Using stochastic physics to represent model error

Sarah-Jane Lock

Ensemble Prediction Section,

Predictability Division

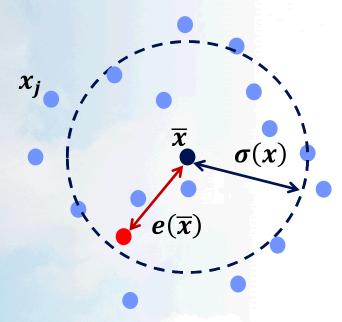
Using stochastic physics to represent model error

- Why represent model error in an ensemble forecast?
- What are the sources of model error?
- How do we represent model error?
 - 2 stochastic physics schemes in the IFS
- Impact of stochastic physics schemes in the IFS:
 - Medium-range ensemble (ENS)
 - Seasonal forecast (S4)



Ensemble reliability

In a reliable ensemble, ensemble spread is a predictor of ensemble error



- Ensemble member
- Ensemble mean
- Observation

i.e. averaged over many ensemble forecasts,

$$e(\bar{x}) \approx \sigma(x)$$

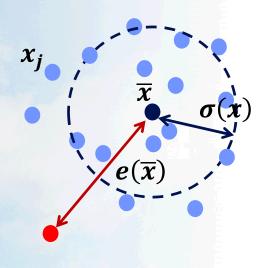
For a thorough discussion of this relationship:

Martin Leutbecher's lectures (22nd/23rd April)

Ensemble reliability

In an under-dispersive ensemble,

$$e(\bar{x}) \gg \sigma(x)$$

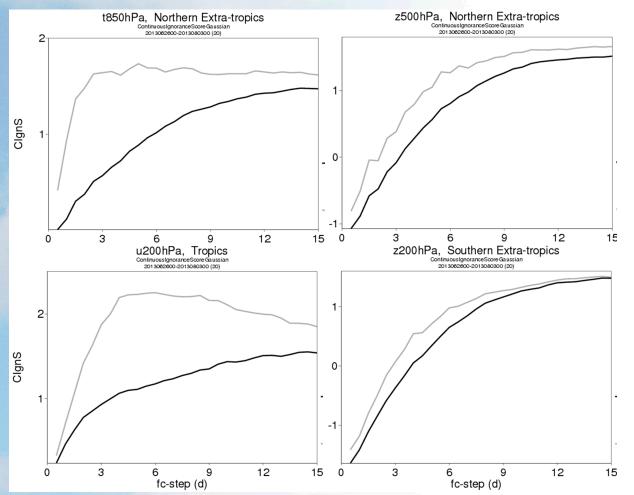


- Ensemble member
- Ensemble mean
- Observation

and ensemble spread does not provide a good estimate of error.

What happens when the ensemble includes no representation of model error?

What happens with no accounting for model error?



Ensemble skill score

(Continuous Ignorance Score) forecast times up to day 15

Key:

Initial perturbations ONLY

Initial + model error perts

For details of skill scores:

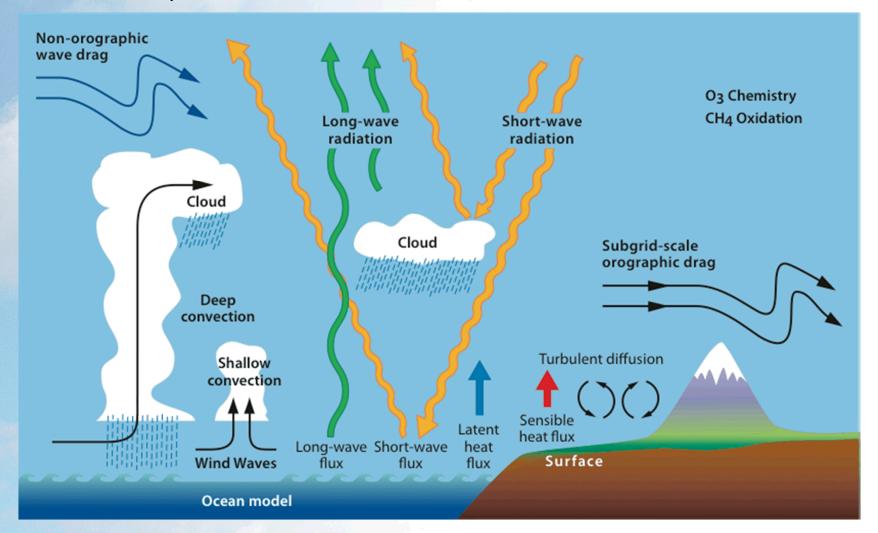
Martin Leutbecher's lectures

(22nd/23rd April)



Model error: where does it come from?

Processes represented in the model:



Model error: where does it come from?

- Any other sources: processes not captured by the underlying model?
- Atmosphere exhibits upscale propagation of kinetic energy (KE)
 - at ALL scales: no concept of "resolved" and "unresolved" scales
 - How can the model represent upscale KE transfer from unresolved to resolved scales?

Model error: how to simulate it?

- What do the model errors look like?
- What is the relative size of model error from different sources?
- How can we represent model errors?
- Multi-model ensembles [Tim Stockdale, 28th April]
- Multi-physics ensembles
- Perturbed parameter ensembles
- "Stochastic parametrisations"

Stochastic physics schemes in IFS

- IFS ensemble forecasts (ENS and S4) include 2 model uncertainty schemes:
 - Stochastically perturbed physics tendencies (SPPT) scheme
 - Stochastic kinetic energy backscatter (SKEB) scheme
- SPPT scheme: simulates uncertainty due to sub-grid parametrisations
- SKEB scheme: parametrises a missing and uncertain process

SPPT scheme

- Initially implemented in IFS, 1998 (Buizza et al., 1999); revised in 2009:
- Simulates model uncertainty due to physical parameterisations by
 - taking the net parameterized physics tendency:

$$\boldsymbol{X} = \left[X_U, X_V, X_T, X_Q \right]$$

coming from radiation gravity wave drag vertical mixing convection cloud physics

• and perturbing with multiplicative noise $r \in [-1, +1]$ as:

$$X' = (1 + \mu r)X$$

where $\mu \in [0,1]$ tapers the perturbations to zero near the surface & in the stratosphere.

Shutts et al. (2011, ECMWF Newsletter); Palmer et al., (2009, ECMWF Tech. Memo.)

- 2D random pattern in spectral space:
- First-order auto-regressive [AR(1)] process for evolving spectral coefficients \hat{r}

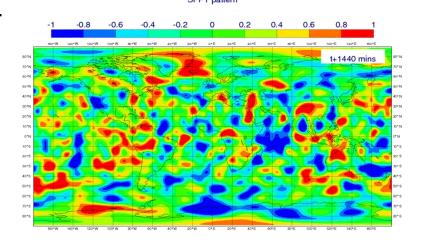
$$\hat{r}(t + \Delta t) = \phi \hat{r}(t) + \rho \eta(t)$$

where $\phi=\exp(-\Delta t/\tau)$ controls the correlation over timestep Δt ; and spatial correlations (Gaussian) for each wavenumber define ρ for random numbers, η

- Resulting pattern in grid-point space r:
- clipped such that $r \in [-1, +1]$
- applied at all model levels to preserve vertical structures**
- **Except: tapered to zero at model top/bottom, avoiding:
 - instabilities due to perturbations in the boundary layer;
 - perturbations in the stratosphere due to well-constrained clear-skies radiation

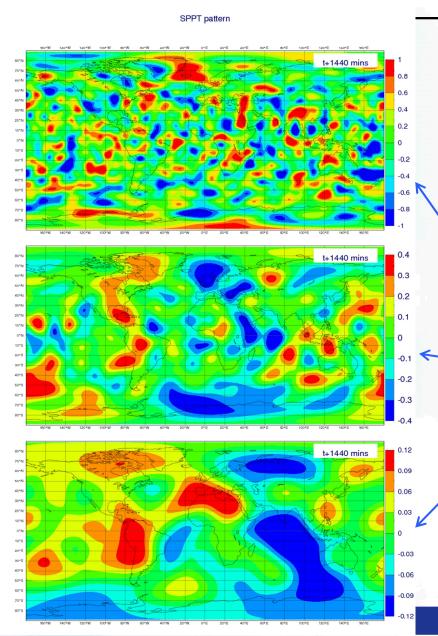


- 2D random pattern of spectral coefficients, r:
- Time-correlations: AR(1)
- Space-correlations: Gaussian
- Clipped such that $r \in [-1, +1]$
- Applied at all model levels to preserve vertical structures**
- **Except: tapered to zero at model top/bottom

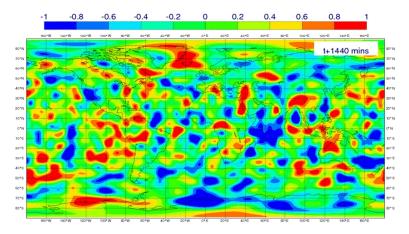


3 correlation scales:

- i) 6 hours, 500 km, $\sigma = 0.52$
- i) 3 days, 1 000 km, $\sigma = 0.18$
- iii) 30 days, 2 000 km, $\sigma = 0.06$

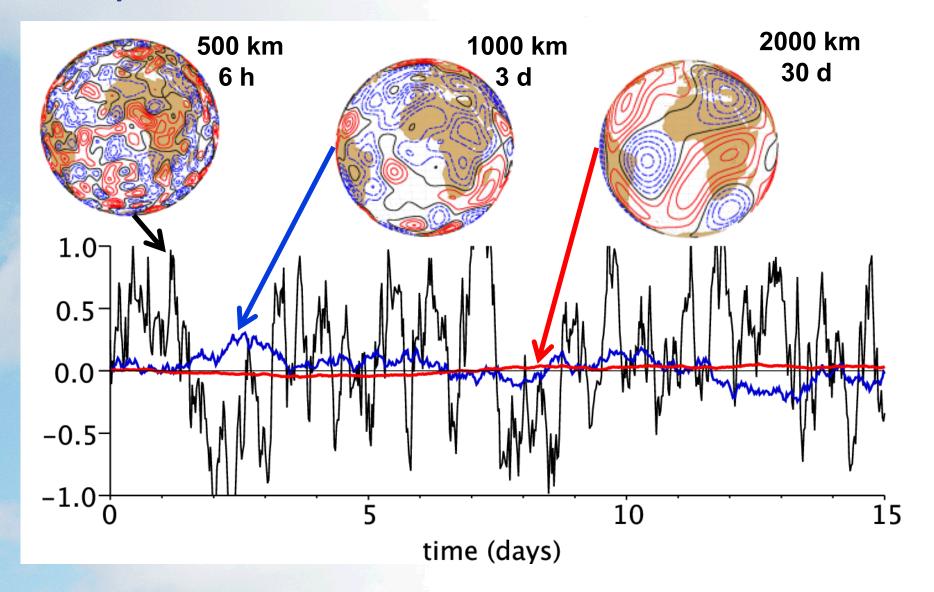






3 correlation scales:

- i) 6 hours, 500 km, $\sigma = 0.52$
- i) 3 days, 1 000 km, $\sigma = 0.18$
- iii) 30 days, 2 000 km, $\sigma = 0.06$





SKEB scheme

- Introduced into IFS, 2010:
- Attempting to simulate a process otherwise absent from the model –
 upscale transfer of energy from sub-grid scales
- ullet Represents backscatter of Kinetic Energy (KE) by adding perturbations to U and V via a forcing term to the streamfunction:

$$F_{\varphi} = \left(\frac{b_R D_{\text{tot}}}{B_{\text{tot}}}\right)^{1/2} F^*$$

where F^* is a 3D random pattern field,

 $B_{\rm tot}$ is the mean KE input by F^* alone,

 D_{tot} is an estimate of the total dissipation rate due to the model,

 $b_{\rm R}$ is the backscatter ratio – a scaling factor.

Shutts et al. (2011, ECMWF Newsletter); Palmer et al., (2009, ECMWF Tech. Memo.);
Shutts (2005, QJRMS); Berner et al. (2009, JAS)

Slide 15

© ECMWF

SKEB pattern

$$F_{\varphi} = \left(\frac{b_R D_{\text{tot}}}{B_{\text{tot}}}\right)^{1/2} F^*$$

- 3D random pattern field F^* :
- First-order auto-regressive [AR(1)] process for evolving F^*

$$F^*(t + \Delta t) = \phi F^*(t) + \rho \eta(t)$$

where $\phi=\exp(-\Delta t/\tau)$ controls the correlation over timestep Δt ; and spatial correlations (power law) for wavenumbers define ρ for random numbers, η

- vertical space-(de)correlations: random phase shift of η between levels

SKEB perturbations

$$F_{\varphi} = \left(\frac{b_R D_{\text{tot}}}{B_{\text{tot}}}\right)^{1/2} F^*$$

- ullet D_{tot} is an estimate of sub-grid scale production of KE, and includes:
- $-D_{\text{num}}$ = numerical dissipation from
 - explicit horizontal diffusion (bi-harmonic, ∇^2); and
 - estimate due to semi-Lagrangian interpolation error
- $(-D_{oGWD}) = dissipation due to orographic Gravity Wave Drag parameterisation)$
- $-D_{
 m con}$ = estimated KE generated by updraughts and detrainment within sub-grid deep convection

How are the perturbation patterns determined?

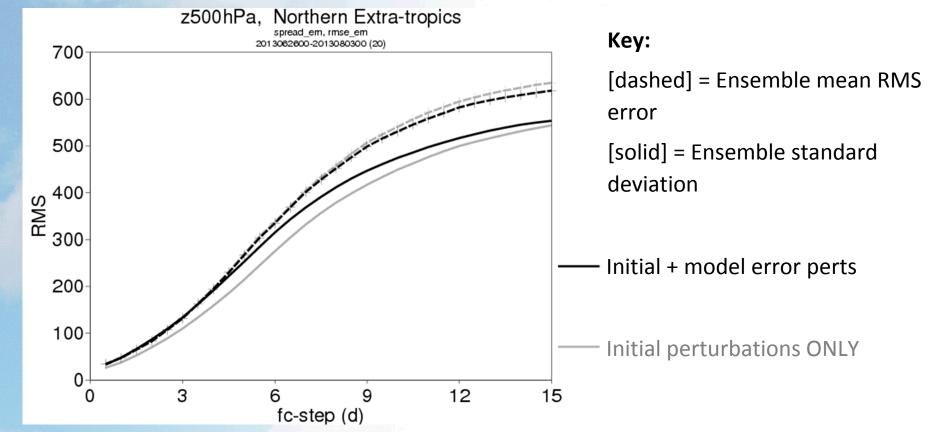
- Characteristics of model errors cannot be determined from observations:
 - uncertain processes small-scale (space and time)
 - lack of observational coverage
- Can attempt to use models: coarse-graining studies (e.g. Shutts and Palmer, 2007)
 - take high-resolution model simulations as "truth"
 - average model fields and tendencies (or streamfunction) to a gridresolution typical of the forecast model
 - compare the contribution of "sub-grid" scales in the coarse-grained simulation with parametrisations in the forecast model
 - coarse-graining studies have been used to justify and inform scales in SPPT and SKEB

IFS ensembles: ENS and System 4 (S4)

- ENS = ensemble prediction system for
 - medium-range forecasts (up to 15 days) and
 - monthly forecasts (up to 32 days) [Frederic Vitart, Friday 24th]
- S4 = seasonal forecasting system [Tim Stockdale, Friday 24th]
 - up to 7 months
- Both systems represent model error with SPPT and SKEB
- ENS:
 - 1 control forecast + 50 perturbed members
 - T639 (~32 km) resolution to day 10; T319 (~65 km) days 10-15
 - 91 vertical levels, up to 0.01hPa



Impact of SPPT and SKEB in ENS

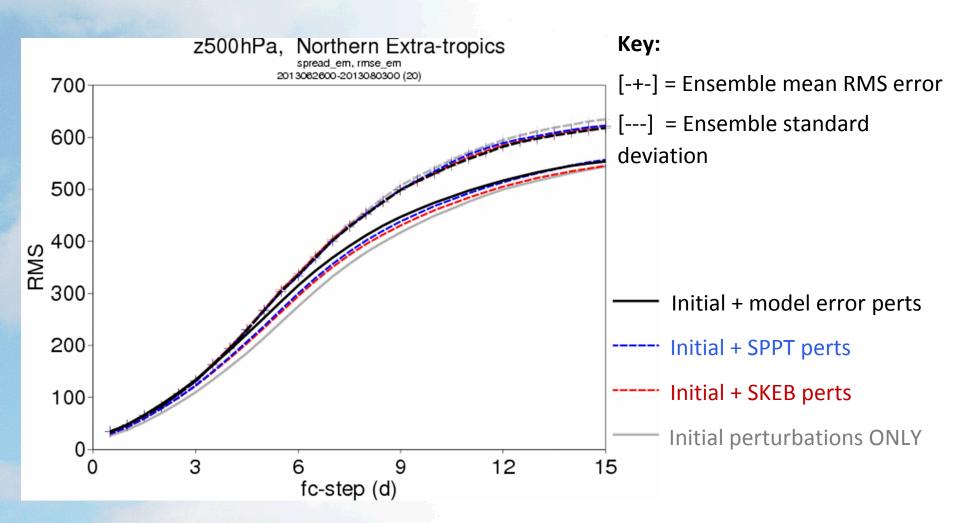


For details of skill measures:

Martin Leutbecher's lectures (22nd/23rd April)



Impact of SPPT and SKEB in ENS



Impact of SPPT and SKEB in ENS

- Adding SPPT + SKEB perturbations:
 - increases ensemble "spread" (= ensemble standard deviation), i.e. ensemble members describe greater region of the parameter space
 - some reduced ensemble mean errors
- In the extra-tropics:
 - SPPT and SKEB each have a similar impact, i.e. perturbations are successfully adopted and evolved by the model
 - Experiments: perturbations in days 0-5 contribute most effect
- In the tropics:
 - SPPT has a much greater impact (in terms of both spread and error) than SKEB, i.e. SPPT perturbations more able to excite modes that the model can evolve
 - Experiments: effect of perturbations rapidly lost at all times



Impact of SPPT and SKEB in S4

- System 4 (S4), November 2011: introduction of (revised) SPPT and SKEB
- Operational configuration:
 - T255 (~80 km), 91 vertical levels (up to 0.01 hPa)
 - Coupled ocean model: NEMOv3.0, 1 degree (~110 km), 42 vertical levels
 - 51 members
 - Initialised on 1st of each month
 - Forecast lead times: to 7 months
- Recent work with S4 to assess impact of stochastic schemes
- For longer time-scales, consider impact in terms of:
 - Noise-induced drift, i.e. change in model mean
 - Noise-activated regime transition, e.g. Pacific-N. American region regimes

Impact of SPPT and SKEB in S4

- Recent work with S4 to assess impact of stochastic schemes:
 - Hindcast period: 1981-2010
 - Start dates: May, Aug & Nov
 - Ensemble size: 51
 - Forecasts to lead times: 4-7 months
- Considers impact of SPPT + SKEB on:
 - Systematic errors
 - Madden-Julian Oscillation (MJO) statistics
 - ENSO forecast quality
 - Circulation regimes over the Pacific-North American region [Franco Molteni, Thurs 23rd]

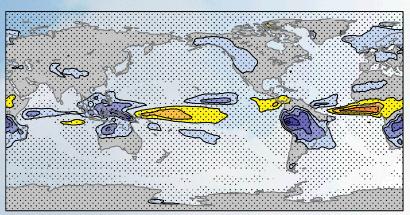
Weisheimer et al., (2014)



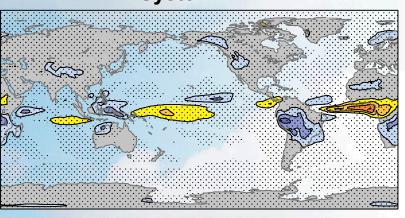
Impact of SPPT and SKEB in S4: biases

Outgoing Longwave Radiation (DJF 1981-2010)

stochphysOFF - ERA-I



System4 - ERA-I



- SPPT+SKEB: reduction of overly active tropical convection
- Similar reductions in excessive:
 - Total cloud cover
 - Total precip
 - Zonal winds (850 hPa)
- SPPT is responsible for most of the difference; SKEB has little impact

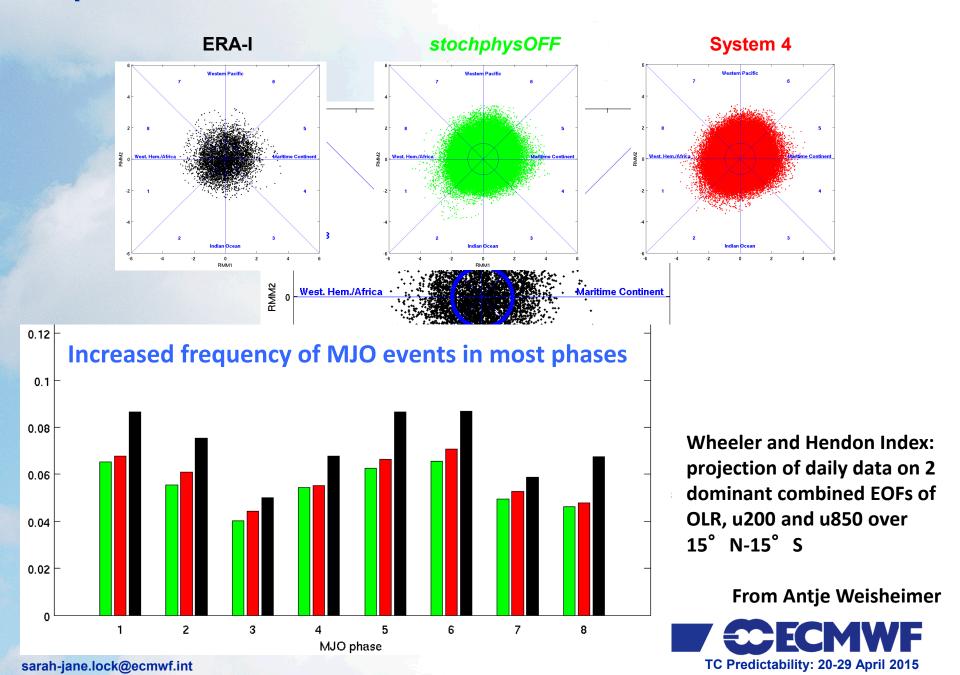
From Antje Weisheimer



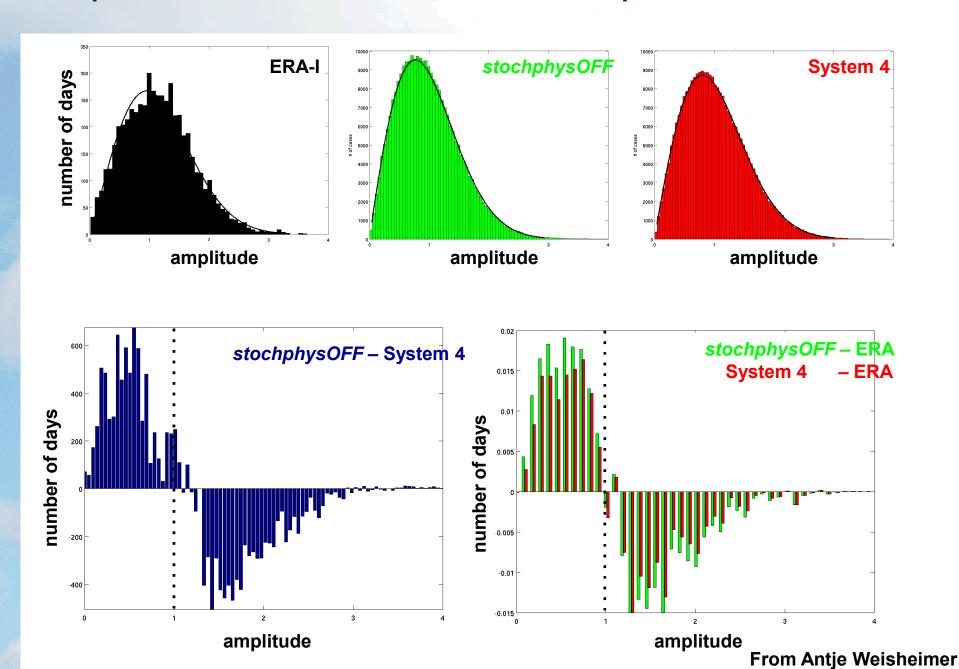
8 16 24 32 40 48 56

-56 -48 -40 -32 -24 -16 -8

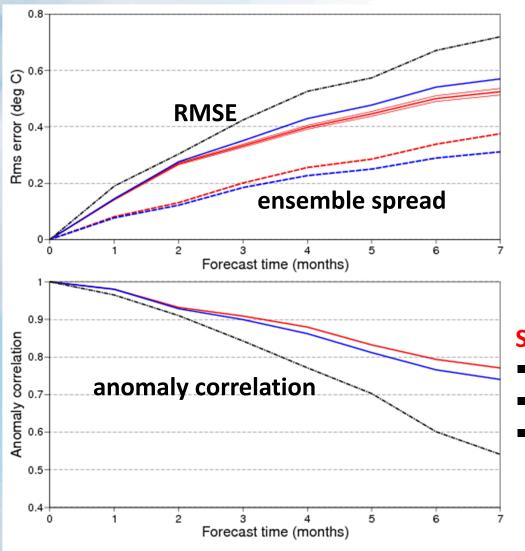
Impact of SPPT and SKEB in S4: Madden Julian Oscillation



Impact of SPPT & SKEB in S4: Increased amplitude of MJO events



Impact of SPPT & SKEB in S4: ENSO forecast quality - Niño4 SSTs



stochphysOFF
System 4

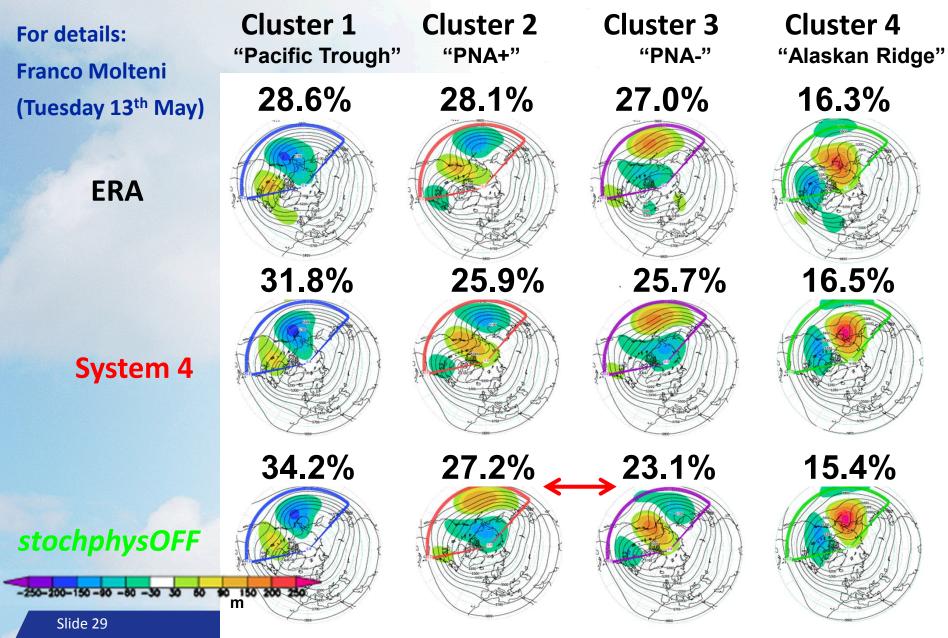
System 4 has:

- Reduced forecast errors
- Increased ensemble spread
- Improved correlation

From Antje Weisheimer



Impact of SPPT & SKEB in S4: Pacific North America (PNA) circulation regimes



From Antie Weisheimer TC Predictability: 20-29 April 2015

Stochastic physics: summary

- Model error occurs due to unresolved and misrepresented processes
 - finite-resolution of a discrete numerical model
 - parametrisations must describe multi-scale sub-grid processes in bulk
- Difficult to characterise sources of model errors due to lack of observations
- Without representing model error, ensemble forecasts are under-dispersive
- Stochastic methods for representing model error improve ensemble reliability
- ECMWF ensembles include 2 stochastic physics schemes:
 - SPPT: representing uncertainty due to sub-grid physics parameterisations
 - SKEB: simulating upscale transfer of kinetic energy from unresolved scales
- Medium-range: increased ensemble spread, greater probabilistic skill
- Seasonal: reduction in biases; better representation of MJO, ENSO, PNA regimes

Stochastic physics: brief outlook for IFS

Upcoming change to SKEB: removing orographic gravity wave drag contribution to dissipation rate estimate – reduces excessive spread in low-level winds near orography

Exploring alternative perturbations for radiation tendencies:

In SPPT, we perturb:

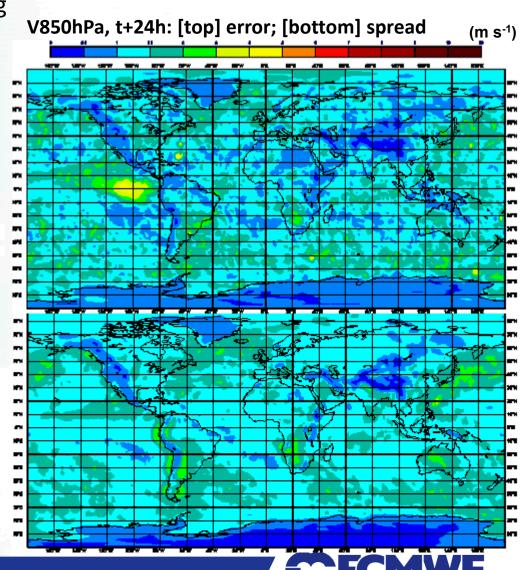
$$X = X_{RAD} + X_{GWD} + X_{MIX} + X_{CON} + X_{CLD}$$

But,

$$X_{RAD} = X_{clr} + X_{cld}$$

and X_{clr} has little uncertainty.

Need a way to perturb relative to X_{cld} .



References & reading

- Berner et al., 2009: A Spectral Stochastic Kinetic Energy Backscatter Scheme and Its Impact on Flow-Dependent Predictability in the ECMWF Ensemble Prediction System, JAS, **66**, 603-626
- Buizza et al., 1999: Stochastic representation of model uncertainties in the ECMWF Ensemble
 Prediction System, QJRMS, 134, 2041-2066
- Palmer et al., 2009: Stochastic parametrization and Model Uncertainty, ECMWF Tech. Mem.,
 598, pp. 42
- Shutts and Palmer, 2007: Convective forcing fluctuations in a cloud-resolving model: Relevance to the stochastic parameterization problem, J. Clim., **20**, 187-202
- Shutts et al., 2005: A kinetic energy backscatter algorithm for use in ensemble prediction systems, QJRMS, **131**, 3079-3102
- Shutts et al., 2011: Representing model uncertainty: stochastic parameterizations at ECMWF,
 ECMWF Newsletter, 129, 19-24
- Weisheimer et al., 2014: Addressing model error through atmospheric stochastic physical parametrisations: Impact on the coupled ECMWF seasonal forecasting system, Phil. Trans. A., in press.