Using stochastic physics to represent model uncertainty

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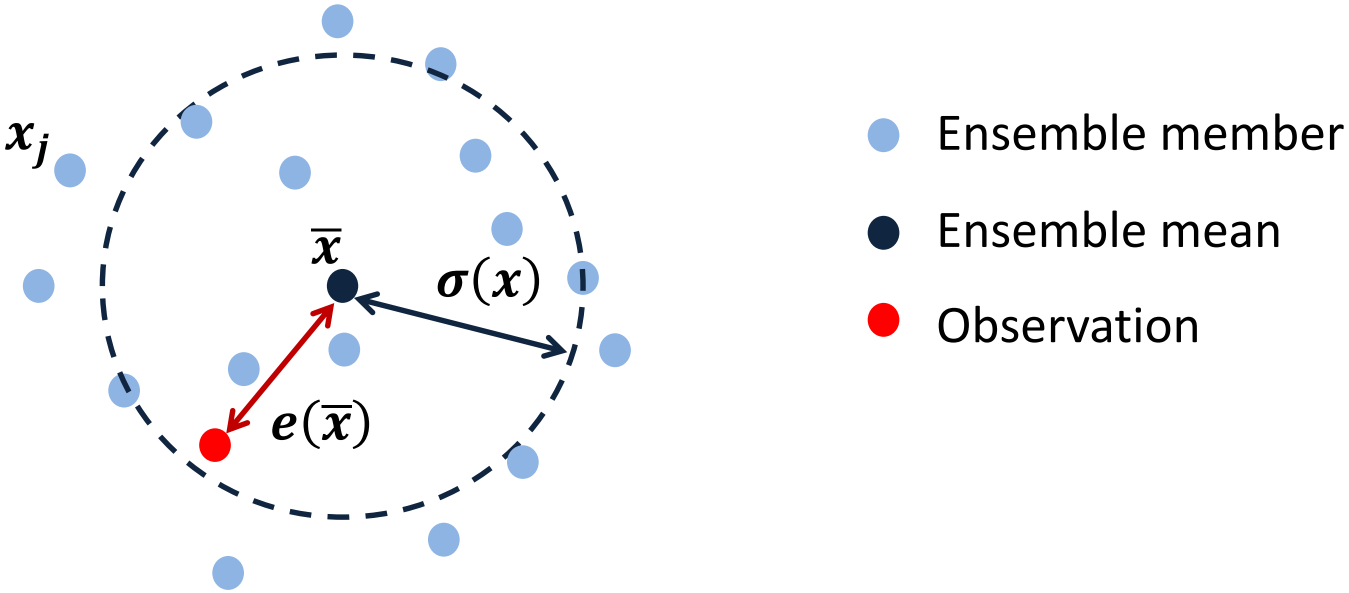
Using stochastic physics to represent model uncertainty

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

Ensemble reliability

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



i.e. averaged over many ensemble forecasts,

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

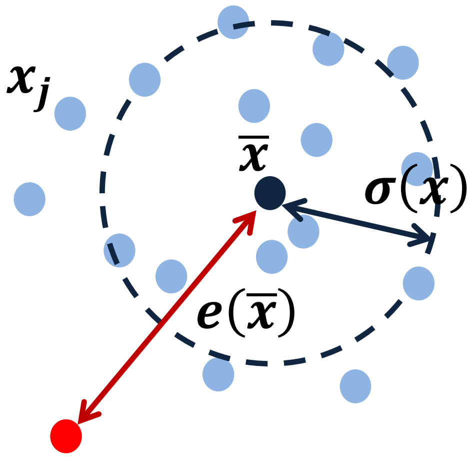
For a thorough discussion of this relationship:

Martin Leutbecher's lectures

Ensemble reliability

- In an under-dispersive ensemble,

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



● Ensemble member

● Ensemble mean

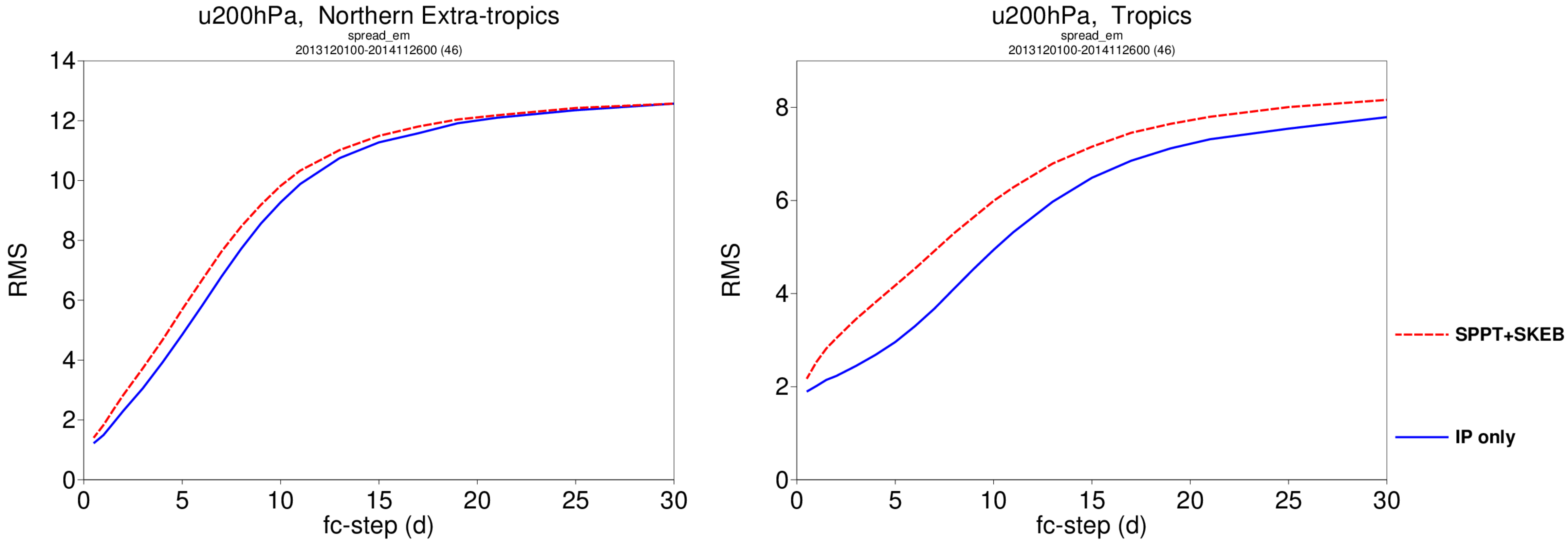
● Observation

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

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

What happens with no representation of model uncertainties?

Ensemble standard deviation ("Spread")



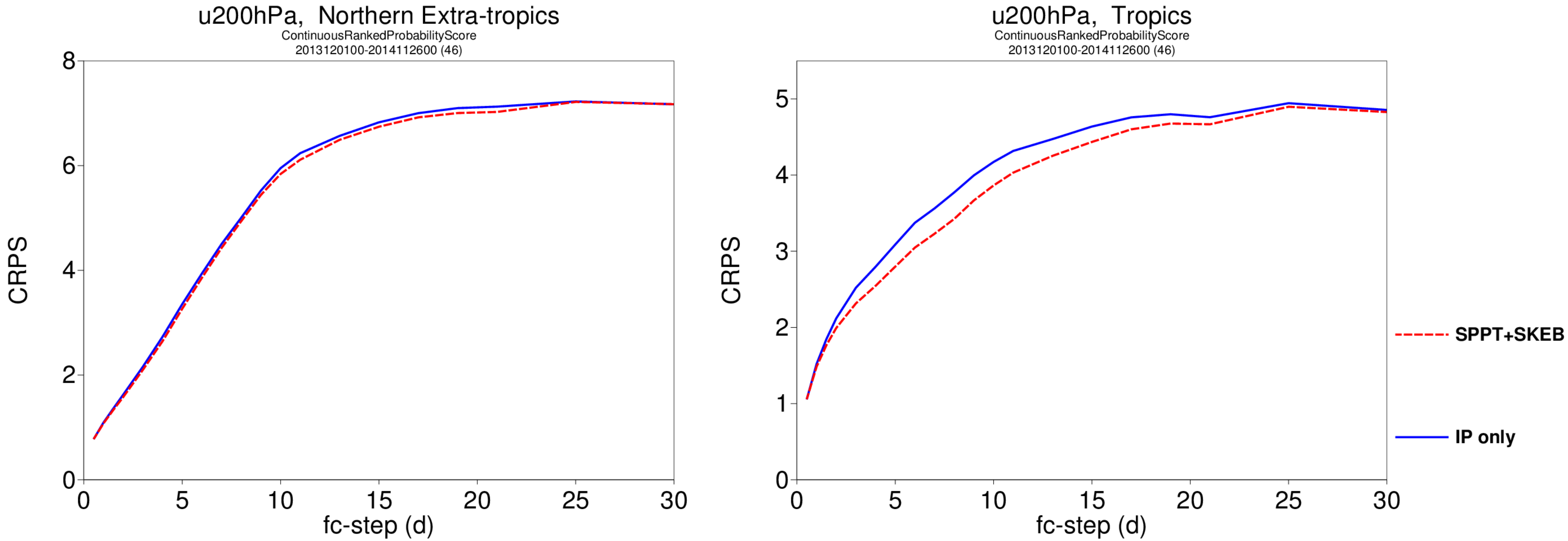
TL399/255, resolution change at D15, 20 members

For details of skill measures:

Martin Leutbecher's lectures

What happens with no representation of model uncertainties?

Probabilistic skill (CRPS)



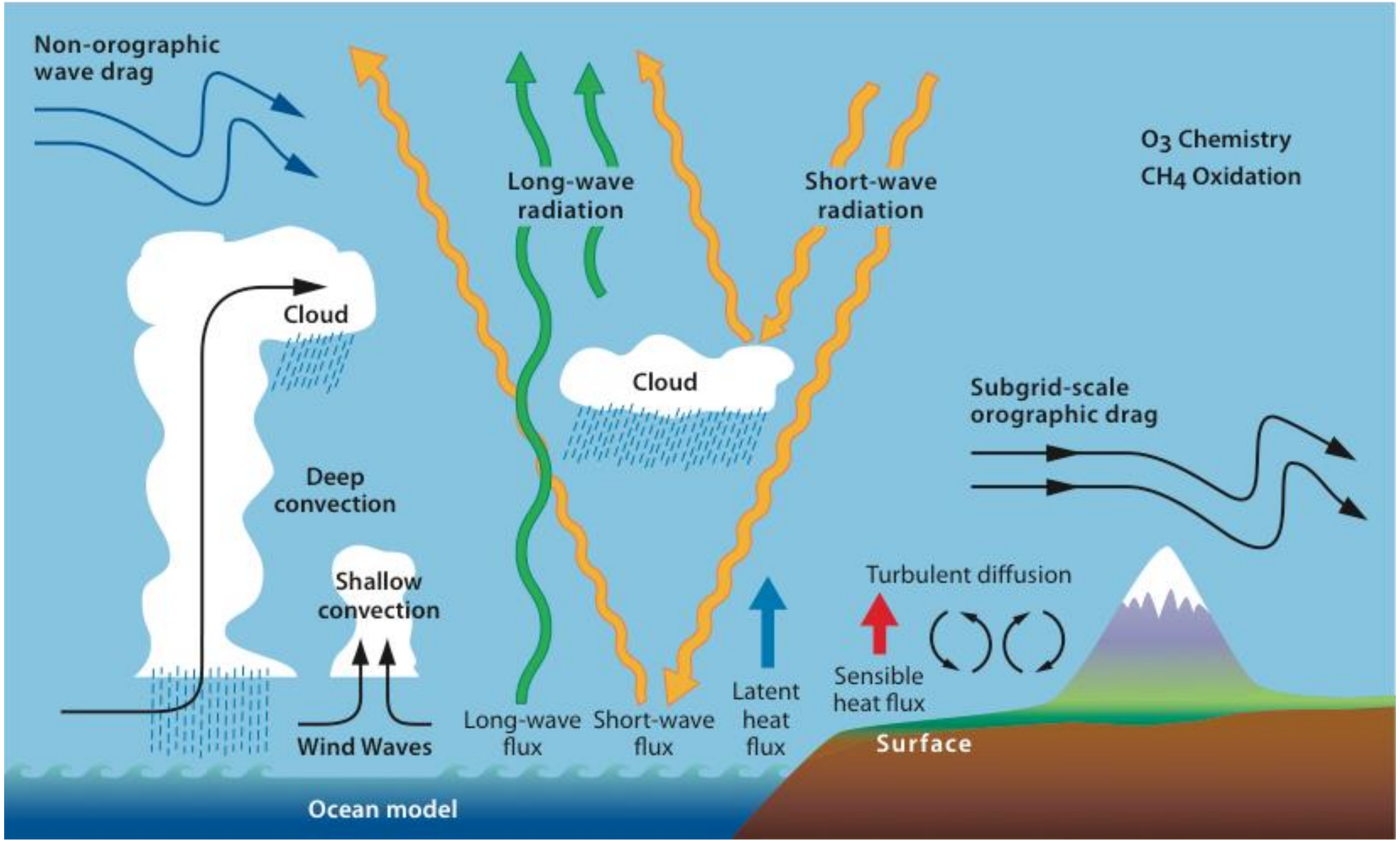
TL399/255, resolution change at D15, 20 members

For details of skill measures:

Martin Leutbecher's lectures

Model uncertainty: where does it come from?

- Atmospheric processes parametrised in the model:



Model error: where does it come from?

- Other parametrised atmospheric processes?
  - Surface coupling
  - Radiation-aerosol interactions
  - …
- Other sources:
  - Dynamics / numerics
  - Coupled system: land-surface / oceans / sea-ice

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

Model uncertainty: how to simulate it?

- What do errors due to model uncertainty look like?
- Can we characterize them: relative size and timescales associated with different sources?

- How can we represent them?

- Multi-model ensembles
- 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 parametrisation tendencies (SPPT) scheme
  - Stochastic kinetic energy backscatter (SKEB) scheme

- SPPT scheme: simulates uncertainty due to sub-grid parametrisations
- SKEB scheme: parametrises missing and uncertain upscale transfer of KE

Stochastically Perturbed Parametrisation Tendencies (SPPT) scheme

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

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

coming from

$$\left[\begin{array}{l} \textit{radiation} \\ \textit{gravity wave drag} \\ \textit{vertical mixing} \\ \textit{convection} \\ \textit{cloud physics} \end{array}\right]$$

schemes

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

$$\boldsymbol{X}' = (1 + \mu r)\boldsymbol{X}$$

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.)

SPPT pattern

- 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 mapped into grid-point space r:

– clipped such that $r \in [-1, +1]$

– same pattern is applied to T, q, u, v

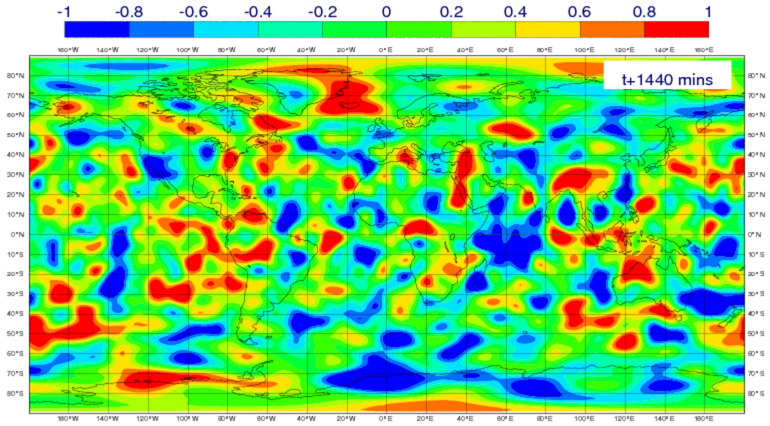
– applied at all model levels to preserve vertical structures**

– ***Except*: tapered to zero at model top/bottom, to avoid:
    - instabilities due to perturbations in the boundary layer;
    - perturbing stratospheric tendencies dominated by well-constrained clear-skies radiation

SPPT pattern

- 2D random pattern, r:
  - Time-correlations: AR(1)
  - Spatial-correlations: Gaussian
  - Clipped such that $r \in [-1, +1]$
- Applied at all model levels to preserve vertical structures**

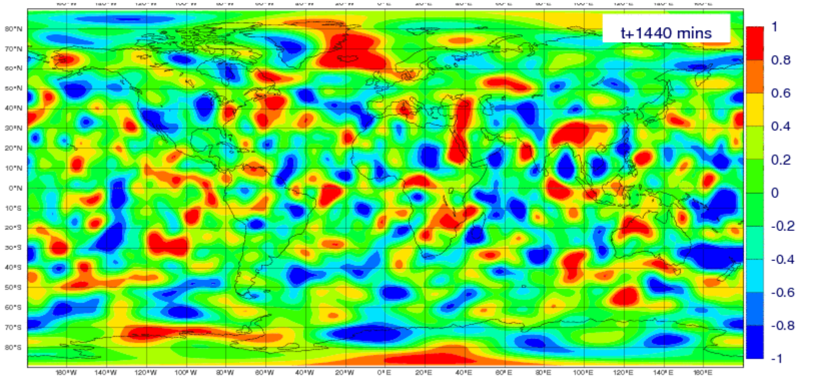
*******Except*: tapered to zero at model top/bottom

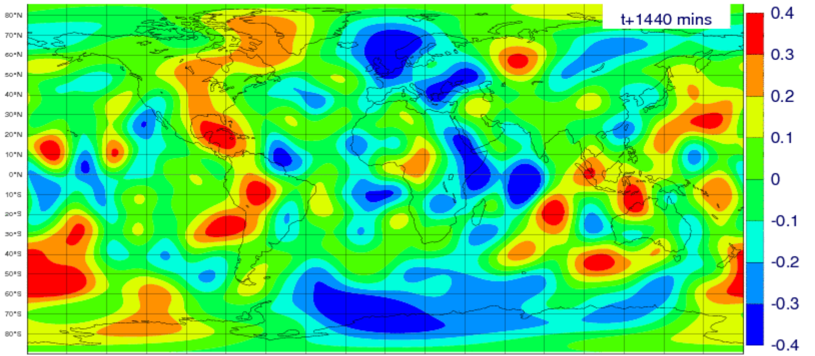


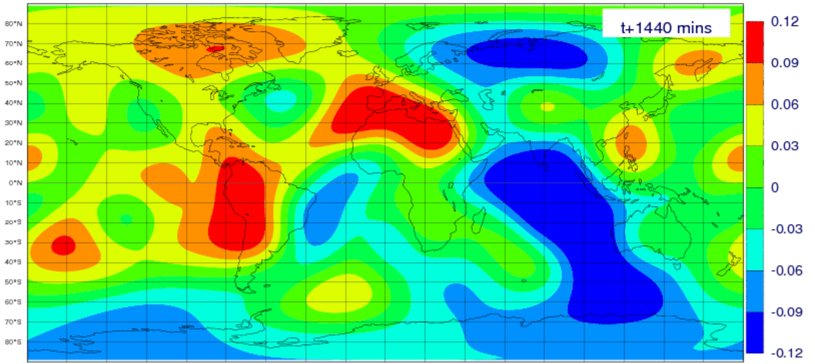
3 correlation scales:

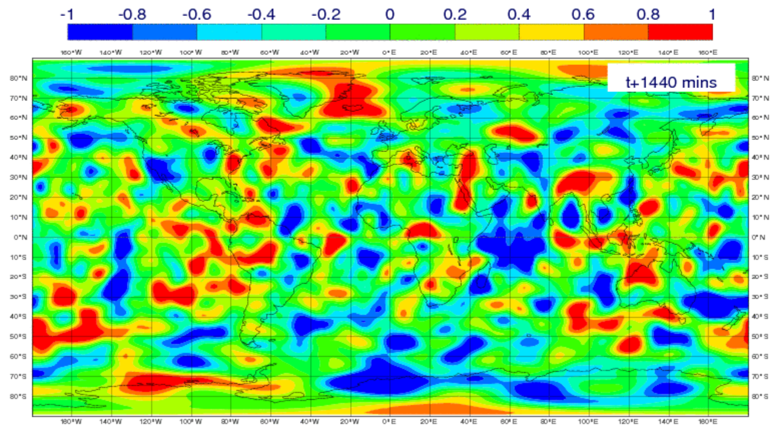
i)	6 hours,	500 km,	$\sigma = 0.52$
ii)	3 days,	1 000 km,	$\sigma = 0.18$
iii)	30 days,	2 000 km,	$\sigma = 0.06$

SPPT pattern









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i)	6 hours,	500 km,	$\sigma = 0.52$
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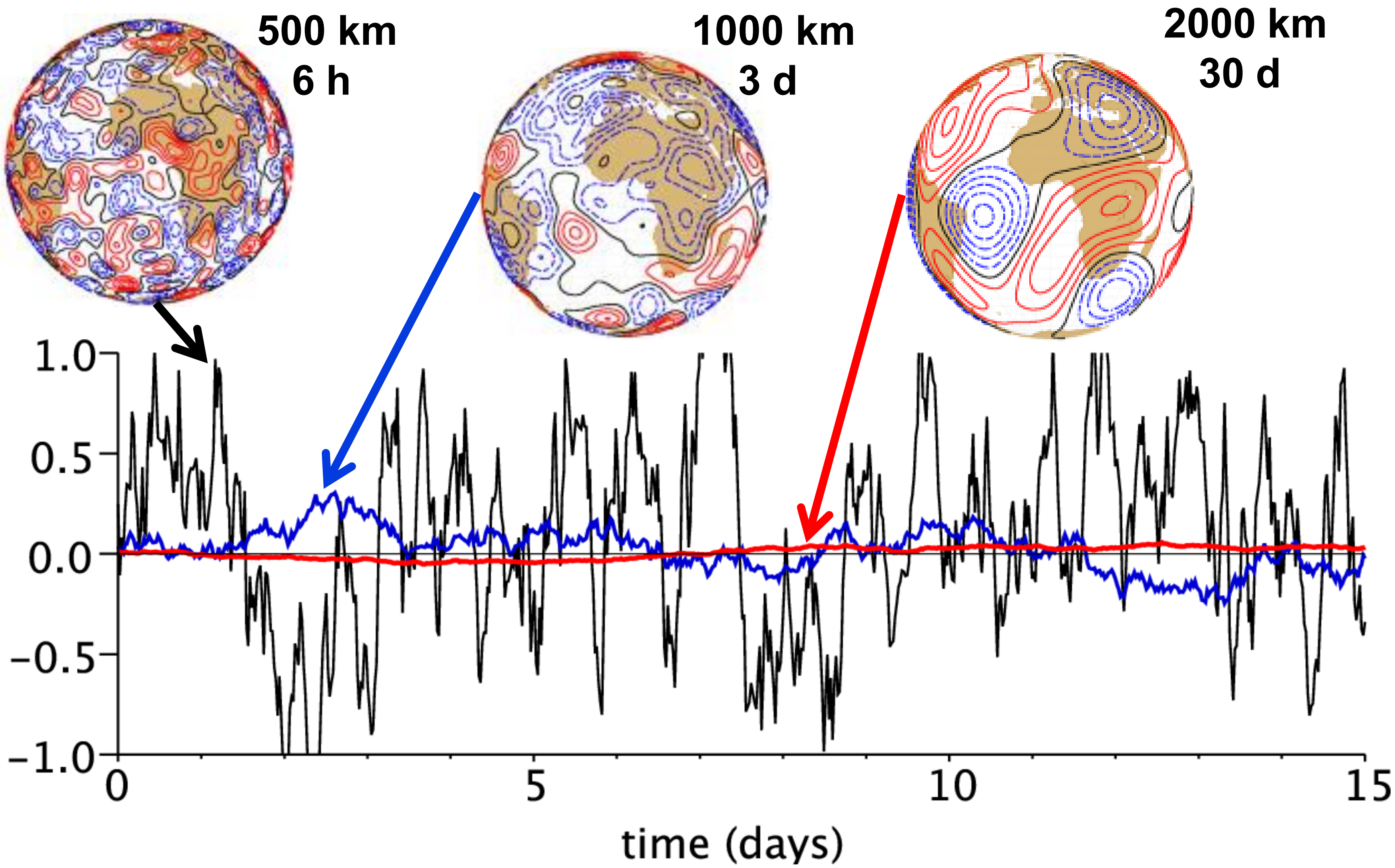
(Note the differences in colour scales)

SPPT pattern



Stochastic Kinetic Energy Backscatter (SKEB) scheme

- Introduced into IFS, 2010:
- Attempts to simulate a process otherwise absent from the model –

upscale transfer of energy from sub-grid scales

- Represents backscatter of Kinetic Energy (KE) by adding perturbations to U and V via a forcing term to the streamfunction:

$$F_\varphi = (b_R D)^{1/2} F^*$$

where

D is an estimate of the (smoothed) total (local) dissipation rate due to the model,

b_R is the backscatter ratio – a scaling factor,

F^* is a 3D evolving random pattern field.

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

SKEB scheme

$$F_{\varphi} = (b_R D)^{1/2} F^*$$

- 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

$$F_{\varphi} = (b_R D)^{1/2} F^*$$

- D is an estimate of sub-grid scale production of KE, and includes:

– D_{num} = numerical dissipation from

  - explicit horizontal diffusion (bi-harmonic, ∇^2); and
  - estimate due to semi-Lagrangian interpolation error

– D_{con} = estimated KE generated by updraughts and detrainment within sub-grid deep convection

- Note: as of the resolution upgrade (32 -> 19 km) in March 2016:
  - New numerical diffusion operator is no longer consistent with the biharmonic diffusion assumed by SKEB (for D_{num}) => numerical dissipation contribution has been deactivated

How are the perturbation patterns determined?

- Characteristics of errors due to model uncertainty cannot easily 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 grid-resolution 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 were used to justify and inform scales in SPPT and SKEB

IFS ensembles: ENS and System 4 (S4)

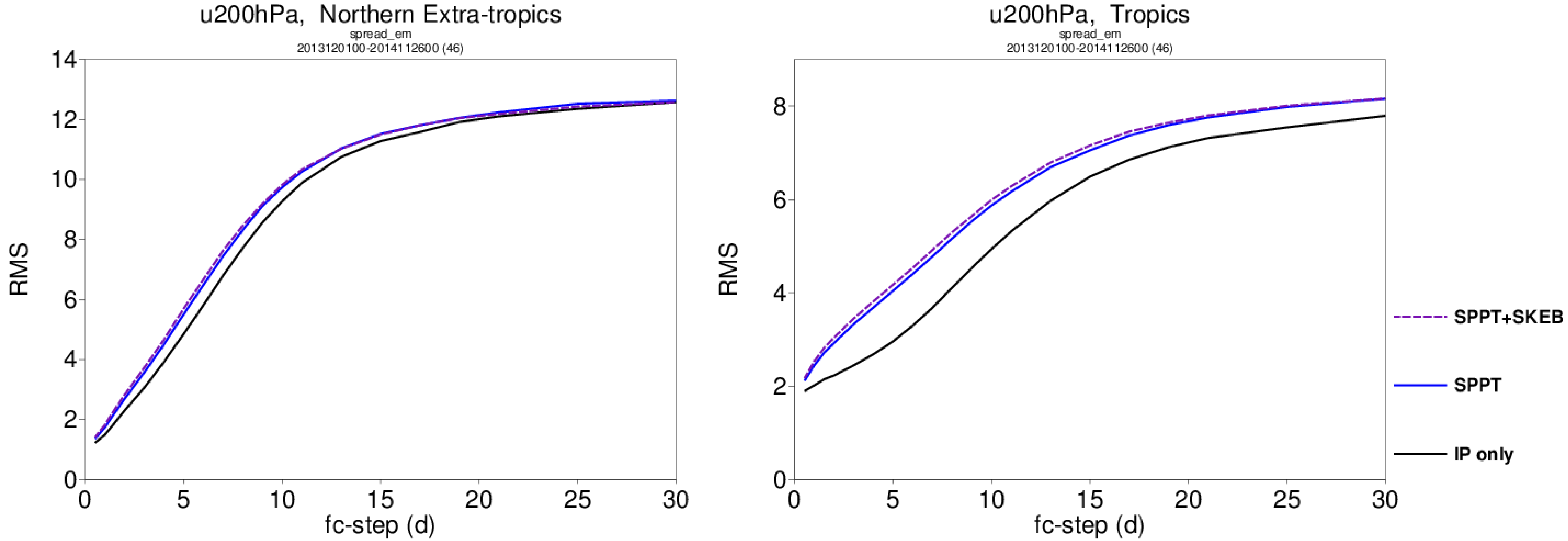
- **ENS** = ensemble prediction system for
  - medium-range forecasts (up to 15 days) and
  - monthly forecasts (up to 32 days) [Frederic Vitart's lecture]
- **S4** = seasonal forecasting system [Tim Stockdale's lecture]
  - up to 7 months

- Both forecast systems include representations of model uncertainty via SPPT and SKEB

- ENS:
  - 1 control forecast + 50 perturbed members
  - T_{Co}639 (~19 km) resolution to day 15; T_{Co}319 (~32 km) days 45
  - 91 vertical levels, up to 0.01hPa

Impact of SPPT and SKEB in ENS

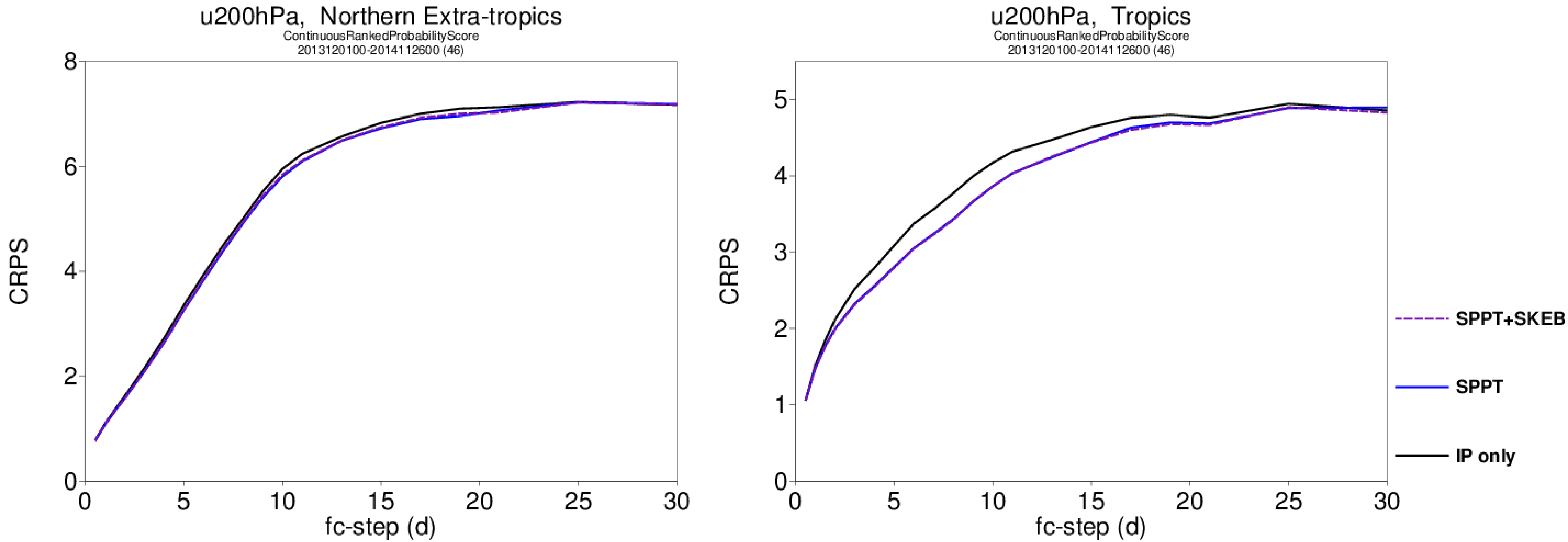
Ensemble standard deviation (“Spread”)



ECMWF

Impact of SPPT and SKEB in ENS

Probabilistic skill (CRPS)



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
  - SPPT has a much greater impact than SKEB
- In the extra-tropics:
  - *Experiments: perturbations in days 0-5 contribute most effect*
- In the tropics:
  - *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
  - Verification of forecasts to lead times: 4-7 months

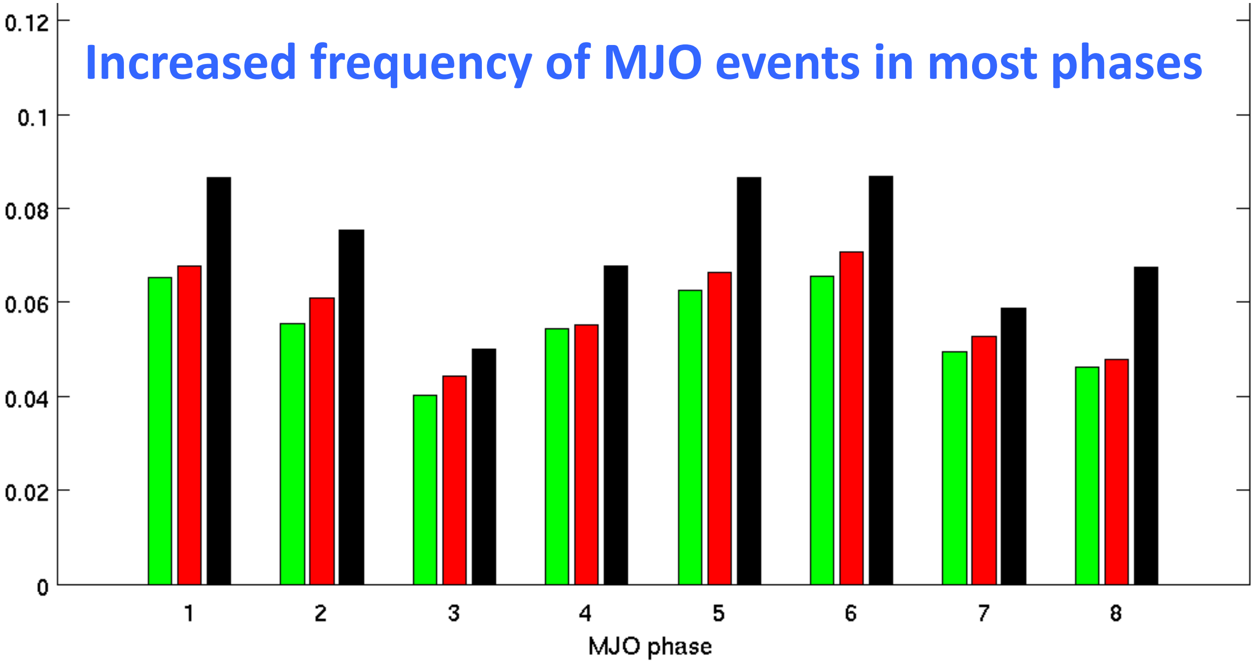
- Considers impact of SPPT + SKEB on:
  - Systematic errors
  - Madden-Julian Oscillation (MJO) statistics
  - ENSO forecast quality
  - Circulation regimes over the Pacific-North American region [Franco Molteni’s lecture]

Impact of SPPT and SKEB in S4: Systematic errors

- Activating SPPT + SKEB reduces some biases:
  - Outgoing longwave radiation (OLR)
  - Total cloud cover
  - Total precipitation
  - Zonal winds (850 hPa)
- Greatest improvements in the tropics: reduces overly active tropical convection
- SPPT is responsible for most of the difference

See Weisheimer et al. (2014, Phil. Trans. R. Soc. A)

Impact of SPPT and SKEB in S4: Madden Julian Oscillation



Increased frequency of MJO events in most phases

Key:

ERA-I

***stochphys*OFF**

System 4

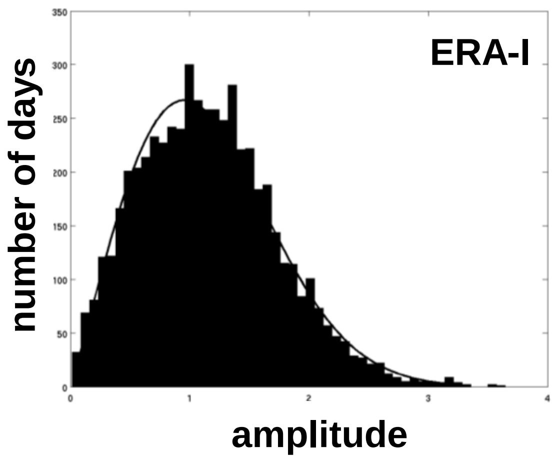
Wheeler and Hendon Index:

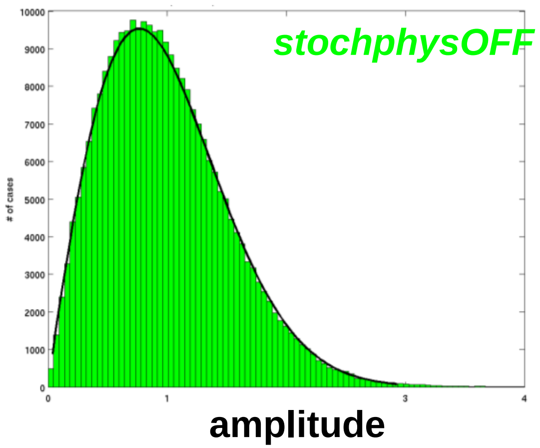
Projection of daily data on 2 dominant combined EOFs

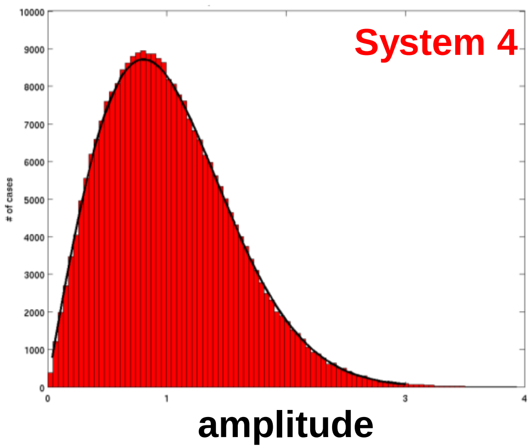
of OLR, u200 and u850 over 15°N-15°S

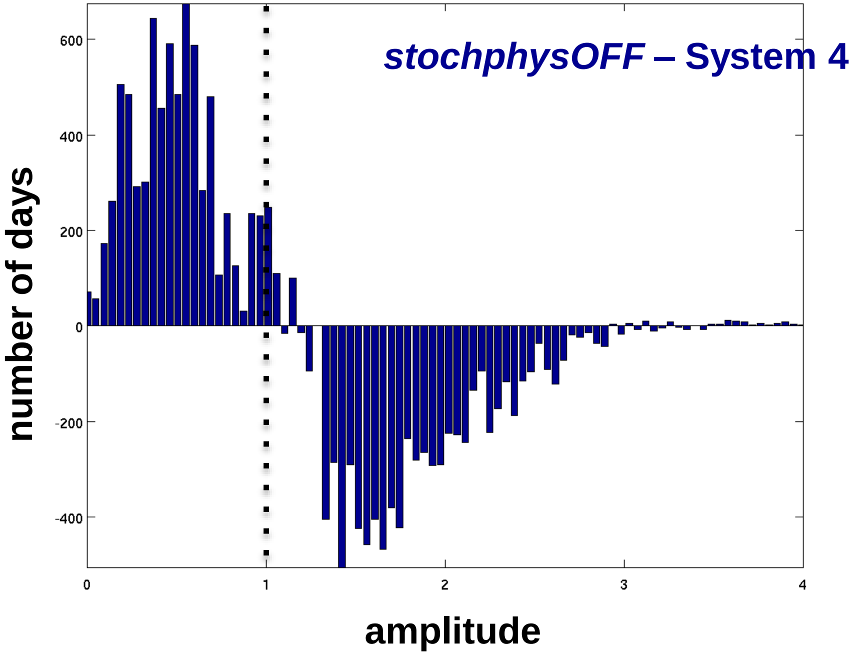
Weisheimer et al. (2014, Phil. Trans. R. Soc. A)

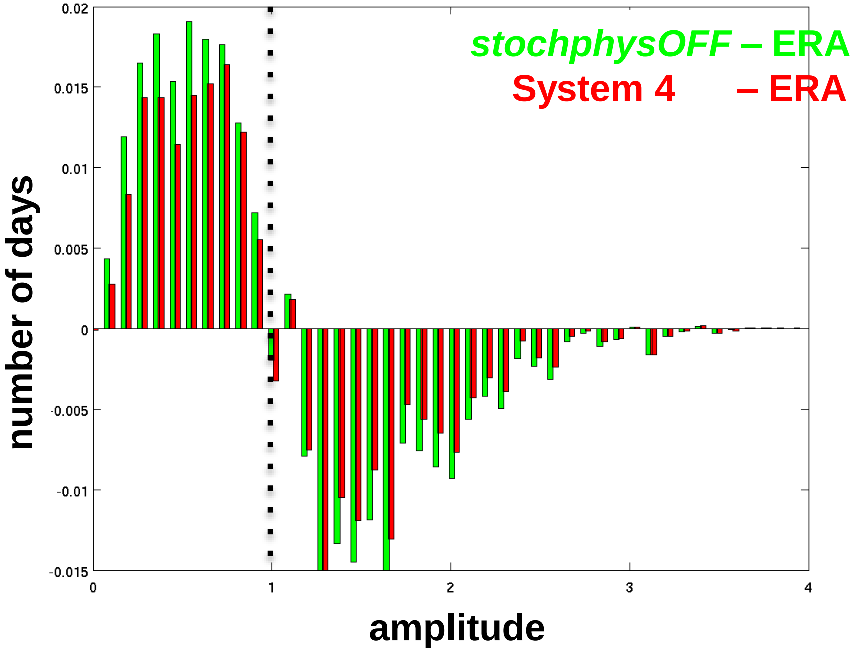
Impact of SPPT & SKEB in S4: Increased amplitude of MJO events



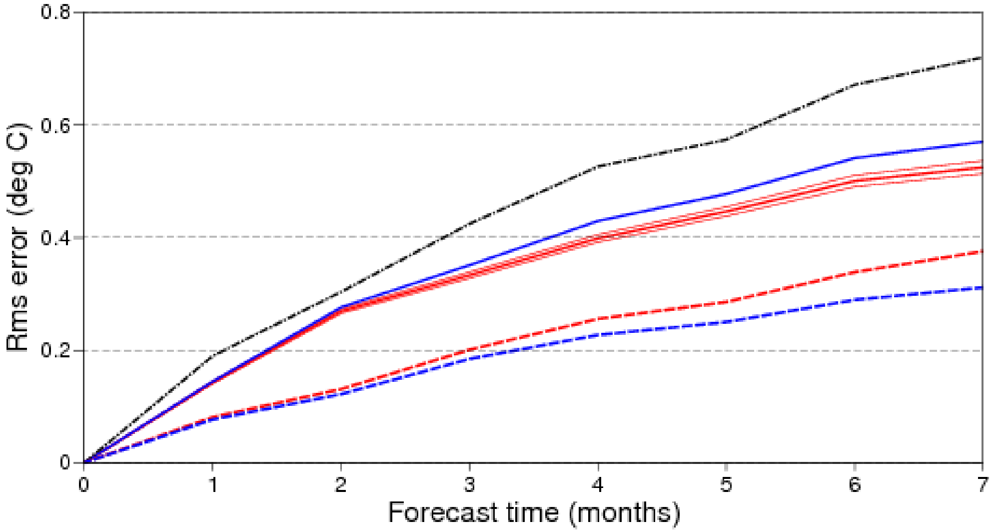


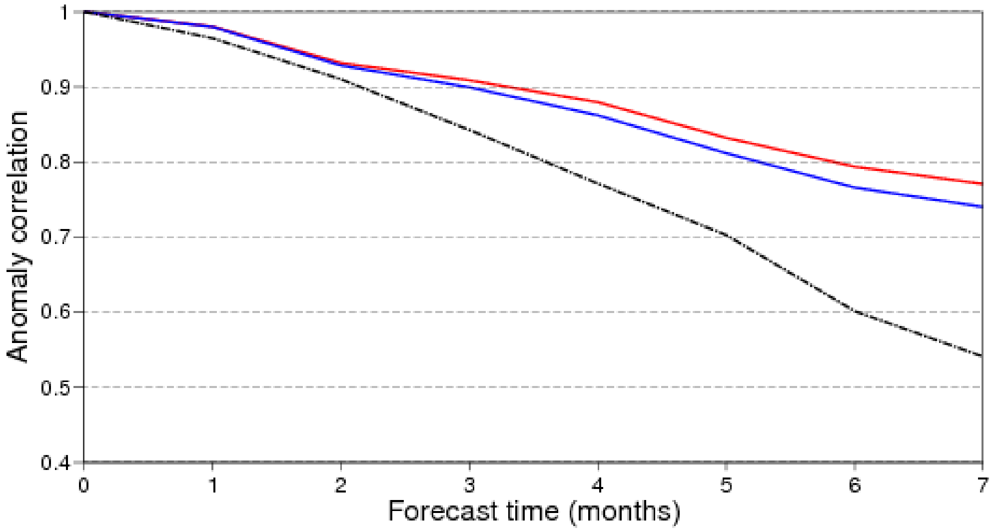






Impact of SPPT & SKEB in S4: ENSO forecast quality - Niño4 SSTs





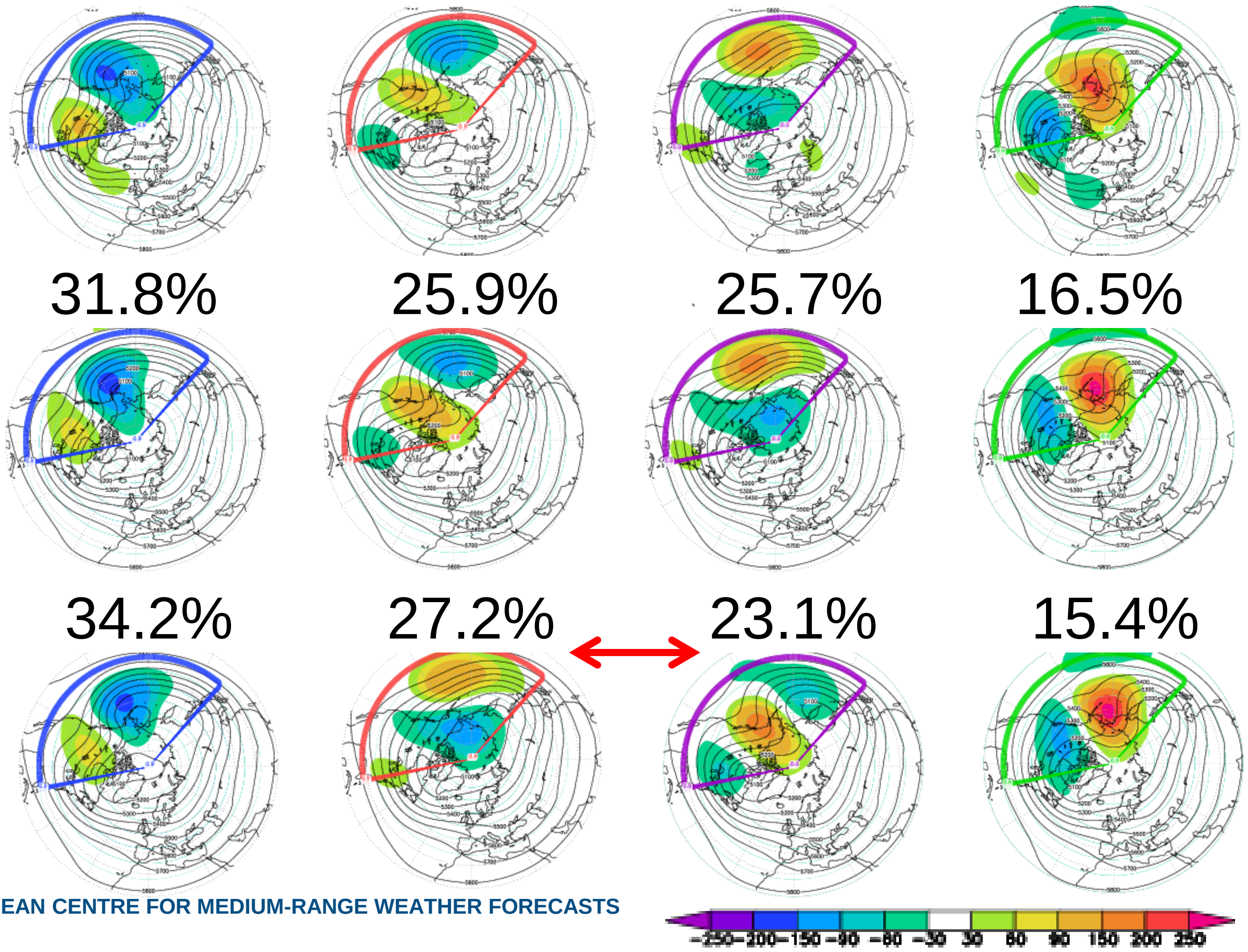
stochphysOFF

System 4

System 4 has:

- Reduced forecast errors
- Increased ensemble spread
- Improved correlation

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



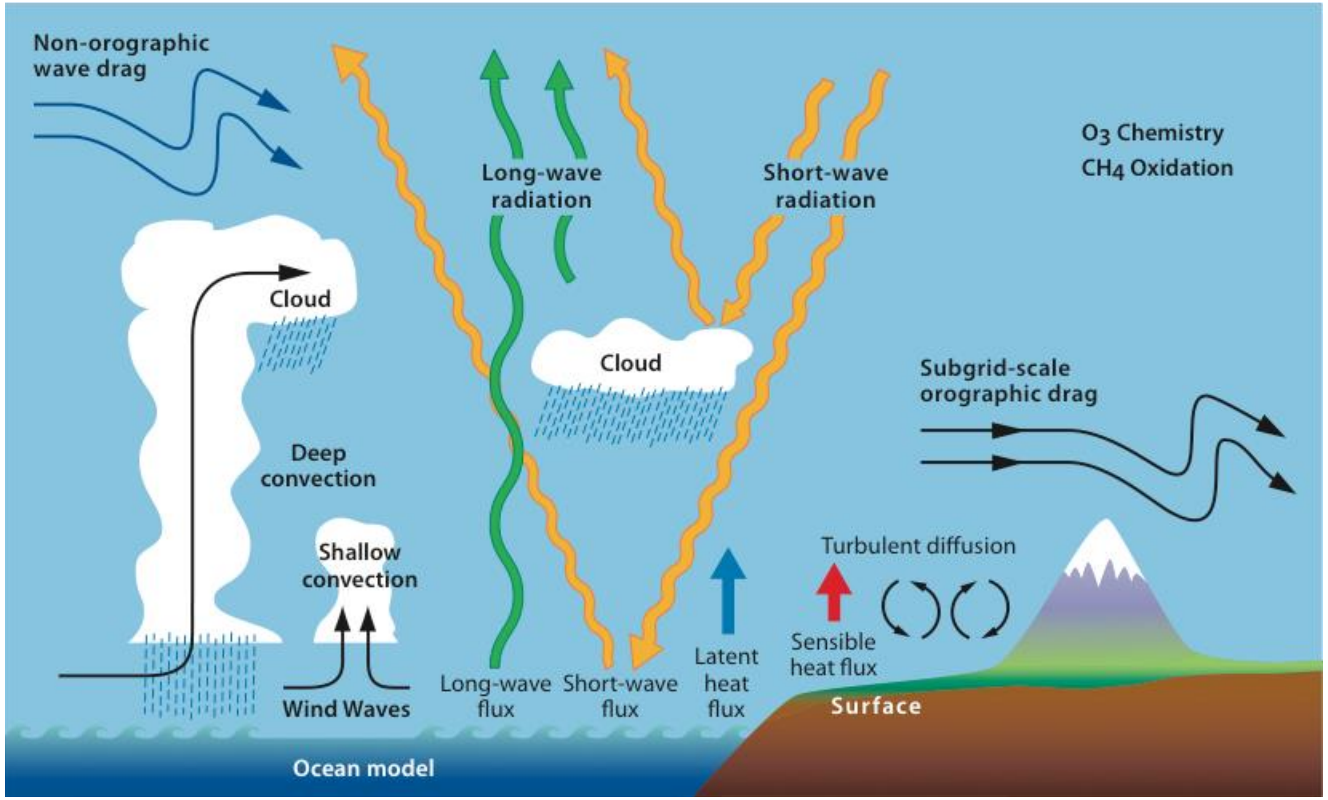
	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**
ERA	28.6%	28.1%	27.0%	16.3%
System 4	31.8%	25.9%	25.7%	16.5%
stochphysOFF	34.2%	27.2% ↔	23.1%	15.4%

Stochastic physics: summary

- Errors due to model uncertainty arise from unresolved and misrepresented processes
  - finite-resolution of a discrete numerical model
  - parametrisations use simplified, bulk methods to represent complex, multi-scale sub-grid processes
- Difficult to characterise sources of model uncertainty due to lack of observations
- Without representing model uncertainty, ensemble forecasts are under-dispersive
- Stochastic methods for representing model uncertainty improve ensemble reliability
- ECMWF ensembles include 2 stochastic physics schemes:
  - SPPT: represents uncertainty due to sub-grid physics parameterisations
  - SKEB: simulates 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

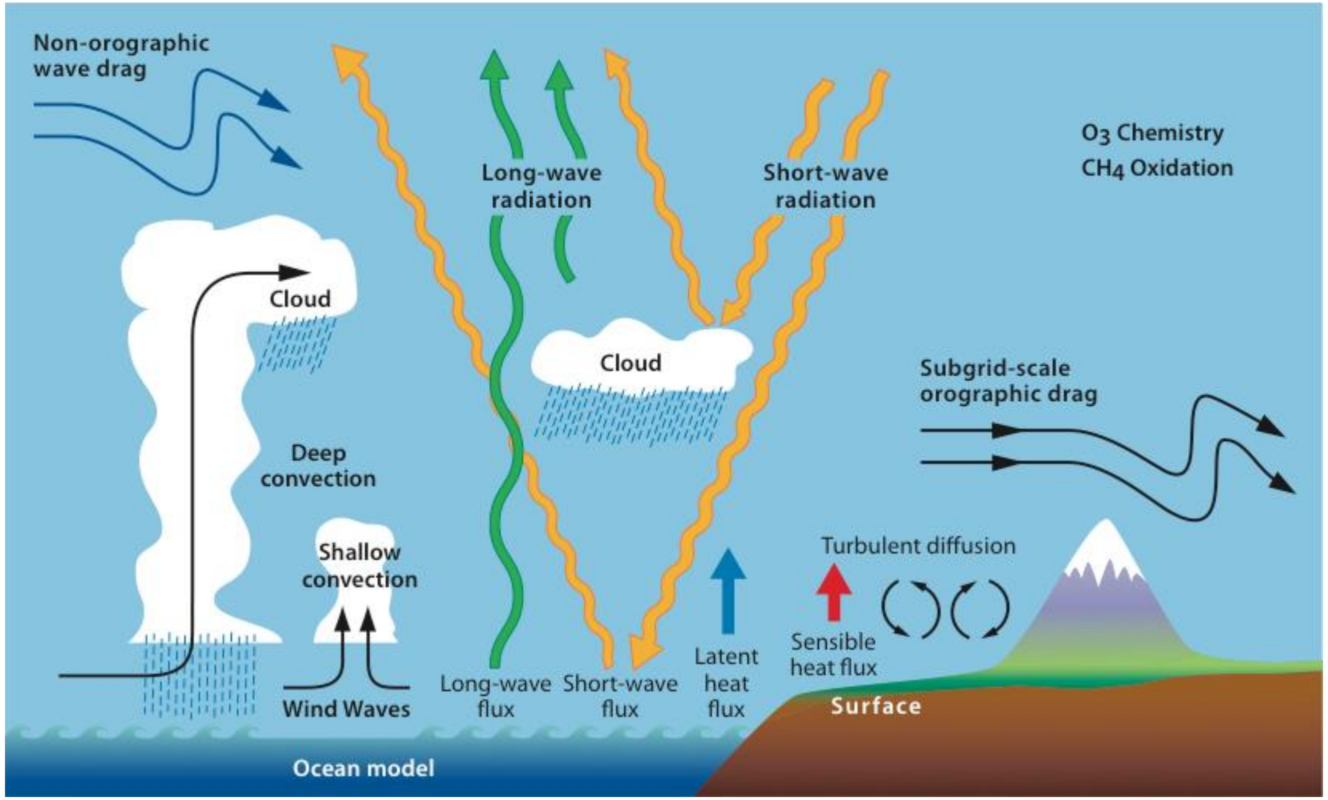
Towards process-level model uncertainty representation



- **Aim**: to improve the physical consistency
- Generate flux perturbations at the top of atmosphere (TOA) and surface that are consistent with tendency perturbations within the atmospheric column
- Conservation of water
- Remove ad hoc tapering in boundary layer and stratosphere
- Include multi-variate aspects of uncertainties

Stochastic physics: brief outlook for IFS

Towards process-level model uncertainty representation



- **Approach**:

Stochastically Perturbed Parametrisations (SPP)

(Ollinaho et al., submitted QJ, 2016)

- Embed stochasticity within IFS parametrisations
- Perturb parameters/variables directly
- Specify spatial/temporal correlations
- Target uncertainties that matter (level of uncertainty and impact)
- Require that stochastic schemes converge to deterministic schemes in limit of vanishing variance

Stochastically Perturbed Parametrisations (SPP) scheme

Towards process-level model uncertainty representation

Stochastic perturbations are applied to unperturbed parameters / variables in the physics parametrisations, $\hat{\xi}_j$:

$$\xi_j = \hat{\xi}_j \exp(\Psi_j)$$

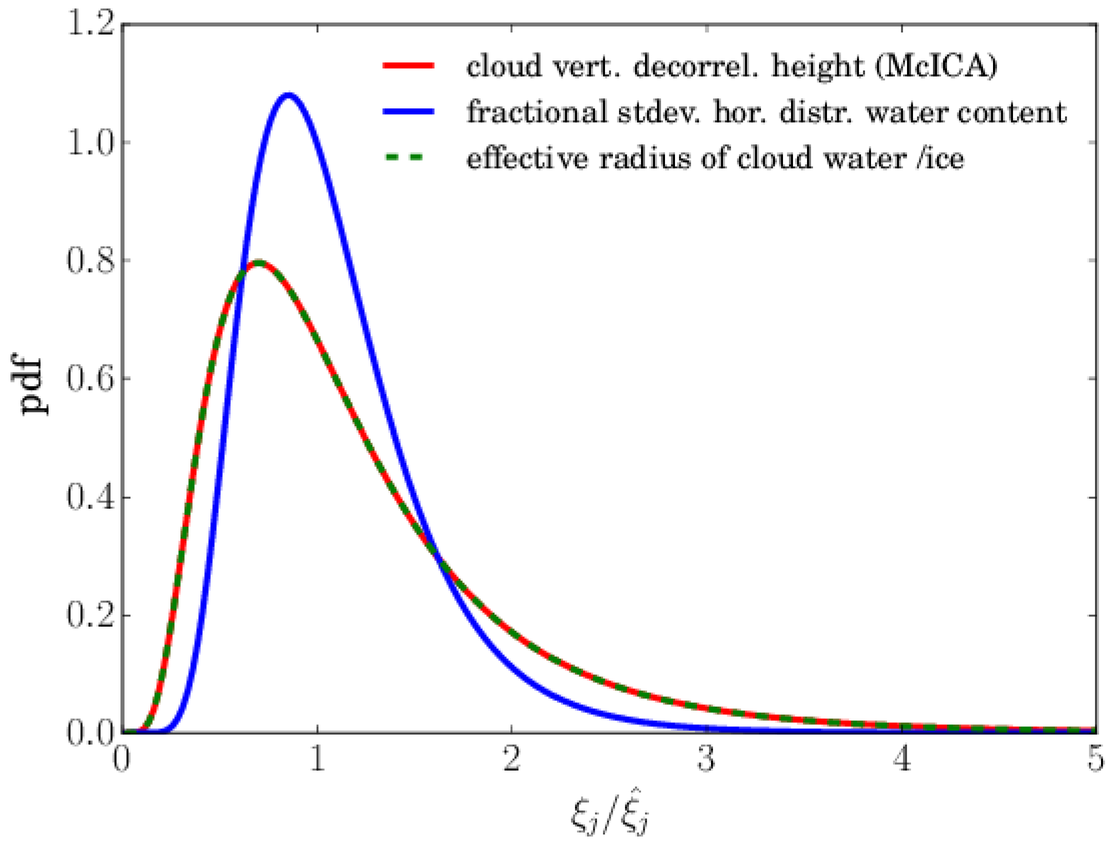
where

$$\Psi_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$$

Development started with parameter perturbations to target cloudy-skies radiation

Now includes parameters/variables from:

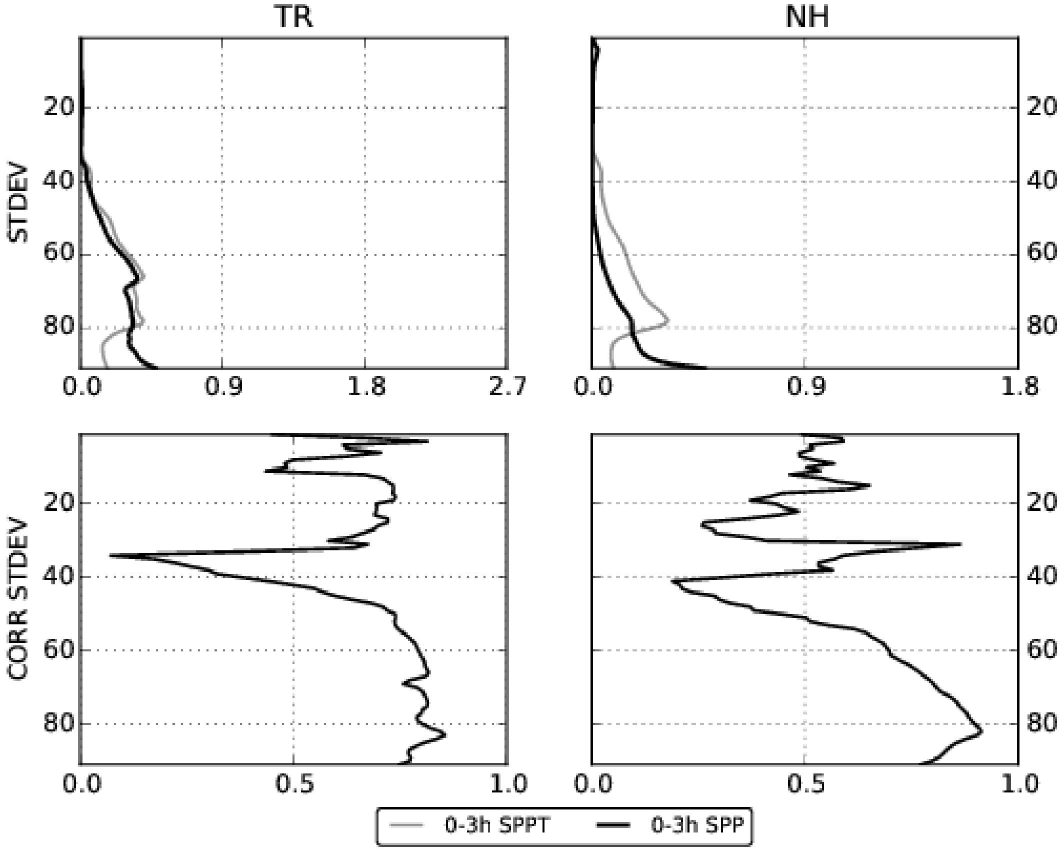
- Turbulent diffusion and subgrid orography
- Cloud and large-scale precipitation
- Radiation
- Convection



(Ollinaho et al., submitted QJ, 2016)

Stochastically Perturbed Parametrisations (SPP) scheme

Towards process-level model uncertainty representation



- **Standard deviation of 0-3h Temperature tendency**
- SPP induces larger (smaller) tendency perturbations within (above) the boundary layer than SPPT
- Correlations between SPP and SPPT standard deviations are small at early lead times => two schemes are generating different perturbation structures

Based on 6 boreal winter cases;

Unit (top panels): K/3h

(Ollinaho et al., submitted QJ, 2016)

References & reading

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