Representation of model error in a convective-scale ensemble

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Met Office and Monsoon computing facilities

Data assimilation (DA) allows information to be squeezed from EO data

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NWP increasingly relies on EO data

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But, DA must be formulated carefully, inc well characterised forecast error statistics

↓

Information from an ensemble can provide information about forecast error statistics

↓

Study a convective-scale ensemble problem

↓

How to generate an appropriately spread ensemble

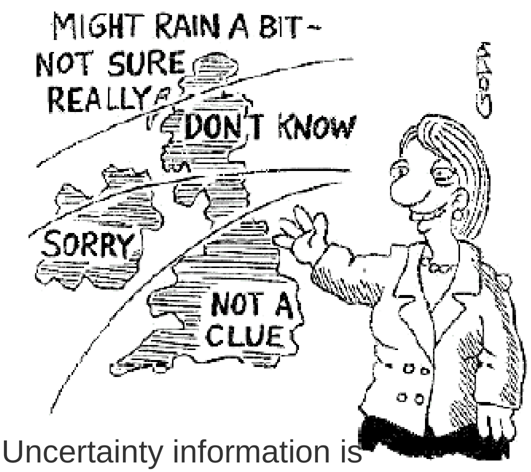
↓

What useful things can we learn from this ensemble?

What can we learn from forecast ensembles?

USING AN ENSEMBLE
Forecast uncertainty and meteorological understanding

- All forecasts are wrong – forecast uncertainty assessment.
- Data assimilation – how to interpret a-priori information.
- How are (errors in) forecast fields correlated?



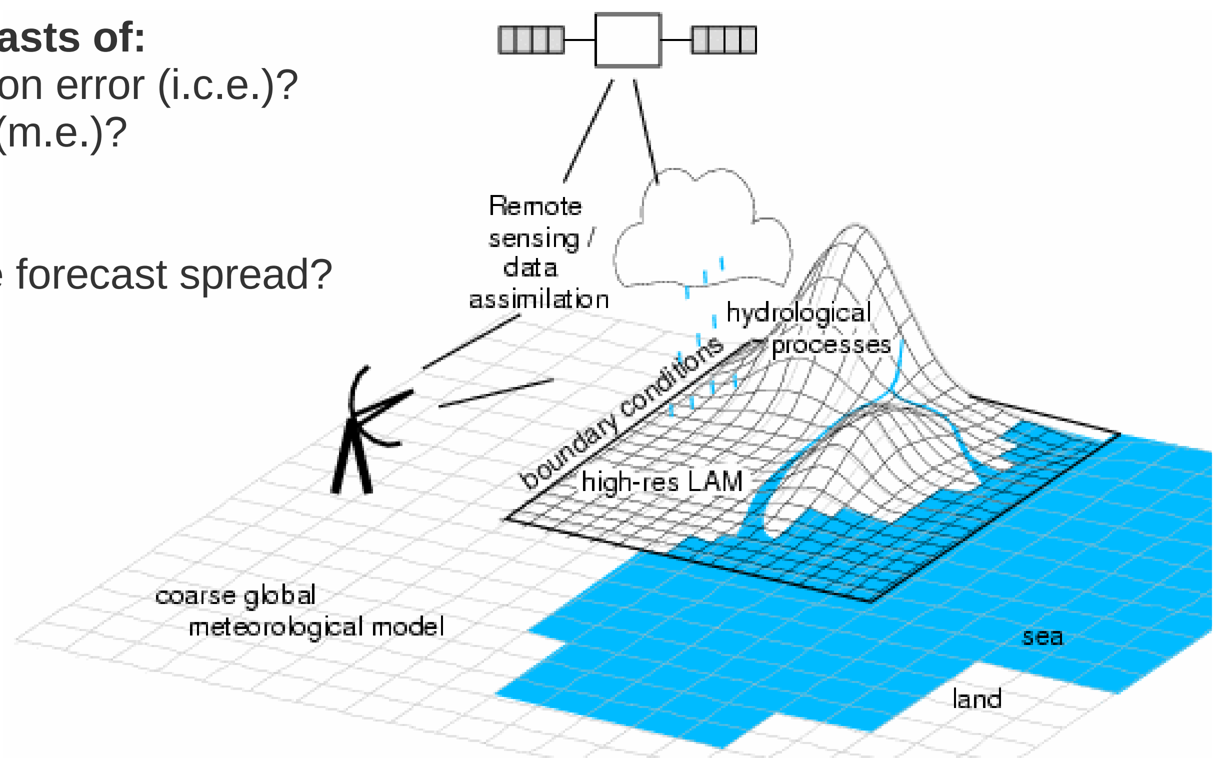
Uncertainty information is important

CONSTRUCTING AN ENSEMBLE
What are the respective effects on forecasts of:

- Introducing variability in the initial condition error (i.c.e.)?
- Introducing variability in the model error (m.e.)?

Forecast assessment and evaluation

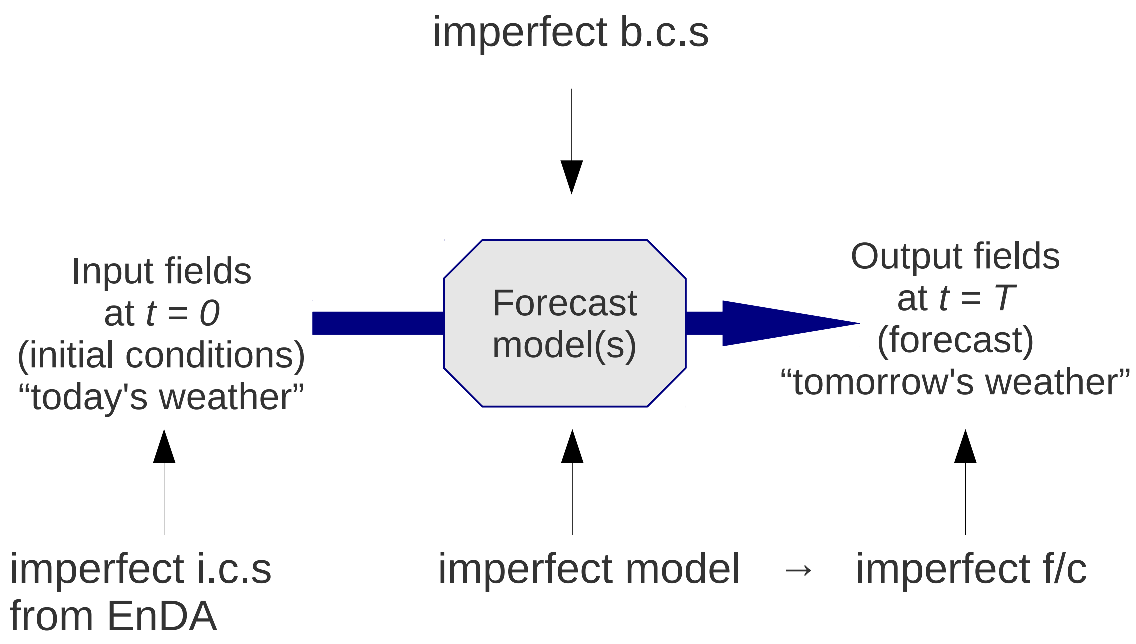
- How does each source of error affect the forecast spread?
- How do they affect the skill?



Simulation of errors

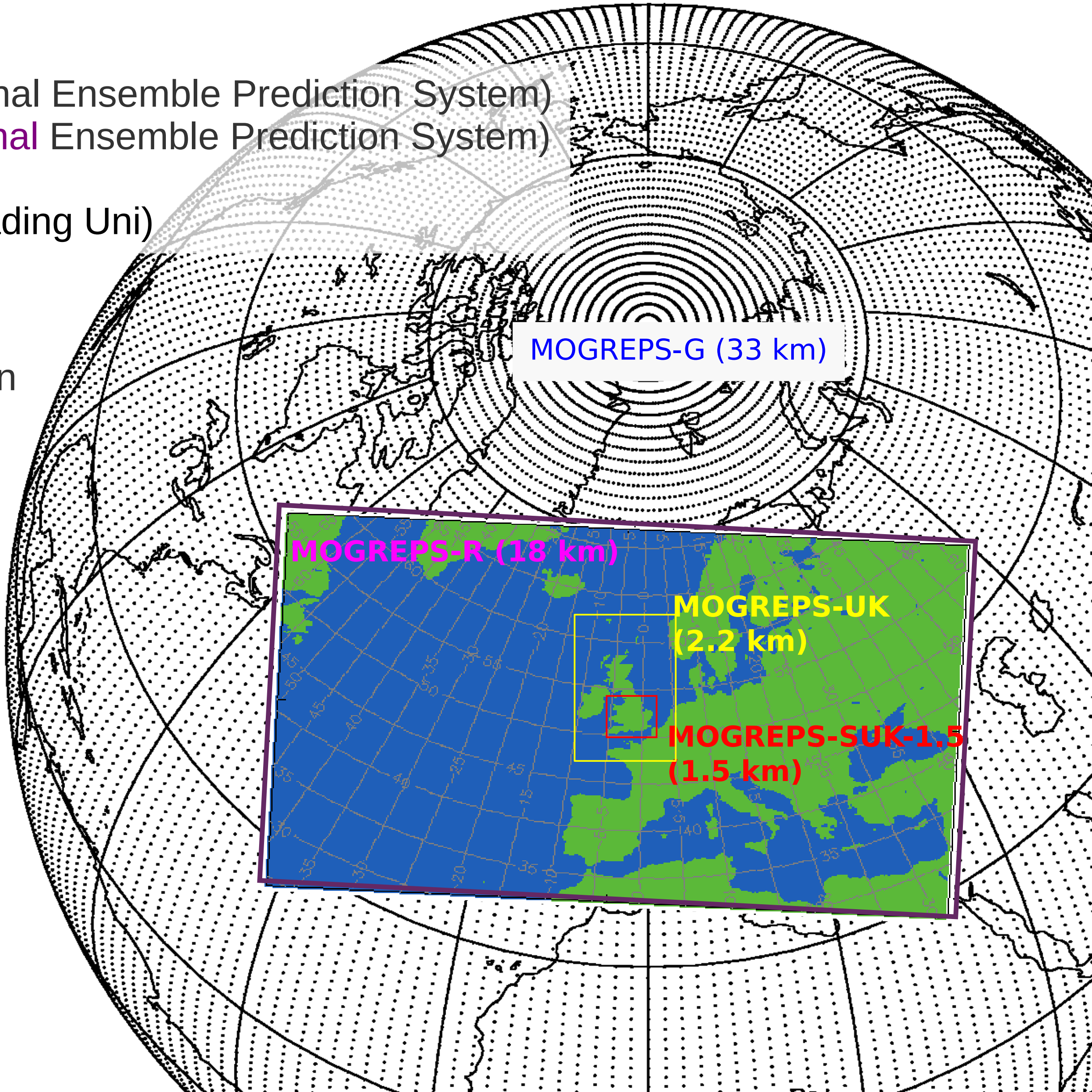
- **Initial conditions must be chosen carefully:**
  - Each written as $x_{ic}(n) = x_0 + \delta x_{ic}(n)$, $1 \le n \le N.$
  - $\delta x_{ic}(n)$ must be consistent with available knowledge and its uncertainty and the behaviour of the atmosphere.
    - Initial condition uncertainty, boundary condition uncertainty, model error uncertainty..
  - If variability of $\delta x_{ic}(n)$ too small → range of possible forecasts not represented.

    too large → forecasts not useful.



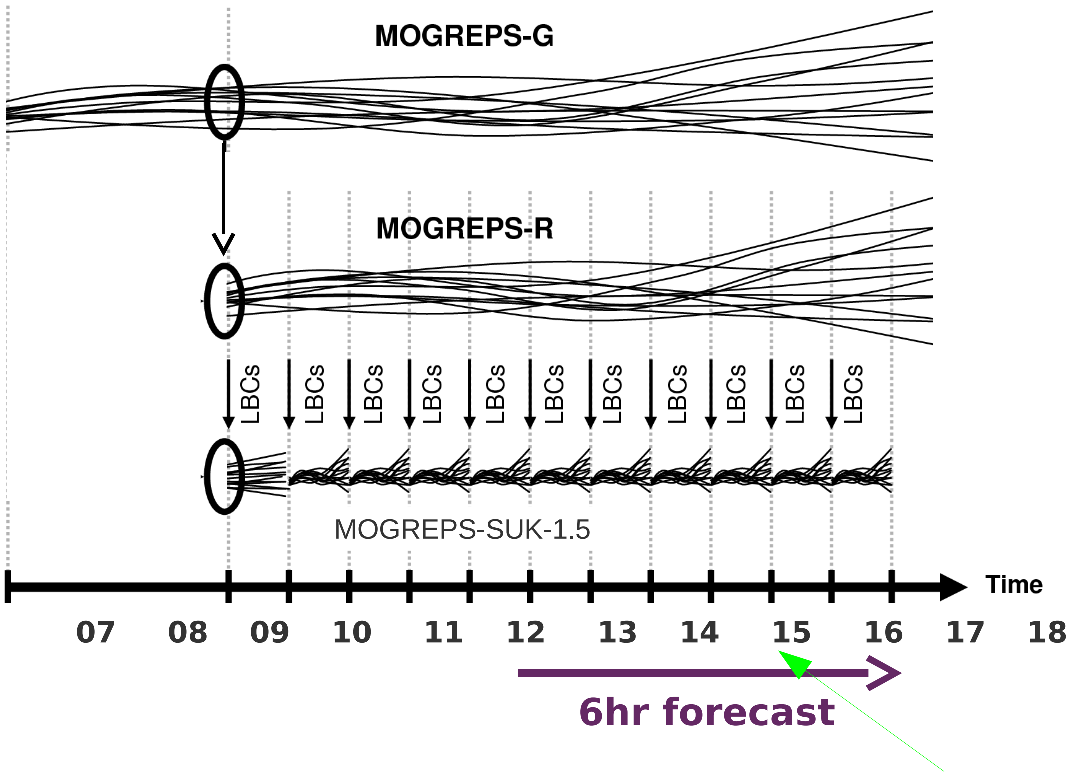
Ensemble prediction in the Southern UK domain

MOGREPS-G (Met Office Global and Regional Ensemble Prediction System)
MOGREPS-R (Met Office Global and Regional Ensemble Prediction System)
MOGREPS-UK
MOGREPS-SUK-1.5 (MetO@Reading / Reading Uni)



- Determine a single set of initial condition fields by VAR.
- Add perturbations based on the a-priori ensemble and properties of the observation network used in VAR (ETKF).
- Have *N* sets of initial condition fields (*N*=24).
- Pass each through forecast model with (optionally) a perturbation of model parameters (the RP – random parameters – scheme).

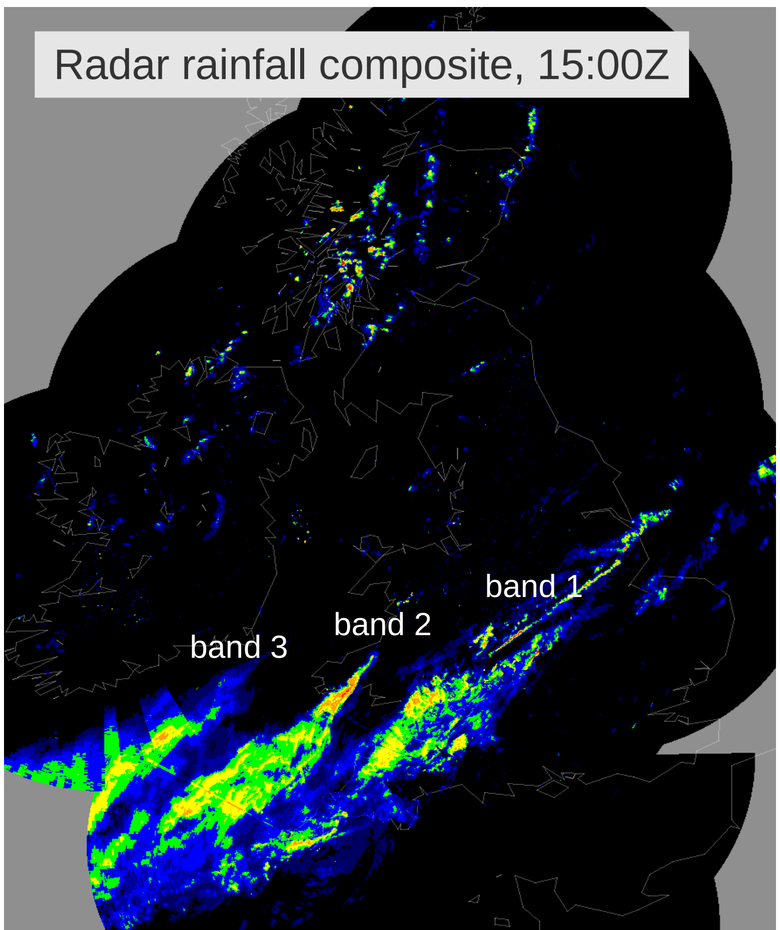
MOGREPS-SUK-1.5 set-up



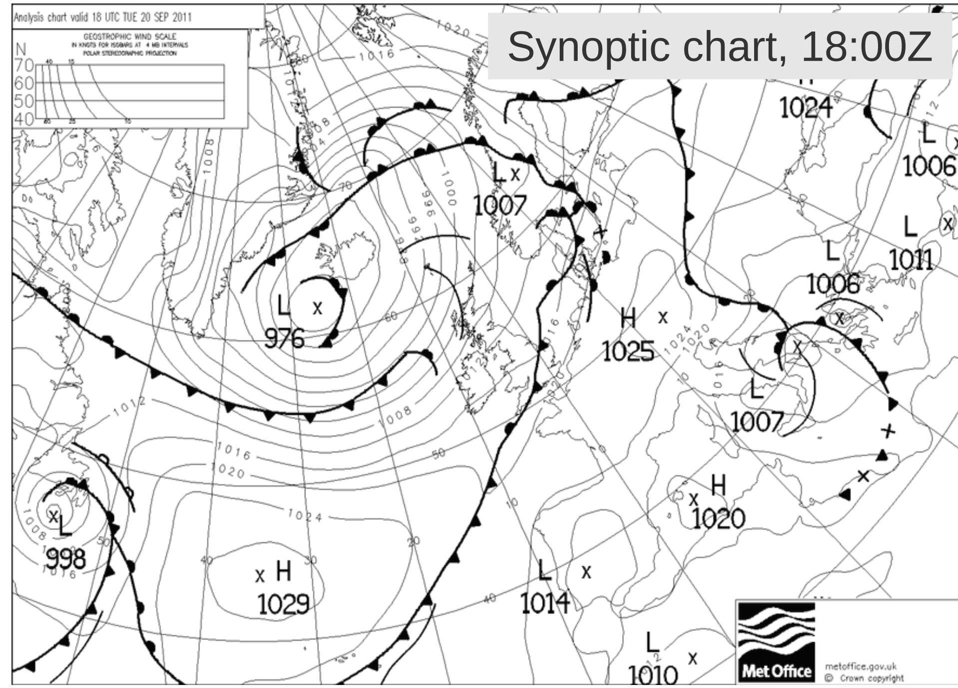
- Domain over southern UK (360 x 288 grid points)
- 1.5 km resolution grid
- Control member from 3D-Var analysis
- 23 perturbed members: initial condition perturbations and LBCs from MOGREPS-R
- Hourly-cycling ETKF for the first 6 hours
- 6 hour forecast from 12z
- Options to simulate model error variability with 'RP scheme'

DIAMET IOP-2 case study

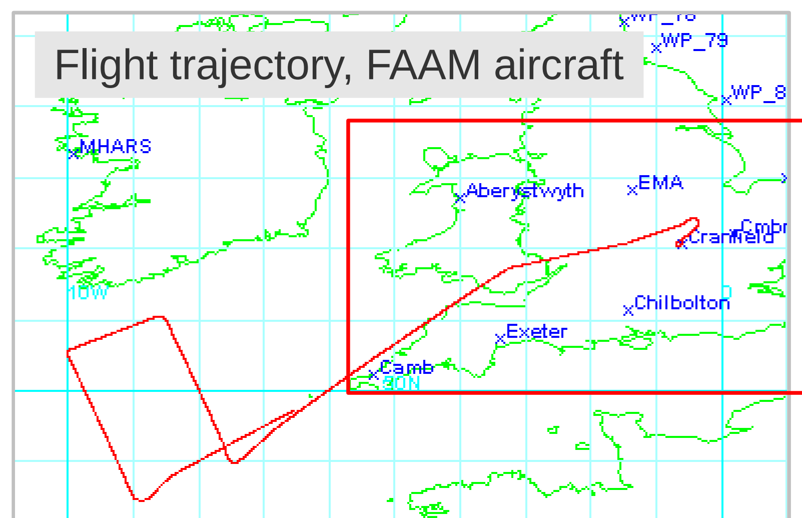
20/09/2011



Radar rainfall composite, 15:00Z



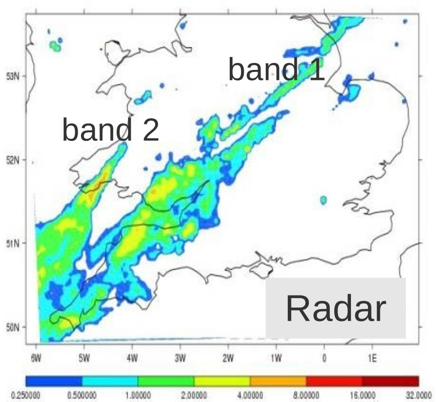
Synoptic chart, 18:00Z

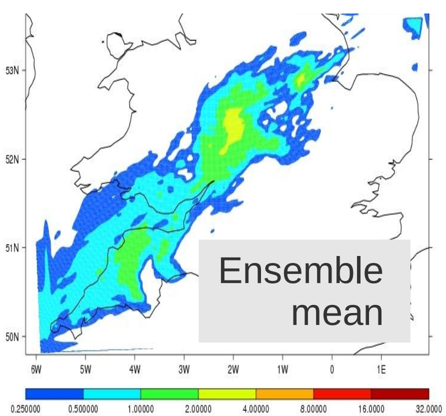


Flight trajectory, FAAM aircraft

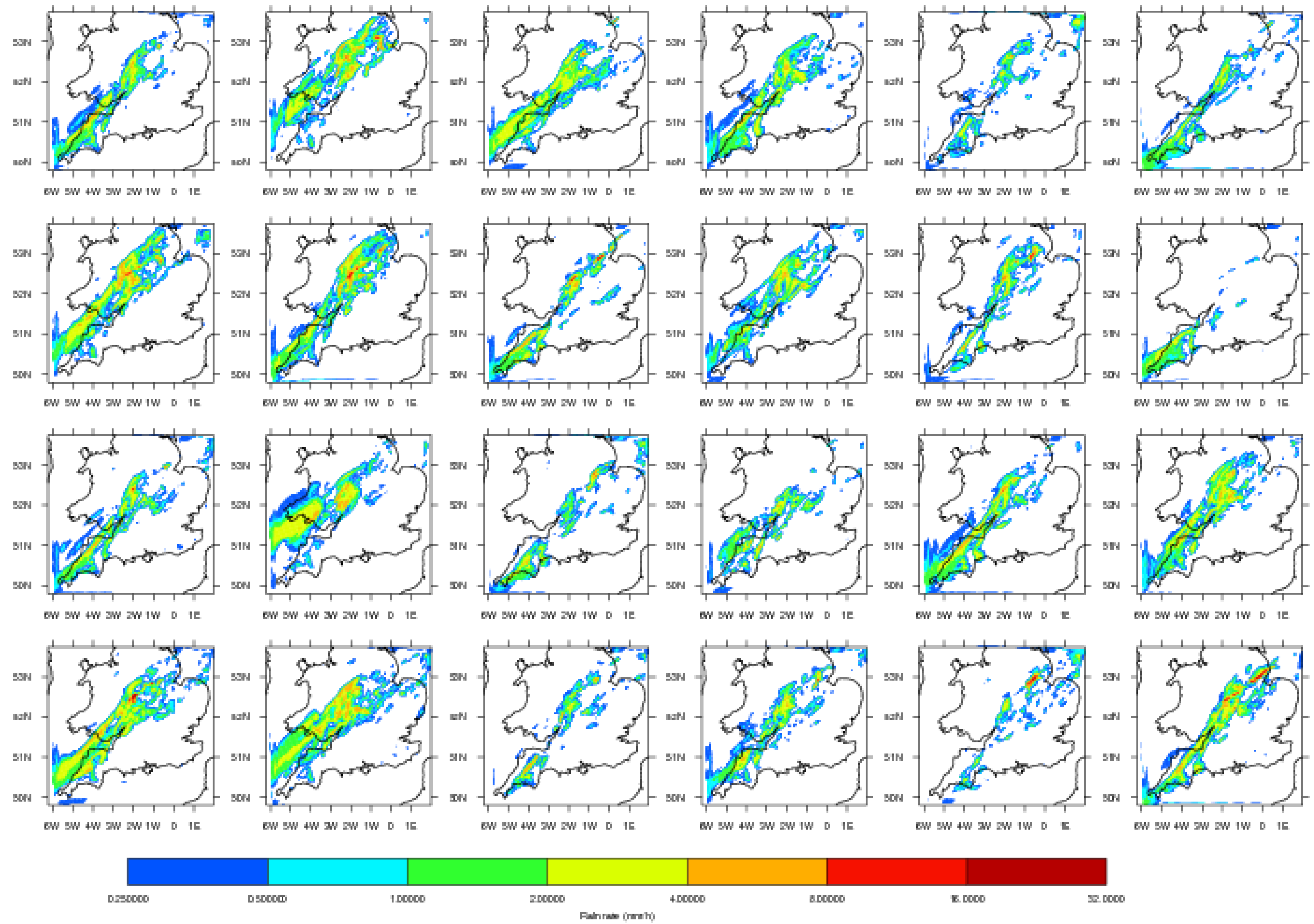
MOGREPS-SUK-1.5 rain rate forecasts

1500 UTC



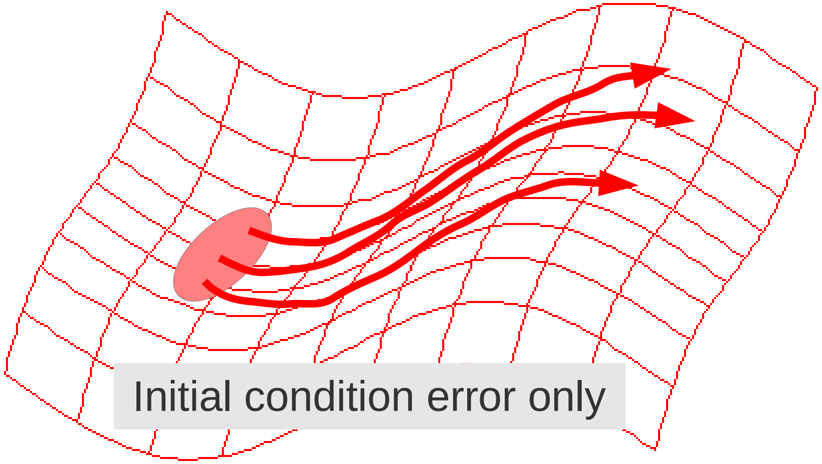


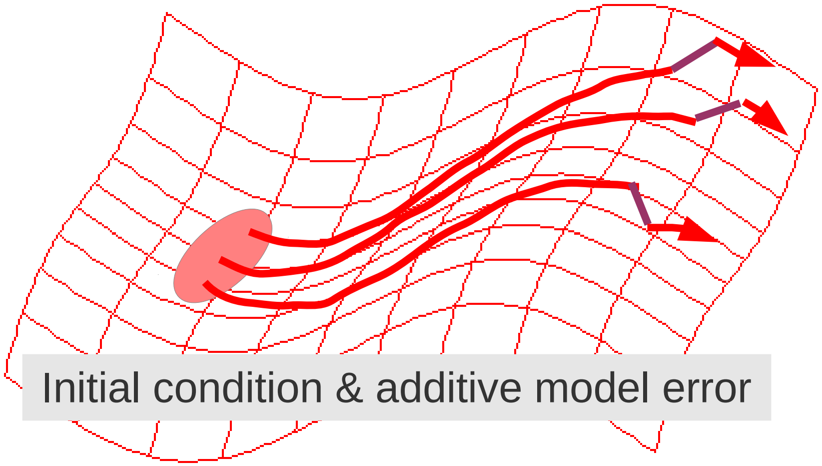
CTL ensemble (i.c. variability only)

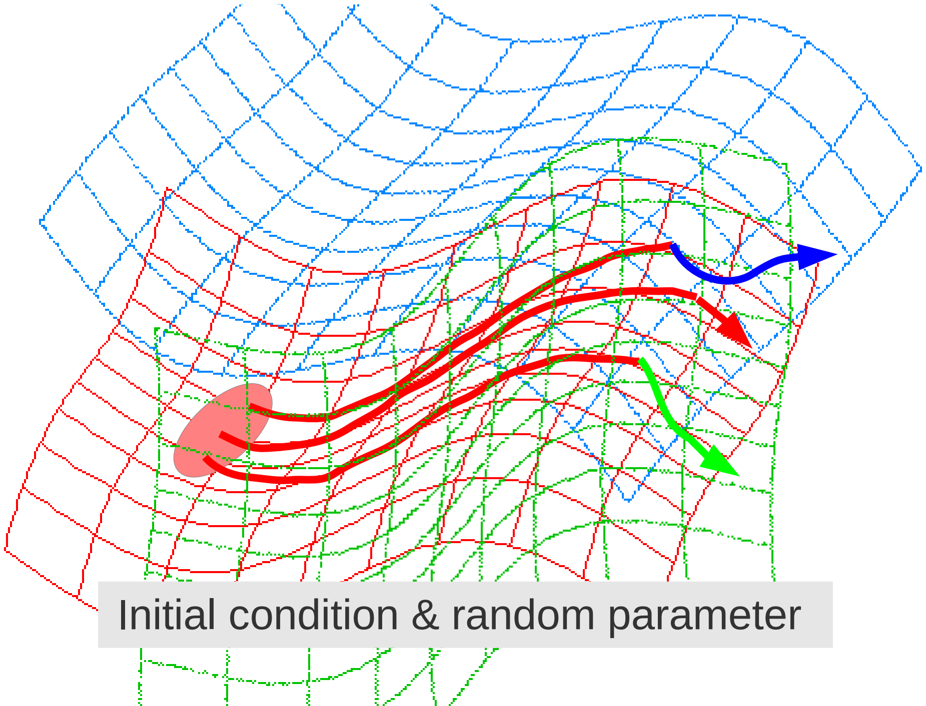


Simulating an additional souce of error – model error variability

- Results on previous slides varied initial conditions only.
- Only one realisation of model error.







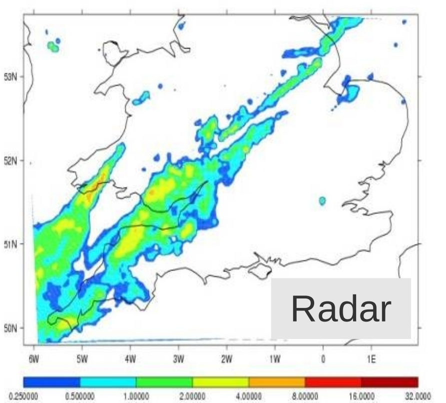
Parameters

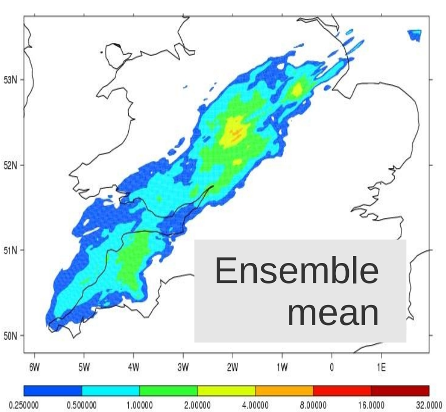
Scheme	Parameter	Description	min	default	max
BL	g0	Flux profile parameter	5	10	20
BL	Ri_c	Critical Richardson number	0.5	1.0	2.0
BL	g_{mezcla}	Neutral mixing length	0.03	0.15	0.45
BL	λ_{min}	Minimum mixing length	8	40	120
BL	Charnock	Charnock parameter	0.010	0.011	0.026
BL	A_1	Entrainment parameter	0.1	0.23	0.4
BL	G_1	Cloud-top diffusion parameter	0.5	0.85	1.5
LSP	RH_{crit}	Critical relative humidity	0.875	0.9	0.910
LSP	m_{ci}	Ice-fall speed	0.3	1.0	3.0
LSP	x1r	Particle size distribution for rain	2×10^6	8×10^6	2×10^9
LSP	xli	Particle size distribution for ice aggregates	1×10^6	2×10^6	1×10^7
LSP	x1ic	Particle size distribution for ice crystals	2×10^7	4×10^7	1×10^8
LSP	ai	Ice aggregate mass diameter	0.0222	0.0444	0.0888
LSP	aic	Ice crystal mass diameter	0.2935	0.587	1.174
LSP	t_{nuc}	Max ice nucleation temperature	-25	-10	-1
LSP	ec_{auto}	Autoconversion efficiency (converting cloud to rain)	0.01	0.55	0.6

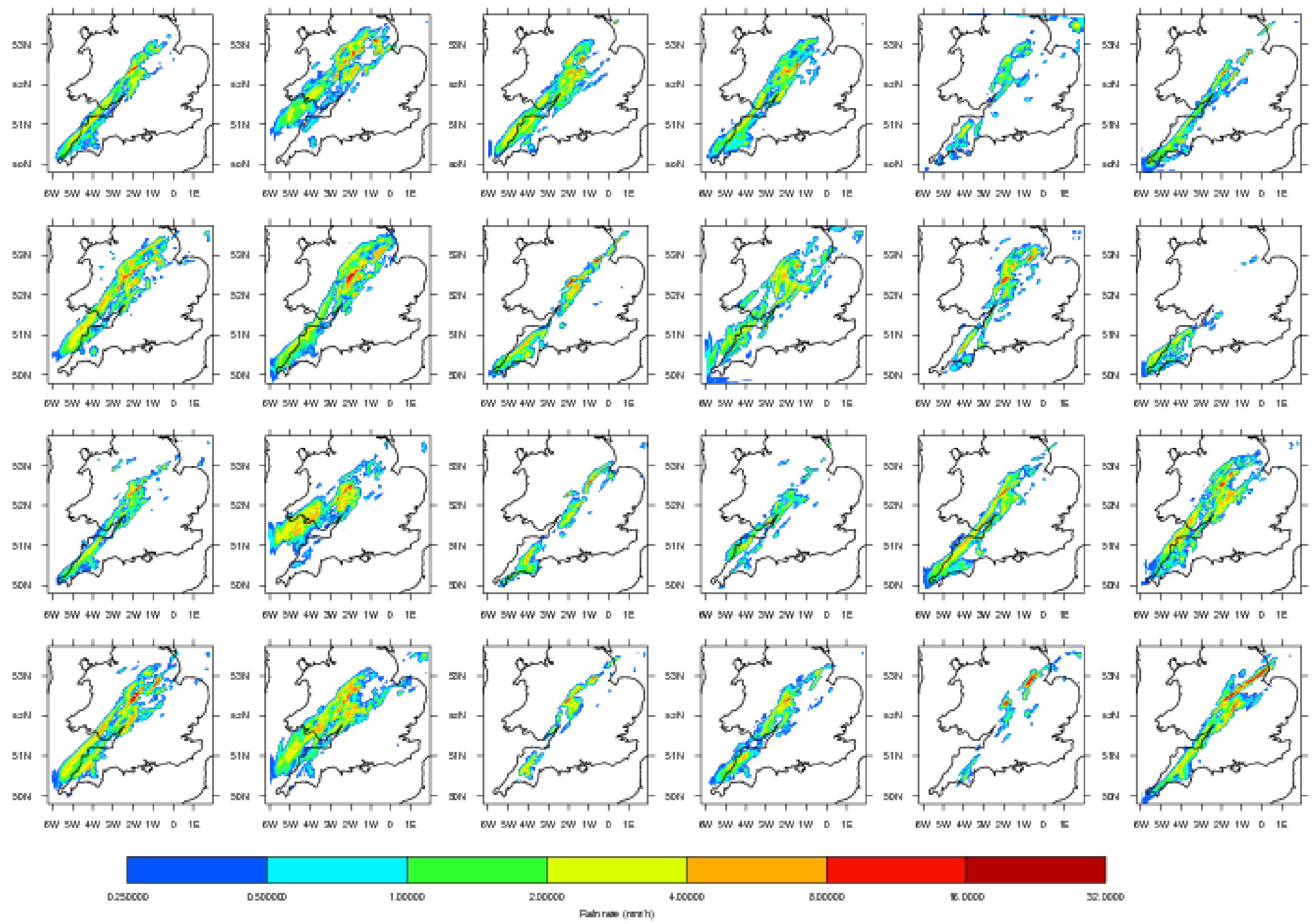
MOGREPS-SUK-1.5 rain rate forecasts

1500 UTC

RP-fix ensemble (i.c. + fixed parameter variability)



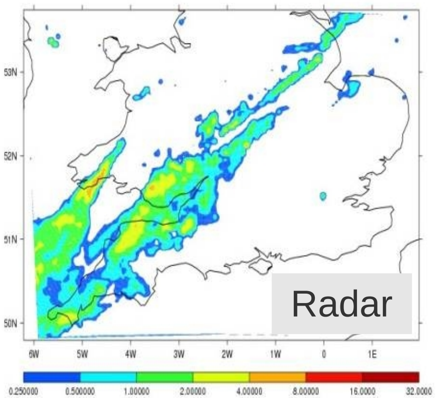


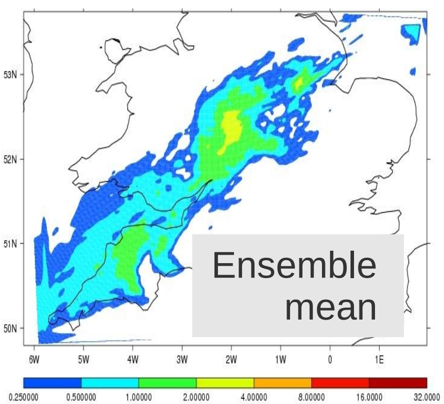


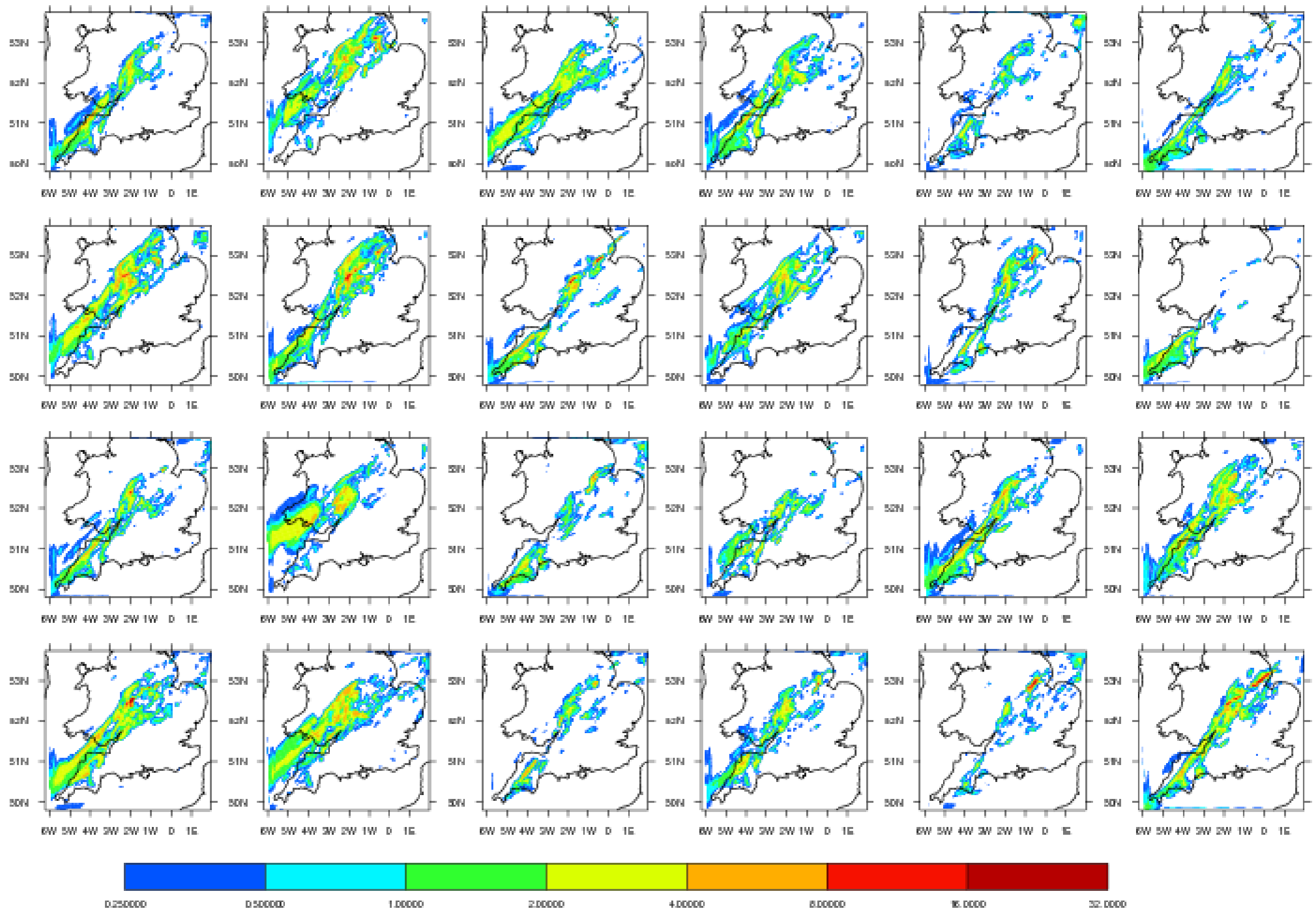
MOGREPS-SUK-1.5 rain rate forecasts

1500 UTC

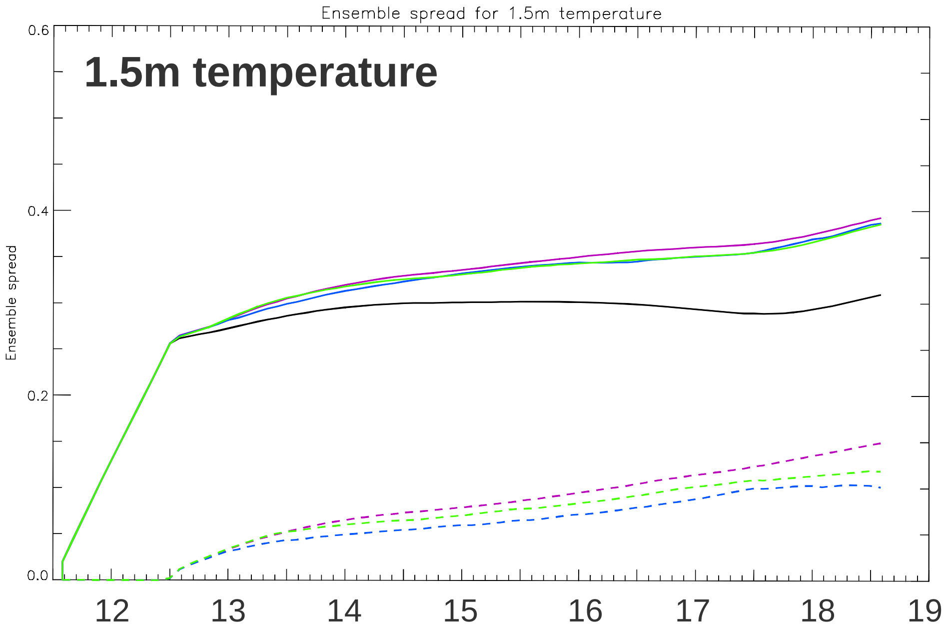
CTL ensemble (i.c. variability only)

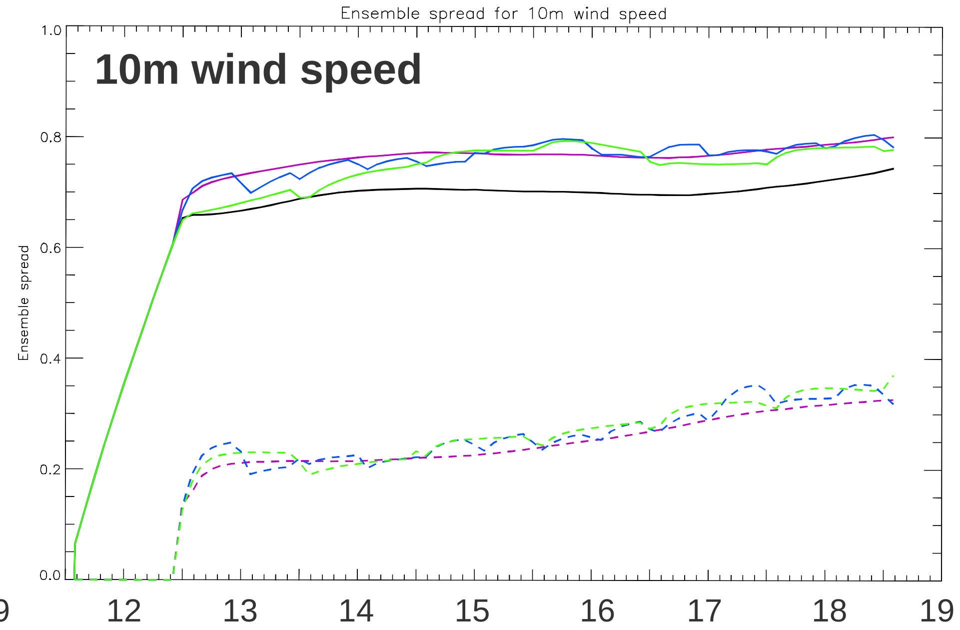






Effect on ensemble spread

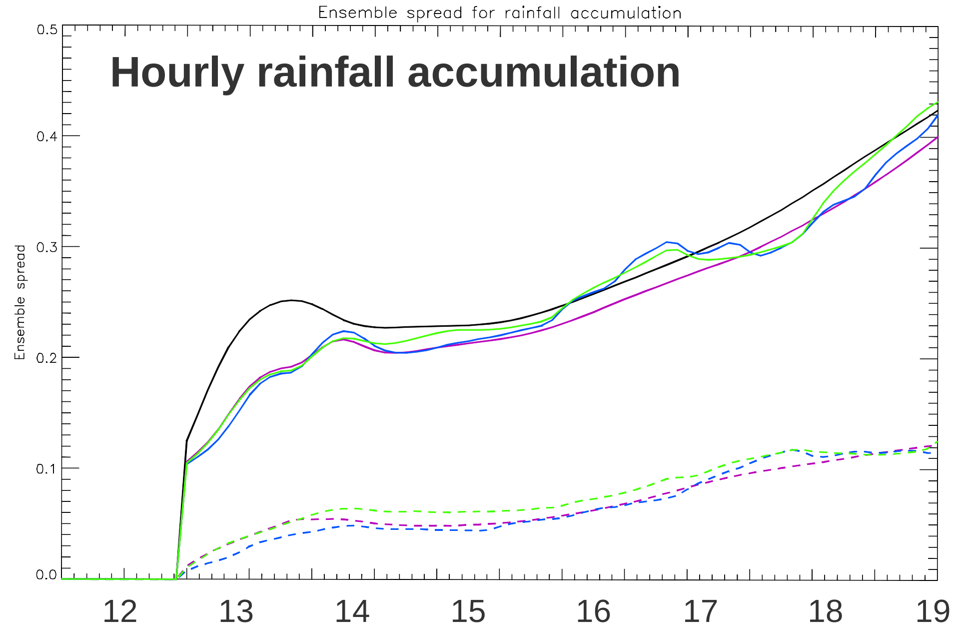




- CTL

- RP-60
- RP-30
- RP-fix

- onlyRP-60
- onlyRP-30
- onlyRP-fix



Effect on forecast skill (CRPS)

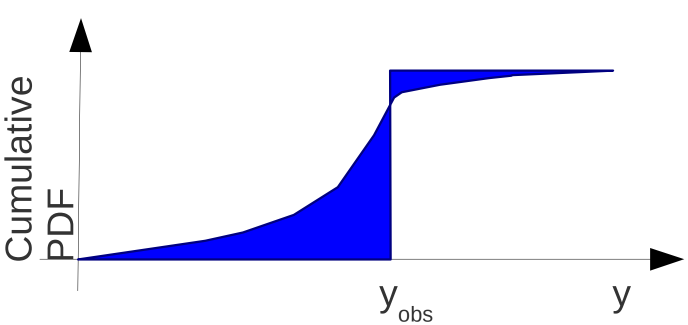
CRPS: Continuous Ranked Probability Score

$$\mathrm{CRPS} = \int_{y=-\infty}^{+\infty} dy\ \left(C_{\mathrm{fore}}(y) - C_{\mathrm{obs}}(y)\right)^2$$

$$C_{\mathrm{fore}}(y) = \int_{y'=-\infty}^{y} dy'\ P_{\mathrm{fore}}(y')$$

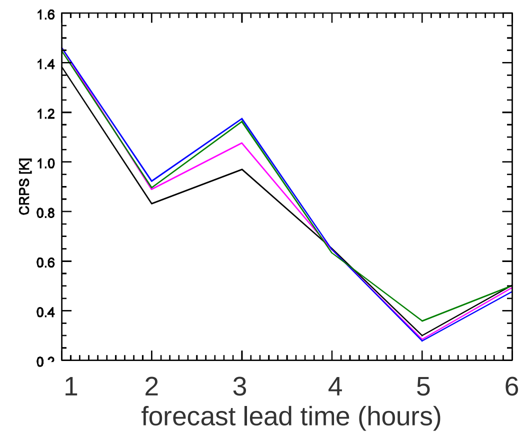
$$C_{\mathrm{obs}}(y) = \int_{y'=-\infty}^{y} dy'\ P_{\mathrm{fore}}(y')$$

$$\sim \int_{y'=-\infty}^{y} dy'\ \delta(y' - y_{\mathrm{obs}})$$

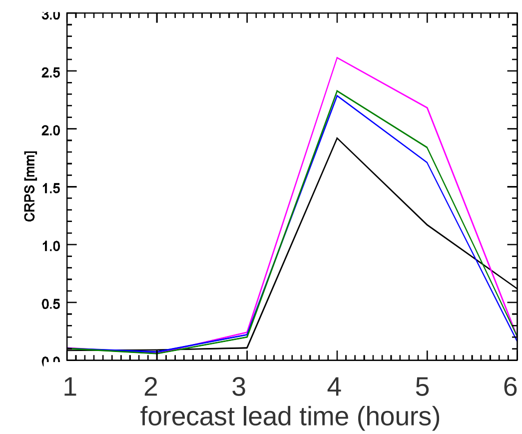


Better skill

surface temperature

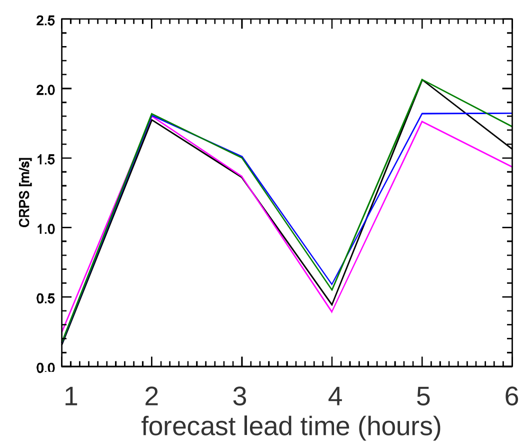


rain accumulation

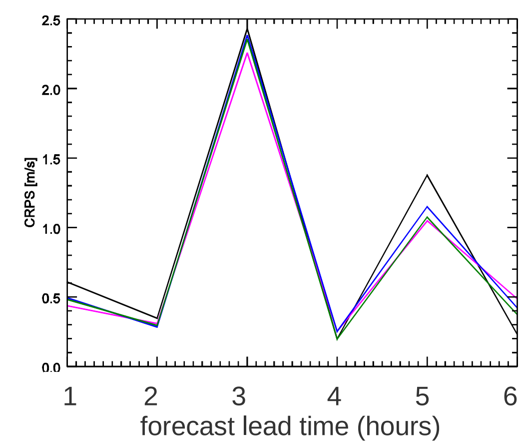


Better skill

u-wind component



v-wind component

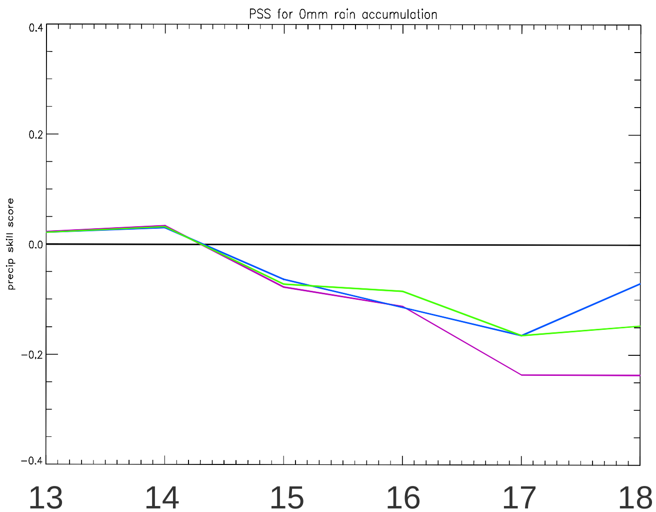


- CTL
- RP-60, RP-30, RP-fix

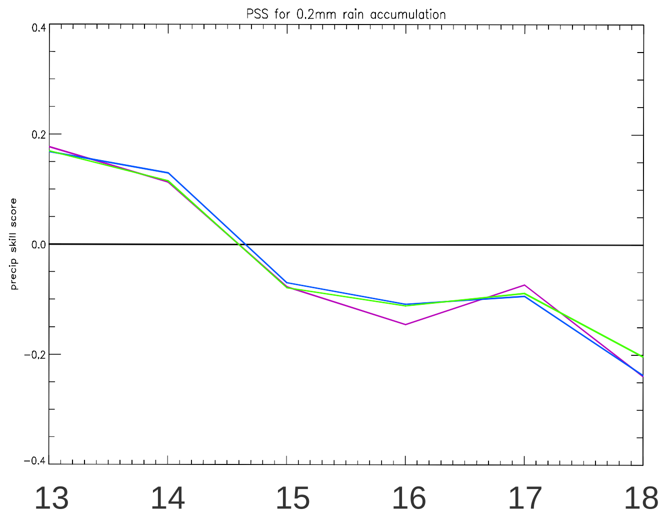
Effect on forecast skill (PSS)

Precipitation skill score for hourly rainfall accumulation

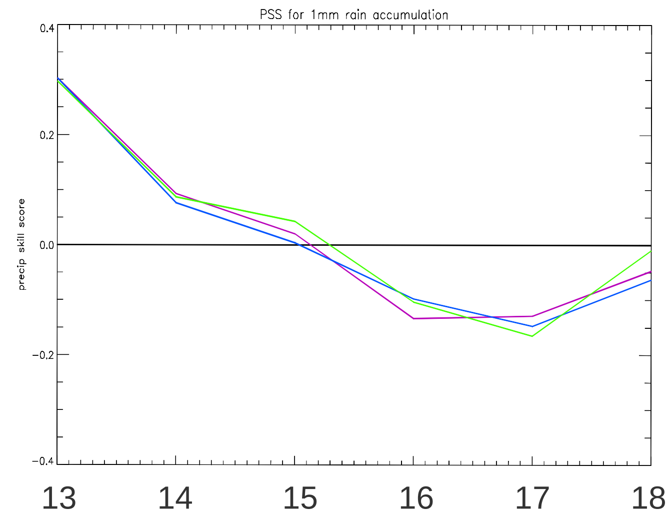
Threshold of 0 mm



Threshold of 0.2 mm



Threshold of 1.0 mm



- CTL
- RP-60, RP-30, RP-fix

PSS: Precipitation Skill Score

$$\mathrm{PSS_{ens}} = 1 - \frac{\mathrm{BS_{ens}}}{\mathrm{BS_{ctl}}}$$

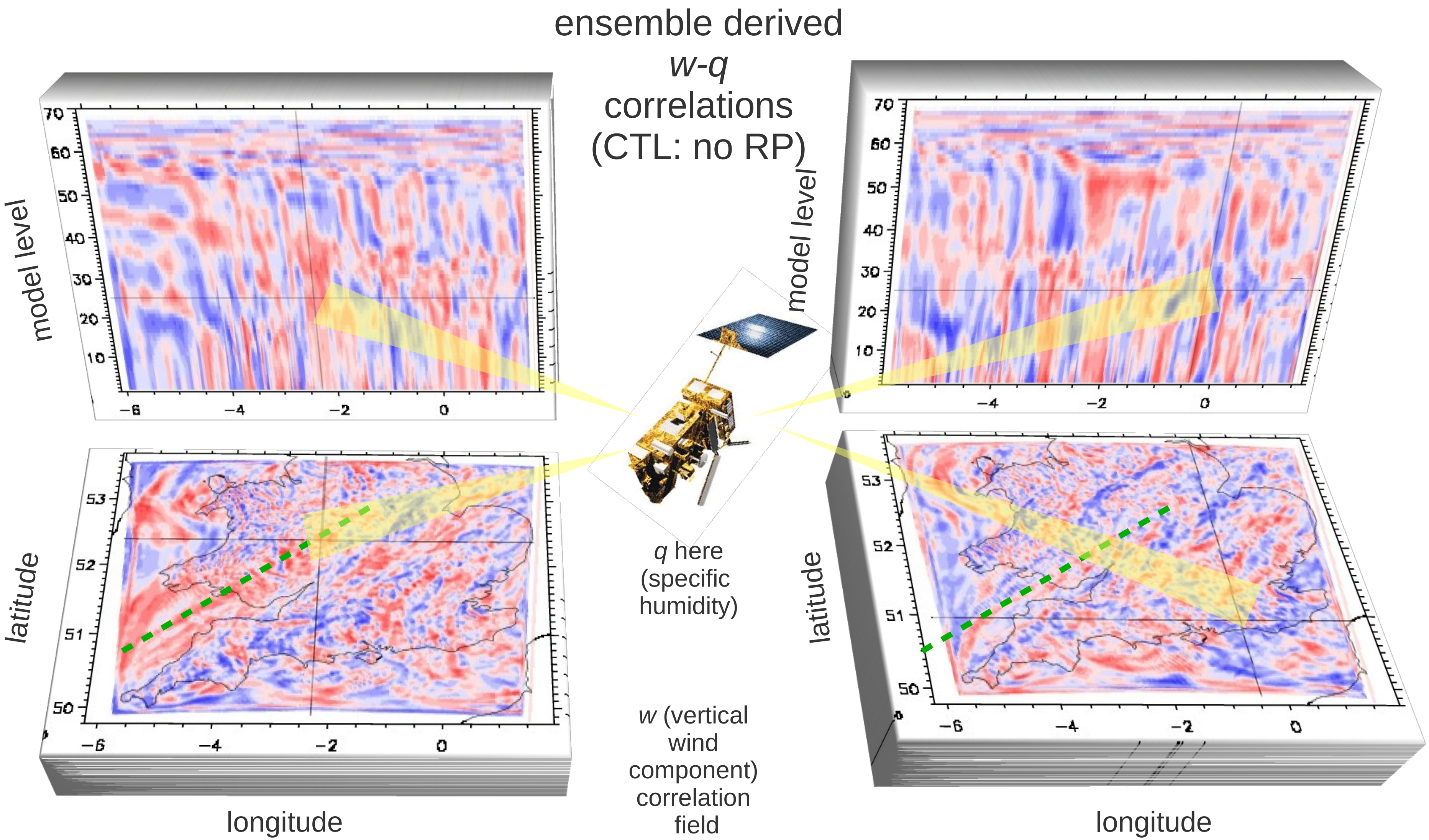
$\mathrm{PSS_{ens}}$ > 0 if “ens” better than “ctl”
$\mathrm{PSS_{ens}}$ = 0 if “ens” as good/bad as “ctl”
$\mathrm{PSS_{ens}}$ < 0 if “ens” worse than “ctl”

BS: Brier Score

$$\mathrm{BS} = \frac{1}{N}\sum_{i=1}^{N}\left(P_{\mathrm{fore}}(i) - P_{\mathrm{obs}}(i)\right)^2$$

P_{fore}: Probability of event forecast
P_{obs}: 1 if event observed, 0 if not

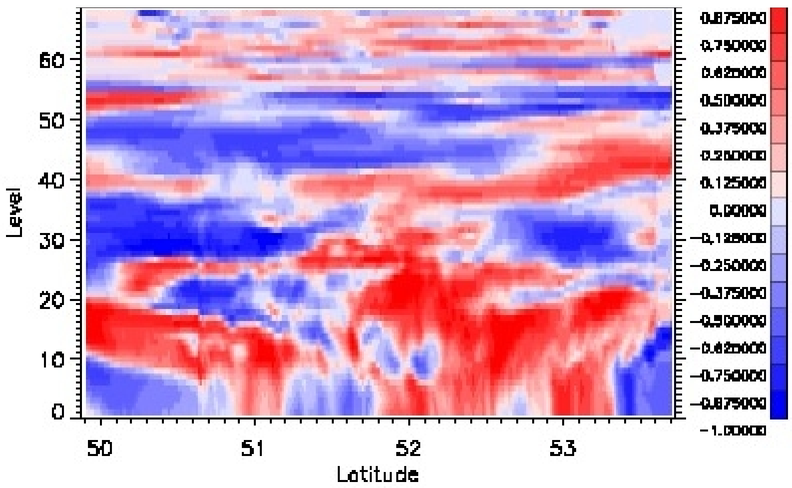
Ensemble-derived correlations (3-D)



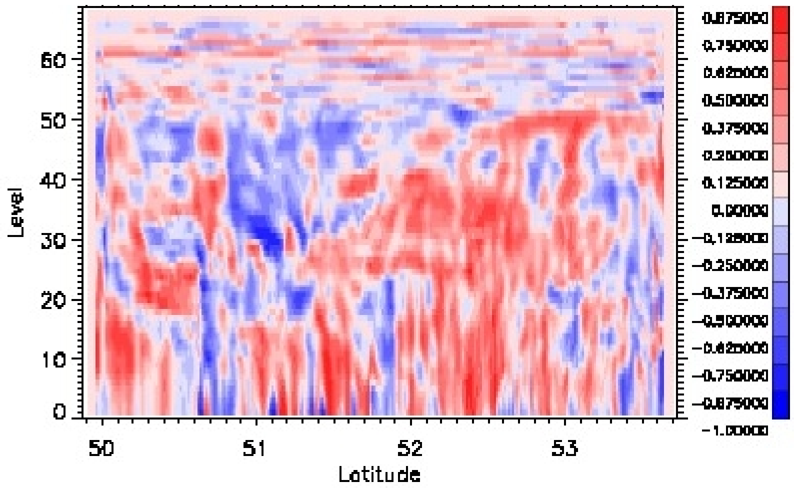
No qualitative changes with model error representation

Ensemble-derived correlations (point-by-point)

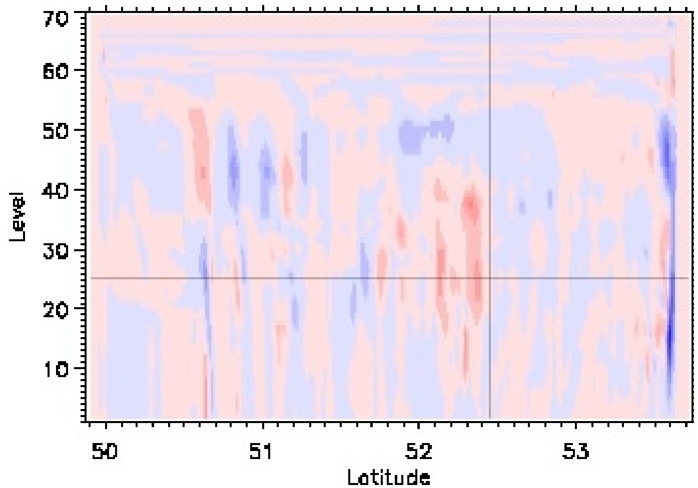
q-*T* correlations



q-*w* correlations



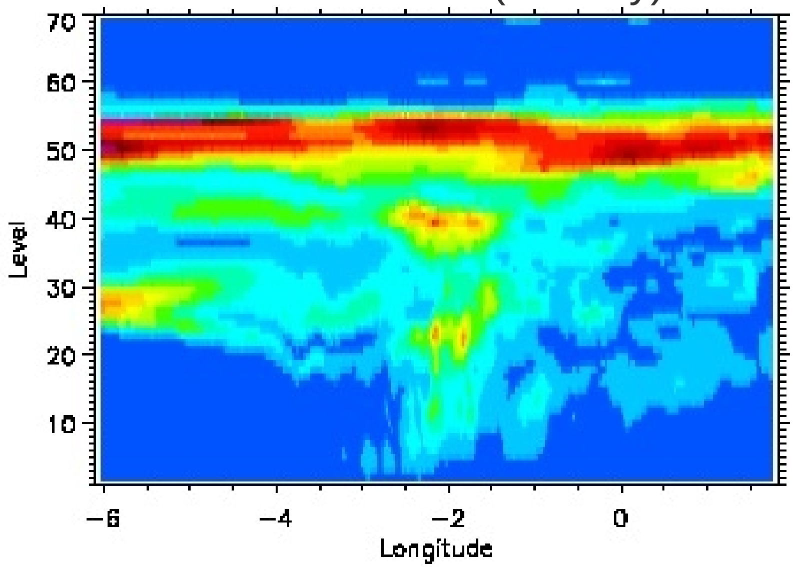
w field



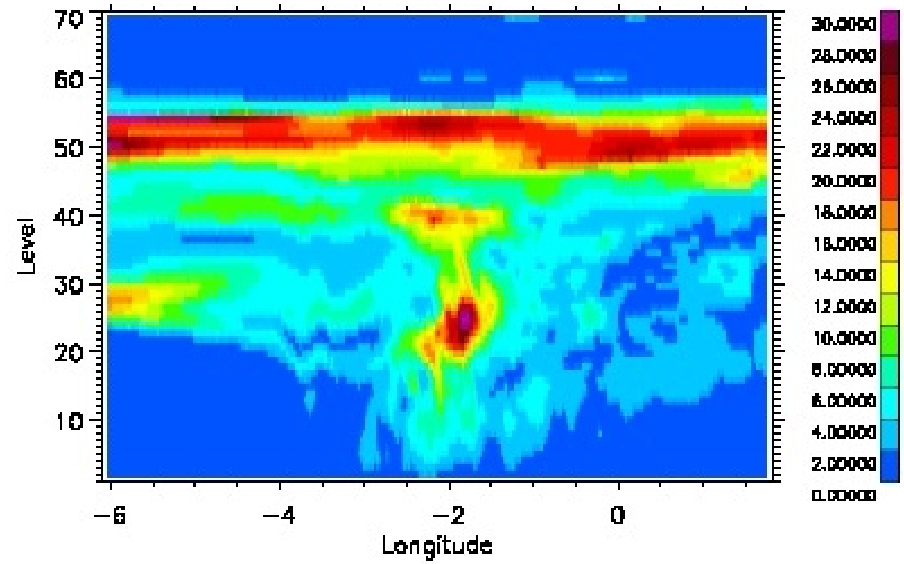
No qualitative changes with model error representation

Ensemble-derived variances (model grid)

CTL: No RP (i.c. only)

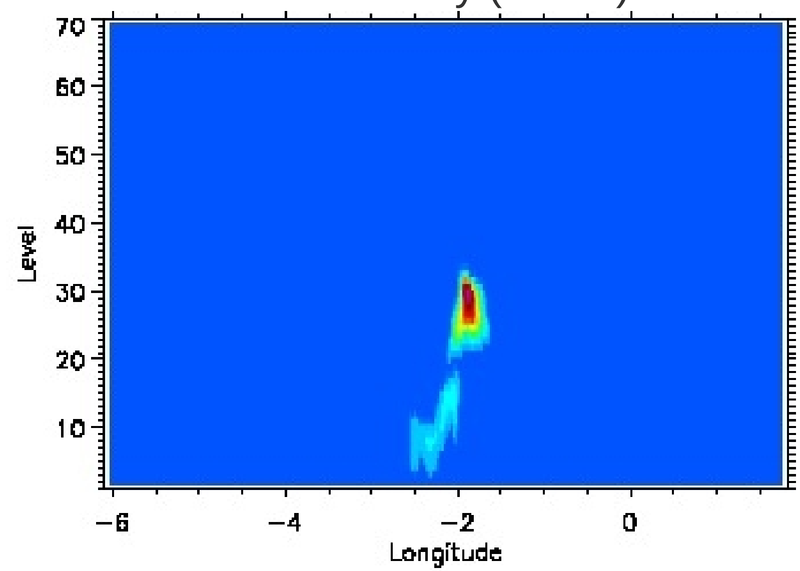


Fix RP + i.c.



Wind speed variance (m^2s^{-2})

Fix RP only (no i.c.)

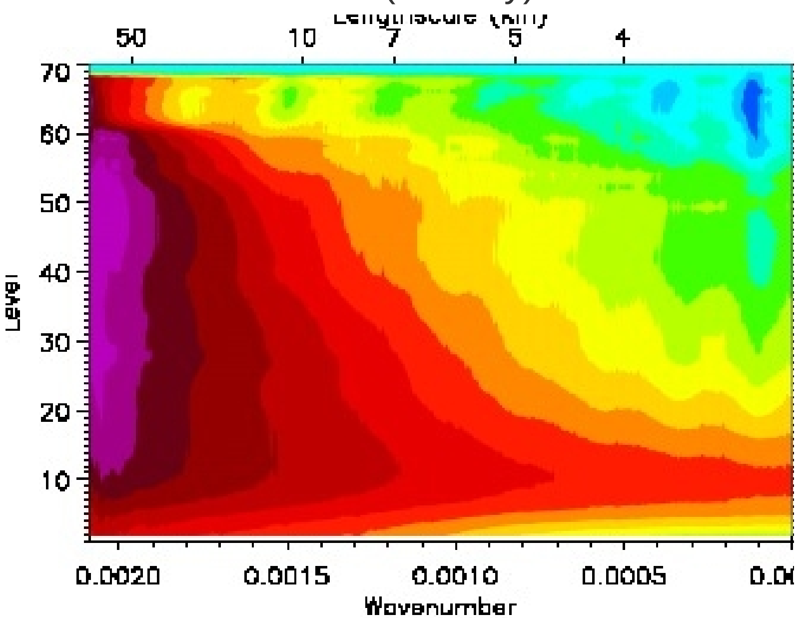


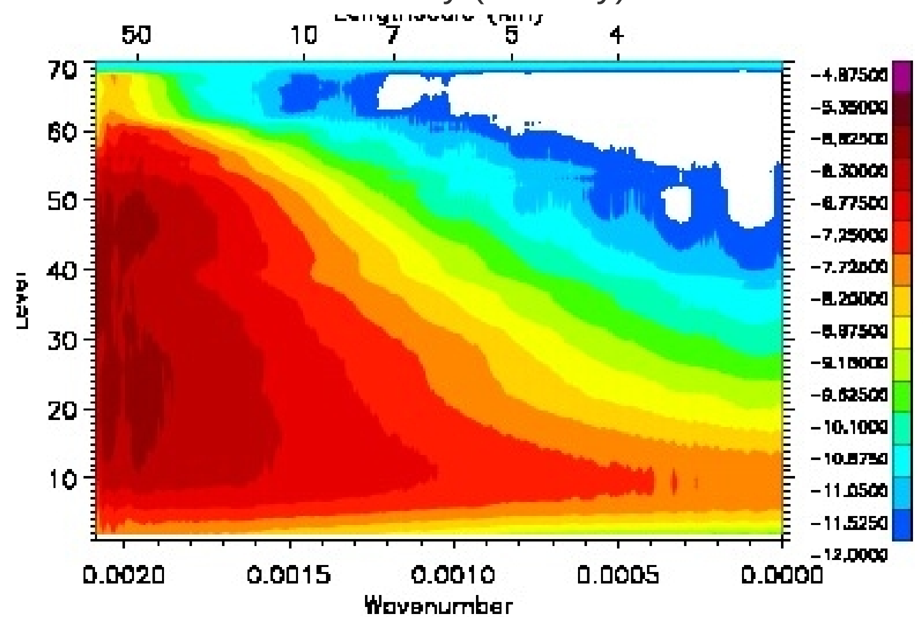
Ensemble-derived variances and correlations (spectral)

CTL: No-RP (i.c. only)

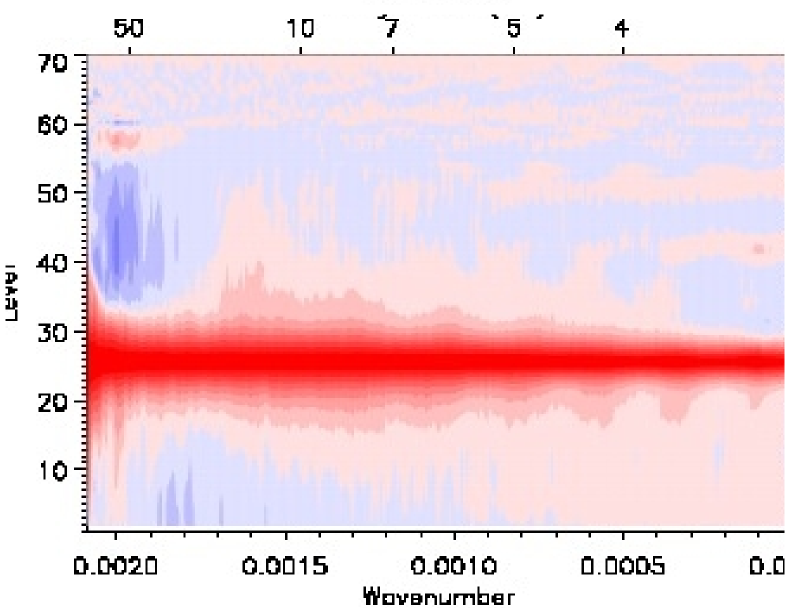
RP-fix-only (RP only)

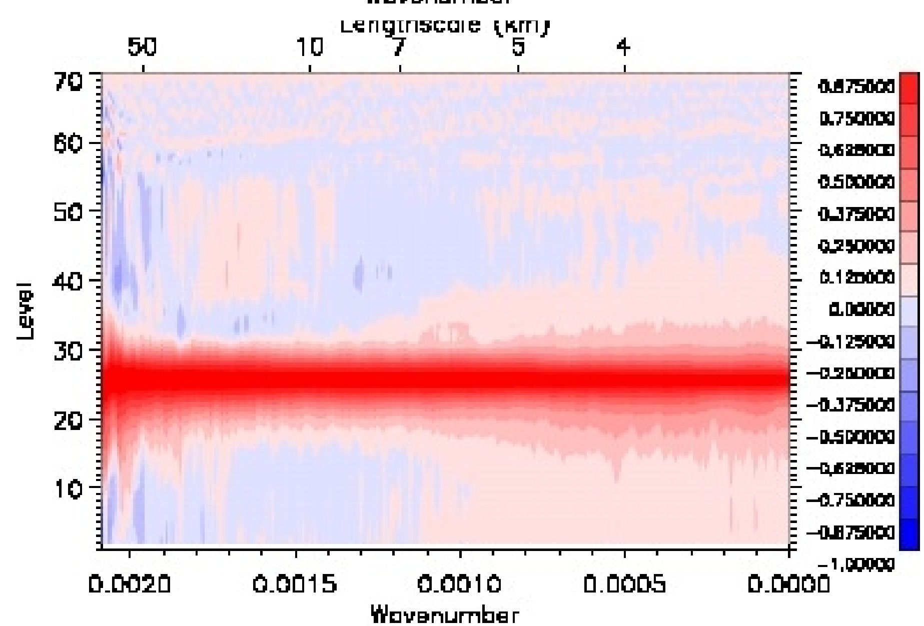
Variances for *w*





Vertical correlations *w*-*w*





Summary

- Have run a convective-scale EPS for DIAMET IOP 2 (20/09/11) with simulation of different sources of error (*initial condition* and *model error*).
  - Central forecast initialized with *3D-VAR* (operational observations).
  - Initial condition perturbations found with the *Ensemble Transform Kalman Filter*.
  - Model error variability with the *Random Parameter* scheme.
  - This is the kind of essential work that has to be done in preparation for the use of high-resolution EO data for weather forecasting.

- Cold front case with multiple banding in the cloud
  - Believe banding is real (not artefact of radar retrieval).
  - Multiple banding is evident in none of the 24-members, but some show rain in areas of both bands.
  - Forecast error covariance info essential for data assimilation. Have shown examples of how these are flow-dependent at the convective scale.

- Ensemble prediction systems generally do not have enough natural spread. Can the inclusion of model error variability help?
  - Model error shown to increase the spread of some quantities (T_s, $|\mathbf{u}_s|$), but to reduce the spread of others (rain rate).
  - Model error can give variability at small scales and where moist diabatic processes are very important.

- Does the RP scheme affect skill?
  - CRPS: RP did not improve skill for T_s and rainfall; neutral for u_s, v_s.
  - BS, PSS: RP better skill for first few hours, worse skill later.

- Have/will also examine for this case:
  - Forecast sensitivity to parameters.
  - Reliability diagrams.
  - Rank histograms.
  - Innovation covariances.
  - 93-member statistics.
  - Large atlas of covariance statistics.
  - Balance properties.
  - Localization techniques.

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