

# Joint uncertainty assessment of models and observations in verification of climate predictions

Omar Bellprat
Francois Massonnet, Stefan Siegert, Martin Ménégoz,
Chloé Prodhomme, Virginie Guemas, Francisco DoblasReyes, David Stephenson









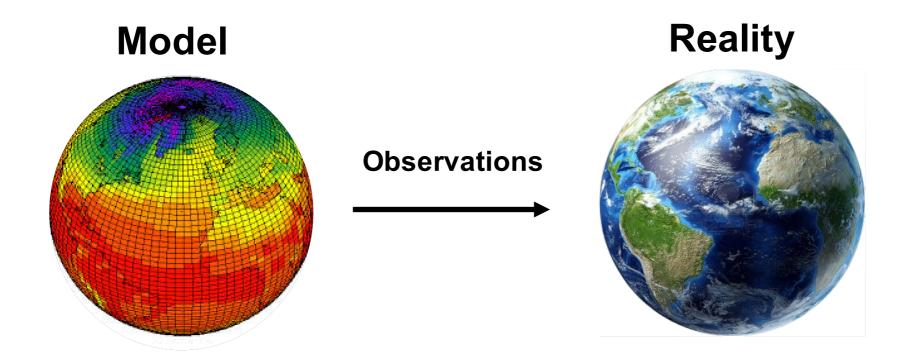






### Traditional evaluation perspective





### A shift in the paradigm



### Reality



**Observation B** 

### A traditional verification question



### Is model system B superior to model system A?

A B

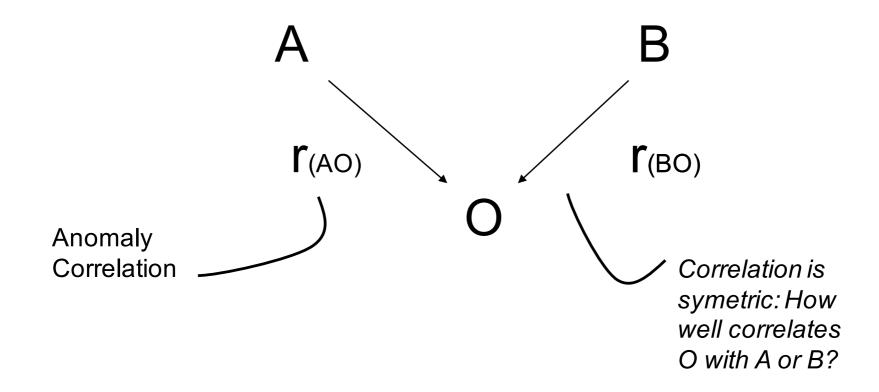
Low horizontal resolution

High horizontal resolution

### Comparing climate forecasts



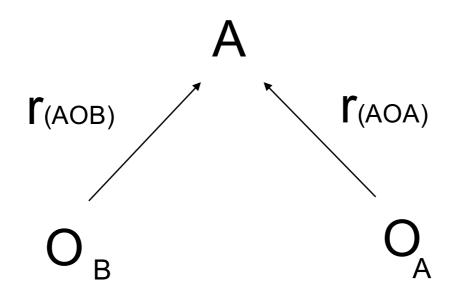
### Compare hindcast skill with an observation



### Reversing the question

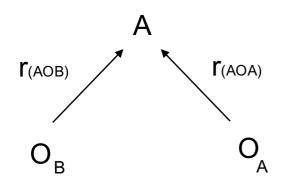


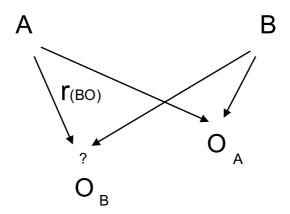
### Which observation is better? A useful question?

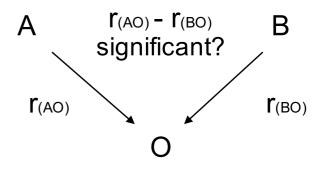


### Overview this presentation









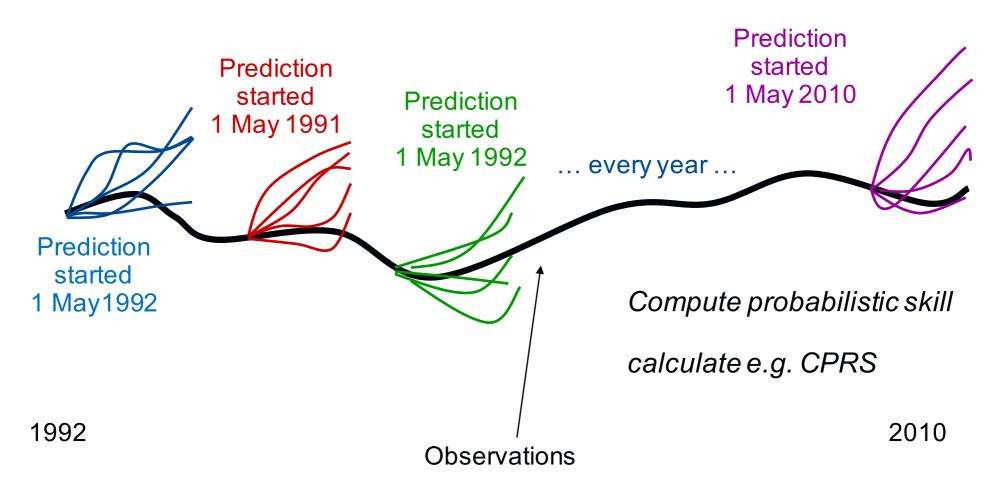
(a) Which observations has the smallest error

(b) How important is observational uncertainty

(c) How to detect improvements in models or observations

### Seasonal forecast skill

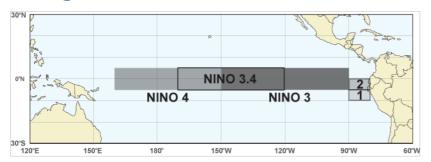




#### Seasonal forecast skill



#### Target: Global and Niño3.4 SST



Observations: 4 Sea-surface Temperature (SST) observations: ESA-CCI, HadISST, ERSST4, ERA-Interim

Prediction started 1 May1992 Prediction started 1 May 1991



Prediction started 1 May 1992



... every year ...



Prediction started 1 May 2010



Compute ensemble-mean to distill climate signal

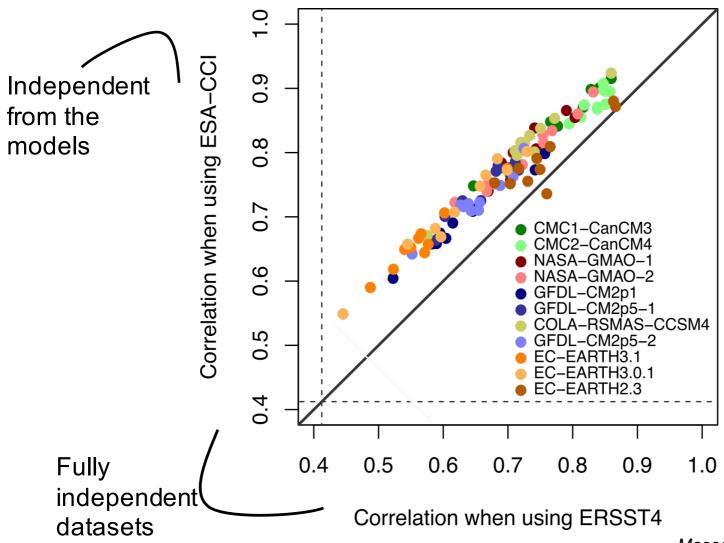
calculate e.g. anomaly correlation

Models: EC-Earth (3 versions), ECMWF S4, North American Multi-Model Ensemble (NMME, 7 models) 10 – member forecast each

### Reversing verification question



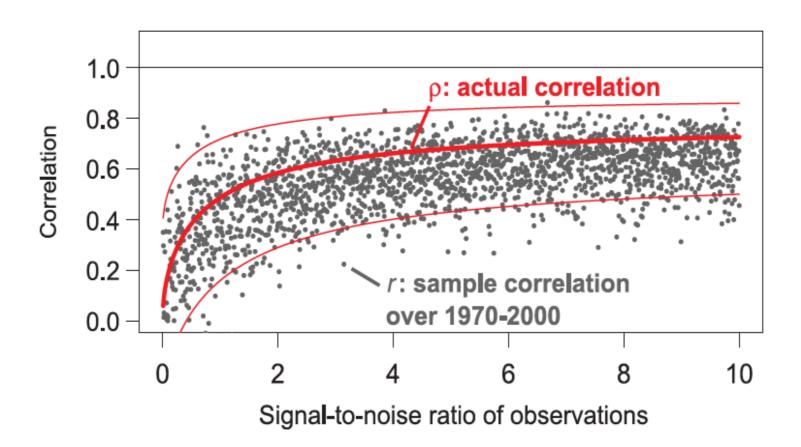
#### CCI SST yields systematic higher correlation skill across many models



### Effect observational uncertainty



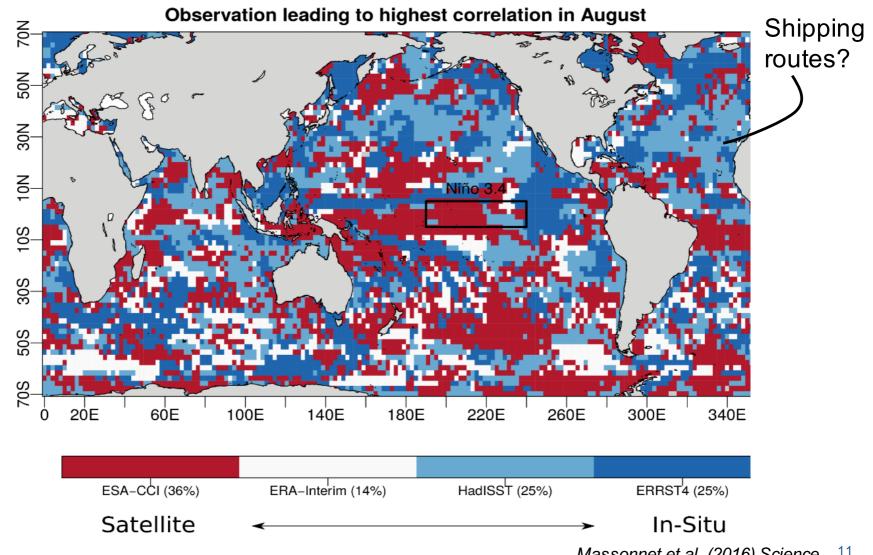
# Correlation reduces with noise either co-variates: observational uncertainty reduces forecast skill



### Reversing verification question



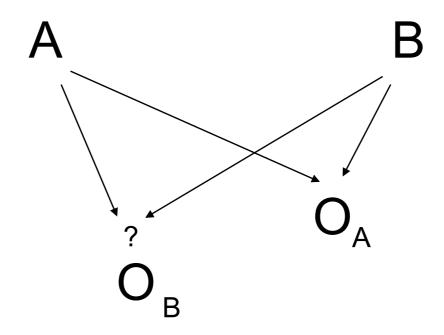
#### Choice of observation may differ on the location, overall CCI best



### Observational uncertainty

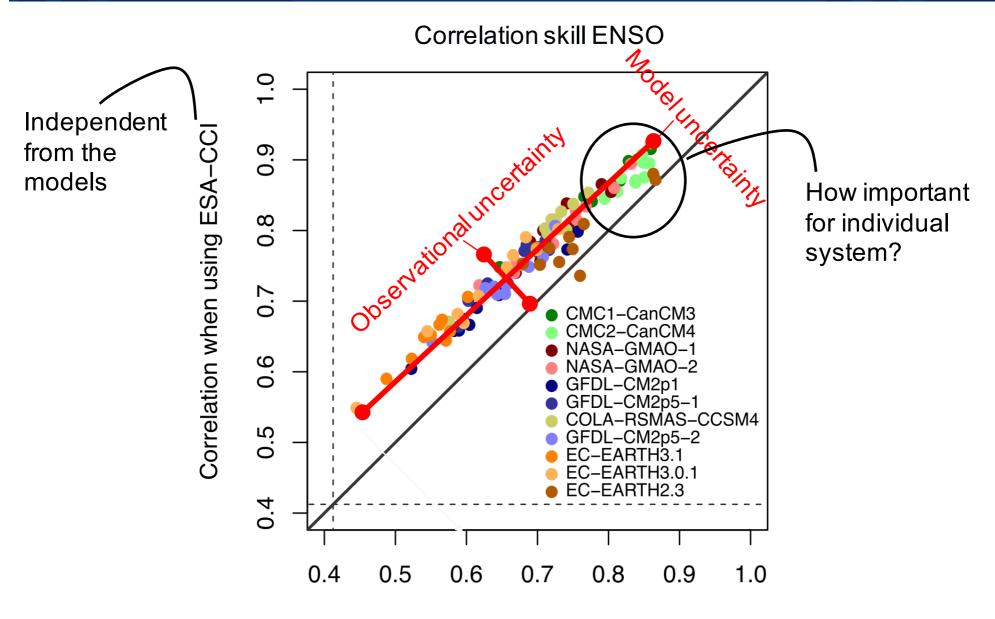


### How important is the observational uncertainty?



### Acknowledging joint uncertainty



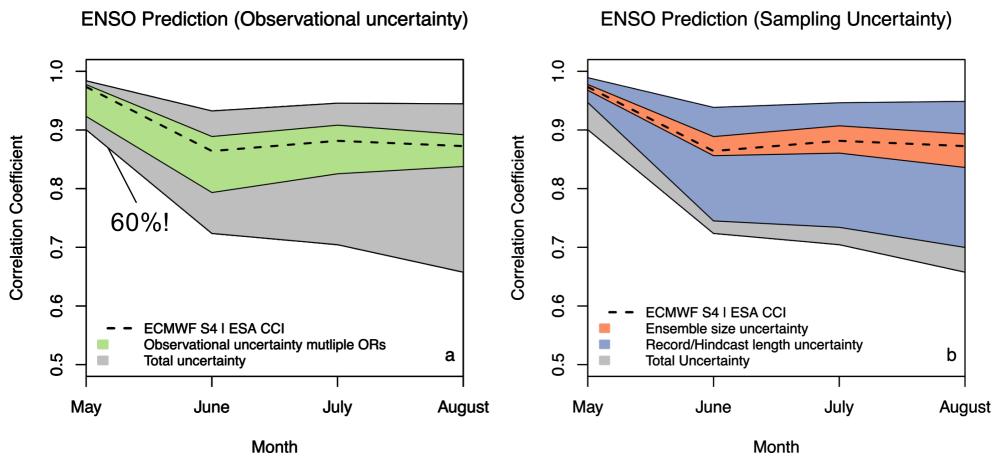


Correlation when using ERSST4

### Decomposition of uncertainties



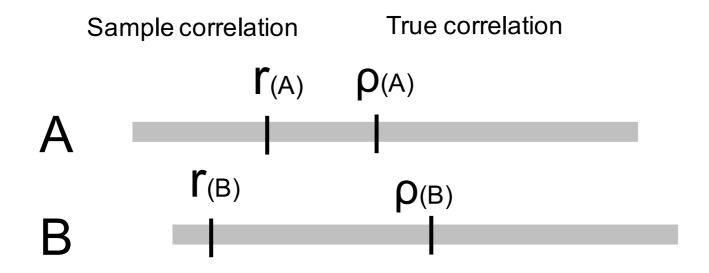
# Comparison to sample uncertainties: observational uncertainty is an important source of verification uncertainty for ENSO



### Detecting statistical differences

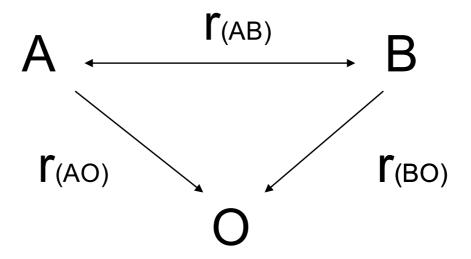


# Are the differences in performance of models or observations significant $r_{(CCI)} > r_{(ERSST)}$ ?





### Models and observations are statistically dependent!



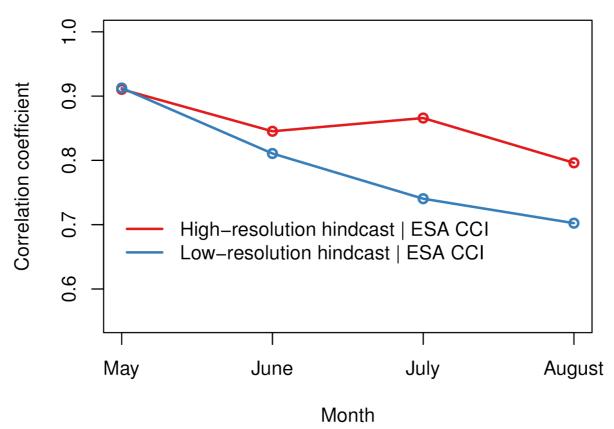
Fisher-test (common test in community) assumes independence while newer tests (Steiger, 1980, Zou, 2007) don't.

### Example ENSO and resolution



# High-resolution hindcasts improves El Niño Southern Oscillation (ENSO) predictions, but change not significant at 5% (Fisher-test)

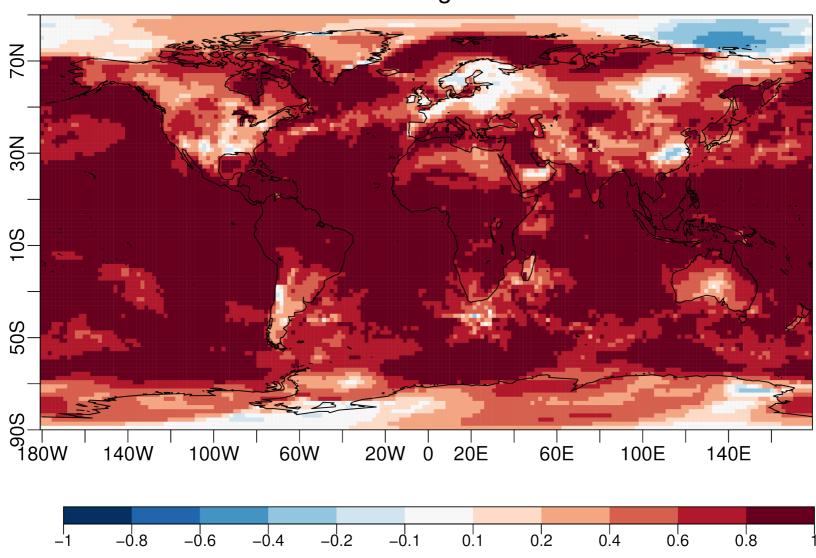
#### Prediction skill ENSO: Increase in resolution



### Model dependence



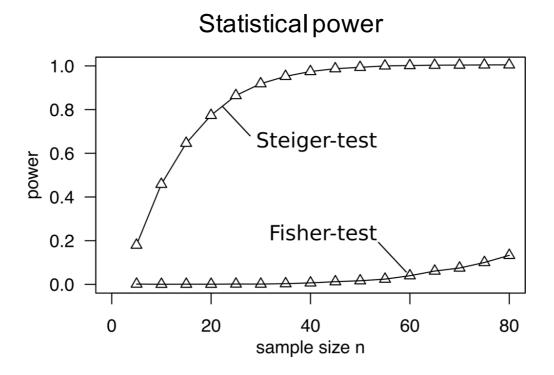
#### Correlation of Low and High-resolution hindcast



### Statistical power dependent tests



Power to detect a difference between increases dramatically. Improvement now statistical significant at 1% level.



In medicinal science only studies with power > 80% are accepted, a guideline for forecasting?

### A joint uncertainty perspective



Models and observations are both approximations of the truth and uncertainty in both sources can be important.

Models can be valuable in assessing observational quality and thus guide a more objective dataset selection

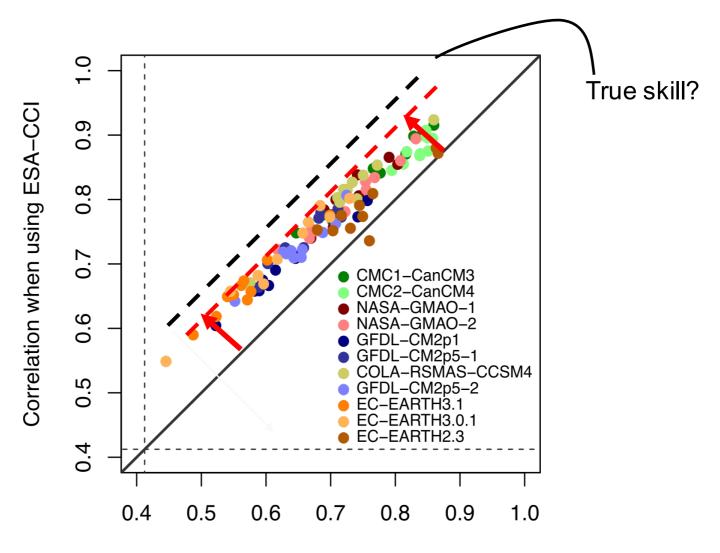
Testing improvements in models and observations requires the consideration of dependence between all source of information



### Outlook: What is the "true" skill?



# True climate predictions skill is systematically underestimated due to uncertainties in the observations

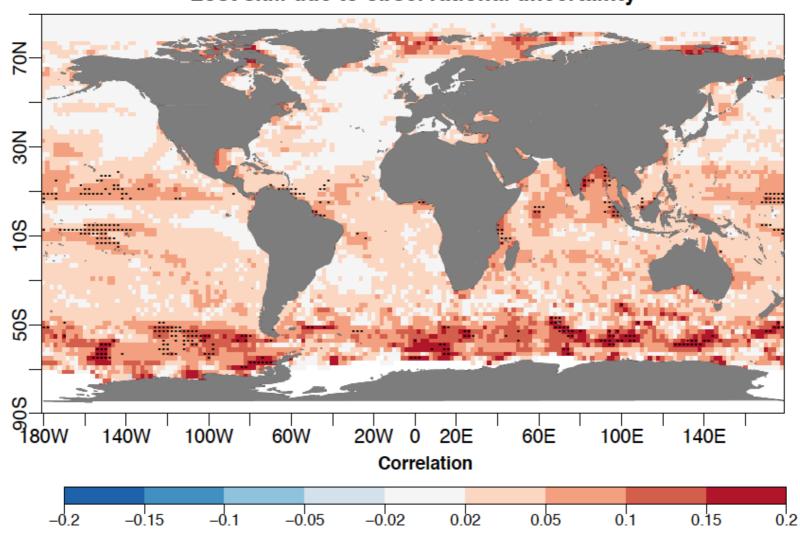


### Underestimation of "true" skill



#### Seasonal SST forecast skill is underestimated up to 0.2 correlation

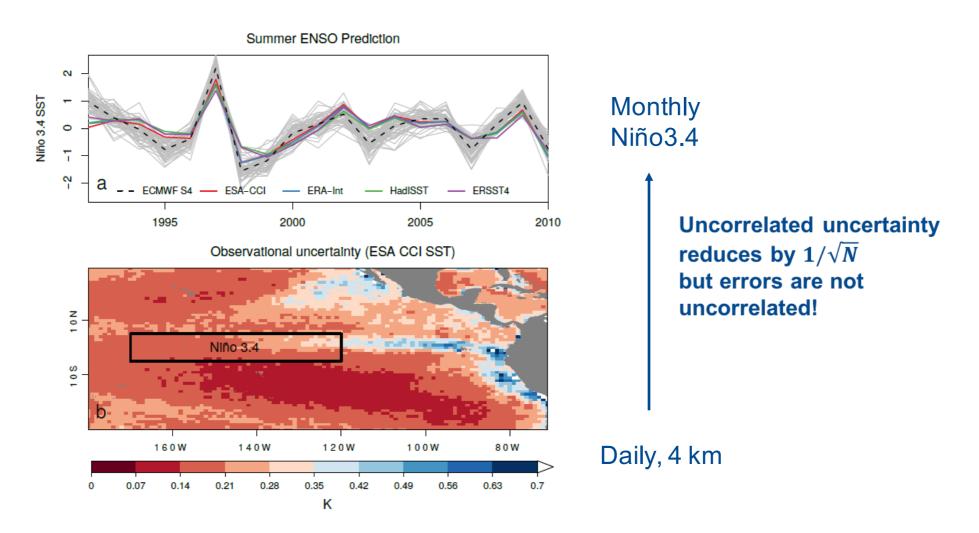
#### Lost skill due to observational uncertainty



### Observational uncertainty CCI



# Model evaluation often requires spatial and temporal averaging, requires the consideration of error correlation scales



### Outlook



Quantifying observational uncertainty is a challenge and propagation scales represented to by the models is a big gap – A stronger interaction is required with the observational data community

ESA *Climate Modelling User Group (CMUG)* is going to explore observational uncertainty in model – observation inter-comparison strongly in the future

Metrics and new statistical tests are required that can make use of the observational uncertainty data that future data sets are going to provide

## Thank you!



Massonnet, F., Bellprat, O., Guemas, V., Doblas-Reyes, F. J., (2016). Using climate models to estimate the quality of global observational data sets, *Science (AAAS)* 

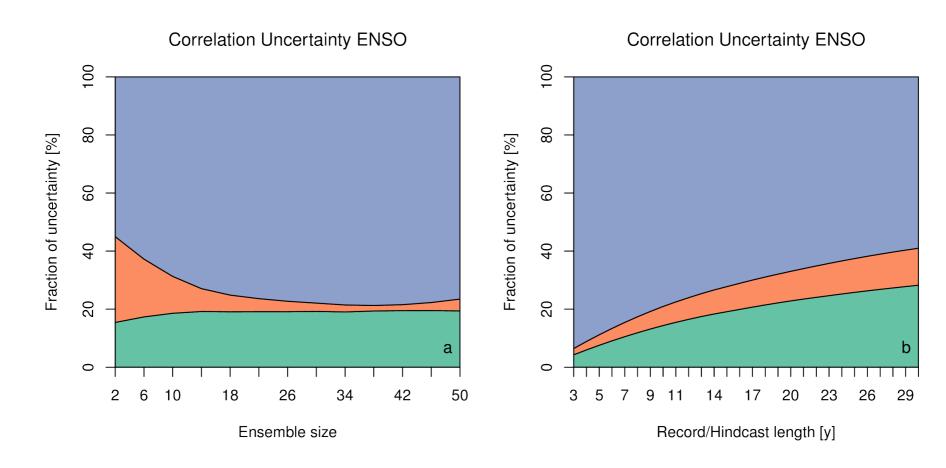
Bellprat, O., Massonnet, F., Siegert, S., Guemas, V., Doblas-Reyes, F. J. (2017). Exploring observational uncertainty in verification of climate model predictions, *Remote Sensing of the Environment (RSE)*, *in review* 

Siegert, S., Bellprat, O., Menegoz, M., Stephenson, D., Doblas-Reyes, F. (2016). Detecting improvements in forecast correlation skill: Statistical testing and power analysis. *Monthly Weather Review* 

# Extra Slides

### Sensitivity to sample



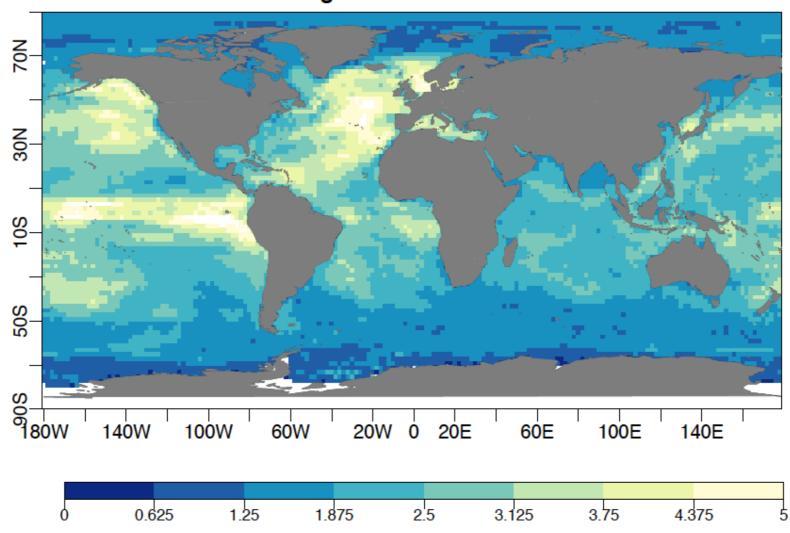


### Signal-to-noise ratio SSTs



#### Signal (inter-annual variability) versus observational uncertainty (noise)

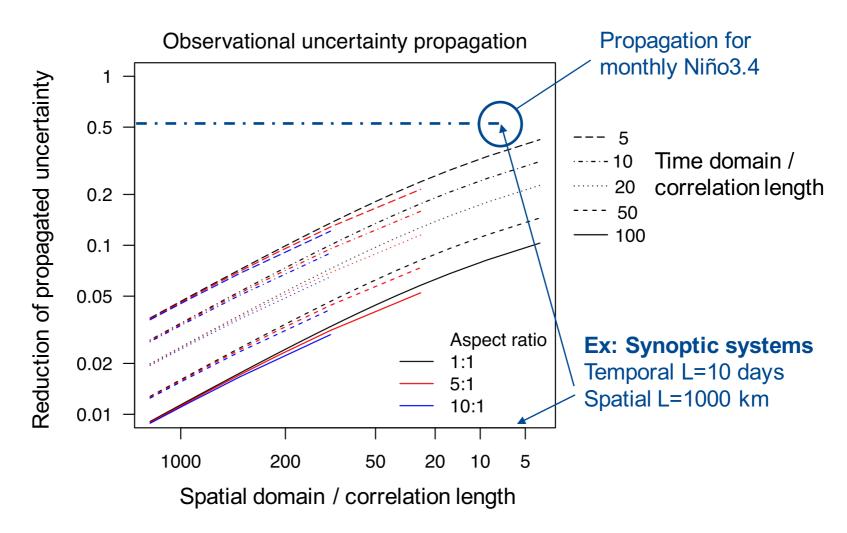
#### Signal-to-noise ratio



### A "look-up" propagation figure



# Use of error correlation scales: analytical solution that allows to look-up propagation factors

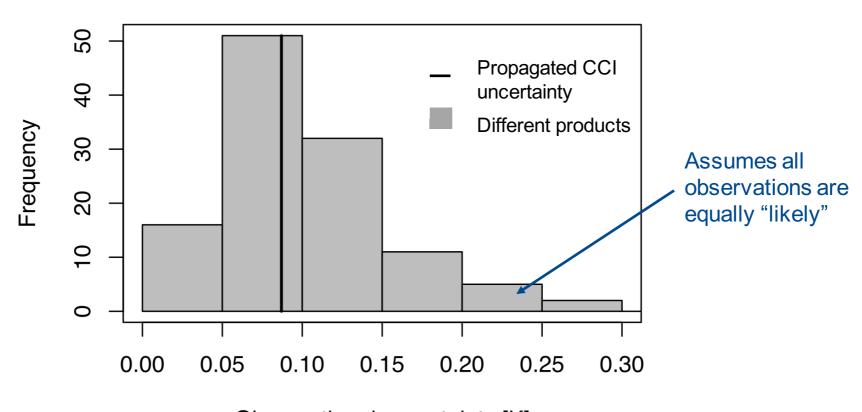


### Comparison to multi-observations



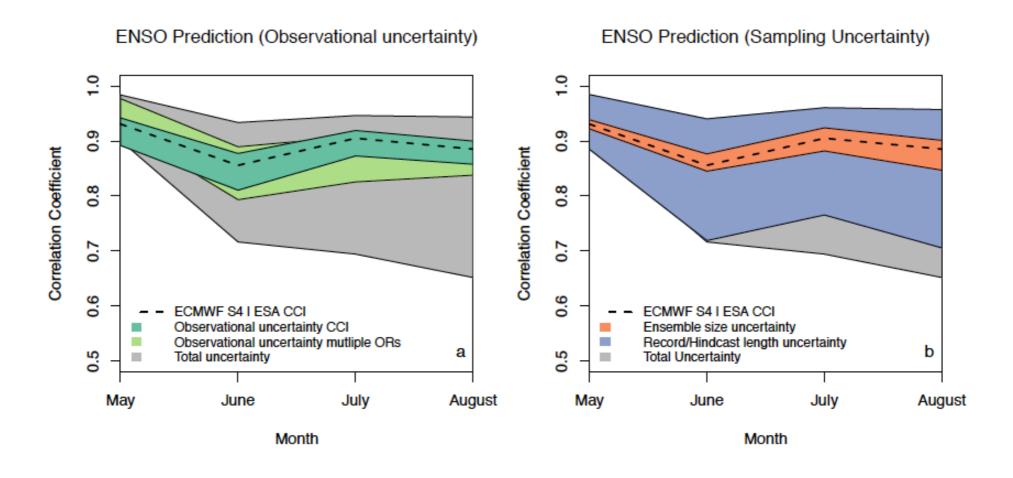
# Propagation assuming synoptic scales (1000 km, 10 days) of weather systems agrees well with deviations between existing products

#### Observational uncertainty Niño3.4 SST



### **ESA CCI Uncertainty estimate**





### Relative contributions



