Stochastic parametrisations – toward a new view of weather and climate

ECMWF/WWRP workshop on model error , April 11-15, 2016

Judith Berner

Stochastic Parameterization: Towards a new view of Weather and Climate Models

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Key question

- Model uncertainty a priori (insert uncertainty where it occurs) or a posteriori ("holistic" approaches: SKEBS, SPPT)

Outline

- Weather application: Improve reliability and reduce ensemble error in analysis and ensemble forecasts
- Climate application: Reducing systematic error in mean and variability, improvement of physical processes
- Seasonal application: Somewhere in between

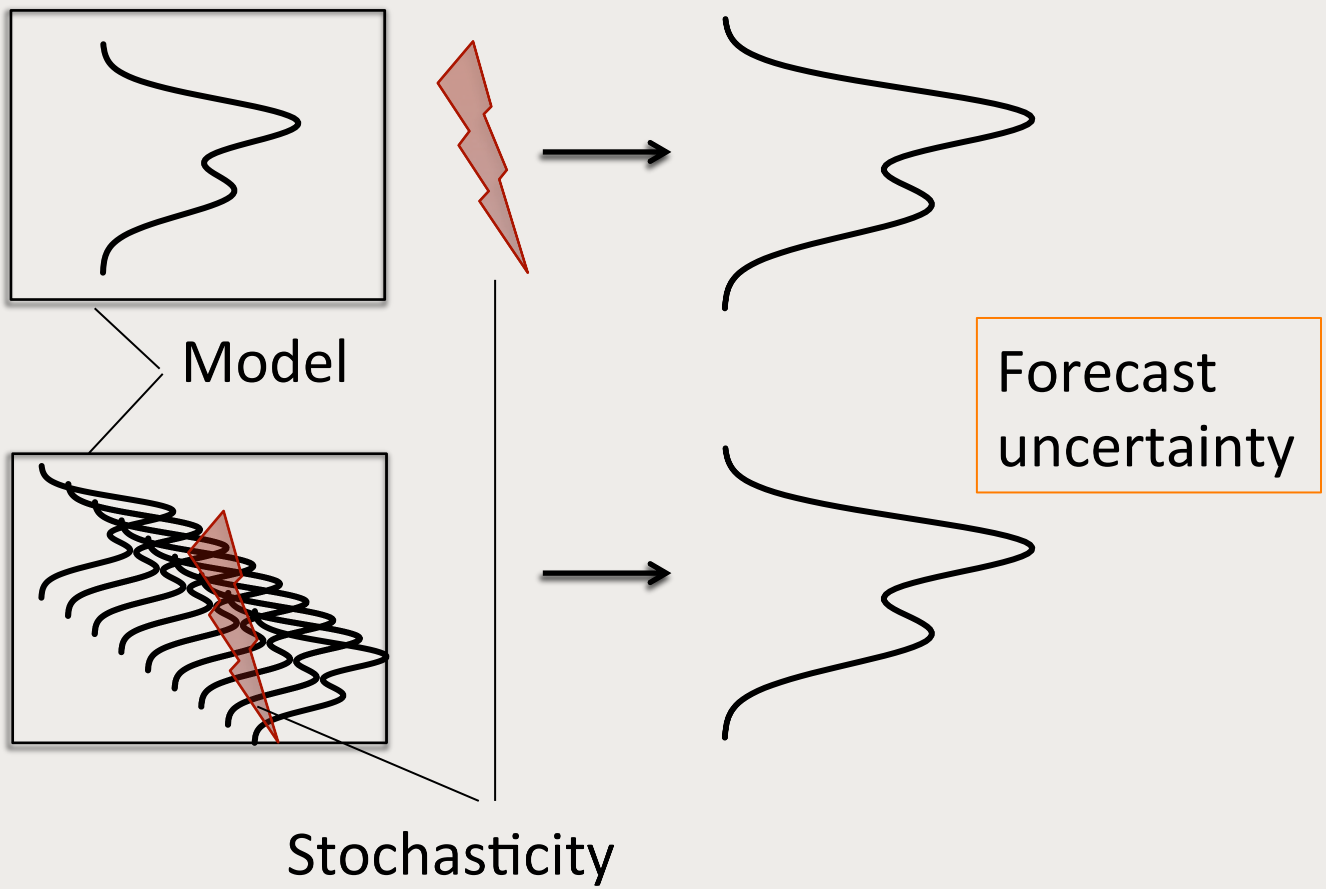
Outline

- Weather application: Improve reliability and reduce ensemble error in analysis and ensemble forecasts
  - increase spread
- Climate application: Reducing systematic error in mean and variability, improvement of physical processes
  - often entails a reduction of reduction of variability, e.g. along a wave train
- Seasonal application: Somewhere in between

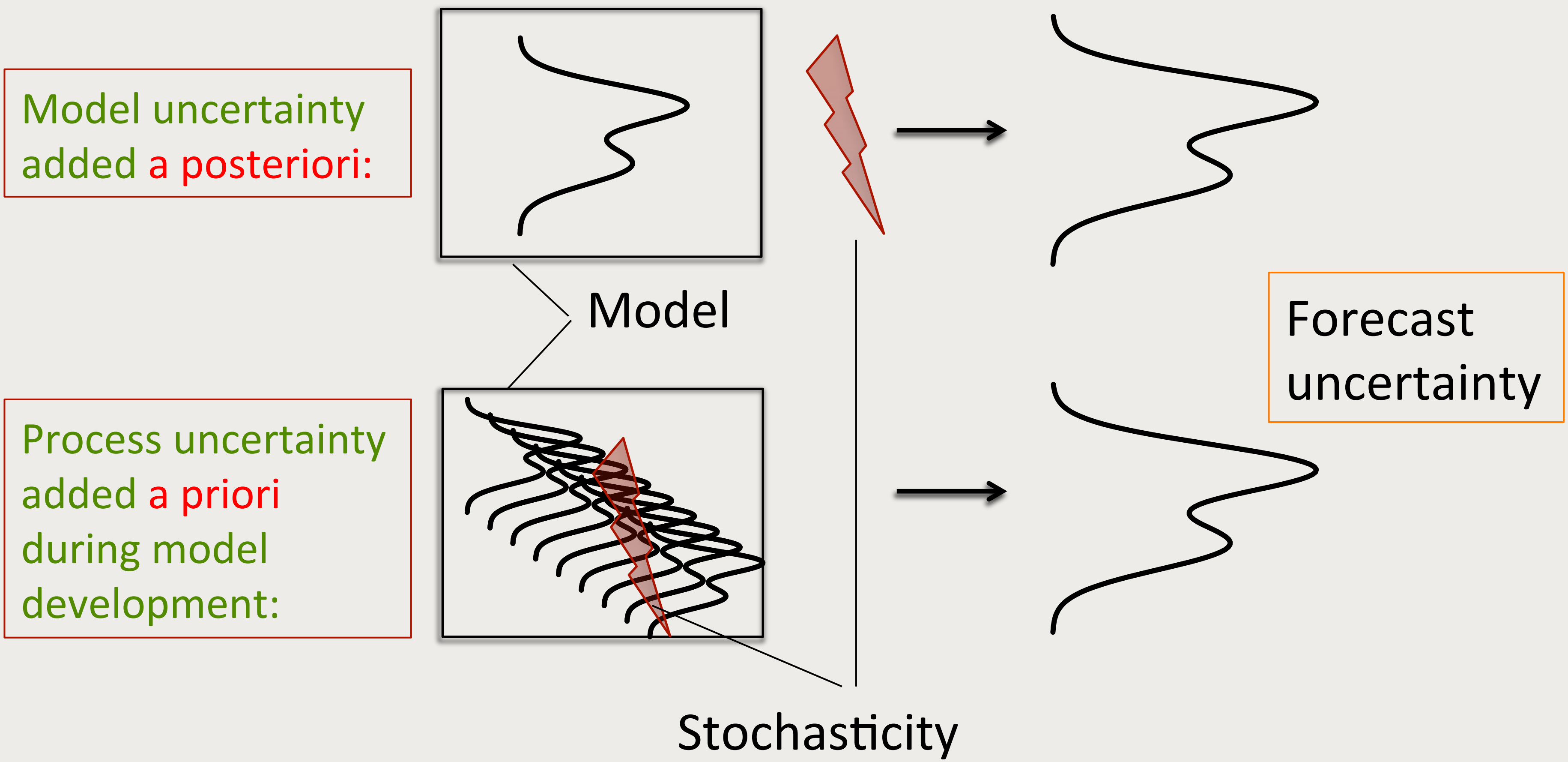
A priori vs a posteriori

Model uncertainty added a posteriori:

Process uncertainty added a priori during model development:



A priori vs a posteriori



(Epstein and Pitcher 1972; Lorenz 1975; Pitcher 1977; Palmer 2001), if only to provide reliable estimates of model uncertainty, then a fundamental conclusion of this study is that such a posteriori addition of stochasticity to an already tuned model is simply not viable. This in turn suggests that stochasticity must be incorporated at a very basic level within the design of physical process parameterizations and improvements to the dynamical core.

Acknowledgments. We thank Paco Doblas-Reyes, Antje Weisheimer, and Roberto Buizza for many motivating discussions throughout the years. The Newton Institute in Cambridge hosted the first and third author during their program on "Stochastic modeling in the climate sciences" in 2010, which gave them the opportunity to work on this manuscript. We are indebted to Annabel Bowen and Bob Hine for improving the graphics. Thanks to Joe Tribbia and three anonymous reviewers whose insightful suggestions and comments improved earlier versions of this manuscript.

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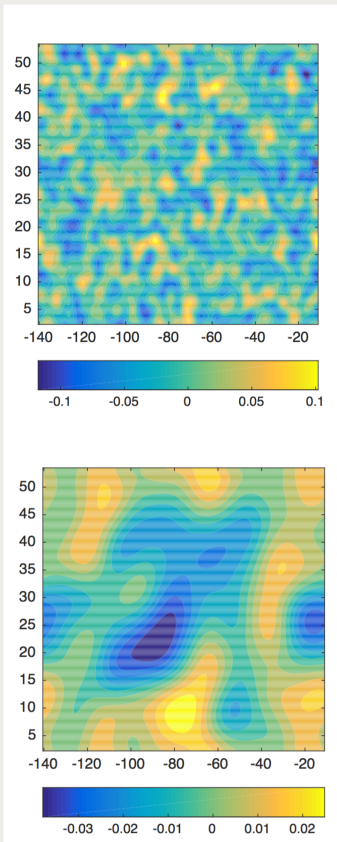
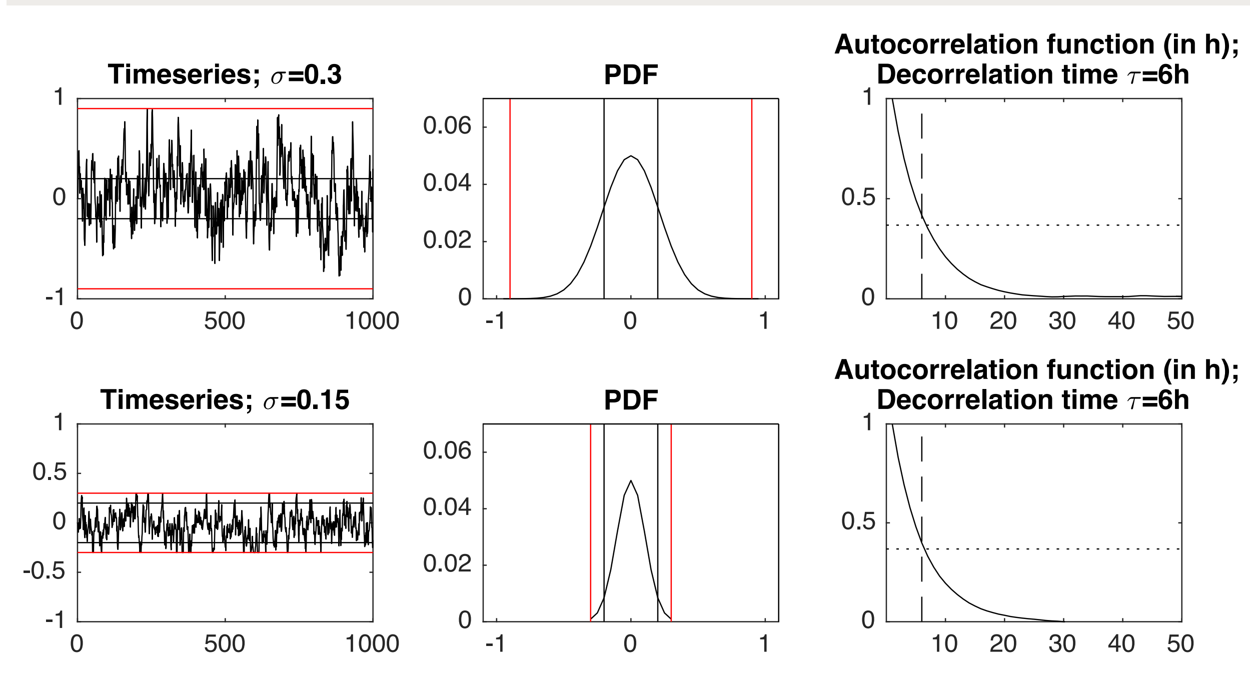
Stochastic parameter perturbations (SPP)

Grell convection scheme

MYNN PBL





With Isidora Jankov, Jeff Beck, George Grell, Joe B, Tanya Smirnova

S

Perturbations to Grell-Freitas Convection Scheme		
Perturbed parameter		Name
Closure		xf_ens
Namelist Parameter	Value (in SI)	Value (other than SI)
rand_perturb2	1	
gridpt_stddev_rand_pert2	0.3	
stddev_cutoff_rand_pert2	3.0	
lengthscale_rand_pert2	150000m	150km
timescale_rand_pert2	21600s	6h

Perturbations to Planetary Boundary Layer Scheme		
Perturbed parameter		Name
Turbulent Mixing length		el
Subgrid Cloud fraction (perfectly correlated with EL)		cldfra_bl
Thermal and Moisture Roughness Length(anticorrelated and twice the amplitude)		CZIL
Namelist parameter	Value (in SI)	Value (other than SI)
rand_perturb3	1	
gridpt_stddev_rand_pert3	0.15	
stddev_cutoff_rand_pert3	2.0	
lengthscale_rand_pert3	700000m	700km
timescale_rand_pert3	21600s	6h

Experiment setup

- Limited area model: Contiguous United States (CONUS)/NARRE
- Weather Research and Forecast Model WRFV3.6.1
- 15km horizontal resolution
- 10-member ensemble, integrated for 24h
- 10 dates in June of 2015, 00Z and 12Z
- Boundary and initial conditions are taken from GEFS

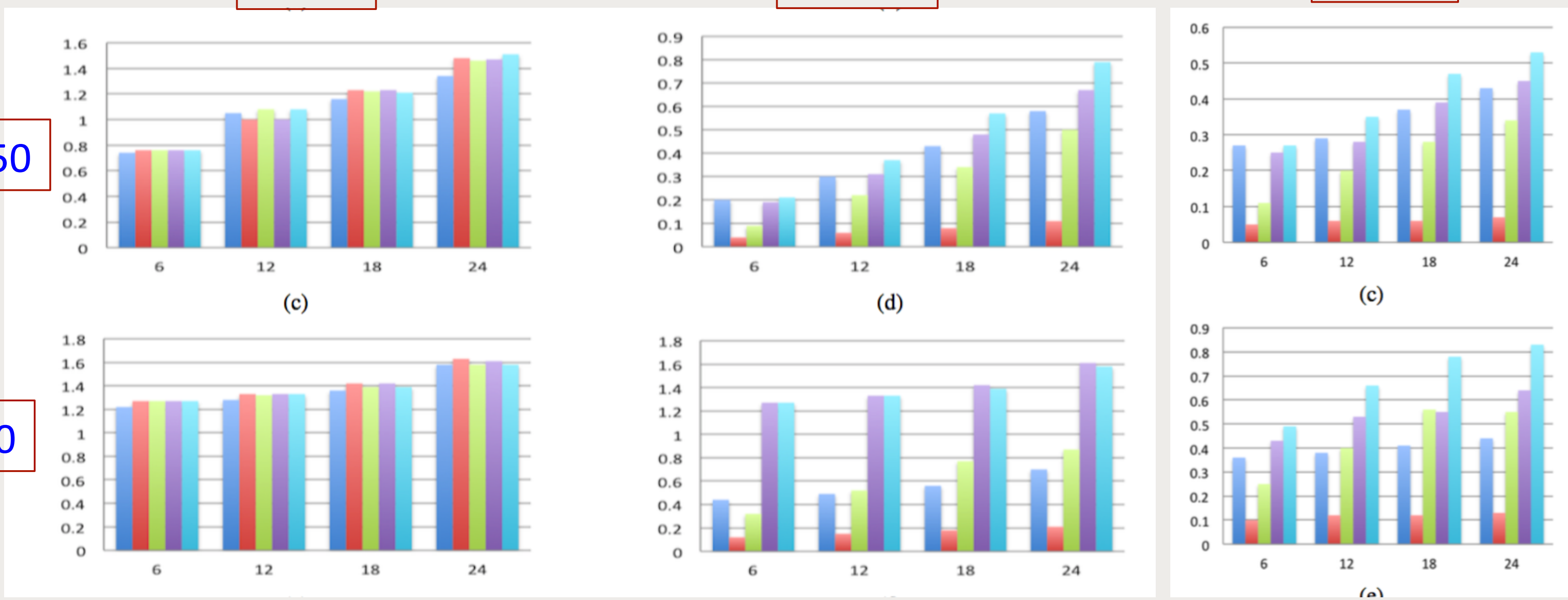
Multi-physics ensemble

multi-physics members	Convective	PBL	LSM
control0	OSAS	MYNN	RUC
control1	BMJ	MYNN	RUC
control2	GF	MYNN	RUC
control3	NSAS	MYNN	RUC
control4	GF	MYJ	RUC
control5	GF	YSU	RUC
control6	GF	BOULAC	RUC
control7	GF	MYNN	RUC

RMSE | Spread | CRPSS

T850

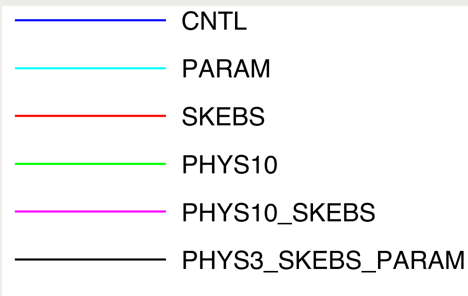
U10

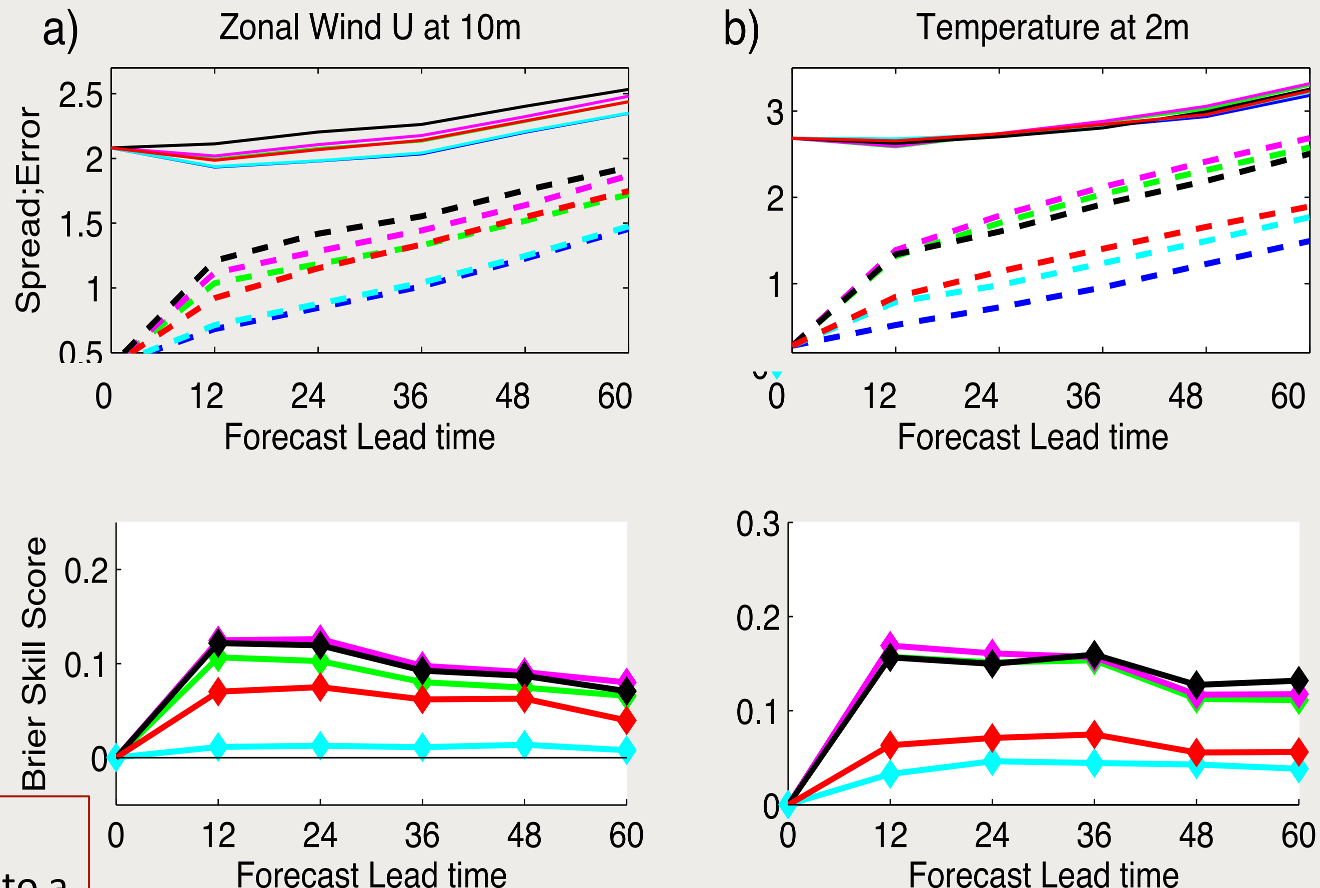


CNTL
SPP
SPPT
SKEBS
SPPT+SKEBS+SPP

Jankov et al., submitted

Brierscore skill score near the surface





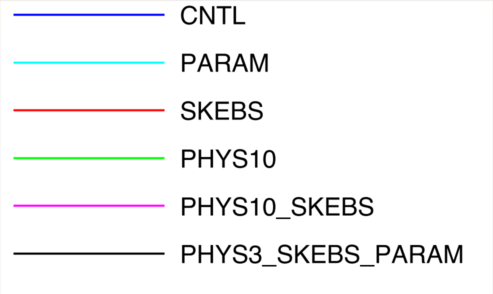
$$BSS_{exp} = \frac{BS_{ref} - BS_{exp}}{BS_{ref}}$$

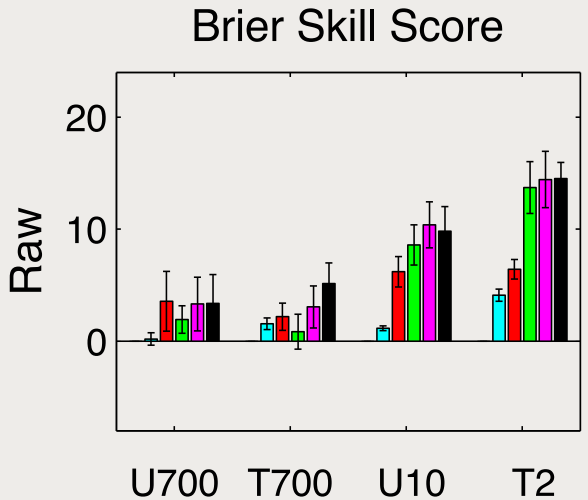
Brier skill measures probabilistic skill in regard to a reference (here CNTL).
Verified event: $\mu < x < \mu + \sigma$

Berner et al., et al 2015

Relative skill improvement

- Average over all forecast lead times
- Variables are U700, T700, U10, T2
- Reference is CNTL

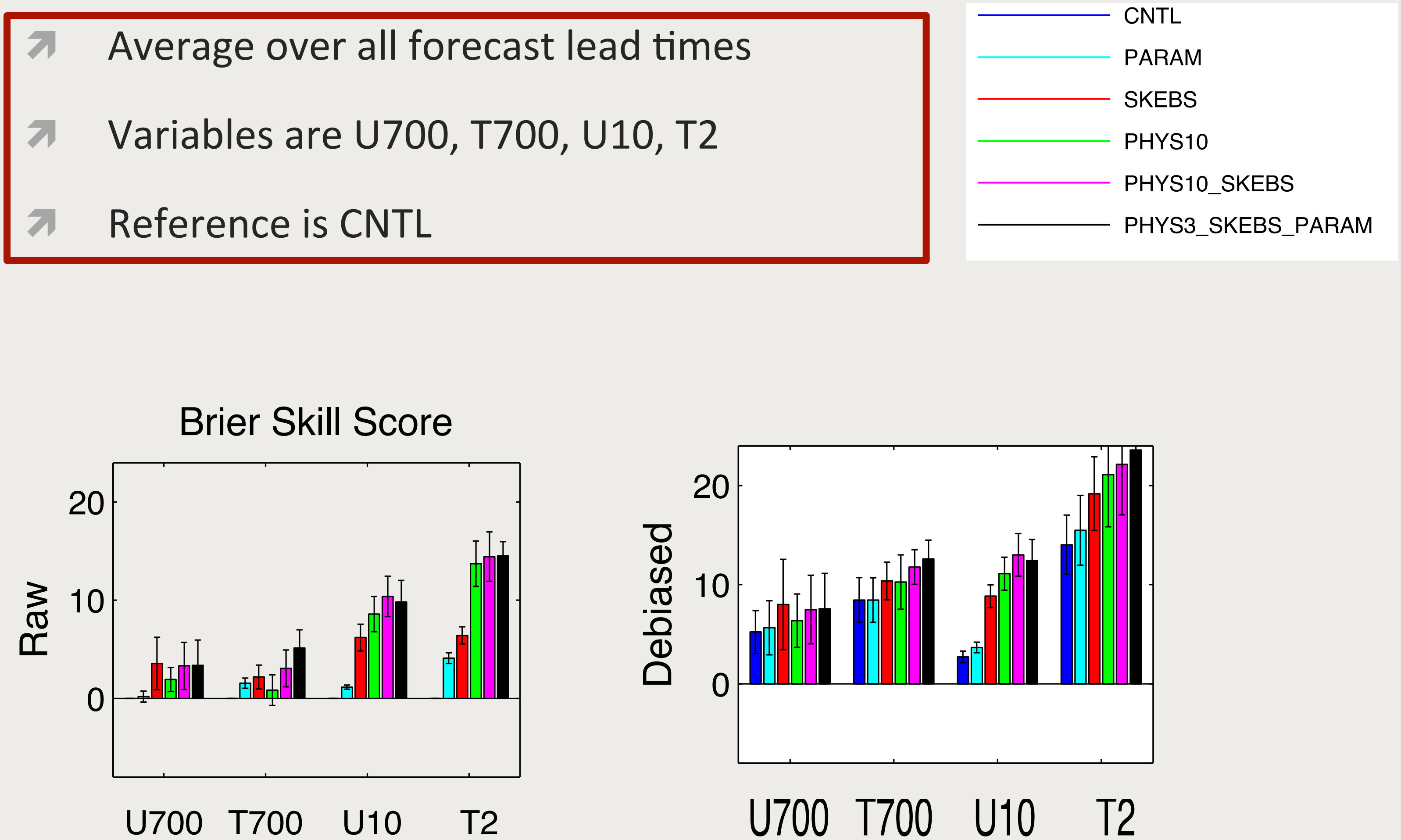




Berner et al., et al 2015

NB: Role of bias

- Average over all forecast lead times
- Variables are U700, T700, U10, T2
- Reference is CNTL

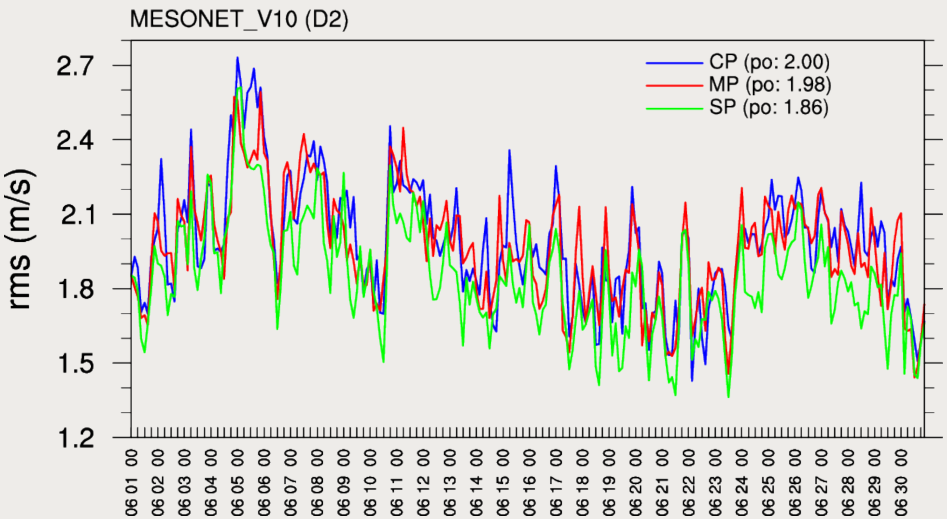


NB

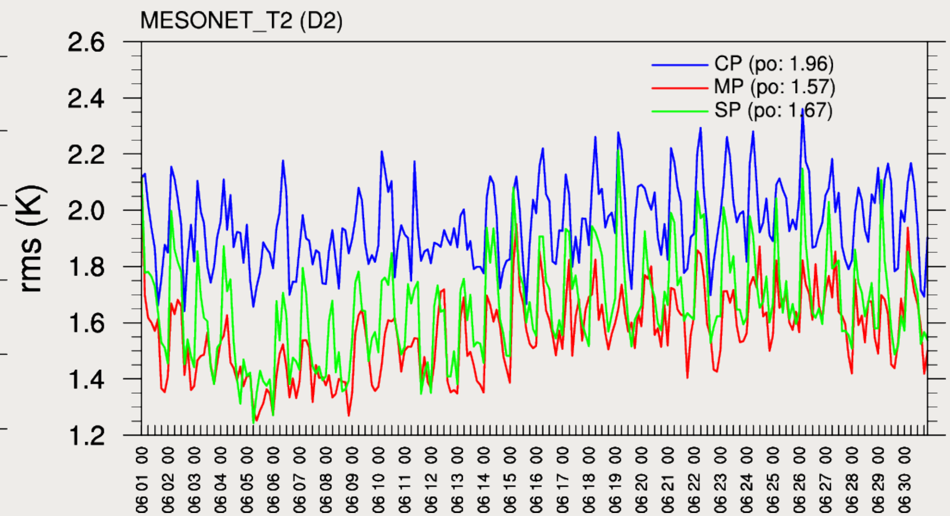
- The relative impact of SKEBS and SPPT will depend on the tuning!

WRF-DART:Verification of surface analysis against independent observations

V-10m



T-2m

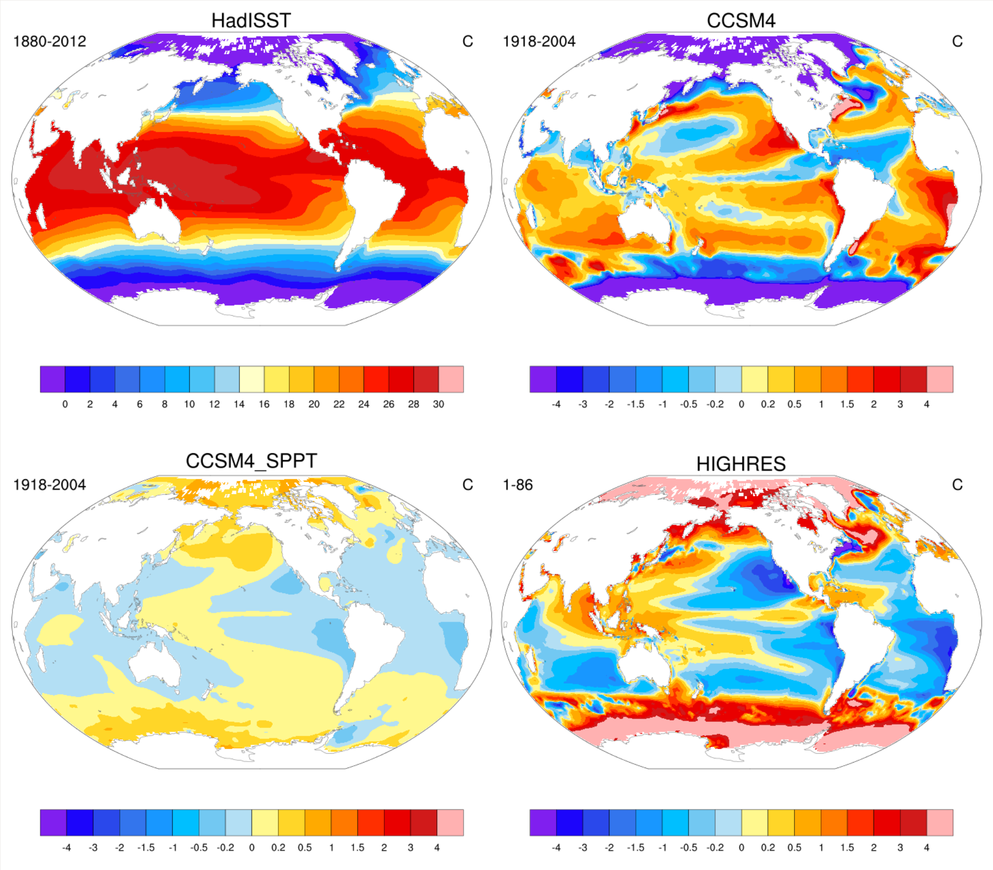


CNTL
SKEBS
PHYS

- Including a model-error representation reduces the RMS error of the surface analysis (also prior) in 10m wind and Temperature at 2m

Ha et al. 2015

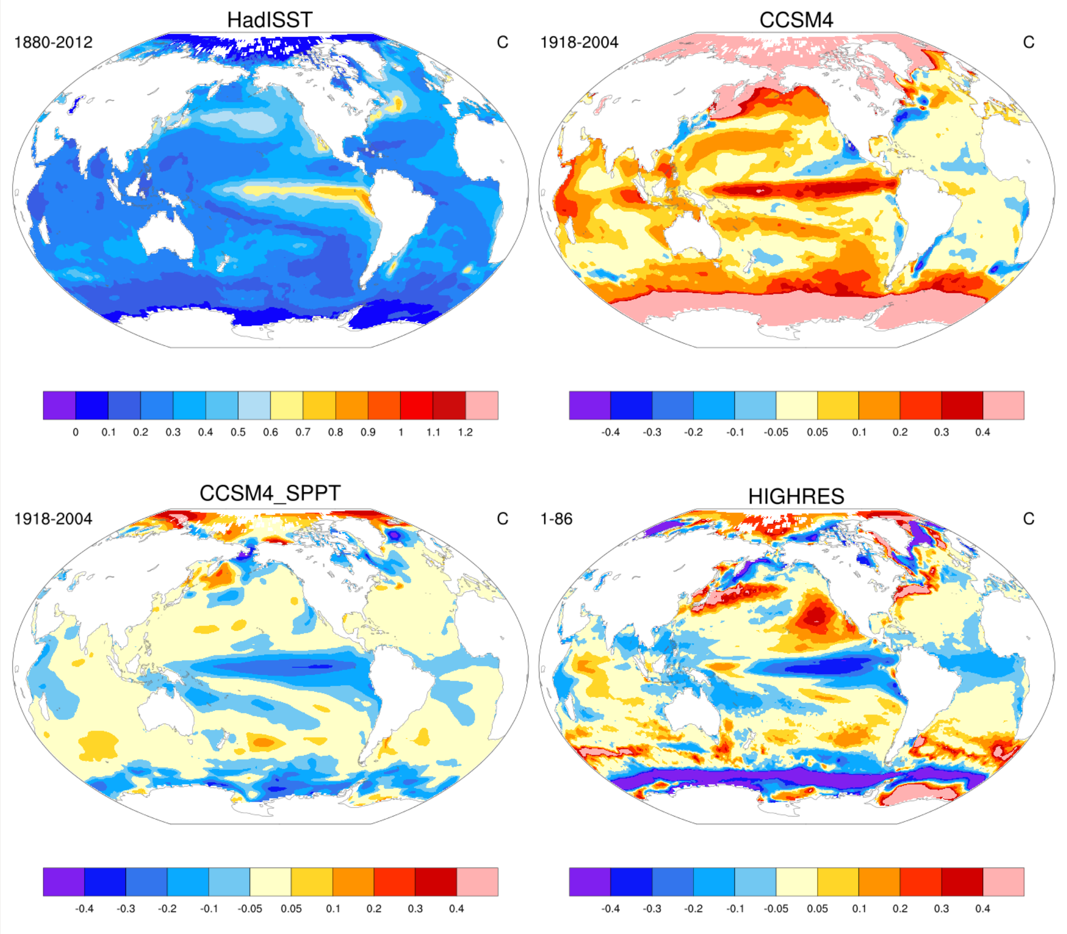
Difference in SST Mean



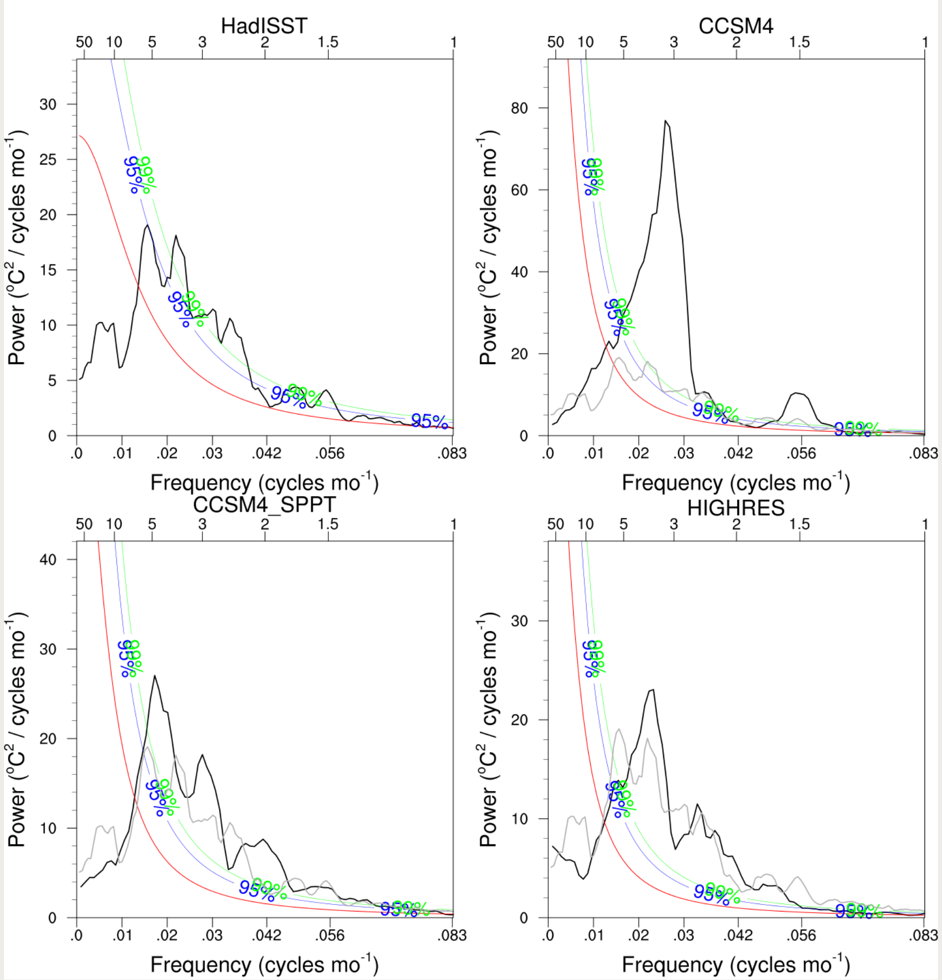
With Hannah Christensen and Justin Small

See Christensen et al. 2016, submitted

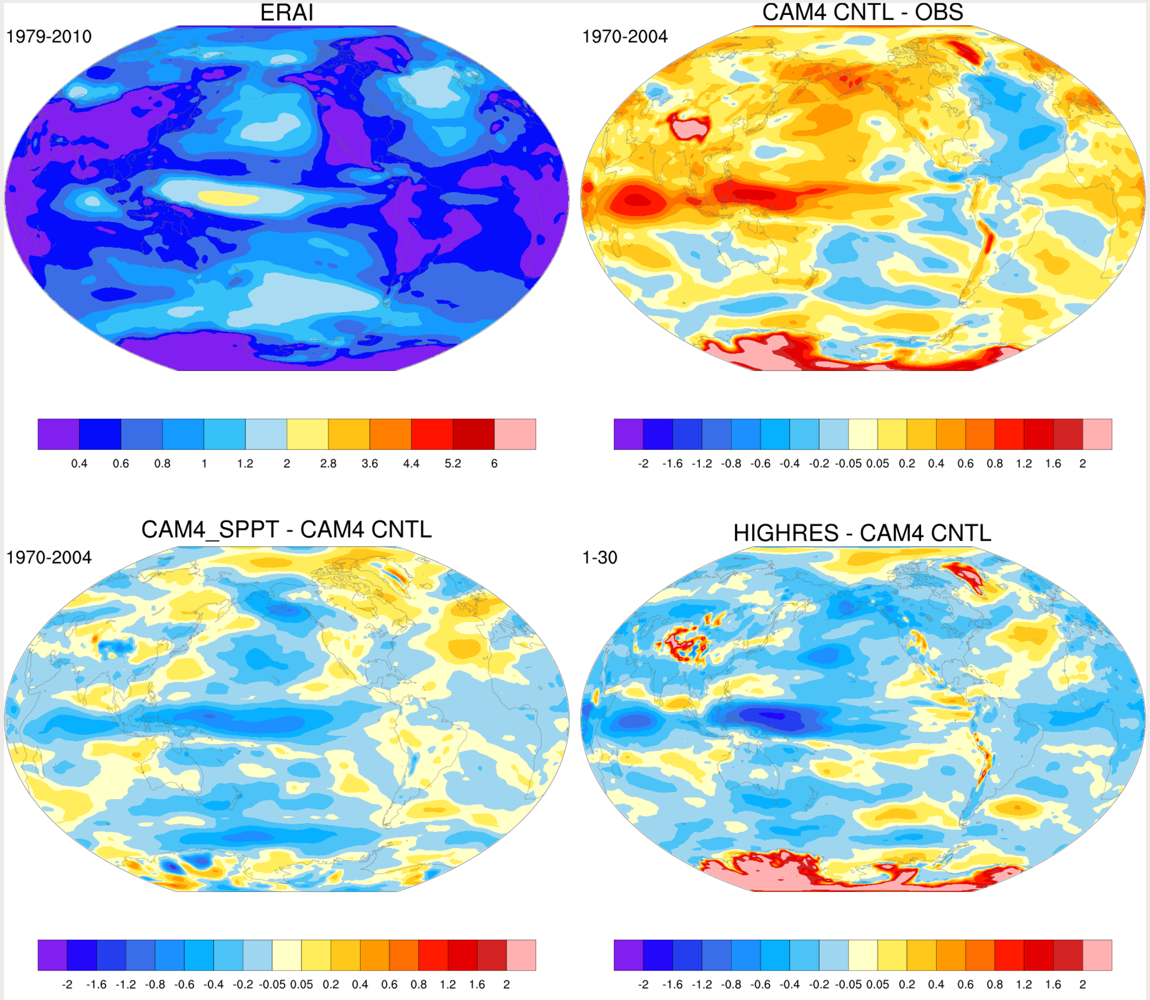
Difference in SST standard deviation



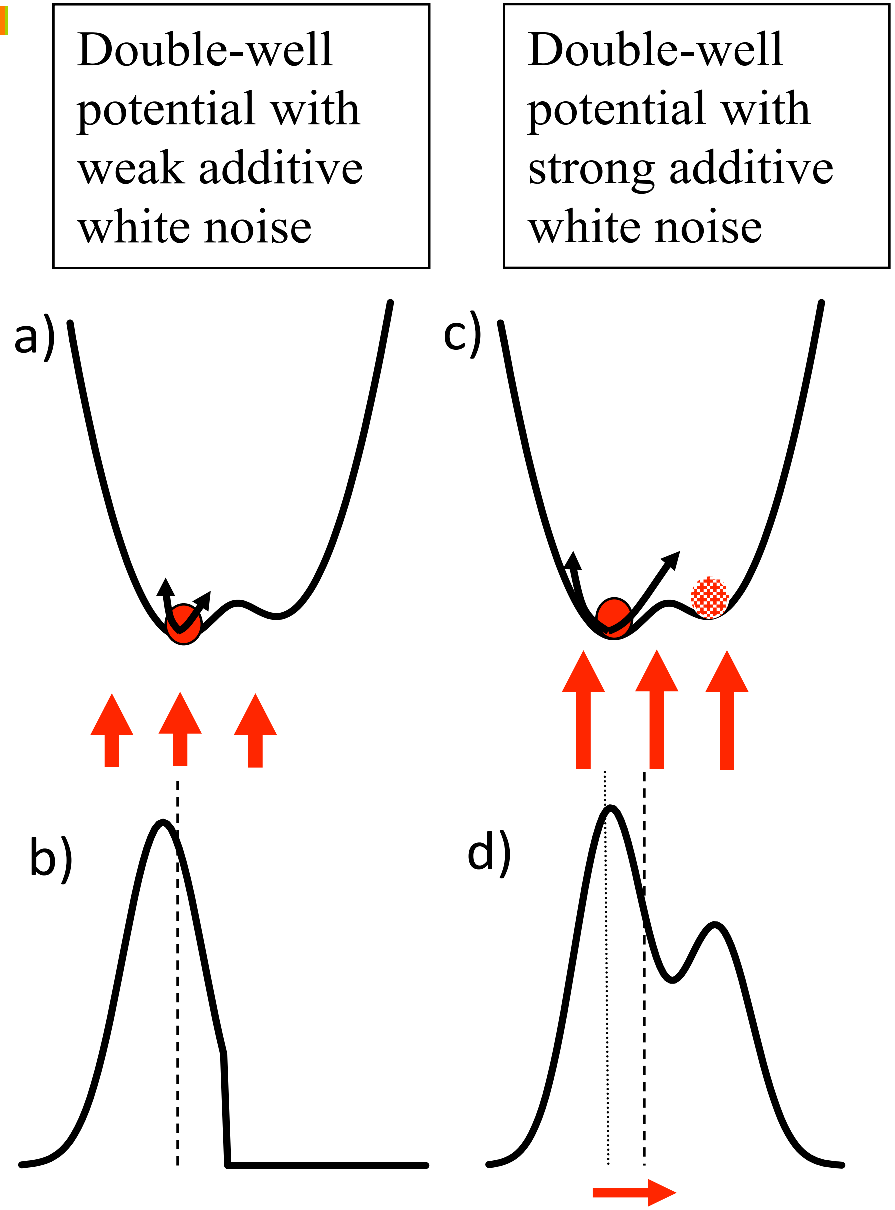
Nino3.4 Power spectra



Difference in U850 standard deviation



- Stochastic parameterizations can change the mean and variance of a PDF
  - Impacts variability
  - Impacts mean bias

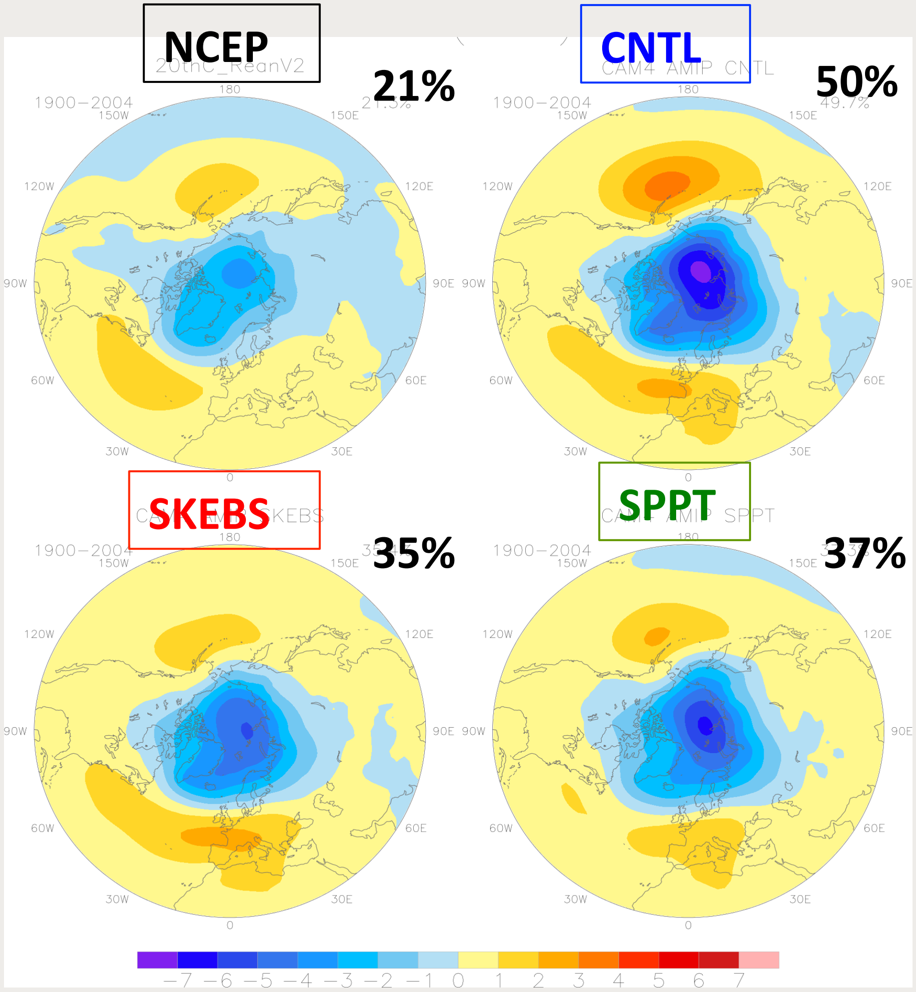


Northern Annular Mode (MAM)

1st EOF of sea level pressure over Northern Hemispheric Extratropics

- CAM4 AMIP simulations (prescribed SSTs), 1900-2004

- Stochastic parameterization improves pattern and reduces explained variance
- Degenerate response: SKEBS and SPPT have same effect



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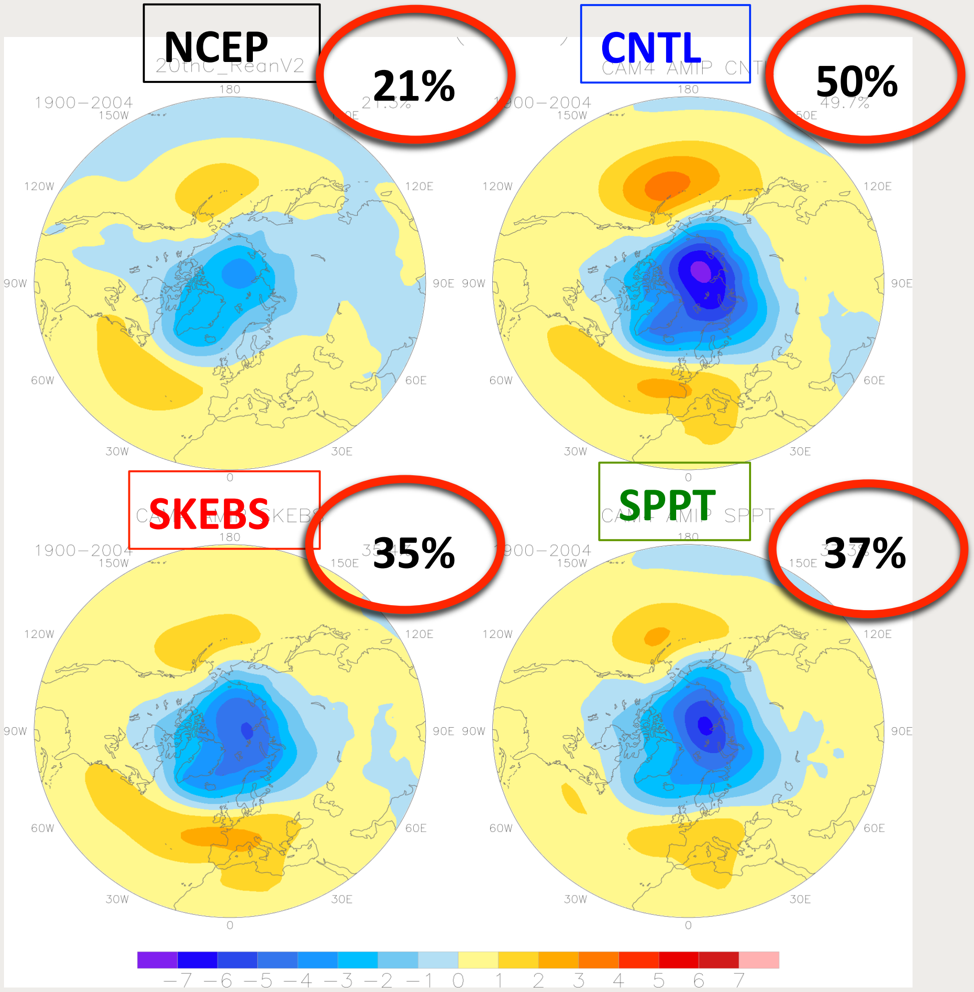

Conclusions

- Parameter perturbations (a priori) do not generate enough uncertainty in ensemble systems. Currently, a posteriori methods (SKEBS, SPPT, residual methods) are necessary for reliable ensemble system
- The same holds for other a priori methods (Plant-Greg scheme, PBL variation scheme)
- In NWP model-error schemes are mainly used to generate spread
  - Role of bias needs to be revisited
- In climate models, stochastic methods can reduce coupling and reduce variability

Future work

- Perturb
  - dynamical tendencies
  - land surface models
  - divergence in skebs
  - stochastic perturbation in GF convection scheme as function of large-scale forcing
- Will impact of stochastic parameterizations change at convection-resolving/allowing scales, where largest uncertainty moves to micro-physics?
- Is climate sensitivity influenced by subgrid-scale variability (Seiffert and von Storch 2009)
- SKEBS will be implemented into MPAS and used to study predictability in the presence of kink in spectrum

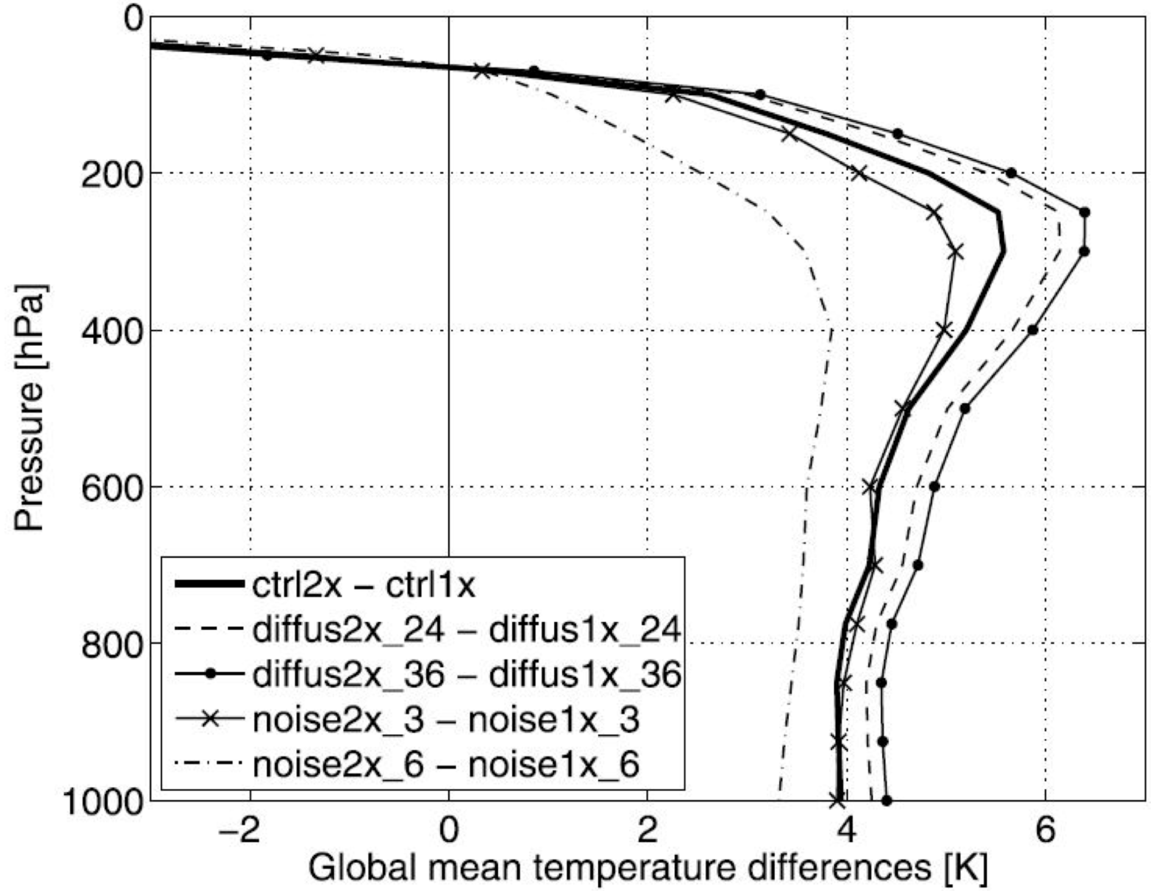

Figure 1: Climate responses of global mean temperature to a CO2 doubling (2x CO2 minus 1x CO2) obtained from the ECHAM5/MPIOM-experiments with different representations of small-scale fluctuations: 'diffus' refers to experiments in which the strength of horizontal diffusion is varied; 'noise' refers to experiments in which white noise is added to small scales of the atmospheric model ECHAM5. From Seiffert and von Storch

Thank you!

- Berner, J, K. Fossell, S.-Y. Ha, J. P. Hacker, C. Snyder 2015: "Increasing the skill of probabilistic forecasts: Understanding performance improvements from model-error representations*, Mon. Wea. Rev.*, **143**, 1295-1320

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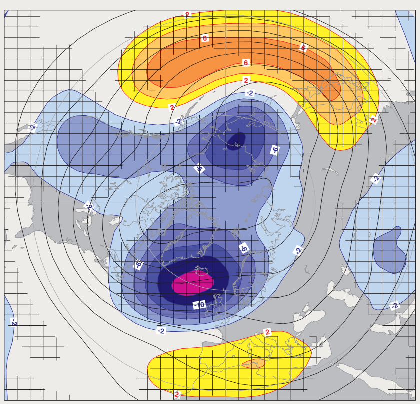
- Romine, G. S., C. S. Schwartz, J. Berner, K. R. Smith, C. Snyder, J. L. Anderson, and M. L. Weisman, 2014: "Representing forecast error in a convection-permitting ensemble system"*, Mon. Wea. Rev*, **142**, 12, 4519–4541

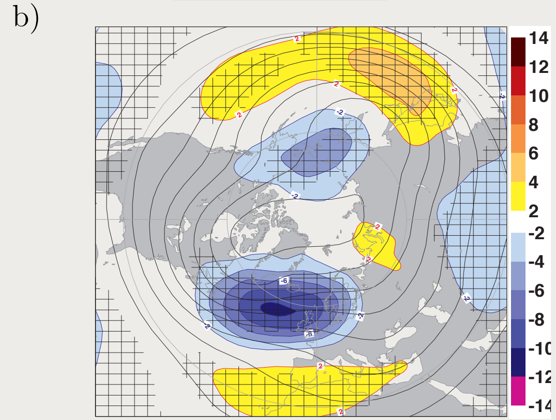
- Ha, S.-Y., J. Berner, C. Snyder, 2015: "Model-error representation in mesoscale WRF-DART cycling", under review at *Mon. Wea. Rev.*

Mean systematic error of 500 hPa geopotential height fields

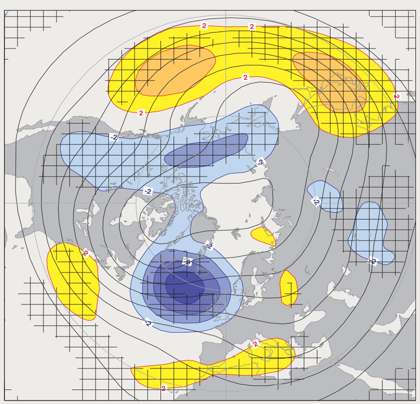
LOWRES



HIGHRES



SKEBS

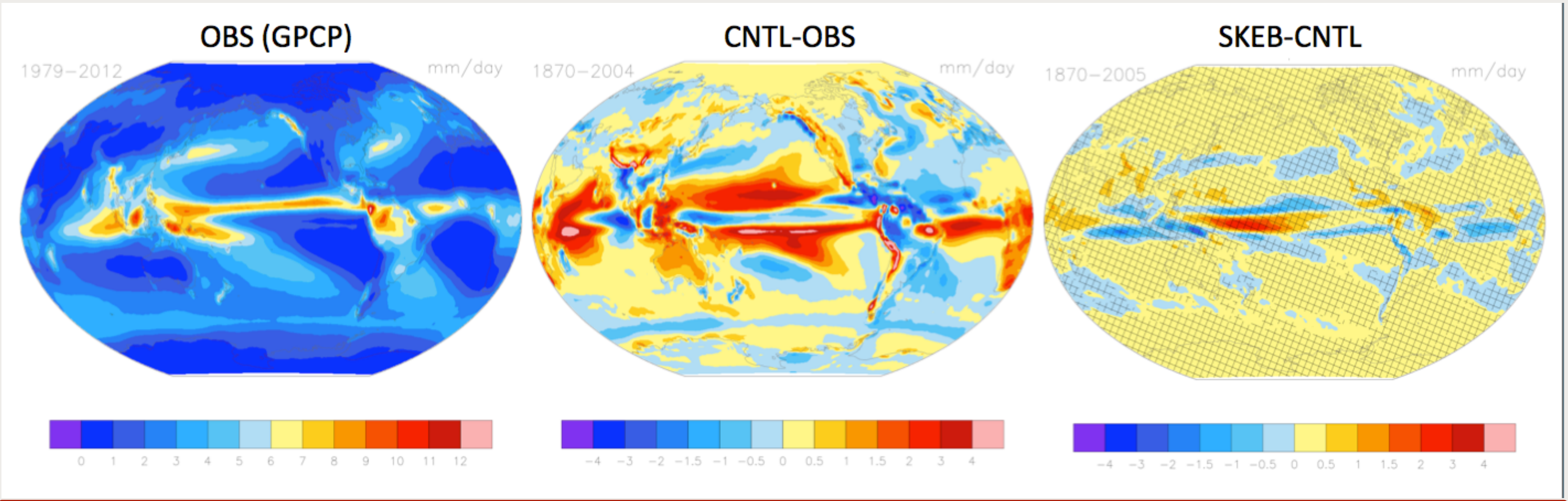


- Reduction of z500 bias in all simulations with model-refinement

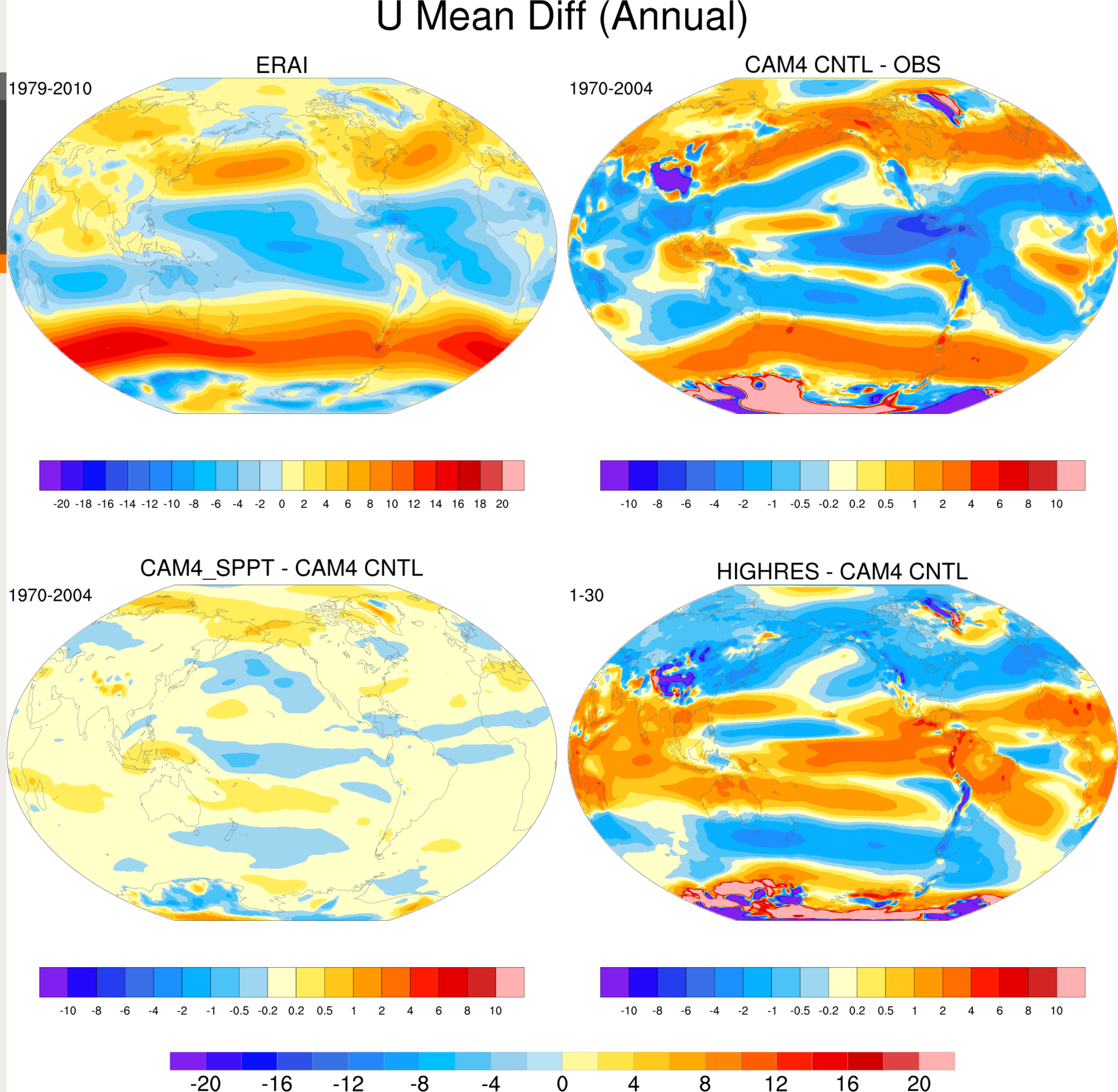
Berner et al., 2012

Impact of SKEBS on precipitation bias

- Coupled control run shows significant bias due to split inter-tropical convergence zone



- SKEBS reduced bias in precipitation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ERAI
1979-2010
CAM4 CNTL - OBS
1970-2004
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CAM4_SPPT - CAM4 CNTL
1970-2004
HIGHRES - CAM4 CNTL
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-10 -8 -6 -4 -2 -1 -0.5 -0.2 0.2 0.5 1 2 4 6 8 10
-20 -16 -12 -8 -4 0 4 8 12 16 20