Model Uncertainty

Using stochastic perturbations

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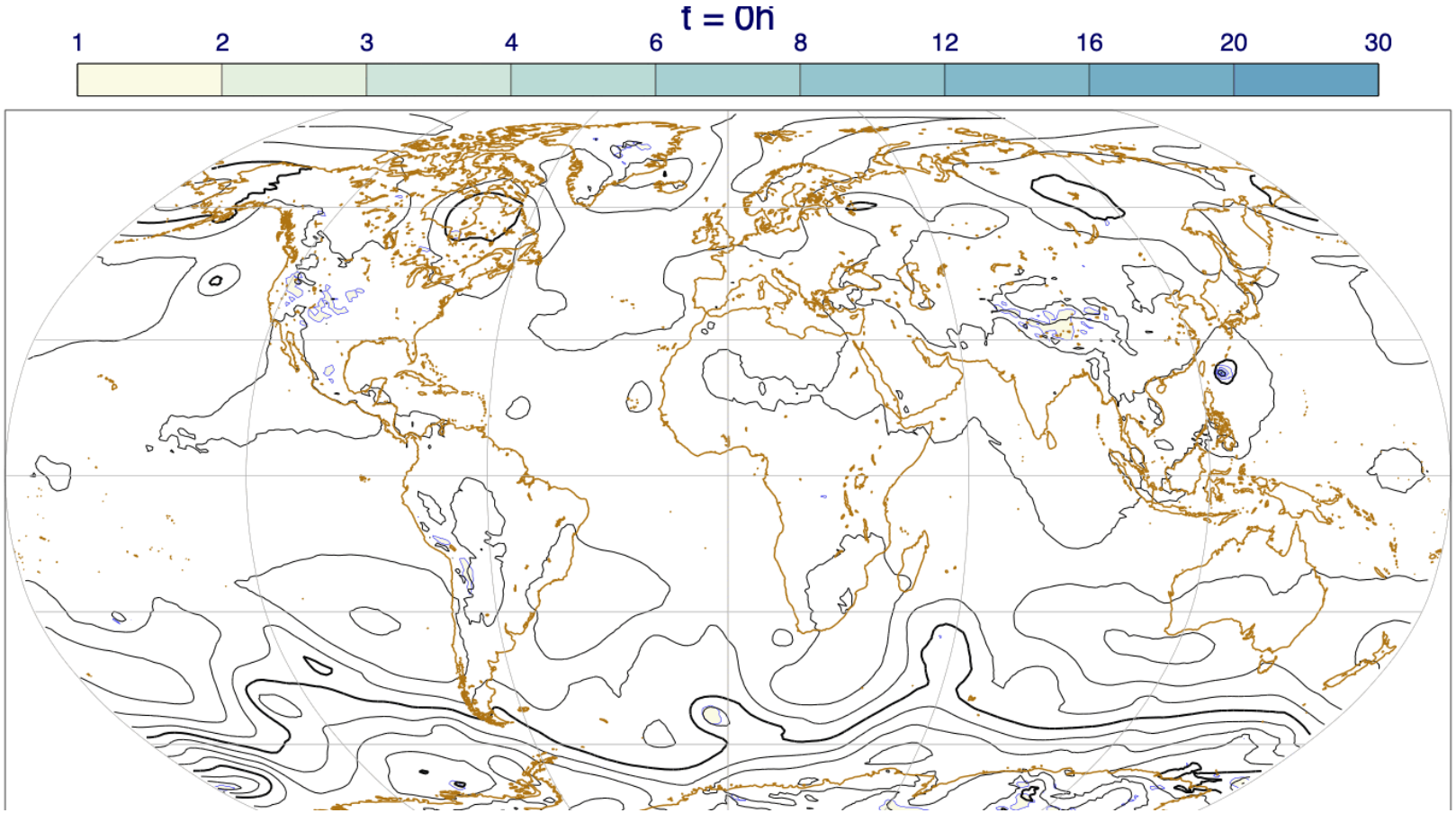
Background: why ensemble forecasts?

- knowing forecast uncertainty helps greatly in decision making
- forecast uncertainty varies
- ensembles predict situation dependent uncertainty



mean sea level pressure, ensemble spread (shading), ensemble mean (contours)
operational medium-range ensemble from 1 Sep 2022, 0 UTC, up to Day 5

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:

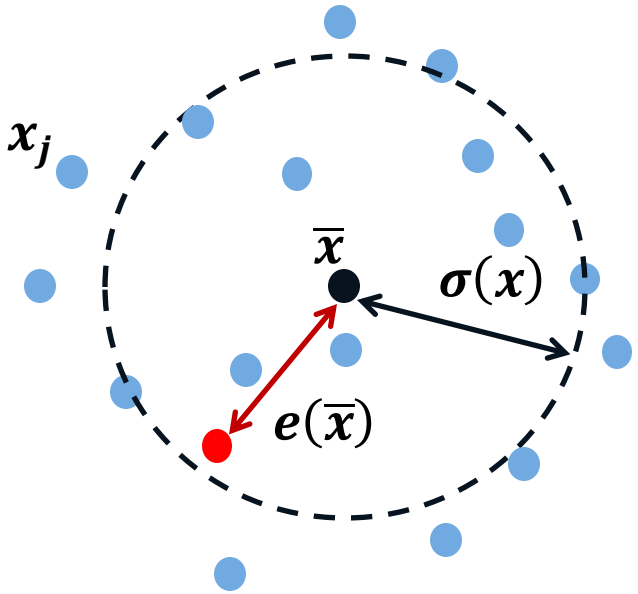
  a) different initial conditions for each member, to sample the uncertainty in our description of the initial state (***Simon Lang’s lecture***); and

  b) a different forecast model for each member, to sample the uncertainty due to the model integrations or the “***model uncertainty***”

- To date, effort has been focused on **model uncertainty** due to the parametrization schemes that describe sub-grid atmospheric physics

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,

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

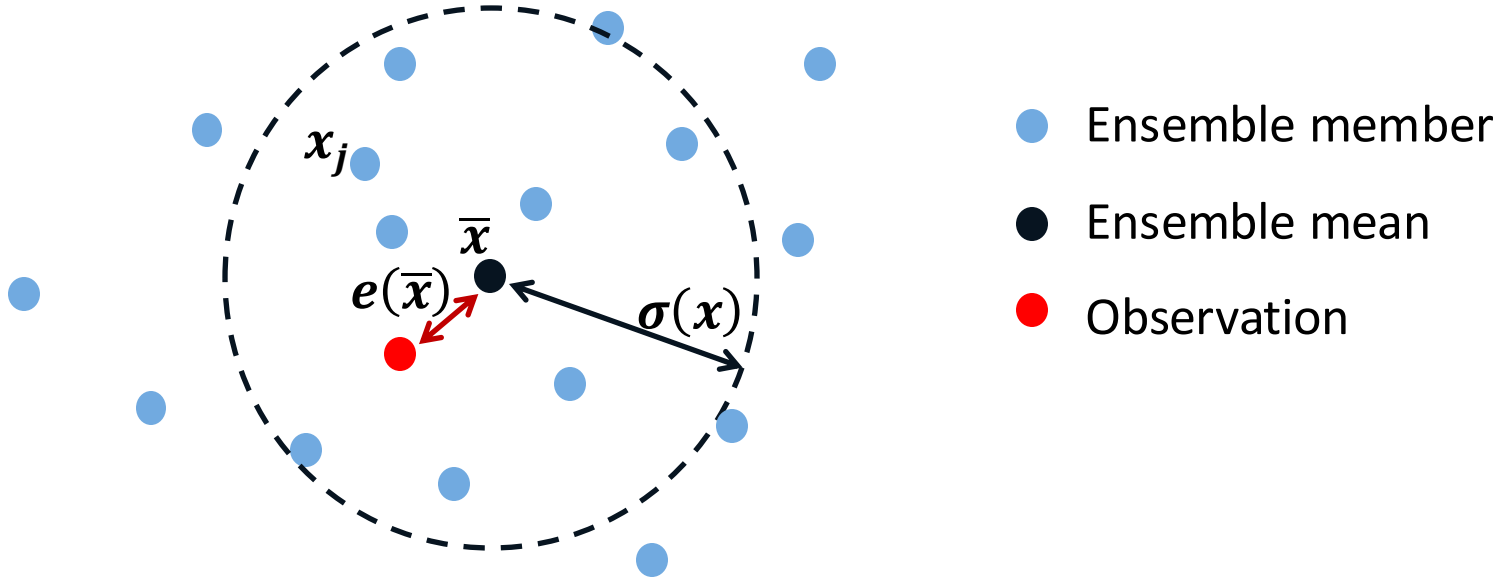
For a thorough discussion of this relationship:

Martin Leutbecher's lectures

Ensemble reliability

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

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



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

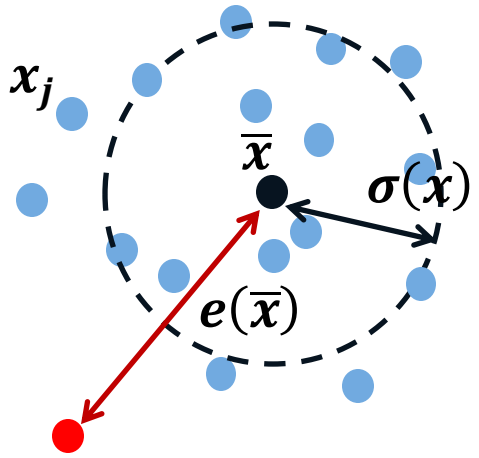
The relatively large spread implies large uncertainty and hence, likely large error:

an “under-confident forecast”

Ensemble reliability

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

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



Ensemble member

Ensemble mean

Observation

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

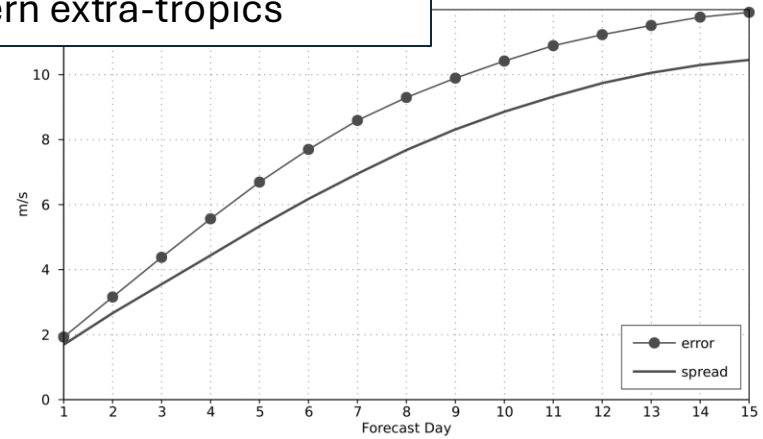
an “over-confident forecast”

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

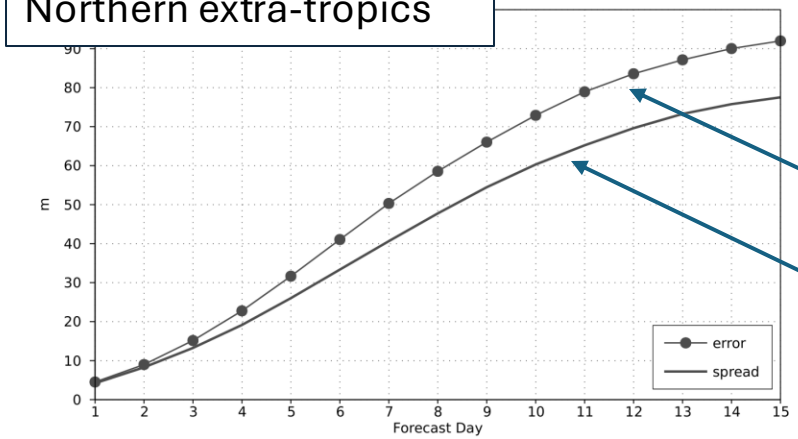
Ensemble forecasts with only initial conditions perturbations

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

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



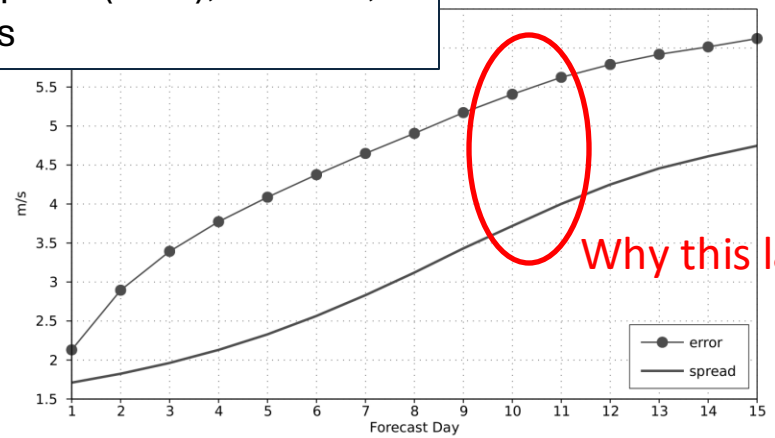
Z, 500hPa, Northern extra-tropics



error

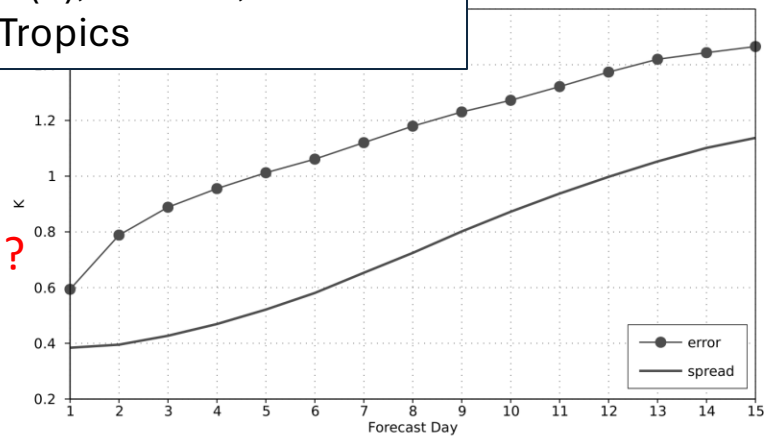
spread

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



Why this lack of spread?

T (K), 850hPa, Tropics



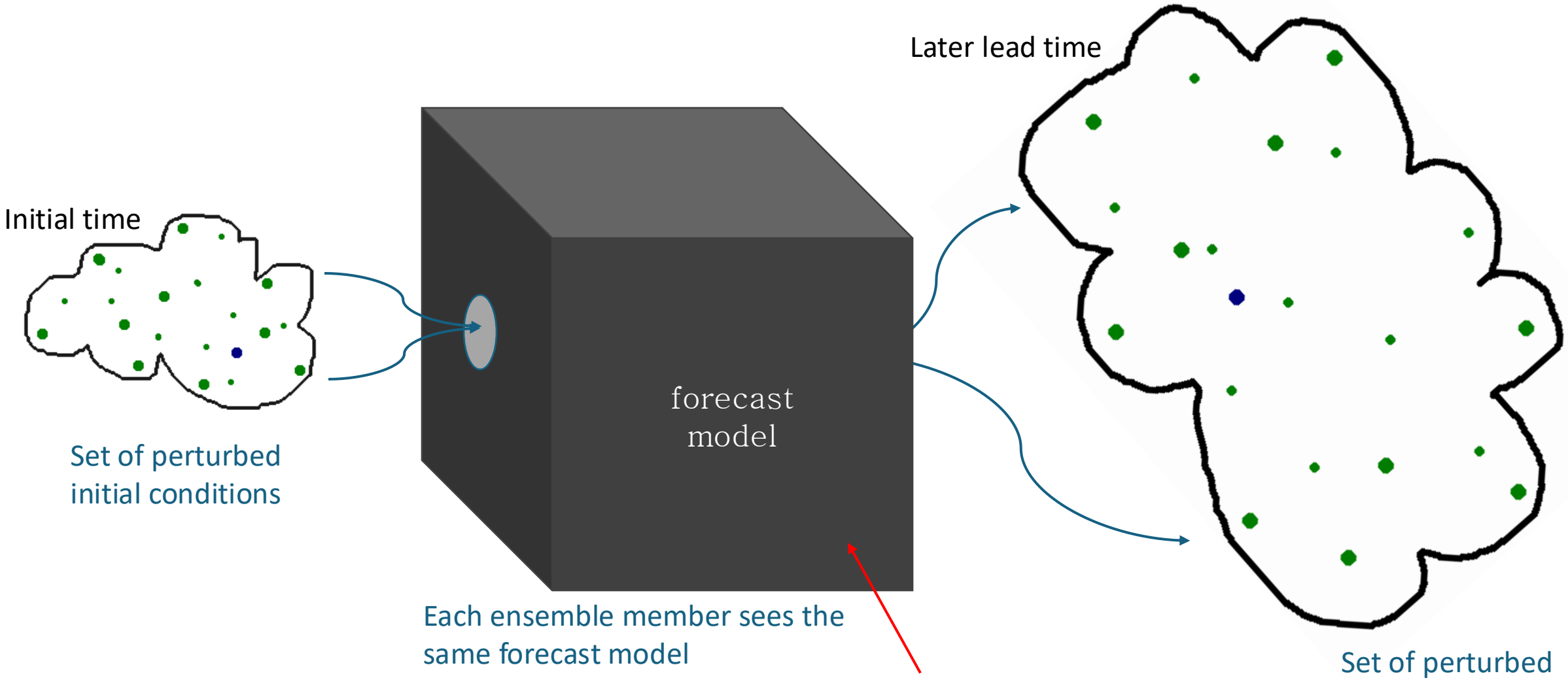
CY50R1

TCo399L137, dt=1200s

JJA 2024 + DJF 24/25

8 perturbed members

Sources of uncertainty: initial conditions



Sources of uncertainty: inside the forecast model?

X

Dynamics

- Discretisation
- Time-integration
- Transport
- Stabilisation

D_X

Physics parametriza-tions

- LW/SW Radiation
- Convection
- Clouds & microphysics
- Composition
- Boundary layer
- Turbulent mixing
- Gravity wave drag

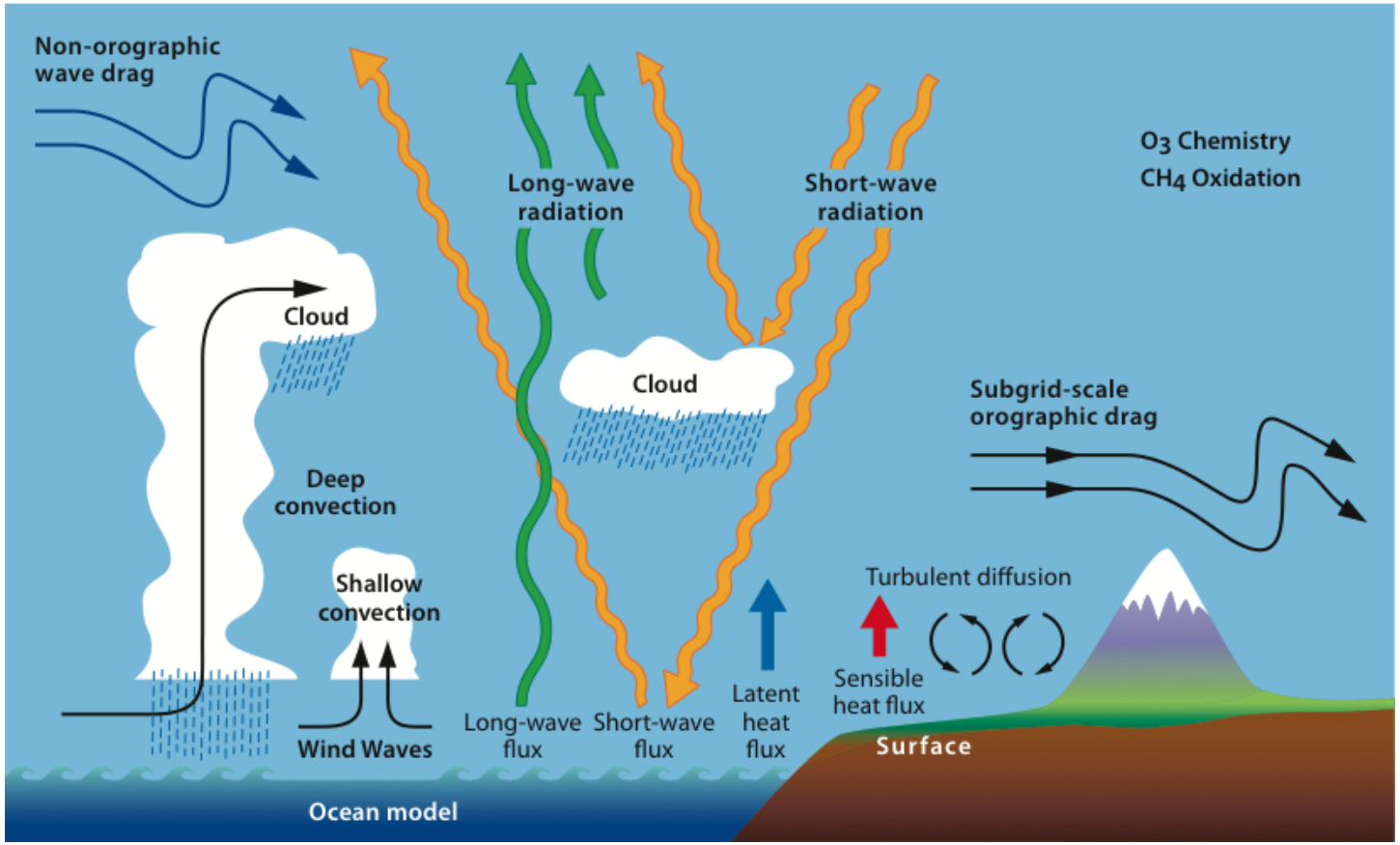
P_X

Coupled processes

- Land-surface
- Ocean
- Sea-ice

C_X

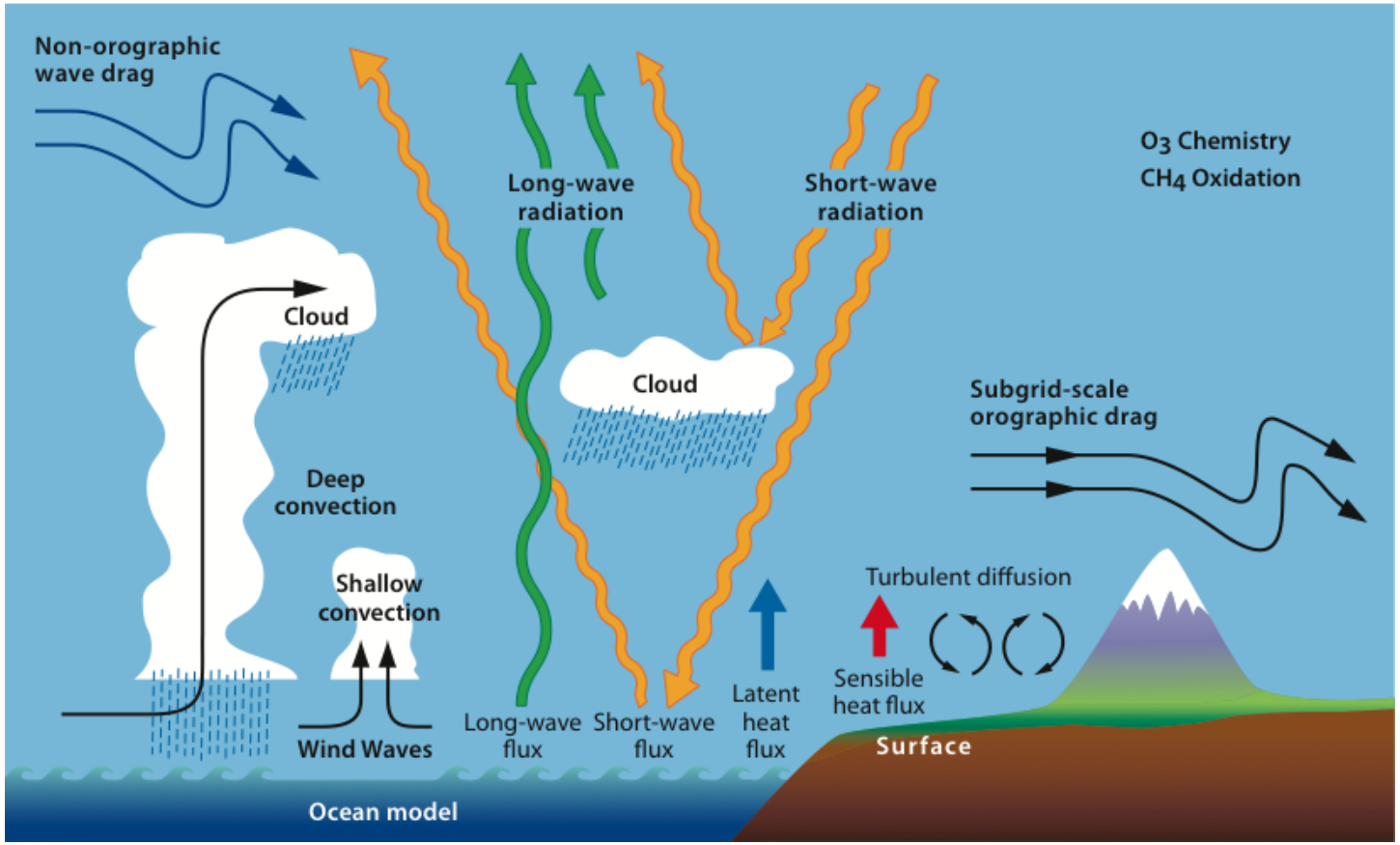
Model uncertainty: parametrized atmospheric physics processes



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



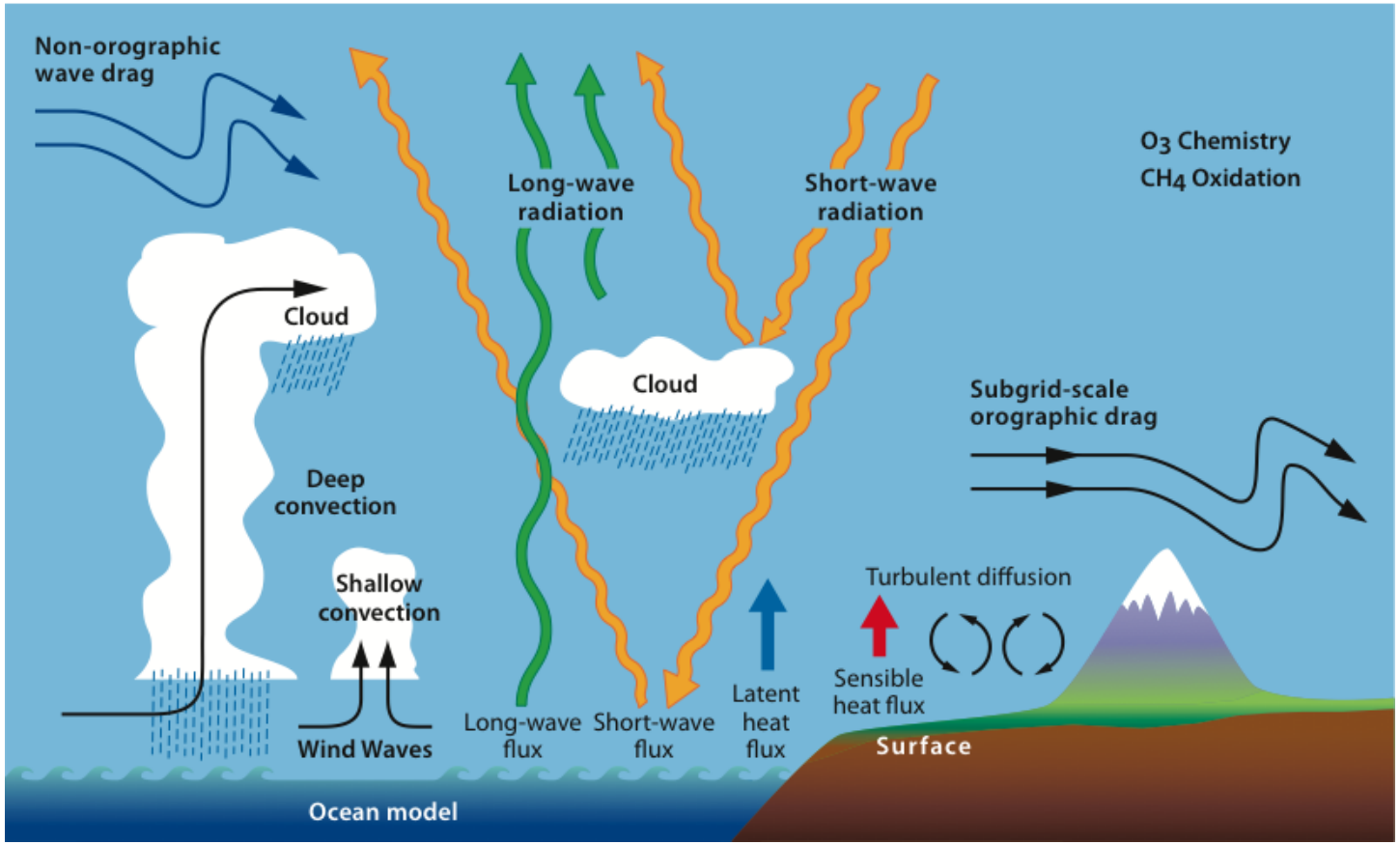
"Let's take the positives"

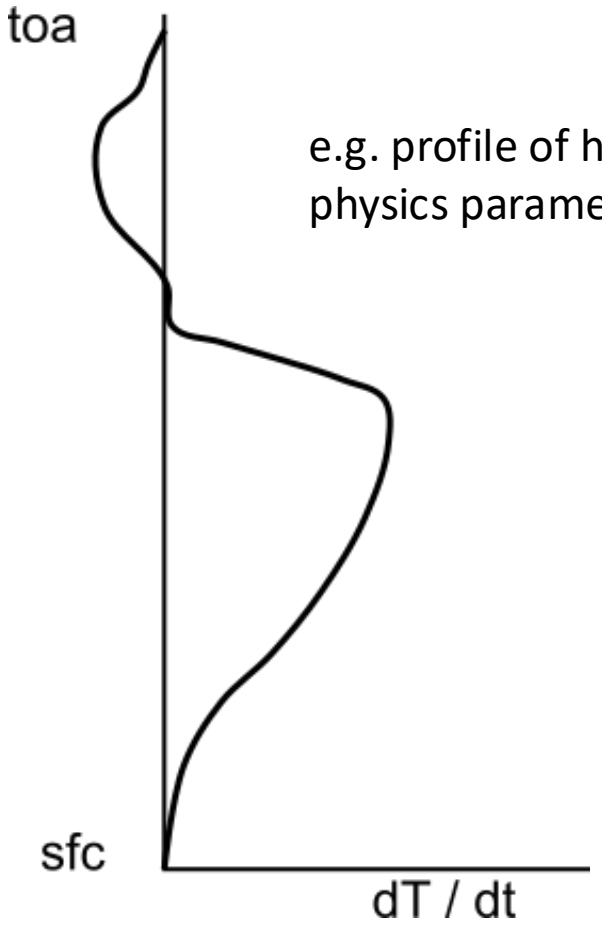
Parametrisation schemes:

- developed/operate together
- highly tuned for best performance

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

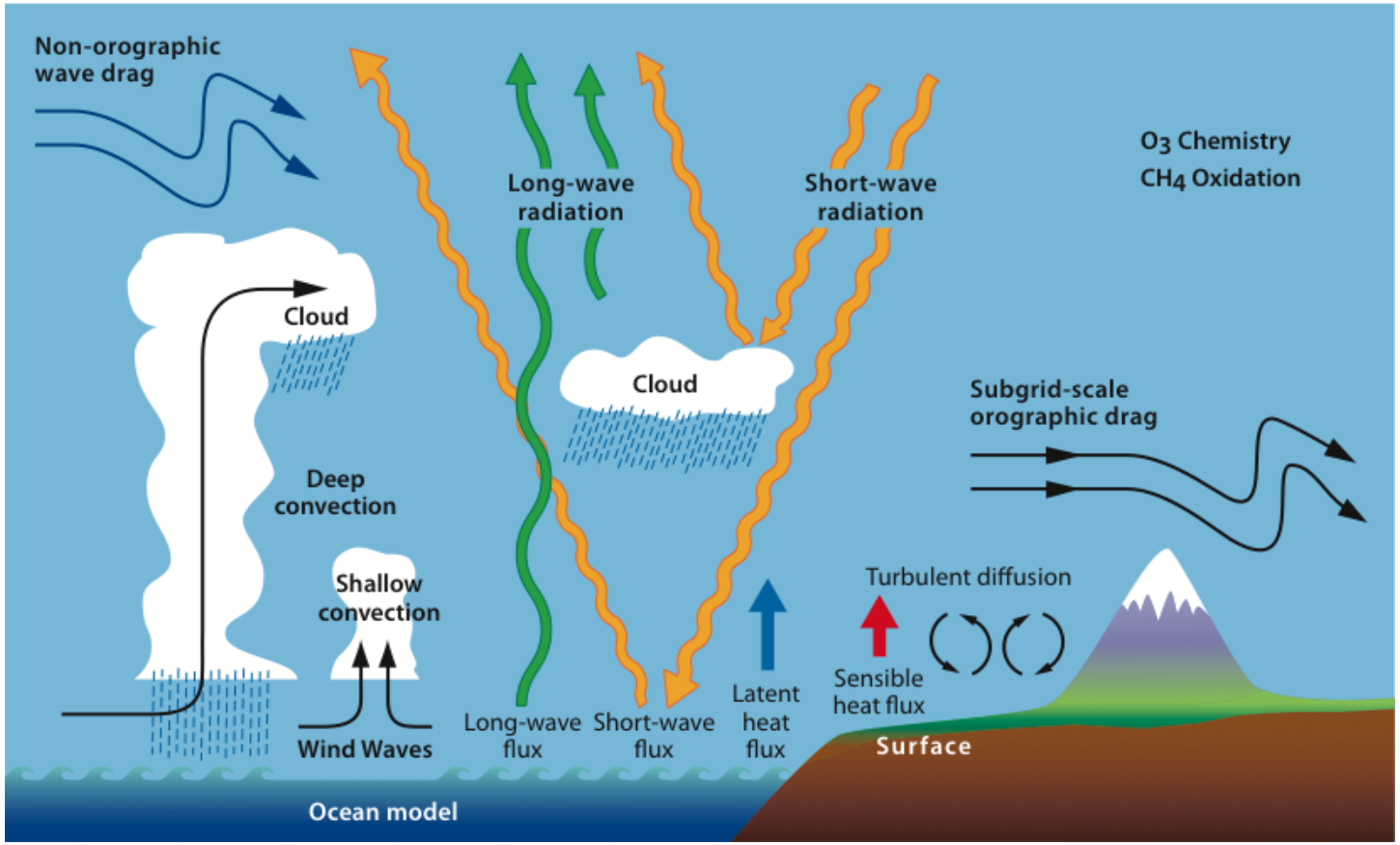
Model uncertainty: parametrized atmospheric physics processes

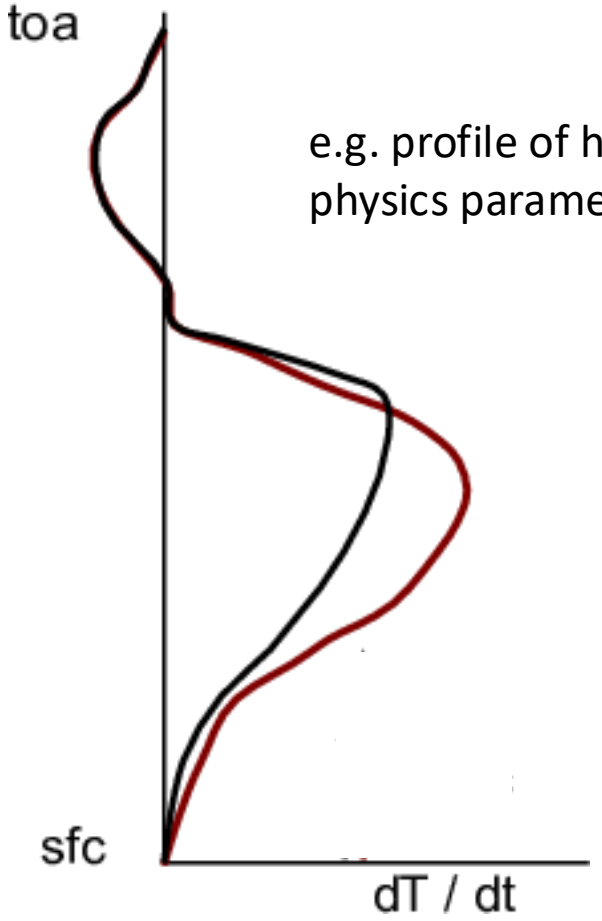




e.g. profile of heating rates from physics parametrisations

Model uncertainty: parametrized atmospheric physics processes





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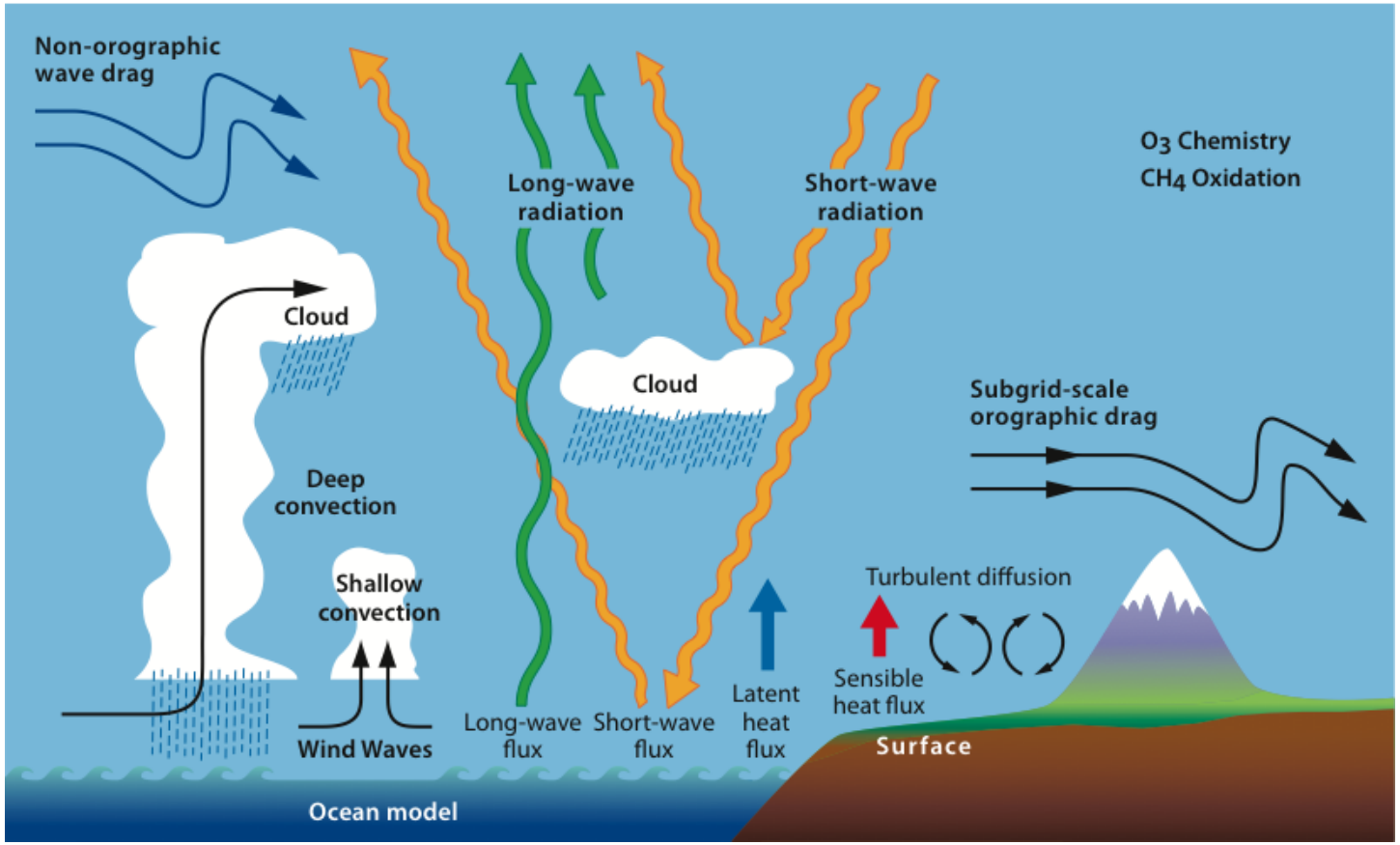

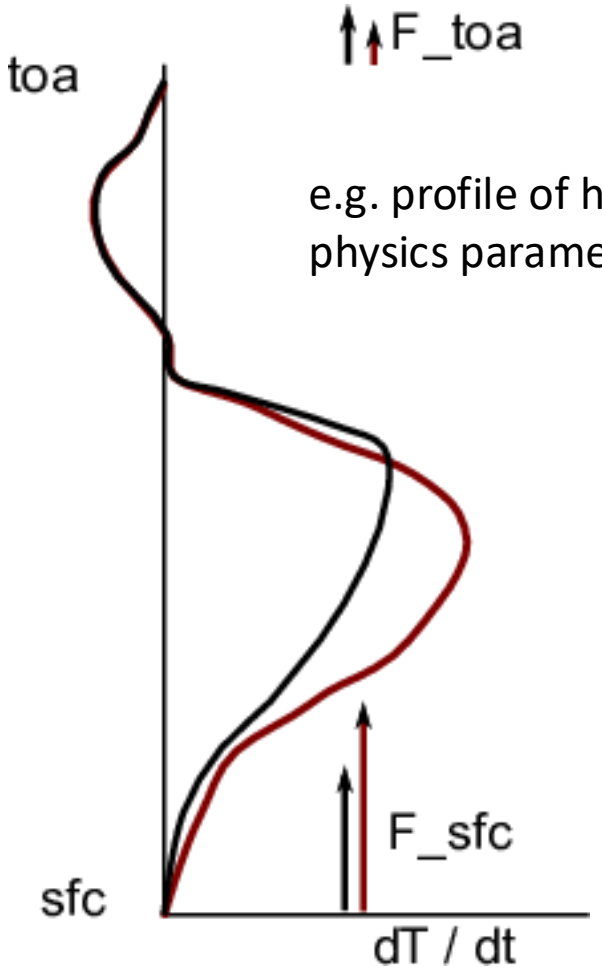

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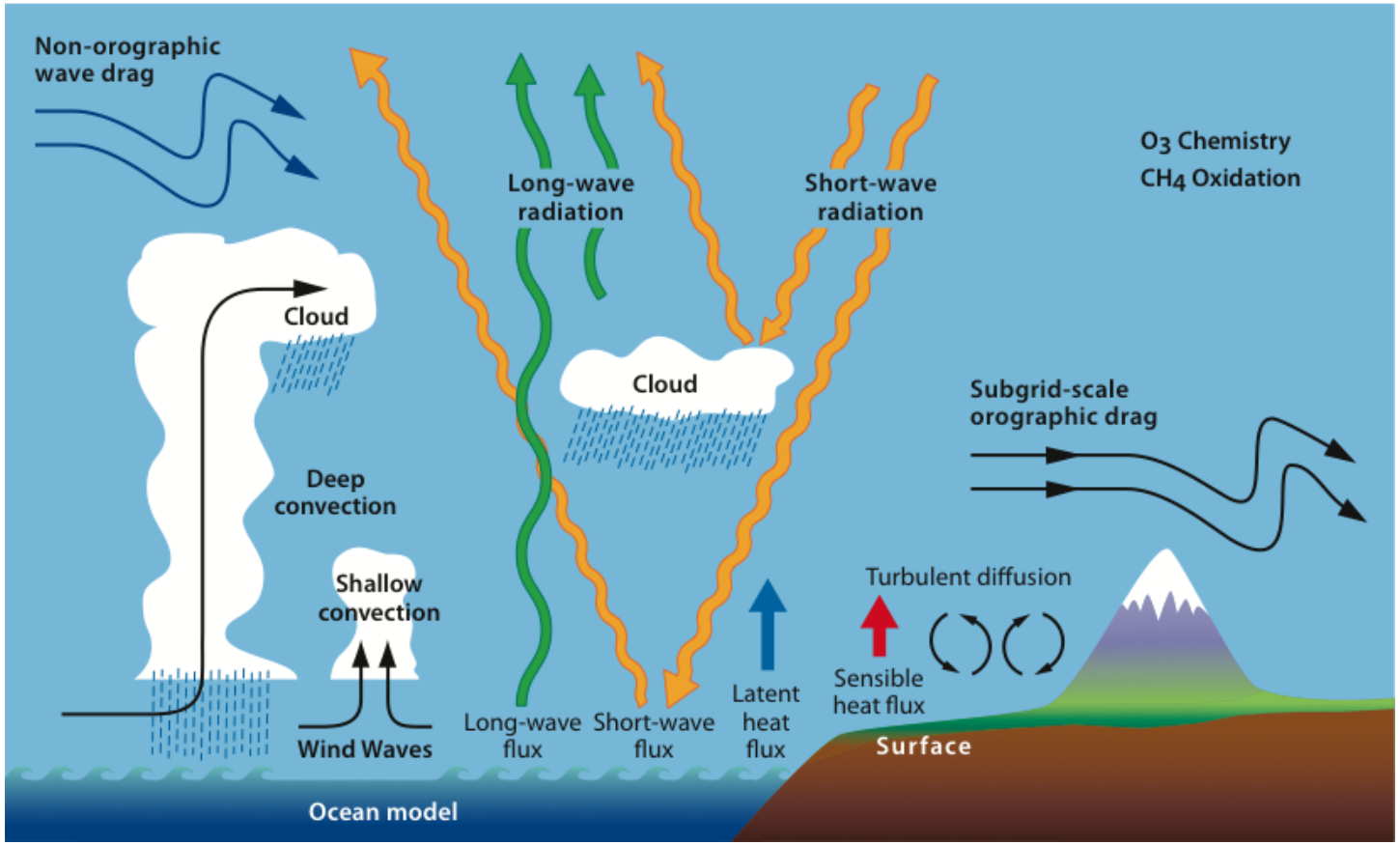
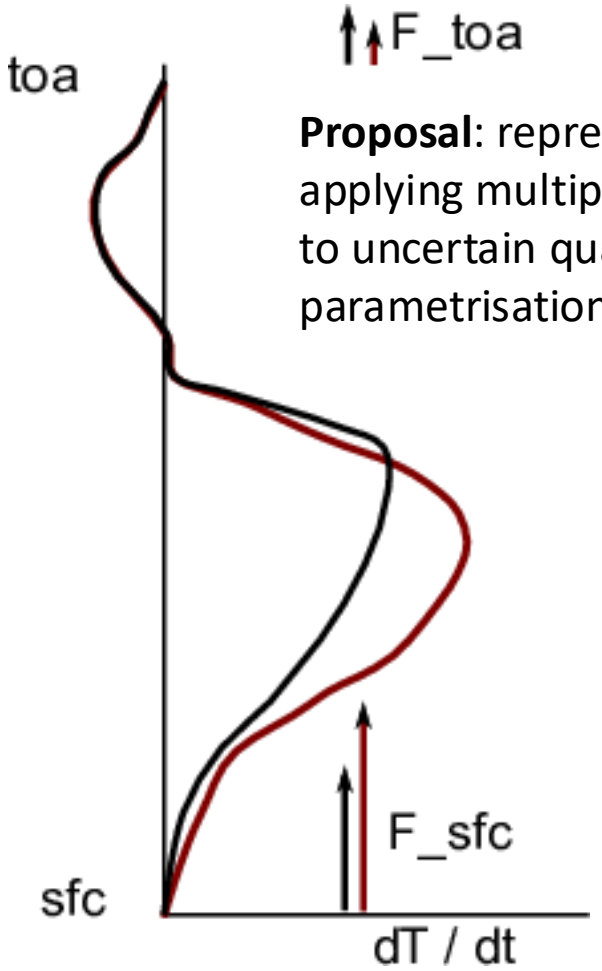
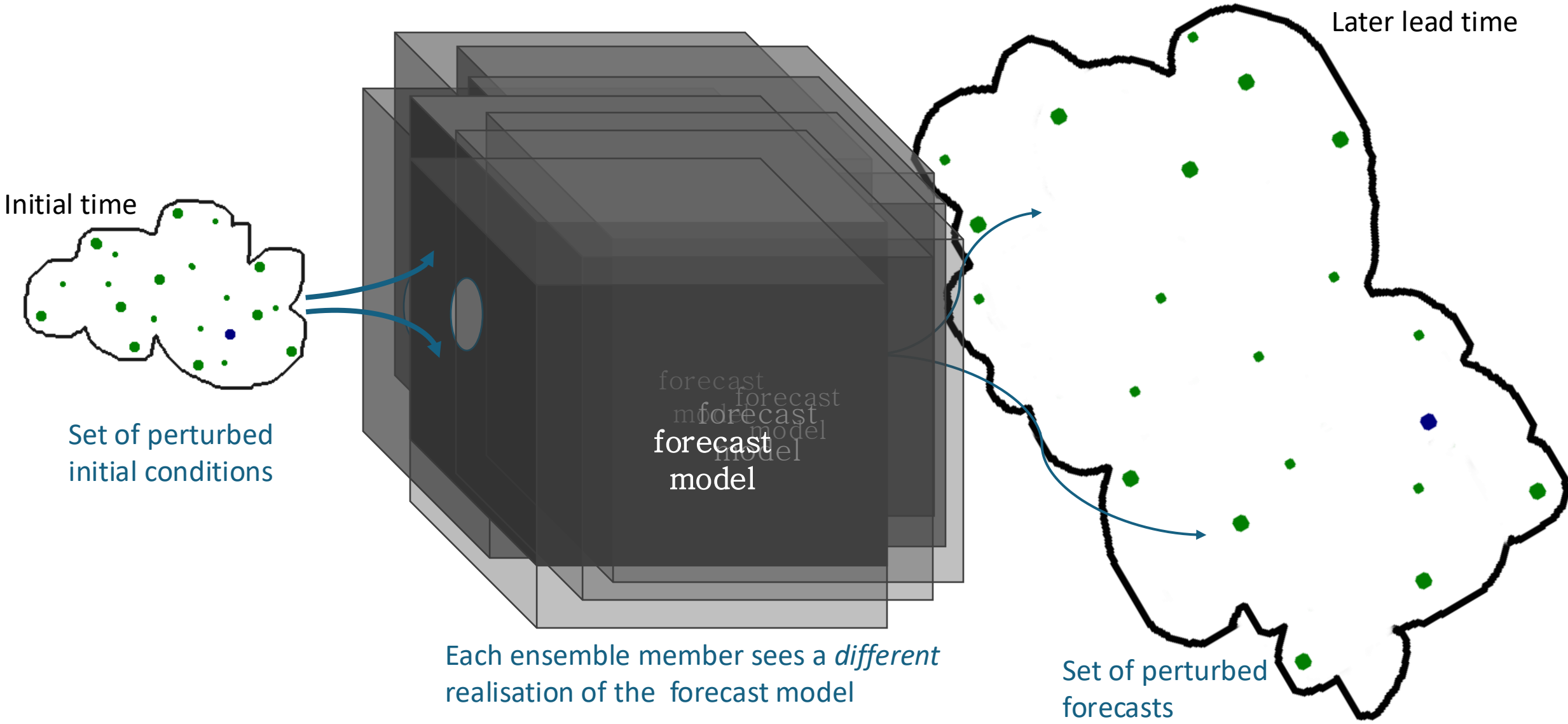




Proposal: represent uncertainties by applying multiplicative perturbations to uncertain quantities within the parametrisations

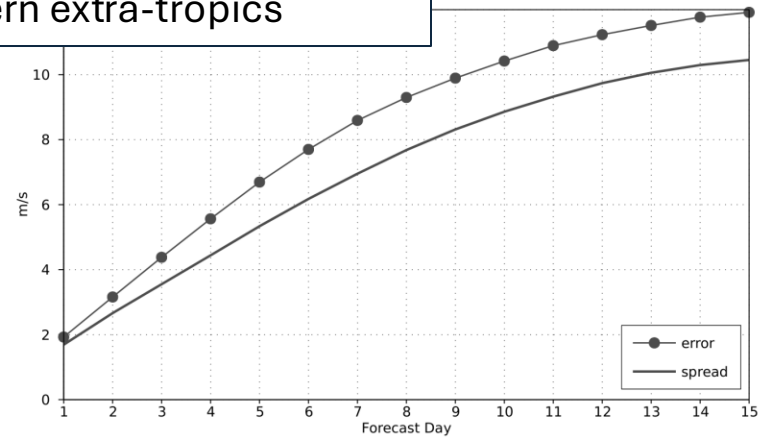
Sources of uncertainty: accounting for model uncertainty



Recall: Ensemble forecasts with only initial conditions perturbations

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

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



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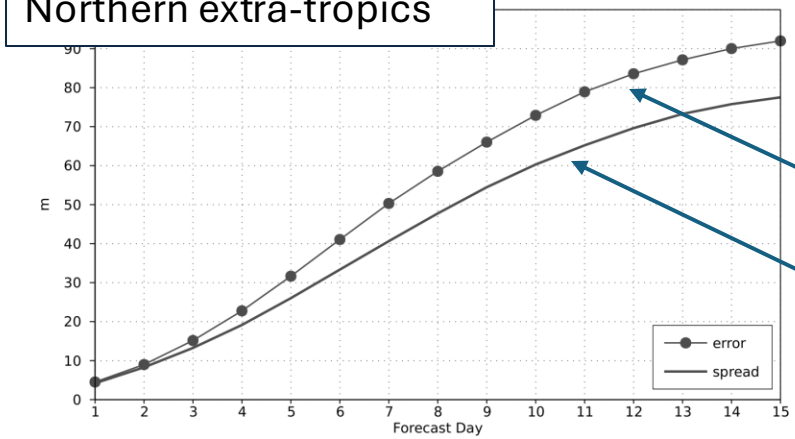
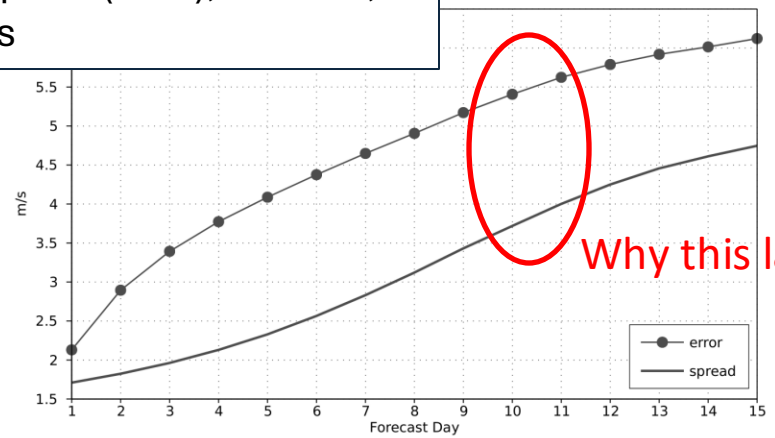


error

spread

IP only

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



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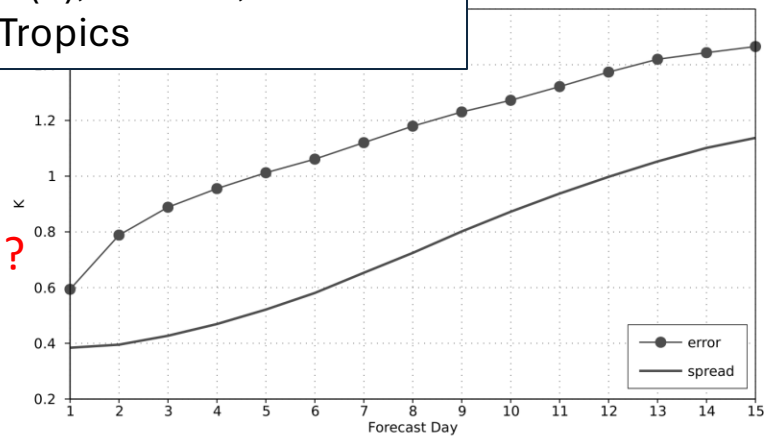

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TCo399L137, dt=1200s

JJA 2024 + DJF 24/25

8 perturbed members

Ensemble forecasts with model uncertainty perturbations

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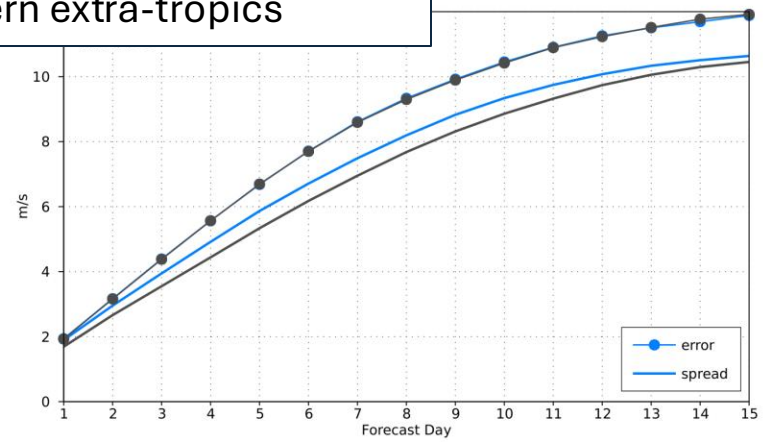

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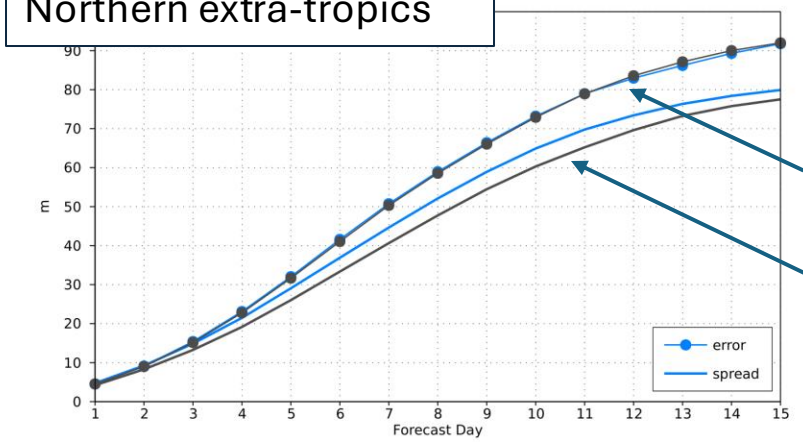
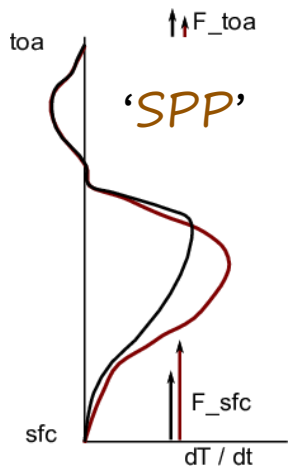




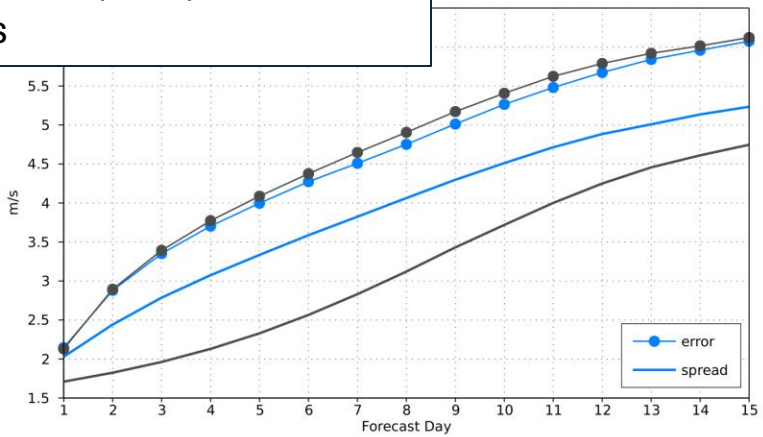
error

spread

IP only

IP + SPP

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



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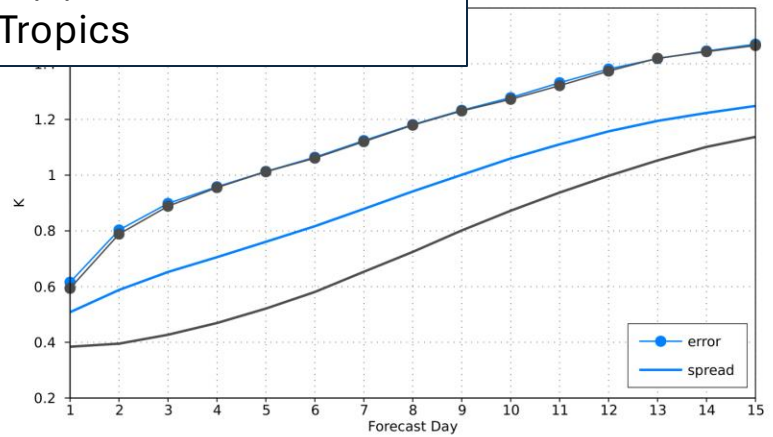

CY50R1

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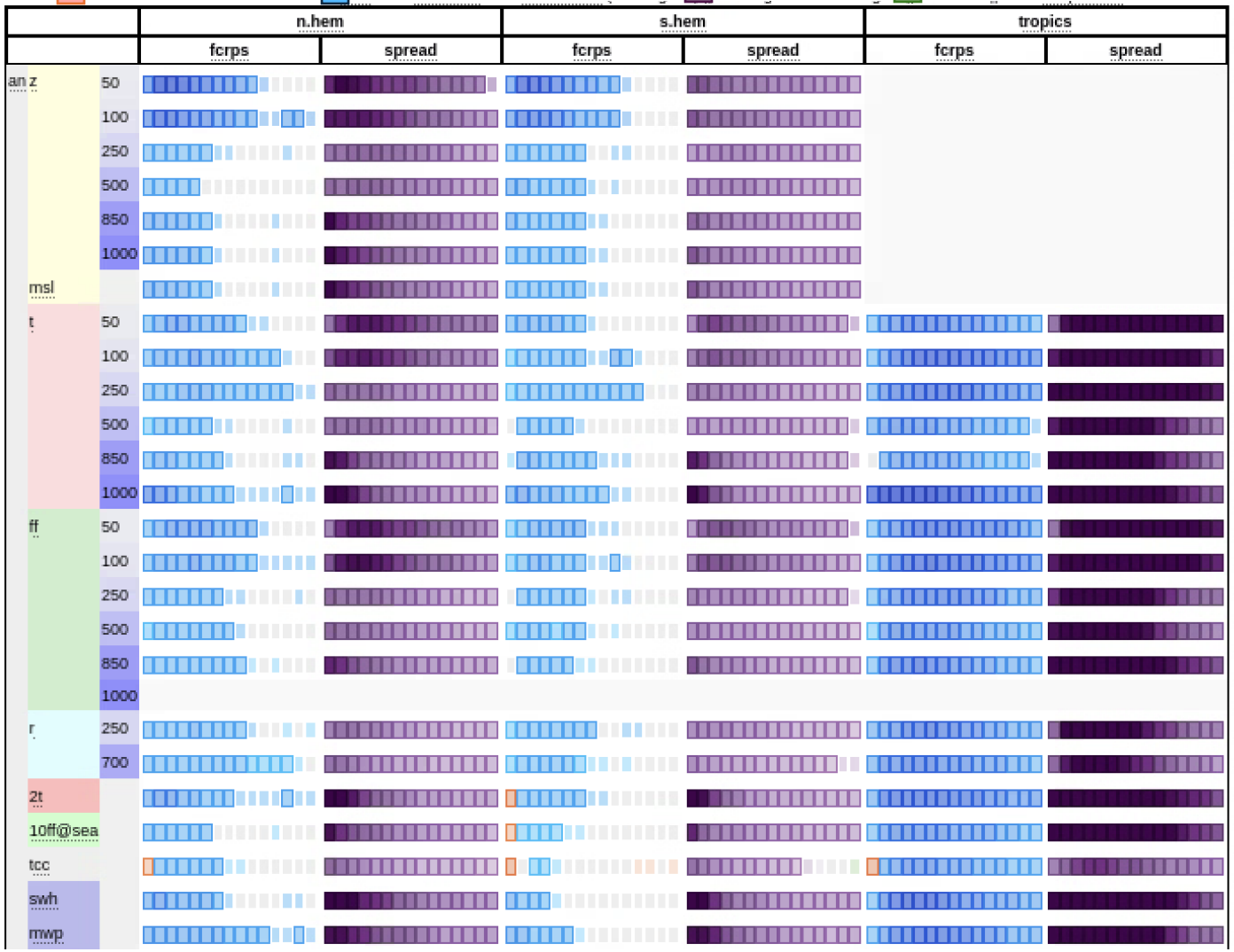
8 perturbed members

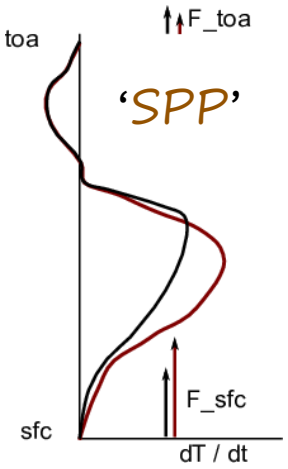
Ensemble forecasts with model uncertainty perturbations

fcrps: *degradation* *improvement*

spread: *increase* *decrease*

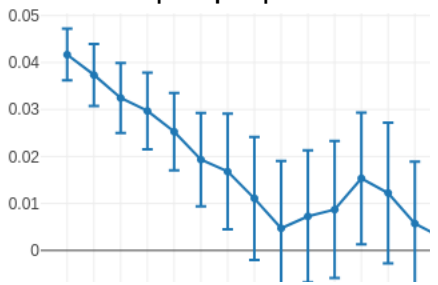


Scorecard of forecast impacts

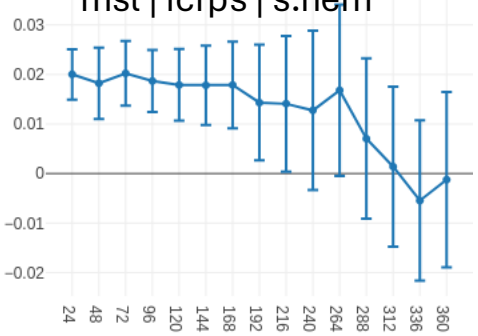


IC Perts + SPP *versus* IC perts

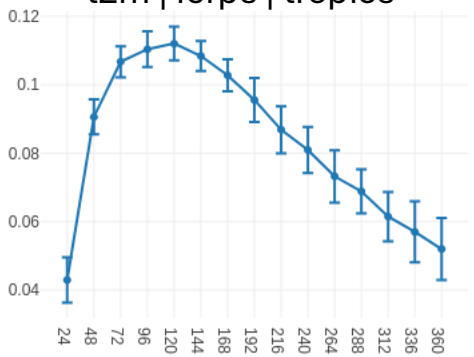
msl | fcrps | n.hem



msl | fcrps | s.hem



t2m | fcrps | tropics



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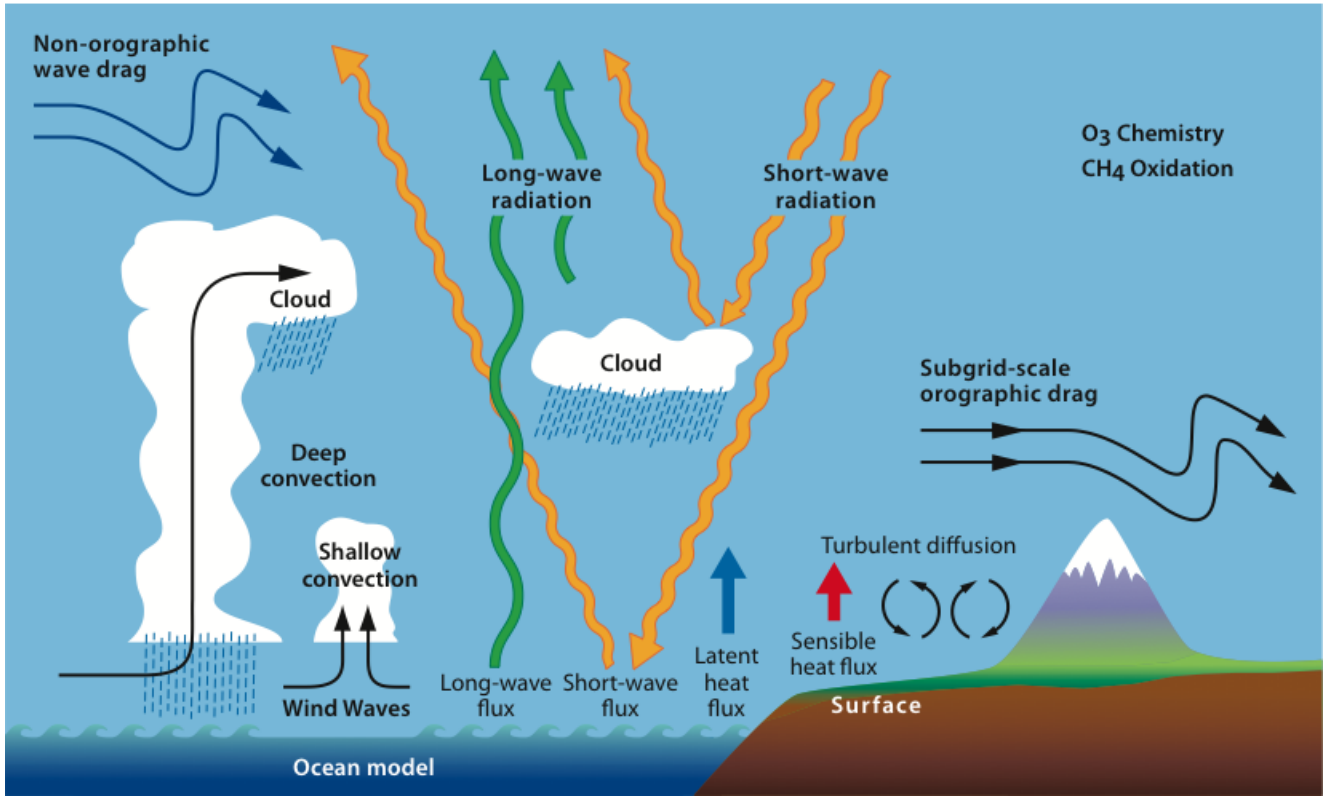
Stochastic representations of model uncertainty in IFS

Process-level model uncertainty representation



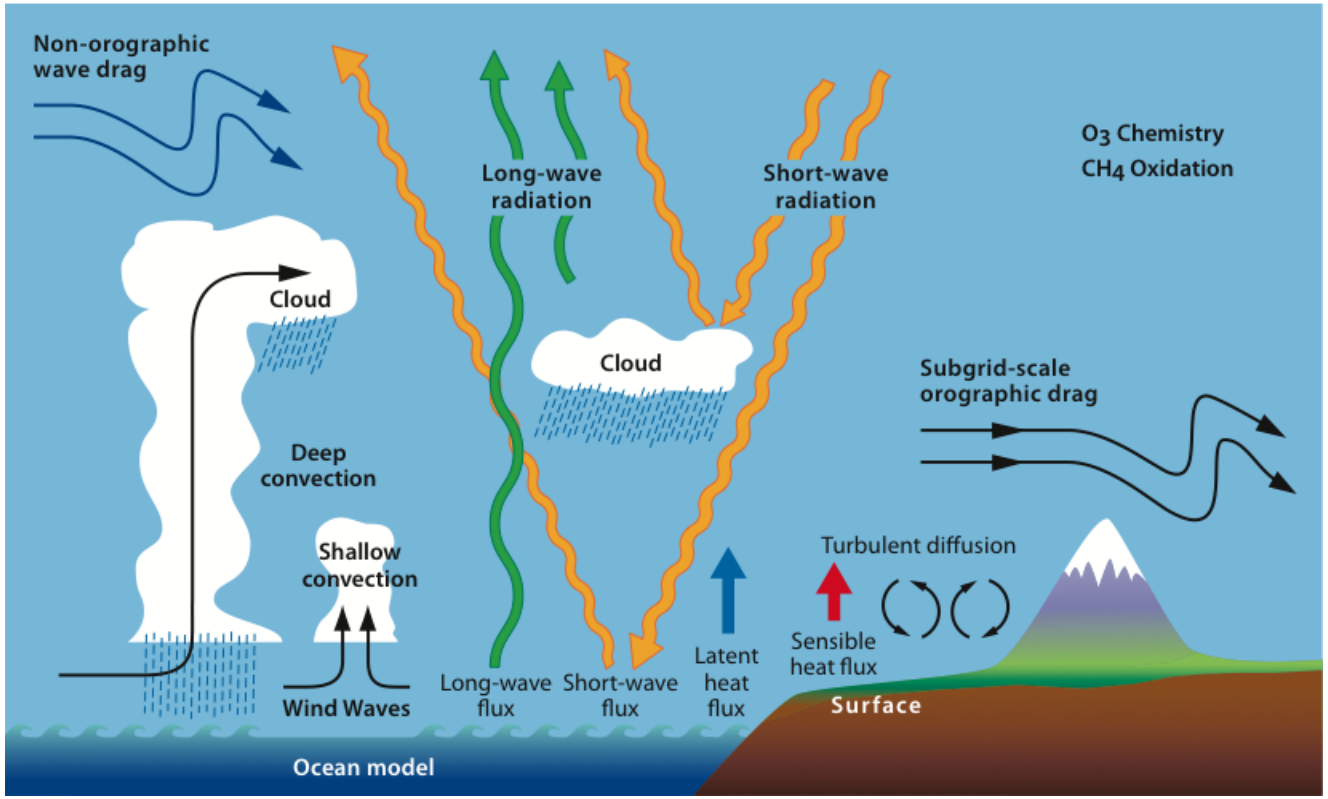
Aim:

- 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
- Include multi-variate aspects of uncertainties

Stochastic representations of model uncertainty in IFS

Since CY49R1

Process-level model uncertainty representation



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

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

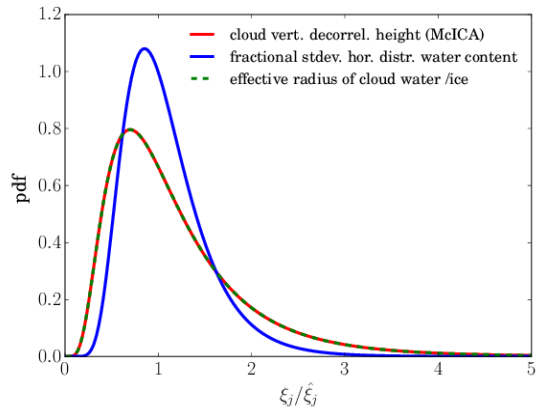
where

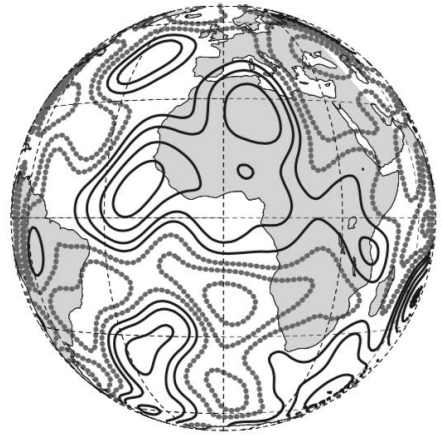
$$\Psi_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$$

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





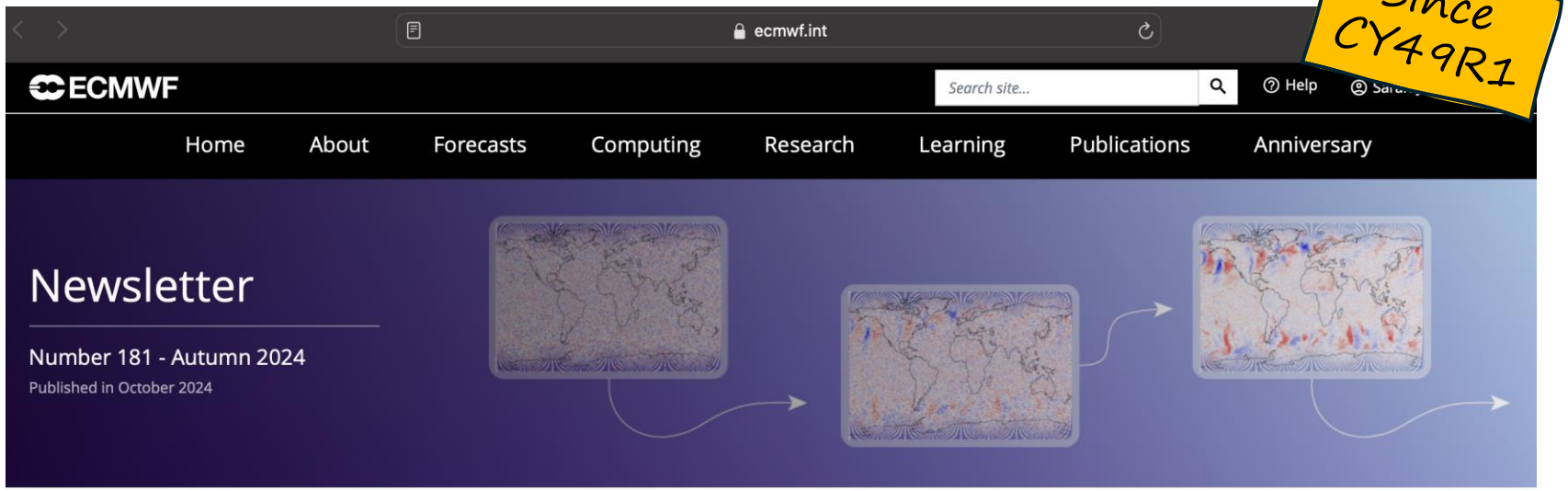
Stochastic representations of model uncertainty in IFS

Article in ECMWF Autumn 2024 Newsletter (Number 181)

Outlines details of the SPP implementation and impacts:

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

Since CY49R1



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Machine learning ensembles

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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 in IFS

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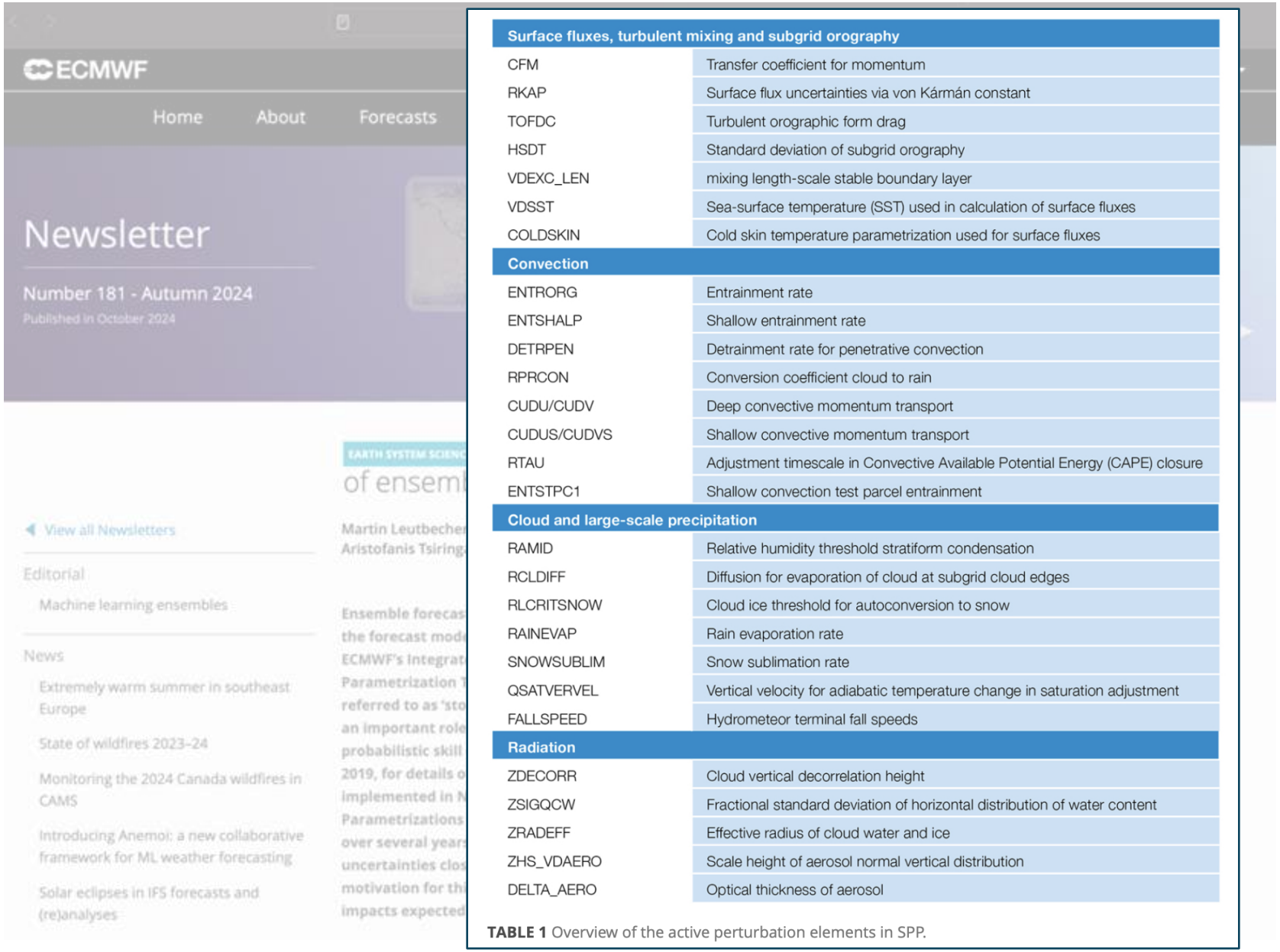

Surface fluxes, turbulent mixing and subgrid orography	
CFM	Transfer coefficient for momentum
RKAP	Surface flux uncertainties via von Kármán constant
TOFDC	Turbulent orographic form drag
HSDT	Standard deviation of subgrid orography
VDEXC_LEN	mixing length-scale stable boundary layer
VDSST	Sea-surface 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 in IFS

Article in ECMWF Autumn 2024 Newsletter (Number 181)

Outlines details of the SPP implementation and impacts:

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

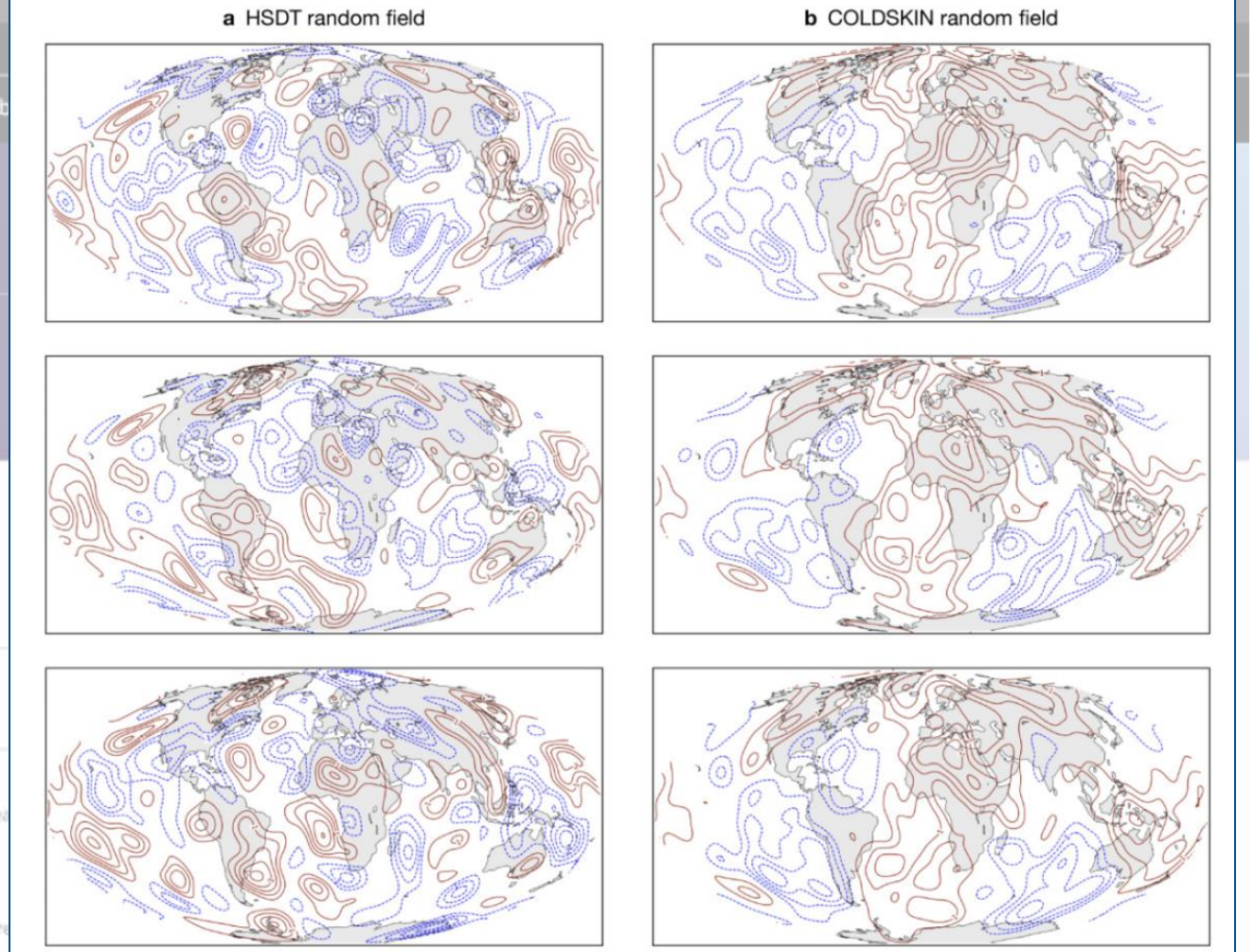

FIGURE 2 Random fields used by SPP in member 1 on 1, 2 and 3 January 2024 (from top to bottom) at 00 UTC for the perturbation elements (a) HSDT and (b) COLDSKIN. The latter has larger spatial and temporal decorrelation scales than the former. The contour interval is 0.5, with values ≥ 0.5 in solid red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

24

Stochastic representations of model uncertainty in IFS

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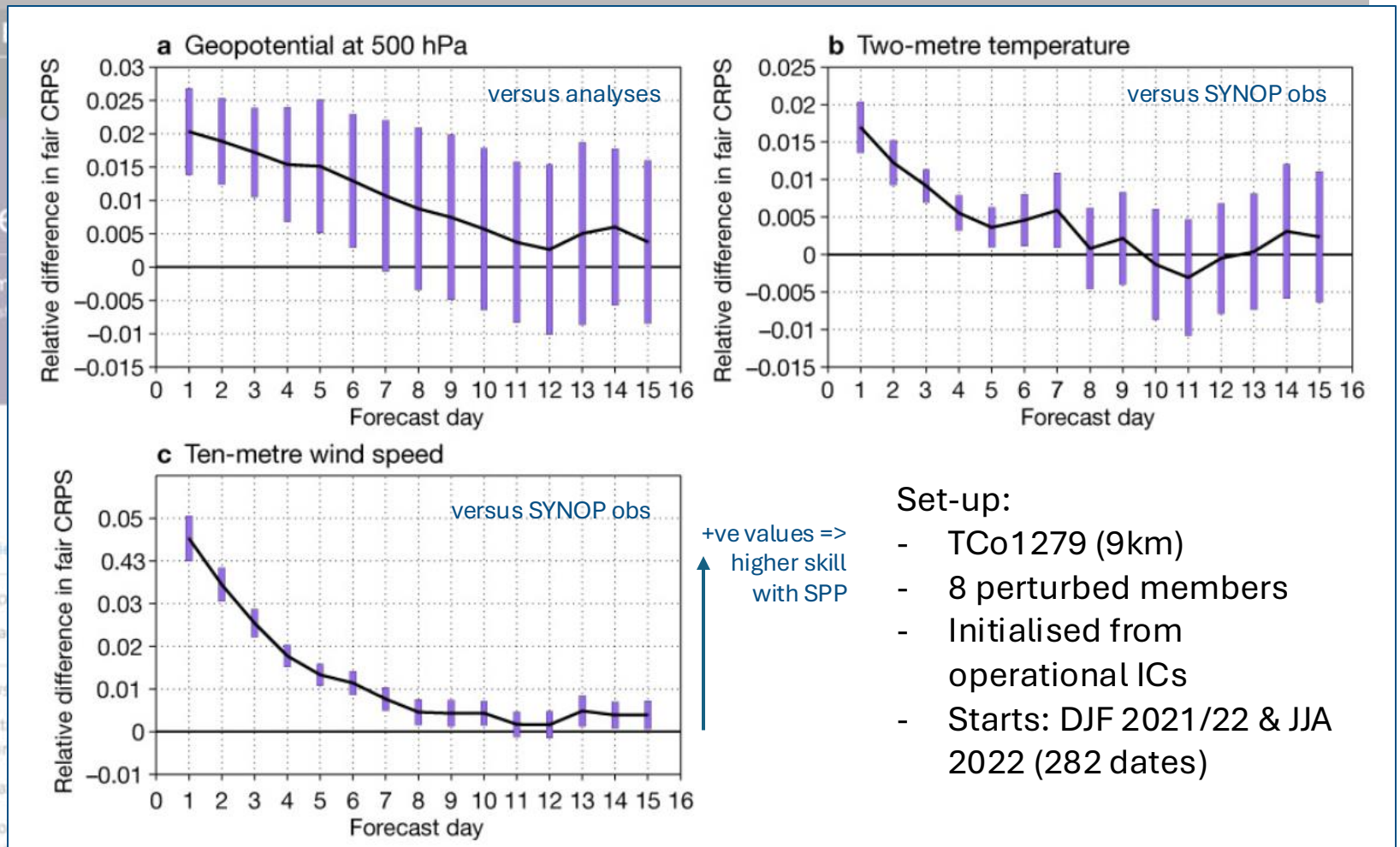

FIGURE 4 Relative differences in fair CRPS (continuous ranked probability score) of an ensemble using SPP and an ensemble using SPPT in the northern extratropics, for (a) geopotential at 500 hPa verified

Set-up:

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

Stochastic representations of model uncertainty in IFS

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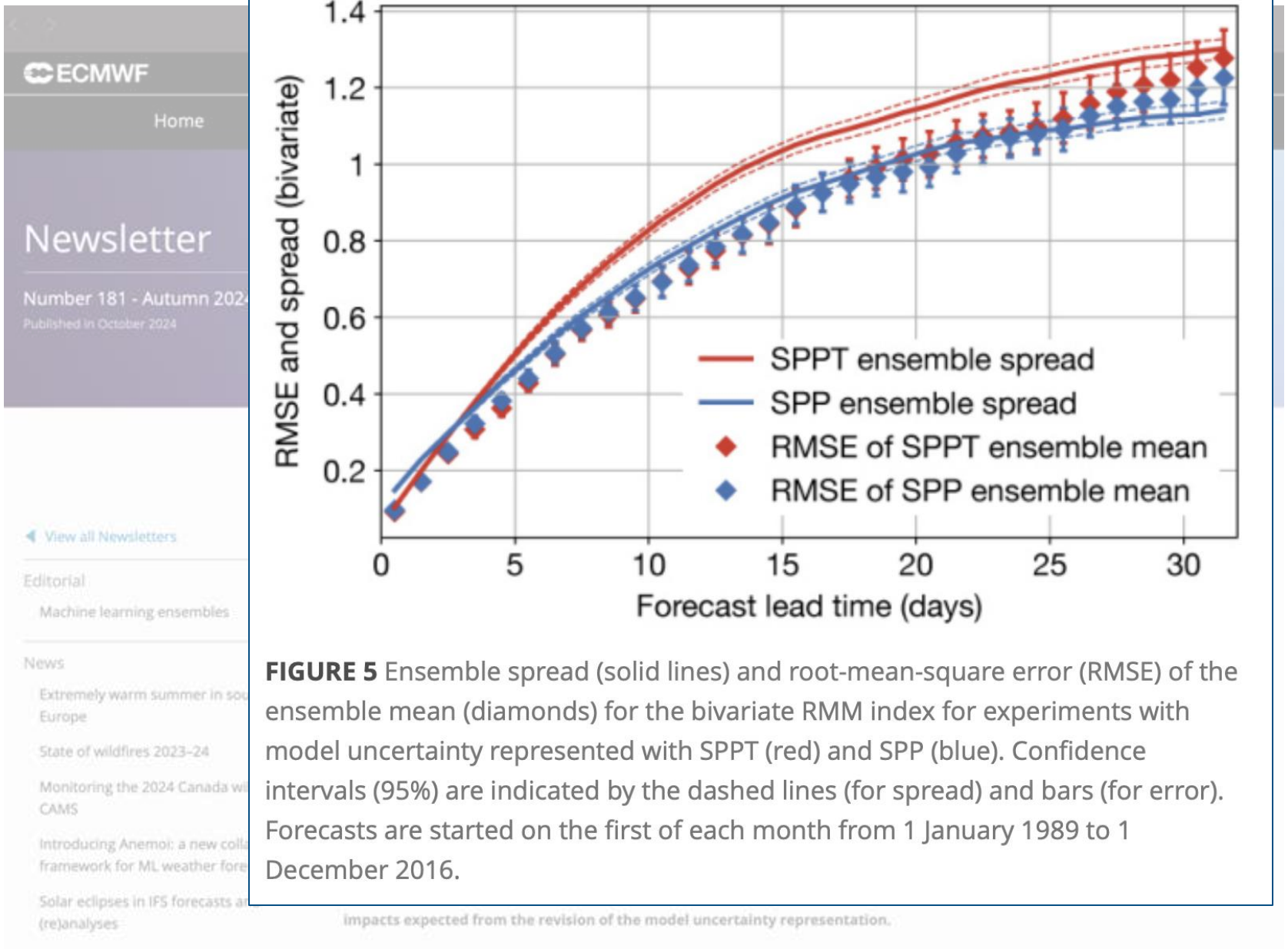


FIGURE 5 Ensemble spread (solid lines) and root-mean-square error (RMSE) of the ensemble mean (diamonds) for the bivariate RMM index for experiments with model uncertainty represented with SPPT (red) and SPP (blue). Confidence intervals (95%) are indicated by the dashed lines (for spread) and bars (for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

Stochastic representations of model uncertainty in IFS

Article in ECMWF Autumn 2024 Newsletter (Number 181)

Outlines details of the SPP implementation and impacts:

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

e.g. moisture budget:

$$\frac{1}{g}\int_{p_{\text{surf}}}^{0}\left(\frac{dq_{\text{v}}}{dt}+\frac{dq_{\text{l}}}{dt}+\frac{dq_{\text{i}}}{dt}+\frac{dq_{\text{r}}}{dt}+\frac{dq_{\text{s}}}{dt}\right)dp = F_{\text{prs}} + F_{\text{e}}$$

Precip-itation

Evap-oration

Vertical integrals of moisture tendencies from physics

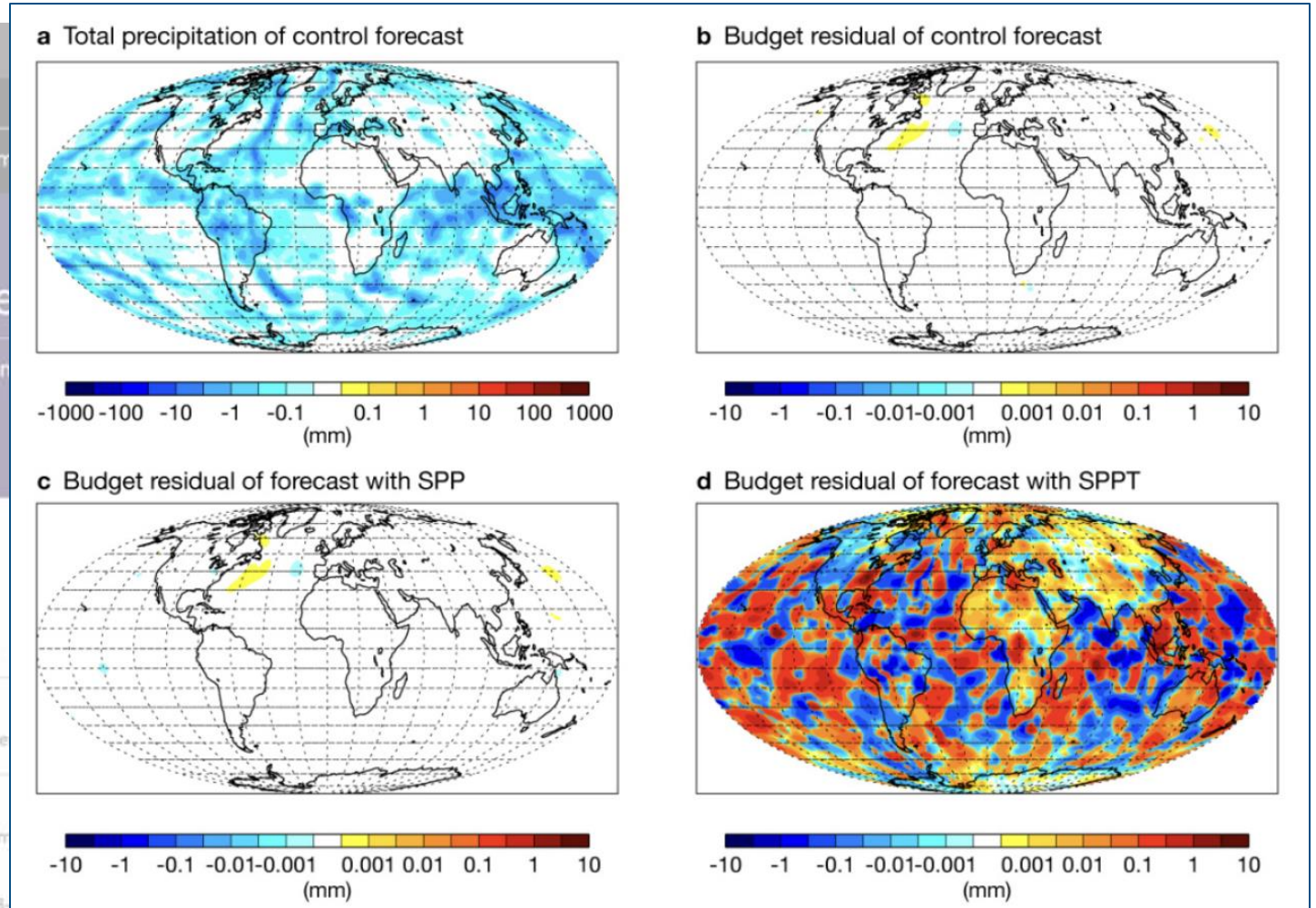


FIGURE 3 Moisture budget terms accumulated during a forecast lead time of 45–48 hours ...

Assessing the impact of SPP perturbations:

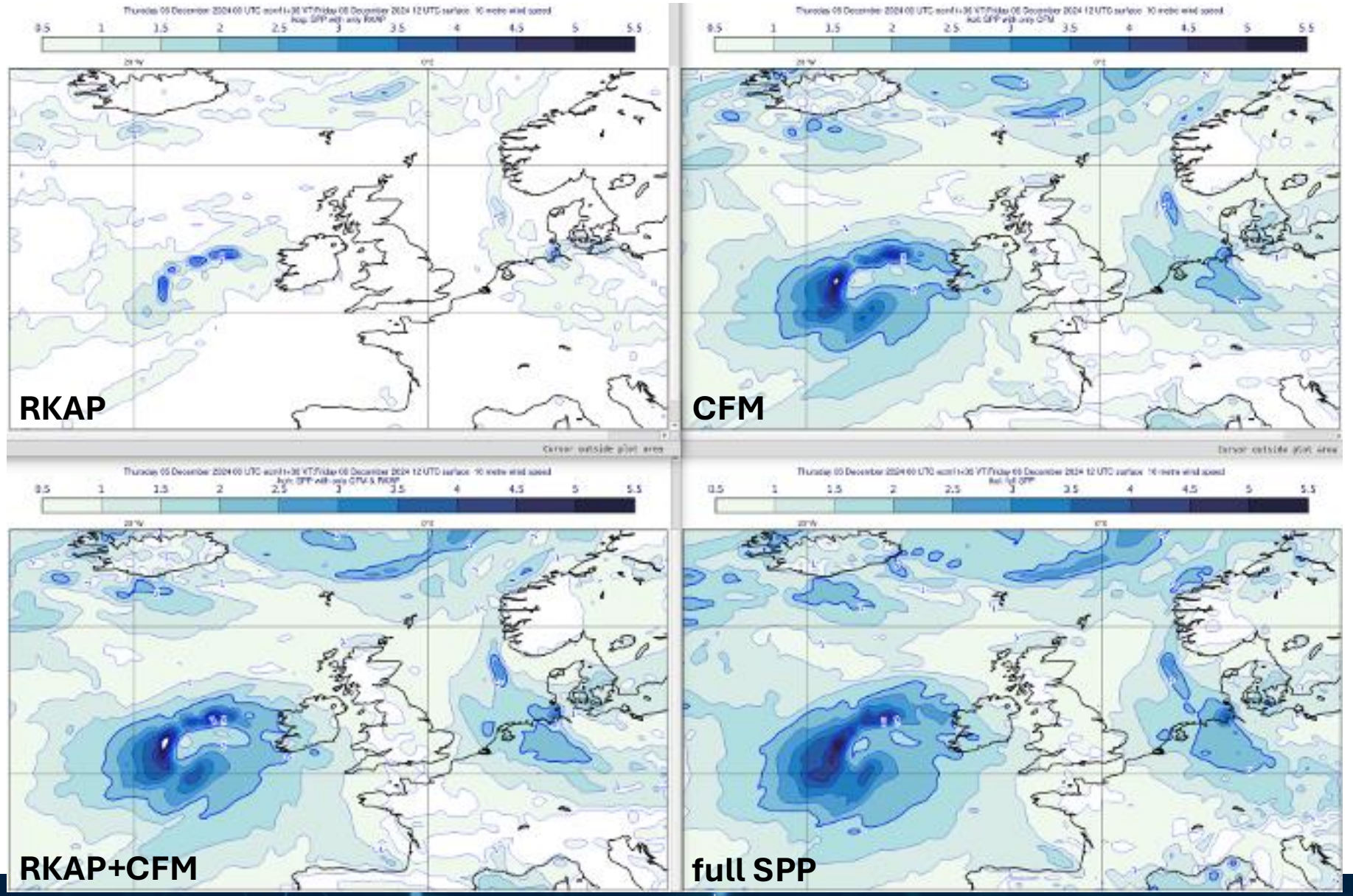
- SPP became operational in November 2024 (CY49R1)
- Analysts quickly spotted signals of excessive 10m windspeeds in the ensemble during strong wind events, e.g. Storm Darragh (Dec '24)
- Approach to assessing SPP contribution & considering a 'solution':
  - Run a single ensemble forecast for Storm Darragh
  - Only include SPP perturbations (no initial conditions perturbations)
  - Assess 10m wind fields for experiments with individual likely-related SPP perturbations
  - Consider related diagnostic fields: from waves, drag coefficient versus 10m windspeed scatter plots
  - Test alternative random number distributions & repeat Storm Darragh analysis
  - Perform probabilistic skill assessments: via 'full' medium-range testing

Assessing the impact of SPP perturbations – an example:

Ensemble spread for 10-metre wind speed, t=36 h

Sensitivity experiments for Storm Darragh (6/12/2024)

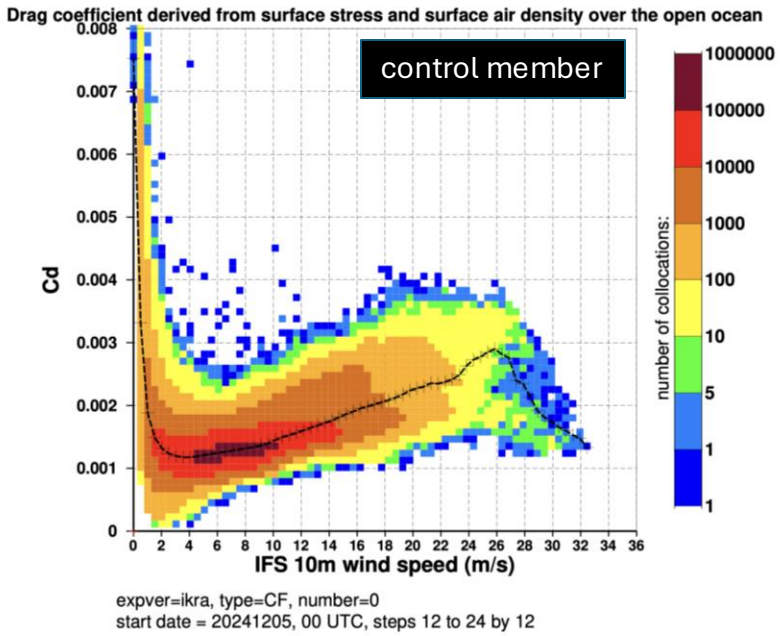
- No initial perturbations
- **RKAP**: von Karman const.
- **CFM**: transfer coeff for momentum exchange
- t+36-hour forecast

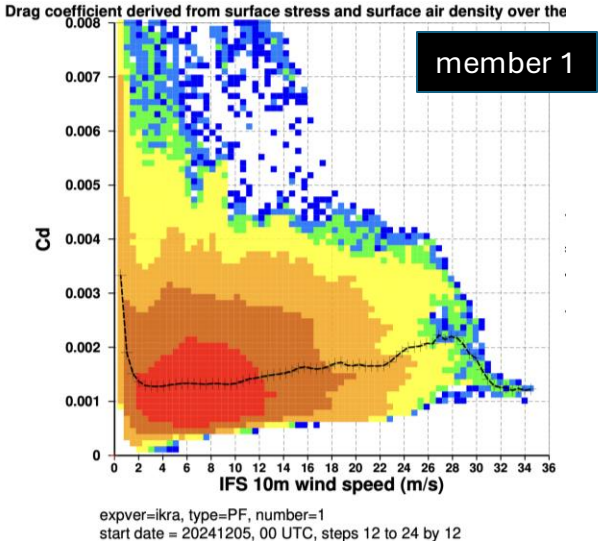


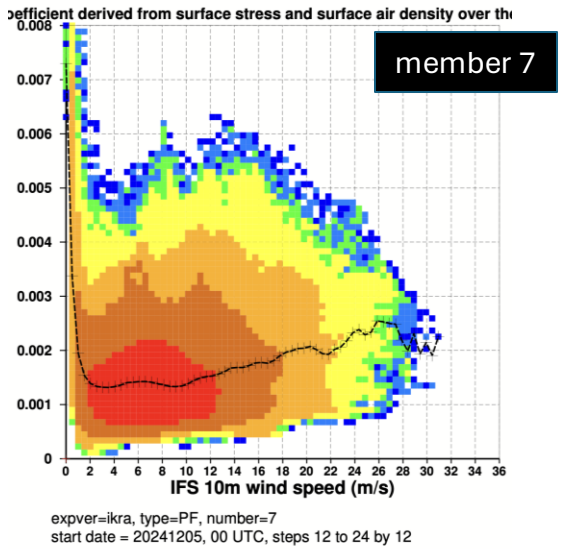
Assessing the impact of SPP perturbations – an example:

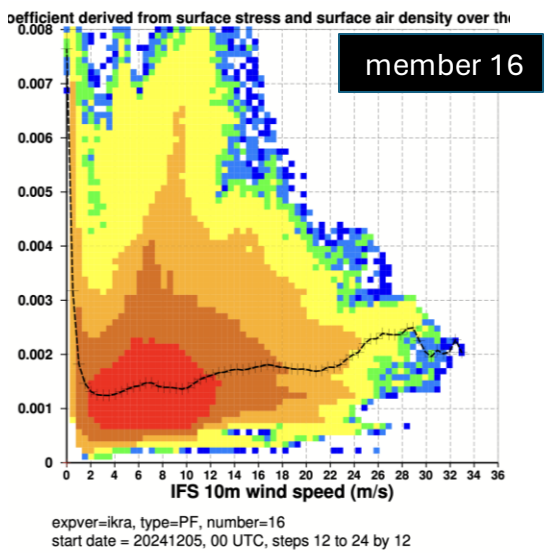
Drag coefficient versus IFS 10m windspeeds

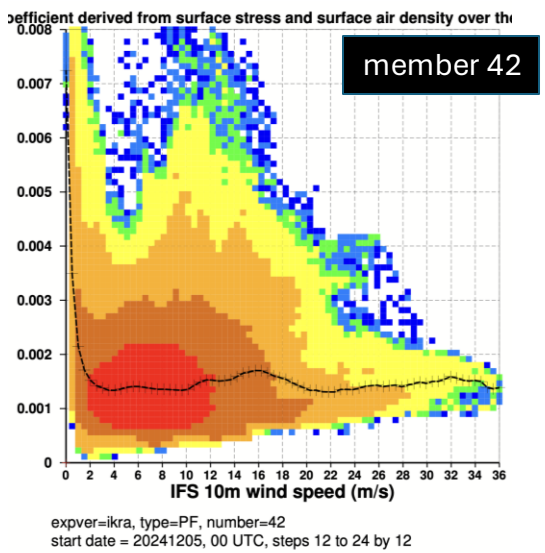
- Storm Darragh case: only SPP **CFM** perturbations
- Diagnosed drag coefficient versus U10m (IFS) over ocean points
- Control member (left) & example perturbed members (below)





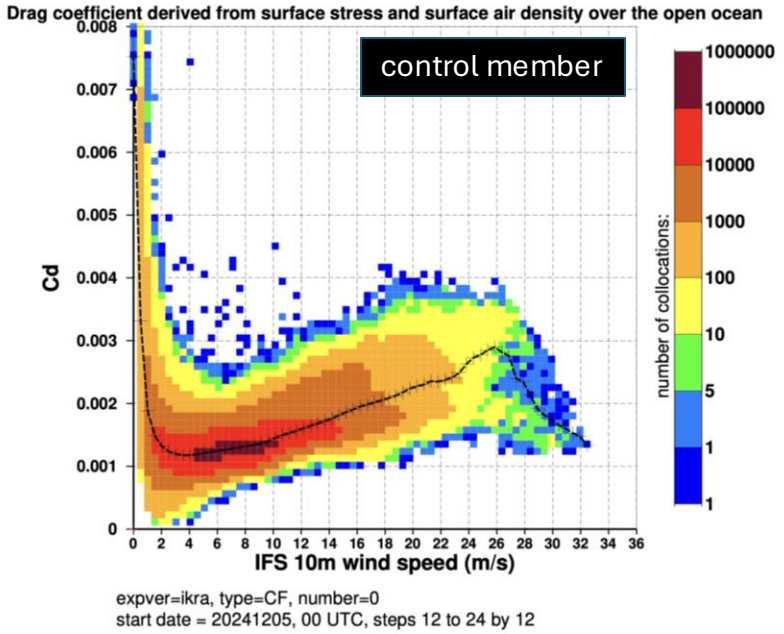


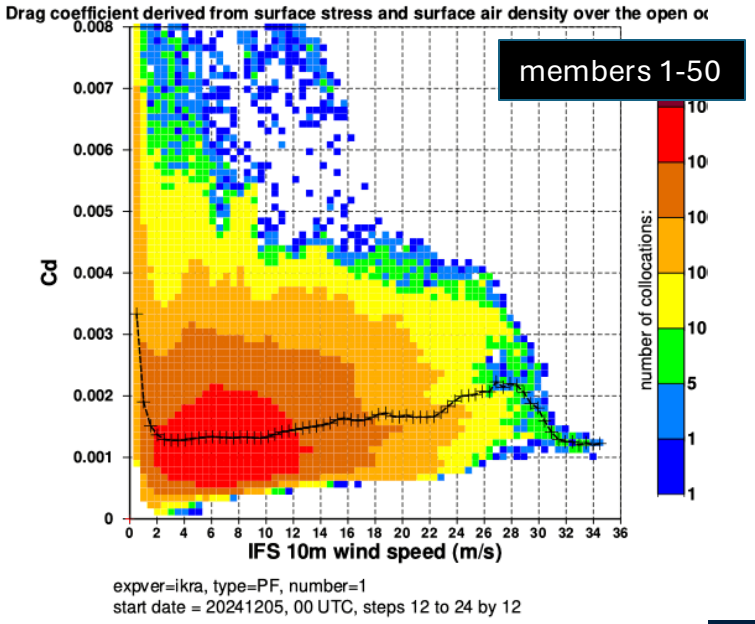




Assessing the impact of SPP perturbations – an example:

Drag coefficient versus IFS 10m windspeeds



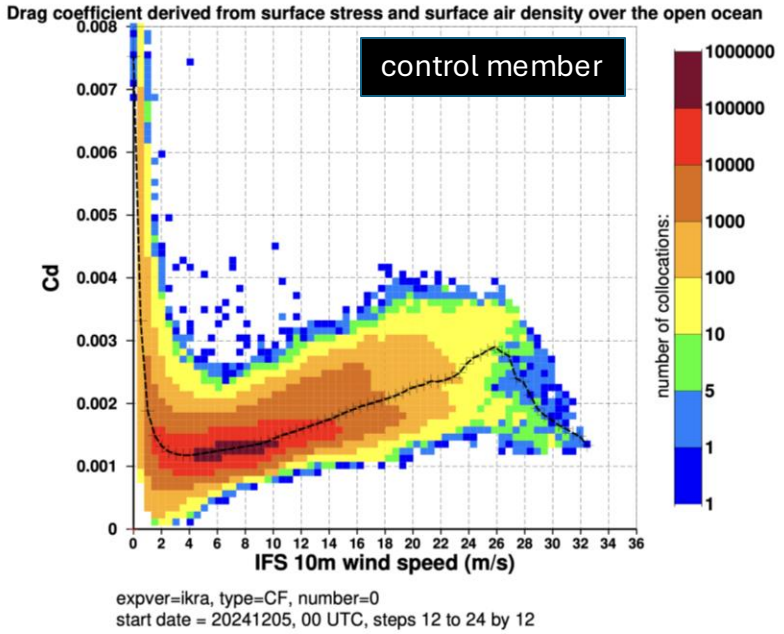


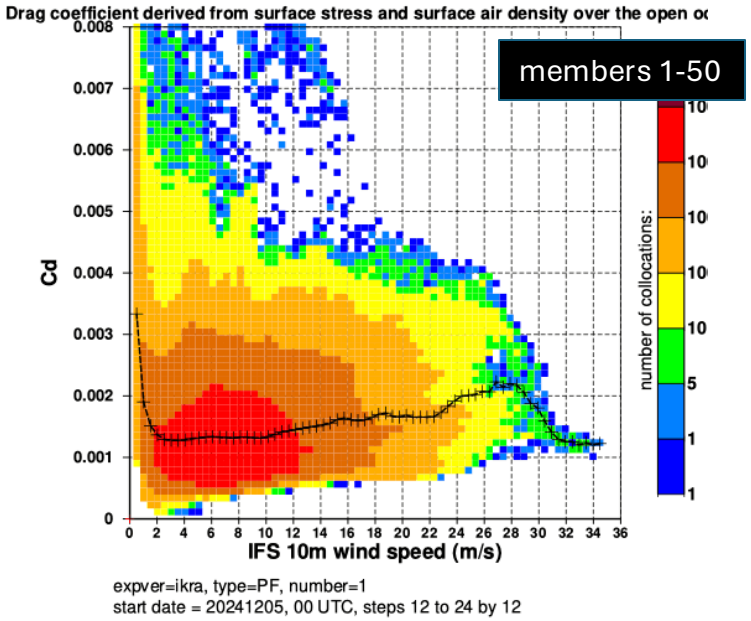
- Storm Darragh case: only SPP **CFM** perturbations
- Diagnosed drag coefficient versus U10m (IFS) over ocean points
- Control member (left) & perturbed members 1--50 (below)

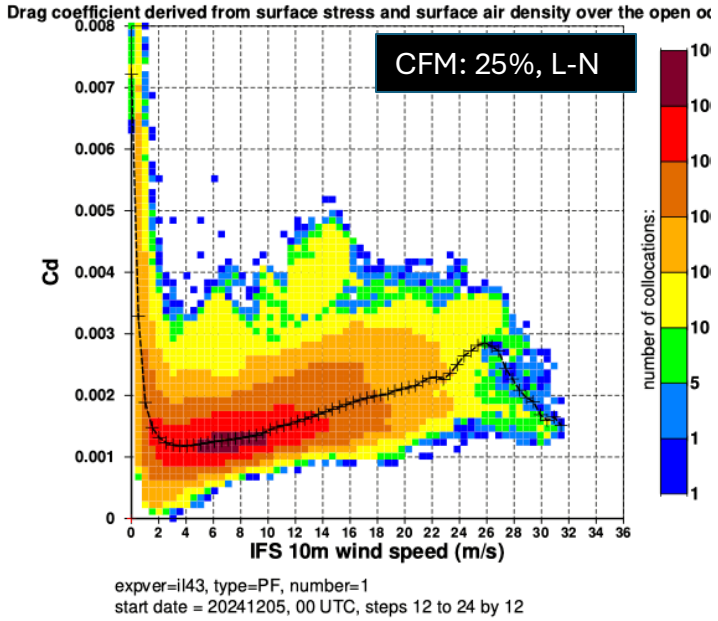
Assessing the impact of SPP perturbations – an example:

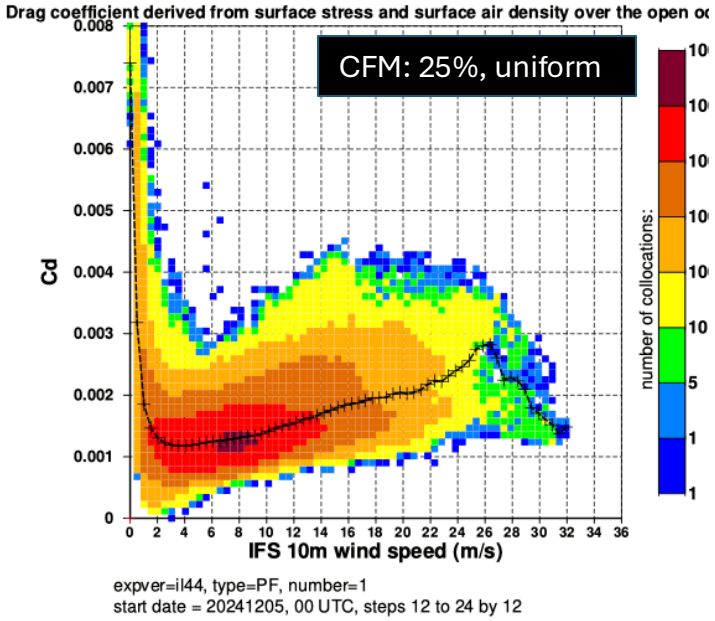
Drag coefficient versus IFS 10m windspeeds

- Storm Darragh case: only SPP **CFM** perturbations
- Diagnosed drag coefficient versus U10m (IFS) over ocean points
- Control member (left) & perturbed members 1--50 (below)
- SPP CFM tests (**CY49R1**, option):
  - amplitude (**100%**, 25%),
  - distribution (**log-normal**, uniform)





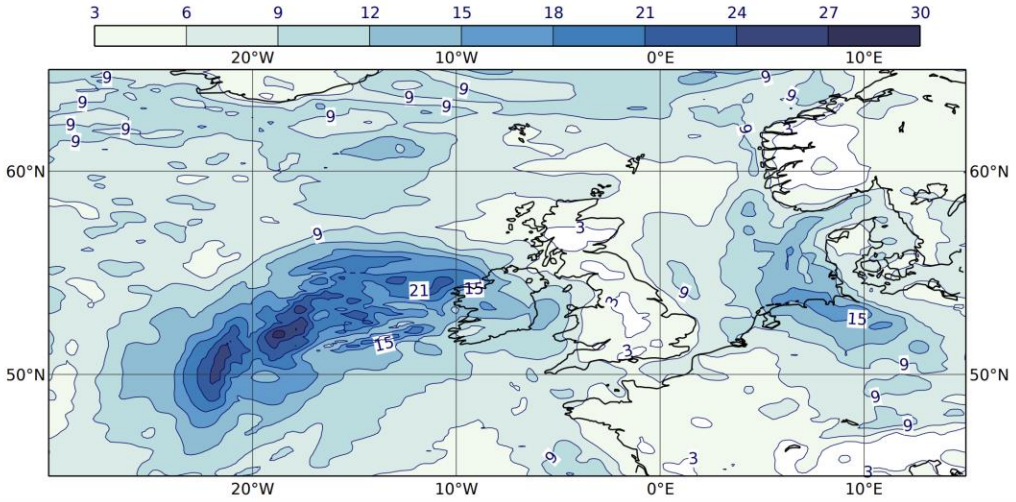




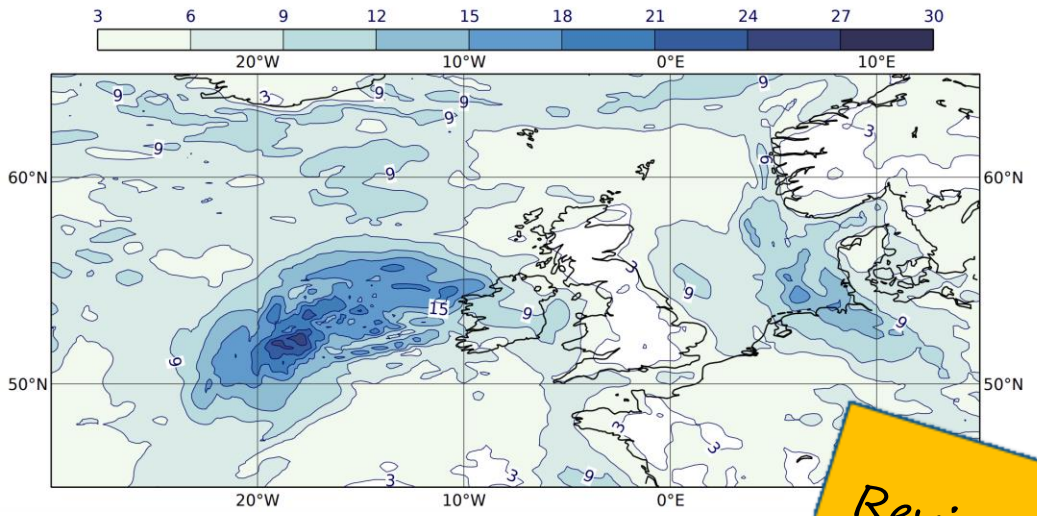
Assessing the impact of SPP perturbations - an example:

Ensemble range* for 10-metre windspeeds (m/s), t=36 h, for Storm Darragh

CY49R1 settings



Revised SPP settings for CY50R1



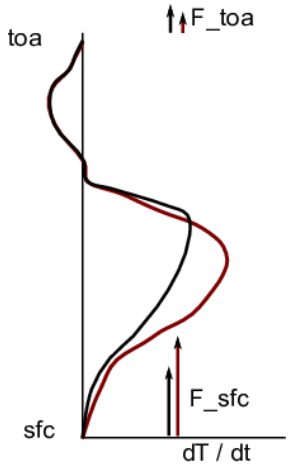
Valid time: Friday 6 December, 12 UTC (Storm Darragh)

- TCo399 (~29km grid-spacing)
- 50 perturbed ensemble members
- initialised with initial conditions from the operational forecast

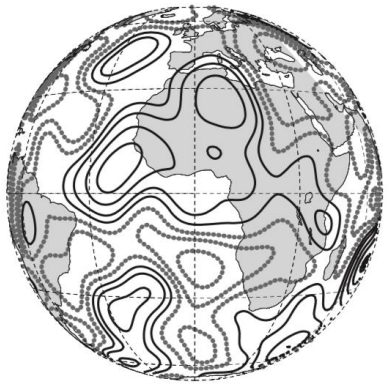
*At each location, ensemble range equals max value across ensemble minus min value

Revised setting into CY50R1 (Spring 2026)

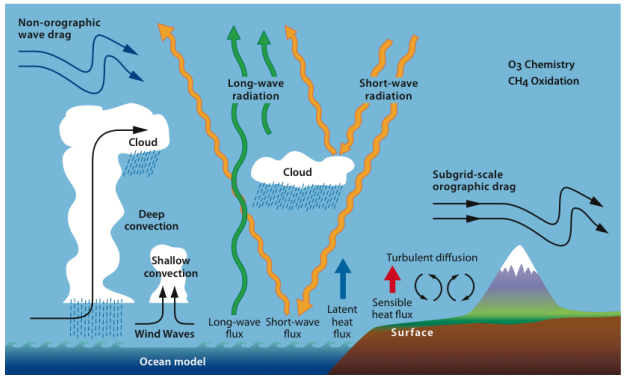
Summary

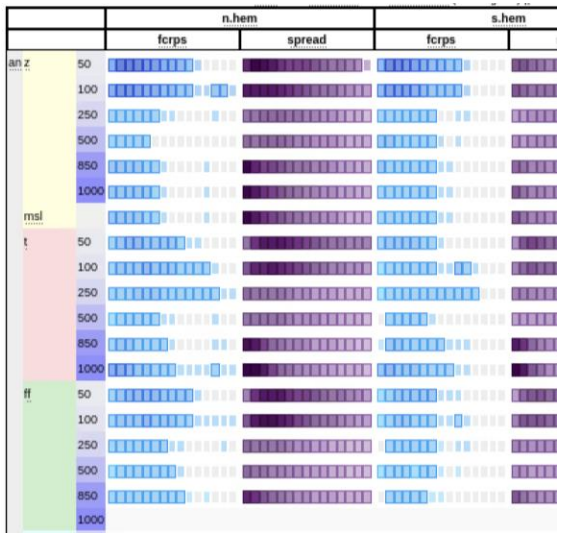


- Ensemble forecasts include perturbations to represent initial conditions uncertainty and **model uncertainty**
- Without model uncertainty representation, the ensemble forecasts are under-dispersive, hence over-confident
- In the IFS, we use the **SPP** scheme to represent model uncertainties due to the sub-grid atmospheric physics parametrisations
- SPP applies multiplicative random perturbations to uncertain quantities within the physics parametrisations



- SPP retains **physical consistencies** of the unperturbed parametrisations
- Activating SPP generates additional spread and enhanced **probabilistic skill**
- Work is ongoing to identify:
  - further refinements to the scheme (a revised package is in preparation)
  - additional sources of uncertainty that could provide enhanced skill via SPP, e.g. sea-ice





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