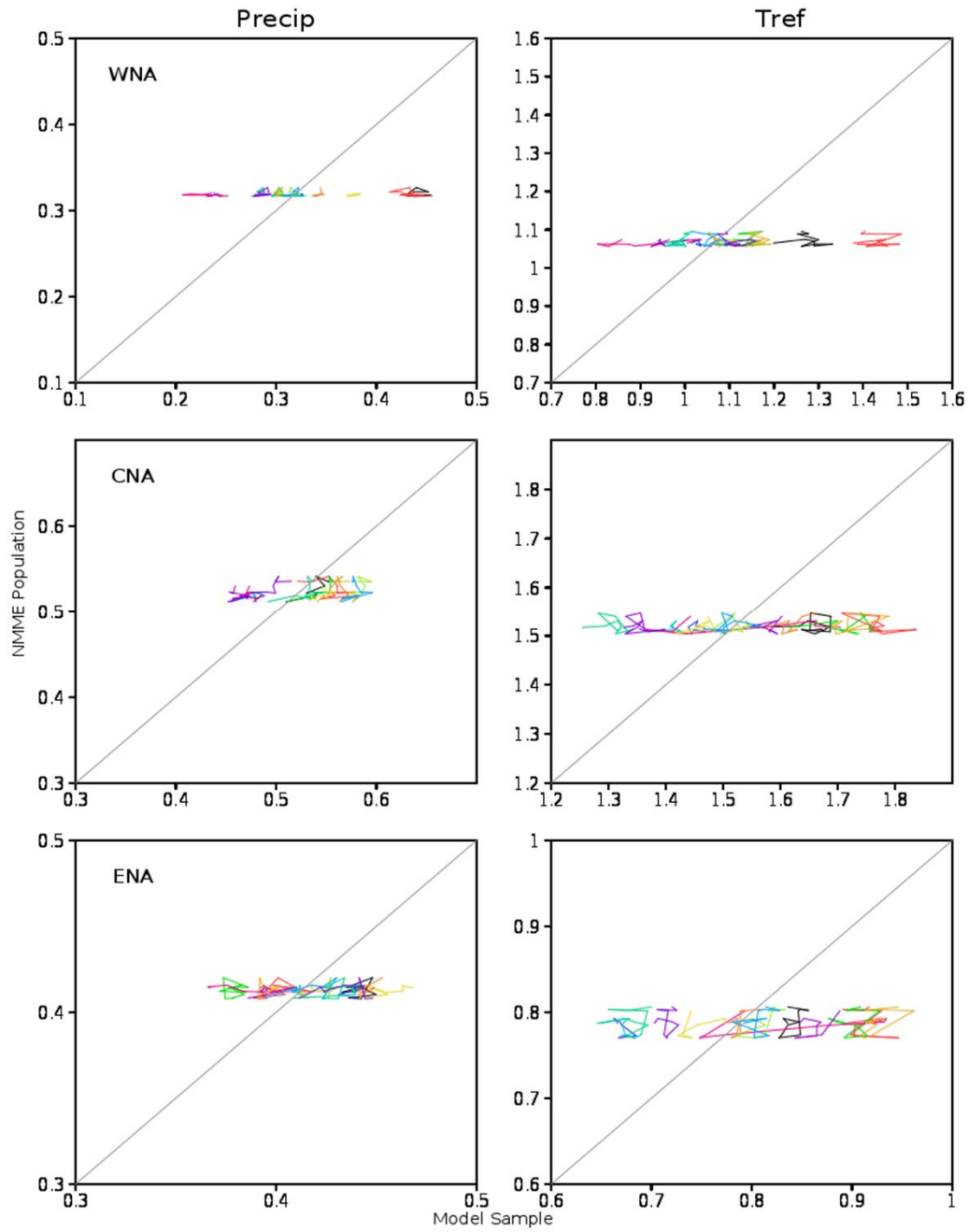
Predictability



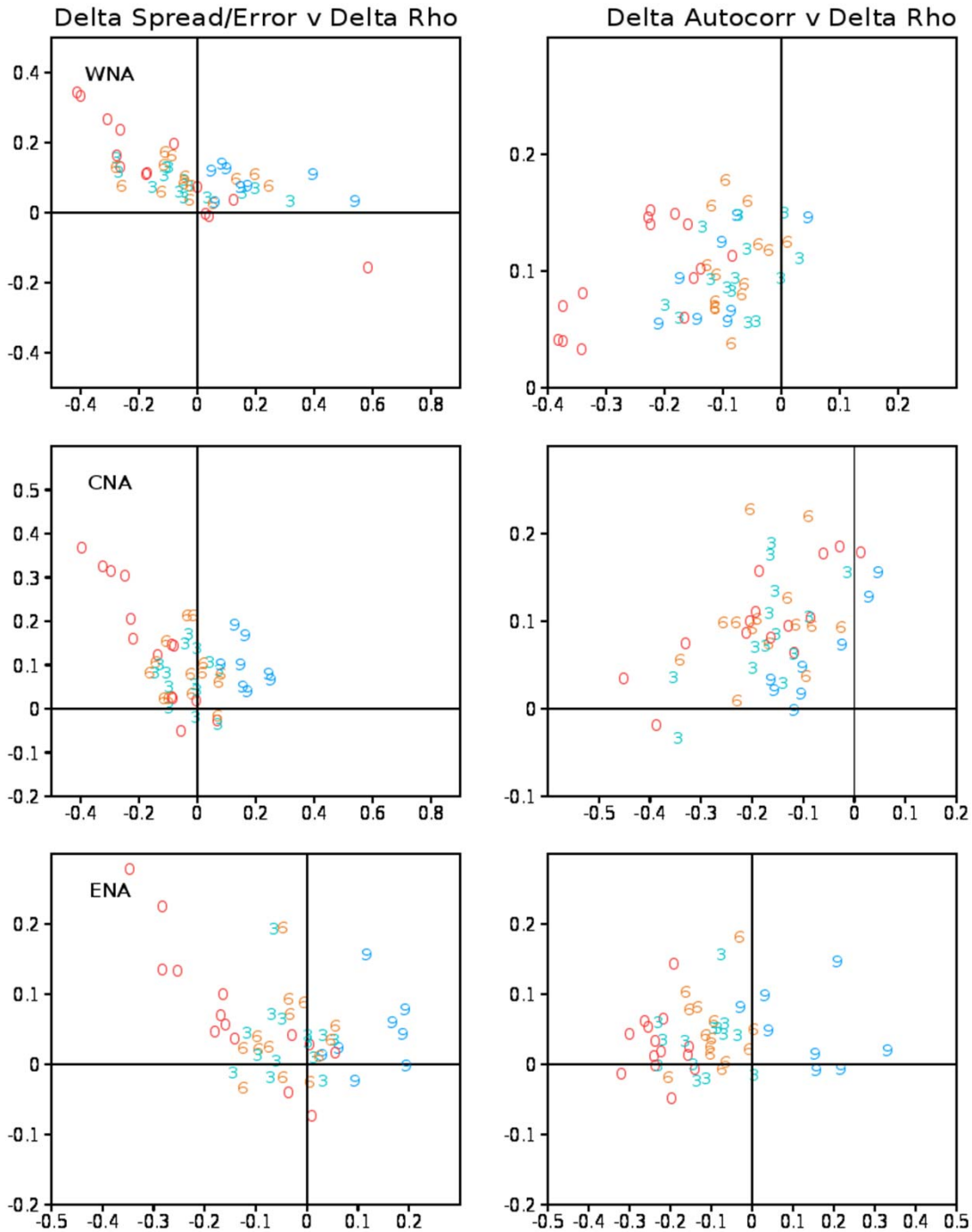
Signal



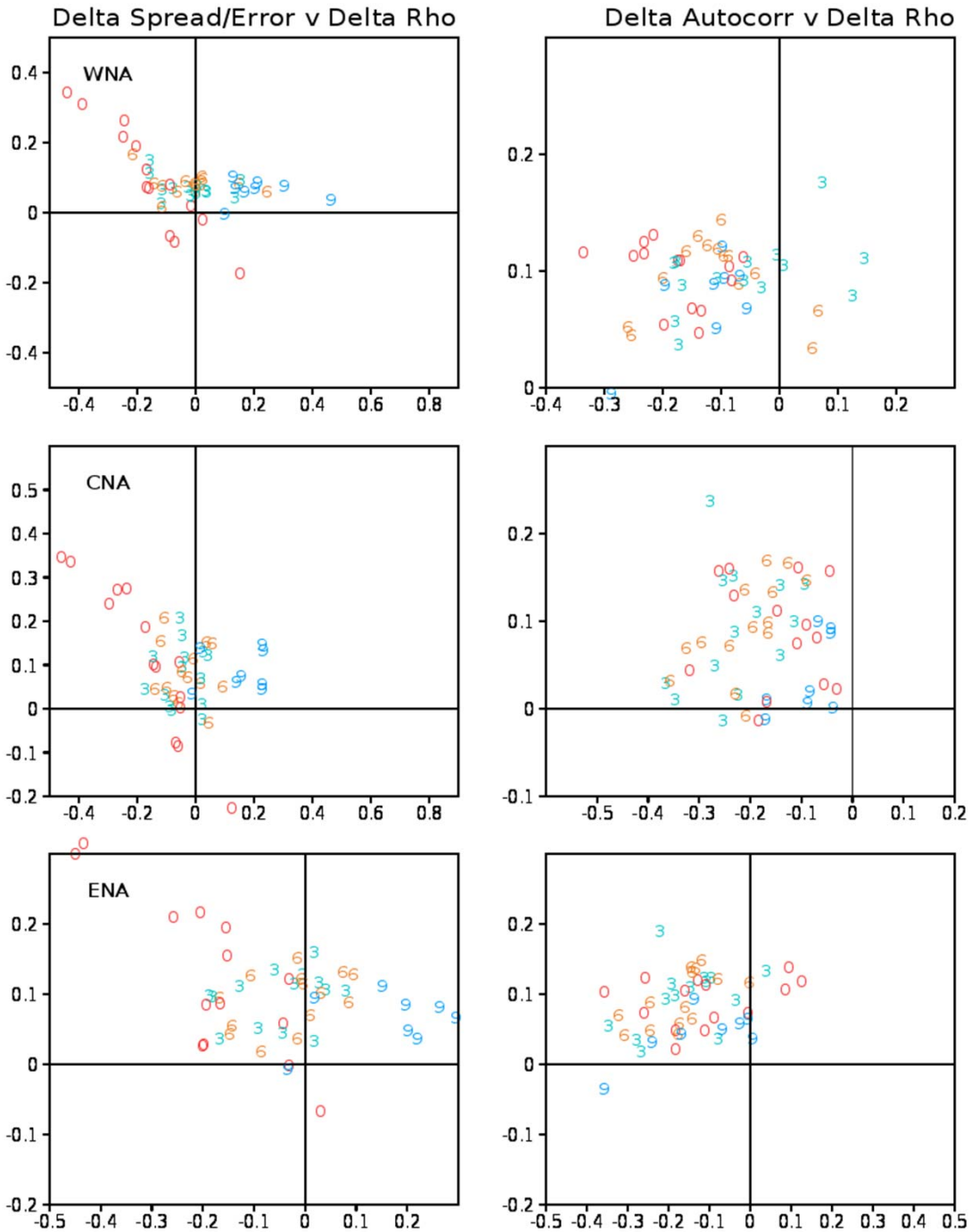
Noise



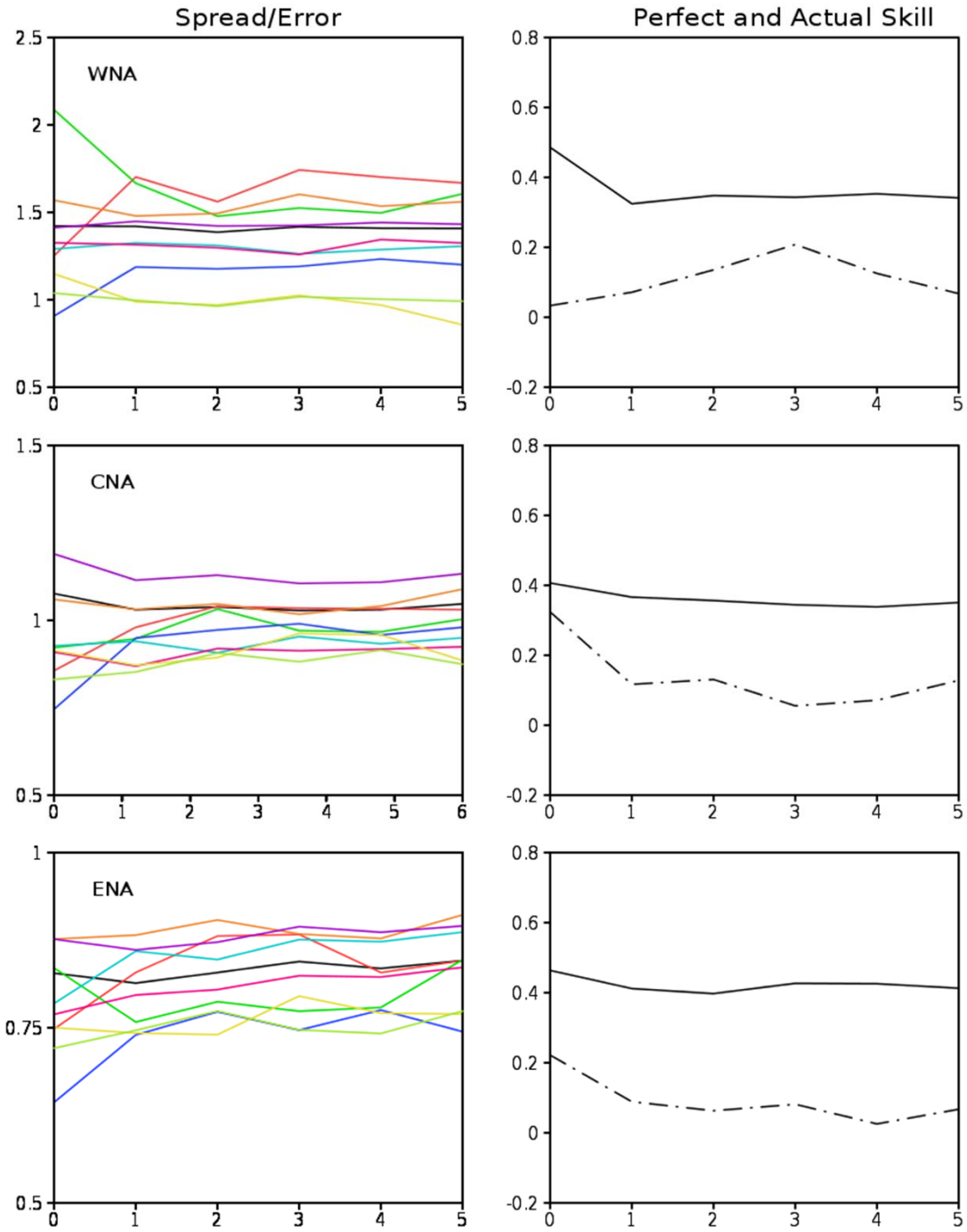
Precip


Delta Spread/Error v Delta Rho
Delta Autocorr v Delta Rho
WNA
CNA
ENA

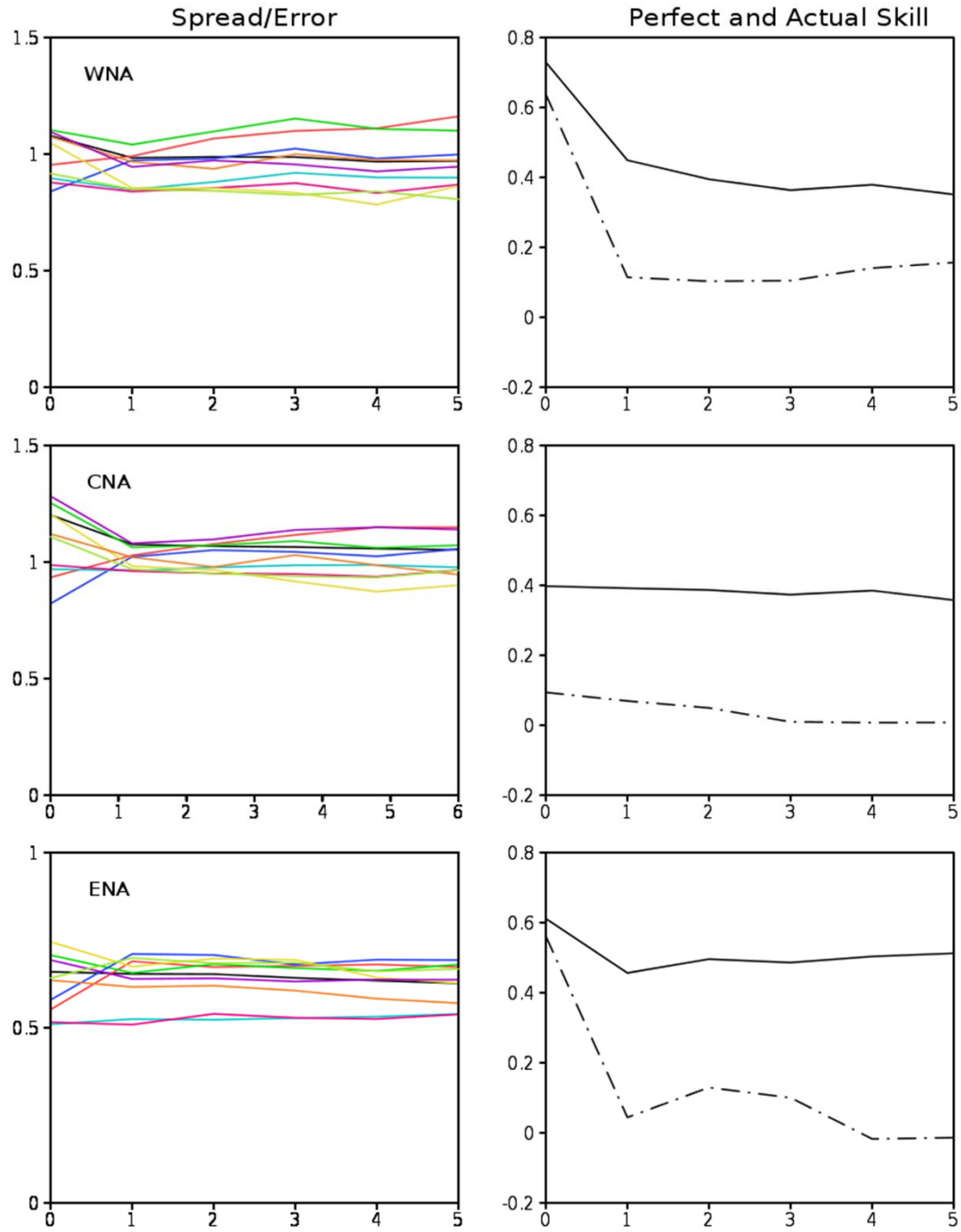
Temperature



Precip



Temperature



Summary & Conclusions

- Overestimation of predictability is a common problem for most models
- For Nino34, underestimation of noise and overestimation of the signal is a problem
- For US temperature and precipitation, overestimation of the signal is a common problem
- Autocorrelation is not useful for providing information about fidelity of predictability estimates
- Spread/error can provide some information about the fidelity of predictability estimates, but only at short lead-times
- MME is not always the best estimate of predictability, nor is any individual model
- MME is a useful tool for evaluating metrics to test fidelity of predictability estimates

Future Work

- Will spread/error be a more useful for predictability on subseasonal timescales?
- Are there other metrics we can use to test the fidelity of predictability estimates?