Using stochastic physics to represent model uncertainty

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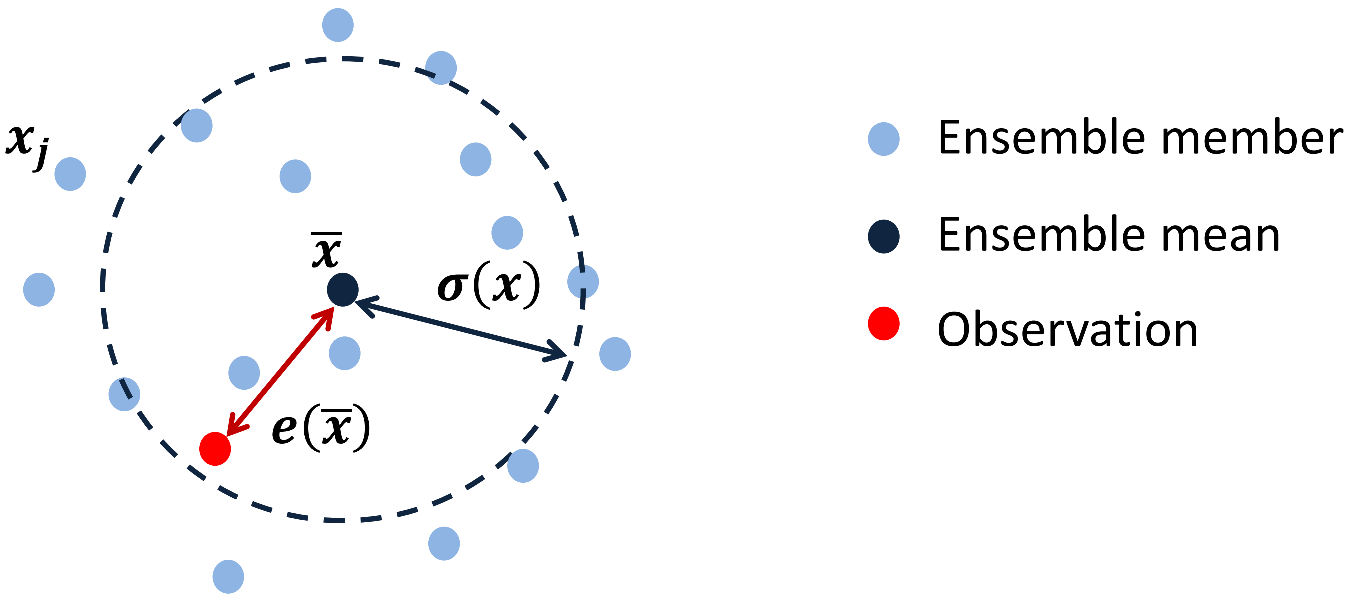
Using stochastic physics to represent model uncertainty

- Why represent model uncertainty in an ensemble forecast?
- What are the sources of model uncertainty?
- How do we currently represent model uncertainty in the IFS?
- 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

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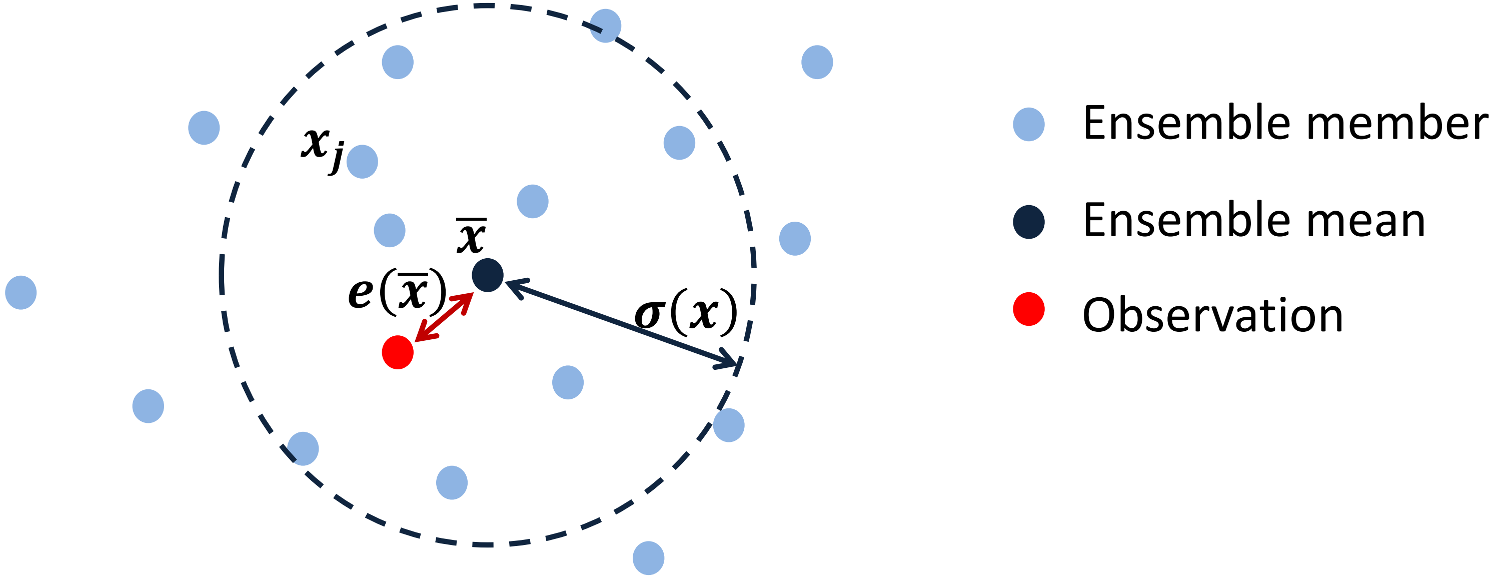
Ensemble reliability

- In an **over**-dispersive ensemble,

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



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

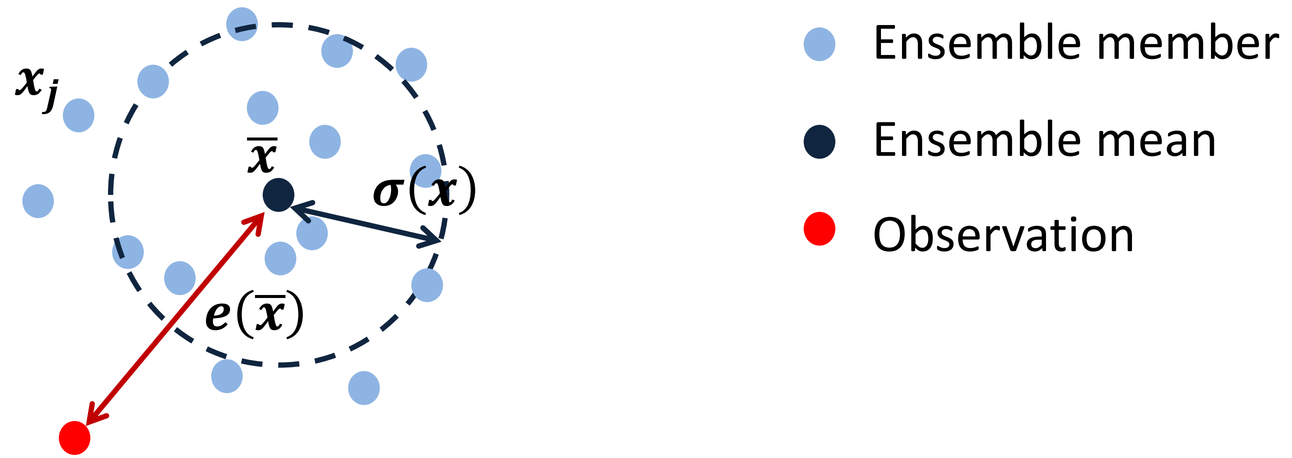
The relatively large spread implies large uncertainty and hence, likely large error:

an “under-confident forecast”

Ensemble reliability

- In an **under**-dispersive ensemble,

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



The small spread implies low uncertainty and hence, small errors:

an “over-confident forecast”

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

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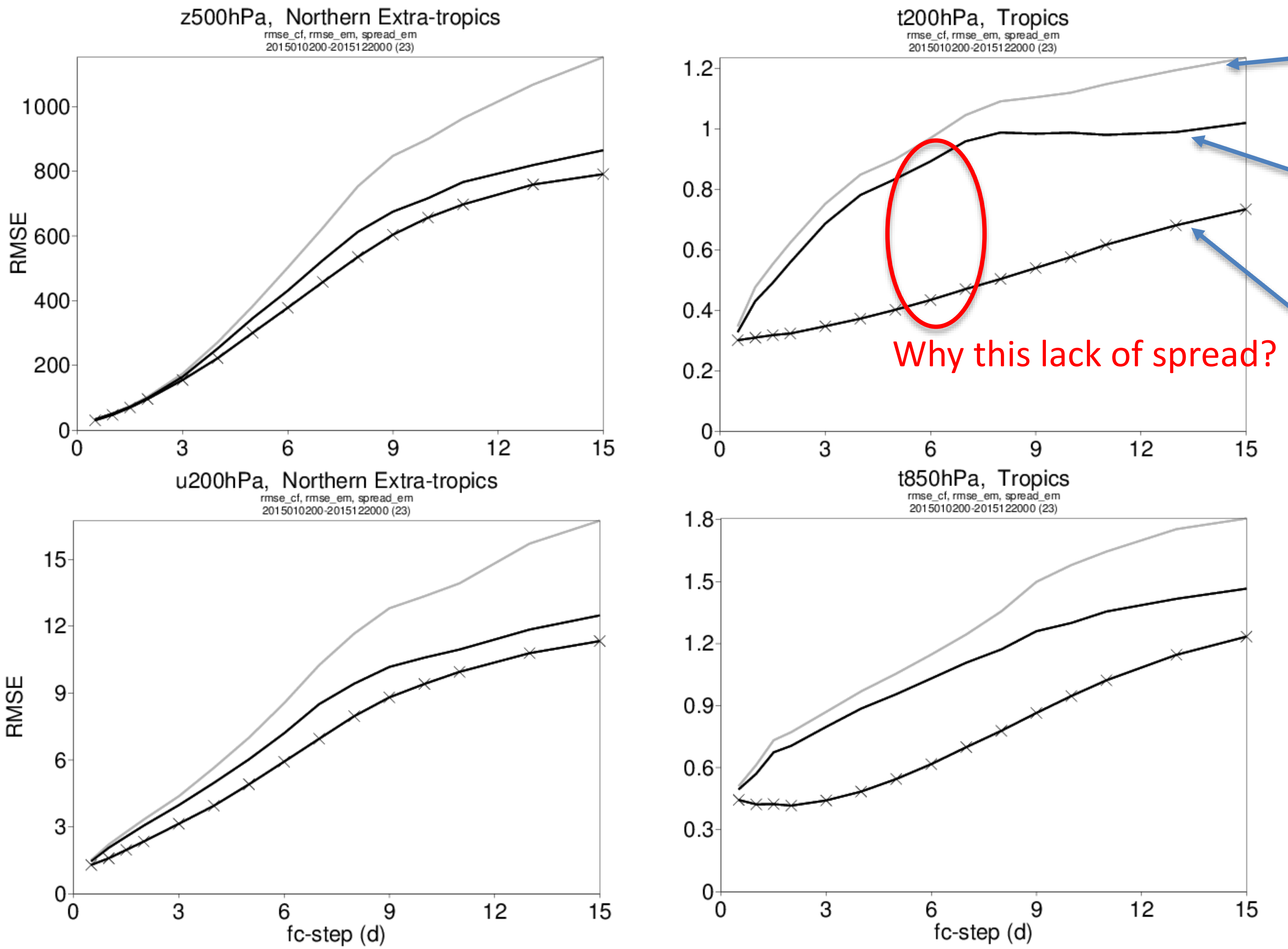
Ensemble forecasts with only initial conditions perturbations

Ensemble mean RMSE (“Error”) & standard deviation (“Spread”)



RMSE unperturbed fc

RMSE ensemble mean

RMS ensemble variance

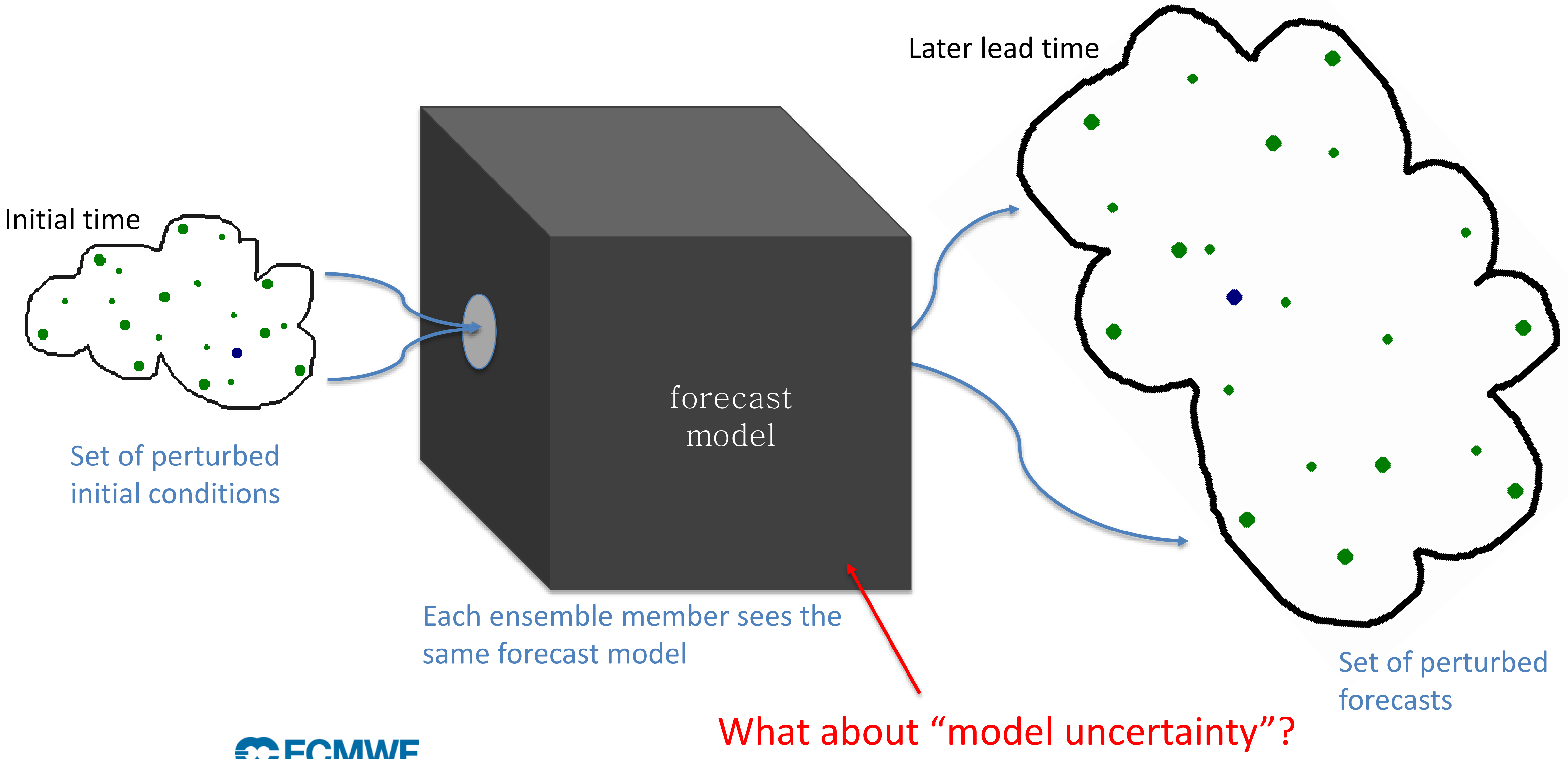
CY43R1

TCo399, dt=900s,

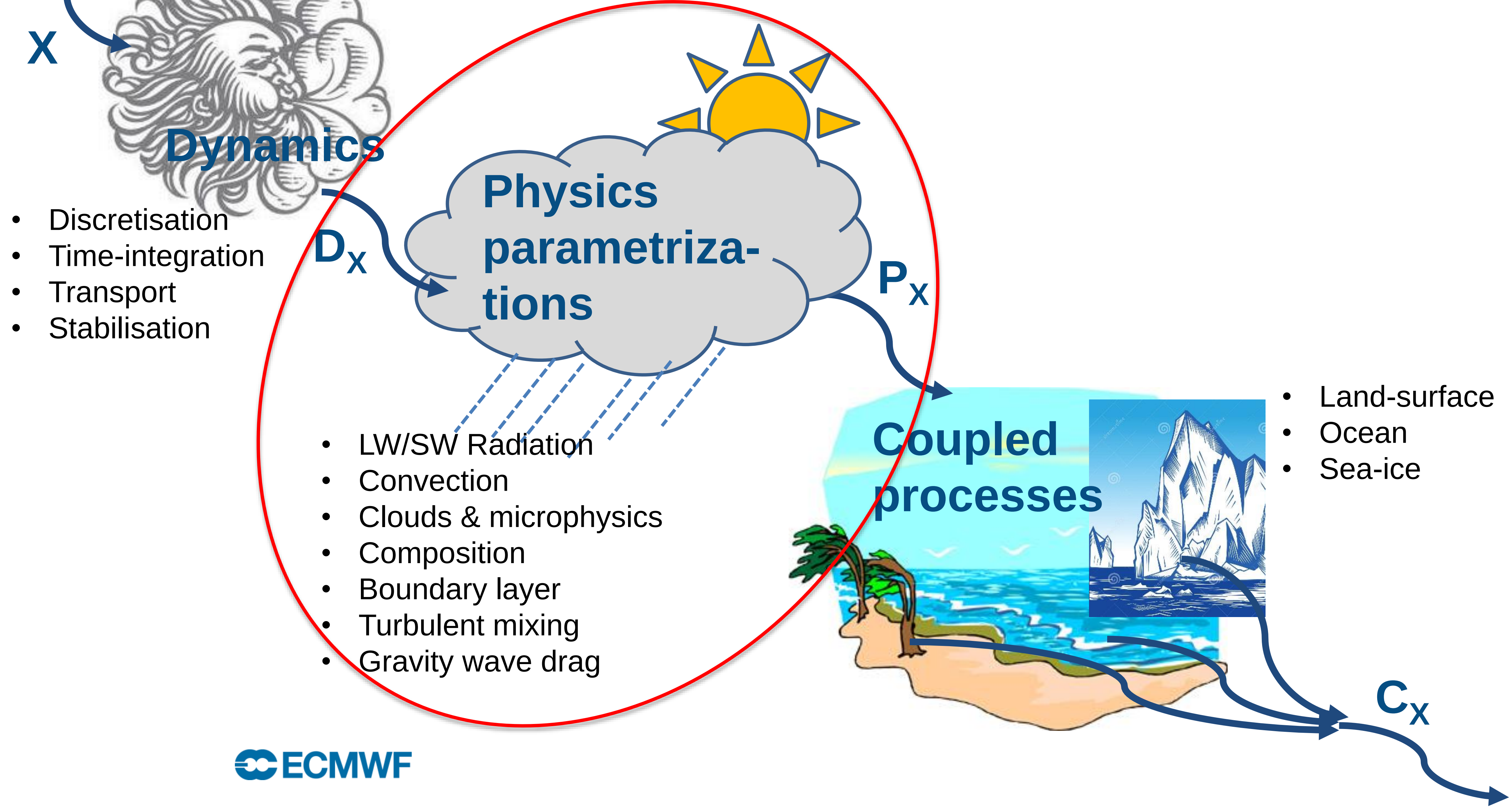
23 dates (2015),

20 perturbed fcs

Sources of uncertainty: initial conditions



Sources of uncertainty: inside the forecast model?



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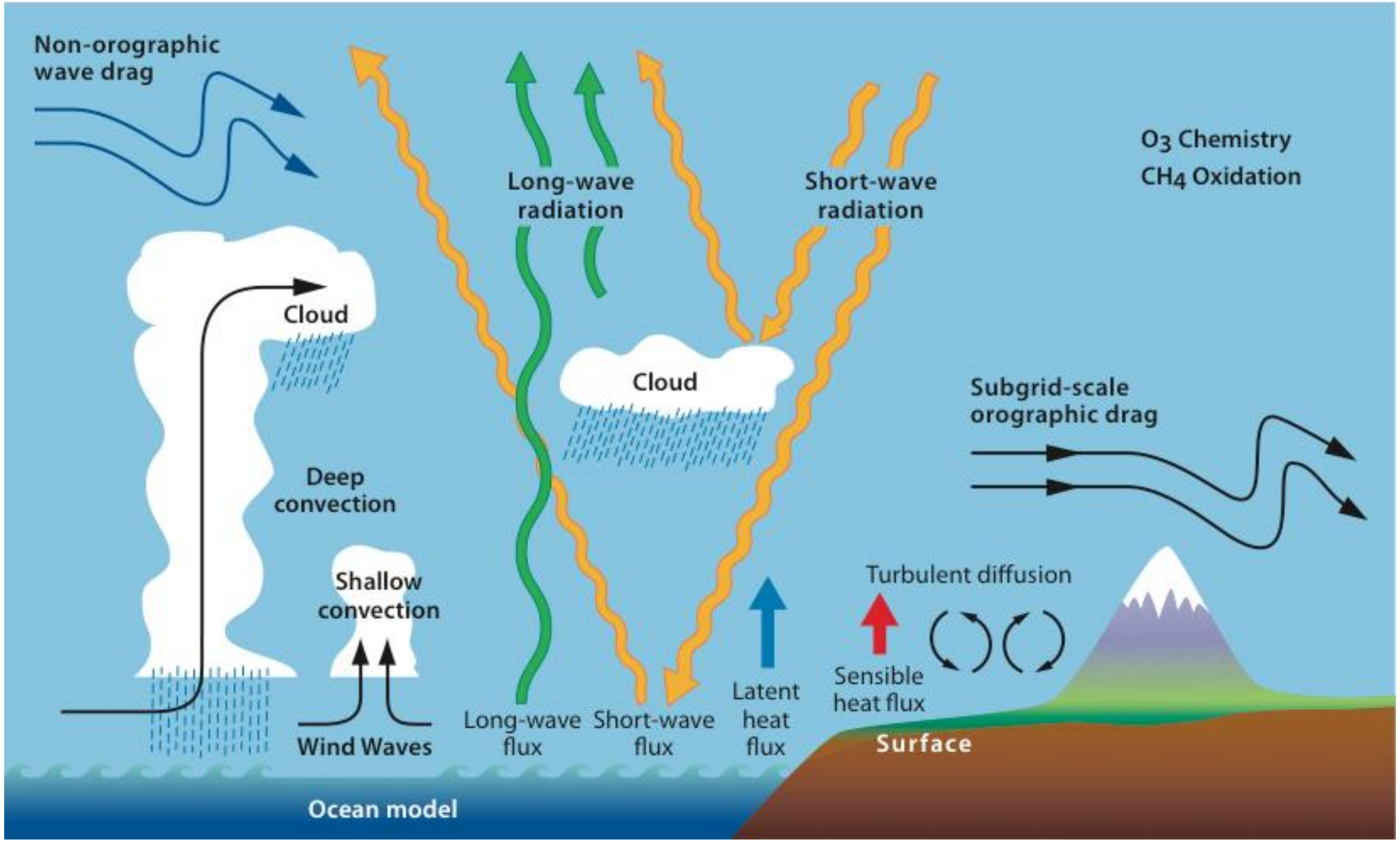
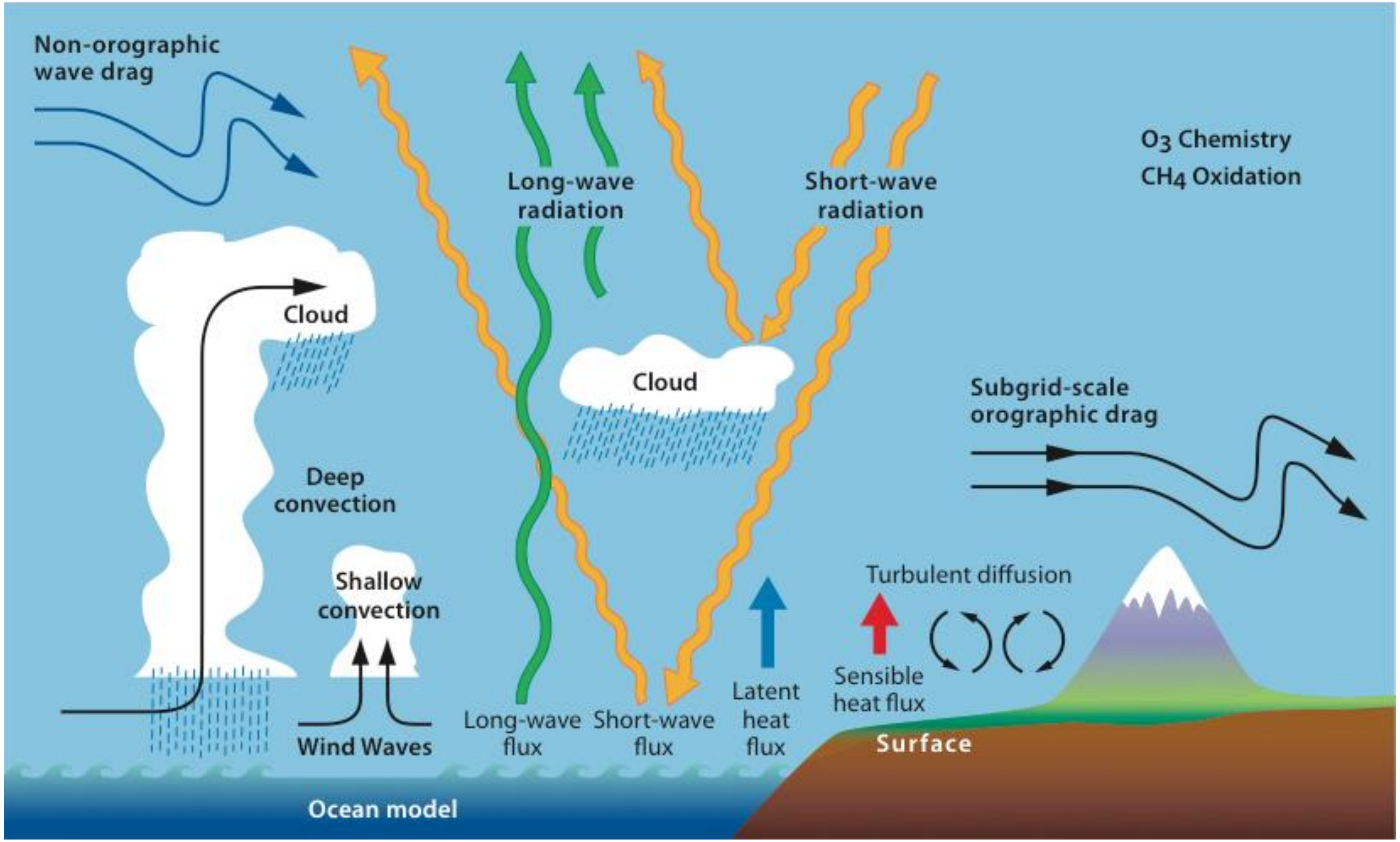
Model uncertainty: parametrized atmospheric physics processes



Uncertainties arise due to:

- Inability to resolve sub-grid scales, e.g.
  - Surface drag (orography/waves)
  - Convection rates (occurrence / en/detrainment)
  - Phase transitions
  - Radiation transfer in cloudy skies
- Poorly constrained parameters, e.g.
  - Vertical cloud-overlap (radiation)
  - Composition
  - Non-orographic drag

Model uncertainty: parametrized atmospheric physics processes



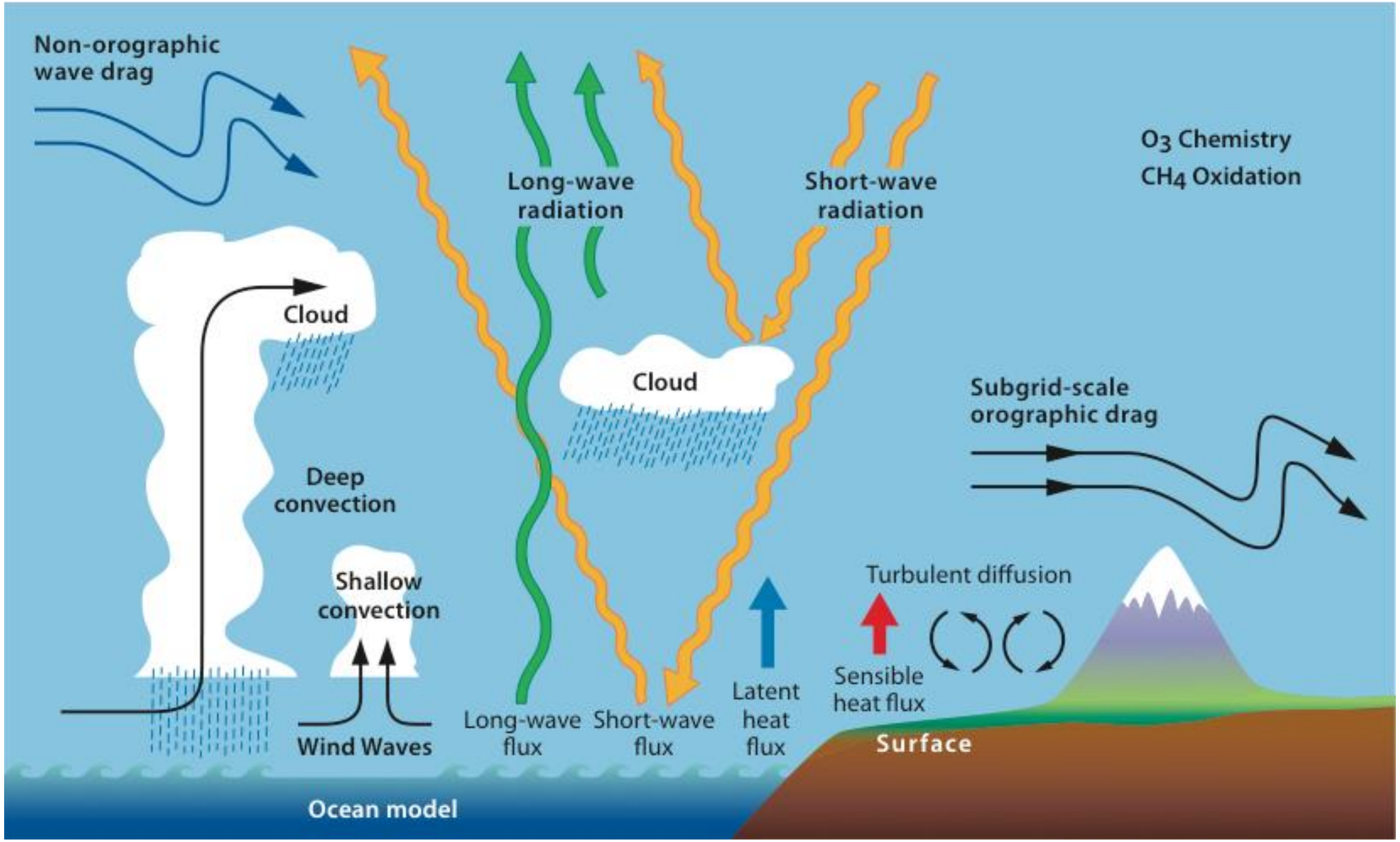
"Don't throw the baby out with the bath water!"

Parametrisation schemes:

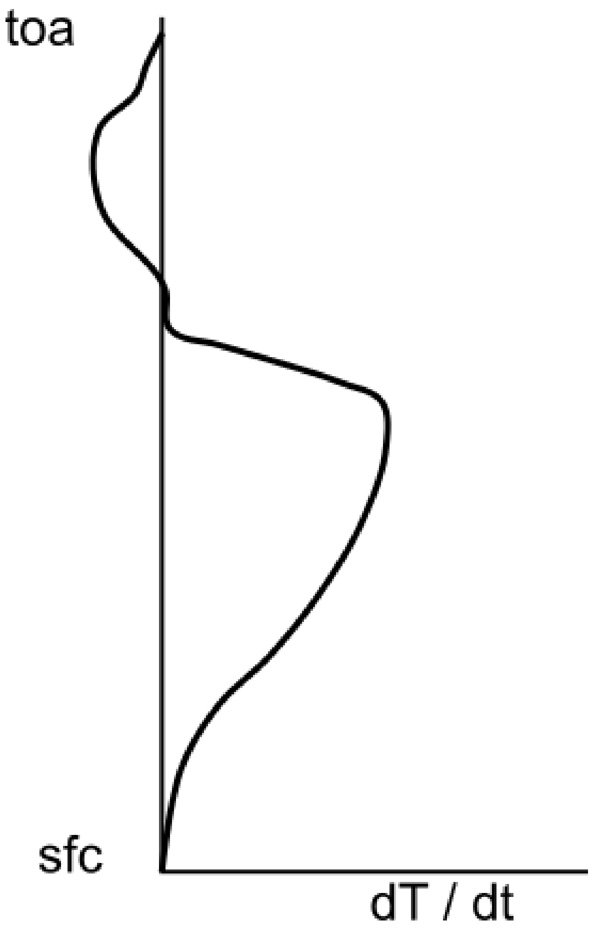
- developed/operate together
- highly tuned for best performance

Seek a description of uncertainty that retains consistencies of the representation of the physical processes.

Model uncertainty: parametrized atmospheric physics processes



e.g. profile of heating rates from physics parametrisations:



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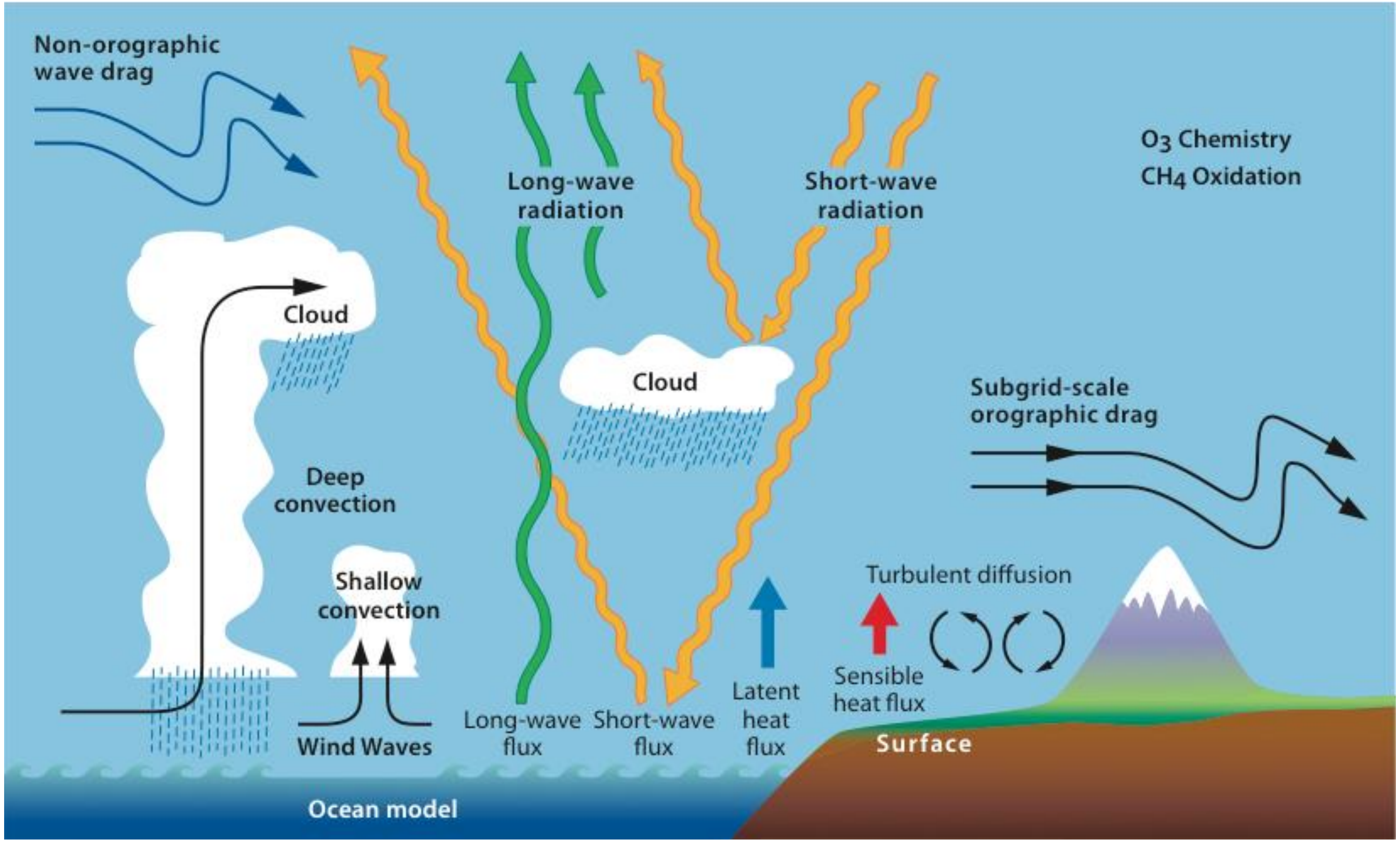
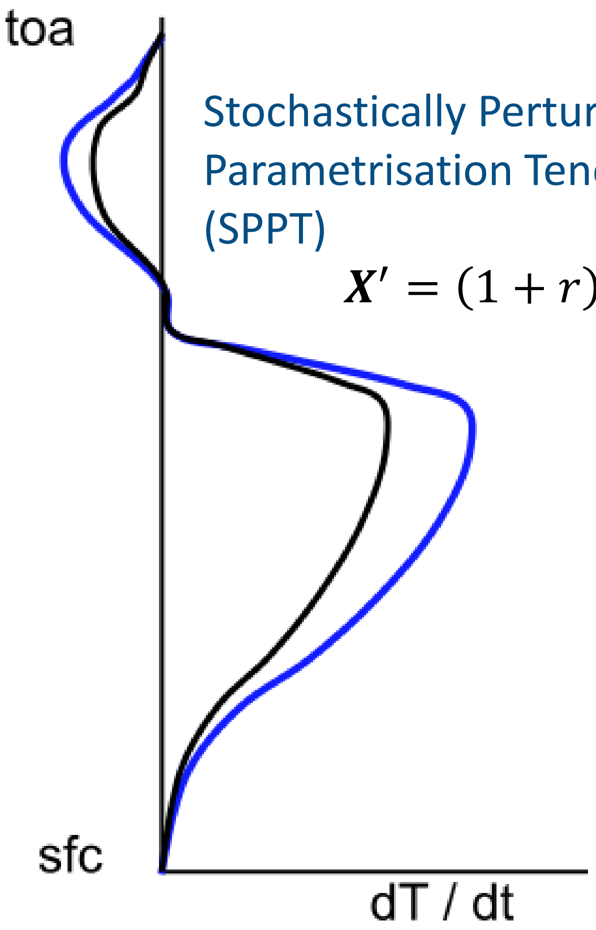
Model uncertainty: parametrized atmospheric physics processes



Proposal: represent uncertainties with a perturbation proportional to the profile of net physics tendencies



Stochastically Perturbed Parametrisation Tendencies (SPPT)

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

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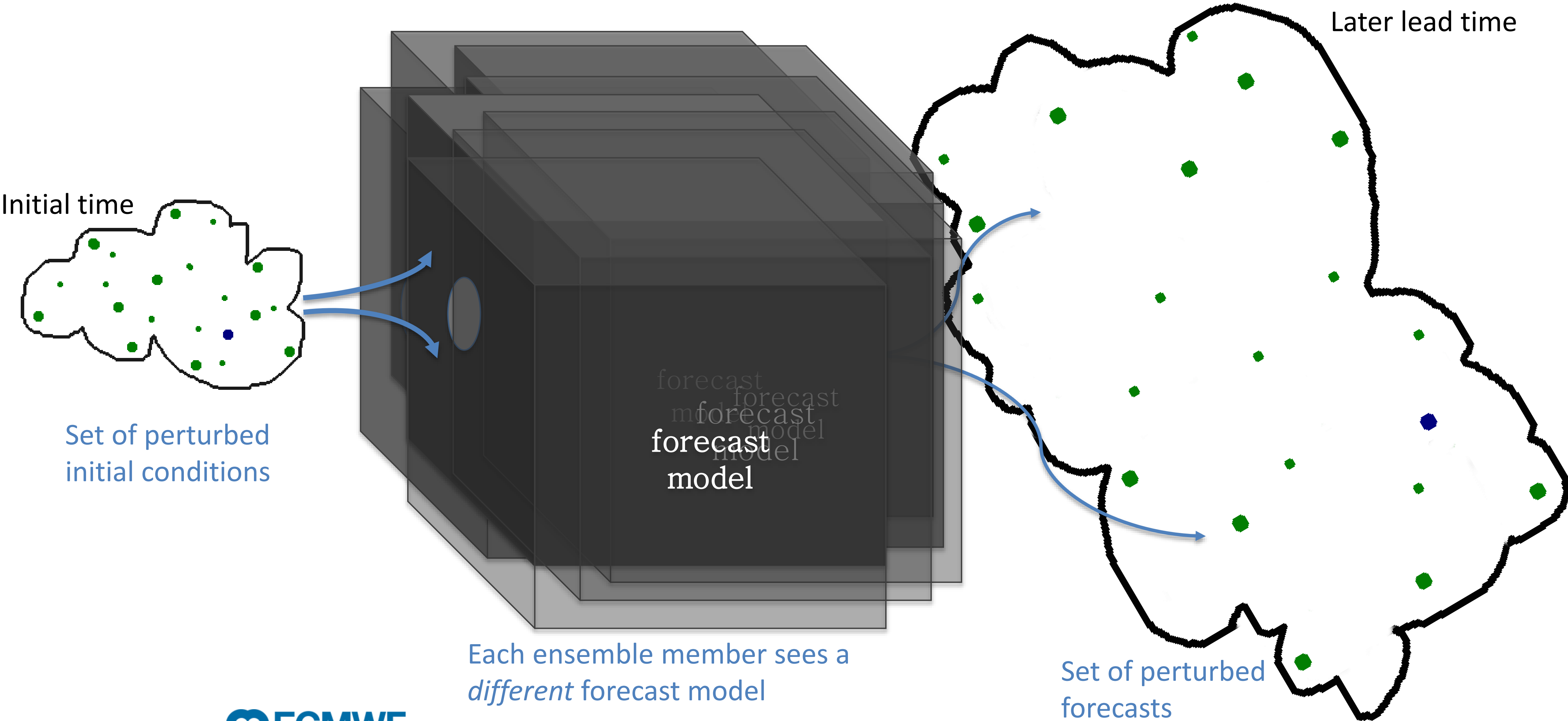
Sources of uncertainty: accounting for model uncertainty



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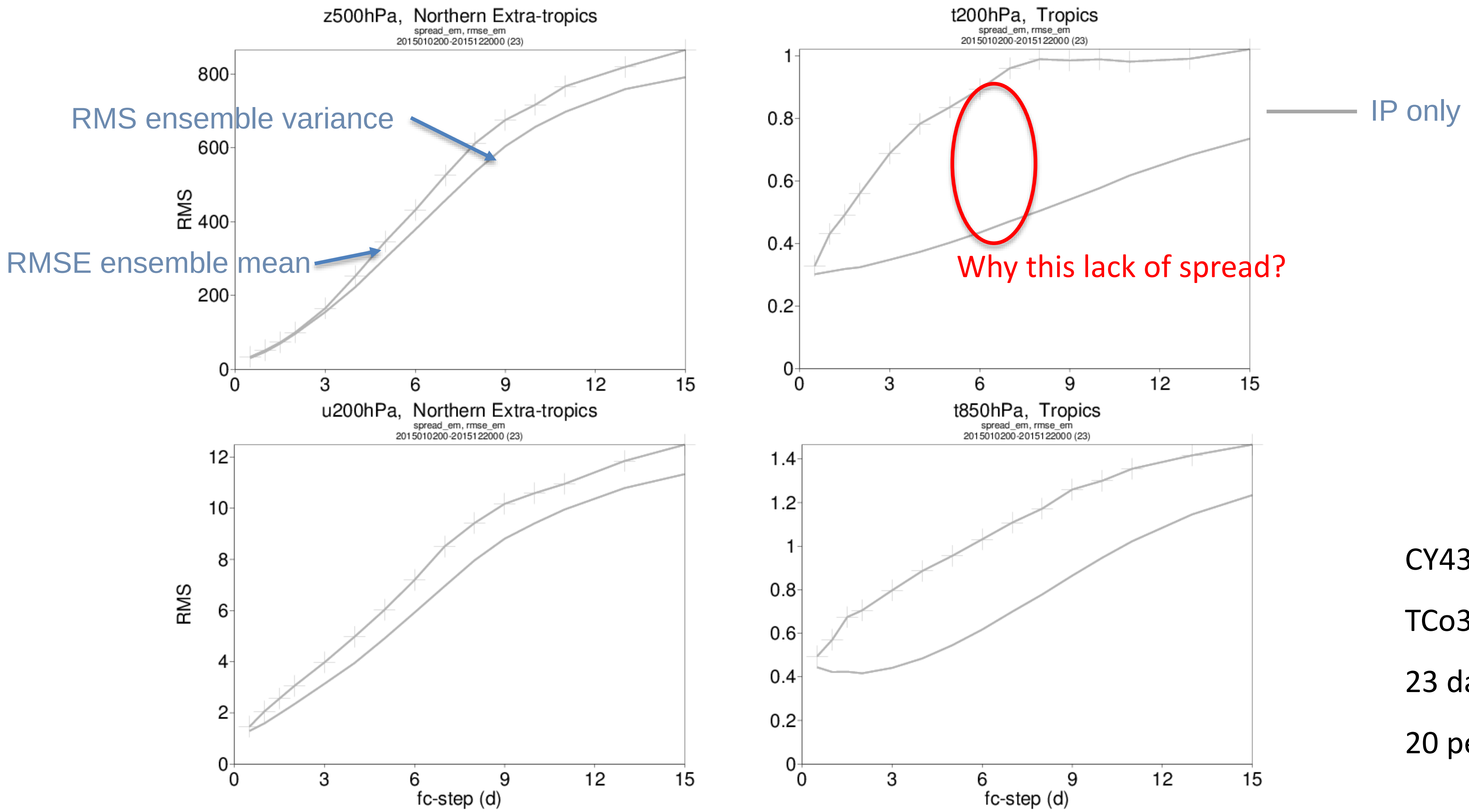
Recall: Ensemble forecasts: with initial conditions perturbations (IP) only

Ensemble mean RMSE ("Error") & standard deviation ("Spread")



CY43R1

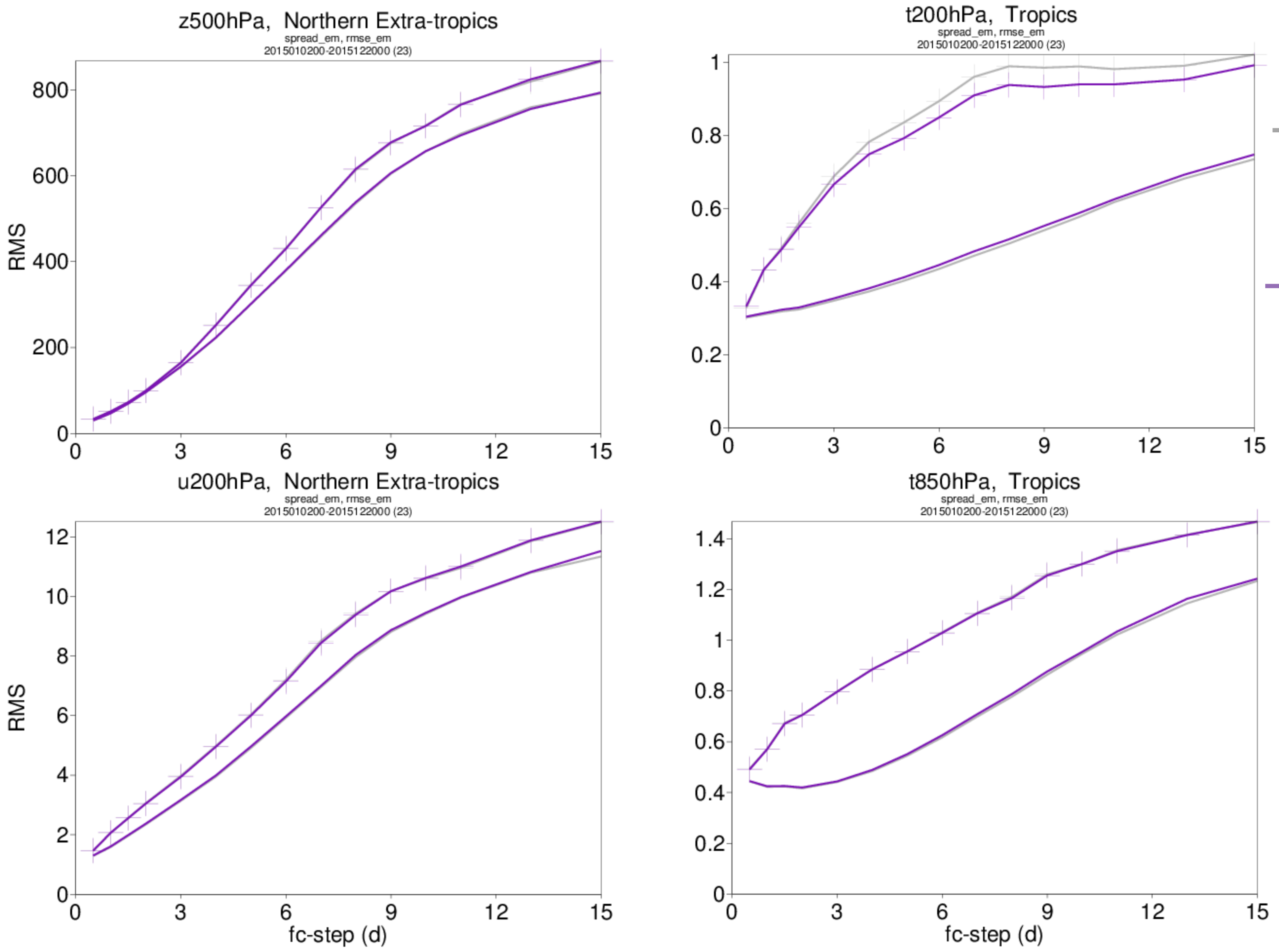
TCo399, dt=900s,

23 dates (2015),

20 perturbed fcs

Ensemble forecasts: with **grid-scale** model uncertainty perturbations (SPPT)

Ensemble mean RMSE (“Error”) & standard deviation (“Spread”)



IP only

IP + SPPT*
(*white noise
wrt time/horizontal)

Uncorrelated noise yields little benefit

CY43R1

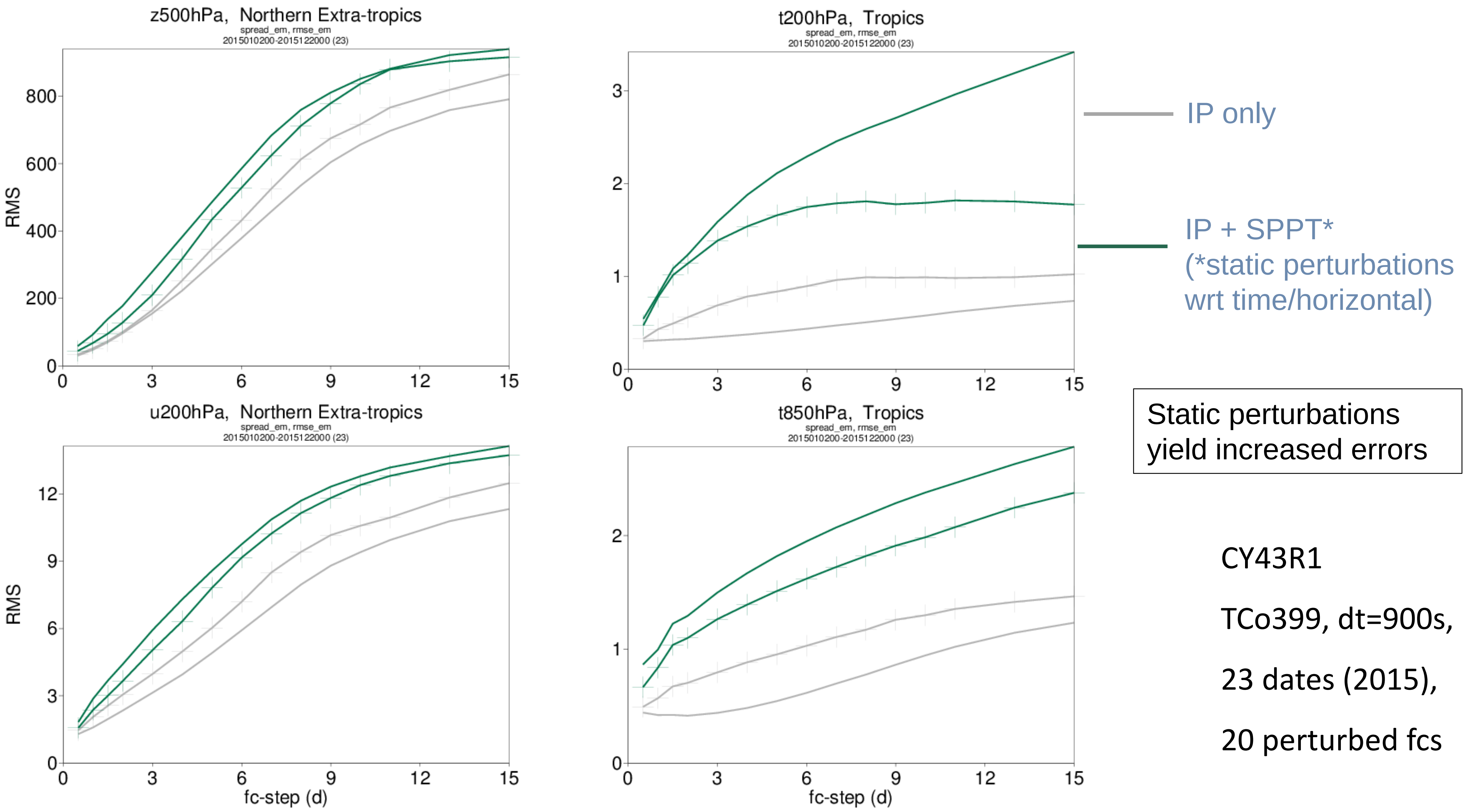
TCo399, dt=900s,

23 dates (2015),

20 perturbed fcs

Ensemble forecasts: with **static** model uncertainty perturbations (SPPT)

Ensemble mean RMSE (“Error”) & standard deviation (“Spread”)



Static perturbations yield increased errors

CY43R1

TCo399, dt=900s,

23 dates (2015),

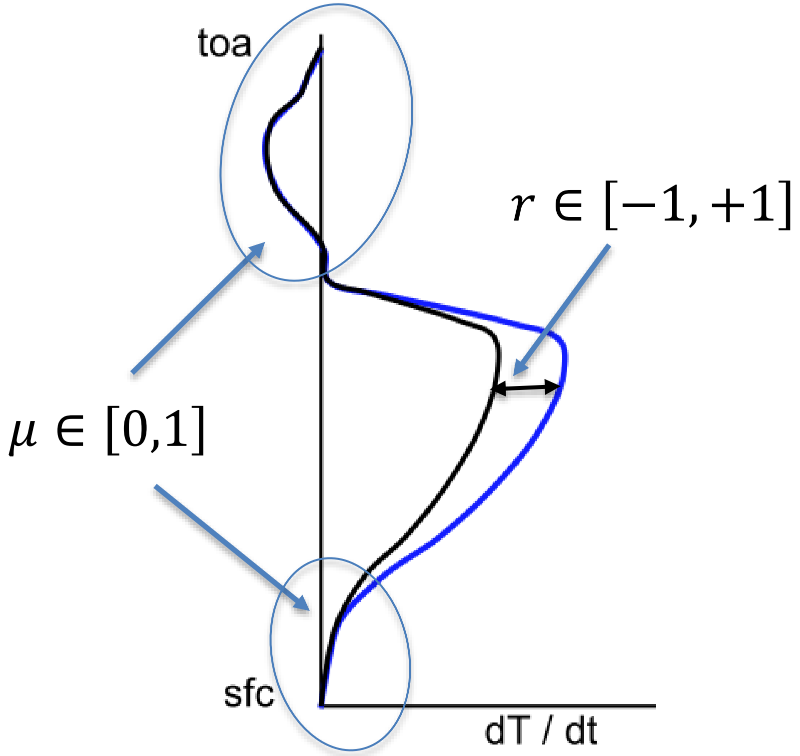
20 perturbed fcs

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:

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

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 random 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 around the globe) for each wavenumber

define ρ for random numbers, η

- Resulting pattern mapped into grid-point space r:

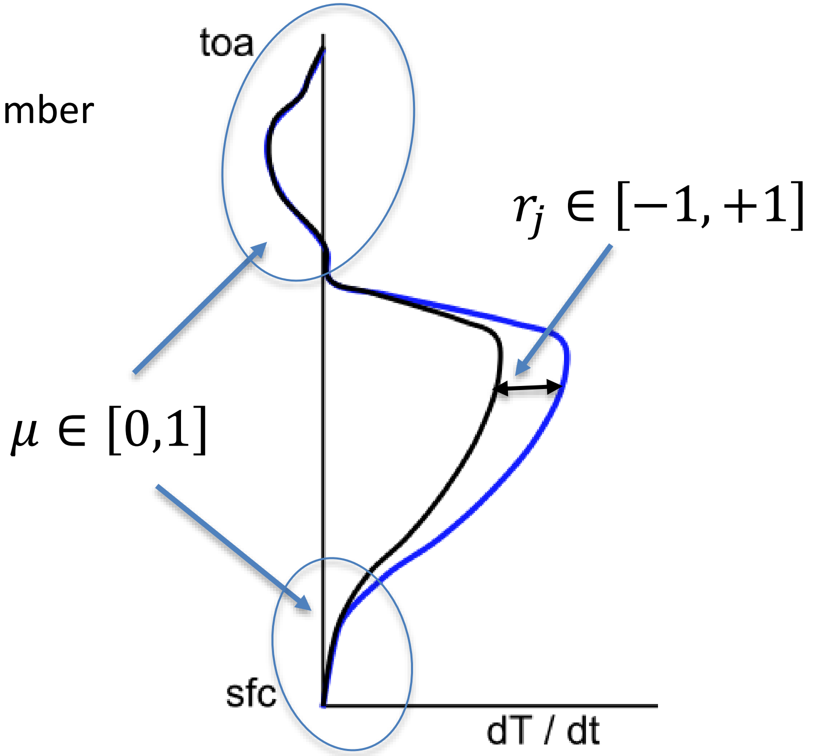
– clipped such that $r \in [-1,+1]$

– 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:

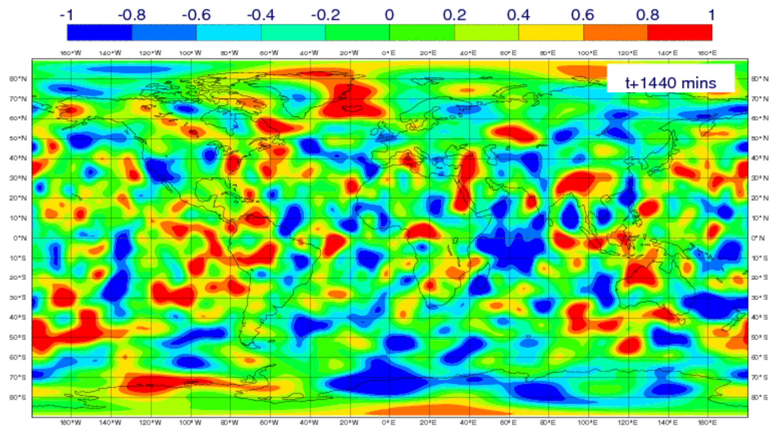
  - instabilities due to perturbations in the boundary layer;
  - perturbing stratospheric tendencies dominated by well-constrained clear-skies radiation



SPPT random pattern

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

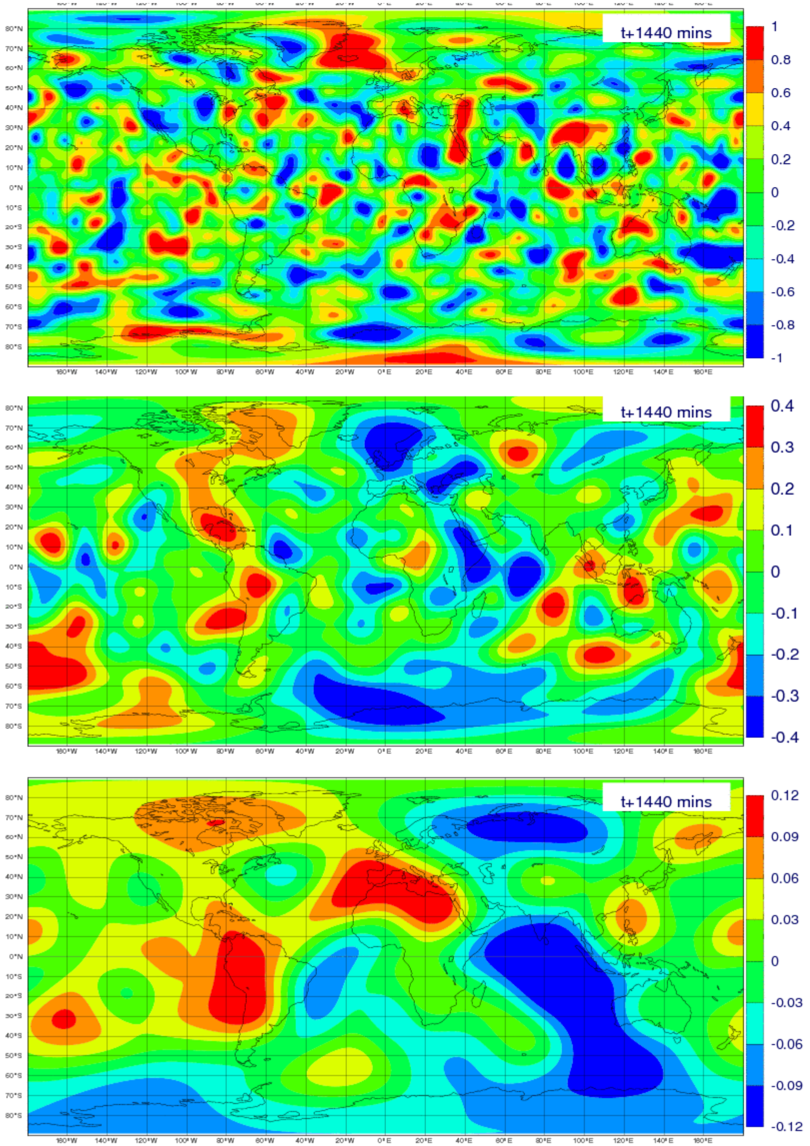
  ***Except*: tapered to zero at model top/bottom

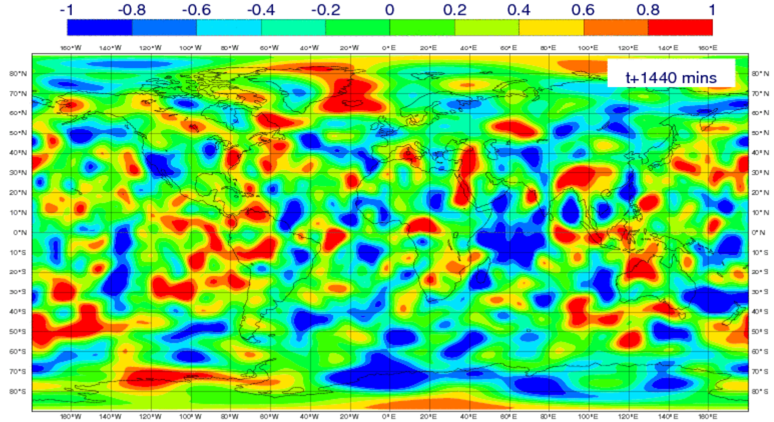


3 correlation scales:

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 random pattern



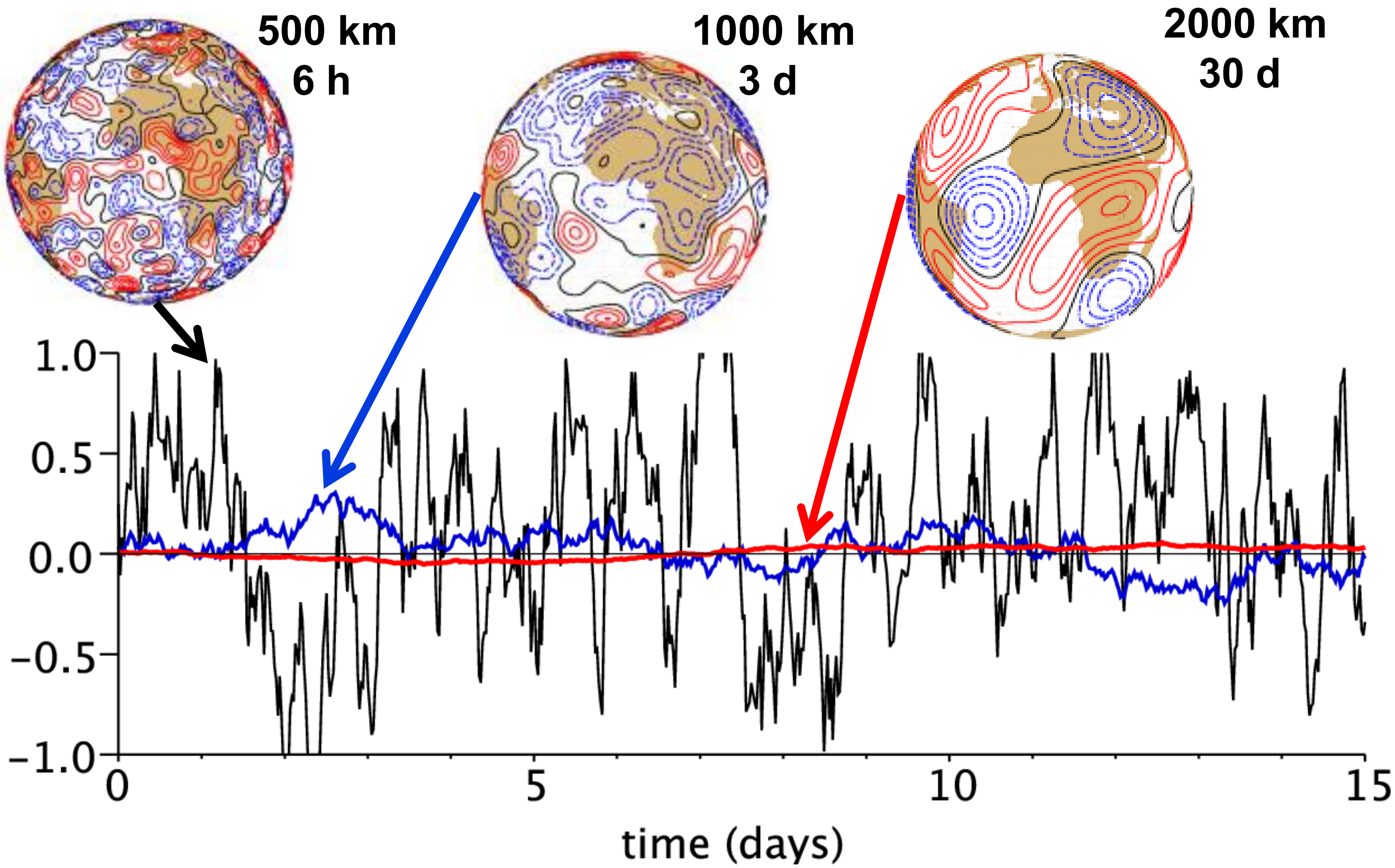


3 correlation scales:

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

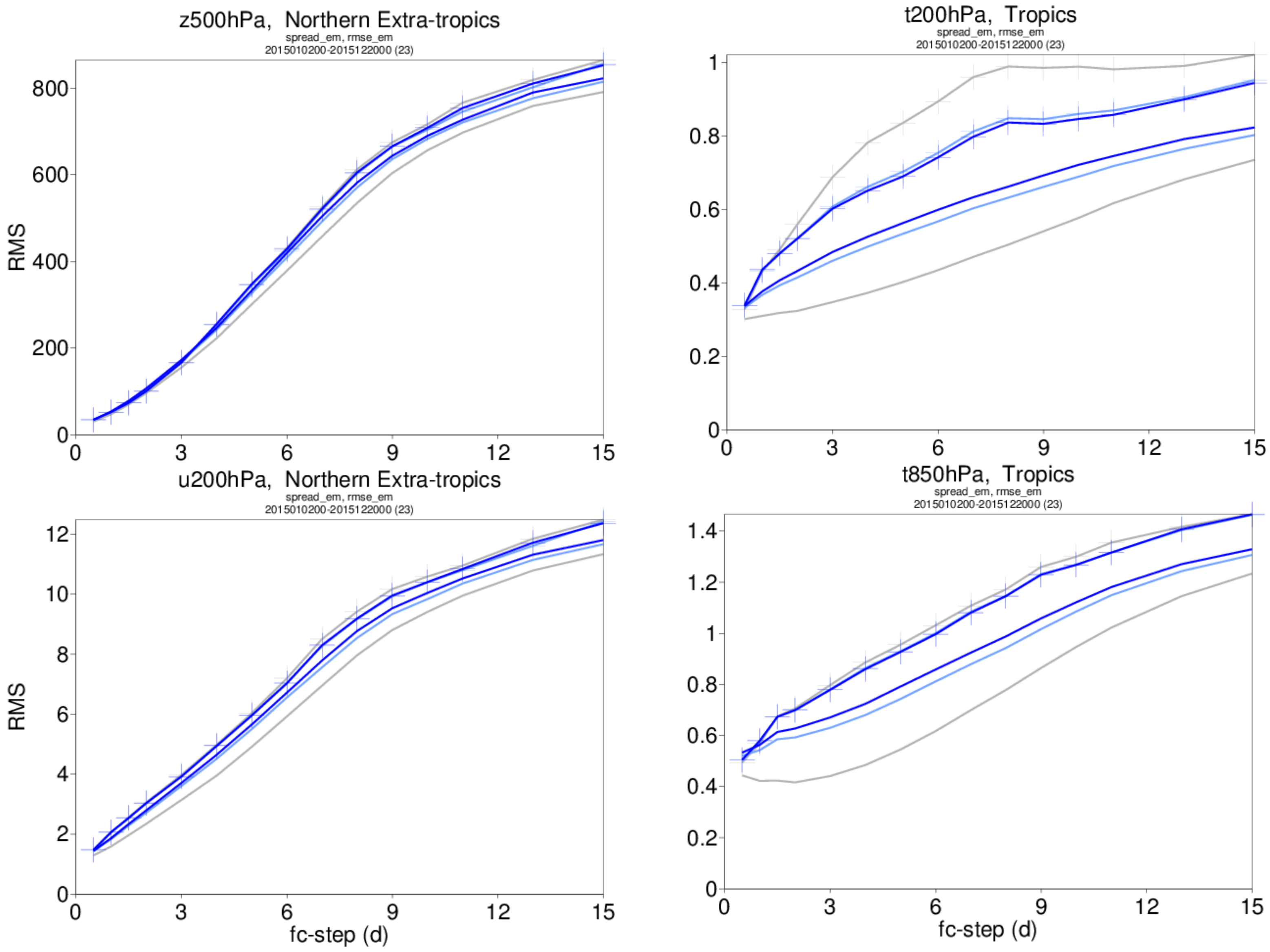
(Note different colour scales)

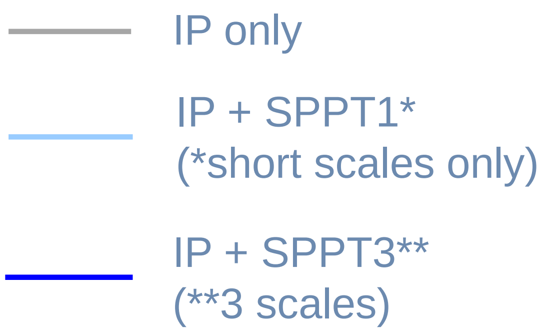
SPPT random pattern



Ensemble forecasts: with **multi-scale** model uncertainty perturbations (SPPT)

Ensemble mean RMSE ("Error") & standard deviation ("Spread")





Some additional spread from SPPT3 – notably in the tropics

CY43R1

TCo399, dt=900s,

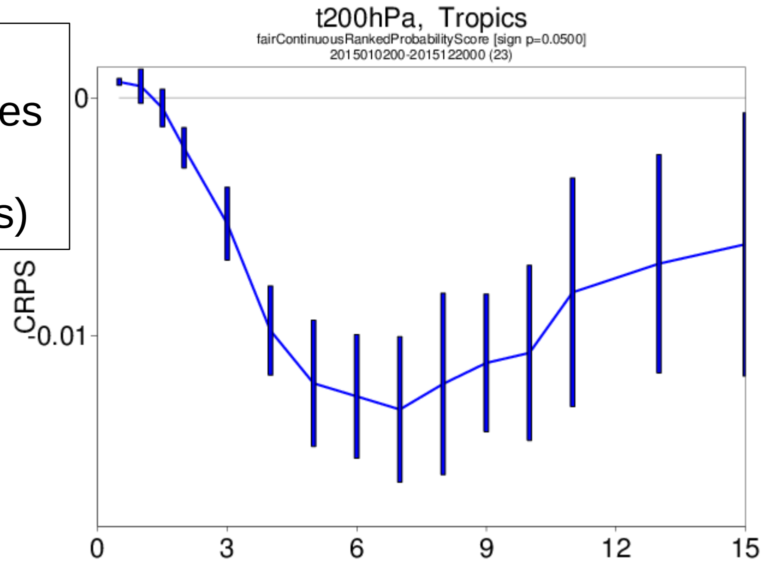
23 dates (2015),

20 perturbed fcs

Ensemble forecasts: with **multi-scale** model uncertainty perturbations (SPPT)

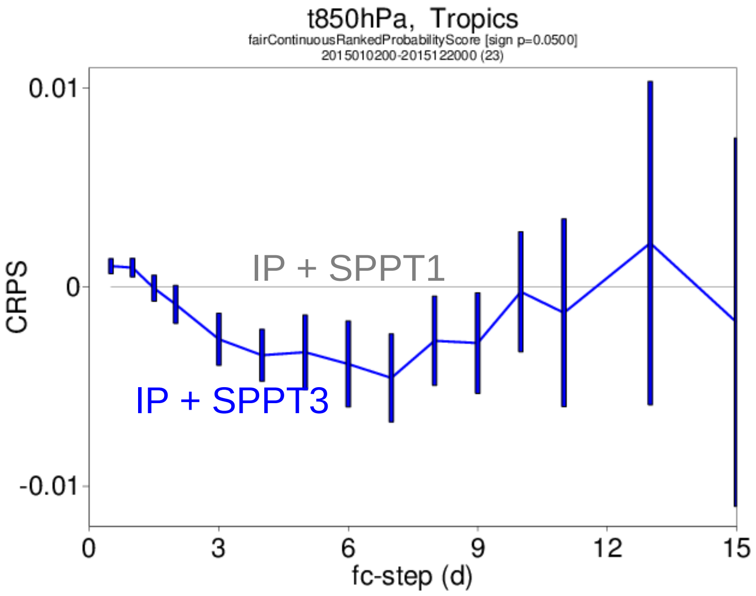
Probabilistic skill (CRPS)

Improved probabilistic scores from SPPT3 (notably in tropics)

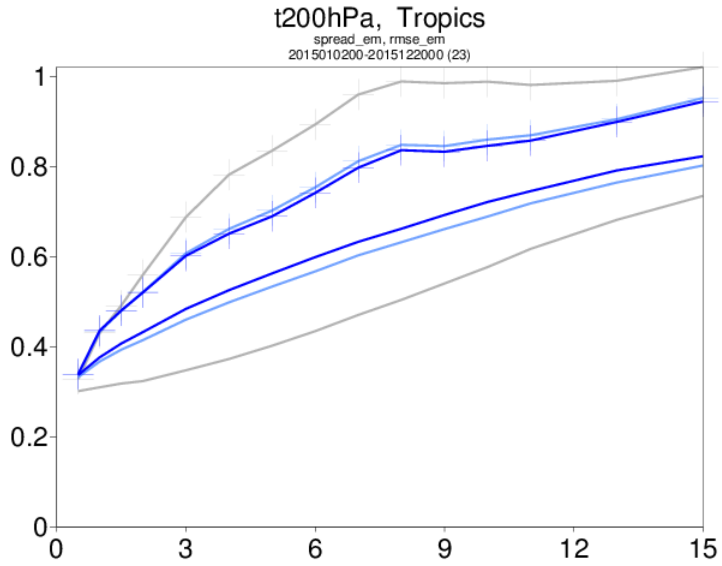


+ve = worse

-ve = better



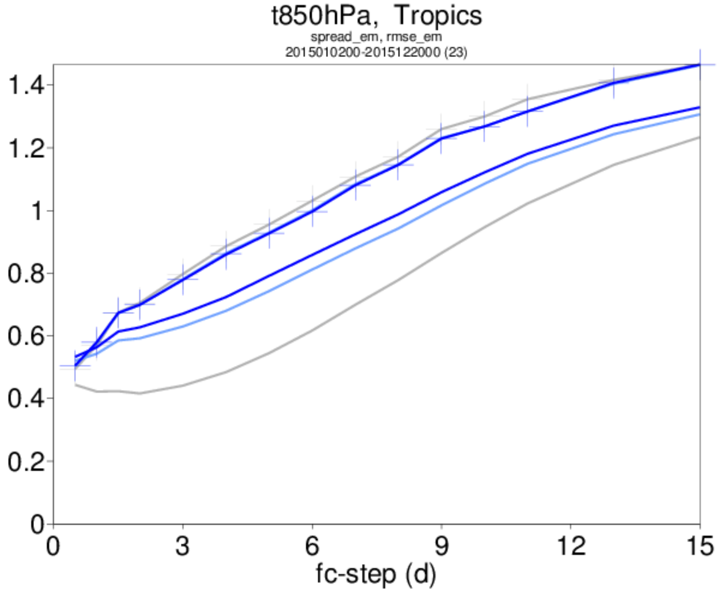
Error & Spread



IP only

IP + SPPT1* (*short scales only)

IP + SPPT3** (**3 scales)



Some additional spread from SPPT3 – notably in the tropics

CY43R1

TCo399, dt=900s,

23 dates (2015),

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Stochastic representations of model uncertainty in IFS

IFS ensemble forecasts (ENS and SEAS) include 2 model uncertainty schemes:

1. Stochastically perturbed parametrisation tendencies (**SPPT**) scheme
    - SPPT scheme: simulates model uncertainty due to sub-grid parametrisations
2. Stochastic kinetic energy backscatter (**SKEB**) scheme
    - SKEB scheme: aims to parametrise a missing process
        - upscale transfer of KE from sub-grid scales to resolved scales
        - real atmosphere exhibits upscale propagation of kinetic energy (KE)
        - occurs at ALL scales: no concept of “resolved” and “unresolved” scales

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 perturbations

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

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

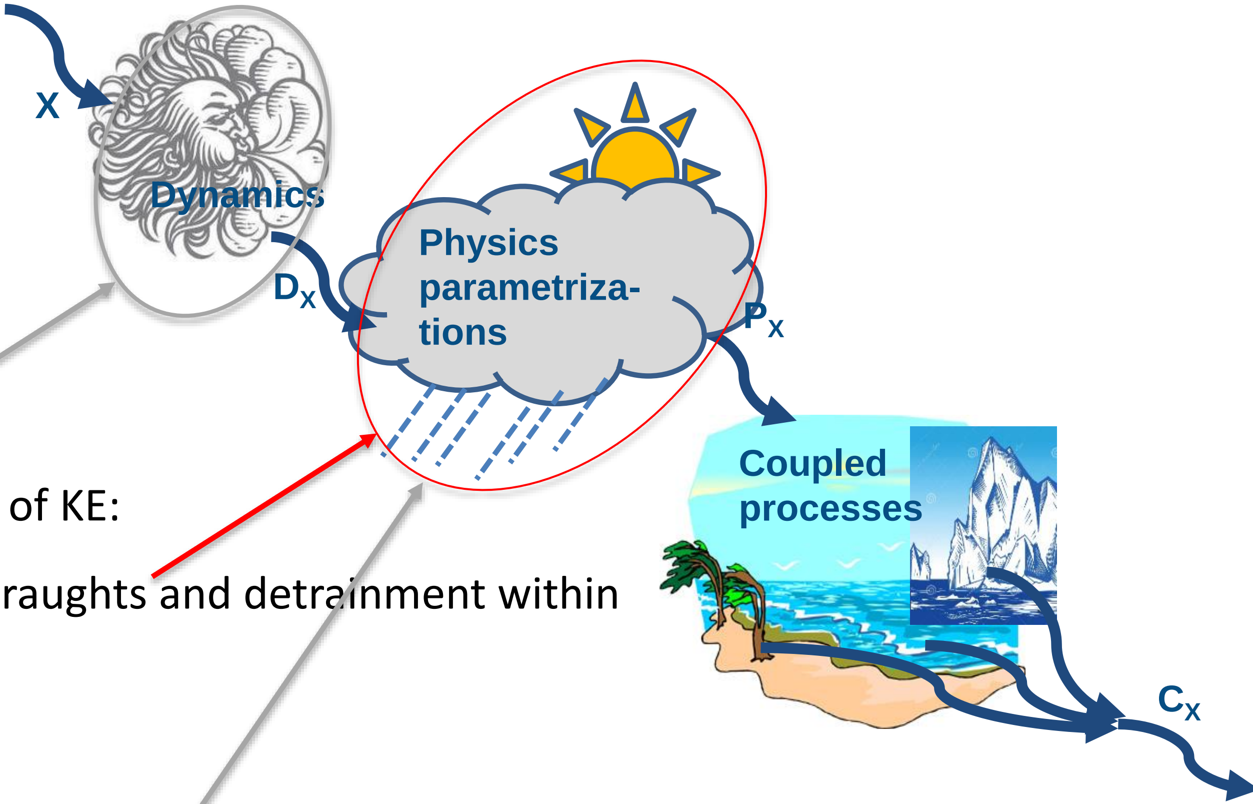
$$F^*(t+\Delta t) = \phi F^*(t) + \rho\eta(t)$$

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:

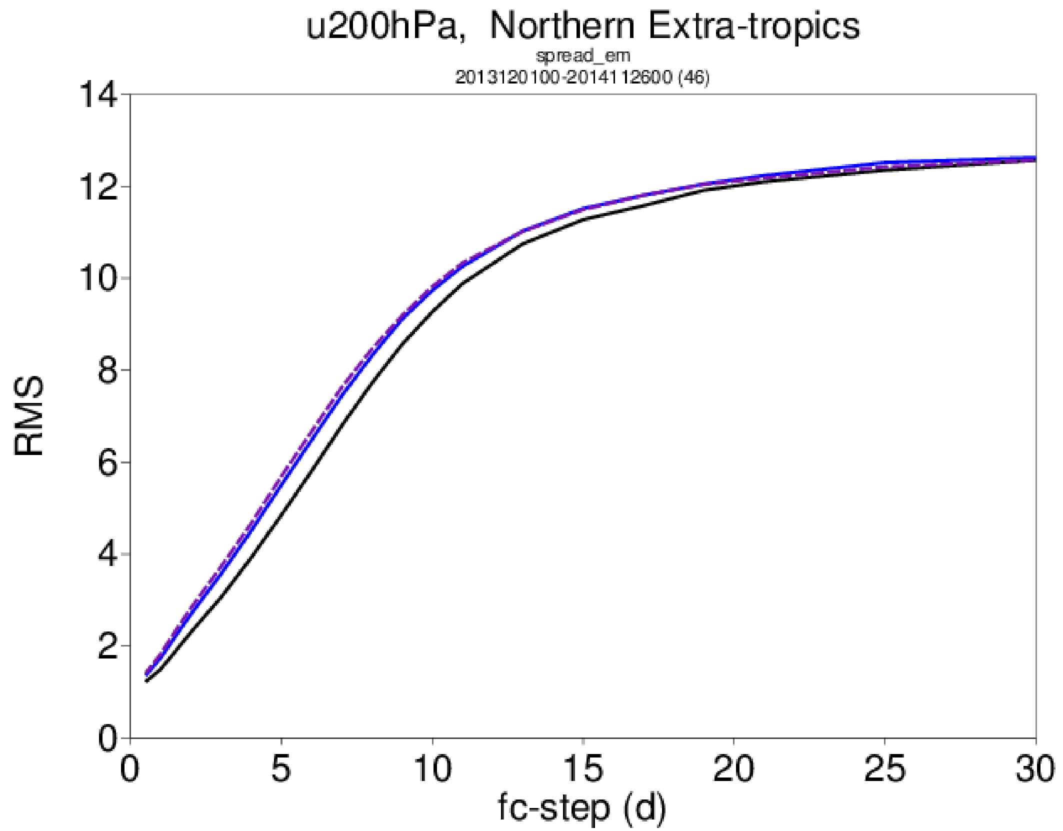
1. D_{con} = estimated KE generated by updraughts and detrainment within sub-grid deep convection

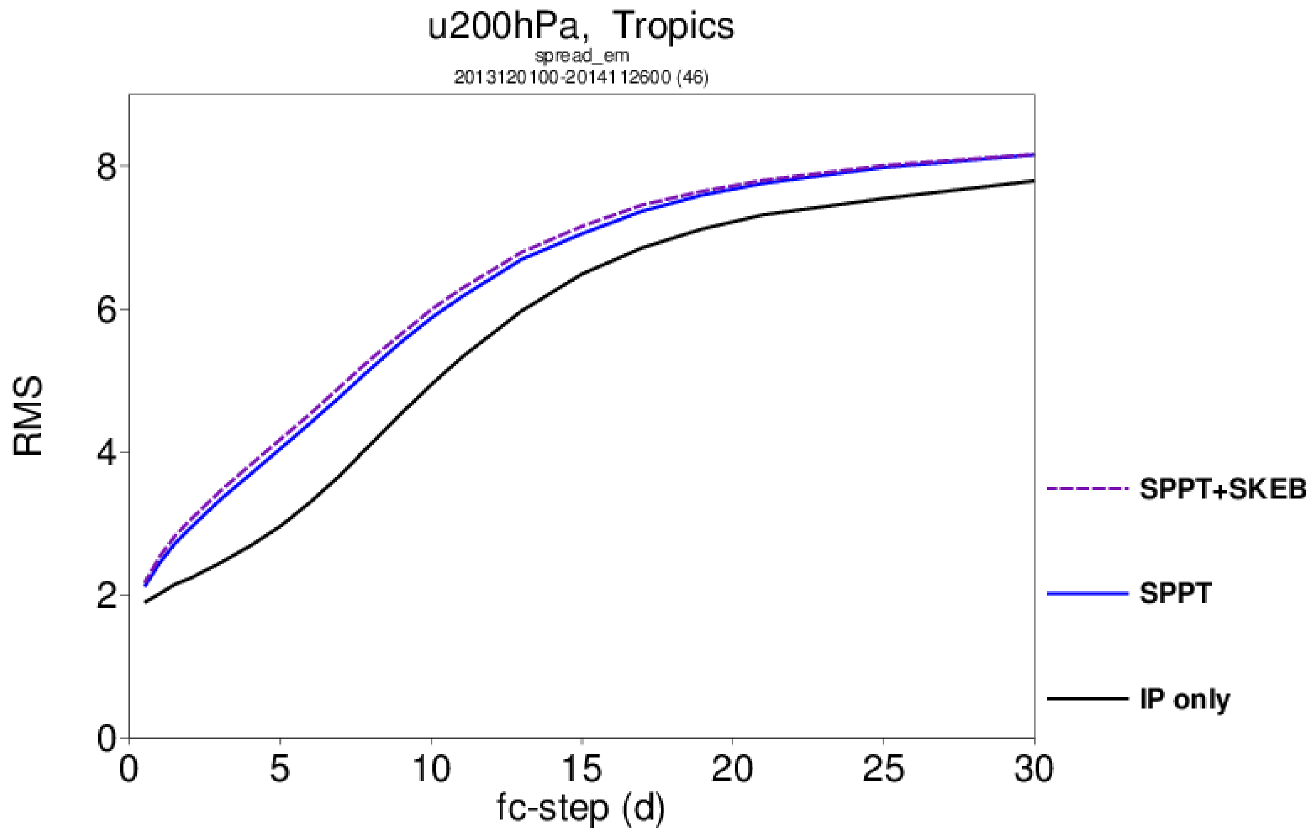
(and in earlier IFS configurations)

2. D_{num} = numerical dissipation from
   - explicit horizontal diffusion (bi-harmonic, ∇^2); and
   - estimate due to semi-Lagrangian interpolation error
3. D_{OGWD} = dissipation due to orographic GWD

Ensemble forecasts: SPPT & SKEB

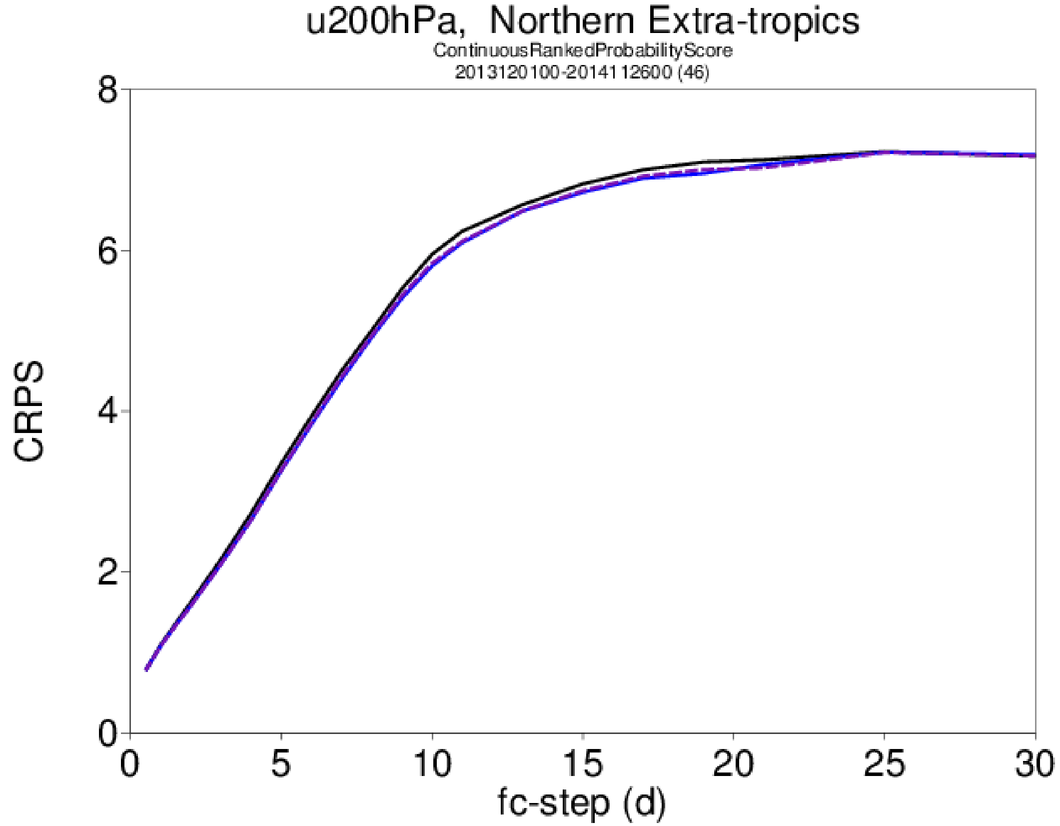
Ensemble standard deviation ("Spread")

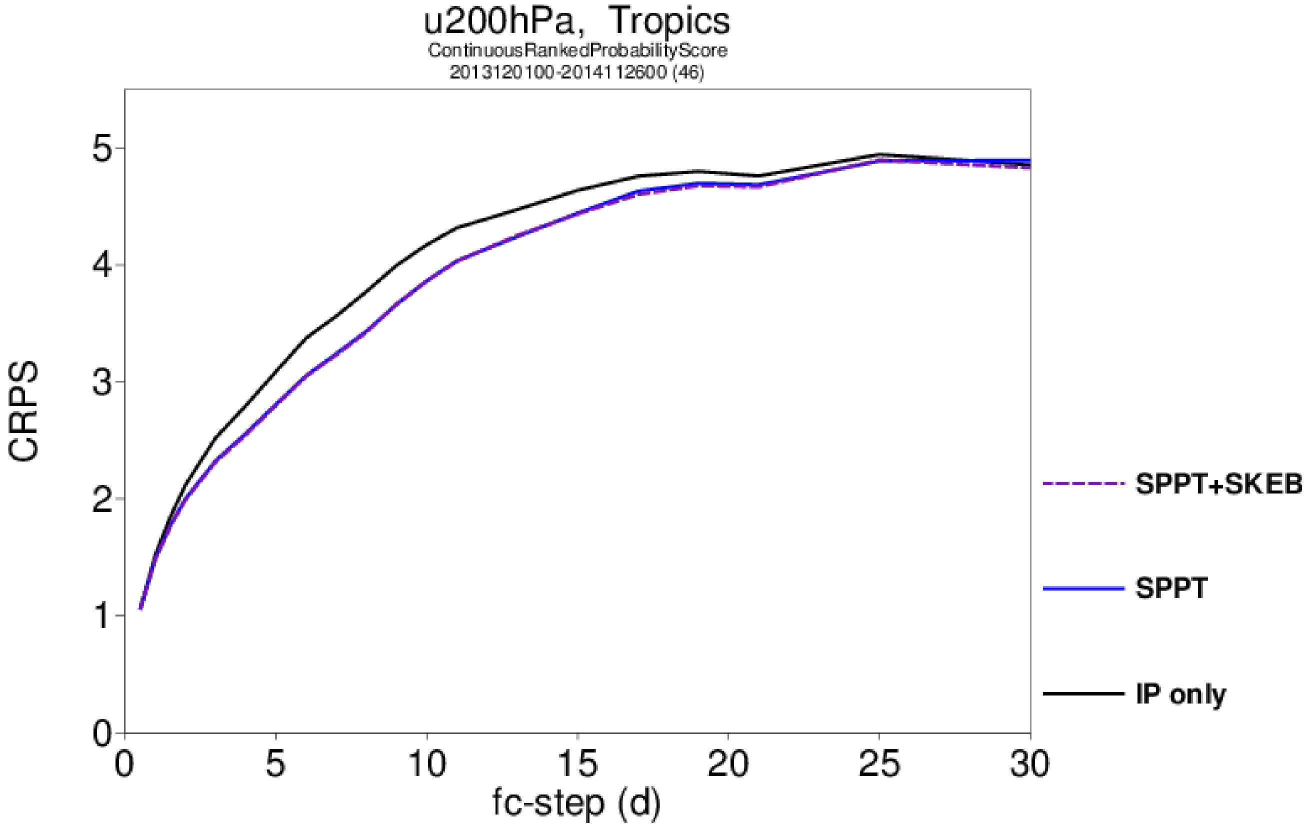




Ensemble forecasts: SPPT & SKEB

Probabilistic skill (CRPS)





Future IFS development: likely that we remove SKEB (cost versus skill improvement)

How are the perturbation patterns determined?

- Characteristics of errors due to model uncertainty are difficult determine:
  - uncertain processes are typically small-scale (space and time)
  - requires verification against high-resolution (space/time) observations (e.g. satellite)

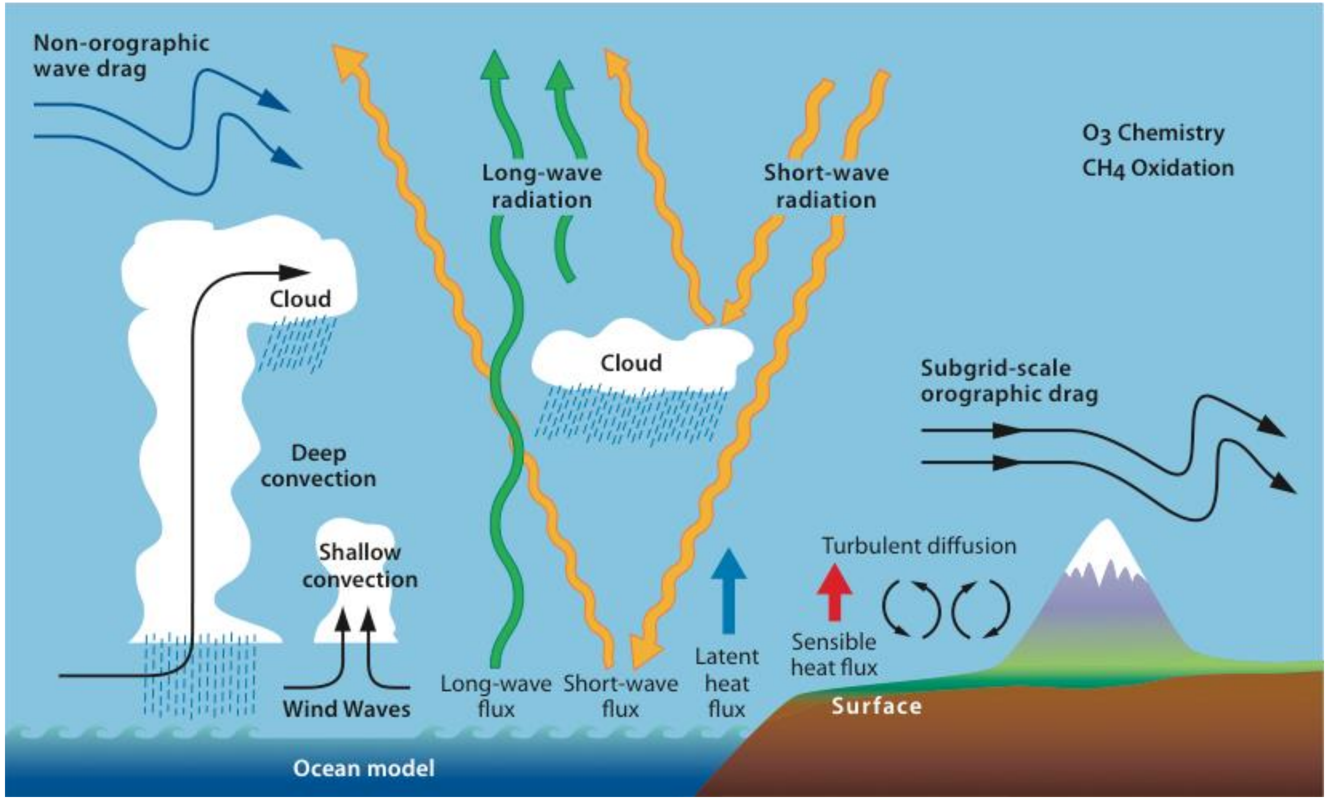
- Can attempt to use models: **coarse-graining** studies (e.g. Shutts and Palmer, 2007)
  - take high-resolution model simulation as "truth"
  - average the high-res model fields/tendencies/streamfunction to a grid-resolution typical of the forecast model
  - characterise differences ("errors") between the coarse-grained "truth" and the parametrised forecast model
  - coarse-graining studies were used to justify and inform scales in SPPT and SKEB

Stochastic representation of model uncertainty in IFS

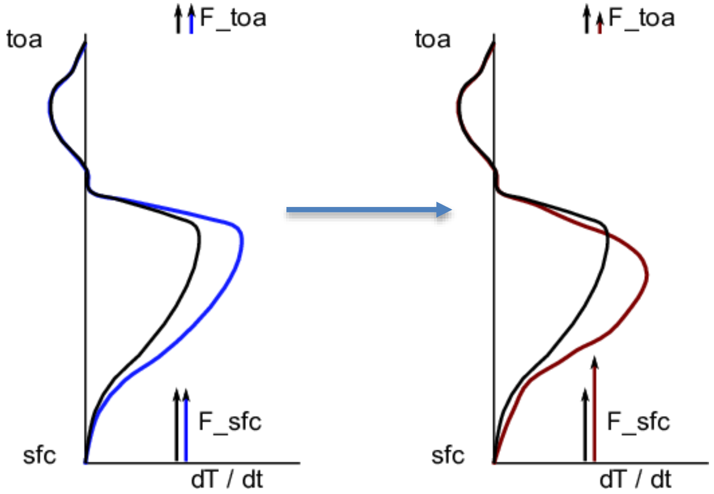
- Errors due to model uncertainty arise from unresolved and misrepresented processes
  - finite-resolution of a discrete numerical model
  - parametrisations use simplified, bulk methods to represent complex, multi-scale sub-grid processes
- Difficult to characterise sources of model uncertainty due to their small scales
- Without representing model uncertainty, ensemble forecasts are under-dispersive => over-confident
- Stochastic representations of model uncertainty improve ensemble reliability
- IFS ensemble forecasts include 2 stochastic schemes:
  - SPPT: represents uncertainty due to sub-grid atmospheric 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 (Weisheimer et al., 2014, Phil. Trans. R. Soc. A)

Stochastic representations of model uncertainty: brief outlook for IFS

Towards process-level model uncertainty representation

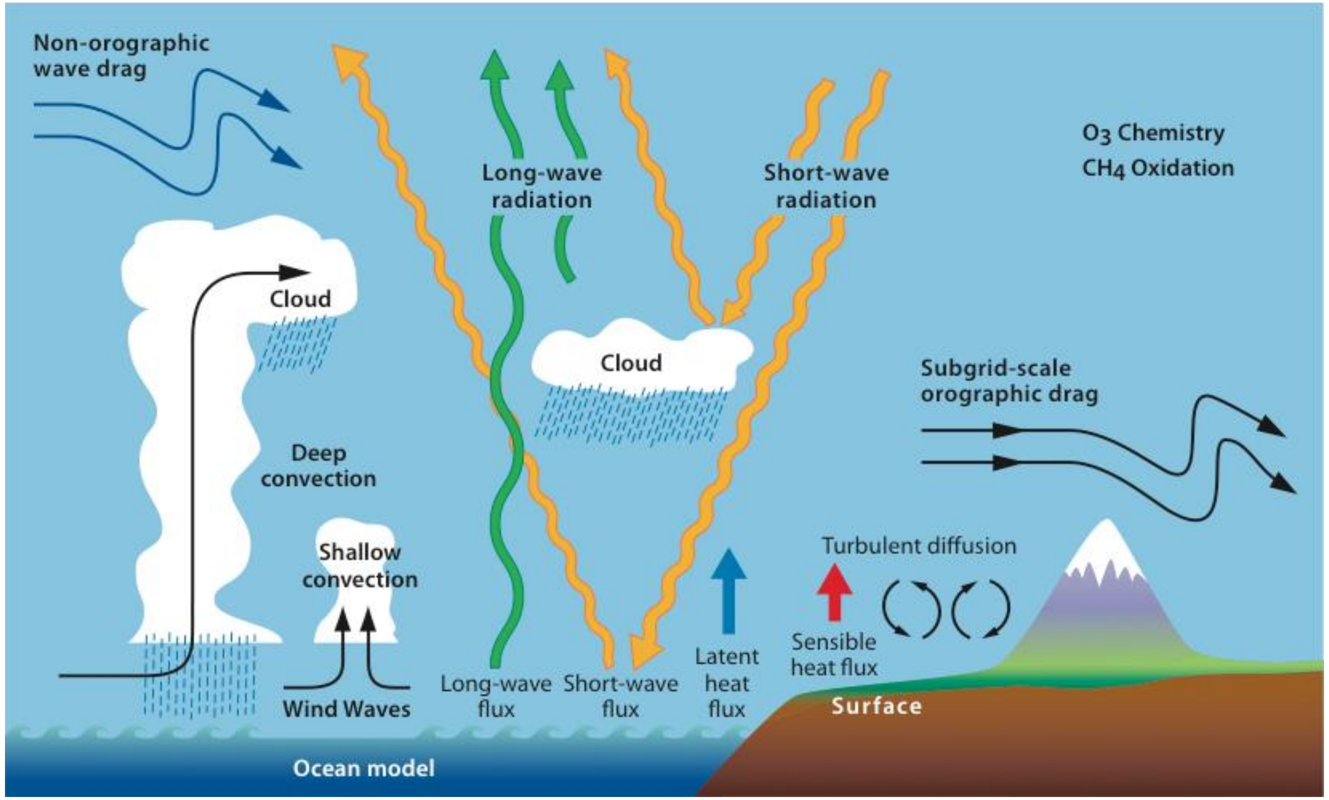


- **Aim**: to improve the physical consistency
- Generate flux perturbations at the top of atmosphere (TOA) and surface that are consistent with tendency perturbations within the atmospheric column
- Conservation of water
- Remove ad hoc tapering in boundary layer and stratosphere
- Include multi-variate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



Stochastic physics: brief outlook for IFS

Towards process-level model uncertainty representation



Stochastically Perturbed Parametrisations (SPP)

(Ollinaho et al., 2017, QJRMS)

- Embed stochasticity inside 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, $\hat{\xi}_j$:

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

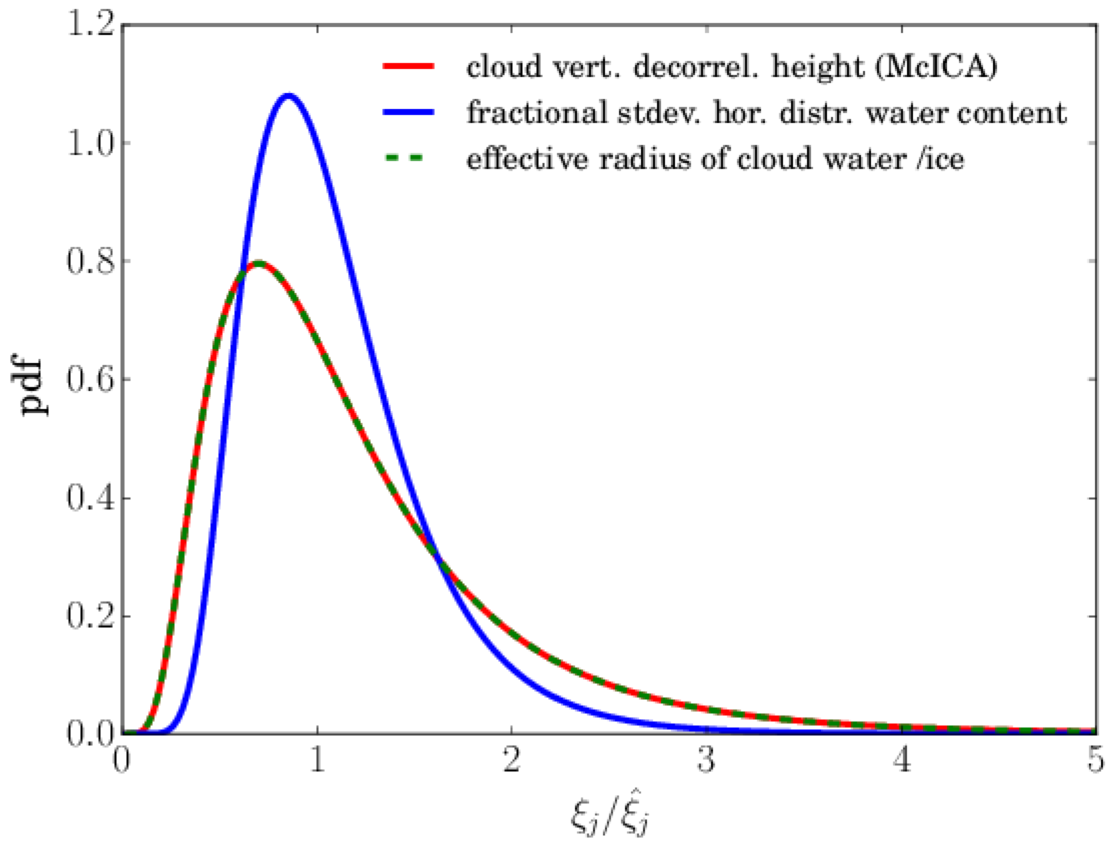
where

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

Development started with parameter perturbations to target cloudy-skies radiation

Now includes 20 parameters/variables from:

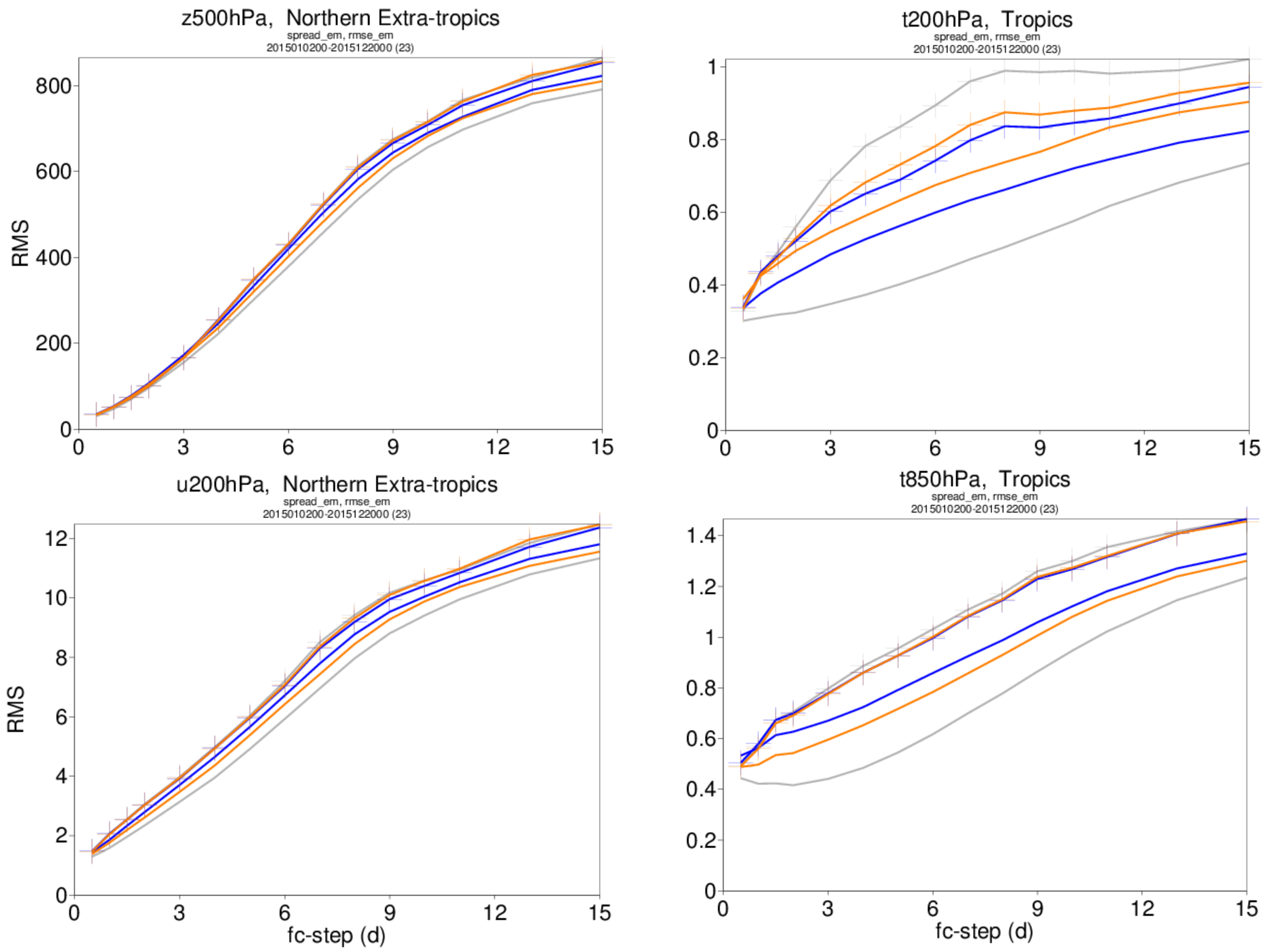
- Turbulent diffusion and subgrid orography
- Cloud and large-scale precipitation
- Radiation
- Convection

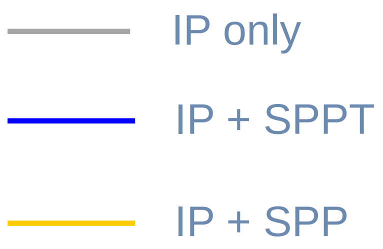


(Ollinaho et al., 2017, QJRMS)

Stochastically Perturbed Parametrisations (SPP) scheme

Ensemble mean RMSE (“Error”) & standard deviation (“Spread”)





More work to do to improve SPP – missing some uncertainty representation (cf. SPPT)?

CY43R1

TCo399, dt=900s,

23 dates (2015),

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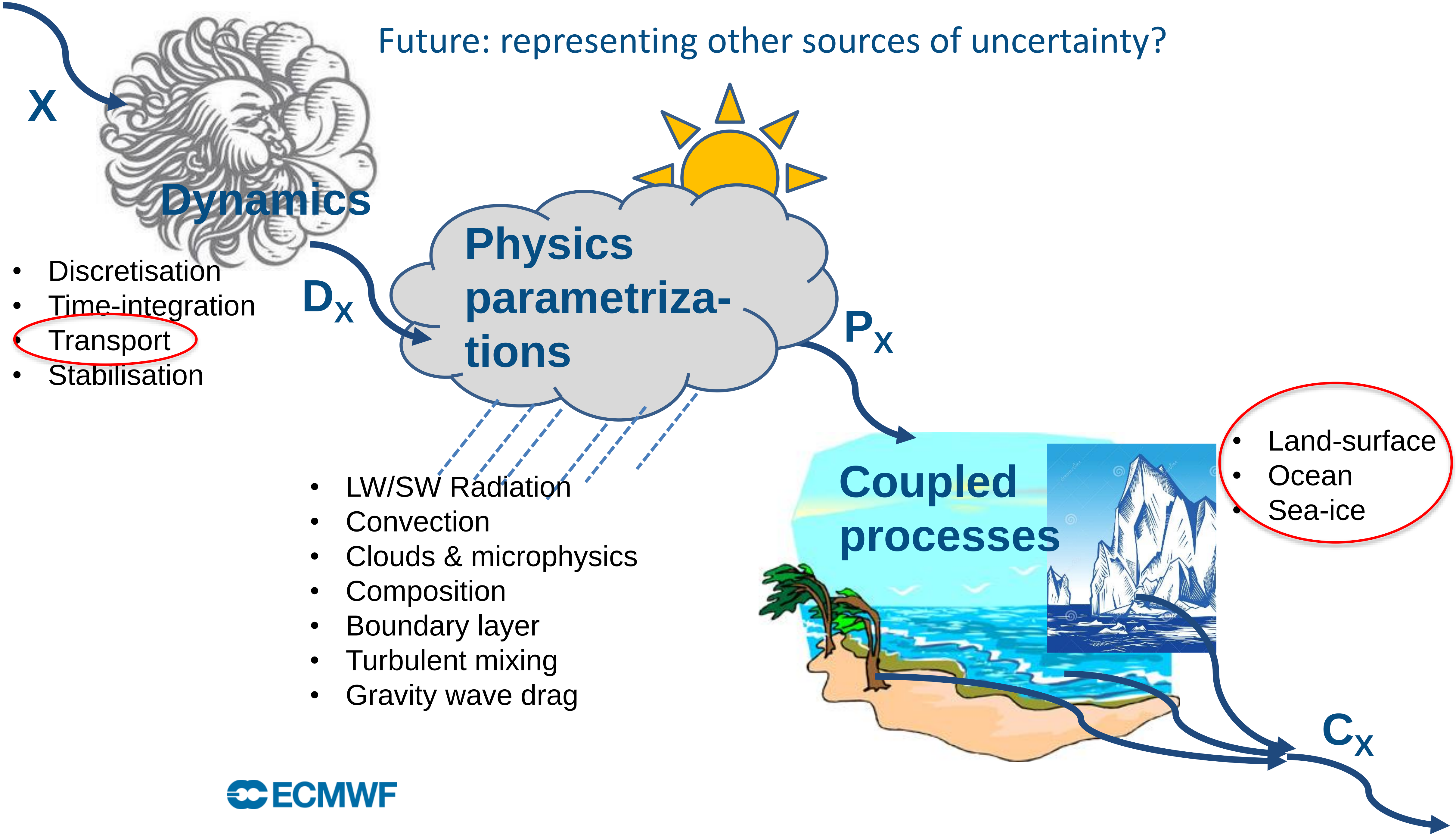
Future: representing other sources of uncertainty?



ECMWF

References

- 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
- Ollinaho et al., 2017: Towards process-level representation of model uncertainties: Stochastically perturbed parametrisations in the ECMWF ensemble, QJRMS, **143**, 408-422
- 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 parametrizations: Impact on the coupled ECMWF seasonal forecasting system*, Phil. Trans. R. Soc. A., **372**, 2018

Further reading

In 2016, we undertook an extensive review of existing and future efforts in model uncertainty representation – a Special Topic paper for our Scientific Advisory Committee:

- Leutbecher et al., 2016: Stochastic representations of model uncertainties at ECMWF: State of the art and future vision, ECMWF Tech Memo, **785**

Report covers:

- Literature review
- Descriptions/discussions of SPPT / SKEB / SPP
- Impacts of the schemes in the IFS (EDA; short / medium / extended / longer ranges)
- Proposals for future directions – improvements to SPPT; extensions to SPP; new approaches

Revised (improved!) version:

- Leutbecher et al., 2017: Stochastic representations of model uncertainties at ECMWF: State of the art and future vision, QJRMS (in review)