Representing model uncertainty

Stochastic perturbations

Sarah-Jane Lock

Model Uncertainty, Earth System Modelling, Research Department

sarah-jane.lock@ecmwf.int

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Introduction: Model Uncertainty

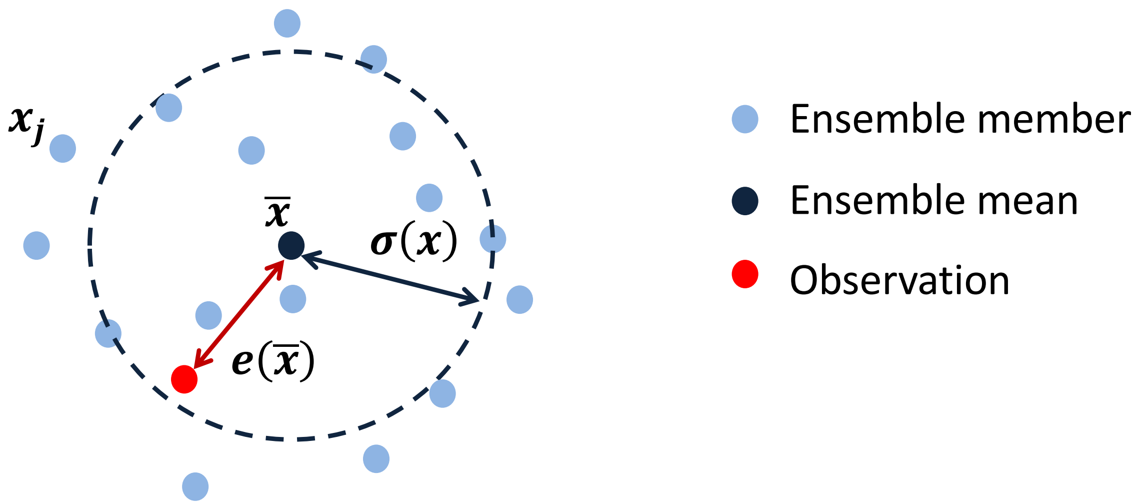
- Ensemble forecasts enable a quantification of the confidence in a forecast, e.g. 10% chance of rain
- An ensemble forecast is made from multiple forecasts or "members", each member perturbed with respect to the others
- The perturbations comprise
  a) different initial conditions for each member, to sample the uncertainty in our description of the initial state (***Simon Lang's lecture***); and
  b) a different forecast model for each member, to sample the uncertainty due to the model integrations or the "***model uncertainty***"
- To date, much effort has been focused on **model uncertainty** due to the parametrization schemes that describe sub-grid atmospheric physics --- representing this with stochastic perturbations gives rise to "***stochastic physics***"

Using stochastic physics to represent model uncertainty

- Why do we represent model uncertainty in an ensemble forecast?
- What are the sources of model uncertainty?
- How do we currently (**CY48R1**) represent model uncertainty in the IFS?
- How *will* we represent MU in **CY49R1**? And why the change?

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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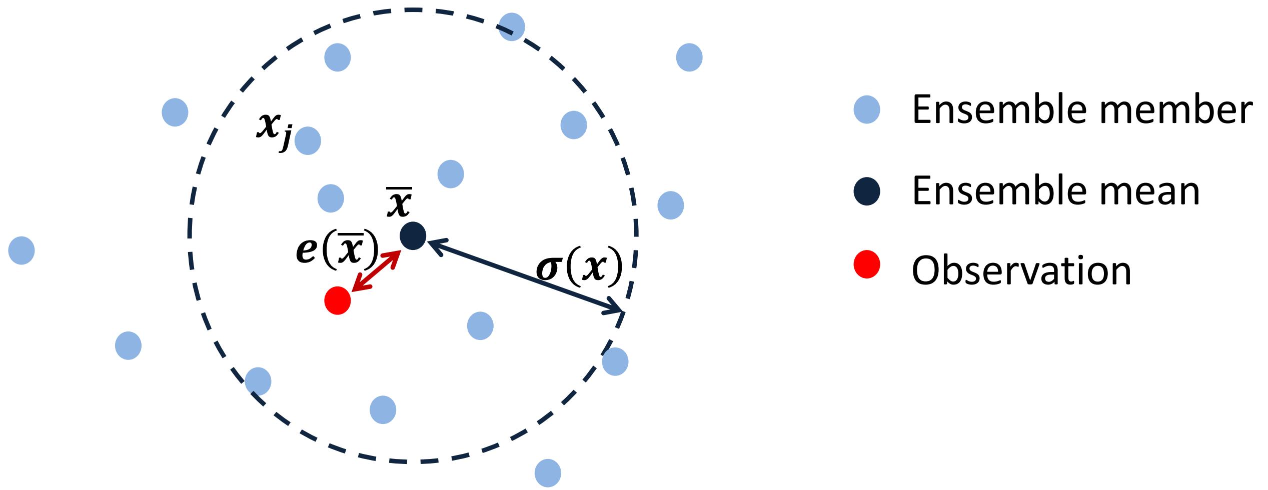
Ensemble reliability

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

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



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

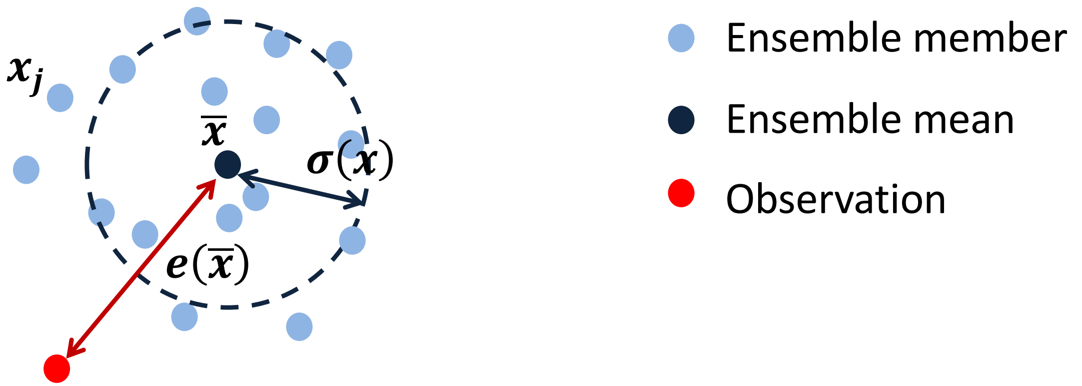
The relatively large spread implies large uncertainty and hence, likely large error:

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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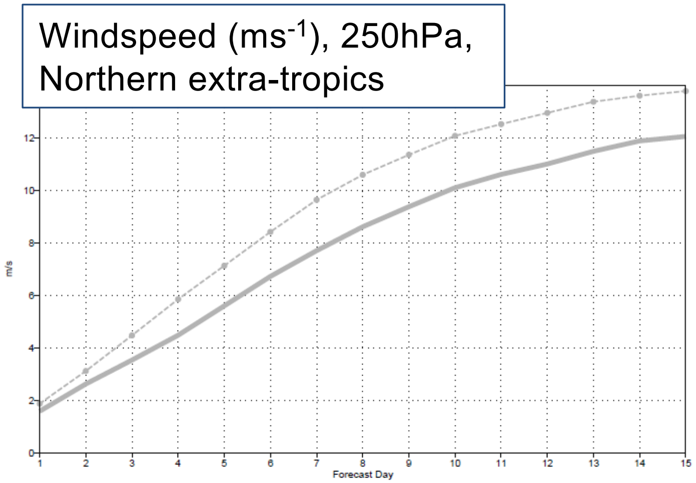
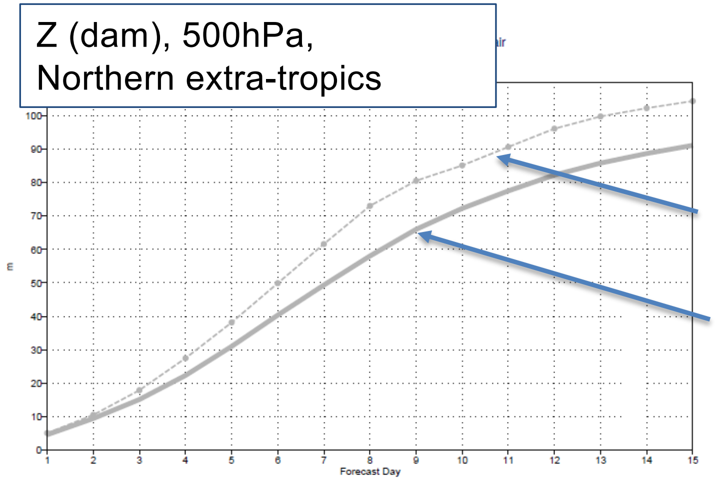
Ensemble forecasts with only initial conditions perturbations

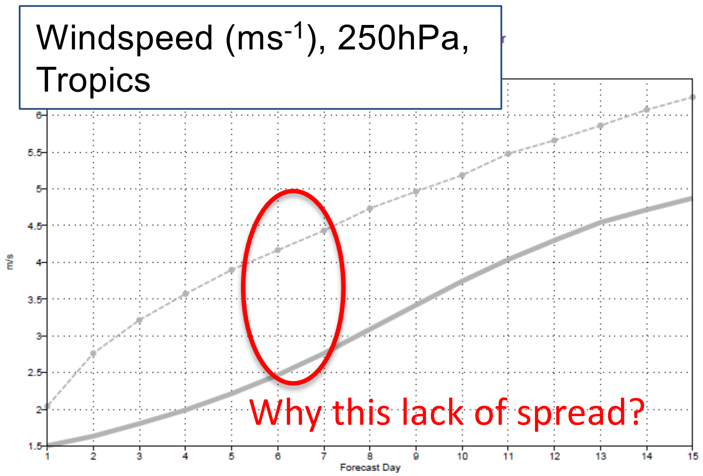
Ensemble mean RMSE (“Error”) & standard deviation (“Spread”)

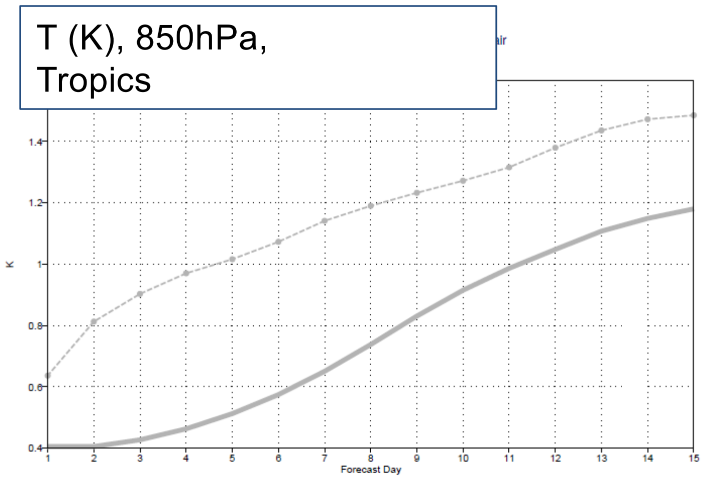




RMSE ensemble mean

RMS ensemble stdev





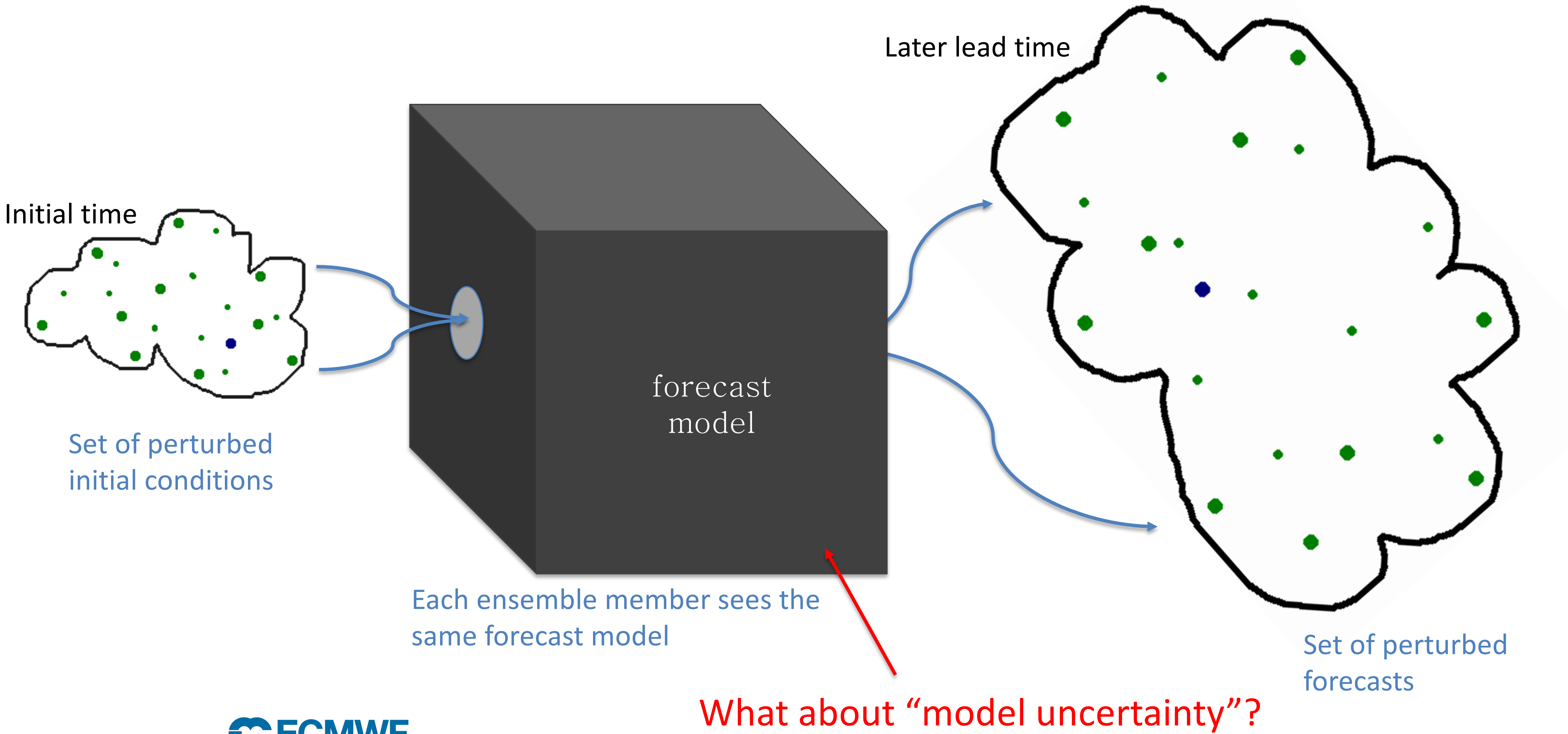
CY47R3

TCo399L137, dt=1200s

30 dates (Dec 2019)

8 perturbed fcs

Sources of uncertainty: initial conditions



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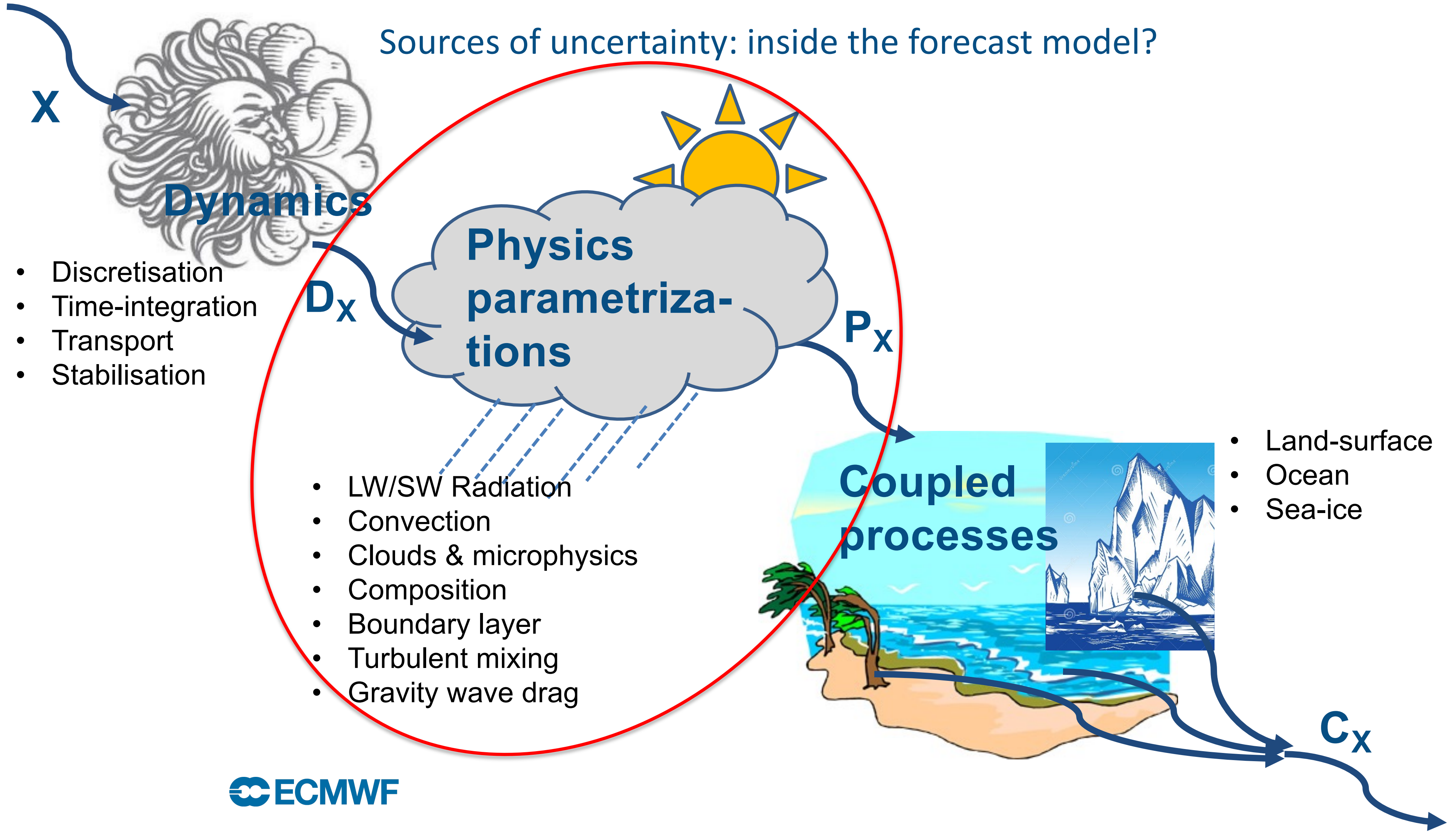
Sources of uncertainty: inside the forecast model?



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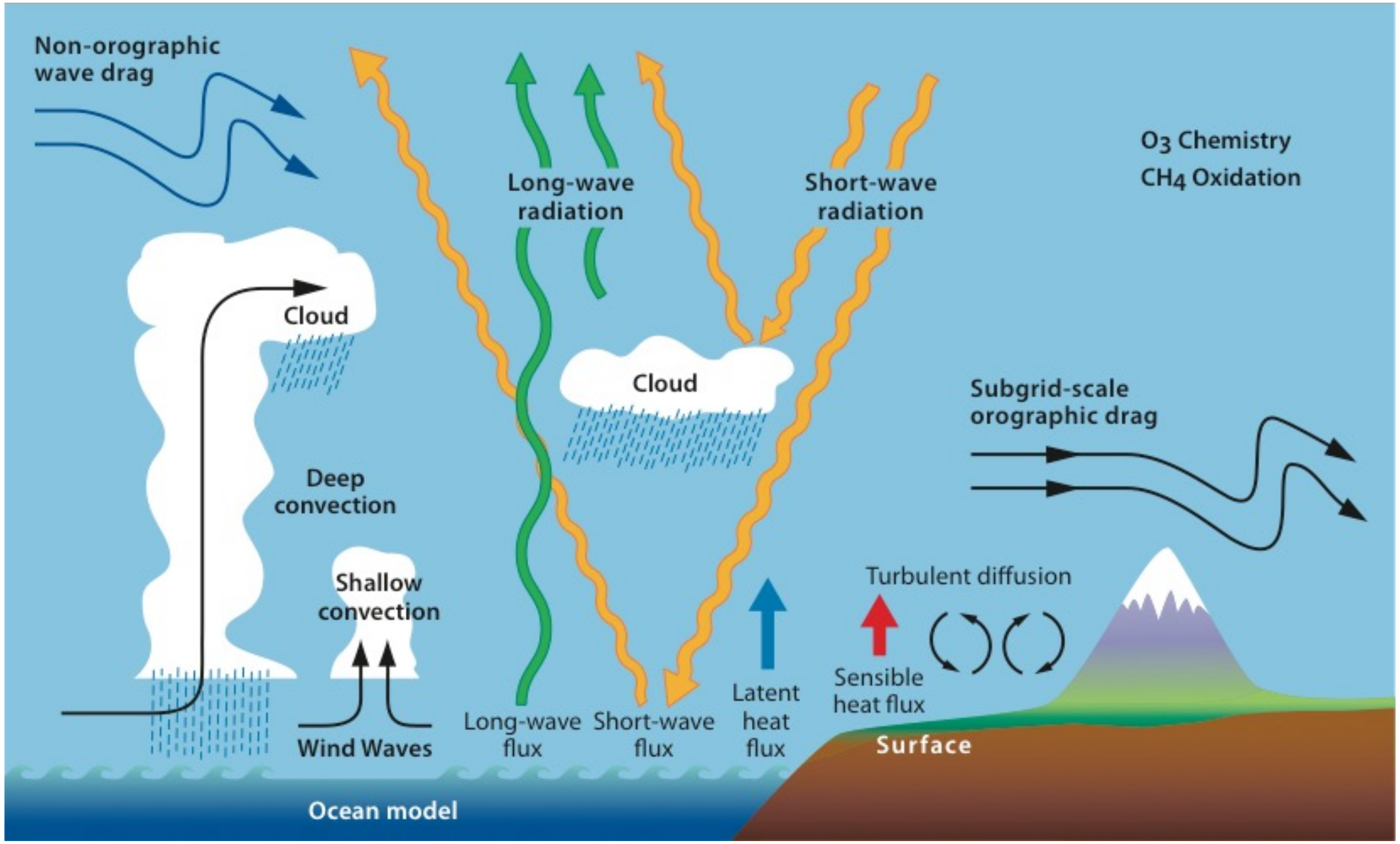
Model uncertainty: parametrized atmospheric physics processes



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

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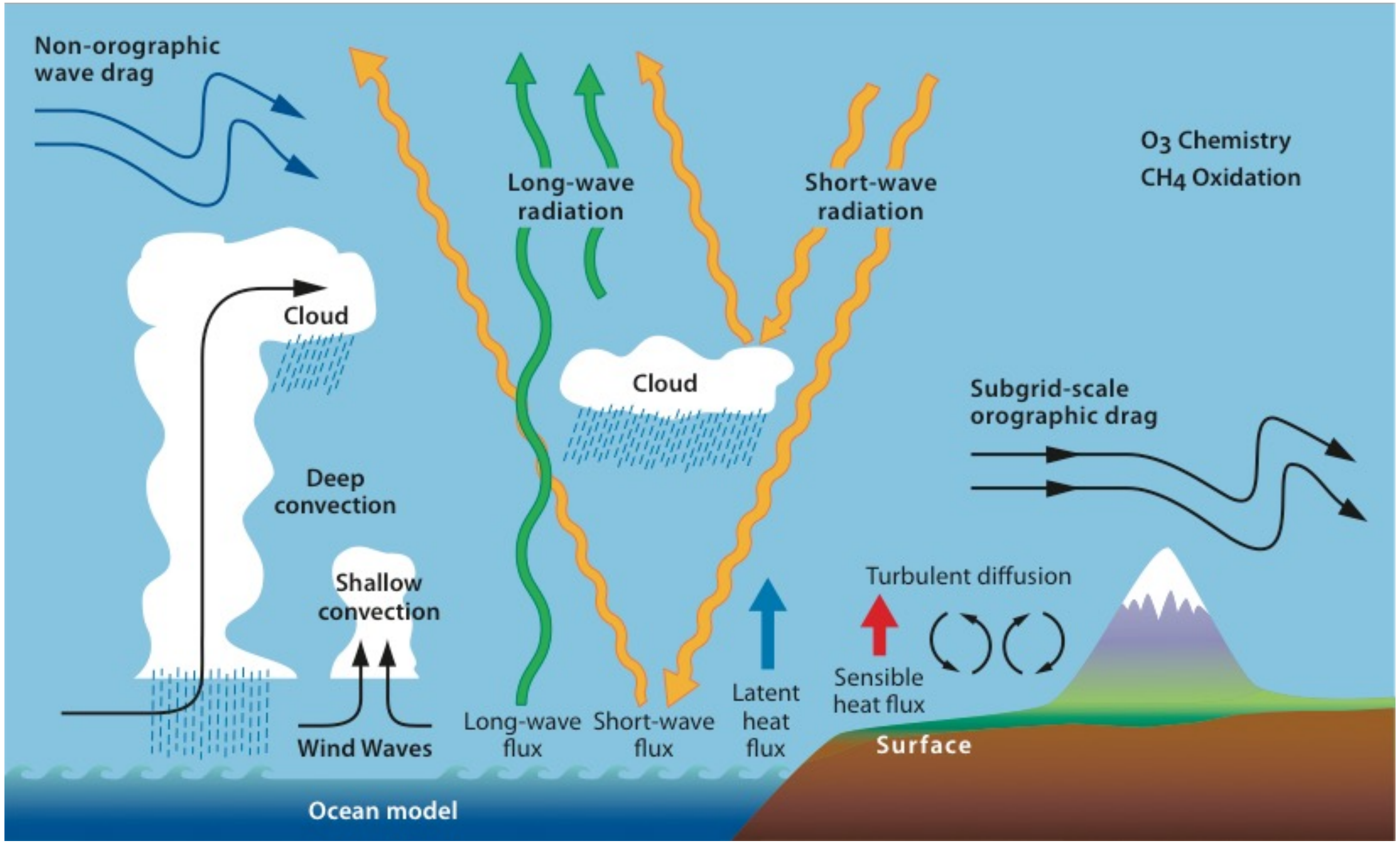
Model uncertainty: parametrized atmospheric physics processes



"Let's take the positives"

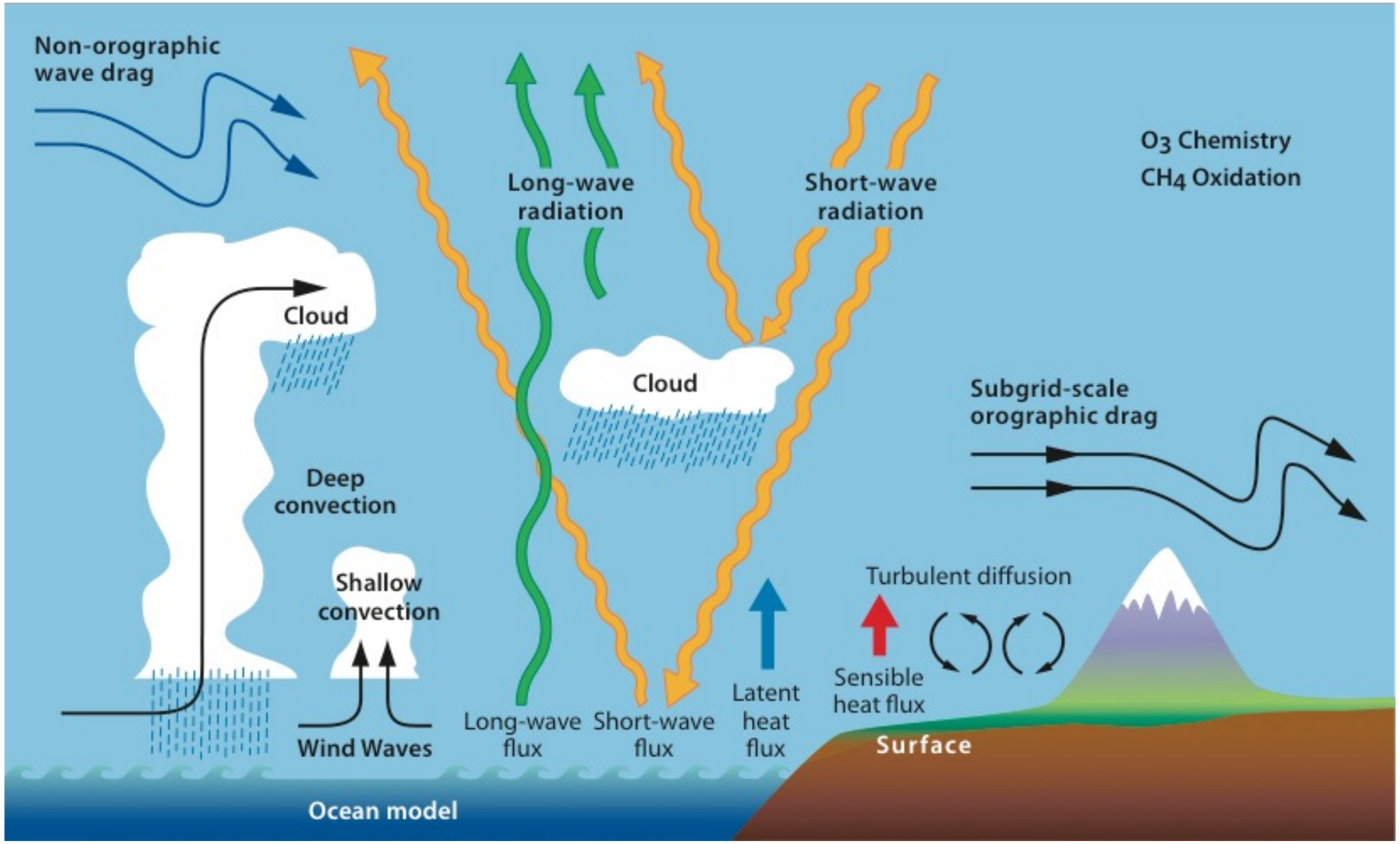
Parametrisation schemes:

- developed/operate together
- highly tuned for best performance

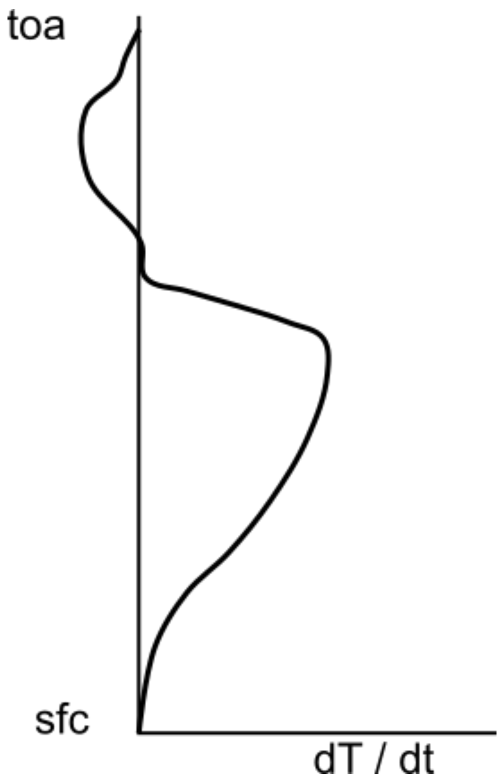
Seek a description of uncertainty that retains consistencies of the representation of the physical processes.

Model uncertainty: parametrized atmospheric physics processes

CY48R1



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



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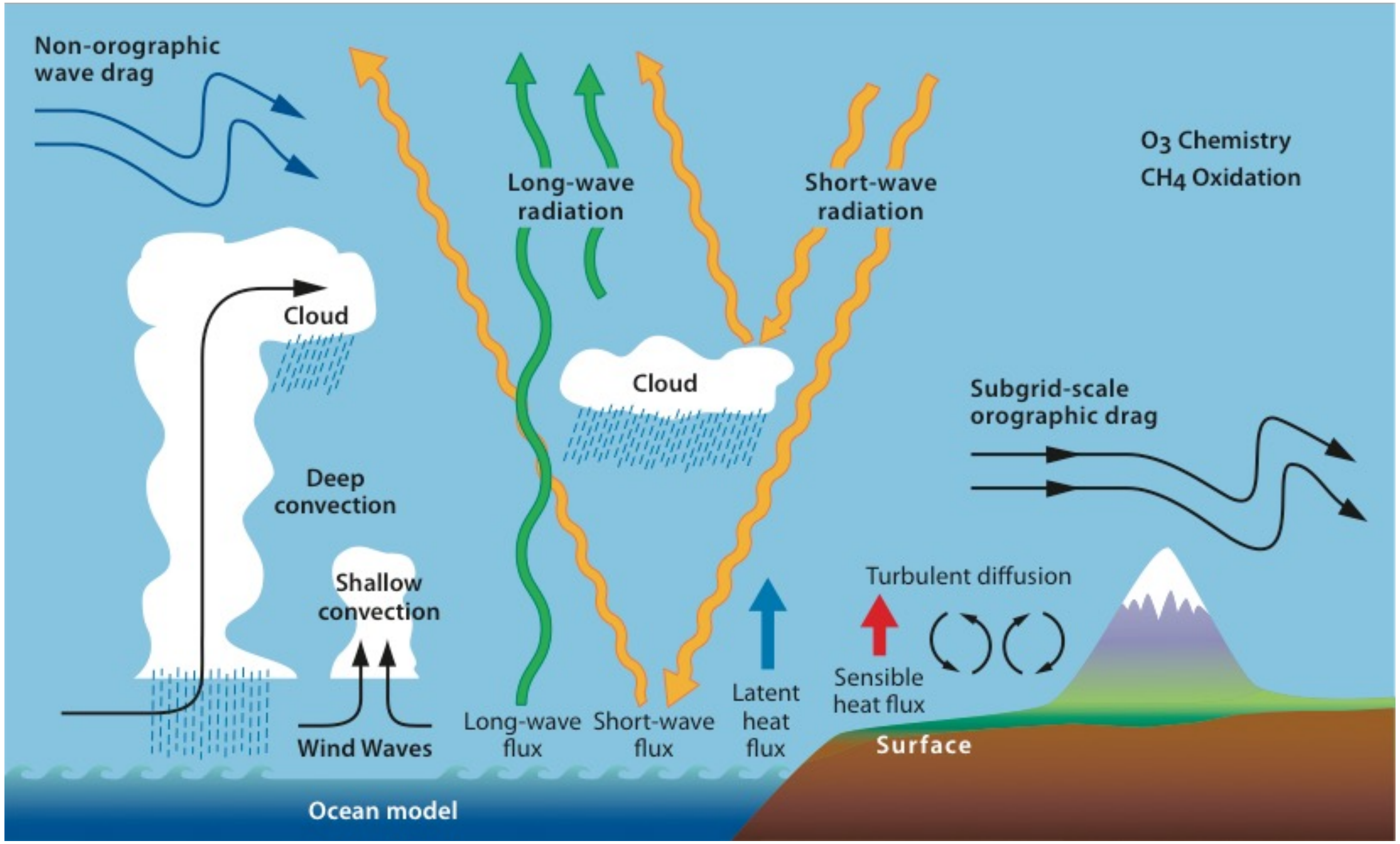
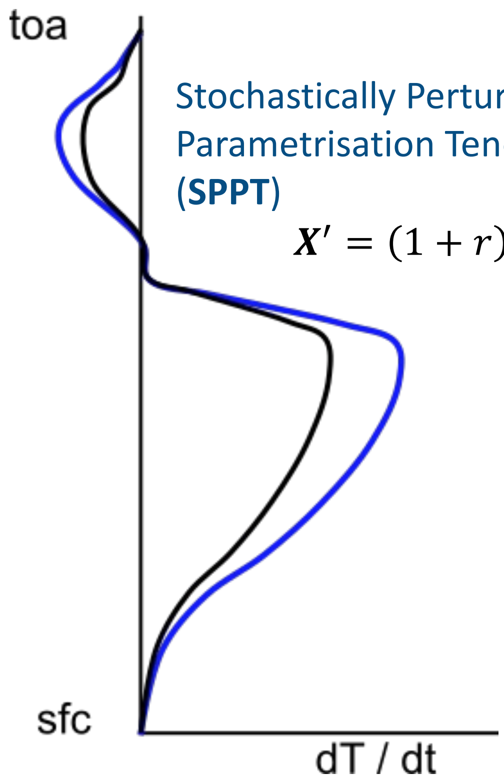
Model uncertainty: parametrized atmospheric physics processes

CY48R1



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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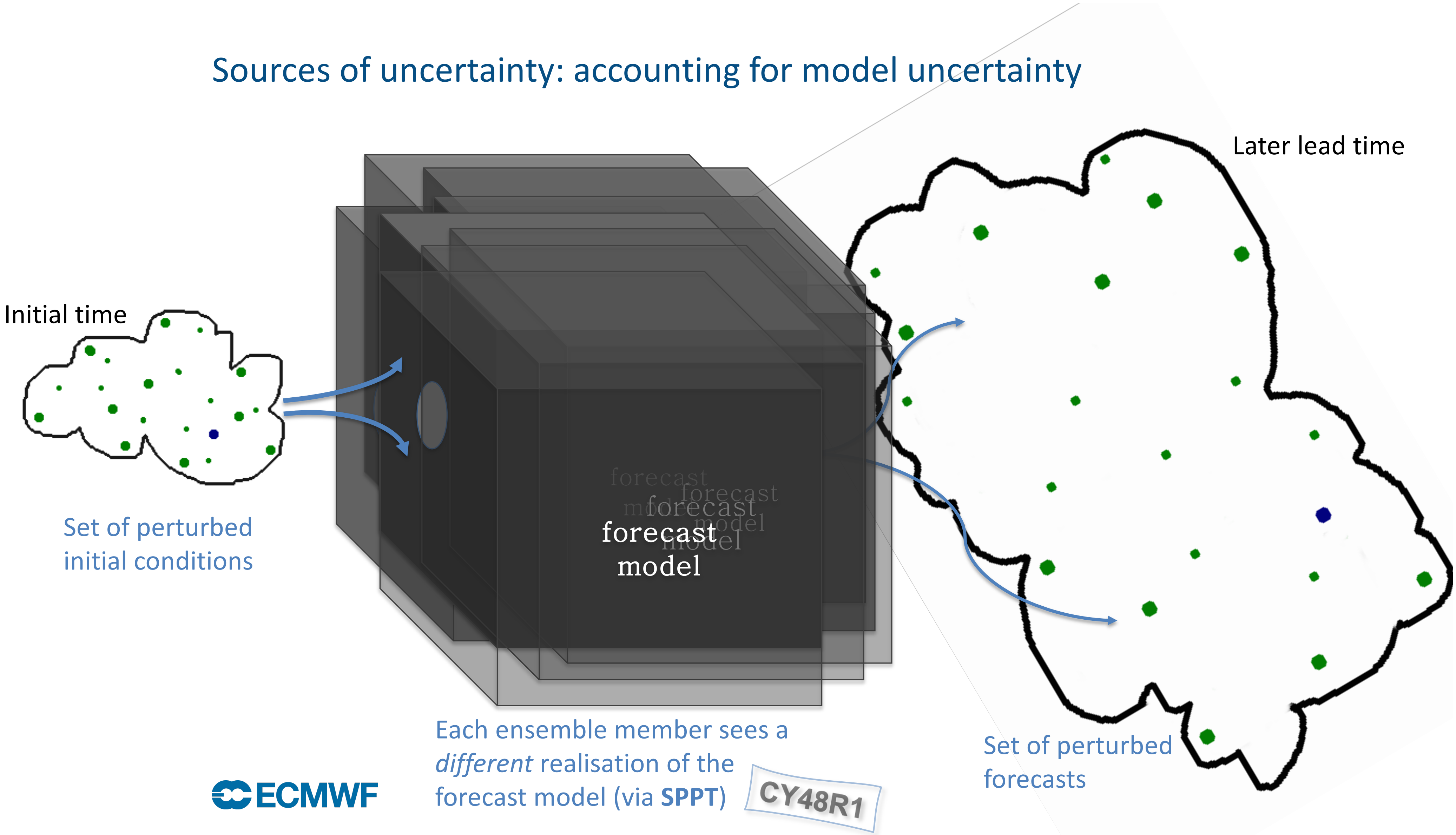
Sources of uncertainty: accounting for model uncertainty



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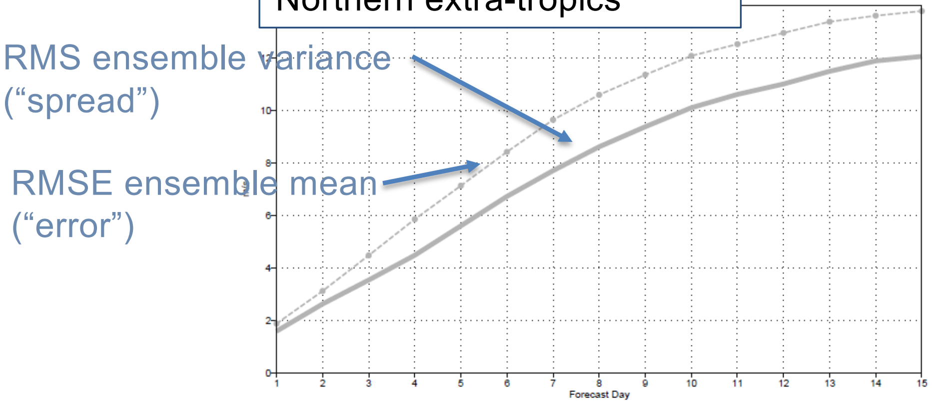
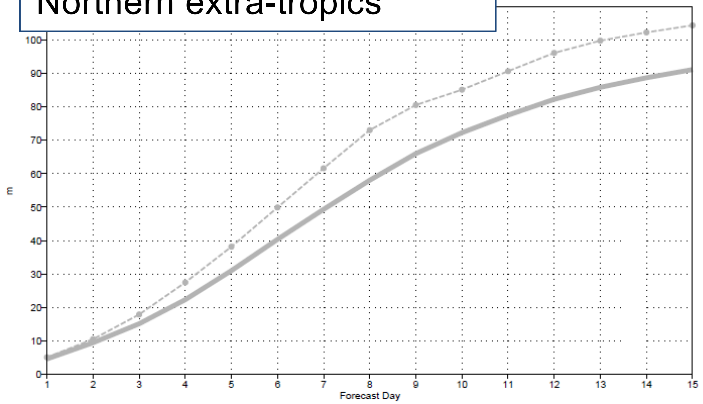
Recall: Ensemble forecasts: with initial conditions perturbations (IP) only

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

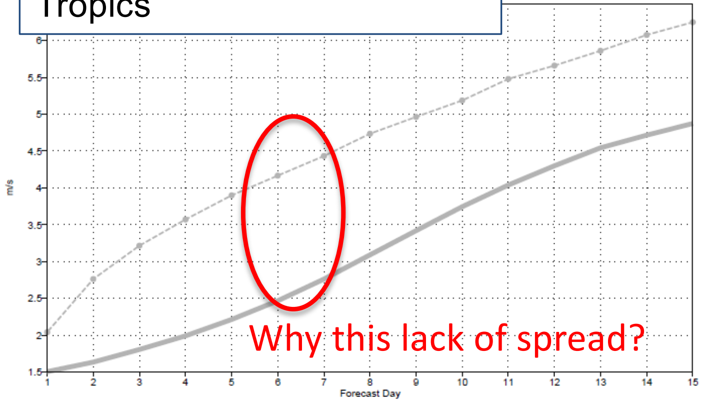
Windspeed (ms^{-1}), 250hPa, Northern extra-tropics



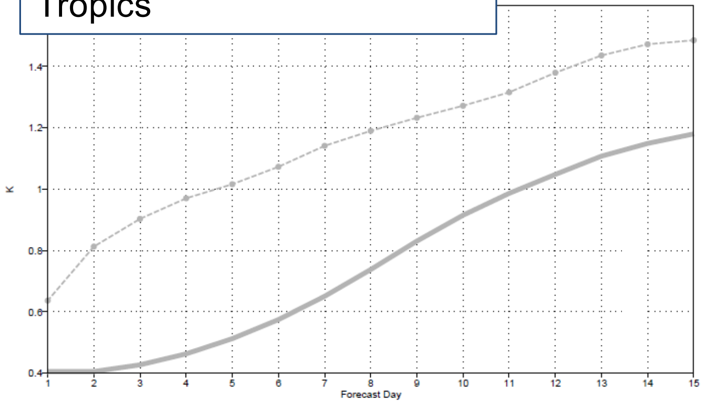
Z (dam), 500hPa, Northern extra-tropics



Windspeed (ms^{-1}), 250hPa, Tropics



T (K), 850hPa, Tropics



CY47R3

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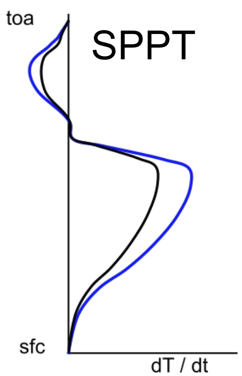
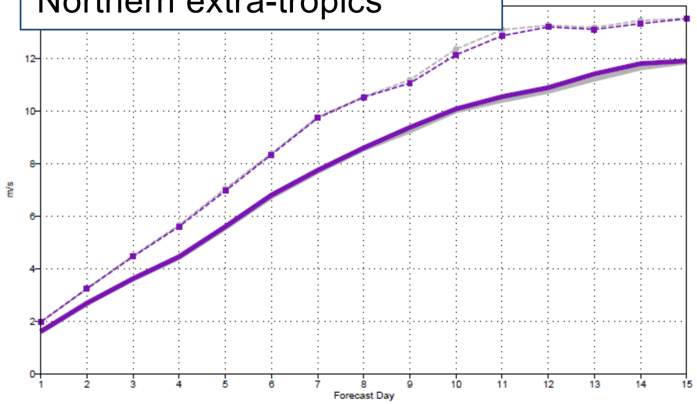


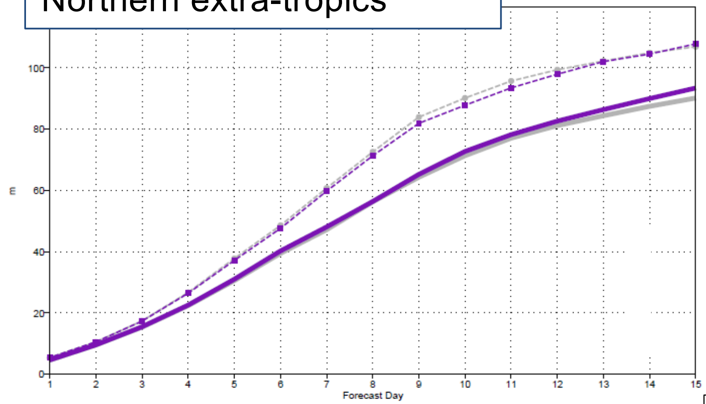
Ensemble forecasts: with grid-scale model uncertainty perturbations (**SPPT**)

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

Windspeed (ms^{-1}), 250hPa,
Northern extra-tropics



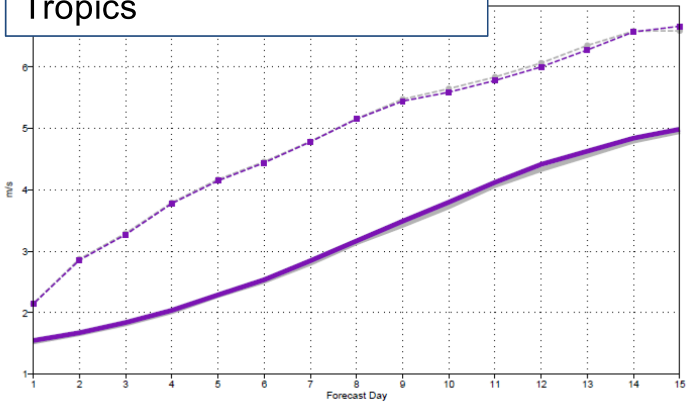
Z (dam), 500hPa,
Northern extra-tropics



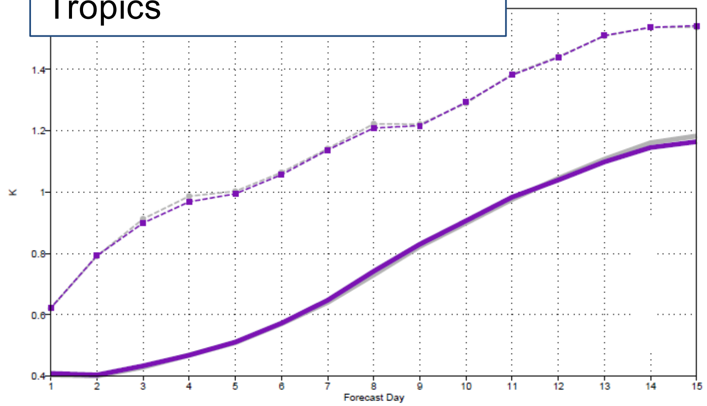
IP only

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

Windspeed (ms^{-1}), 250hPa,
Tropics



T (K), 850hPa,
Tropics



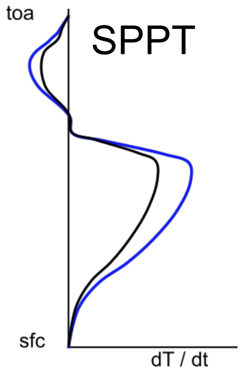
Uncorrelated noise
yields little benefit

CY47R3

TCo399L137, dt=1200s

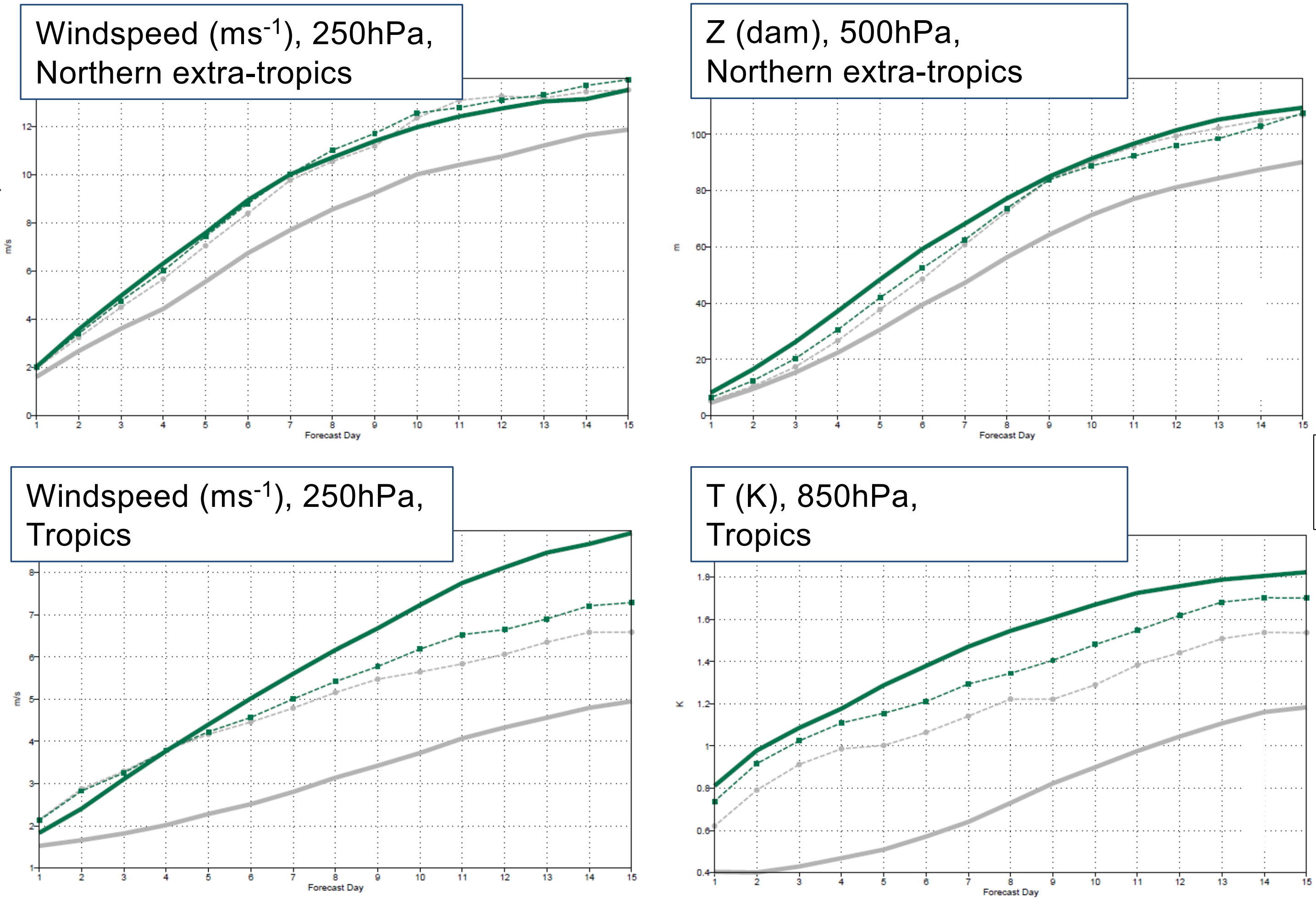
11 dates (Dec 2019/Jan 2020)

8 perturbed fcs



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

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



IP only

IP + SPPT*
(*fixed perts wrt time/horizontal)

Fixed perturbations yield increased errors

CY47R3

TCo399L137, dt=1200s

11 dates (Dec 2019/Jan 2020)

8 perturbed fcs

Stochastically Perturbed Parametrisation Tendencies (**SPPT**) scheme

- History (IFS): implemented, 1998 (**Buizza et al., 1999**); revised, 2009 (**Palmer et al., 2009**), 2019 (**Lock et al., 2019**):
- Simulates model uncertainty due to ***physics parameterisations*** by
  - taking the net tendencies from the physics parametrisations (excl. clear-sky heating rates):

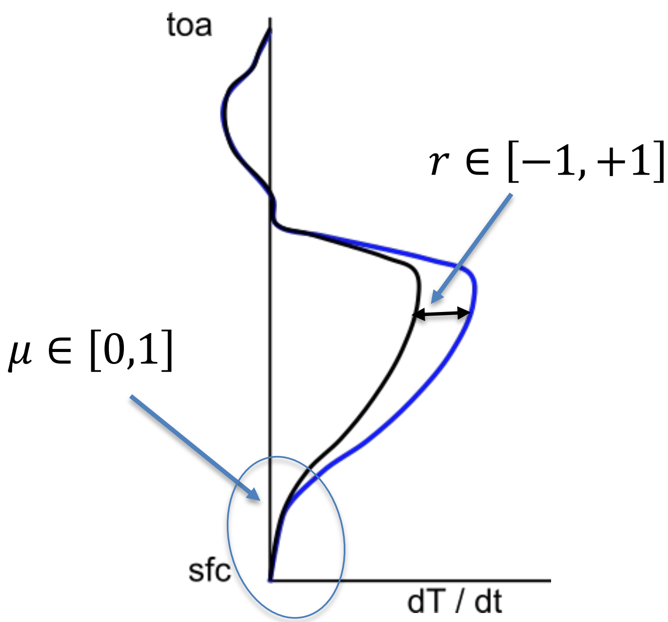
$$\boldsymbol{X} = [X_U, X_V, X_T, X_Q]$$

coming from
radiation (cloudy-skies)
gravity wave drag
vertical mixing
convection
cloud physics
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.

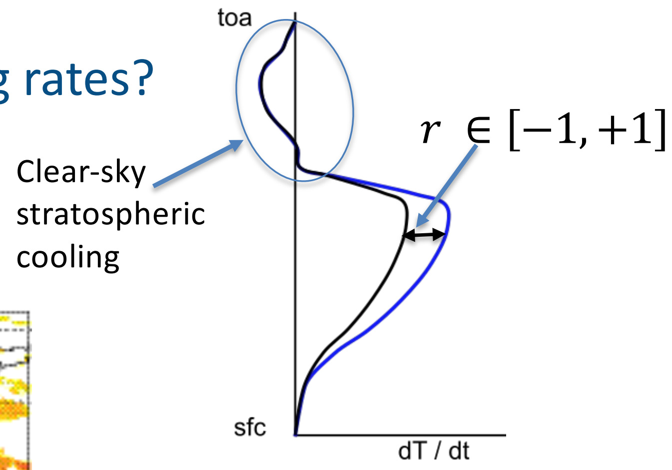


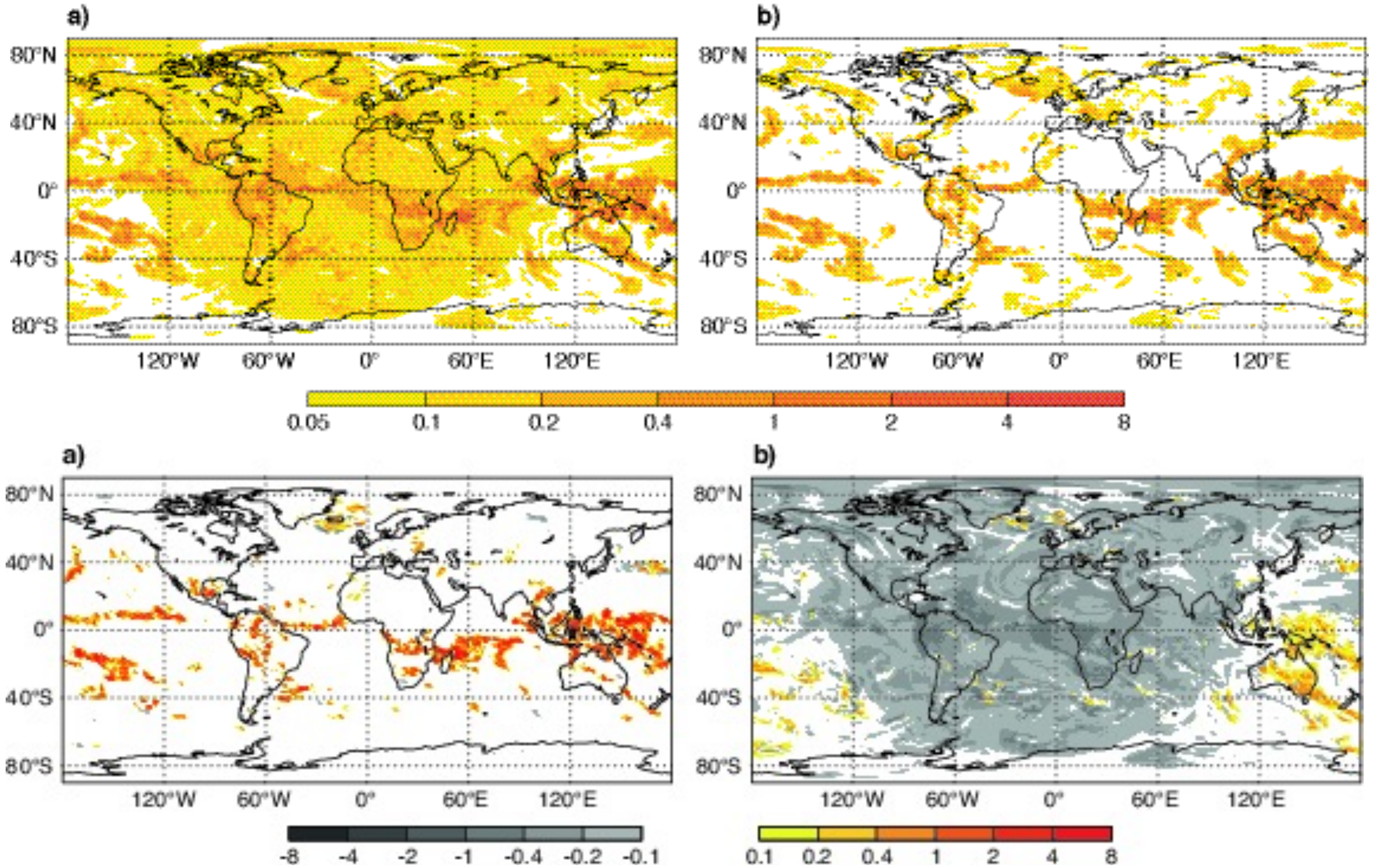
Shutts et al. (2011, ECMWF Newsletter);
Palmer et al., (2009, ECMWF Tech. Memo.);
Lock et al., (2019, QJRMS)

SPPT perturbations: why exclude clear-sky heating rates?

- SPPT perturbs net physics tendencies (***excluding clear-sky heating rates***) with multiplicative noise $r \in [-1, +1]$ as:

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





T tendencies from a model level in mid-troposphere accumulated during t+0-3h (K/3h):

Top: Ensemble stdev with SPPT perturbations with (a) clear-sky HRs (a) included & (b) excluded.

Bottom: From control forecast, from (a) convection & (b) radiation schemes

Figure 2 & Figure 1,from Lock et al. (2019, QJRMS)

SPPT random pattern

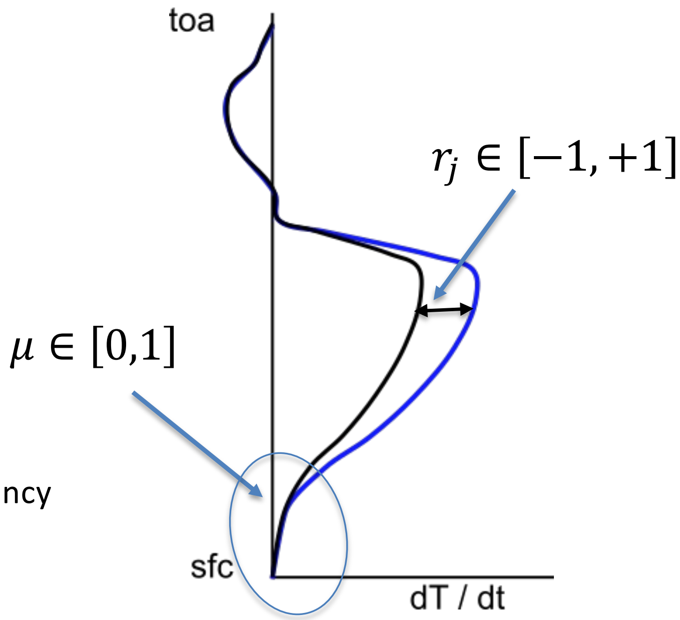
- 2D random pattern in spectral space:
  - First-order auto-regressive [AR(1)] process for evolving spectral coefficients $\hat{r}$

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

where $\phi = \exp(-\Delta t/\tau)$ controls the correlation over timestep Δt;

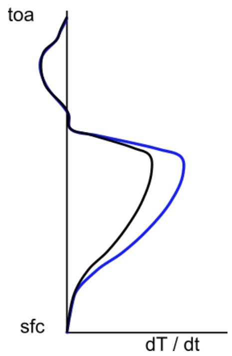
and spatial correlations (Gaussian around the globe) for each wavenumber define ρ for random numbers, η

- Resulting pattern mapped into grid-point space r:
  - clipped such that $r \in [-1, +1]$ --- prevents perturbation ***changing the sign*** of the tendency
  - same pattern is applied to T, Q, U, V (***excluding clear-sky heating rates from radiation***)
  - applied at all model levels to preserve vertical structures**
  - ***Except*: tapered to zero at model bottom, to avoid:
    - excessive spread in the boundary layer caused by applying perturbations to large wind tendencies.



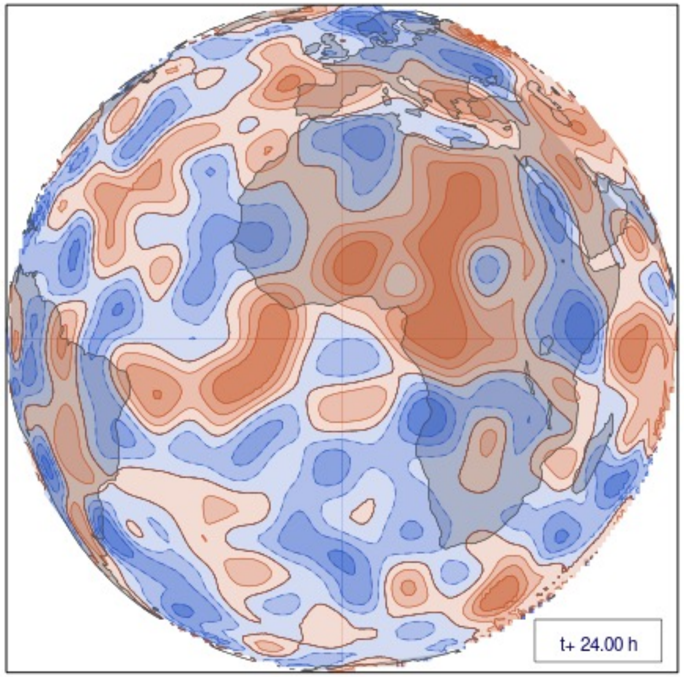
SPPT random pattern

- 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 bottom

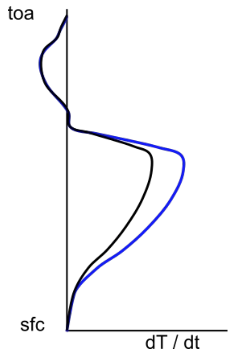


Example random pattern:

- Perturbed member, number 1
- Pattern at t = 24h
- Colours: blues = [-1,0), reds = (0,1]

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**

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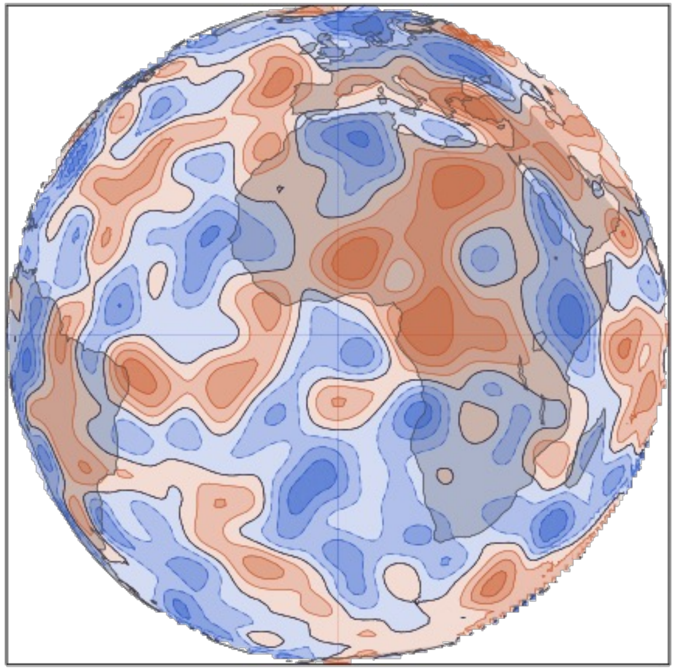
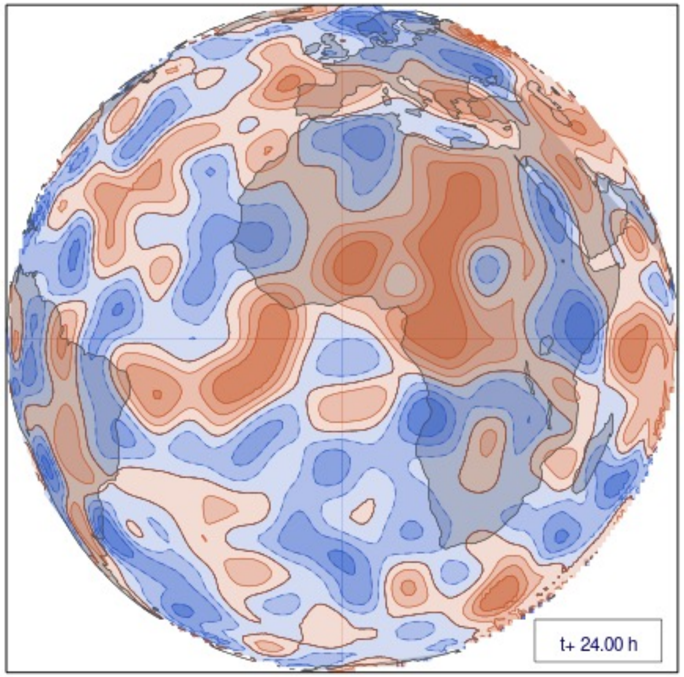


Example random pattern:

- Perturbed member, number 1
- Pattern at t = 0 .. 48h (dt = 15 min)
- Colours: blues = [-1,0), reds = (0,1]

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 bottom

- Multi-scale pattern:
- 3 time/space scales
- Shortest scales dominate
- $\sigma_{3-scale} = 0.4453$

sppt1	6 hours,	500 km,	$\sigma = 0.42$
sppt2	3 days,	1 000 km,	$\sigma = 0.14$
sppt3	30 days,	2 000 km,	$\sigma = 0.048$

SPPT random pattern: multi-scale

sppt1	6 hours,	500 km,	$\sigma = 0.42$
sppt2	3 days,	1 000 km,	$\sigma = 0.14$
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Example random patterns:

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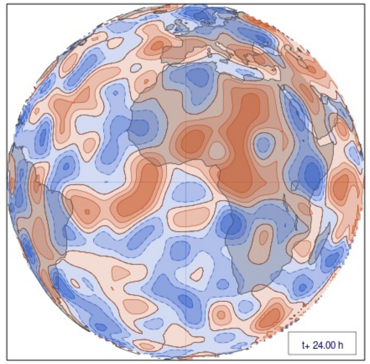
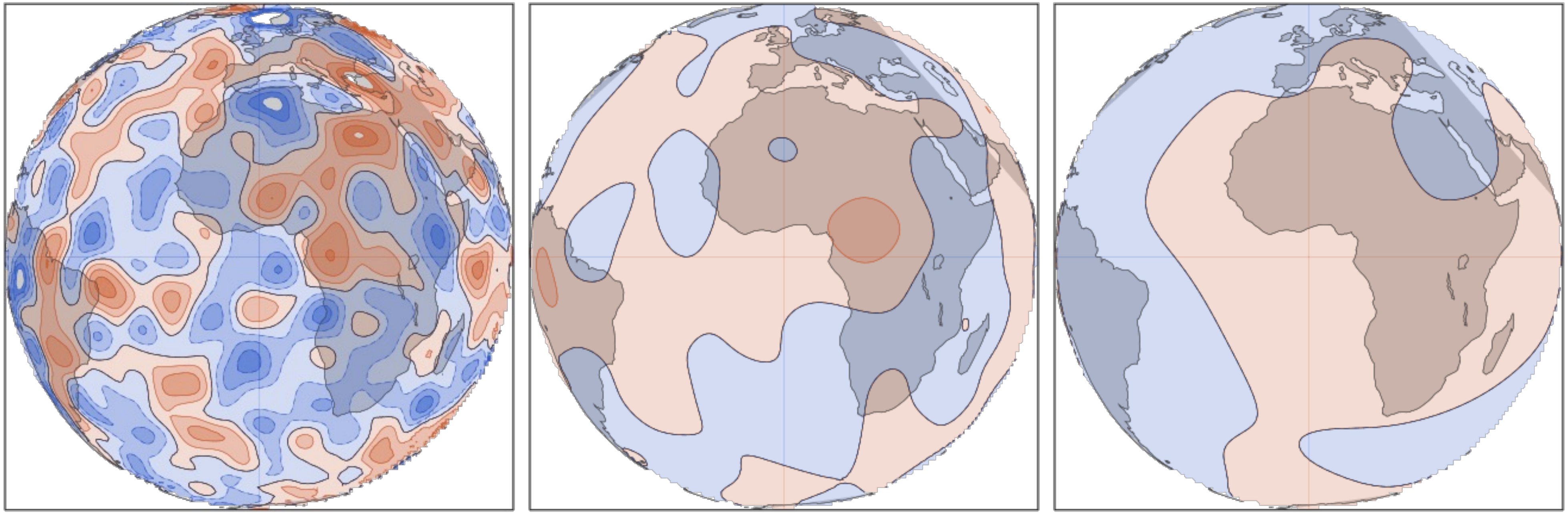


sppt1 sppt2 sppt3



SPPT random pattern

sppt1	6 hours,	500 km,	$\sigma = 0.42$
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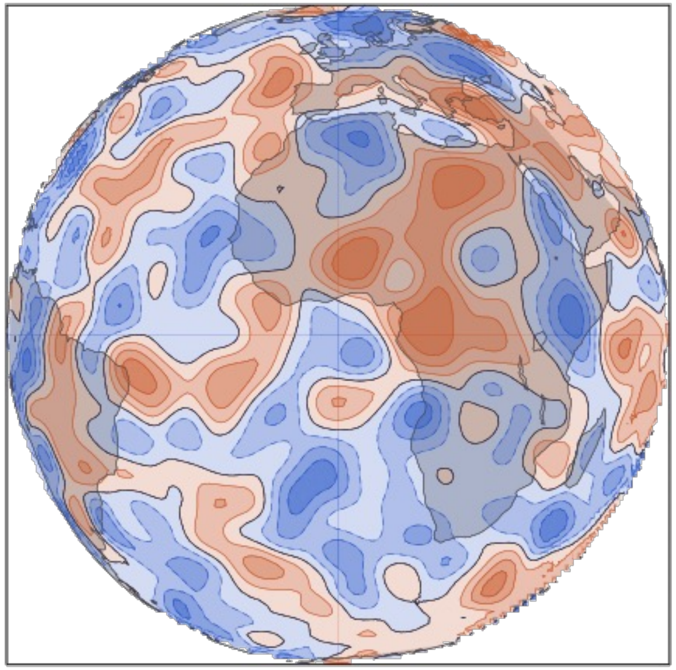
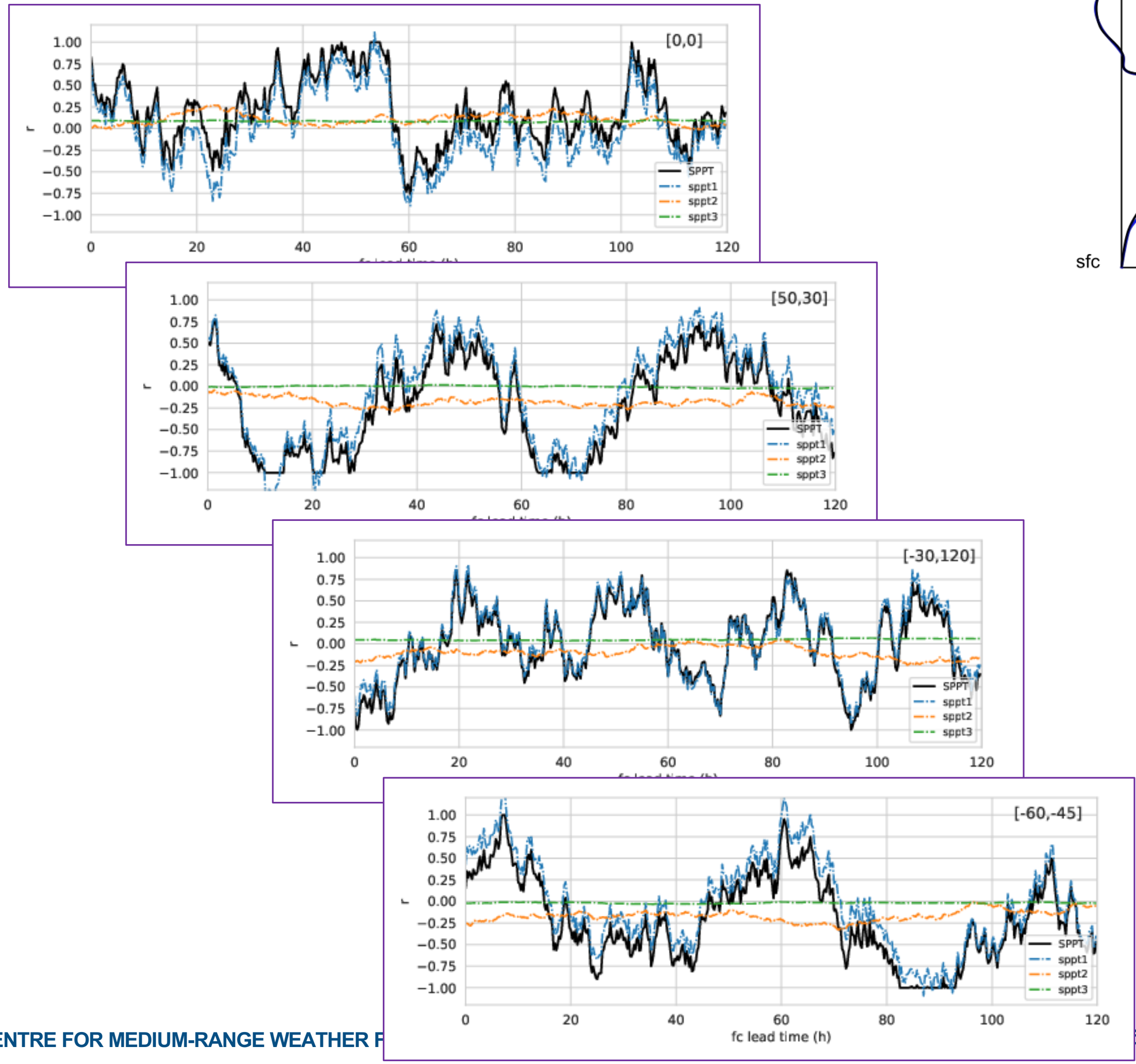
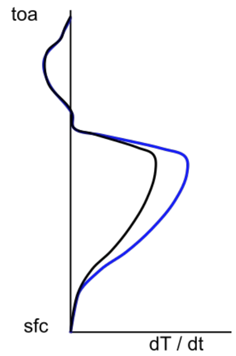
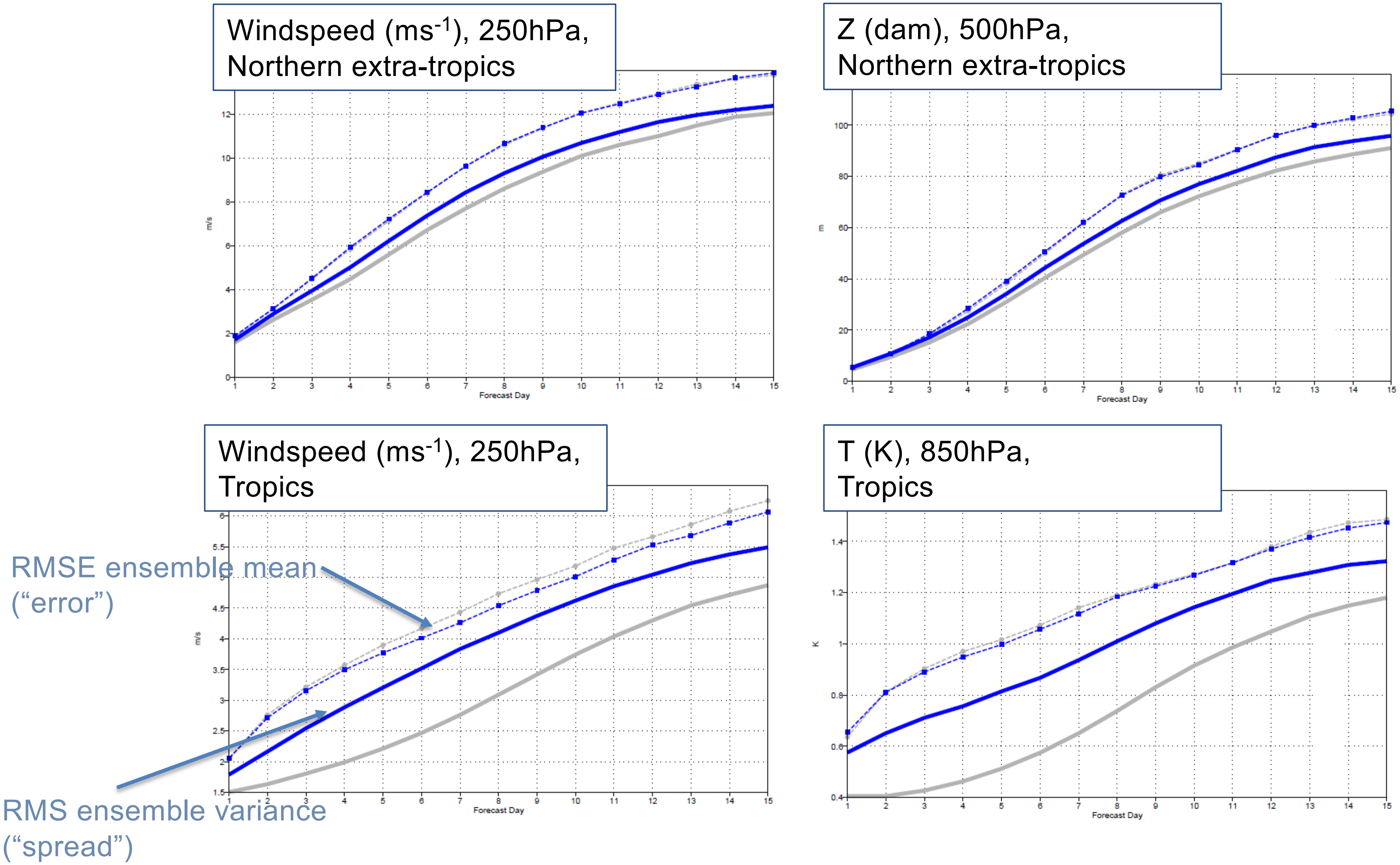






Ensemble forecasts: with **multi-scale** model uncertainty perturbations (**SPPT**)

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



IP only

IP + SPPT3*
(*3 scales)

CY47R3

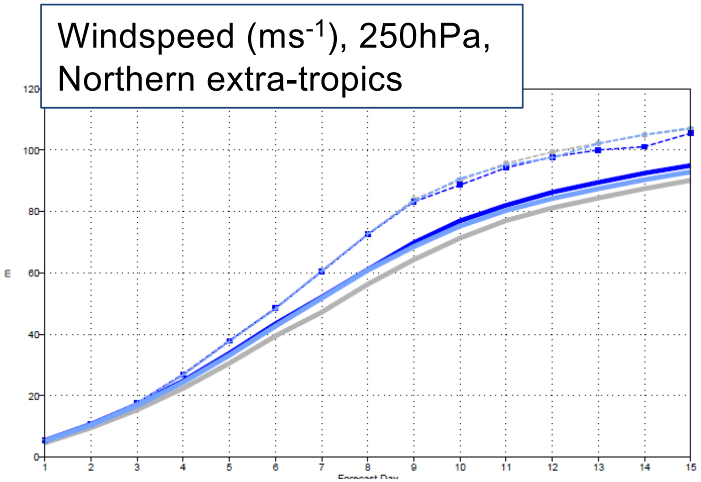
TCo399L137, dt=1200s

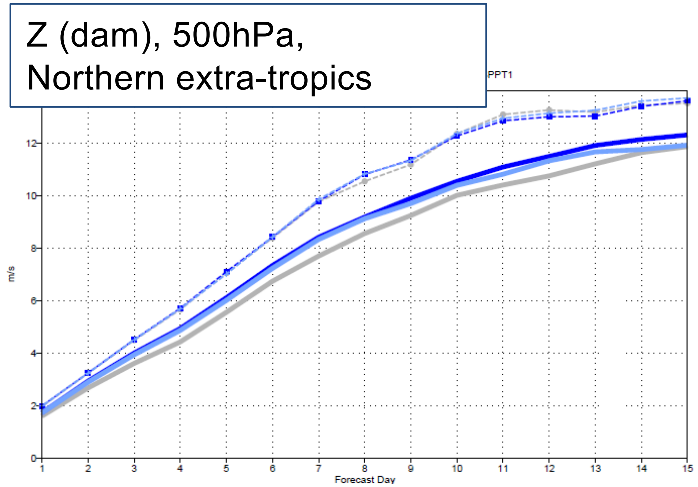
30 dates (Dec 2019)

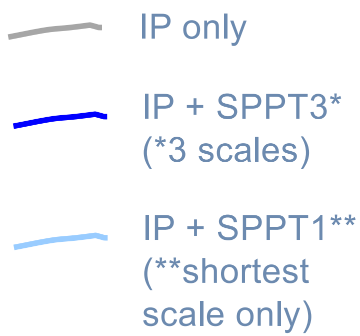
8 perturbed fcs

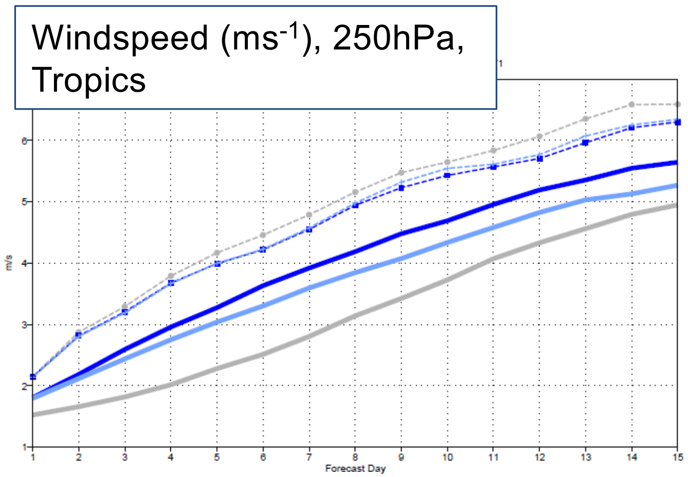
Ensemble forecasts: with **multi-scale** model uncertainty perturbations (**SPPT**)

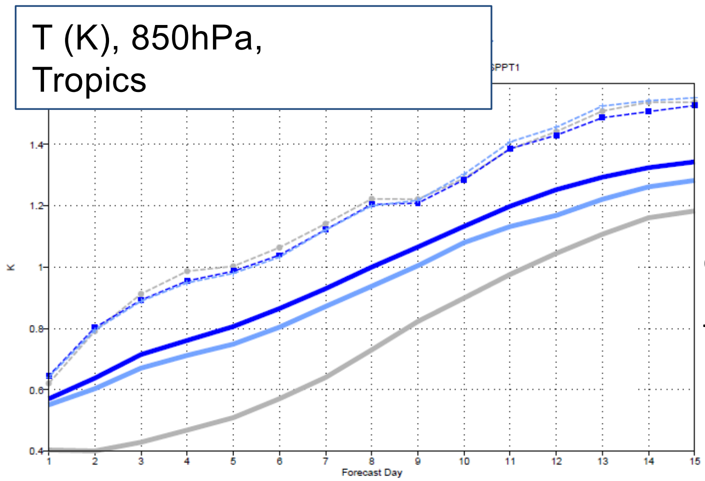
Ensemble mean RMSE ("Error") & standard deviation ("Spread")











Some additional spread from SPPT3
- 3rd scale deemed important for longer-range forecasts

CY47R3

TCo399L137, dt=1200s

11 dates (Dec 2019/Jan 2020)

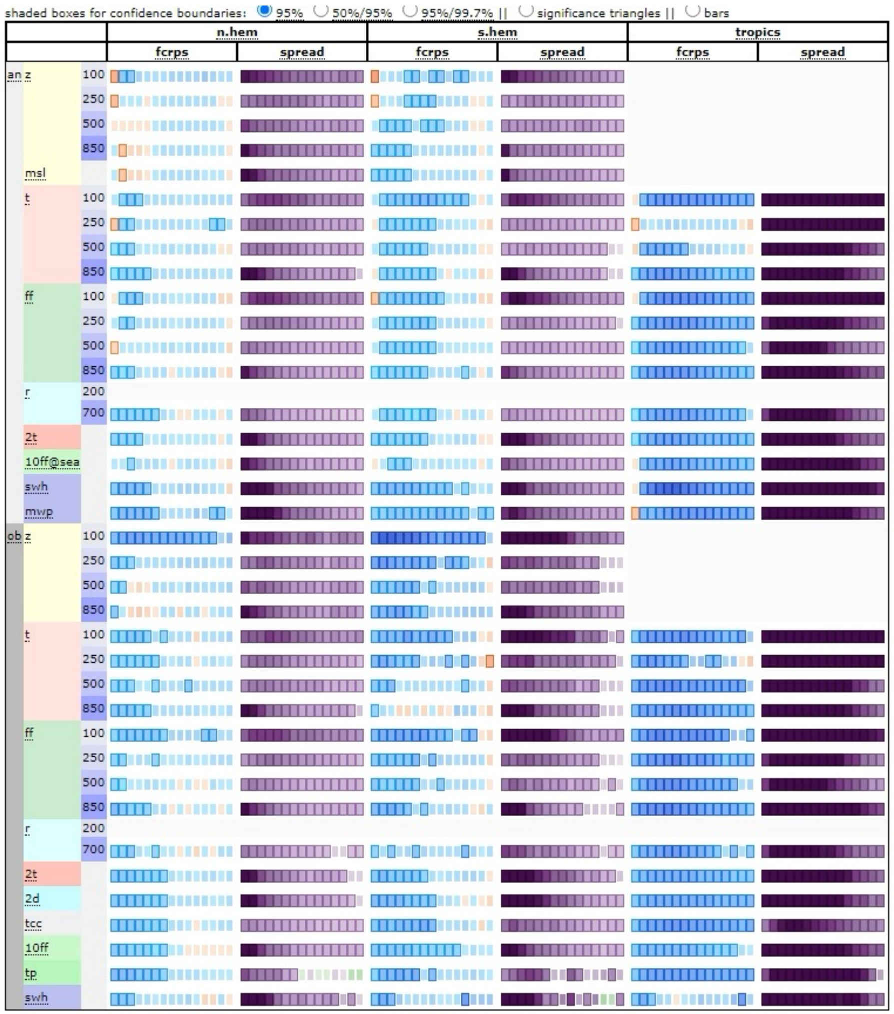
8 perturbed fcs

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

Scorecard of probabilistic skill ("fCRPS") & ensemble standard deviation ("Spread")

verified against analysis

verified against observations



Scorecard (summary):

IP + SPPT3* (*3 scales) *versus* IP only

Spread:
Purple = more spread / Green = less spread

fCRPS:
Blue = more skillful / Red less skillful

Framed cell indicates statistically significant differences at the 95% confidence interval

CY47R3

TCo399L137, dt=1200s

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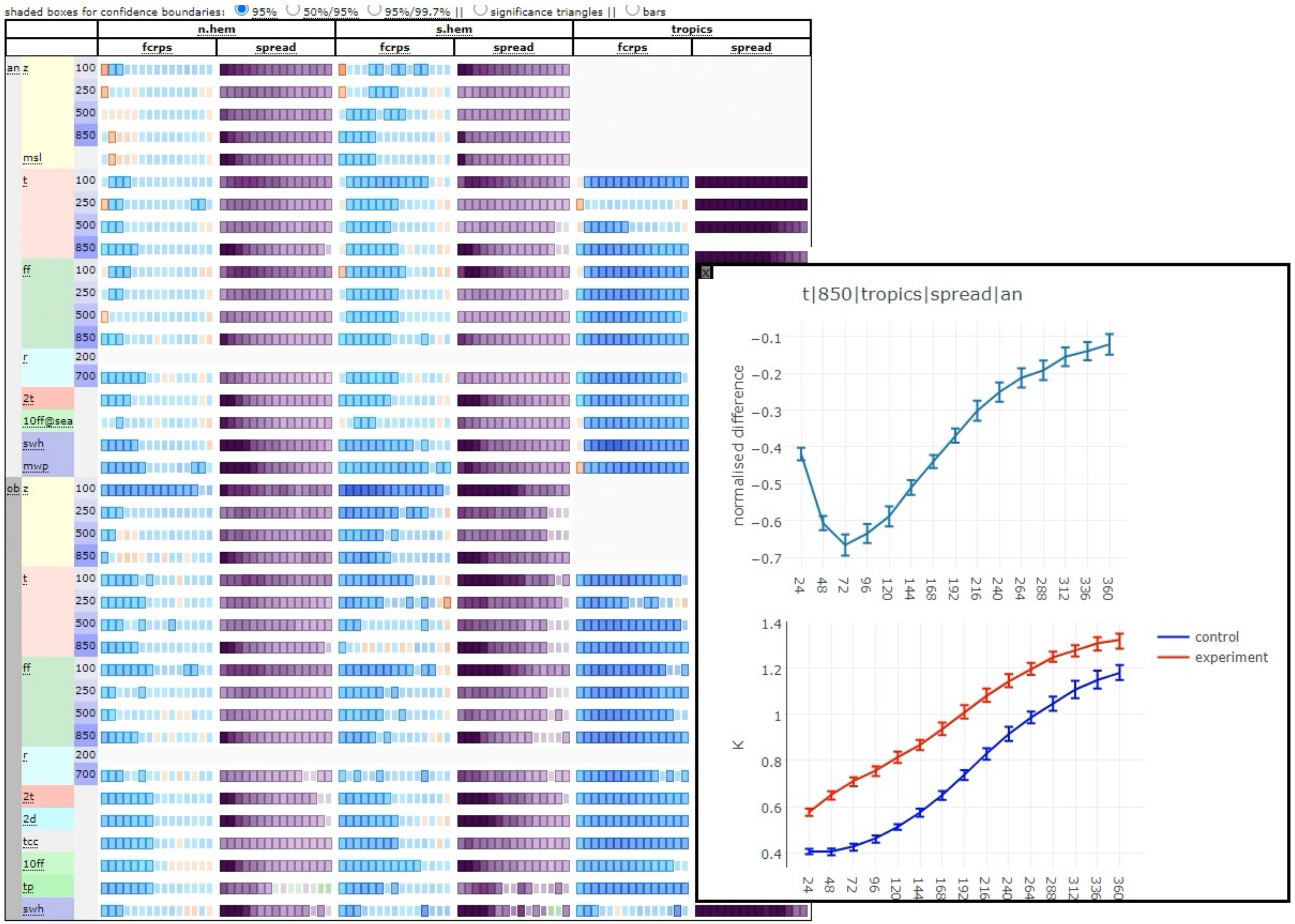
Ensemble forecasts: with **multi-scale** model uncertainty perturbations (**SPPT**)

Scorecard of probabilistic skill ("fCRPS") & ensemble standard deviation ("Spread")

verified against analysis

verified against observations



CY47R3

TCo399L137, dt=1200s

30 dates (Dec 2019)

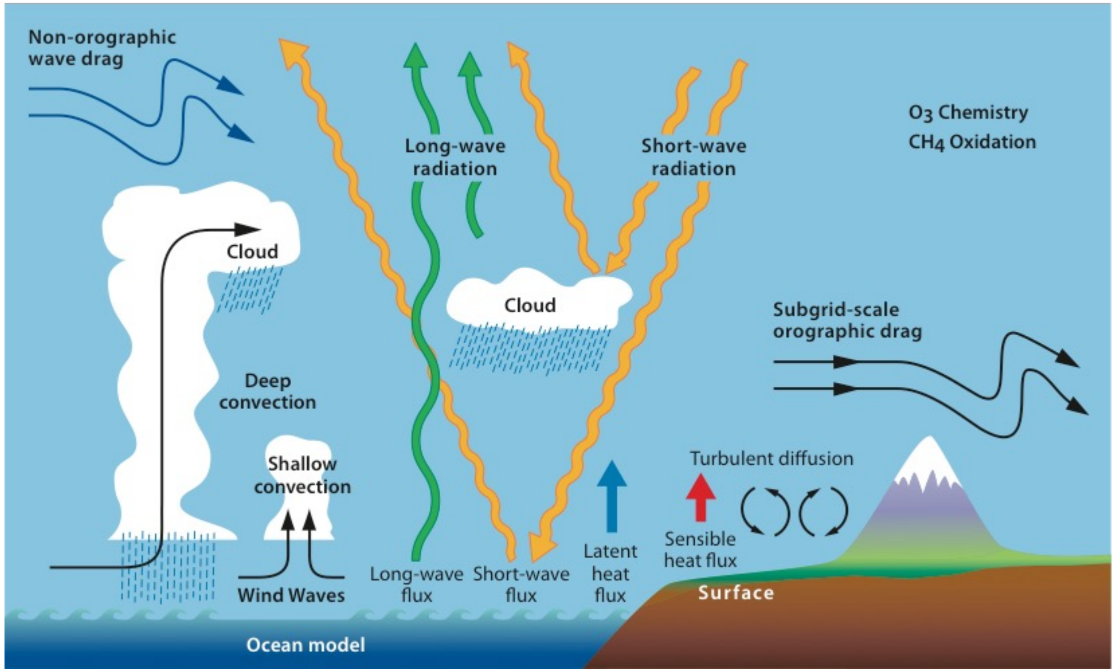
8 perturbed fcs

Summary: stochastic representation of model uncertainty in IFS

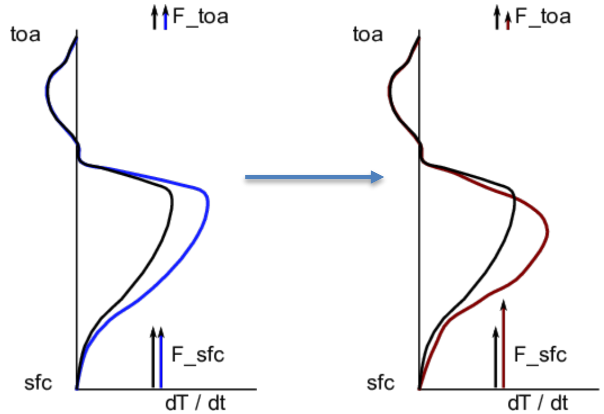
- Model uncertainty (MU) due to unresolved and misrepresented processes
- Without representing MU, ensemble forecasts are under-dispersive => over-confident
- Stochastic representations of model uncertainty can improve ensemble reliability
- SPPT: represents uncertainty due to sub-grid atmospheric physics parameterisations
  - 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)
- *Difficult to characterise sources of model uncertainty due to their small scales*

Stochastic representations of model uncertainty: **new scheme in IFS CY49R1**

Process-level model uncertainty representation

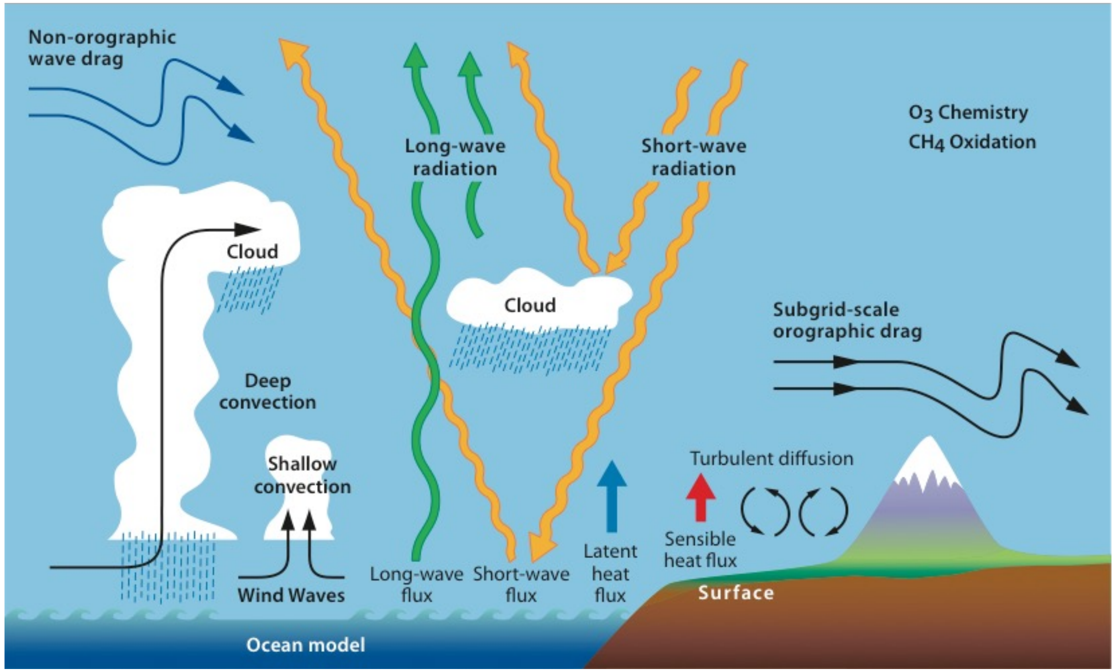


- **Aim**: to improve the physical consistency
- Preserve local conservation properties: moisture, momentum, energy
- Generate flux perturbations at the top of atmosphere (TOA) and surface that are consistent with tendency perturbations within the atmospheric column
- Remove ad hoc tapering in boundary layer
- Include multi-variate aspects of uncertainties



Stochastic representations of model uncertainty: **new scheme in IFS CY49R1**

Process-level model uncertainty representation



Stochastically Perturbed Parametrisations (SPP)

(Lang et al., 2021, QJRMS; Ollinaho et al., 2017, QJRMS)

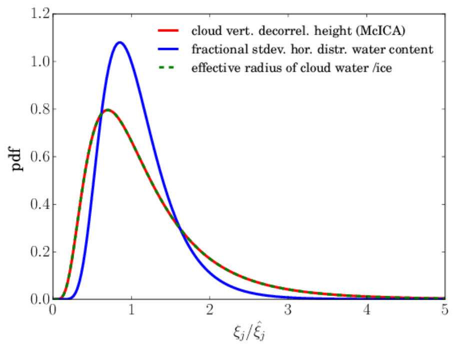
- Embed stochasticity **inside** IFS parametrisations
- Perturb parameters/variables directly
- Specify spatial/temporal correlations
- Target uncertainties that matter (level of uncertainty and impact)
- Require that stochastic schemes converge to deterministic schemes in limit of vanishing variance

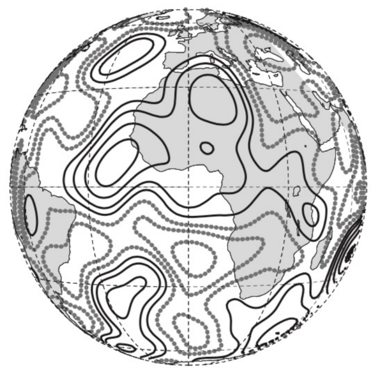
Stochastically perturb parameters/variables in the physics parametrisations ($\hat{\xi}_j$):

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

where

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



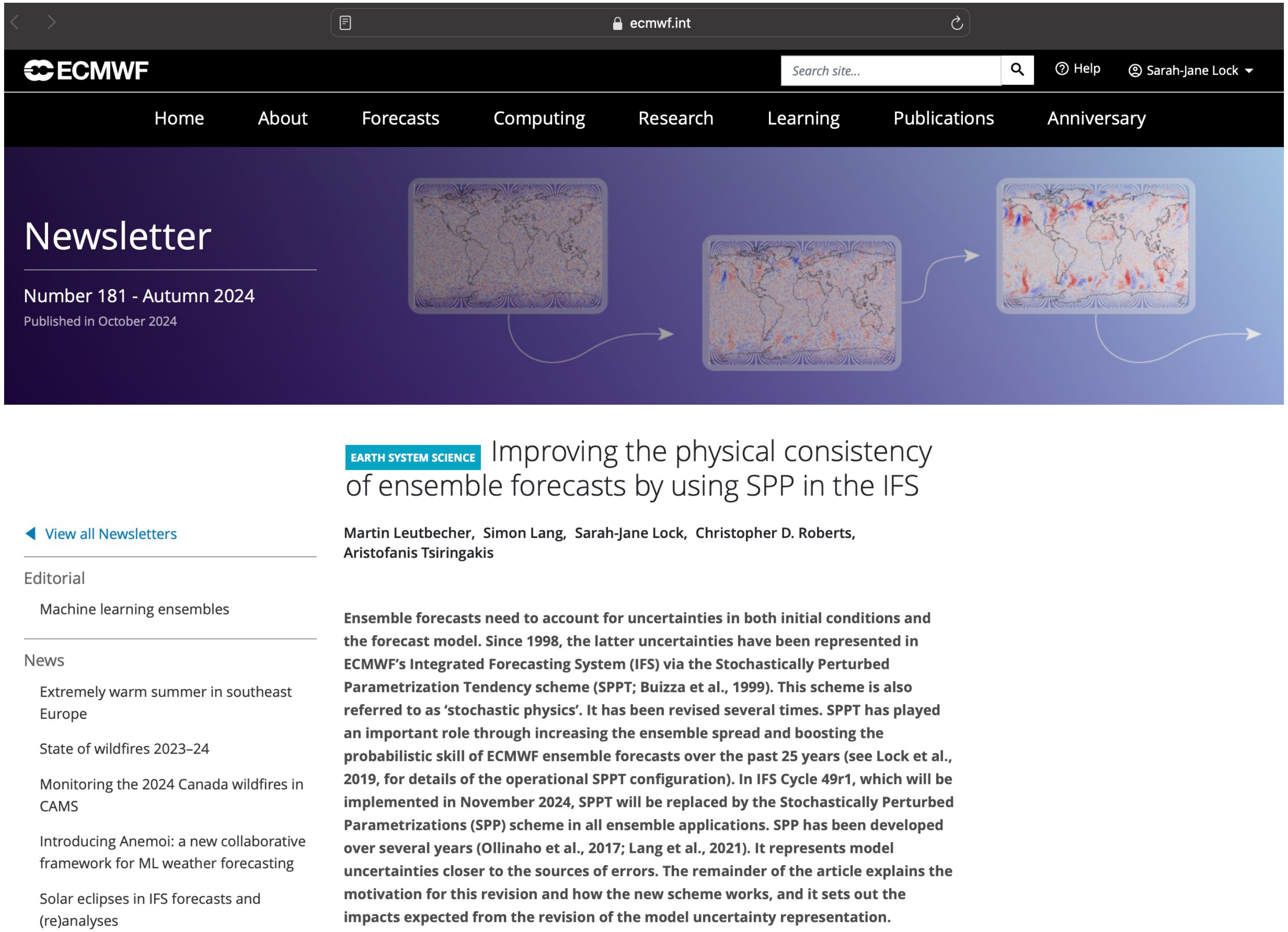


Stochastic representations of model uncertainty: **new scheme in IFS** **CY49R1**

Article in recent Autumn 2024 Newsletter (Number 181)

Outlines details of the SPP implementation and impacts:

- Perturbed parameters
- Random patterns
- Forecast skill impacts
- Conservation properties



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Monitoring the 2024 Canada wildfires in CAMS

Introducing Anemoi: a new collaborative framework for ML weather forecasting

Solar eclipses in IFS forecasts and (re)analyses

EARTH SYSTEM SCIENCE Improving the physical consistency of ensemble forecasts by using SPP in the IFS

Martin Leutbecher, Simon Lang, Sarah-Jane Lock, Christopher D. Roberts, Aristofanis Tsiringakis

Ensemble forecasts need to account for uncertainties in both initial conditions and the forecast model. Since 1998, the latter uncertainties have been represented in ECMWF's Integrated Forecasting System (IFS) via the Stochastically Perturbed Parametrization Tendency scheme (SPPT; Buizza et al., 1999). This scheme is also referred to as 'stochastic physics'. It has been revised several times. SPPT has played an important role through increasing the ensemble spread and boosting the probabilistic skill of ECMWF ensemble forecasts over the past 25 years (see Lock et al., 2019, for details of the operational SPPT configuration). In IFS Cycle 49r1, which will be implemented in November 2024, SPPT will be replaced by the Stochastically Perturbed Parametrizations (SPP) scheme in all ensemble applications. SPP has been developed over several years (Ollinaho et al., 2017; Lang et al., 2021). It represents model uncertainties closer to the sources of errors. The remainder of the article explains the motivation for this revision and how the new scheme works, and it sets out the impacts expected from the revision of the model uncertainty representation.

Stochastic representations of model uncertainty: **new scheme in IFS CY49R1**

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Surface fluxes, turbulent mixing and subgrid orography	
CFM	Transfer coefficient for momentum
RKAP	Surface flux uncertainties via von Kármán constant
TOFDC	Turbulent orographic form drag
HSDT	Standard deviation of subgrid orography
VDEXC_LEN	mixing length-scale stable boundary layer
VDSST	Sea-surface temperature (SST) used in calculation of surface fluxes
COLDSKIN	Cold skin temperature parametrization used for surface fluxes
Convection	
ENTRORG	Entrainment rate
ENTSHALP	Shallow entrainment rate
DETRPEN	Detrainment rate for penetrative convection
RPRCON	Conversion coefficient cloud to rain
CUDU/CUDV	Deep convective momentum transport
CUDUS/CUDVS	Shallow convective momentum transport
RTAU	Adjustment timescale in Convective Available Potential Energy (CAPE) closure
ENTSTPC1	Shallow convection test parcel entrainment
Cloud and large-scale precipitation	
RAMID	Relative humidity threshold stratiform condensation
RCLDIFF	Diffusion for evaporation of cloud at subgrid cloud edges
RLCRITSNOW	Cloud ice threshold for autoconversion to snow
RAINEVAP	Rain evaporation rate
SNOWSUBLIM	Snow sublimation rate
QSATVERVEL	Vertical velocity for adiabatic temperature change in saturation adjustment
FALLSPEED	Hydrometeor terminal fall speeds
Radiation	
ZDECORR	Cloud vertical decorrelation height
ZSIGQCW	Fractional standard deviation of horizontal distribution of water content
ZRADEFF	Effective radius of cloud water and ice
ZHS_VDAERO	Scale height of aerosol normal vertical distribution
DELTA_AERO	Optical thickness of aerosol

TABLE 1 Overview of the active perturbation elements in SPP.

Stochastic representations of model uncertainty:
new scheme in IFS
CY49R1

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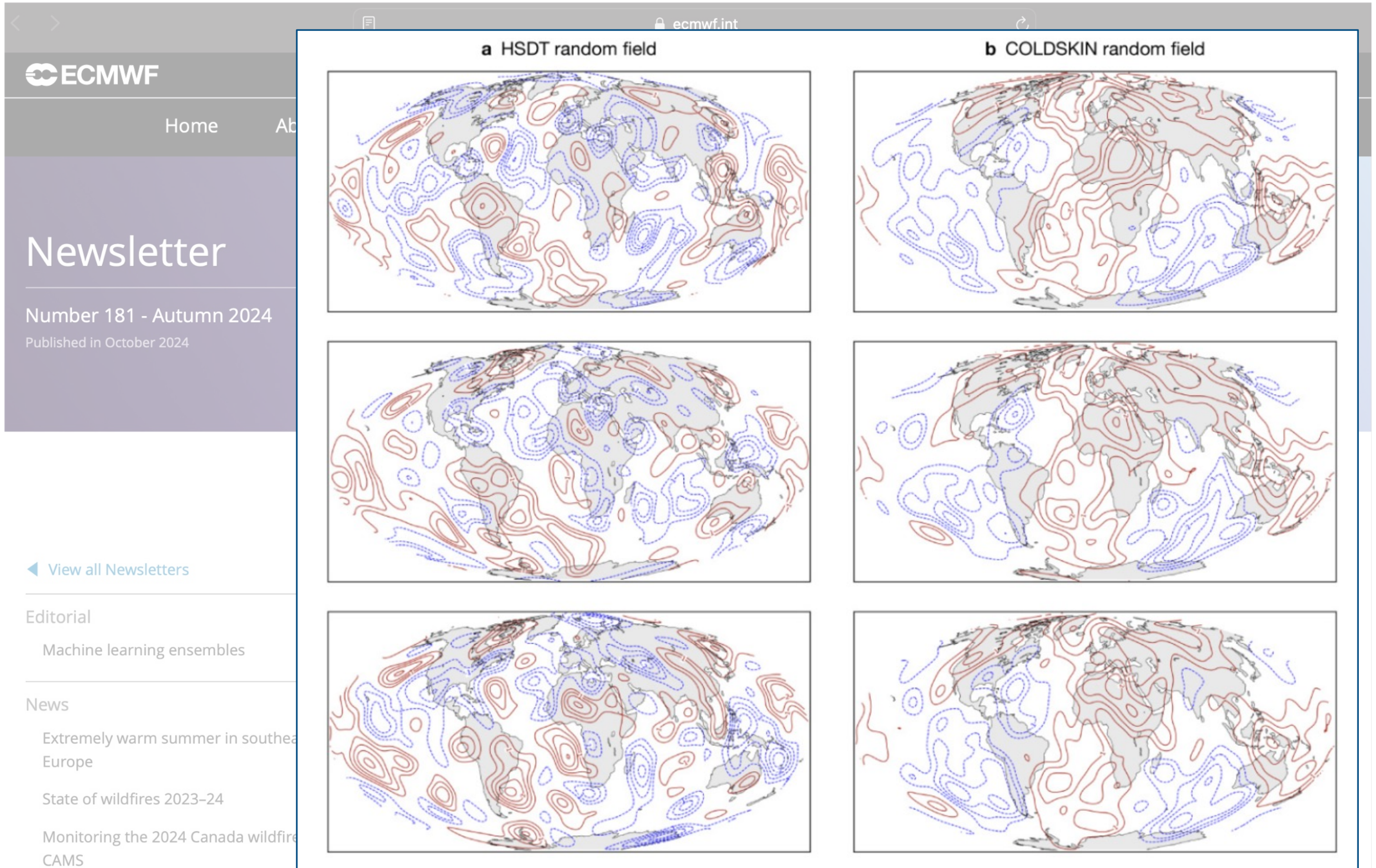

FIGURE 2 Random fields used by SPP in member 1 on 1, 2 and 3 January 2024 (from top to bottom) at 00 UTC for the perturbation elements (a) HSDT and (b) COLDSKIN. The latter has larger spatial and temporal decorrelation scales than the former. The contour interval is 0.5, with values ≥ 0.5 in solid red contours and values ≤ –0.5 in blue dashed contours.

Stochastic representations of model uncertainty: **new scheme in IFS** CY49R1

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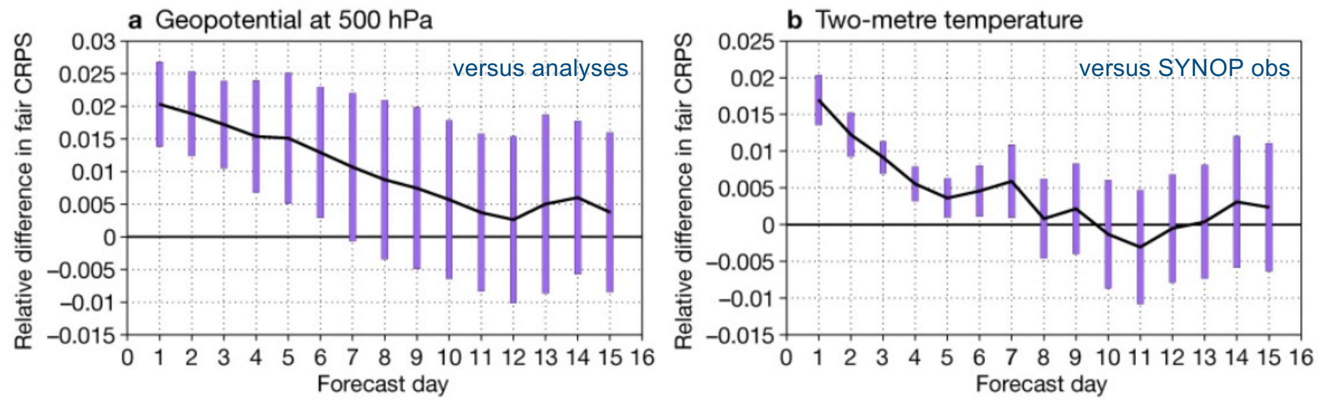

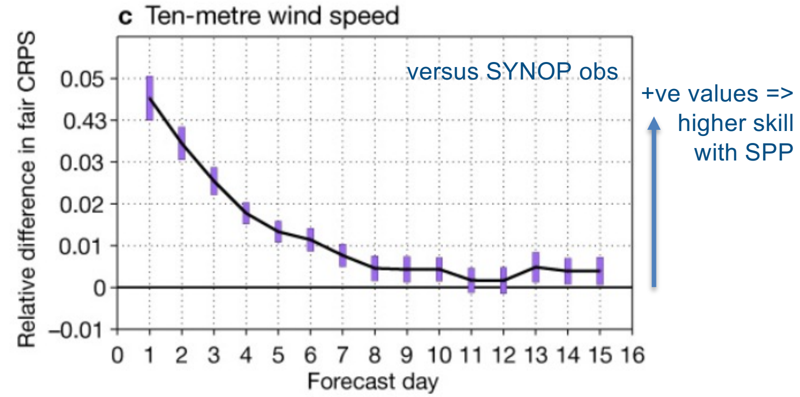

Set-up:
- TCo1279 (9km)
- 8 perturbed members
- Initialised from operational ICs
- Starts: DJF 2021/22 & JJA 2022 (282 dates)

FIGURE 4 Relative differences in fair CRPS (continuous ranked probability score) of an ensemble using SPP and an ensemble using SPPT in the northern extratropics, for (a) geopotential at 500 hPa verified

impacts expected from the revision of the model uncertainty representation.

Stochastic representations of model uncertainty: **new scheme in IFS**

CY49R1

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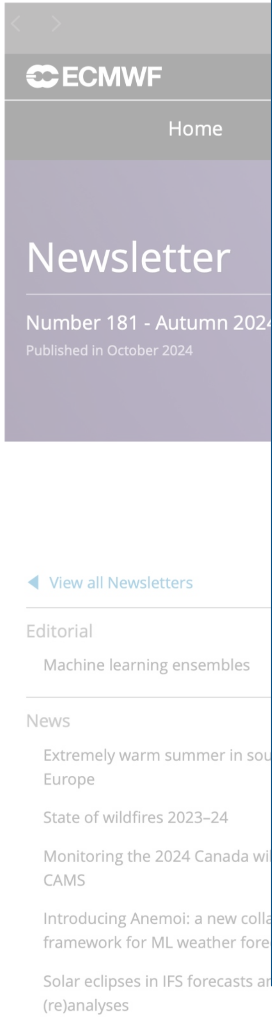
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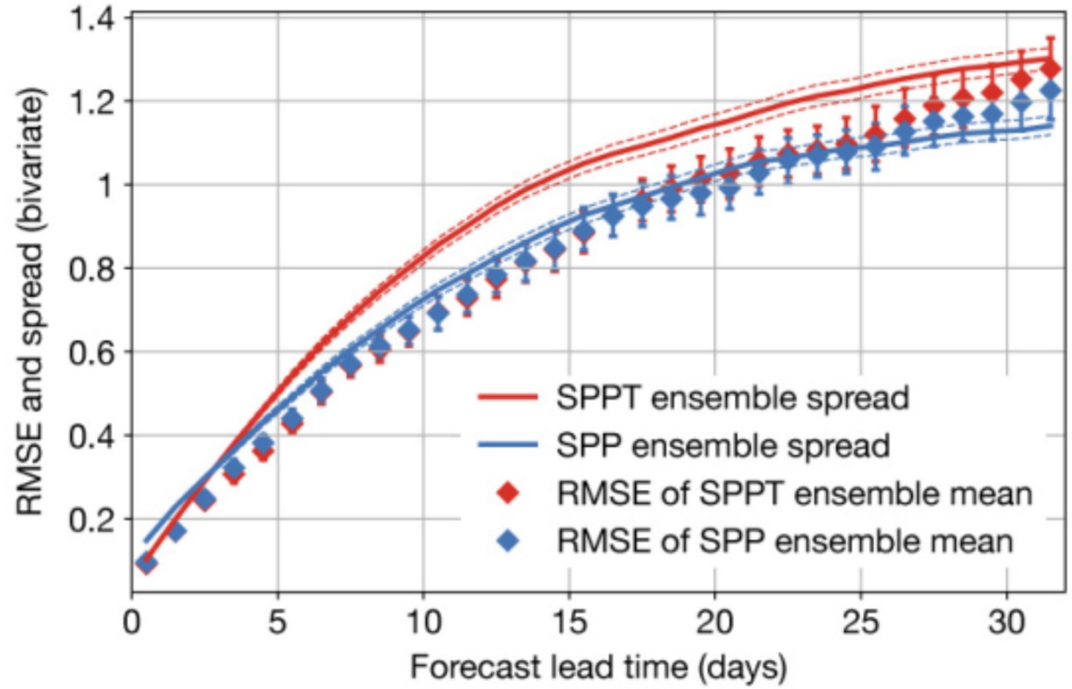

FIGURE 5 Ensemble spread (solid lines) and root-mean-square error (RMSE) of the ensemble mean (diamonds) for the bivariate RMM index for experiments with model uncertainty represented with SPPT (red) and SPP (blue). Confidence intervals (95%) are indicated by the dashed lines (for spread) and bars (for error). Forecasts are started on the first of each month from 1 January 1989 to 1 December 2016.

Stochastic representations of model uncertainty: **new scheme in IFS** **CY49R1**

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- **Conservation properties**

e.g. moisture budget:

$$\underbrace{\frac{1}{g}\int_{p_{\mathrm{surf}}}^{0}\left(\frac{dq_v}{dt}+\frac{dq_l}{dt}+\frac{dq_i}{dt}+\frac{dq_r}{dt}+\frac{dq_s}{dt}\right)dp}_{\text{Vertical integrals of moisture tendencies from physics}} = \overbrace{F_{\mathrm{prs}}}^{\text{Precipitation}} + \underbrace{F_e}_{\text{Evaporation}}$$

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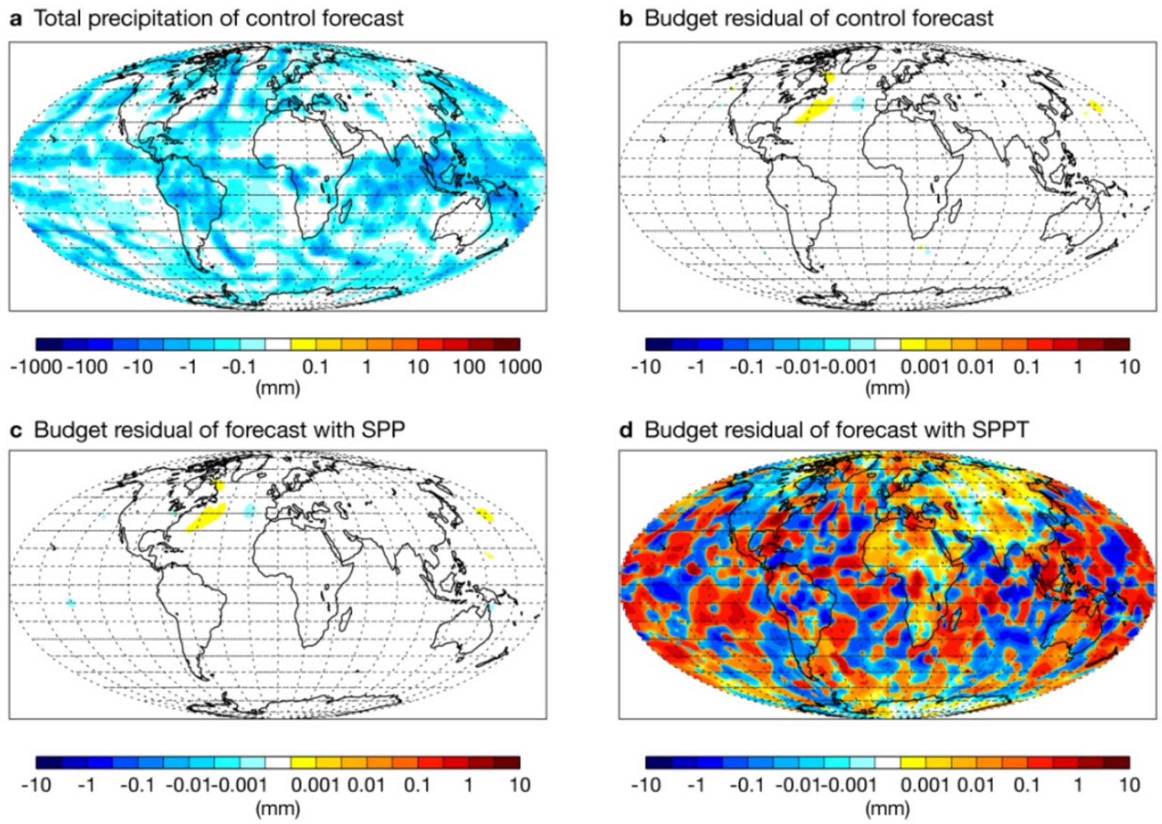
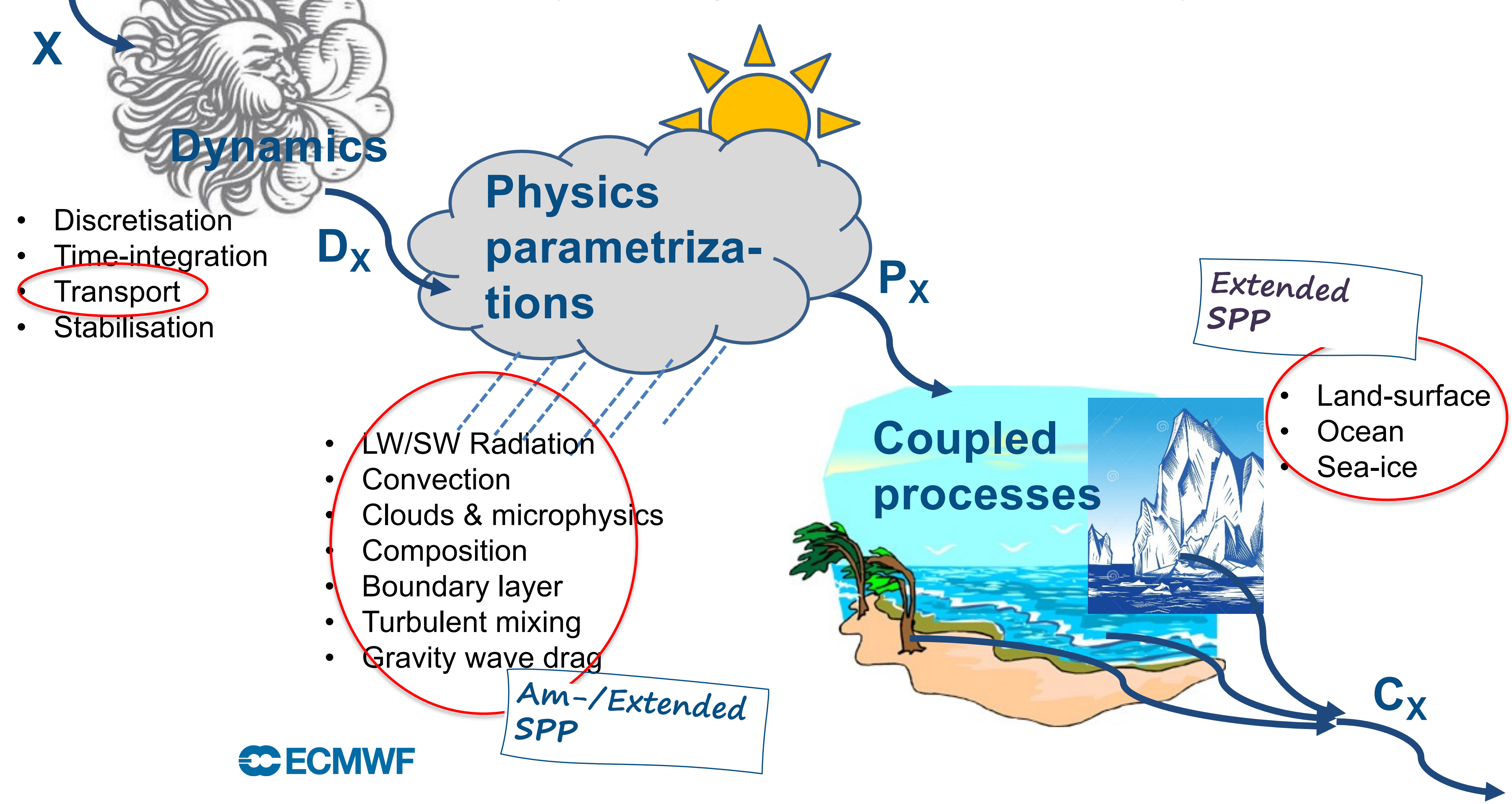


FIGURE 3 Moisture budget terms accumulated during a forecast lead time of 45–48 hours …

uncertainties closer to the sources of errors. The remainder of the article explains the motivation for this revision and how the new scheme works, and it sets out the impacts expected from the revision of the model uncertainty representation.

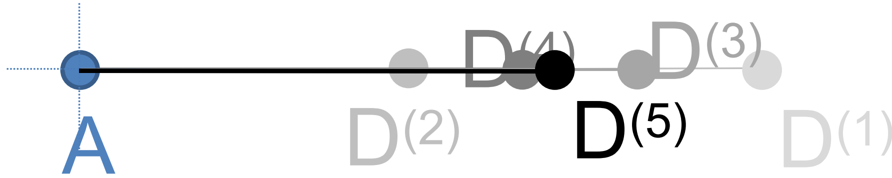
Future: representing other sources of uncertainty?



ECMWF

STOCHDP:

Stochastically perturbed semi-Lagrangian (SL) departure point (DP) estimates



Diamantakis & Magnusson (2016):

- Explored convergence rate of the iterative DP estimate
- Slowest convergence ←→ most complex flow (strong shear / curvature)
- Example: Typhoon Neoguri:
  - HRES forecast: initialised: 2014-07-05, 00UTC

Fig. 1c: t+96h, 850hPa windspeeds

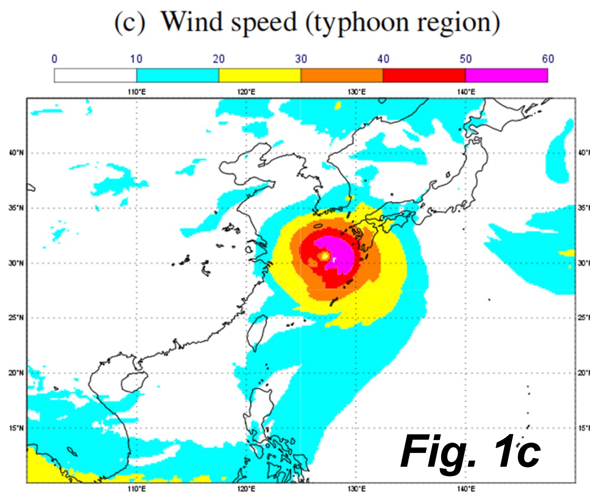
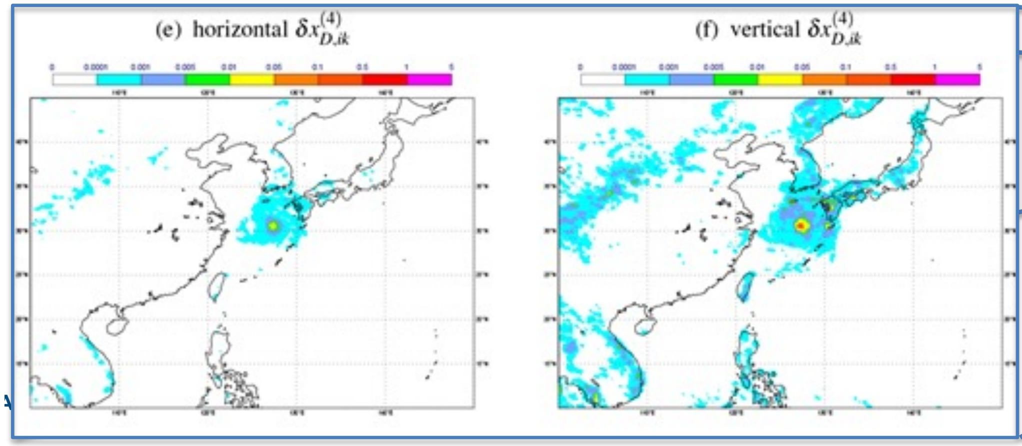
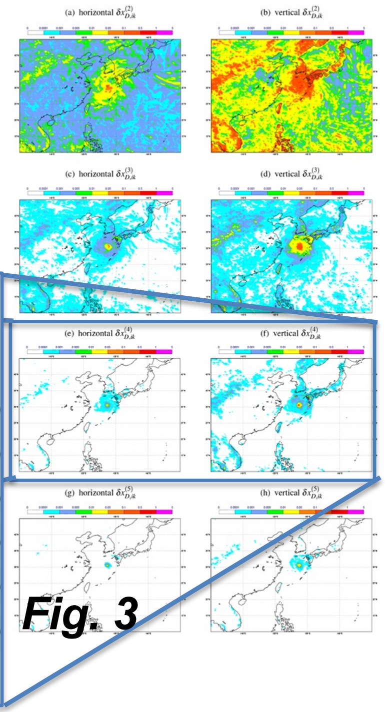


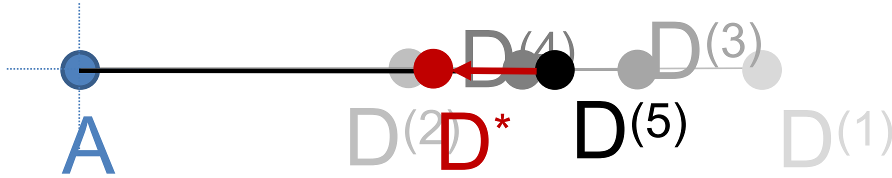
Figure 3: difference in DP estimate between consecutive iterations (scaled)





STOCHDP:

Stochastically perturbed semi-Lagrangian (SL) departure point (DP) estimates



Model uncertainty scheme, “STOCHDP”:

- use the DP estimate convergence rate to attribute MU:

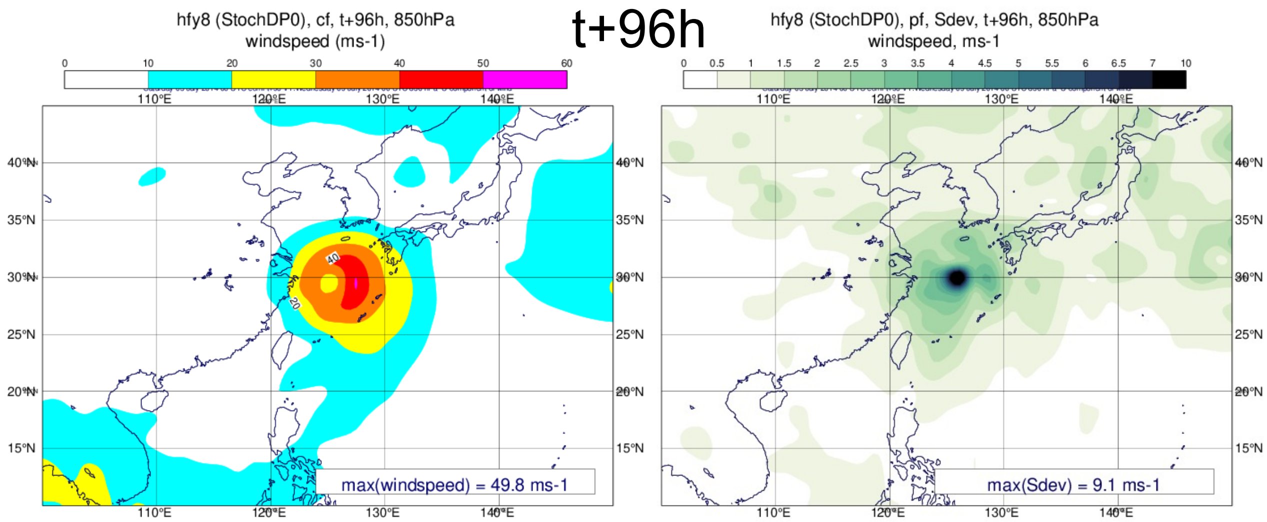
$$D^* = D^{(5)} + r\left(D^{(5)} - D^{(5-i)}\right), i = 1..4$$

where D^* is the perturbed DP and r is a random number

➢ STOCHDP represents MU from SL advective winds

Early results, e.g.:

- Typhoon Neoguri case
- ENS: STOCHDP only
- TCo639L91, dt=720s
- 20+1 members
- Peak ENS stdev develops and tracks with TC



Control forecast

Ensemble stdev

Summary

- Including a representation of model uncertainty can improve the reliability of ensemble forecasts
- ”Model uncertainty” describes inaccuracies due to the model integrations
- Using stochastic physics schemes enables representation of the model uncertainty arising from the parametrization of unresolved atmospheric physics
- Current stochastic physics scheme used in the IFS: **SPPT**
- Upcoming (**CY49R1**): new scheme ”**SPP**” improves the physical consistency of the stochastic physics perturbations
- Ongoing: refinements and extensions of **SPP**; exploring perturbations to represent model uncertainty in the dynamics – **STOCHDP**

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