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Exeter, 6th of October 2016

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

EXCELENCIA SEVERO OCHOA

Expanding the concept of forecast verification

François Massonnet

Omar Bellprat, Stefan Siegert, Virginie Guemas, Francisco J. Doblas-Reyes

SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

What Is a Good Forecast?
An Essay on the Nature of Goodness in Weather Forecasting

ALLAN H. MURPHY

College of Oceanic and Atmospheric Sciences, Oregon State University, Corvallis, Oregon

(Manuscript received 11 August 1992, in final form 20 January 1993)

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Consistency	1) The forecast corresponds to the best judgment based on **a priori knowledge**	(Expert)
Quality	2) The forecast corresponds to **observed conditions** during the forecast period	(Method)
Value	3) The forecast results in **incremental** economic and/or other **benefits**	(User)

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The quality of a forecast does not only depend on the forecast itself

Observational reference

Model forecast

Performance metric (correlation, RMSE,...)

correlation between forecast and observational reference

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Irreducible (inherent) error

correlation between forecast and observational reference

Lorenz, *J. Atm. Sci.*, 1963

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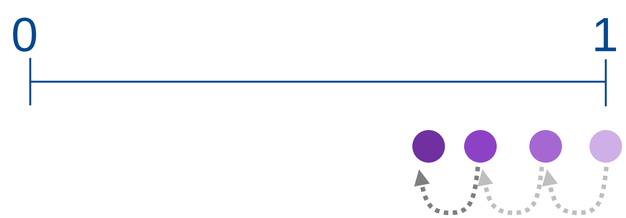

Lorenz, *J. Atm. Sci.*, 1963; Orrell et al., *Nonlin. Proc. Geoph.*, 2001; Okuro et al., *Int. J. Rem. Sens.*, 2014

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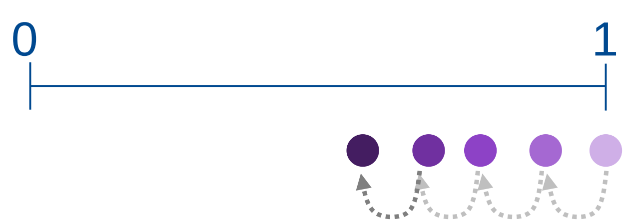

Irreducible (inherent) error

Model error

Observational error

Limited sampling

Lorenz, *J. Atm. Sci.*, 1963; Orrell et al., *Nonlin. Proc. Geoph.*, 2001; Okuro et al., *Int. J. Rem. Sens.*, 2014; Scaife et al., *GRL*, 2014.

Outline

1. Joint estimation of model and observational error

2. Decomposition of forecast error

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1. Joint estimation of model and observational error

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Seasonal forecasts of summer sea surface temperature

NMME Ensemble + 3 versions of EC-EARTH

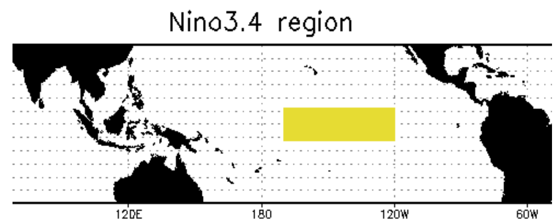
11 models

10 members

4-month forecasts initialized in May

440 forecasts (not independent from each other)

Period for evaluation: 1993-2009



ESA-CCI **ERA-Int** **ERSST4** **HadISST**

4 observational datasets for verification

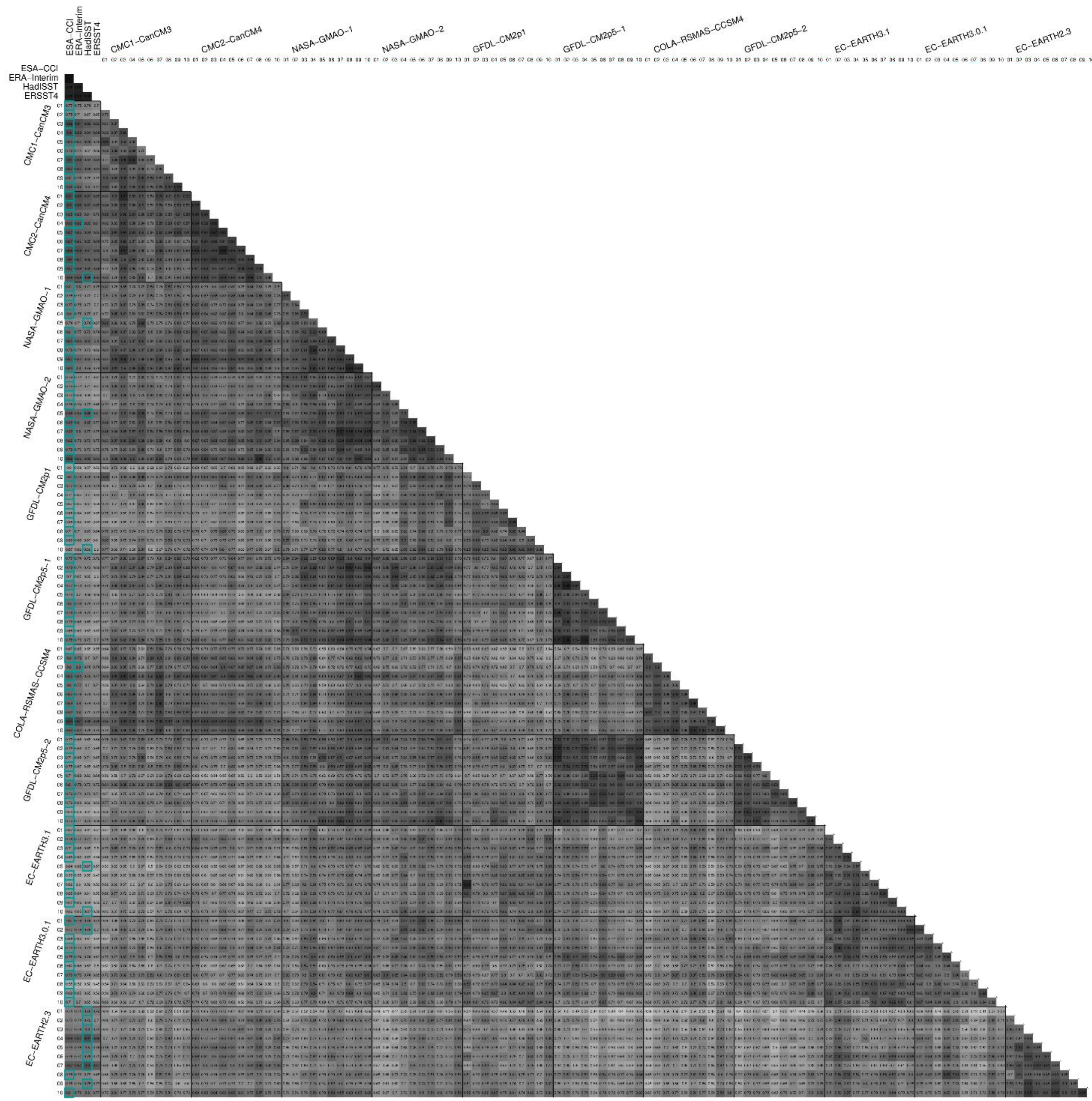
(not independent from each other either)

Joint Correlation Matrix of Models and Observations: a wealth of information

1

0

Correlation of August Niño3.4 SST (1993-2009)



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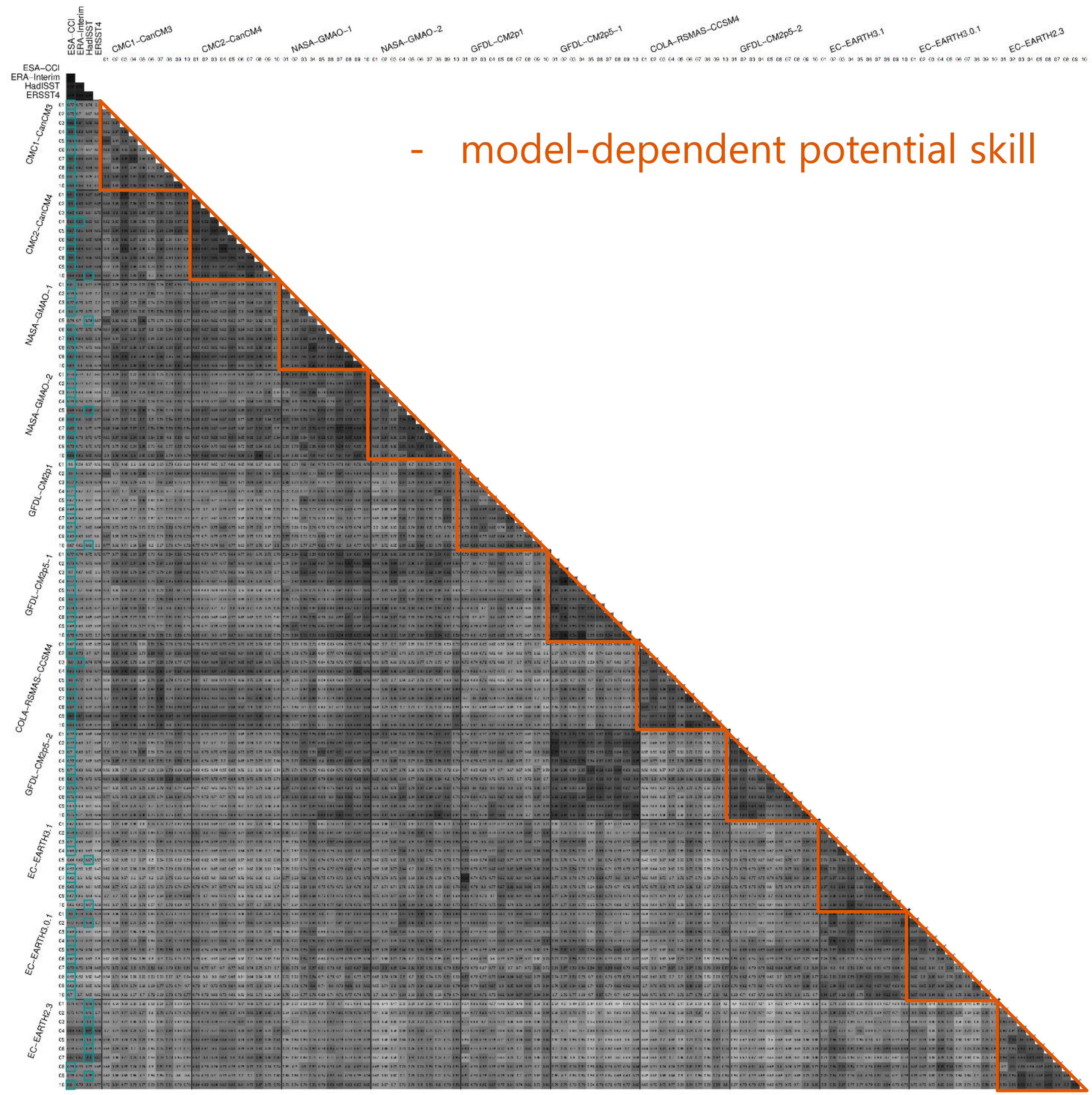

- model-dependent potential skill

1

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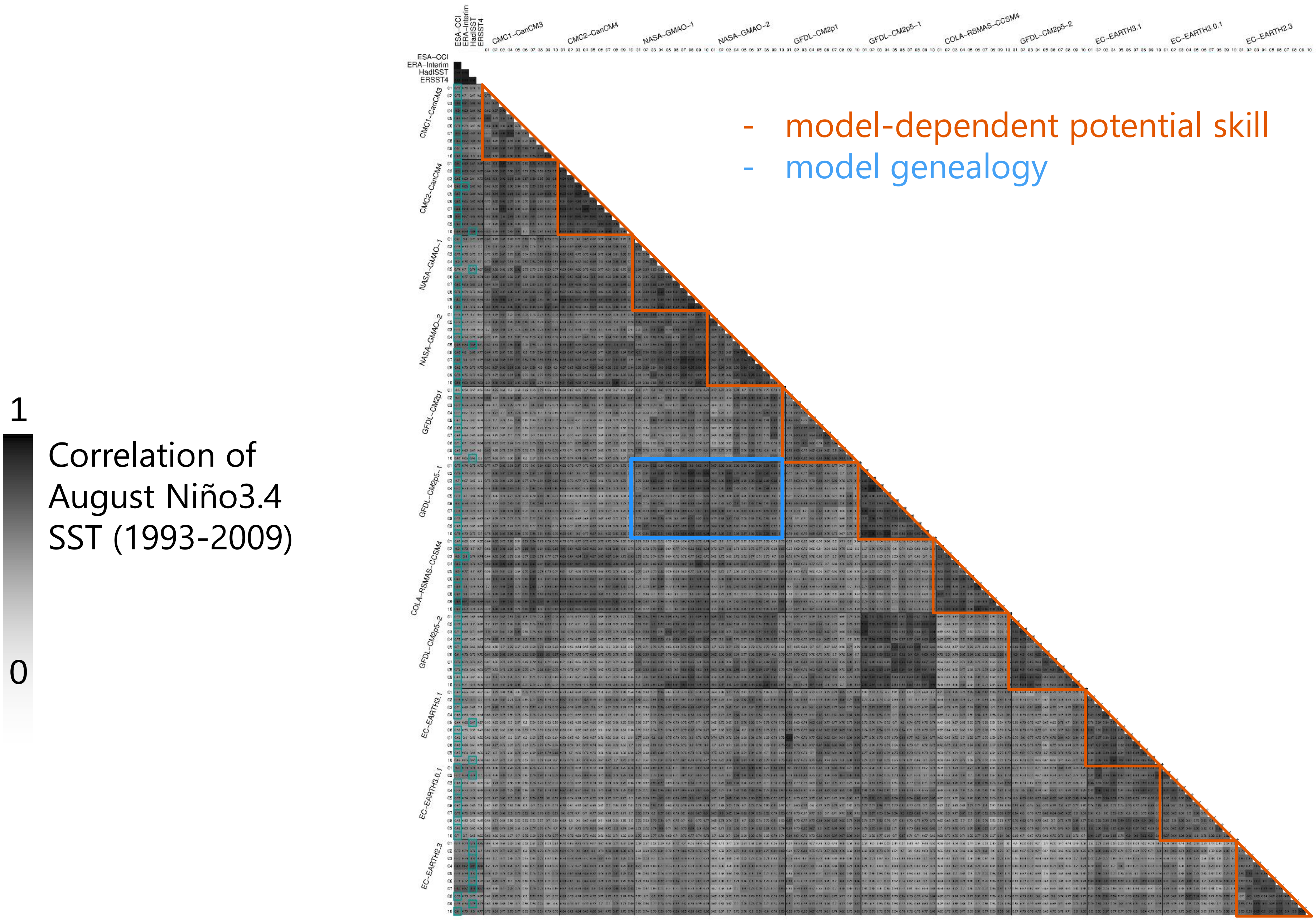

Joint Correlation Matrix of Models and Observations: a wealth of information

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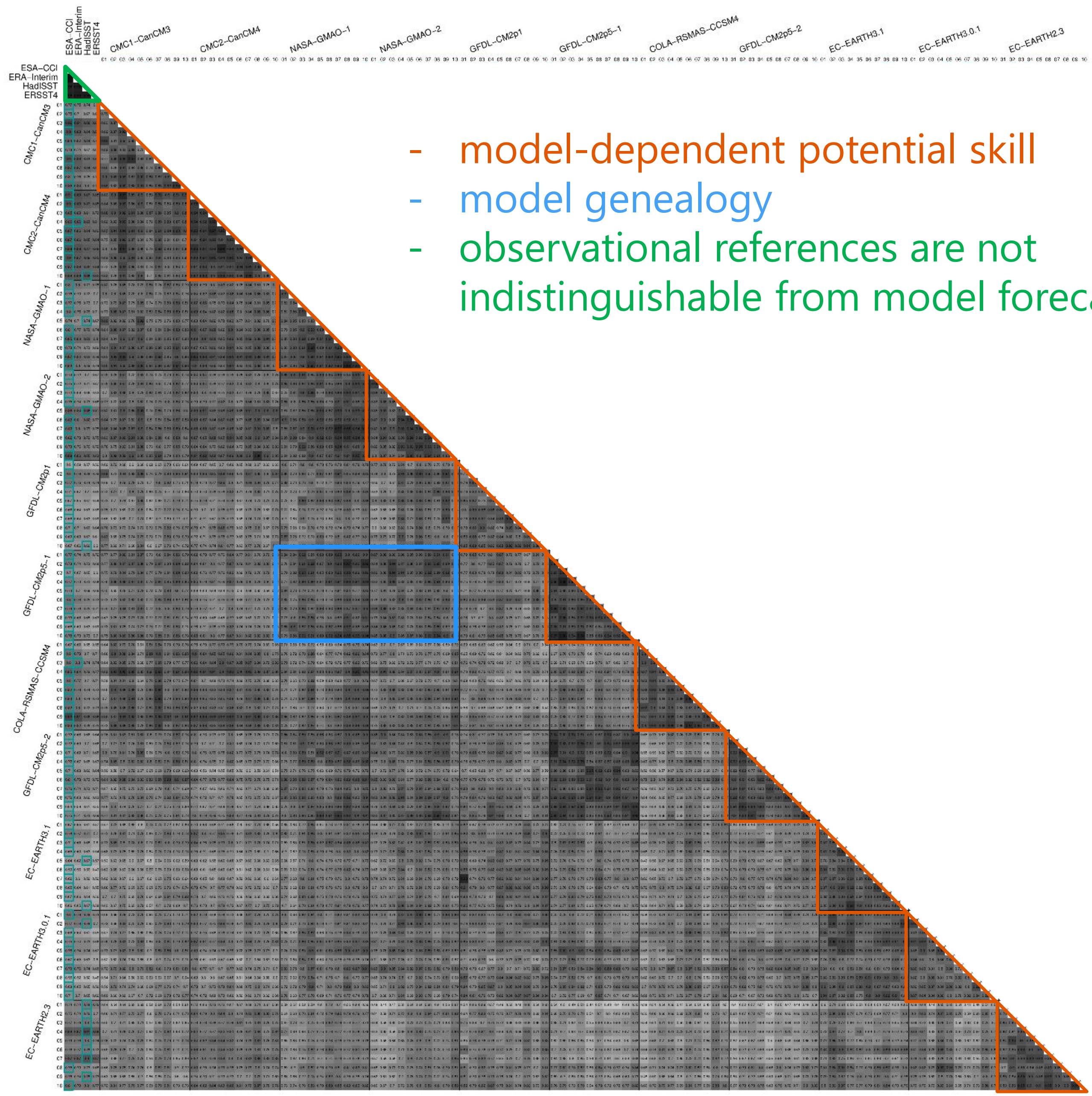
- model-dependent potential skill
- model genealogy
- observational references are not indistinguishable from model forecasts



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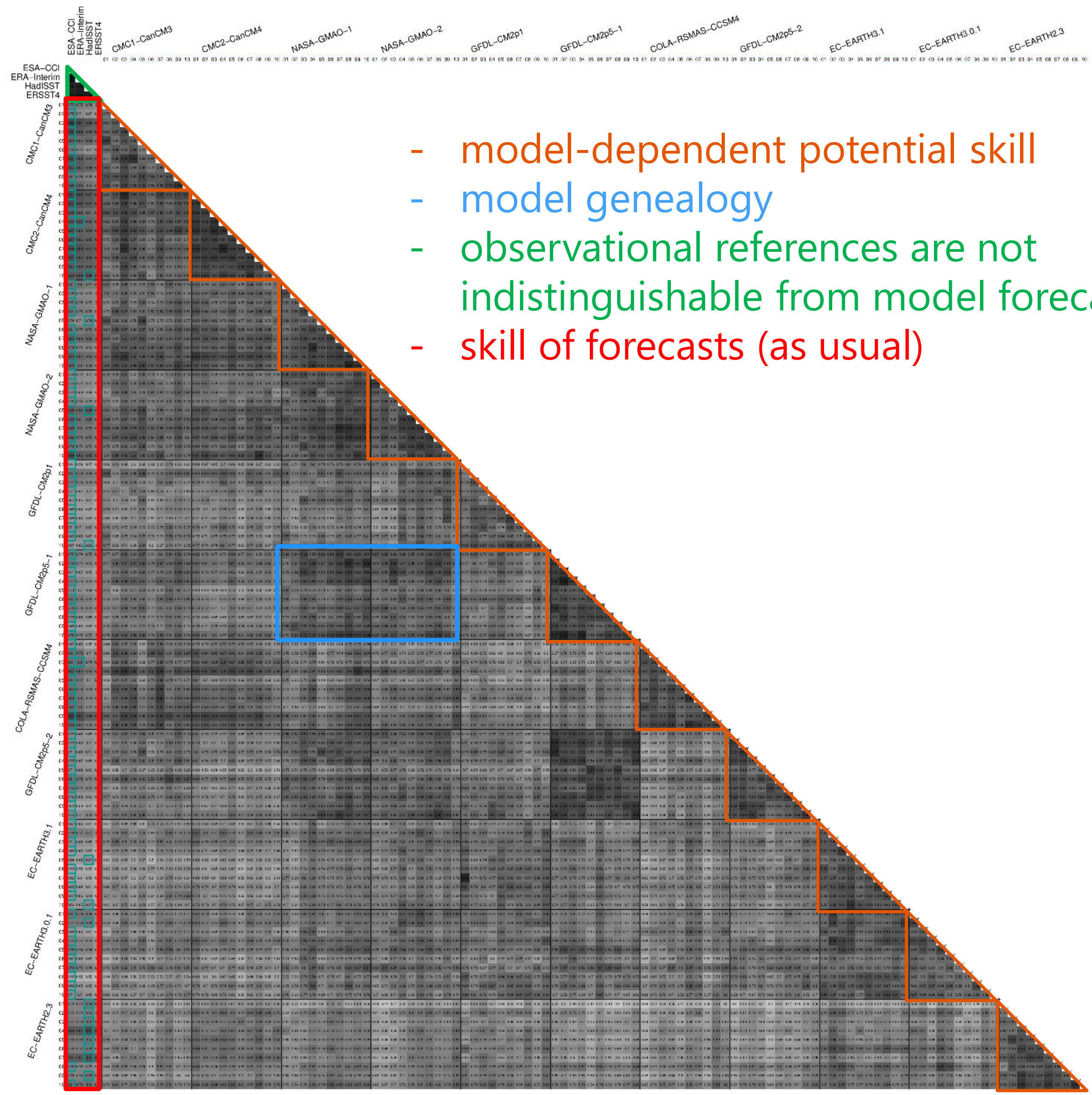

- model-dependent potential skill
- model genealogy
- observational references are not indistinguishable from model forecasts
- skill of forecasts (as usual)

1

Correlation of August Niño3.4 SST (1993-2009)

0

Outline

1. Joint estimation of model and observational error

We have developed a tool to track the performance
of observations and models all together

2. Decomposition of forecast error

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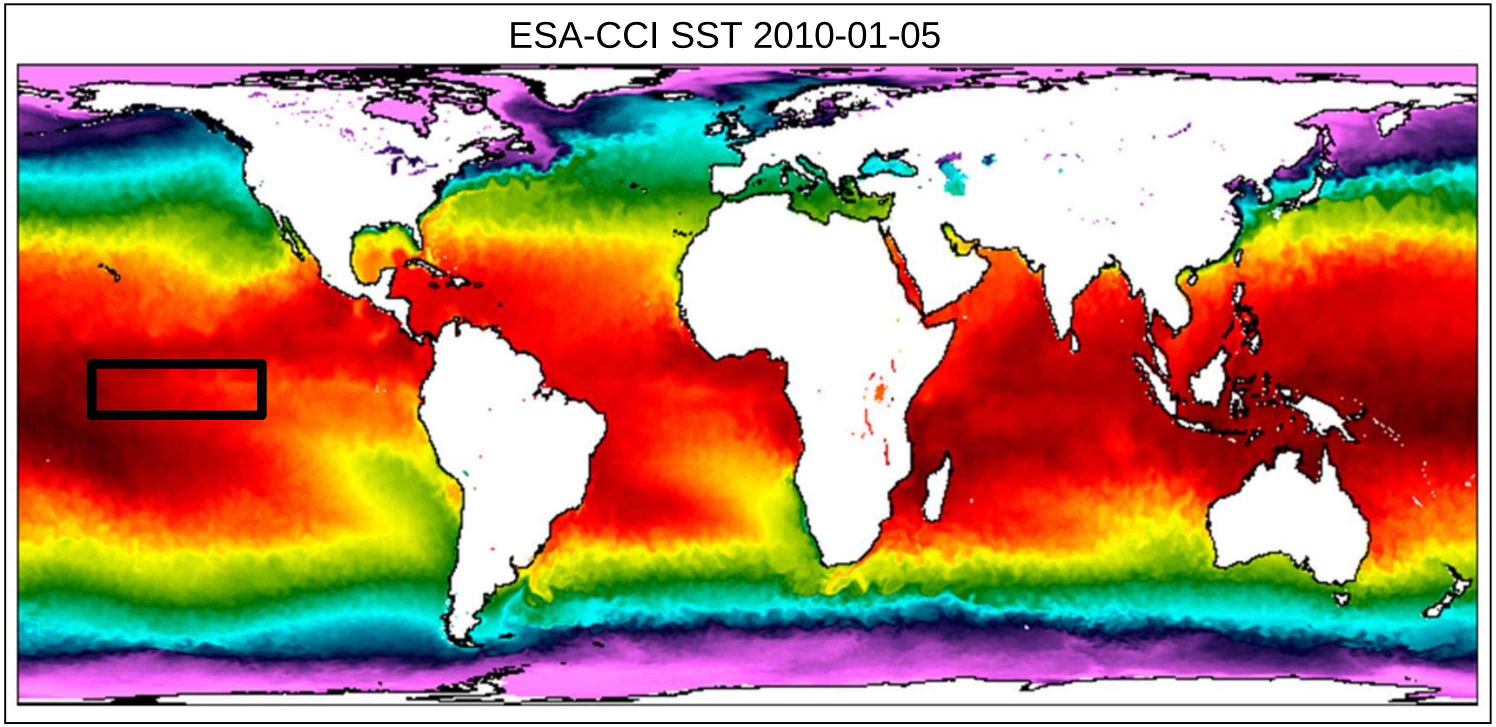
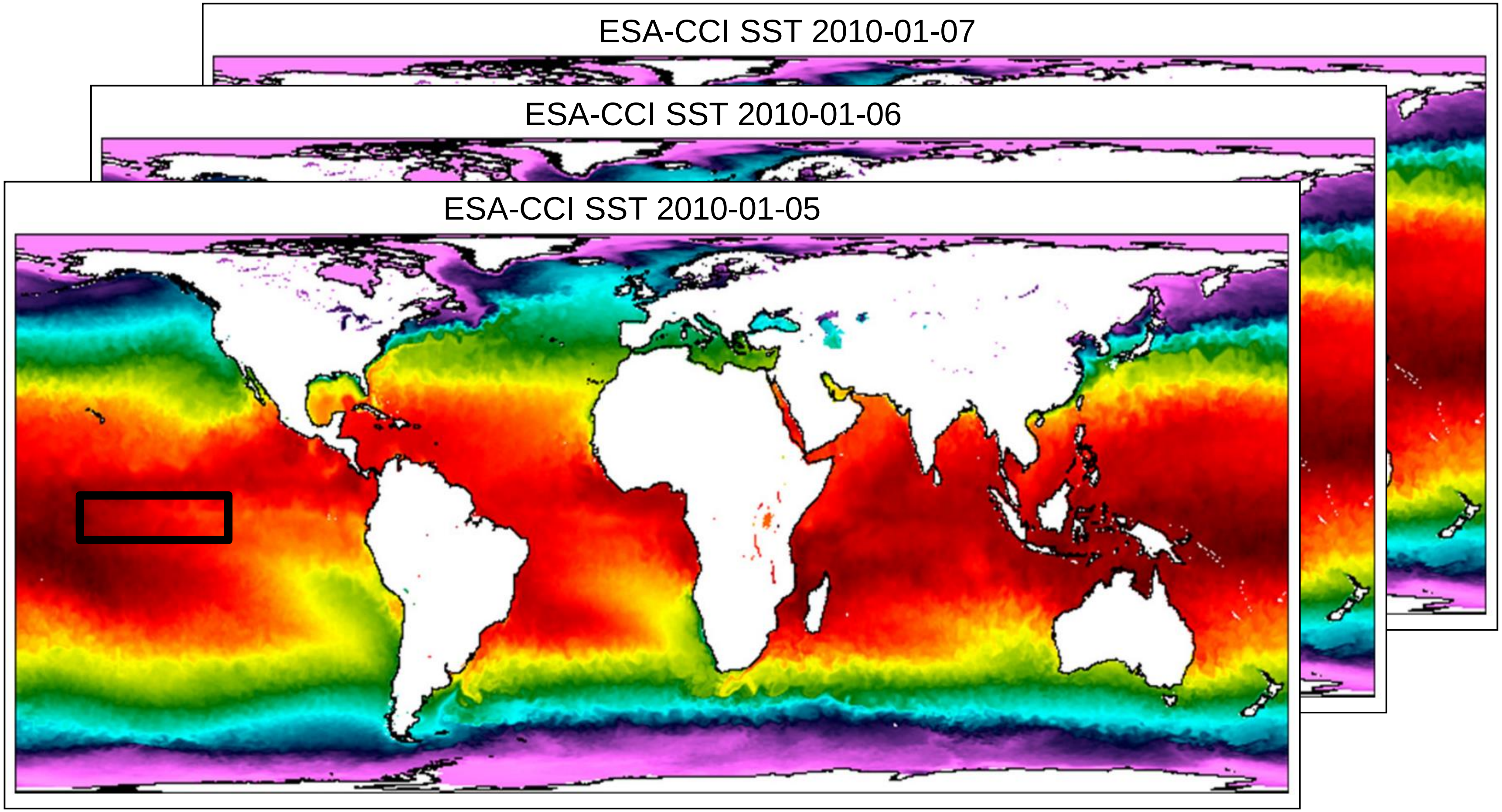
Propagating error from daily/local to monthly/regional scales is challenging



Merchant et al., Geosci. Data J., 2014

✓ ESA-CCI provides uncertainty in their SST product (daily, each grid point)

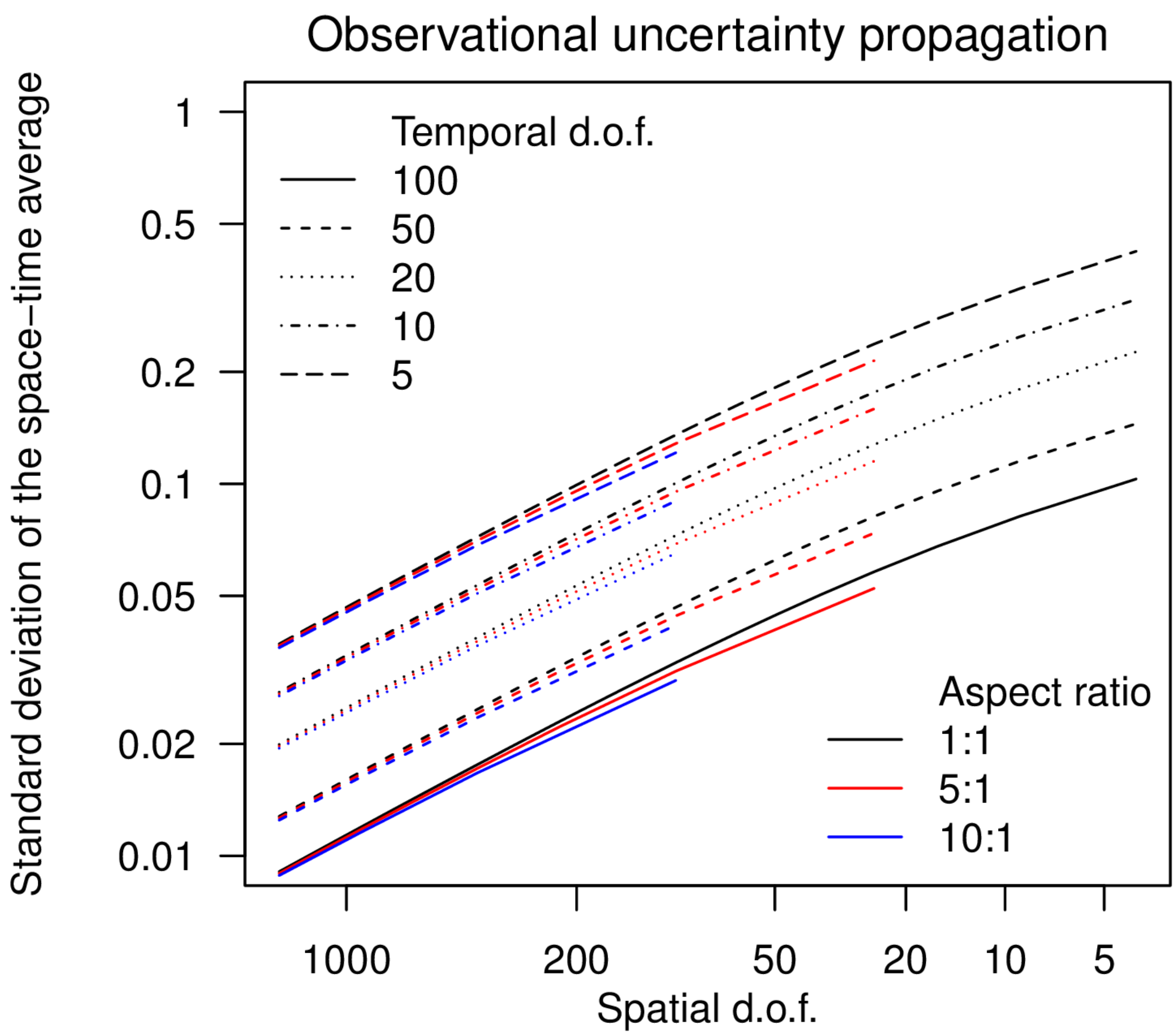
Propagating error from daily/local to monthly/regional scales is challenging



Merchant et al., Geosci. Data J., 2014

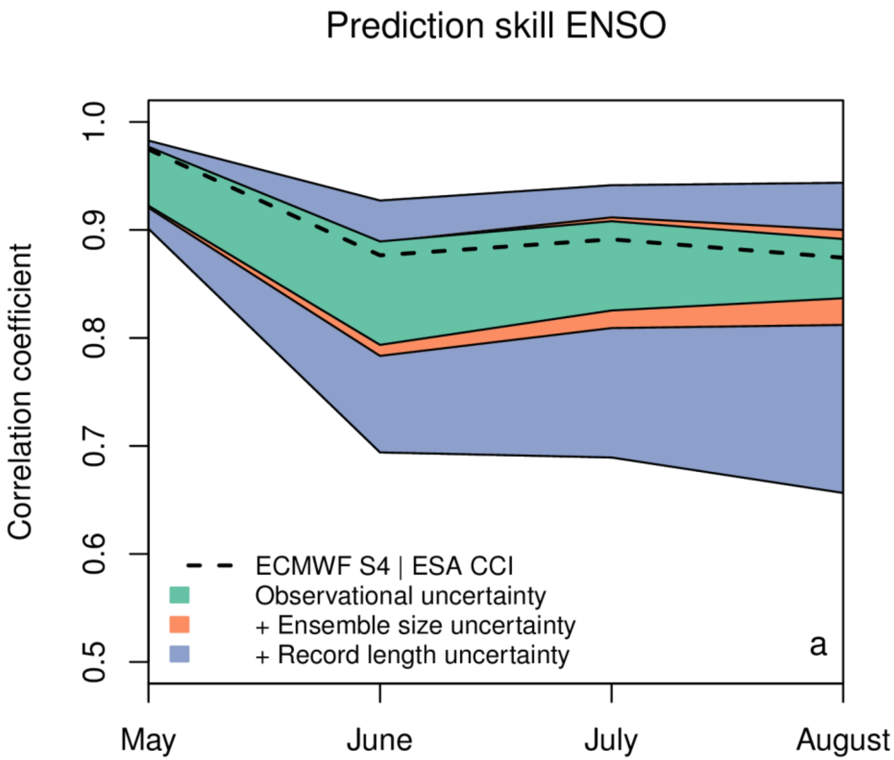
- ✓ ESA-CCI provides uncertainty in their SST product (daily, each grid point)
- ✗ But errors are correlated in space and time → tricky to estimate the uncertainty on the monthly-mean SST in a given region

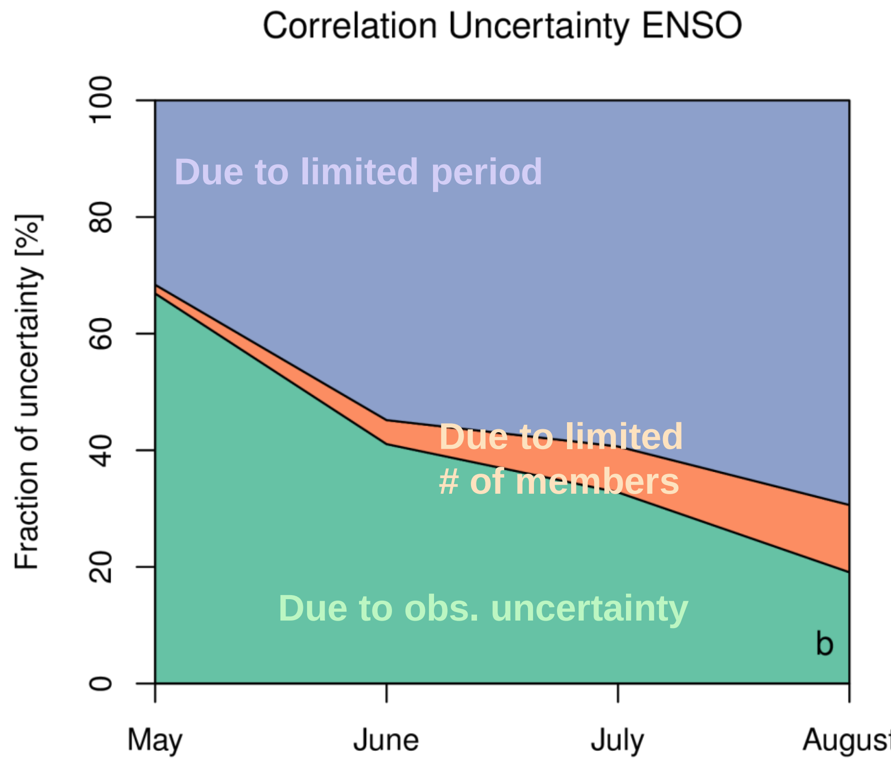
A look-up figure to quantify error propagation



Partitioning forecast uncertainty

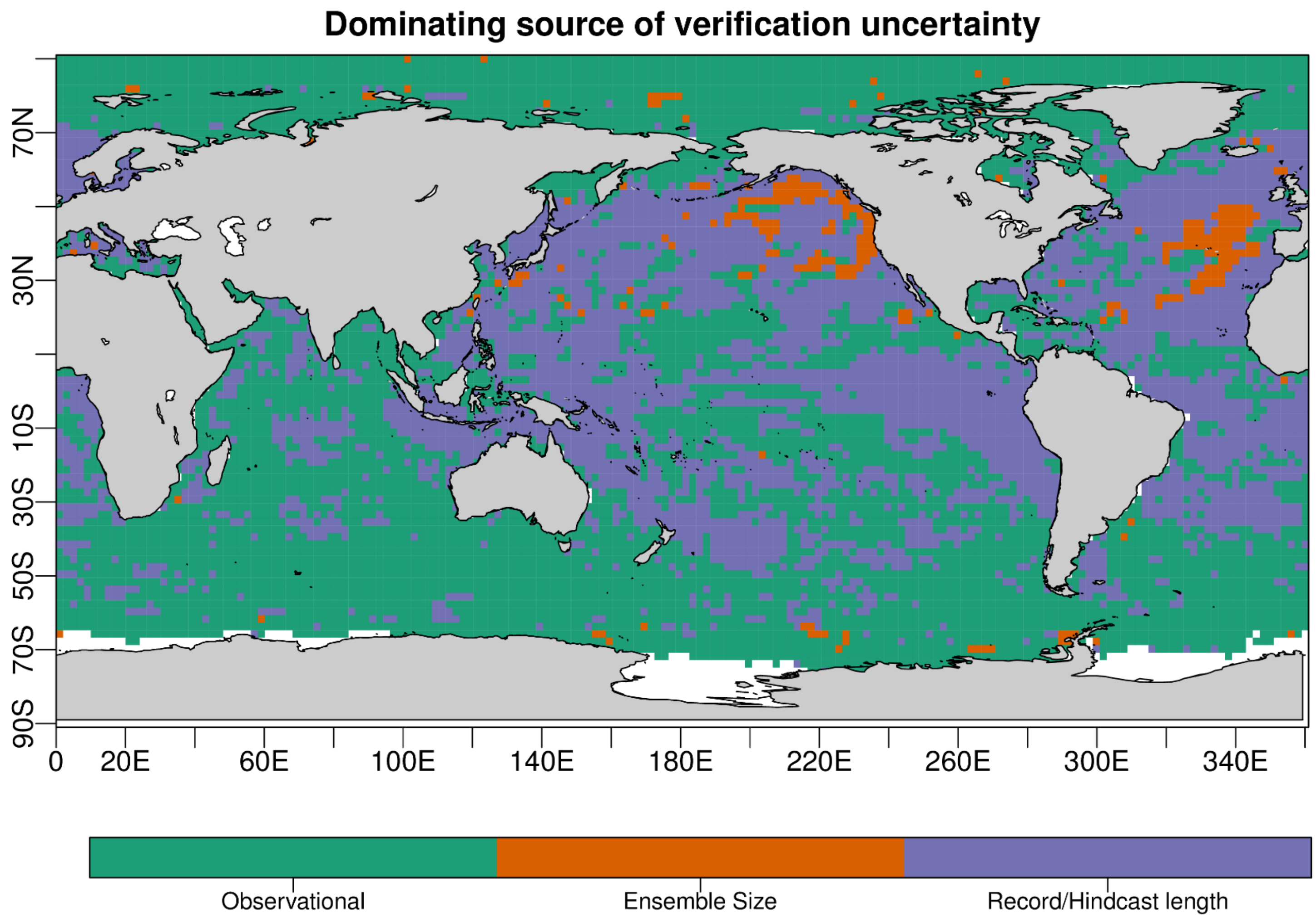
- Ensemble forecast: ECMWF's S4 (10 members)
- Verification product: ESA-CCI
- Uncertainty envelopes estimated by bootstrapping





Observational uncertainty accounts for 20-60%
of total uncertainty in skill score!

Partitioning forecast uncertainty



The verification of SST forecasts is limited by observational uncertainty at high latitudes

Outline

1. Joint estimation of model and observational error

We have developed a tool to track the performance of observations and models all together

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Observational uncertainty cannot be neglected in seasonal climate forecasting

Take home messages

Summary | Climate forecast verification encodes much more information than usually thought: inter-dependence of models and observational references as well as the role of respective sources of uncertainty on the perceived model quality.

Recommendations | Models cannot always be blamed for low performance. The shortness of period of investigation and the inherent uncertainty in observational products used in the validation also introduce uncertainty in the performance as we measure it classically.

Outlooks | Forecast quality assessment should move away from a deterministic framework and better reflect the uncertain nature of model-observation comparison.

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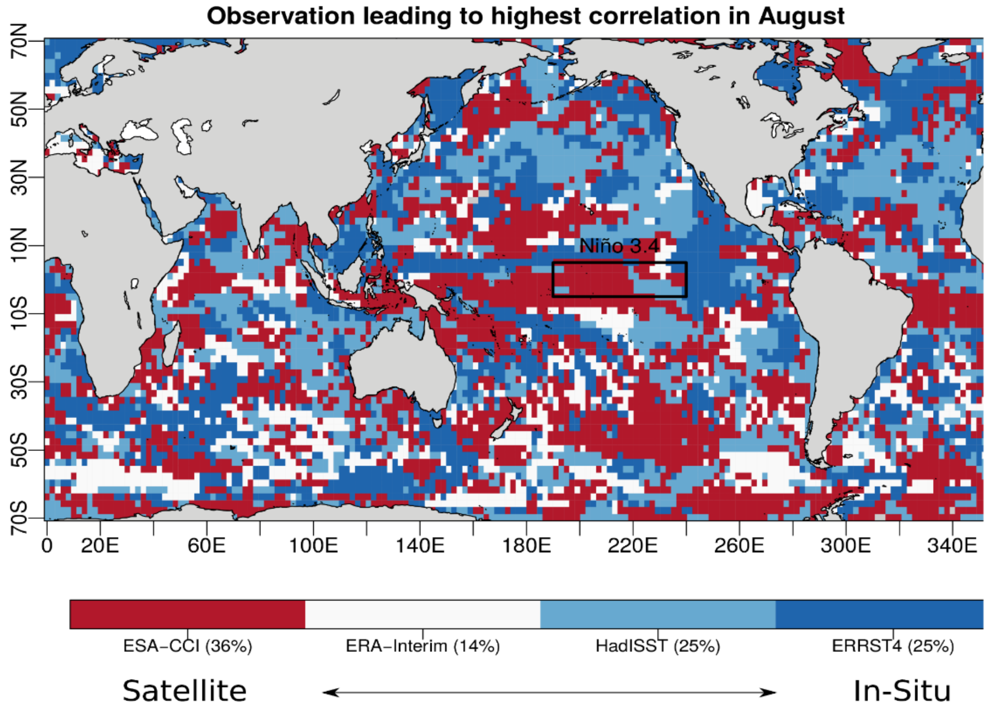
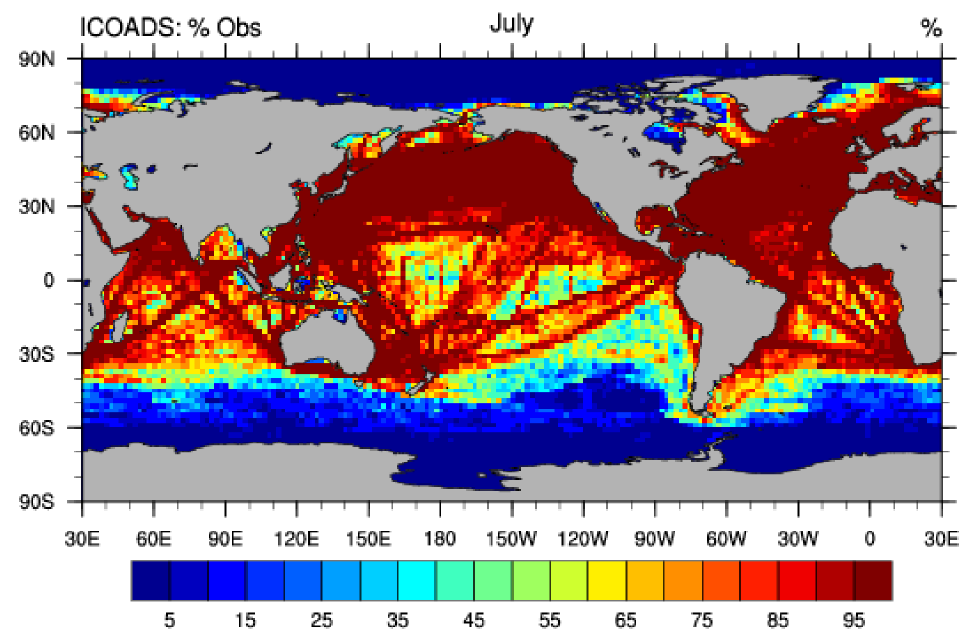
Thank you!

francois.massonnet@bsc.es

Bellprat, O., Massonnet, F., Siegert, S., Guemas, V., Doblas-Reyes, F. J., Exploring observational uncertainty in verification of climate model predictions, *in preparation*

Massonnet, F., Bellprat, O., Guemas, V., Doblas-Reyes, F. J., Utilizing climate models to estimate the quality of global observational data sets, *Science*, in press.

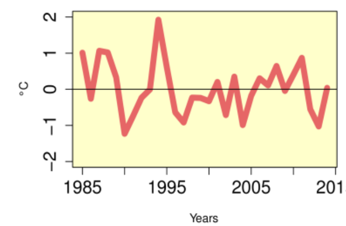

Observation leading to highest correlation in August
70N
50N
30N
10N
10S
30S
50S
70S
0
20E
60E
100E
140E
180E
220E
260E
300E
340E
Niño 3.4
ESA-CCI (36%)
ERA-Interim (14%)
HadISST (25%)
ERRST4 (25%)
Satellite
In-Situ


ICOADS: % Obs
July
%
90N
60N
30N
0
30S
60S
90S
30E
60E
90E
120E
150E
180
150W
120W
90W
60W
30W
0
30E
5
15
25
35
45
55
65
75
85
95

A signal-plus-noise toy model

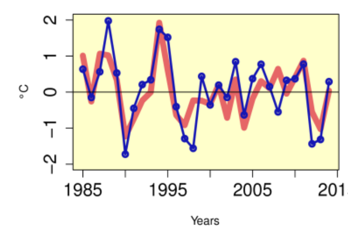
Interannual variability

TRUTH $X_t = \boxed{\epsilon}$ $\qquad \epsilon \sim \mathcal{N}(0, \sigma_\epsilon)$



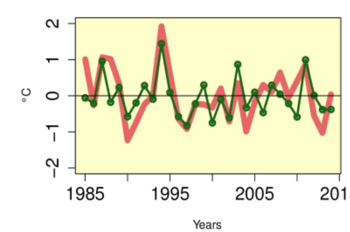
Measurement and representativity error

OBS $X_o = \epsilon + \boxed{\eta_o}$ $\qquad \eta_o \sim \mathcal{N}(0, \sigma_o)$



Model forecast error (physics, initial conditions, resolution) + irreducible error (atmosphere)

MODEL $X_f = \alpha\epsilon + \boxed{\eta_f + \eta_m}$ $\qquad \eta_f \sim \mathcal{N}(0, \sigma_f), \quad \eta_m \sim \mathcal{N}(0, \sigma_m)$



All error terms are assumed to be uncorrelated

[Model from Weigel et al., *QJRMS*, 2008. See also Siegert et al., 2015]

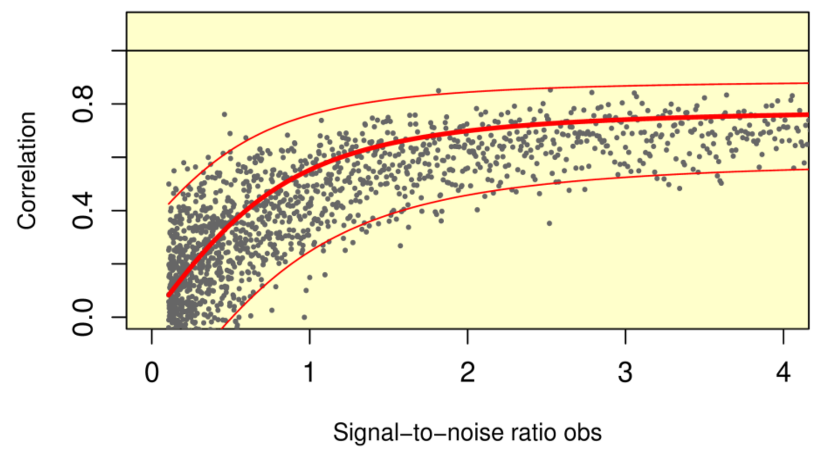
In this very simple paradigm, observational error is also a source of low skill

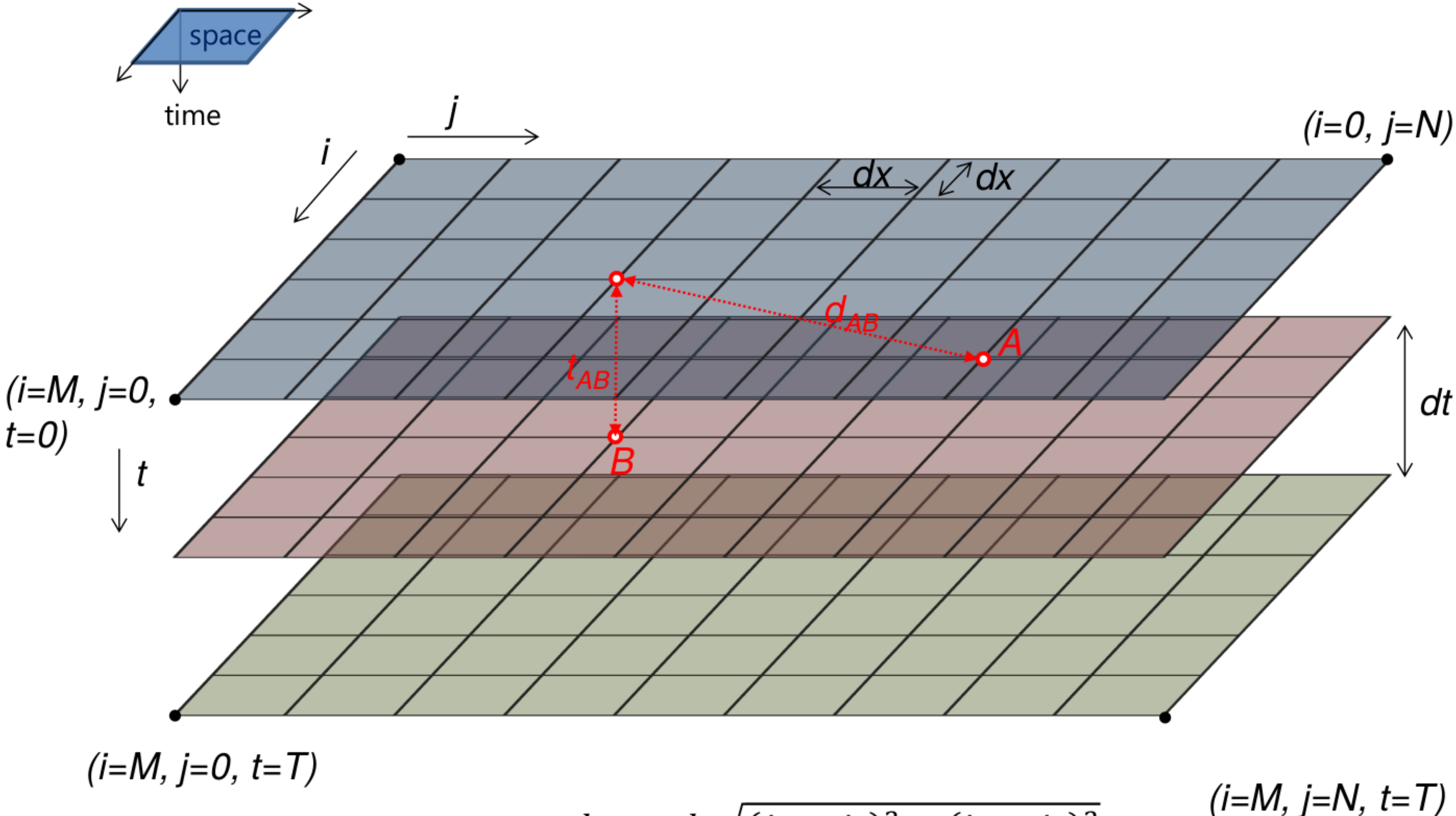
$$\rho(X_o, X_f) = \frac{1}{\sqrt{\left(1+\frac{\sigma_o^2}{\sigma_\epsilon^2}\right)\cdot\left(1+\frac{(\sigma_f^2+\sigma_m^2)/\alpha^2}{\sigma_\epsilon^2}\right)}}$$

Correlation **increases** when

- Model explains more variability,
- Model error decreases,
- Climate signal is stronger,
- Observational error decreases.

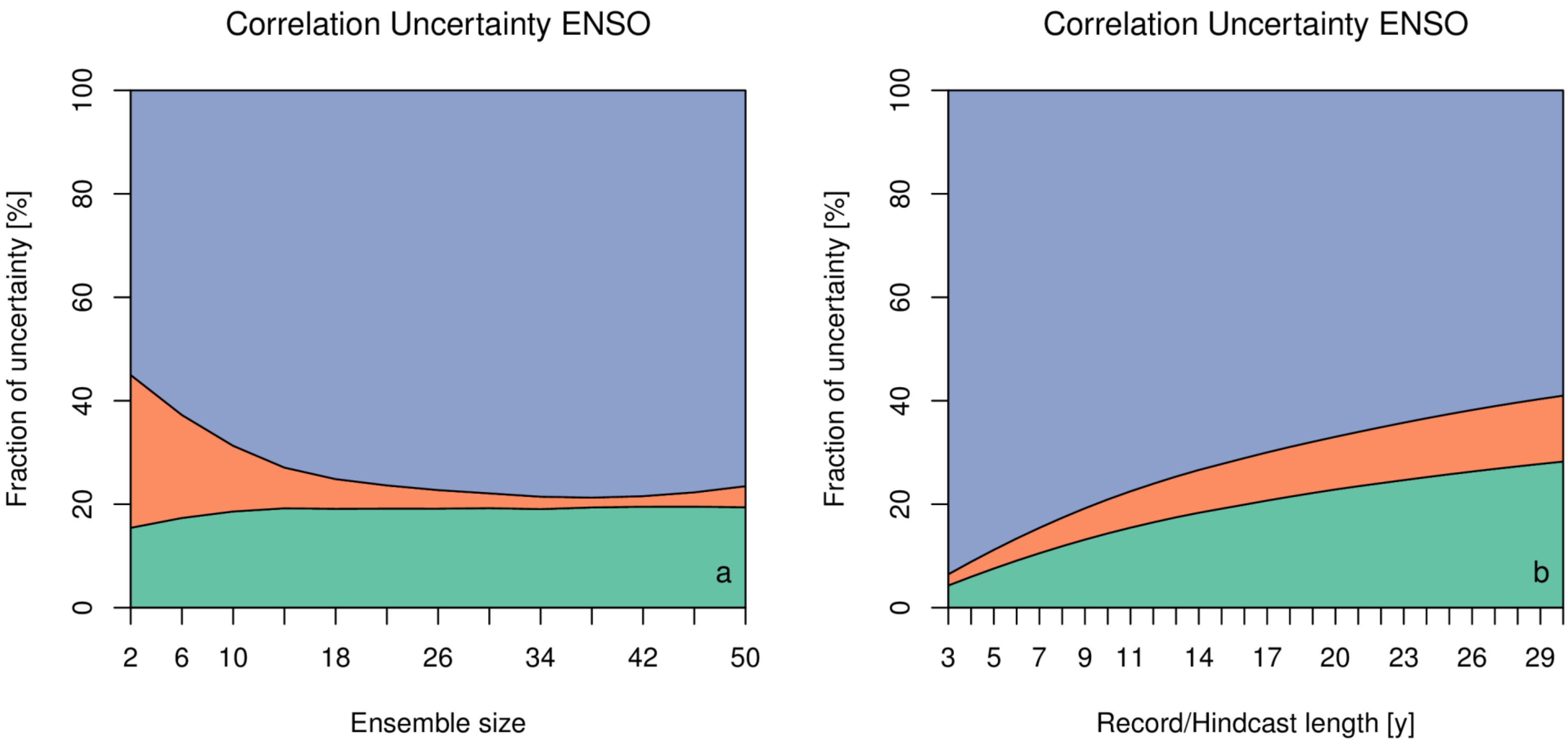
If error statistics are known, the dependence can be predicted





$$d_{AB} = dx\sqrt{(j_B - j_A)^2 + (i_B - i_A)^2}$$

$$t_{AB} = dt|t_B - t_A|$$


Correlation Uncertainty ENSO
Fraction of uncertainty [%]
0
20
40
60
80
100
a
2
6
10
18
26
34
42
50
Ensemble size
Correlation Uncertainty ENSO
Fraction of uncertainty [%]
0
20
40
60
80
100
b
3
5
7
9
11
14
17
20
23
26
29
Record/Hindcast length [y]