Predictability in the presence of model-error

Transport in Unsteady Flows: from Deterministic Structures to Stochastic

Models and Back Again

BIRS, Banff, Canada, Jan 14-21, 2017

Judith Berner

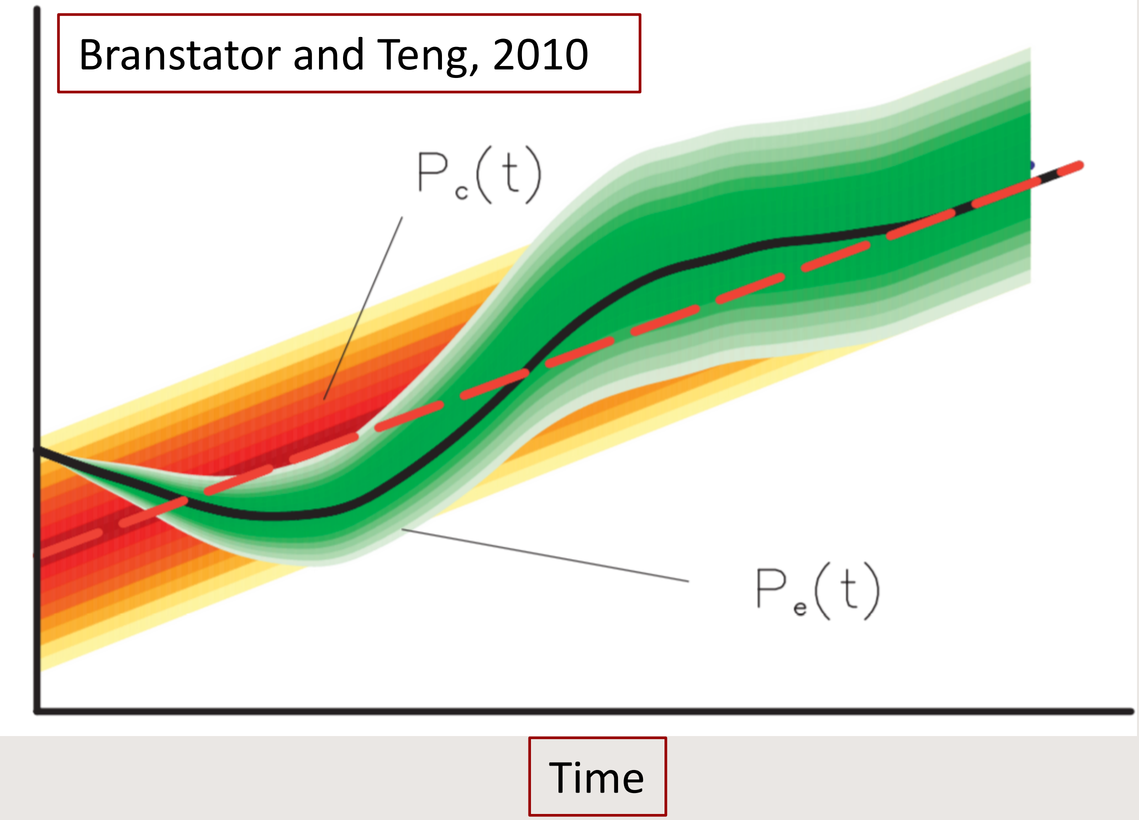
National Center for Atmospheric Research

Outline

- Sources of predictability in weather and climate simulations.
- Theoretical limits of predictability
- Additional limits due to the presence of model-error
- Potential remedy by
  - Stochastic parameterizations
  - Increasing numerical resolution
  - Improving physical parameterizations

Sources of predictability

- Predictability from knowledge of initial condition (weather timescales)
- Predictability from knowledge of boundary condition (climate timescales)
- Conditional predictability (subseasonal timescales)



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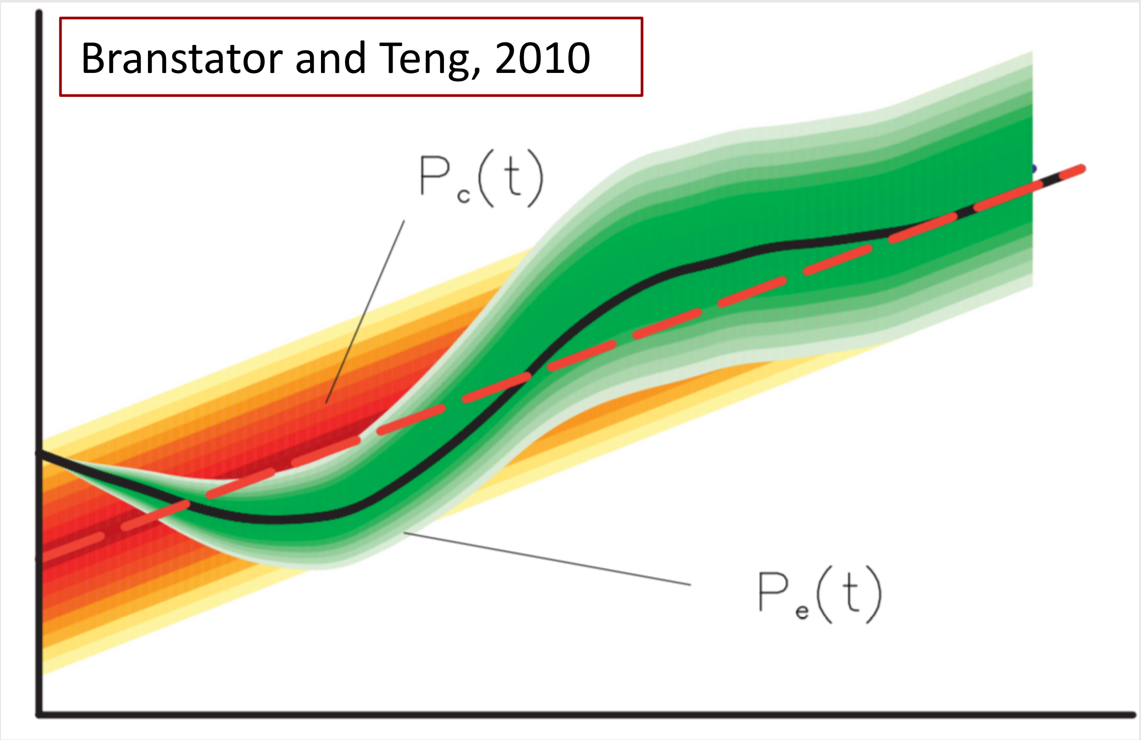
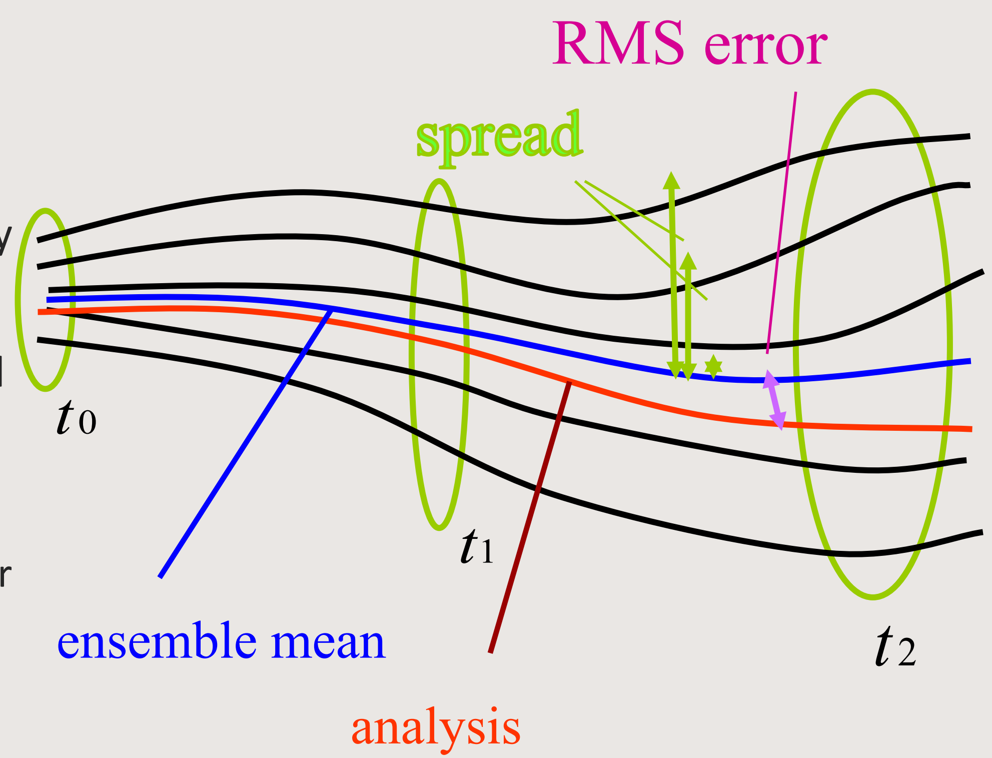


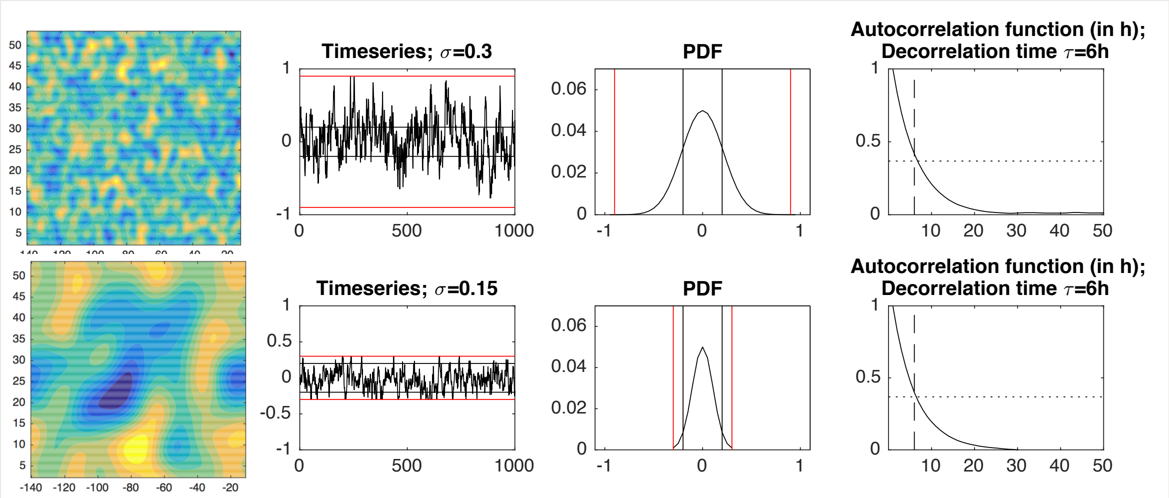
For atmospheric system:	Weather	Suseasonal/seasonal	Climate
For coupled a/o system:	Weather	Decadal timescales	Climate

Representing initial uncertainty by an ensemble of states

- Forecast uncertainty in weather models: \
  - Initial condition uncertainty
  - Model uncertainty
  - Boundary condition uncertainty
- Represent initial forecast uncertainty by ensemble of states
- Reliable forecast system: Spread should grow like ensemble mean error
  - Predictable states with small error should have small spread
  - Unpredictable states with large error should have large spread



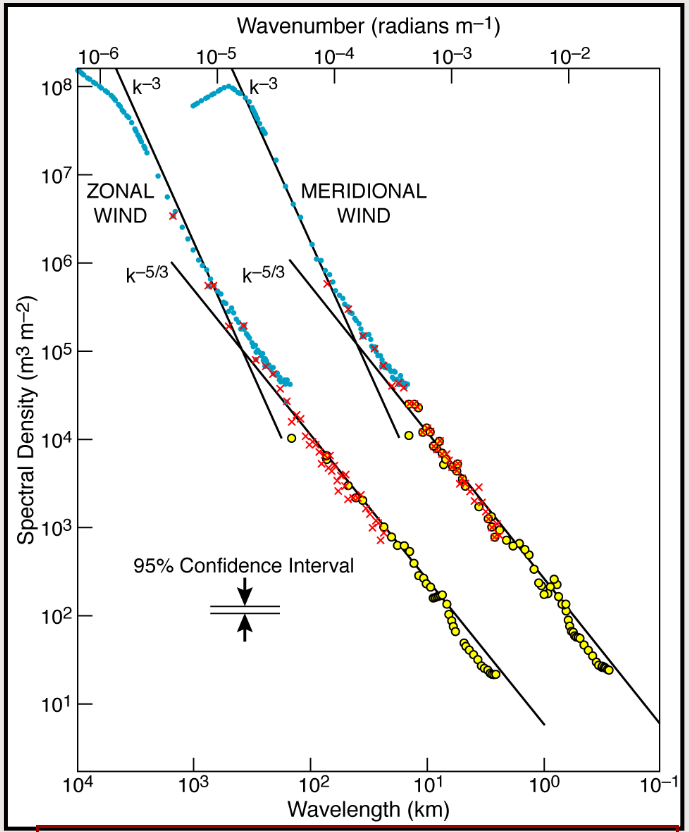
Stochastic parameter perturbations (SPP)



- Stochastically perturbs parameters in convection and PBL scheme
  - Grell convection scheme: Closure tendencies
  - MYNN PBL: Turbulent mixing length, subgrid cloud fraction, thermal and moisture roughness lengths (perturbations correlated and anti-correlated informed by expert knowledge)
- Results from RAP ensemble system @15km, currently tested in 3km

Jankov et al., 2017

Kinetic energy spectra



Nastrom and Gage, 1985

Limited vs unlimited predictability in Lorenz 1969

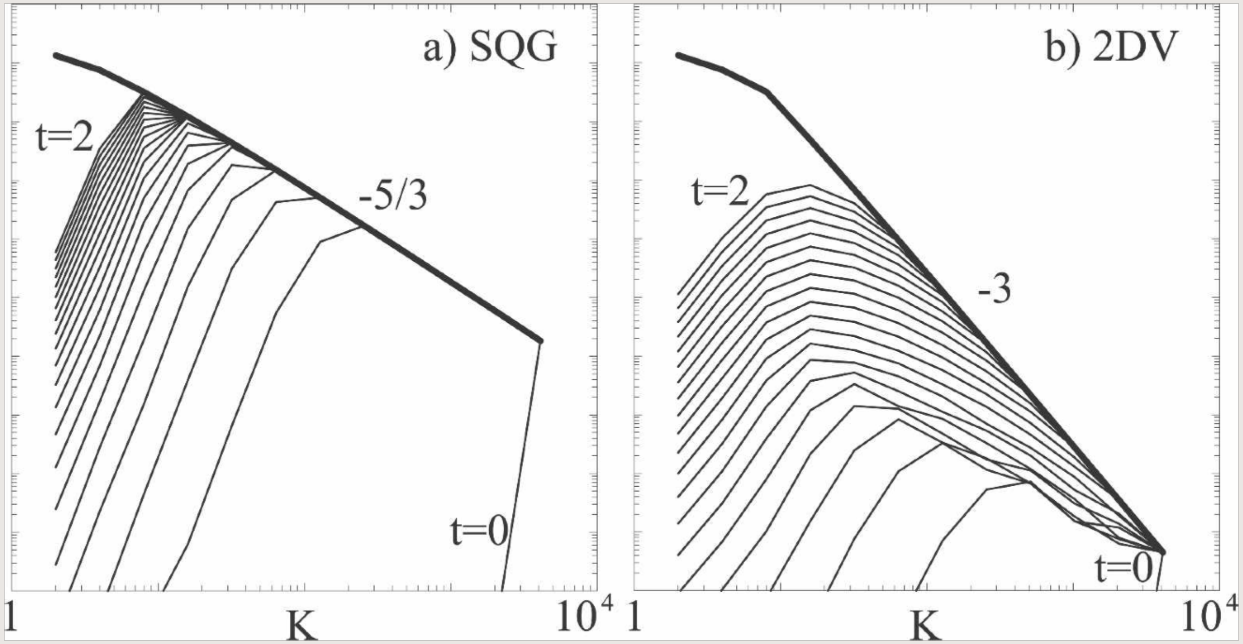
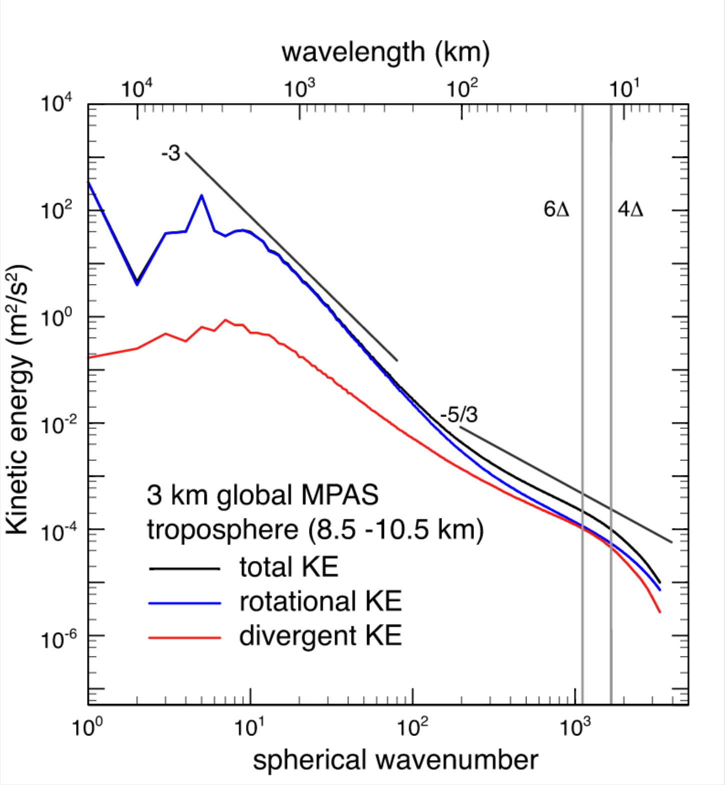


FIG. 1. Error energy per unit wavenumber, $K^{-1}Z(K, t)$ for $t = 0, 2$ in steps of 0.1 for (a) SQG turbulence and (b) 2DV turbulence. The heavy solid line indicates the base-state kinetic energy spectra per unit wavenumber, $K^{-1}X(K)$, which has a $-5/3$ slope for SQG and a -3 slope for 2DV.

Rotunno and Snyder, 2008

see also: Tribbia and Baumhefner 2004

Weather timescales: Kinetic-energy spectra



Skamarock et al. 2014

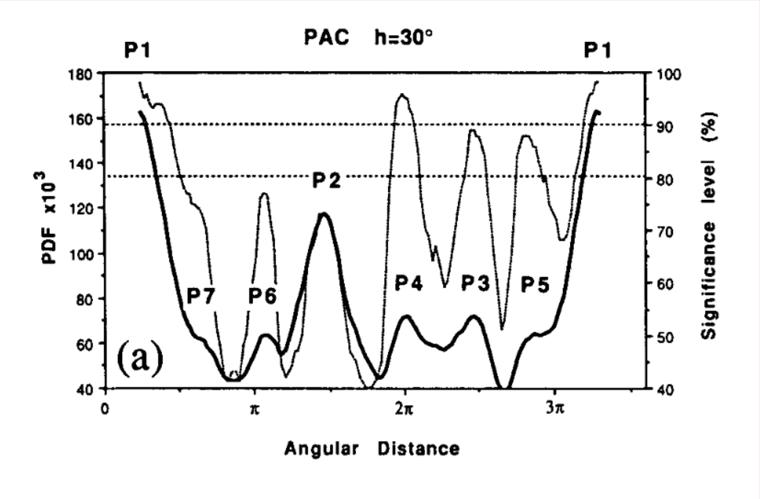
The problem (1)

- Best estimates of initial condition uncertainty do not introduce the necessary spread for reliable forecasts on the short-, medium- and seasonal scales.
  - One source of model-error are uncertainties in the physical parameterization schemes.
    - Our best estimate of parameterization uncertainties does not yield sufficient spread.
  - There are other sources of model-error, e.g. the absence of a -5/3 slope in the kinetic energy spectra, leading to incorrect dispersion between any two ensemble members.
    - Some ad-hoc stochastic parameterization schemes address this issue and yield more reliable ensemble systems.

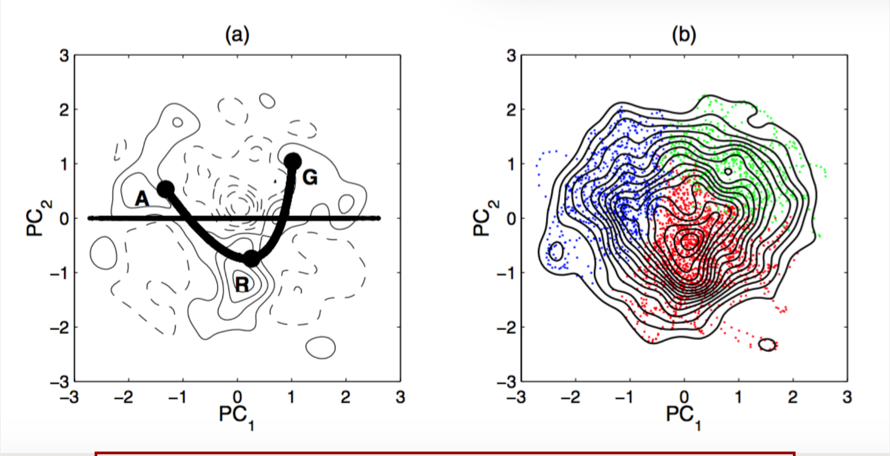
Predictability on sub-seasonal timescales

- Some knowledge of initial condition (Sun 2011, Vitart 2014)
  - Ocean state
  - Stratospheric state
  - Tropical MJO
- Conditional predictability, Regime-transitions

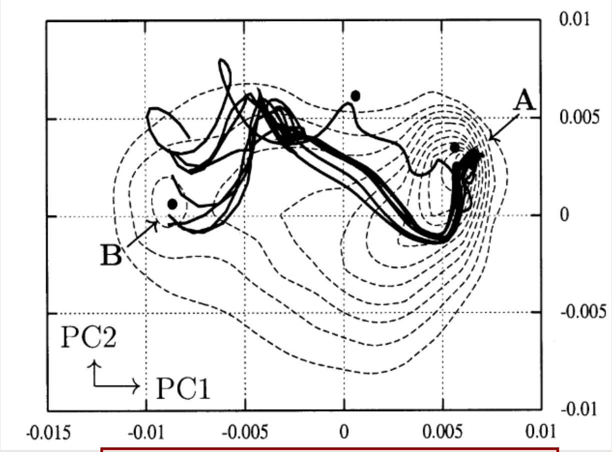
Regime-behavior, dynamical systems



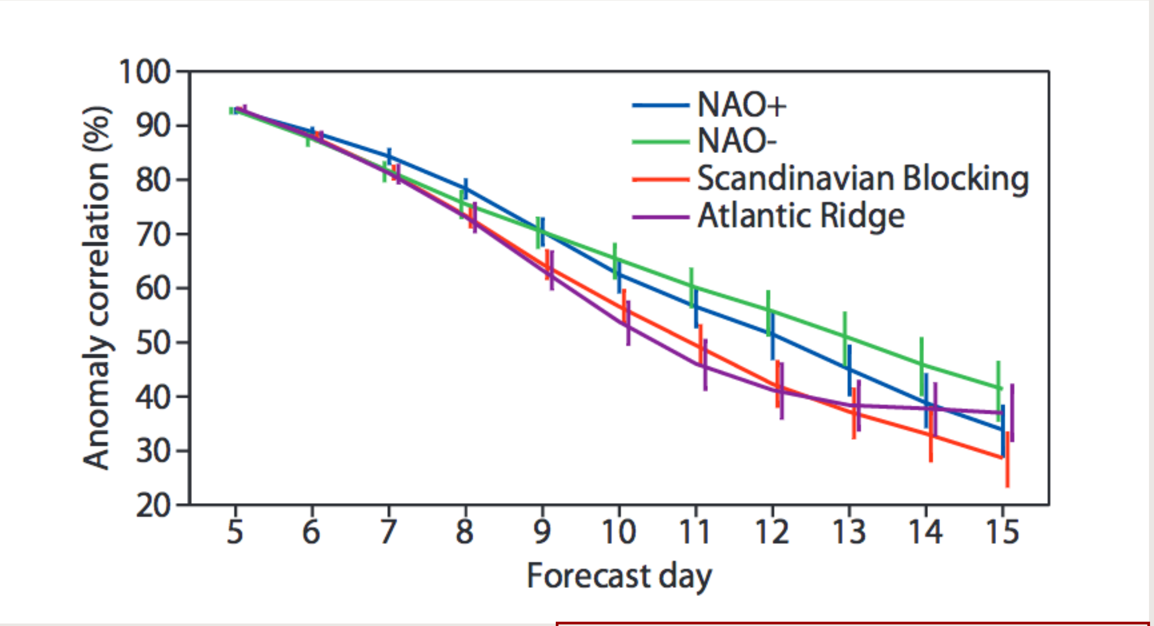
Kimoto and Ghil '93



Monahan and Pandolfo 2001

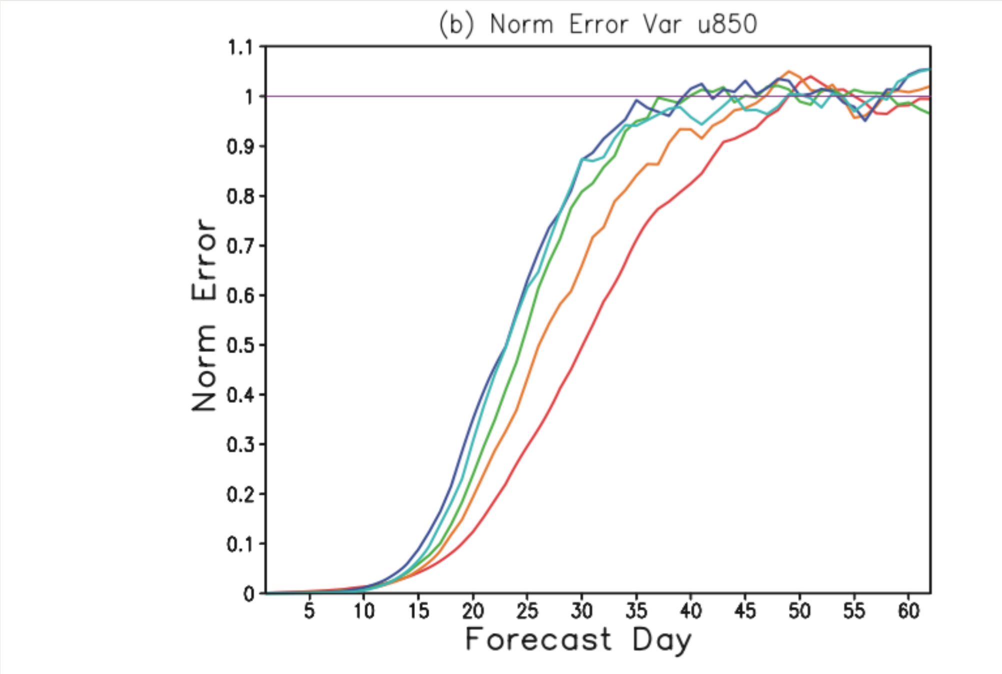


Crommelin 2003



Ferranti and Corti , 2015

Predictability, geographic differences

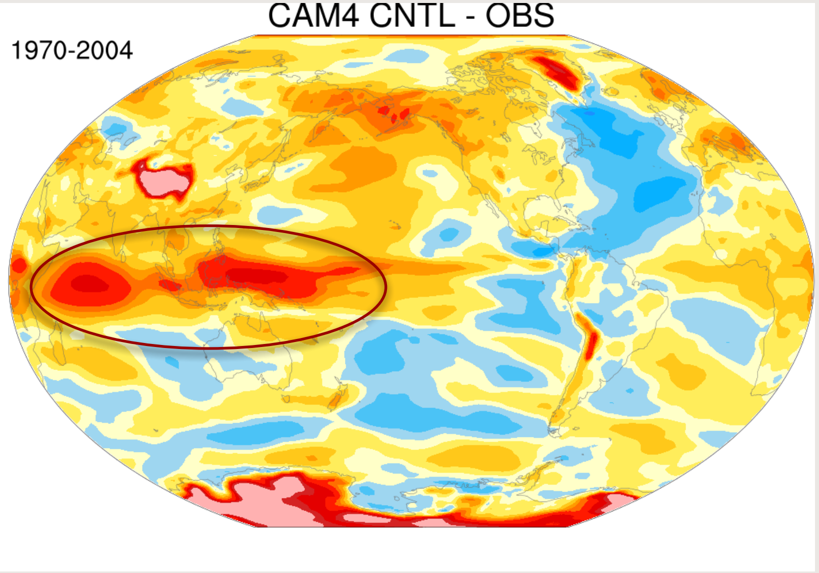


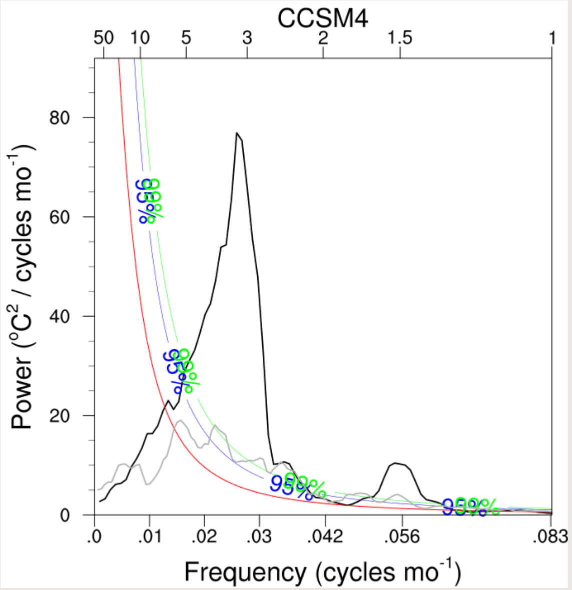
Straus and Paolino 2008

The problem (2)

- In climate simulations, there remain biases in the mean and variance (and higher-order moments), which will affect the results in “signal-to-noise” calculations (e.g. effect of stratosphere on the troposphere) as well as climate change projections.

Bias in SST variability





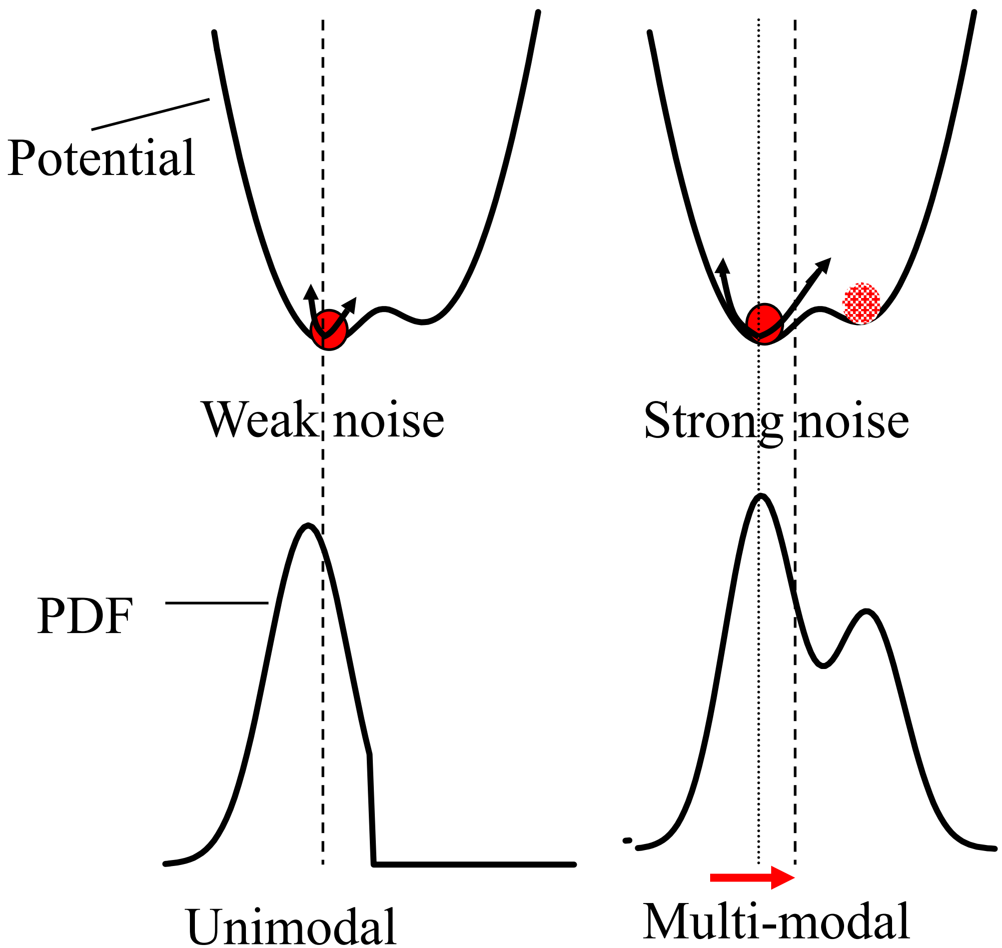
Christensen et al. 2017

The problem (2)

- In climate simulations, there remain biases in the mean and variance (and higher-order moments?), which will affect the results in “signal-to-noise” calculations, e.g. effect of stratosphere on the troposphere.
  - What is the effect of using such models for estimating predictability limits of the real atmosphere on sub-seasonal and longer timescales ?
  - How does this effect estimates for climate change distributions and especially their tails?
    - (but maybe trends okay)

Toward a solution

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



Forecast error spectra

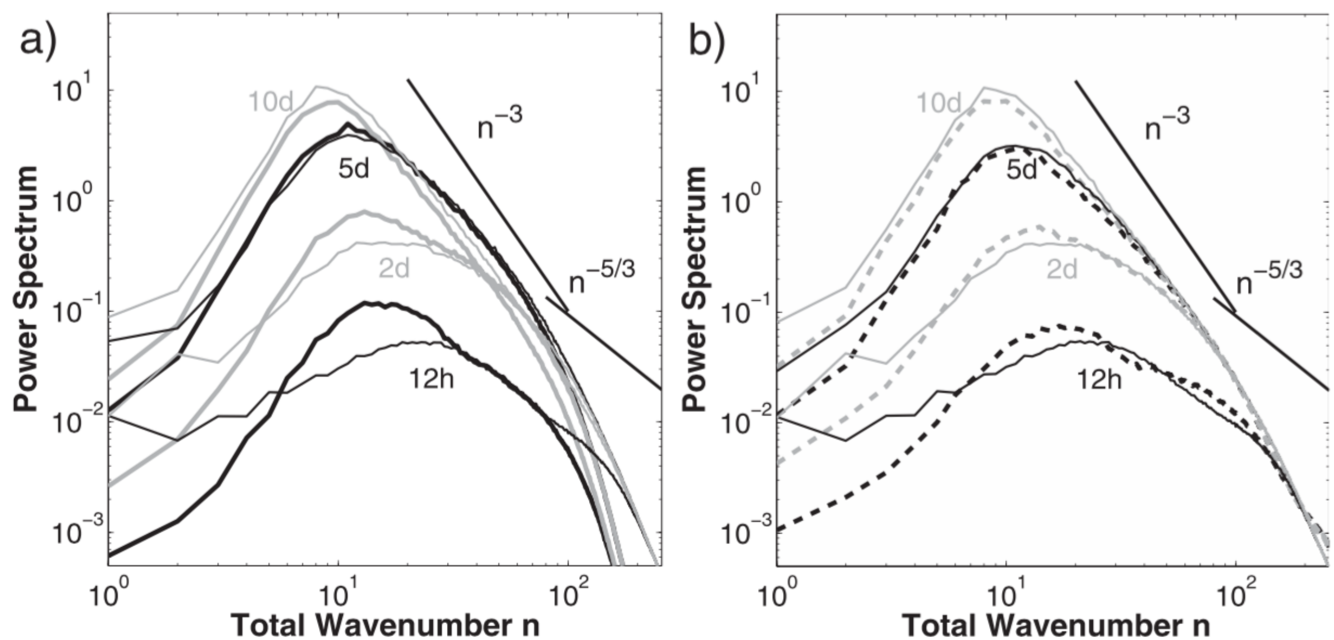
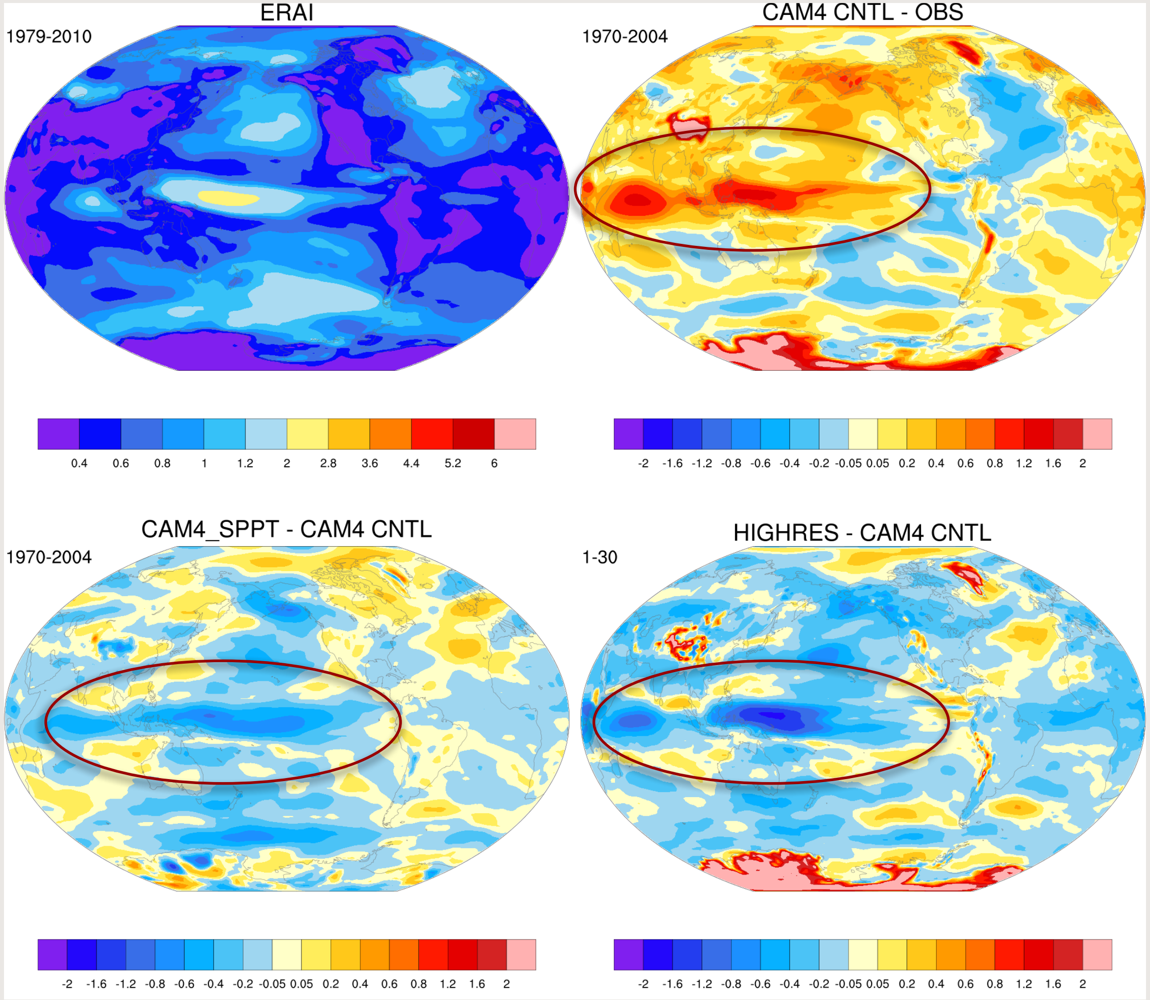


FIG. 8. Power spectrum of the error of the ensemble-mean forecast (thin solid lines) and spread (thick lines) in 500 hPa for fixed forecast lead times of 12 h, 2 days, 5 days, and 10 days for (a) the operational ensemble configuration (spread in OPER: thick solid line) and (b) the ensemble system with a stochastic backscatter scheme and reduced initial perturbations (spread in SSBS: thick dashed line). SSBS is short for SSBS-FULLDISS. Lines for forecast lead times of 12 h and 5 days are shown in black and for 2 days and 10 days in gray. See text for details.

Berner et al. 2009

Bias in SST variability



Judith's perspective: Potential of stochastic parameterizations (and open questions)

- Can change the kinetic-energy spectra and divergence properties in ensemble systems.
  - Does a model with an artificial -5/3 slope have the same limited predictability as theory.
- Can change the bias in the mean and variance.
  - But for right reasons? Compensating model-errors.
- Sub-seasonal prediction is a hot topic right now.
  - How does regime-behavior fit in with classical predictability views and studies? (IC and/or BC – depends on system)?
  - Stochastic parameterization improve sub-seasonal forecasts, since they are underdispersive, but is there more?
  - Linear inverse models make excellent predictions on this timescale. Why and what can we learn from it?

Bulletin of the American Society, March

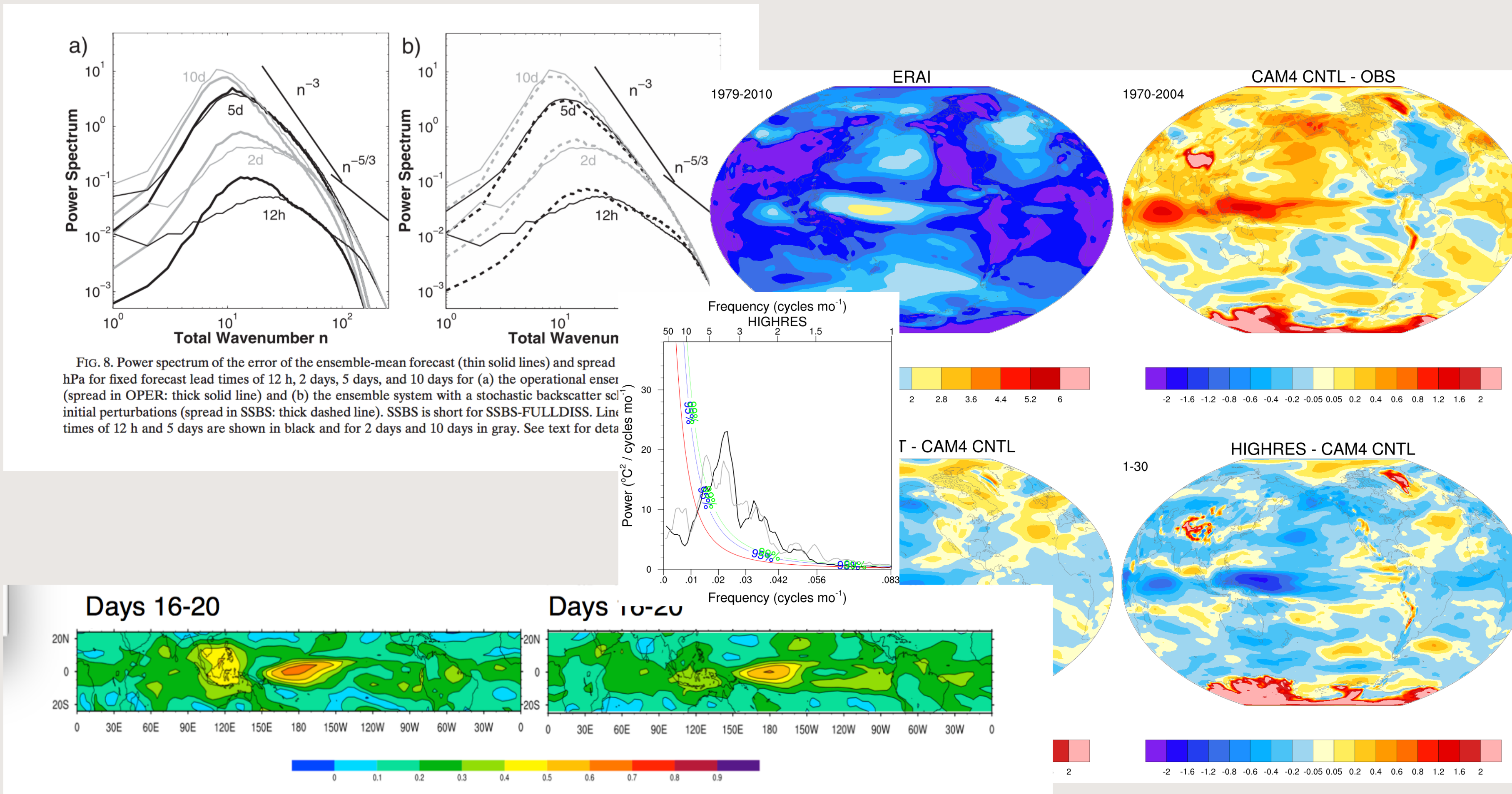
STOCHASTIC PARAMETERIZATION
Toward a New View of Weather and Climate Models

Judith Berner, Ulrich Achatz, Lauriane Batté, Lisa Bengtsson, Alvaro de la Cámara, Hannah M. Christensen, Matteo Colangeli, Danielle R. B. Coleman, Daan Crommelin, Stamen I. Dolaptchiev, Christian L. E. Franzke, Petra Friederichs, Peter Imkeller, Heikki Järvinen, Stephan Juricke, Vassili Kitsios, François Lott, Valerio Lucarini, Salil Mahajan, Timothy N. Palmer, Cécile Penland, Mirjana Sakradzija, Jin-Song von Storch, Antje Weisheimer, Michael Weniger, Paul D. Williams, and Jun-Ichi Yano

Stochastic parameterizations—empirically derived or based on rigorous mathematical and statistical concepts—have great potential to increase the predictive capability of next-generation weather and climate models.

Thank you!

Evidence



a)
b)
Power Spectrum
Total Wavenumber n
10d
5d
2d
12h
n^{-3}
$n^{-5/3}$
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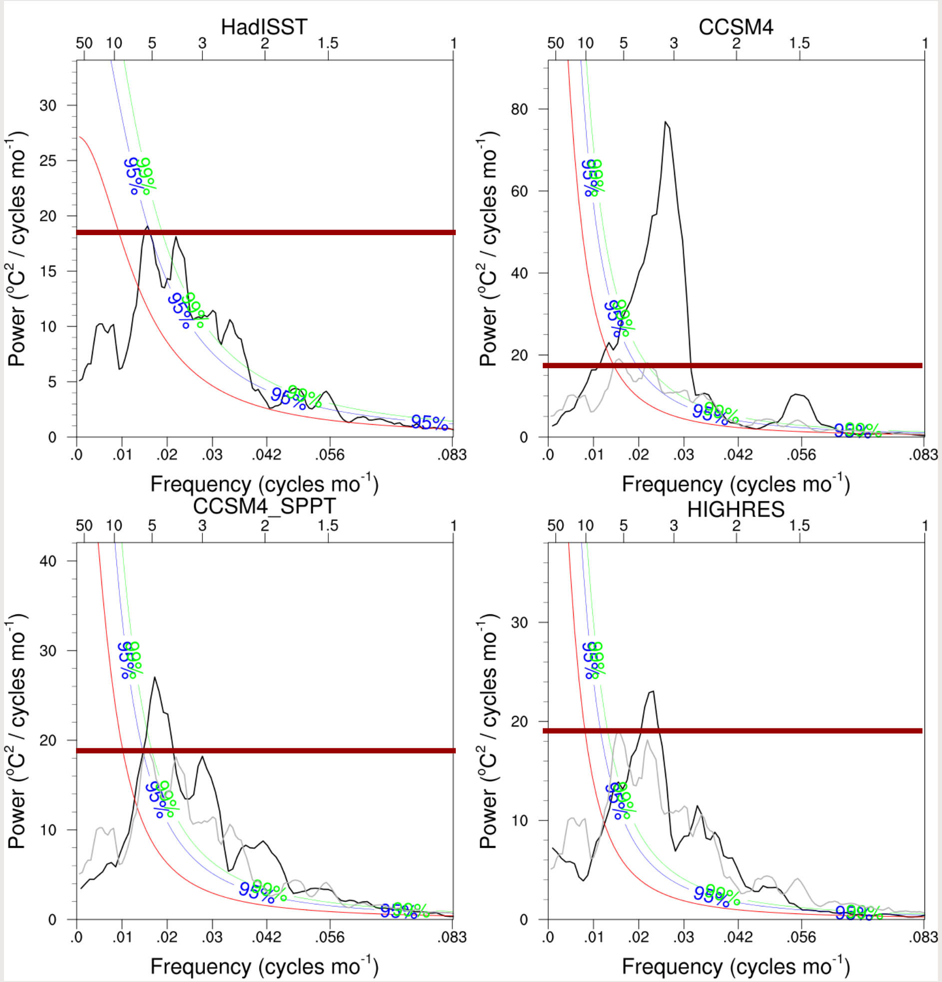
ERAI
1979-2010
CAM4 CNTL - OBS
1970-2004
T - CAM4 CNTL
HIGHRES - CAM4 CNTL
1-30
Frequency (cycles mo^{-1})
HIGHRES
Power (°C^2 / cycles mo^{-1})
95%
Days 16-20
Days 16-20

Nino3.4 Power spectra



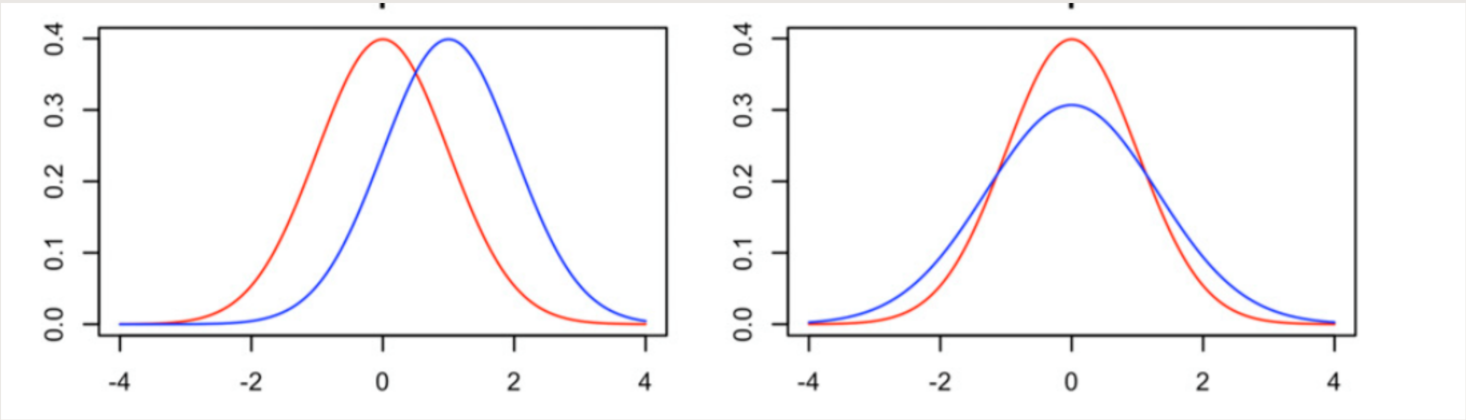
Christensen et al. 2017

Judith’s definition of “perfect”

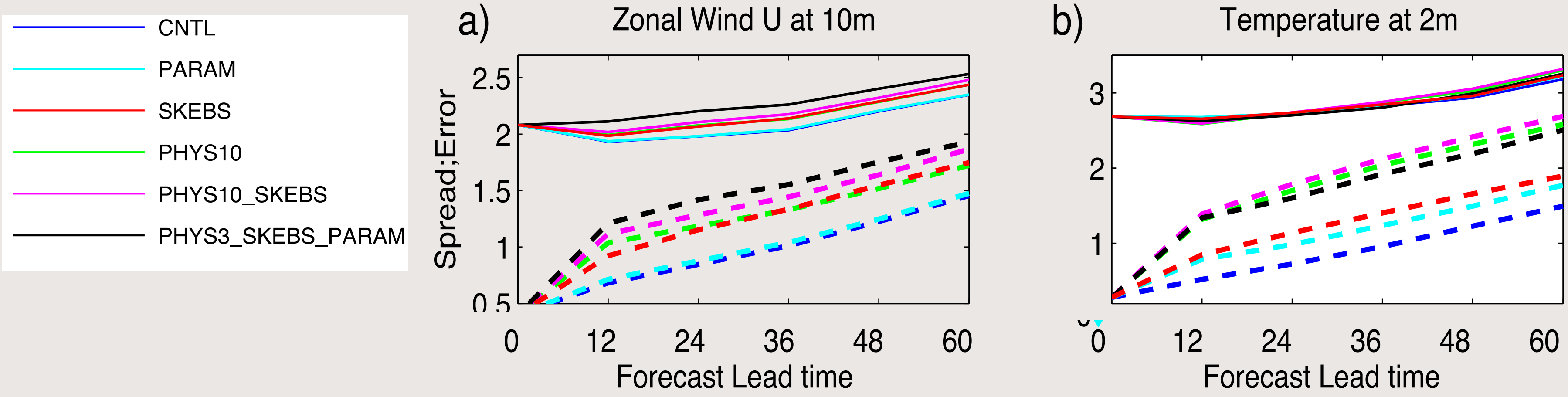
- A stochastic parameterization is perfect, if simulations with a low-resolution model with stochastic parameterization are statistically indistinguishable from a high-resolution model

Information theory

- Comes from comparing distributions, e..g. using information theory
  - Kleeman 2002; Majda 2002; Abramov et al. 2005;



Spread and error near the surface

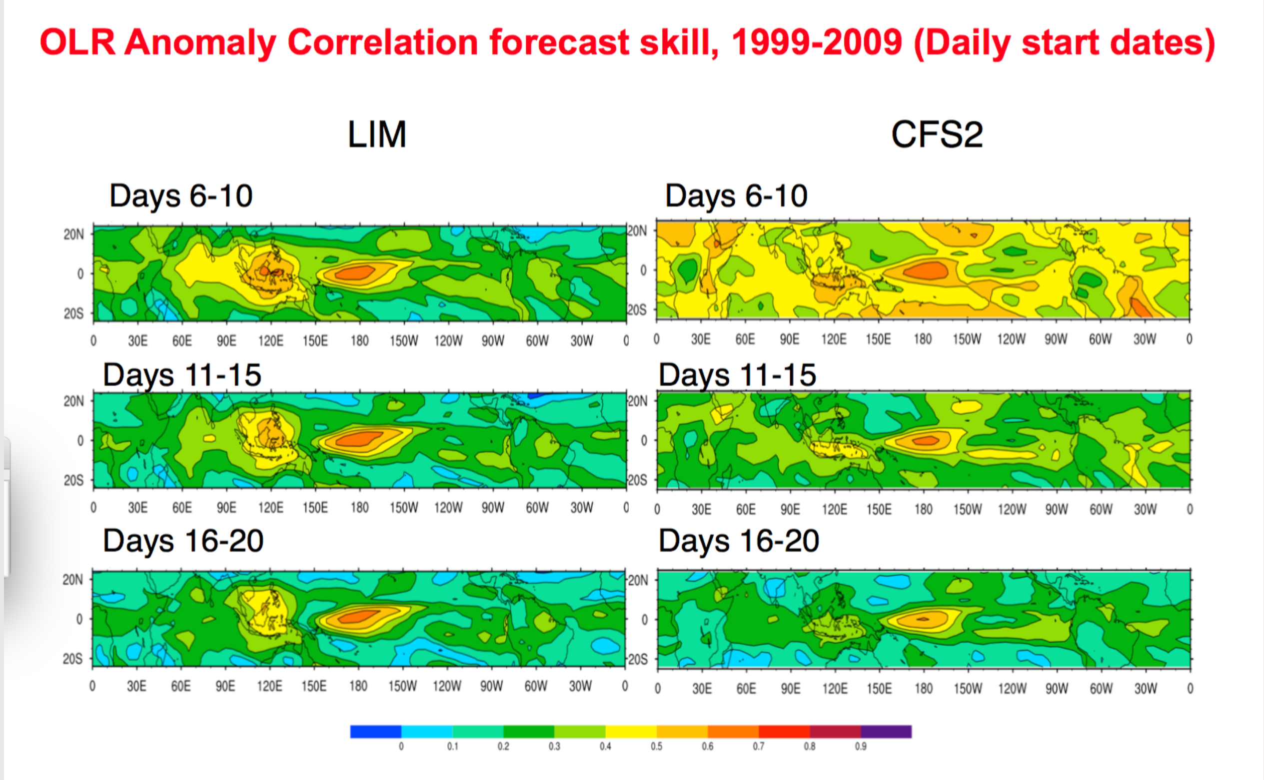


Solid lines: rms error of ensemble mean

Dashed: spread

- Ensemble is underdispersive (= not enough spread)
  - Unreliable and over-confident
  - Depending on cost-loss ration potentially large socio-economic impact (e.g. should roads be salted)

Subseasonal predictability



Newmann and Sardeshmukh