



# Representing Model Uncertainty in Earth-System Modelling:

Stochastic and Perturbed Parameter Approaches

**Hannah Christensen, Fenwick Cooper, Andrew Dawson, Stephan Juricke,  
Dave MacLeod, Aneesh Subramanian, Peter Watson, Antje Weisheimer**

**Visit of Andy Majda, December 1<sup>st</sup> 2015**



Changes of solar radiation



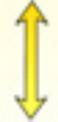
Terrestrial radiation

H<sub>2</sub>O, N<sub>2</sub>, O<sub>2</sub>, CO<sub>2</sub>



Andrew Dawson

Atmosphere-land coupling



Peter Watson



Antje Weisheimer



Hannah Christensen



Aneesh Subramanian

Is

and stress



Changes of atmospheric composition



Dave MacLeod

land features  
topography, vegetation,  
albedo, etc



Stephan Juricke

Heat exchange



Precipitation  
Evaporation

Atmosphere-coupling

Changes of ocean  
shape, salinity



Fenwick Cooper

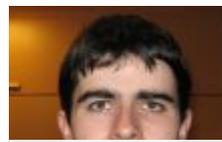


Changes of solar radiation

Terrestrial radiation

H<sub>2</sub>O, N<sub>2</sub>, O<sub>2</sub>, CO<sub>2</sub>

Atmosphere-land coupling



Andrew Dawson

1. Consider new approaches we are working on at Oxford
2. Consider performance of SPPT scheme in seasonal and climate forecasts
3. Constraining stochastic schemes



Dave MacLeod



Stephan Juricke



Fenwick Cooper

Changes of atmospheric composition

Land features: topography, vegetation, albedo, etc

Atmosphere-coupling

Changes of ocean shape, salinity

Heat exchange

Precipitation / Evaporation

Land stress



Changes of solar radiation



Terrestrial radiatio

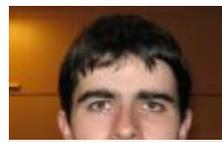


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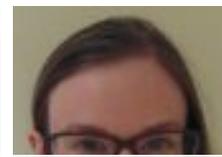
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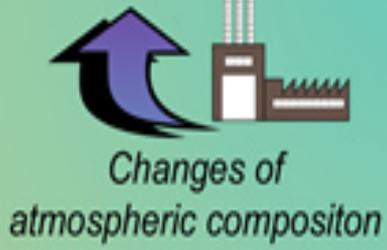
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land features  
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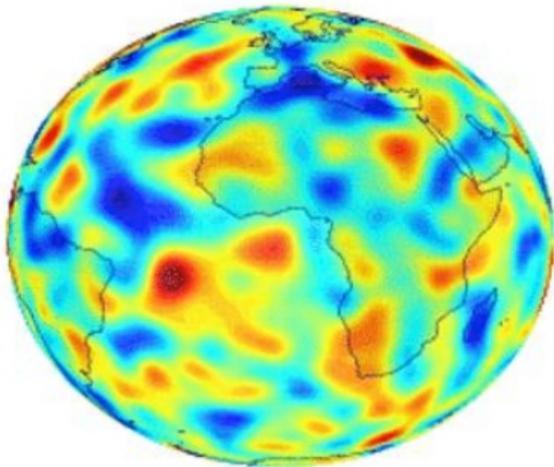
Changes of ocean shape, salinity



land stress

# Stochastic schemes used/developed at Oxford

- Stochastically Perturbed Parametrisation Tendencies (SPPT)
  - Represents errors due to the parametrisation schemes
  - Multiplicative noise perturbs the parametrised tendencies  
(Palmer et al., 2009)



$$T = D + (1 + e) \sum_{i=1}^5 P_i$$

**T** – Total tendency

**D** – Dynamics tendency

**P** – Physics tendency

convection, clouds, radiation,  
turbulence, gravity waves

- Stochastically varying parameter schemes
  - Represents uncertainty in poorly constrained physical parameters

# Perturbing Parameters in IFS Convection Scheme

Hannah Christensen

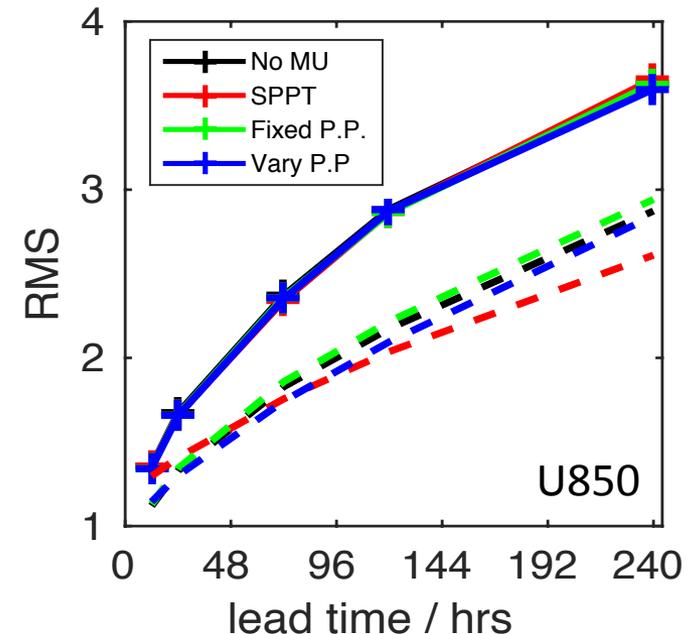
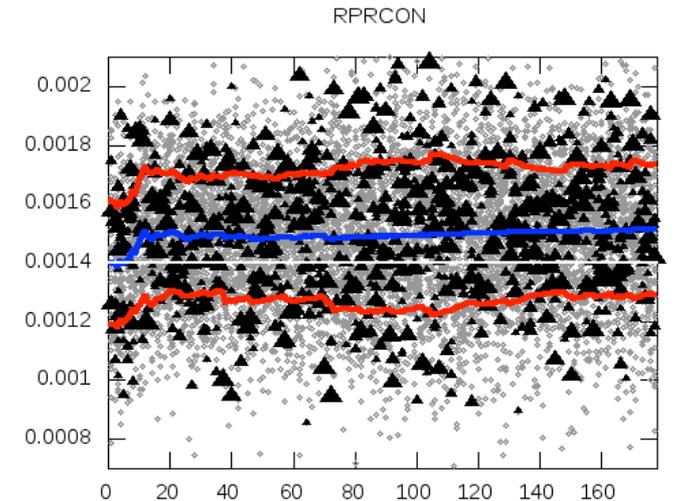
- Estimate uncertainty using Bayesian parameter estimation approach → posterior probability densities of closure parameter

Pirkka Ollinaho (FMI) & Peter Bechtold (ECMWF)

- **Joint uncertainty** in four parameters:

**ENTROrg, ENTSHALP, DETRPEN, RPRCON.**

- Fixed & stochastically varying parameter perturbations
- Perturbed parameter scheme **significantly increases spread** over SPPT
- Fixed PP scheme improves forecast skill



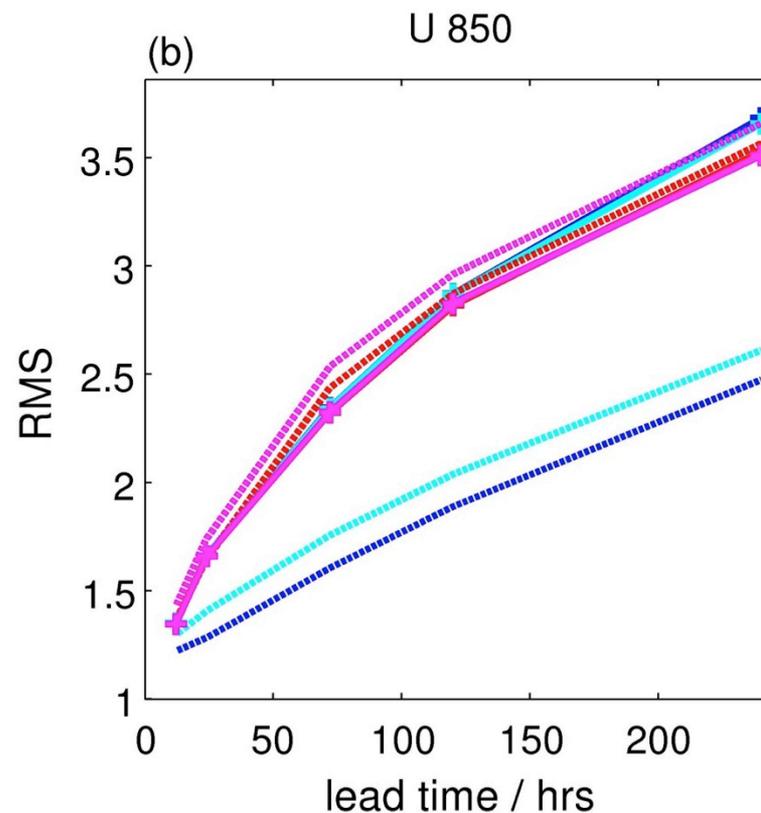
# Independent SPPT in IFS

Hannah Christensen

**SPPTi** 
$$T = D + \sum_{i=1}^5 (1 + e_i) P_i$$

- Perturb IFS physics schemes with independent random fields
  - Assumes errors from different schemes are uncorrelated
  - No tuning performed – same  $\sigma$ ,  $\phi$  as operational SPPT

— SPPT — SPPT+SPBS  
— SPPTi — SPPTi+SPBS



# Why does independent SPPT have such a big impact?

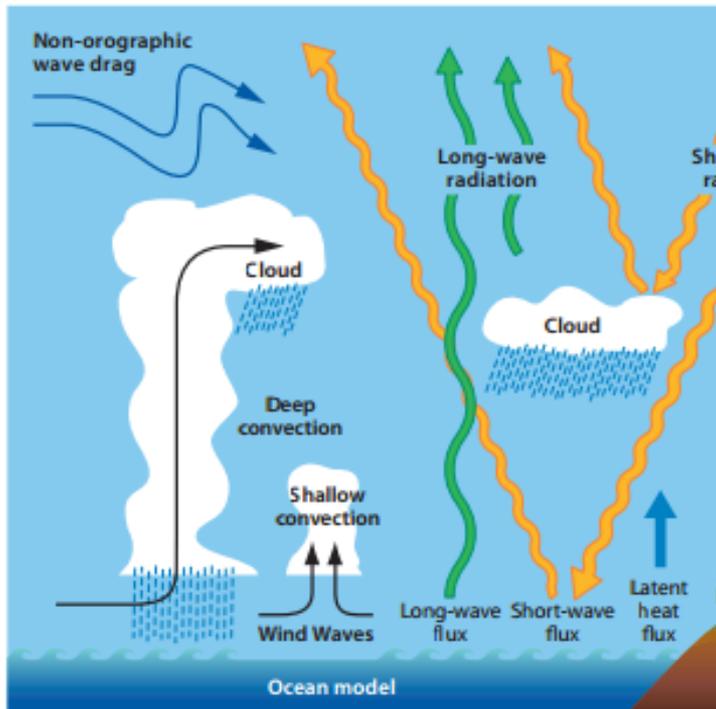


Figure 1.1 Schematic diagram of the different physical

- e.g. Warming from convection associated with cooling from clouds
- If you apply a different pattern to each tendency, the **large convection tendency** correctly has a **large associated uncertainty**, which will then dominate the spread

# Stochastic NEMO Ocean Model

Stephan Juricke

- 1. Multiplicative perturbation within the GM parametrisation scheme

$$\frac{\partial T}{\partial t} = -\nabla(T(U + U_G)) + D_T + F_T$$

Where, e.g.

$$u_G = -\frac{\partial}{\partial z}(AS)$$

SPPT:

$$u_G = -\frac{\partial}{\partial z}((1+r)AS)$$

$U$  – 3D velocity

$U_G$  – GM eddy velocity

$R$  – Resolved tendency

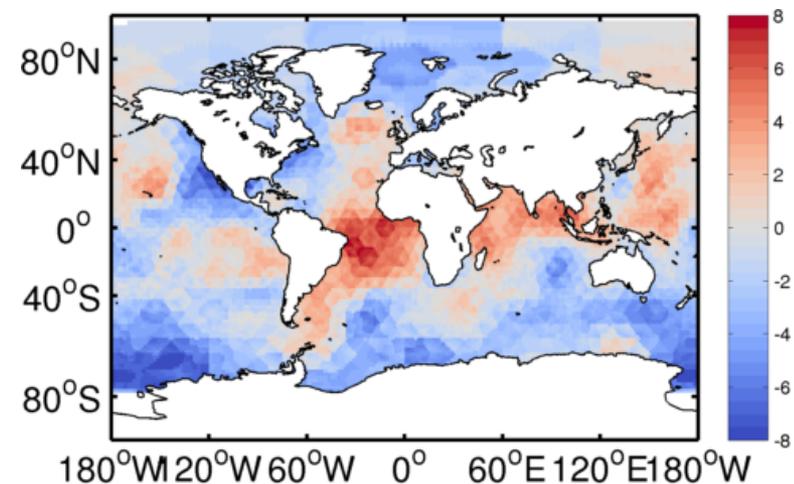
$D_T$  – parametrised diffusion/mixing

$F_T$  – Forcing

$A$  – eddy induced velocity coefficient

$S$  – slope isoneutral surfaces

$r$  – zero mean random number



# Stochastic NEMO Ocean Model

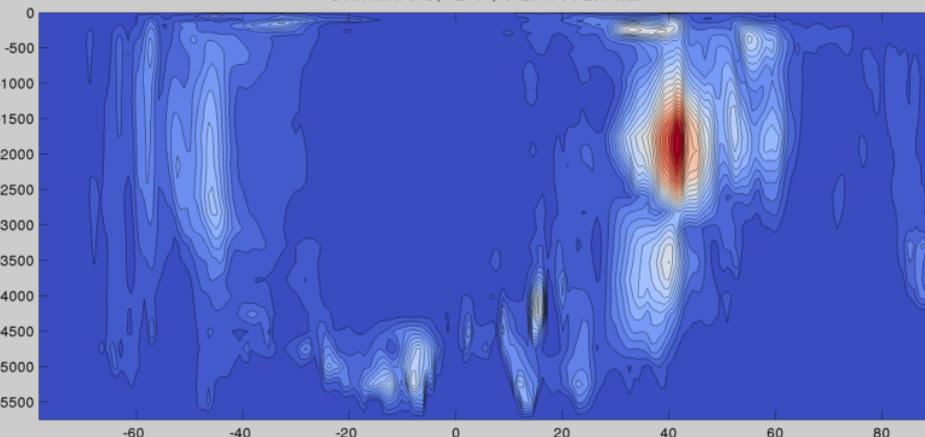
Stephan Juricke

- 2. Perturbing parameters within eddy kinetic energy calculation
  - eddy kinetic energy sets vertical mixing
  - Multiplicative perturbation to vertical eddy diffusivity and vertical eddy viscosity coefficients
  - impacts shear and buoyancy terms in eddy kinetic energy calculation

**Interannual standard deviation of eddy induced MOC over 60 years: colour = overturning (Sv)**

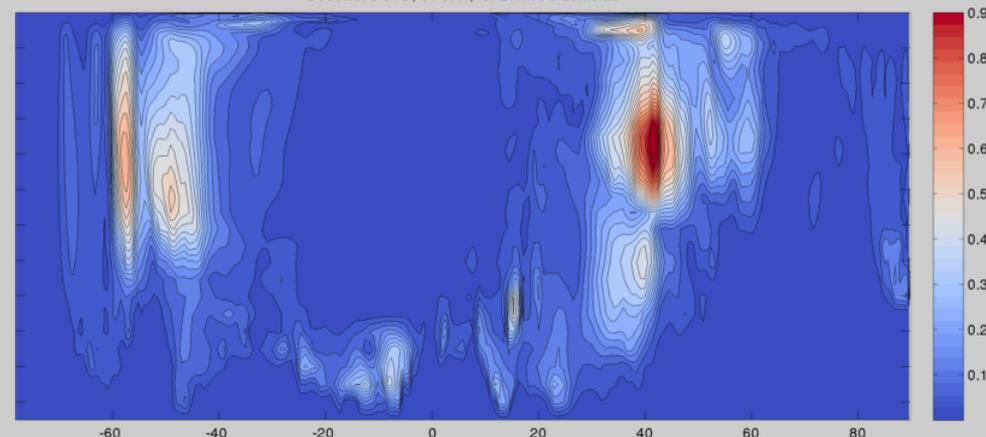
**Reference**

Detrended STD, REF01, for EIVMOC zomstat



**Stochastic**

Detrended STD, STOA1, for EIVMOC zomstat



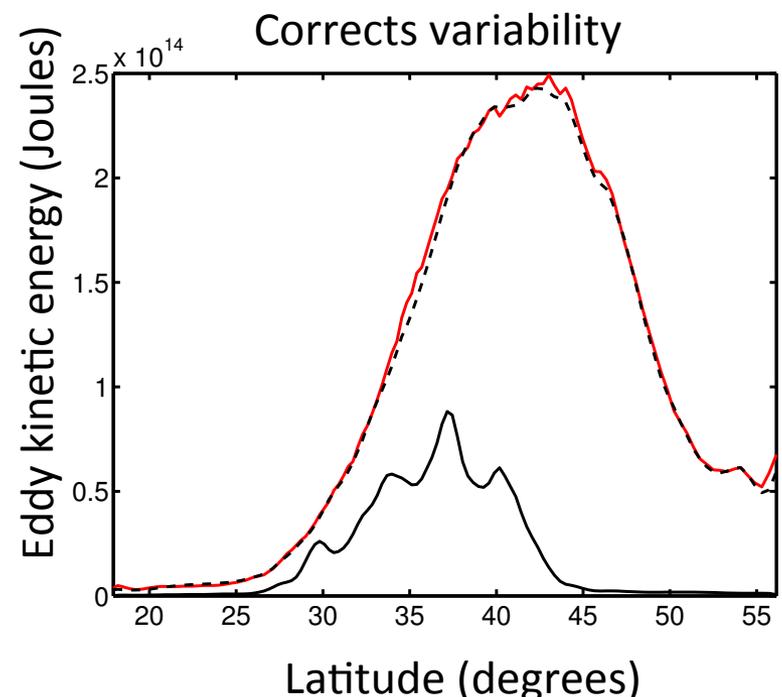
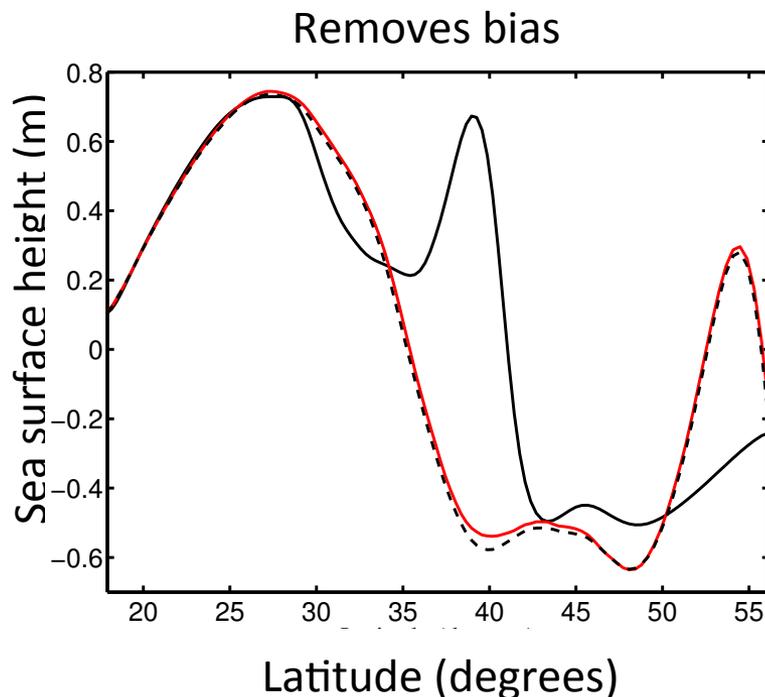
# Generalised stochastic parametrisation for eddies

Fenwick Cooper

## Linear stochastic system for sub-grid scale turbulent eddy-eddy interactions

Tests with an idealised ocean model. Stochastic forcing term represents unresolved eddies

$$\frac{\partial \mathbf{u}}{\partial t} = \text{Advection} + \text{Other forces} + \text{Viscosity} + \xi(x,y,z,t)$$



— Low resolution — Parameterised - - - High resolution

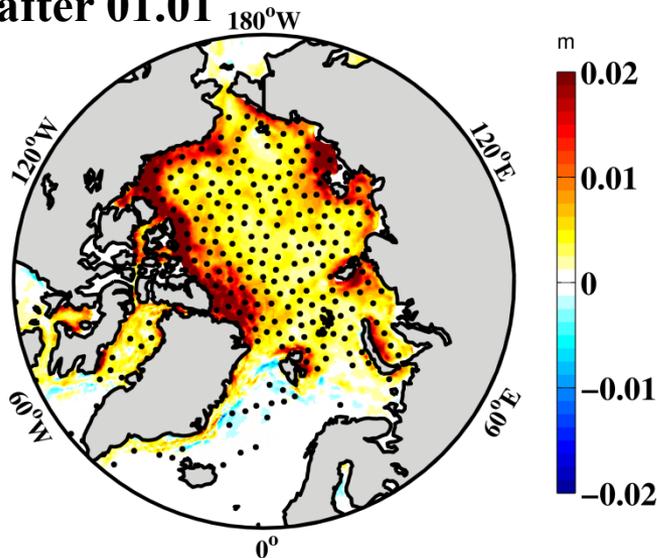
# Perturbation of Sea Ice Strength Parameter

Stephan Juricke

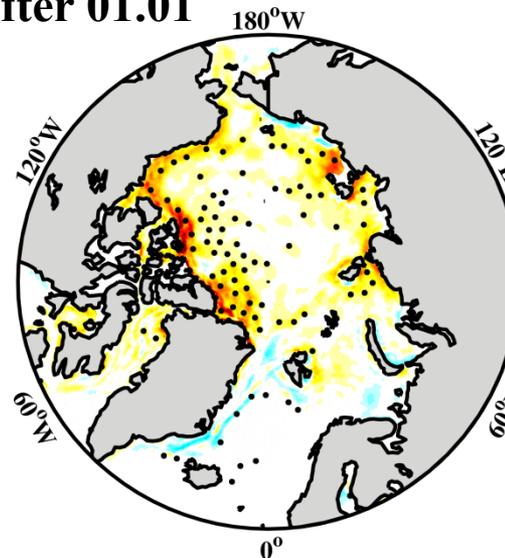
$$P^*(i, j) = (1 + x(i, j))P^*(ref)$$

- Small  $P^*$  means weak ice and higher velocities under convergence
- $X(i, j)$  spatially and temporally correlated noise
- See significant increase in ensemble spread in ice thickness

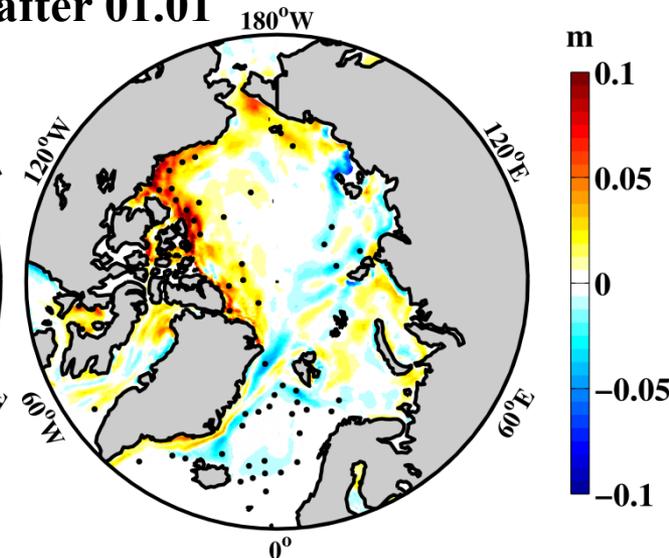
1 to 10 days  
after 01.01



11 to 30 days  
after 01.01



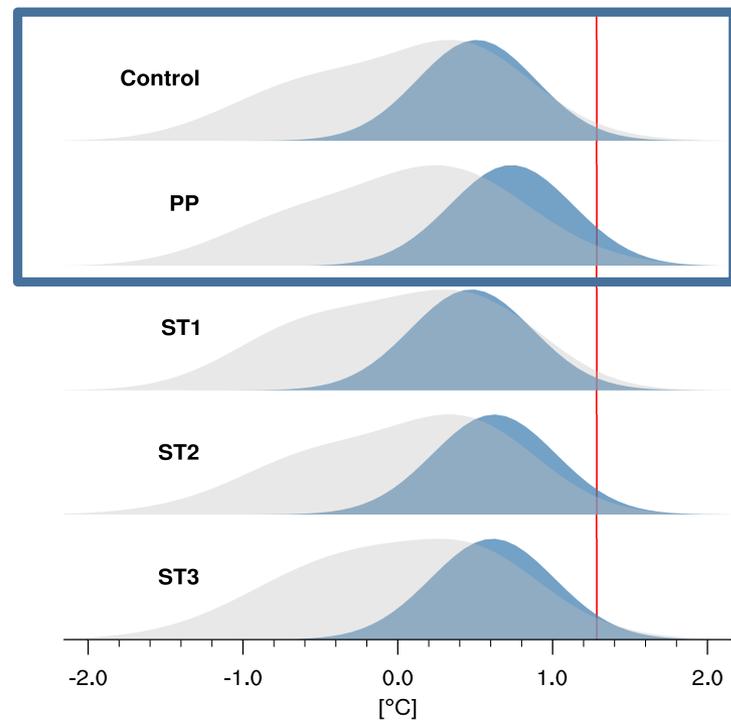
31 to 90 days  
after 01.01



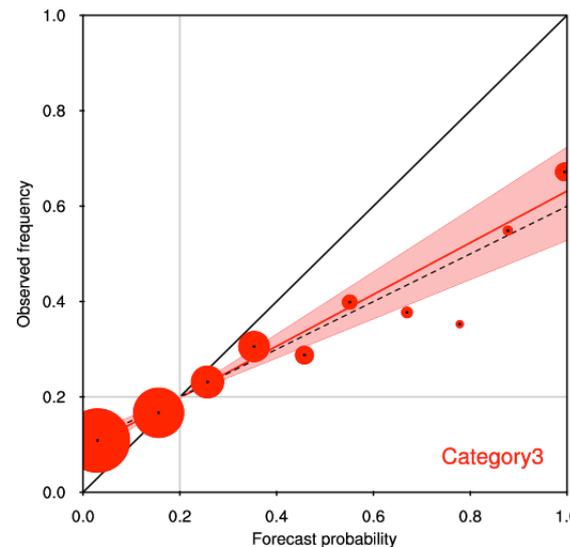
# Uncertainty in HTESSEL Land Surface Schemes

Dave MacLeod and Antje Weisheimer

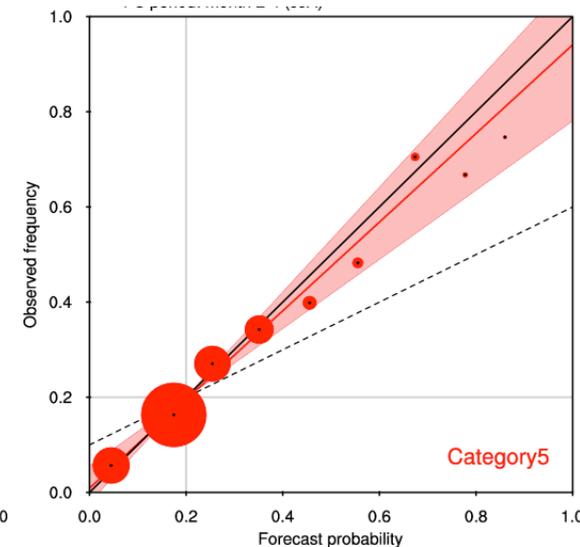
- Perturbed parameter experiment (PP): static perturbation of saturated hydraulic conductivity and van Genuchten alpha
  - Compare to multiplicative perturbation of soil T and moisture tendencies
- Impact on seasonal forecasts of 2003 European summer heatwave



## Reliability: upper quintile soil moisture CTRL



## PP





Changes of solar radiation



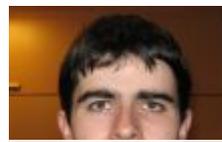
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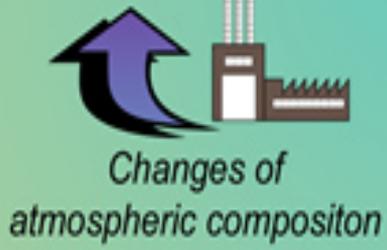
Dave MacLeod



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Fenwick Cooper



Atmosphere-land coupling



Atmosphere-coupling

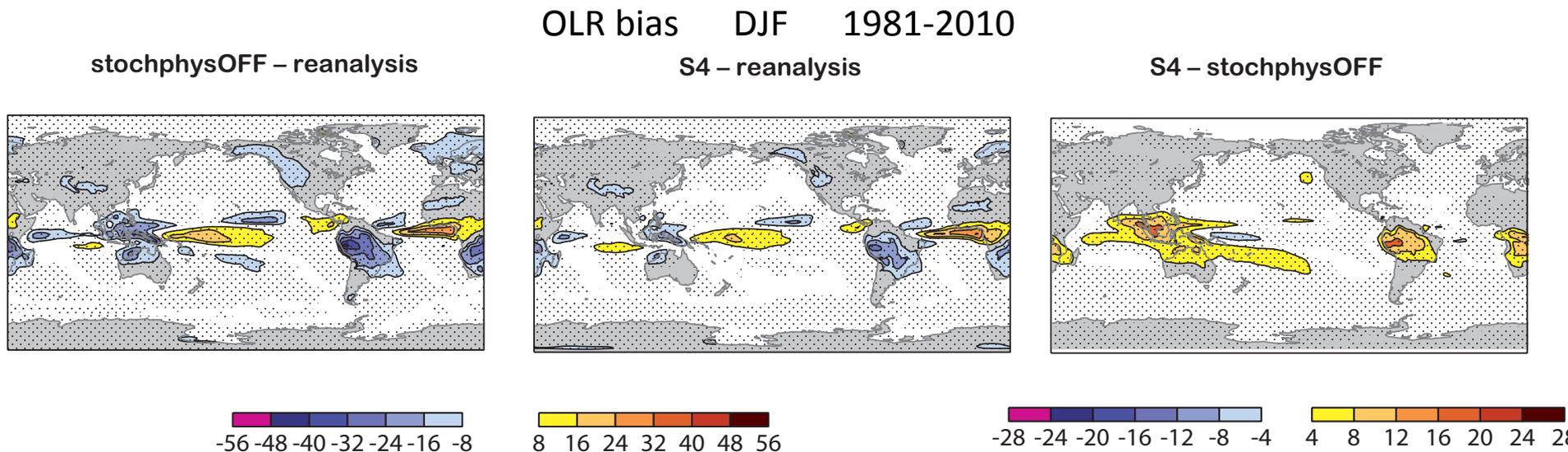
Changes of ocean shape, salinity

land features  
topography, vegetation, albedo, etc

# Impact of SPPT in System 4

Antje Weisheimer

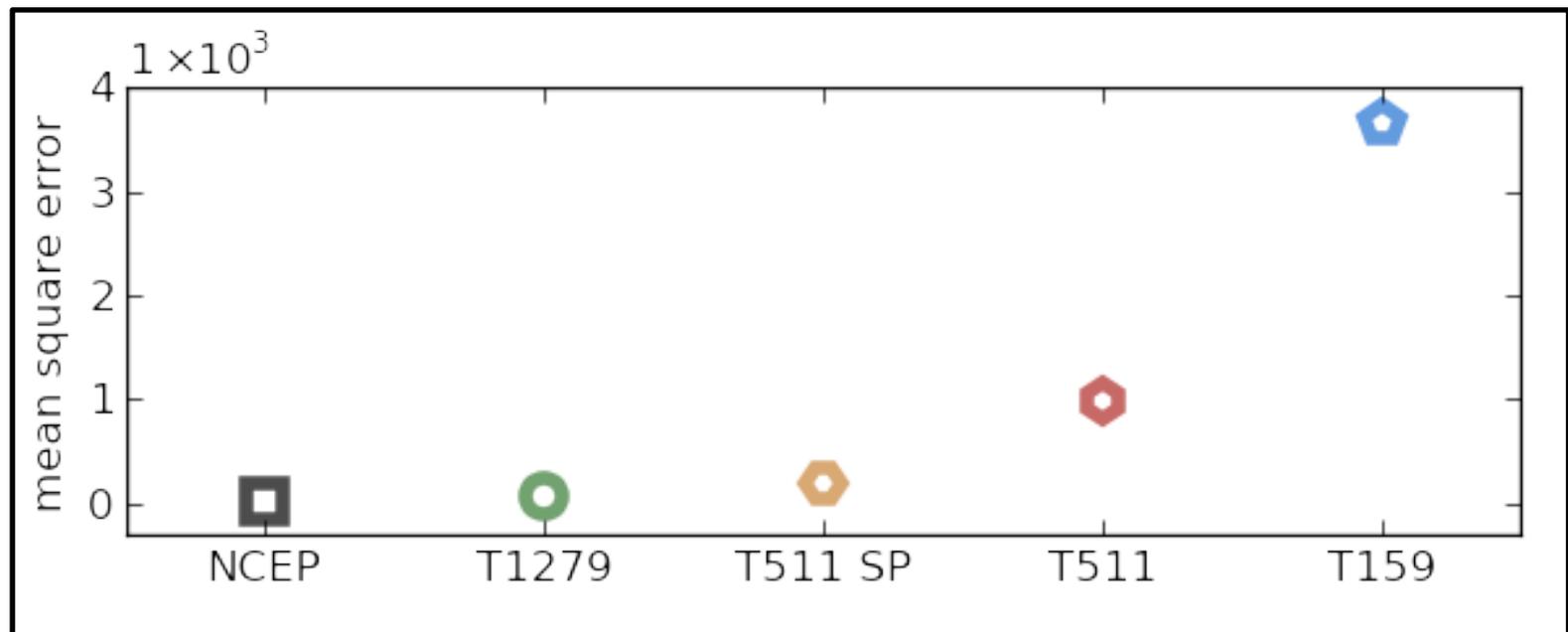
- Stochastic physics reduces the overly active tropical convection (OLR plots)
- Reduced biases also observed for cloud cover, precipitation and winds, especially over the Western tropical Pacific (crucial for ENSO)
- Stochastic physics impacts on MJO statistics with more and stronger MJO events under SPPT (but model still underestimates MJOs)
- Seasonal forecast quality of tropical Pacific SSTs is improved
- Pacific-North American (PNA) weather regime statistics improve



# Impact of SPPT in Climate Models: Regimes in IFS

Andrew Dawson

- Compare ERA40 North Atlantic Regimes (blocking, NAO, ...) with those from IFS at different resolutions (prescribed SST)
- Stochastic physics improves the regime structure of a T511 run to make it comparable to a T1279 run



# Impact of SPPT in Climate Models: ENSO in CAM

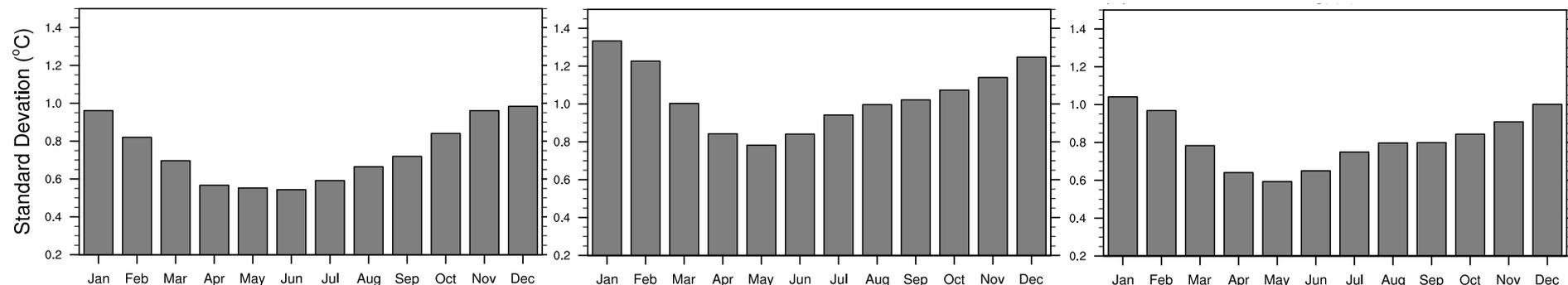
Hannah Christensen

- Test SPPT in coupled runs of CAM4 (1° atmosphere and ocean), 1870-2005
- Large improvement in representation of ENSO (e.g. Nino 3.4 variability)

OBS

CTRL

SPPT



# Impact of SPPT in Climate Models: ENSO in CAM

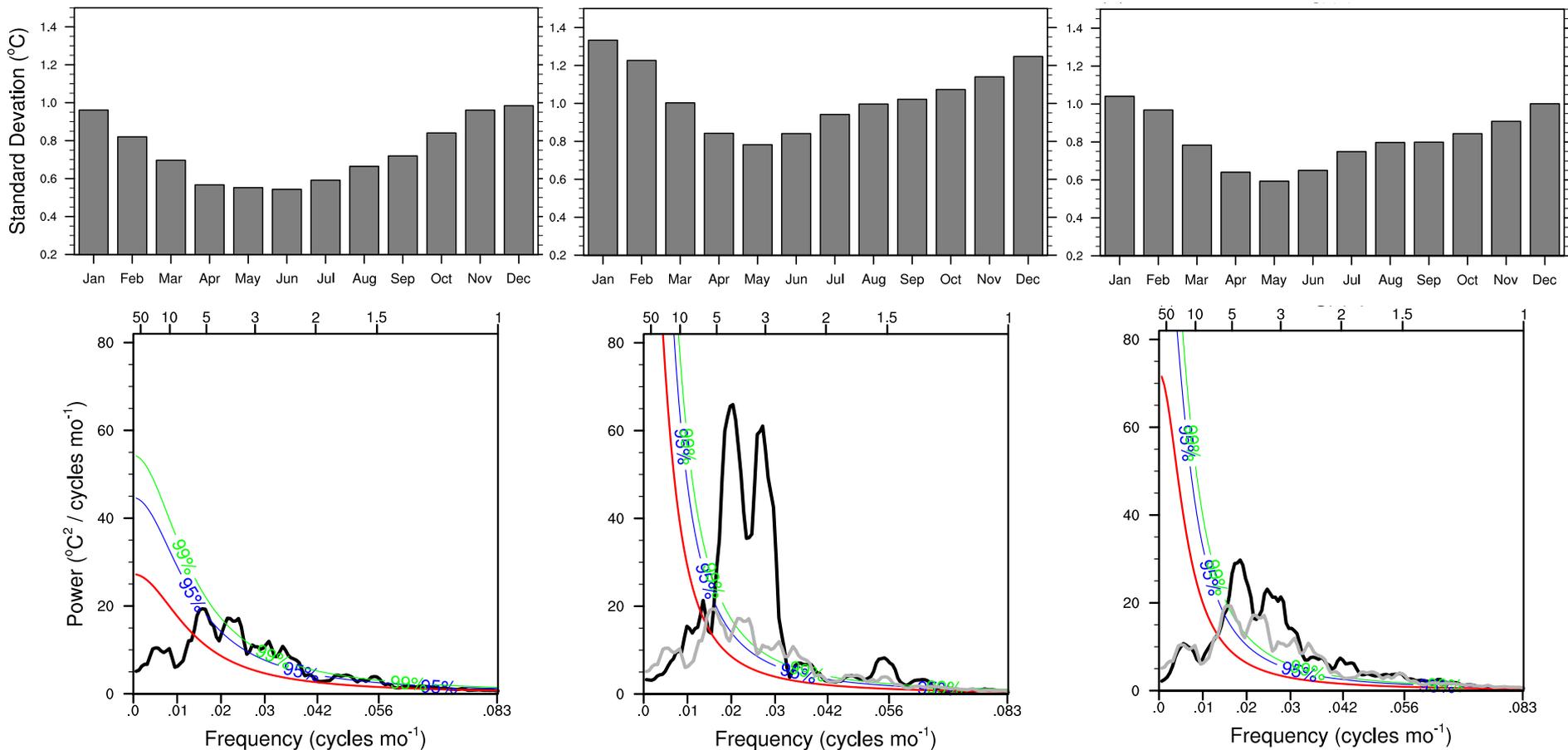
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SPPT



# SPPT is in the atmosphere: how do we impact SSTs?

Hannah Christensen

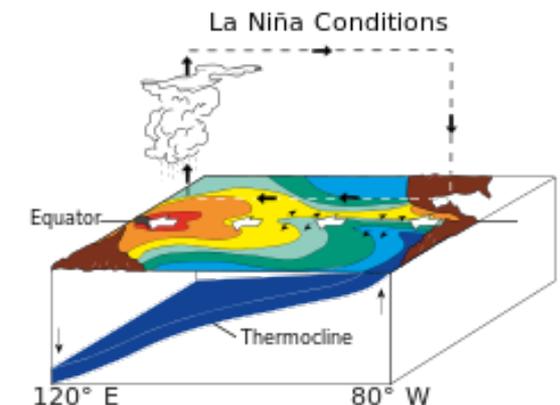
Variable	Variability improved in AMIP?	Variability improved in coupled?
Wind – U 850, U surface	Y	Y
Precipitation	N	Y
$\omega$ 500	N	Y
Cloud cover	N	Y
SST	n/a	Y

convection

Due to combination of

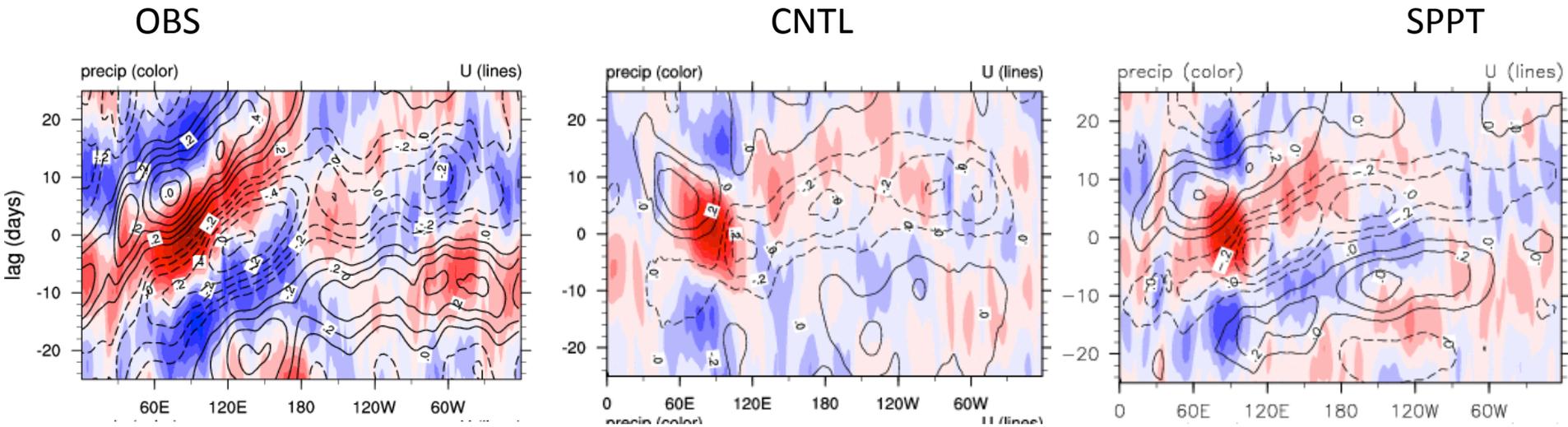
- asymmetry in impact of stochastic perturbations on convective heating in La Nina phase
- Improved statistics of WWBs

N.b. Also see reduction in ENSO amplitude in both simple DO model and CZ model when multiplicative noise is applied

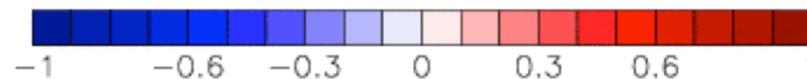


# Consider impact of SPPT on MJO in CAM AMIP runs

Hannah Christensen



- Lag correlation of precipitation (colours) and winds (lines) correlated against precipitation at reference point in Indian Ocean, Nov-April



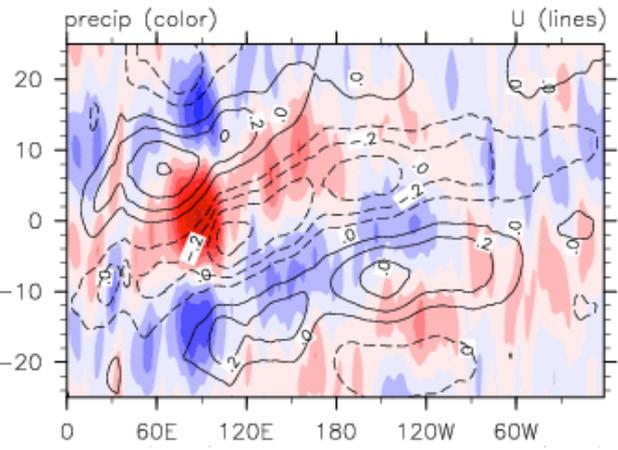
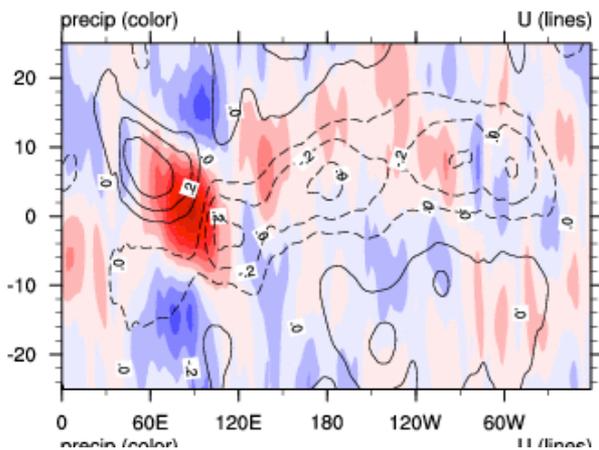
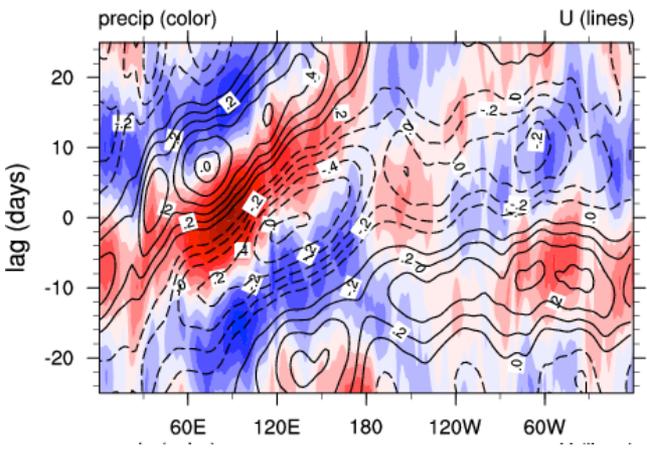
# Consider impact of SPPT on MJO: Compare CAM and EC-Earth

Hannah Christensen and Aneesh Subramanian

OBS

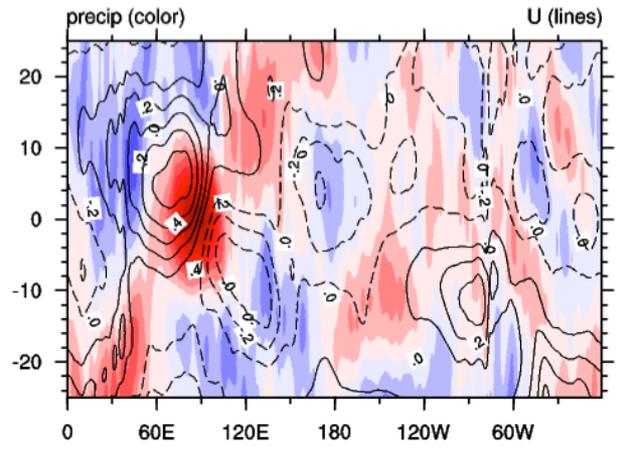
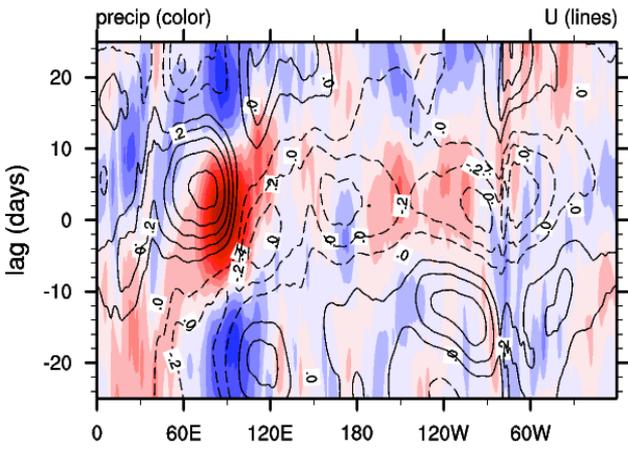
CNTL

SPPT



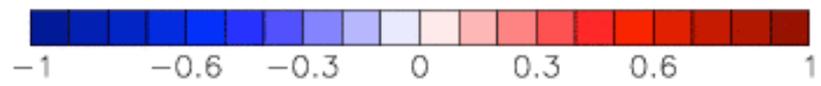
↑ CAM

EC-Earth →



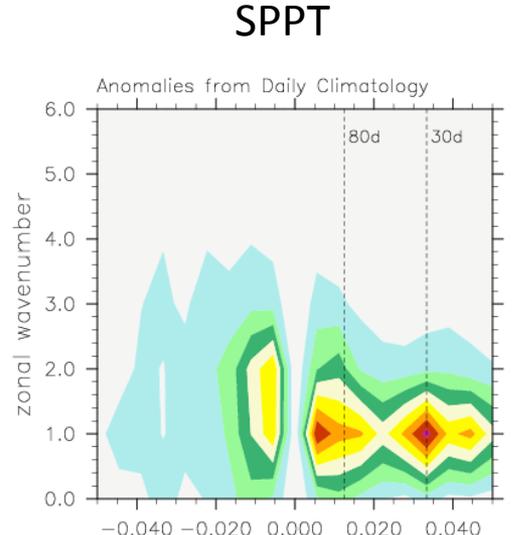
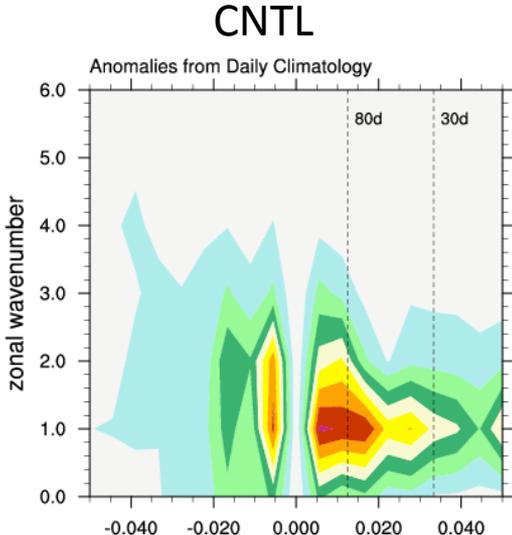
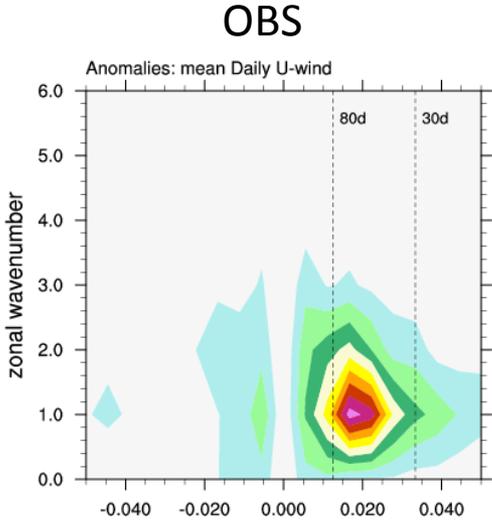
AMIP runs:  
 CAM: 1deg. (110km)  
 EC-E: T255 (80km)

With Susanna Corti and  
 Jost von Hardenberg



# Consider impact of SPPT on MJO: Compare CAM and EC-Earth

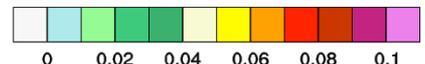
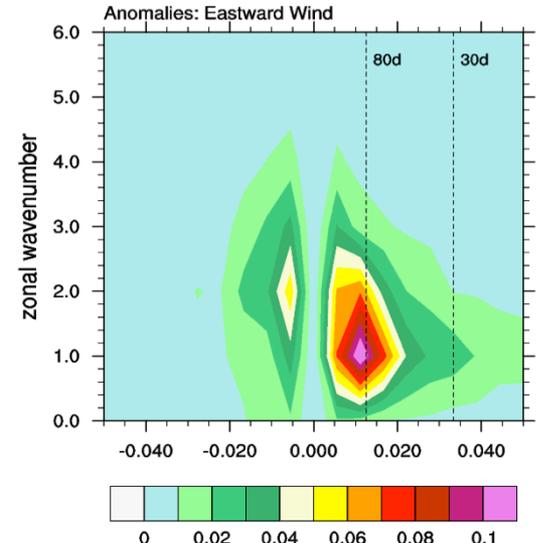
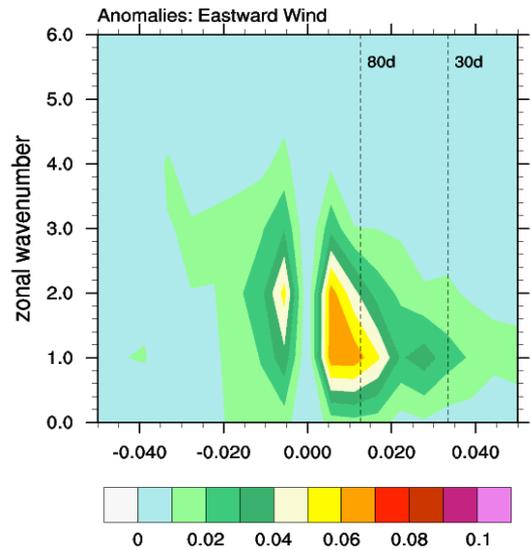
Hannah Christensen and Aneesh Subramanian



↑ CAM

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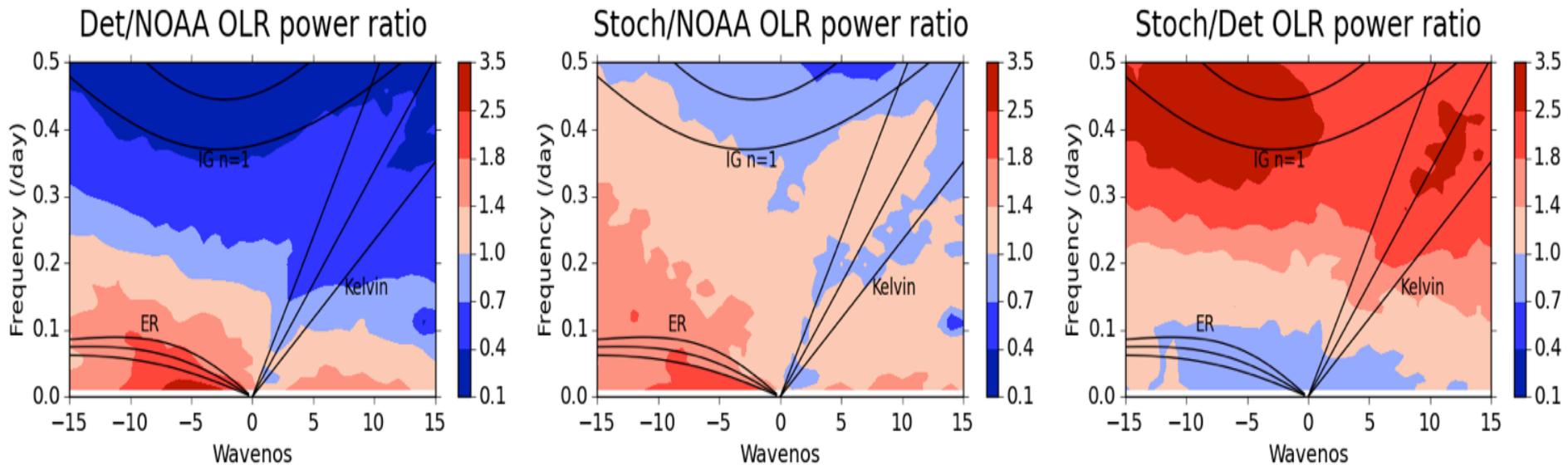
- Winter Power spectra for U



# Impact of SPPT on Tropical Variability

Peter Watson

- SPPT in IFS AMIP runs increases variability at frequencies more than about 0.1/day, reducing the bias in this model.



Ratio of power in symmetric modes in OLR data: ratio between power in model without SPPT and NOAA satellite data (left), between power in model with SPPT and NOAA satellite data (centre) and between models with and without SPPT (right).

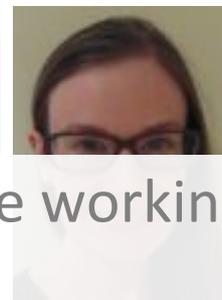
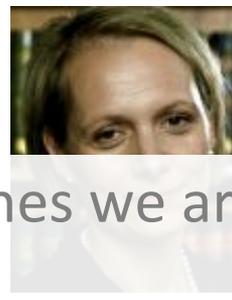


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Atmosphere-land coupling

Land features: topography, vegetation, albedo, etc

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Changes of ocean shape, salinity

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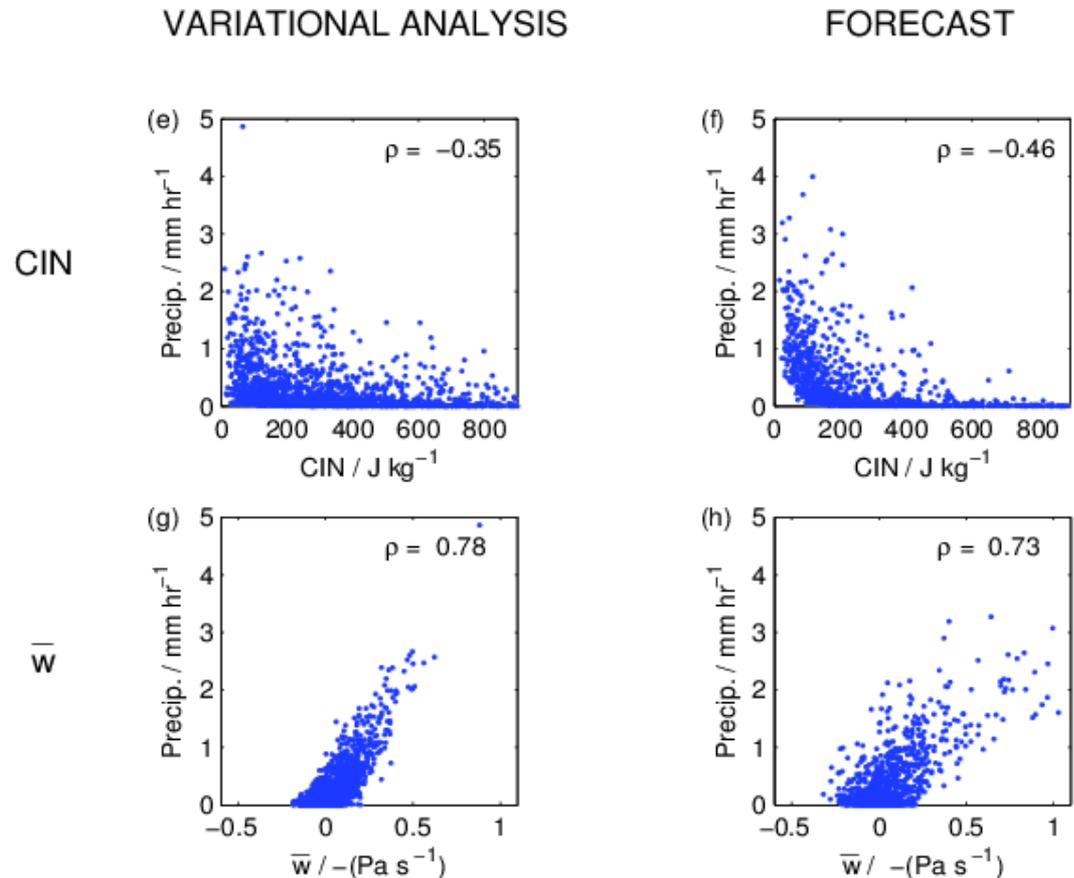
Precipitation / Evaporation

Land stress

# Consistency of Stochastic Schemes with Observations

Peter Watson and Hannah Christensen

- IFS forecasts have similar statistics to observations (Watson et al. 2015).
- Contrary to some expectations (Davies et al., Peters et al. 2013), use of multiplicative noise is consistent with obs.
- Results are similar with and without stochastic physics – can observations be found to test different ways of adding stochasticity?



# New: Coarse graining experiments to constrain SPPT

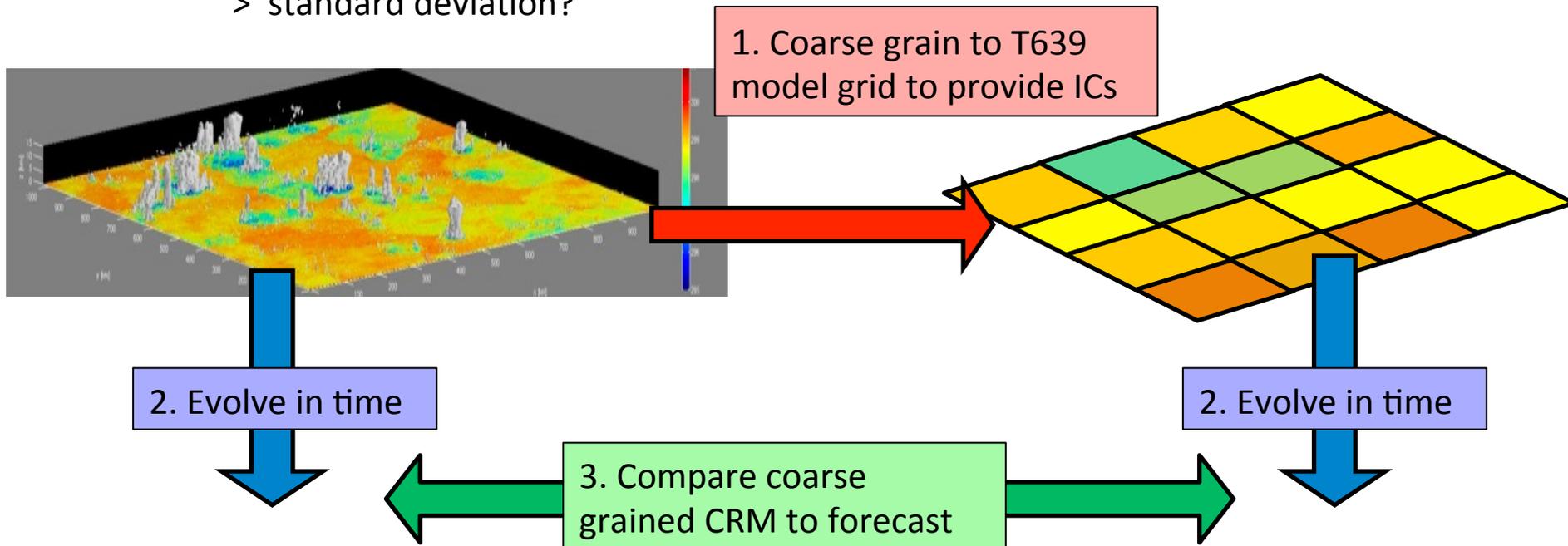
Hannah Christensen and Andrew Dawson

**AIM: To use high resolution model data sets as “truth” for coarse graining experiments?**

> CASCADE warm pool dataset (4km)

**Q: Is it possible to use this data to measure characteristics of the stochastic noise term?**

- > spatial and temporal correlations?
- > correlation of errors between tendencies?
- > standard deviation?



Thank you for listening  
... any questions?