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Ensemble prediction systems in parameter estimation and forecast skill optimization

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Outline

(1) Motivation to the model parameter estimation

- A dilemma on the uniqueness of parameter values

(2) Ensemble prediction & parameter estimation

- The EPPES concept
- Parameter estimation in the Lorenz-95
- Forecast skill optimization in ECHAM5 & IFS models

1. Motivation to the model parameter estimation

- **Forecast model closure parameters**
  - In parameterizations of sub-grid scale physical process

- **Anchor parameter values to the observables**
  - Laboratory measurements
  - Observations from dedicated field campaings
  - Large-eddy simulations, etc.
- **However, let us consider the following prediction system:**

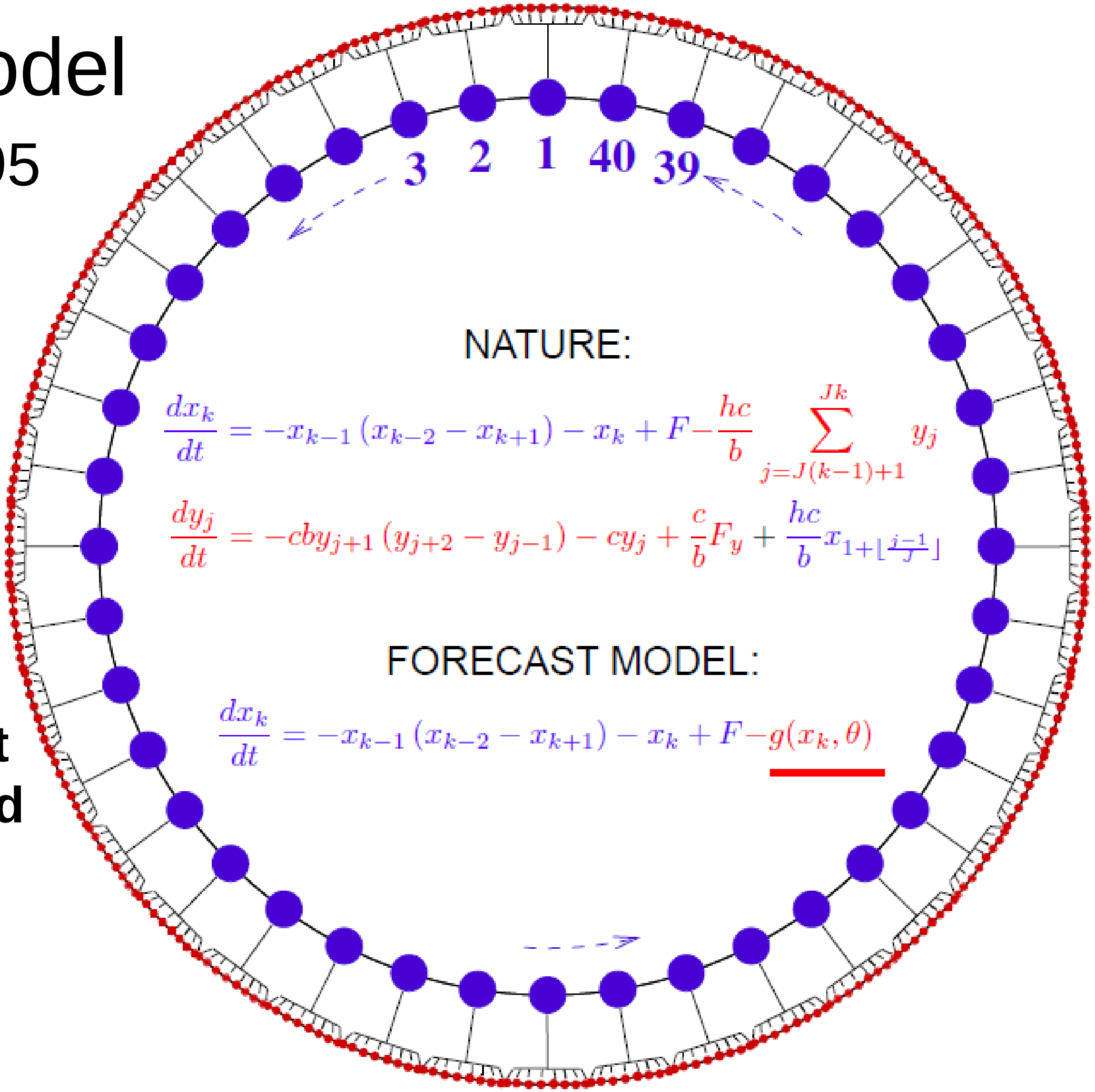
(i) Prediction model

- a modified Lorenz-95

- **40 slow variables**
- **320 fast variables**

The net effect of the fast valiables is parameterized

$$g(x_k;\theta) = \theta_1 + \theta_2 x_k$$



NATURE:

$$\frac{dx_k}{dt} = -x_{k-1}\left(x_{k-2} - x_{k+1}\right) - x_k + F - \frac{hc}{b}\sum_{j=J(k-1)+1}^{Jk} y_j$$

$$\frac{dy_j}{dt} = -cby_{j+1}\left(y_{j+2} - y_{j-1}\right) - cy_j + \frac{c}{b}F_y + \frac{hc}{b}x_{1+\lfloor\frac{j-1}{J}\rfloor}$$

FORECAST MODEL:

$$\frac{dx_k}{dt} = -x_{k-1}\left(x_{k-2} - x_{k+1}\right) - x_k + F - \underline{g(x_k,\theta)}$$

Wilks (2005, QJRMS); Leutbecher (2010, ECMWF Lectures)

(ii) Data assimilation

a) Extended Kalman filter (EKF)

b) Ensemble Adjustment KF (EAKF)

- **Let us study the optimal parameter values in these two prediction systems**

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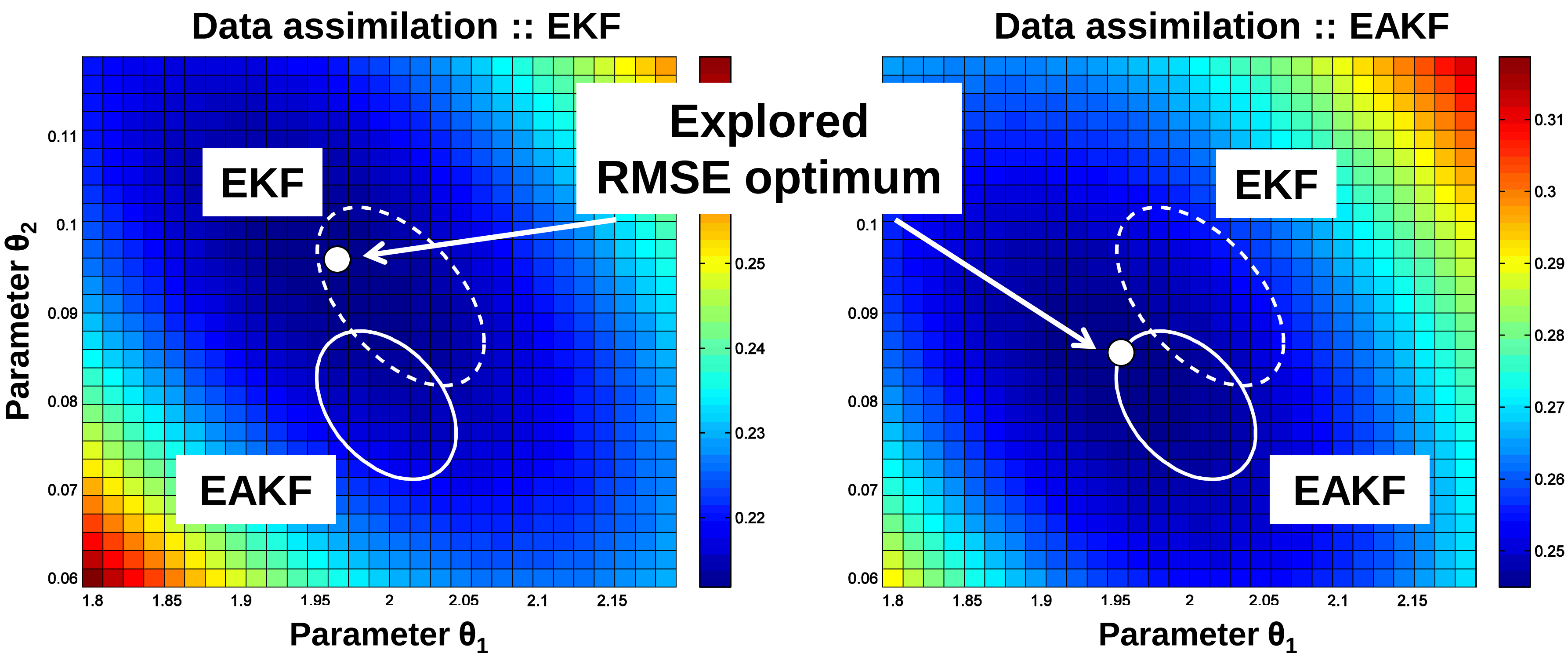
RMSE accuracy of the two prediction systems



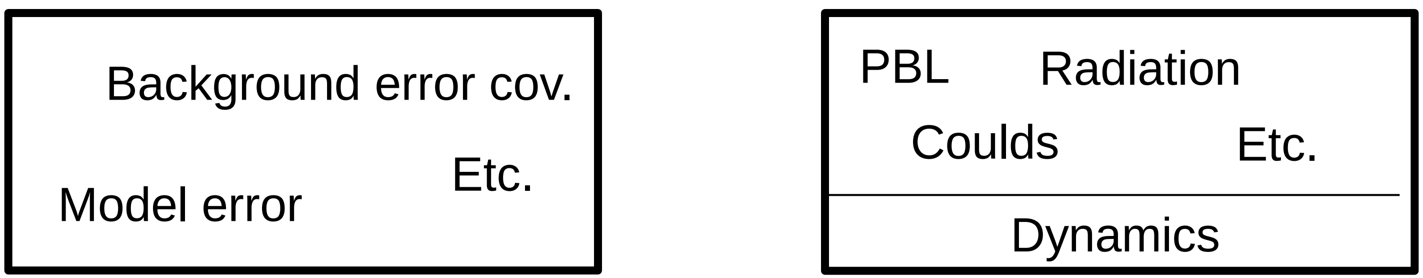
A dilemma

- **An identical model has two parameter optima depending on the approximations in data assimilation**
- **Both cannot simultaneously correspond to the ”observables”**
- **Model parameter values do not seem to be unique**

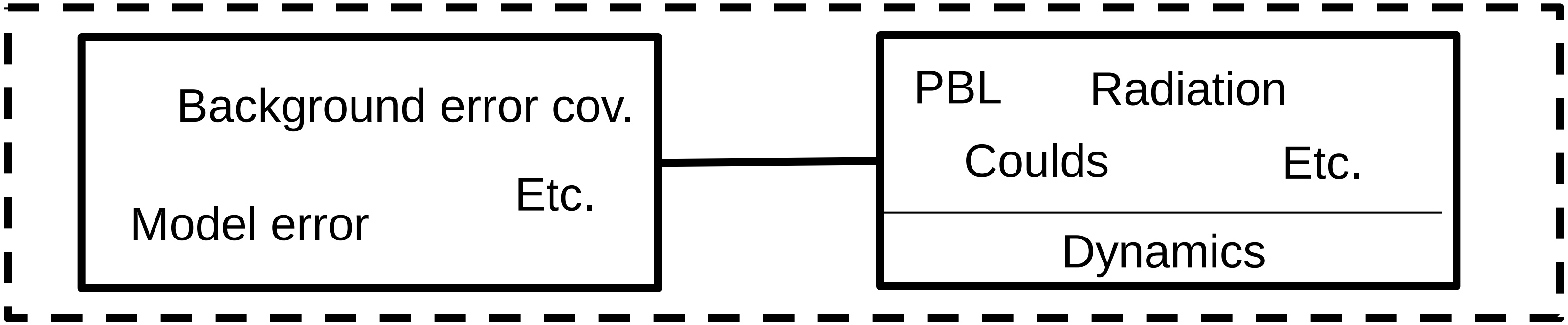
A conclusion

- **Consider the entire prodiction system**

Data assimilation **Forecast model**



Data assimilation + Forecast model

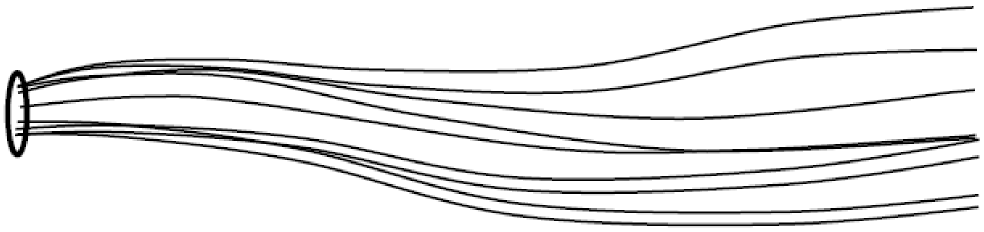


Ensemble prediction & parameter estimation

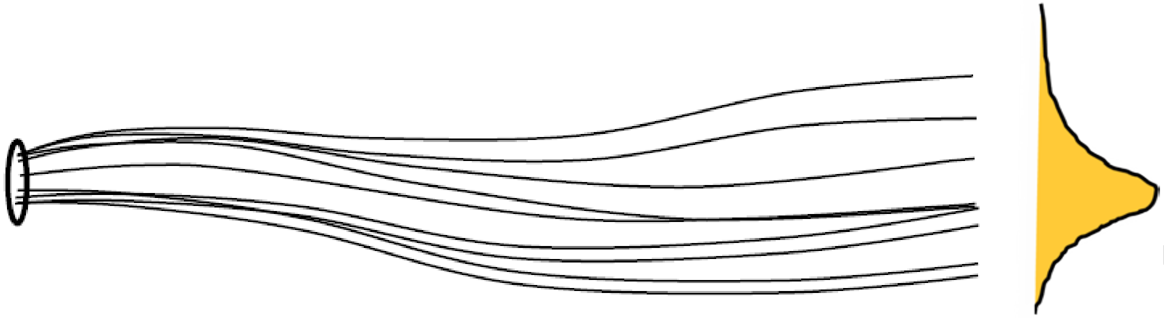
- **Long term improvements :: (model generations)**
  - improve representation of atmospheric phenomena in all spatial and temporal scales
- **Short term improvements :: (model releases)**
  - tune the physics so that processess are in harmony
  - currently:: manual, trial-and-error, time-consuming, …

- **The EPPES concept for model tuning**

Let us consider an ensemble prediction system



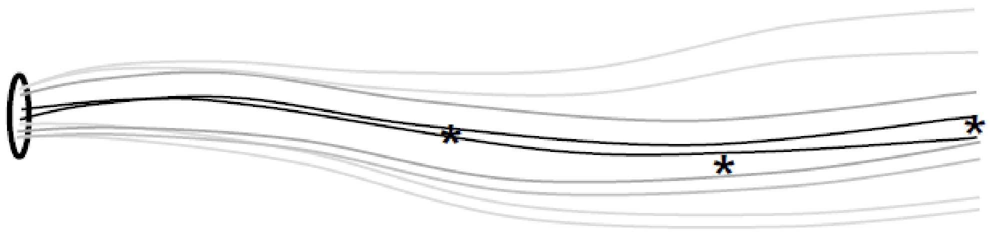
The aim is to estimate forecast uncertainty



”PDF” of forecast uncertainty

<u>A priori</u>, all ensemble members are equally likely

… whereas in algorithmic parameter estimation



Verifying observations + An objective measure of fit

<u>A posteriori</u>, some ensemble members appear more likely than others

EPS + parameter estimation = EPPES

ASSUME background uncertainty in the model parameters θ

$$\theta \sim N(\mu, \Sigma)$$

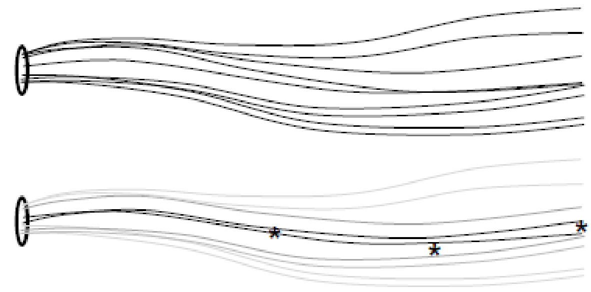
SAMPLE parameters θ from this distribution

EVALUATE a likelihood function

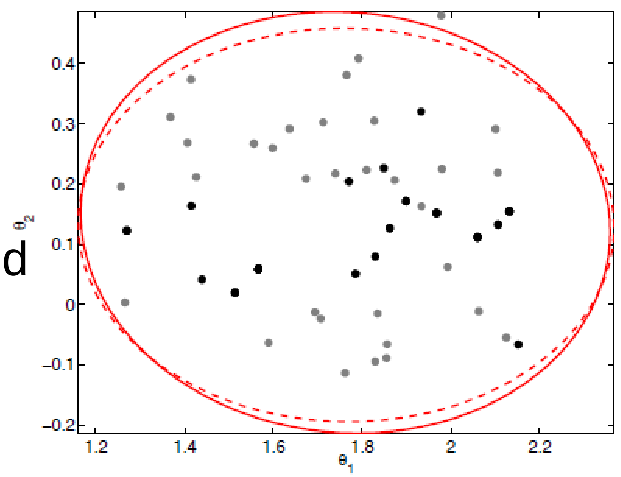
WEIGHT parameters according to their likelihood

UPDATE distribution parameters μ and Σ sequentially

State space



Parameter space



Posterior distribution $p(\theta_i|y_i) \propto p(y_i|\theta_i)p(\theta_i)$

Prior $p(\theta_i) \propto \exp\left(-\frac{1}{2}(\theta_i - \mu_i)' \Sigma_i^{-1} (\theta_i - \mu_i)\right)$

Likelihood $p(y_i|\theta_i) \propto \exp\left(-\frac{1}{2}\big(y_i - F(x_i;\theta_i)\big)' \Sigma_{\text{obs}}^{-1} \big(y_i - F(x_i;\theta_i)\big)\right)$

Importance weights $w(\tilde{\theta}_i^j) \propto \dfrac{p(\tilde{\theta}_i^j|y_i)}{p(\tilde{\theta}_i^j)} \propto \dfrac{p(y_i|\tilde{\theta}_i^j)p(\tilde{\theta}_i^j)}{p(\tilde{\theta}_i^j)} = p(y_i|\tilde{\theta}_i^j)$

A sample from the prior ⇒ importance weights ⇒ a sample from the posterior

But: this sample is very small (too small to estimate the posterior distribution)

Only the posterior sample <u>mean</u> is used from one ensemble

Hierarchical model

$$\theta_i \sim N(\mu, \Sigma)$$

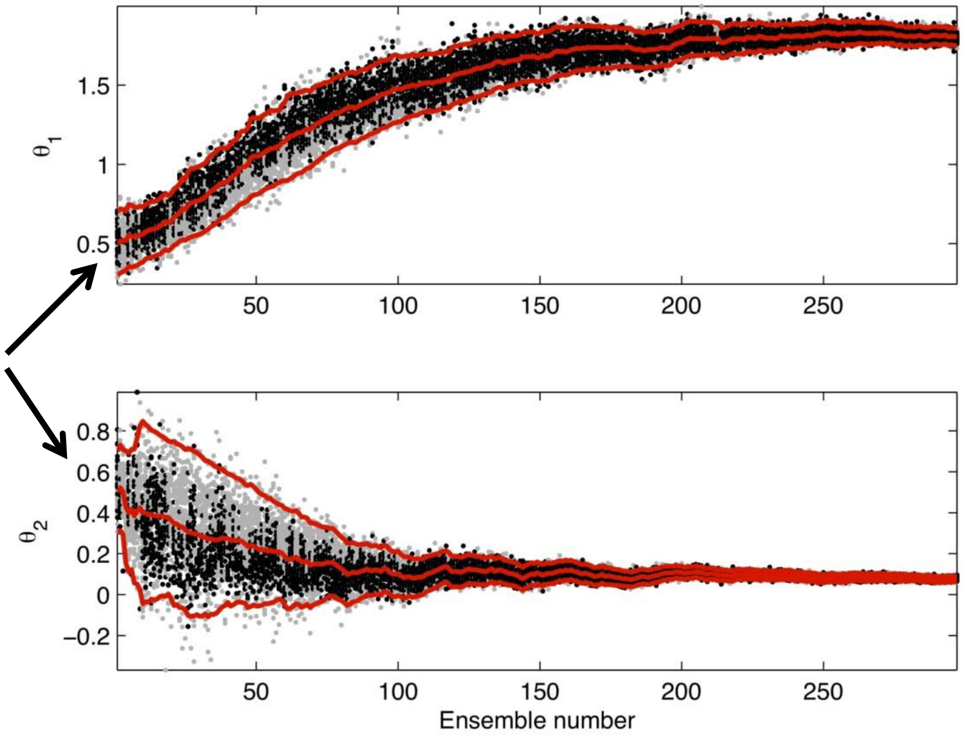
$$\mu \sim N(\mu_{i-1}, W_{i-1})$$

$$\Sigma \sim \text{iWish}(\Sigma_{i-1}, n_{i-1})$$

+ cumulative update formulas for μ (Σ is the variability of θ between samples)

Modified Lorenz-95 parameters θ_1 and θ_2

Badly selected initial values



Small uncertainty in the final values

Final θ -values correspond to the optimal skill

300 sequential ensembles
50 members in each ensemble
Cost function: ”6 day” forecast skill

ECHAM5 T42L31 climate model in ”EPS mode”

- **”An EPS emulator”**
  - Initial states + perturbations from the ECMWF EPS
- **50+1 members, 3 months, twice daily, 10 day forecasts**
- **Sample size:: 2 × 90 × 51 = 9180**

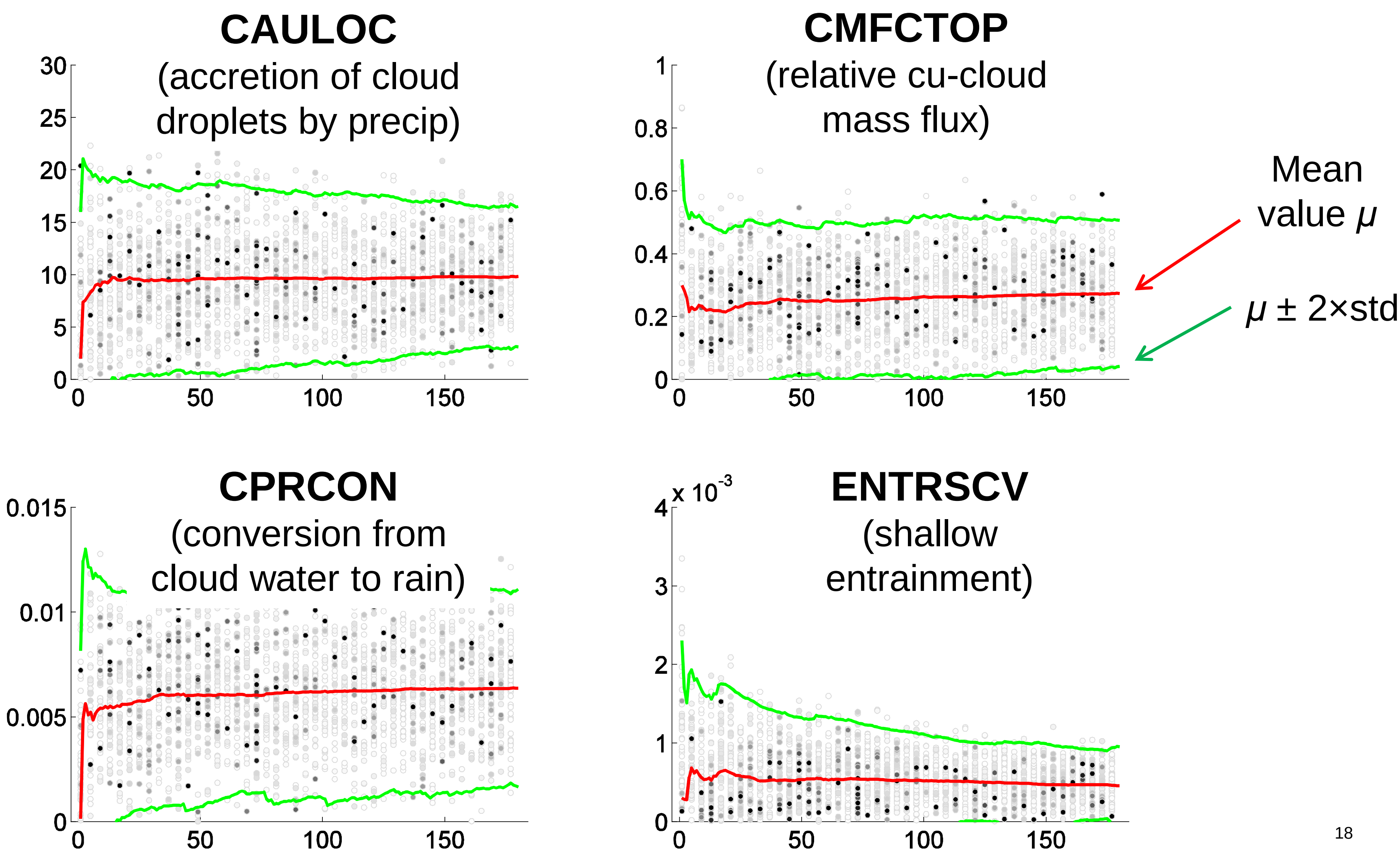
EPPES in ECHAM5

- **Parameters (clouds and precipitation)**
  - CAULOC - accretion of cloud droplets by precipitation
  - ENTRSCV - shallow entrainment
  - CMFCTOP - relative cu-cloud mass flux
  - CPRCON - conversion from cloud water to rain

- **Cost function (3 and 10 day forecast skill of Z500)**

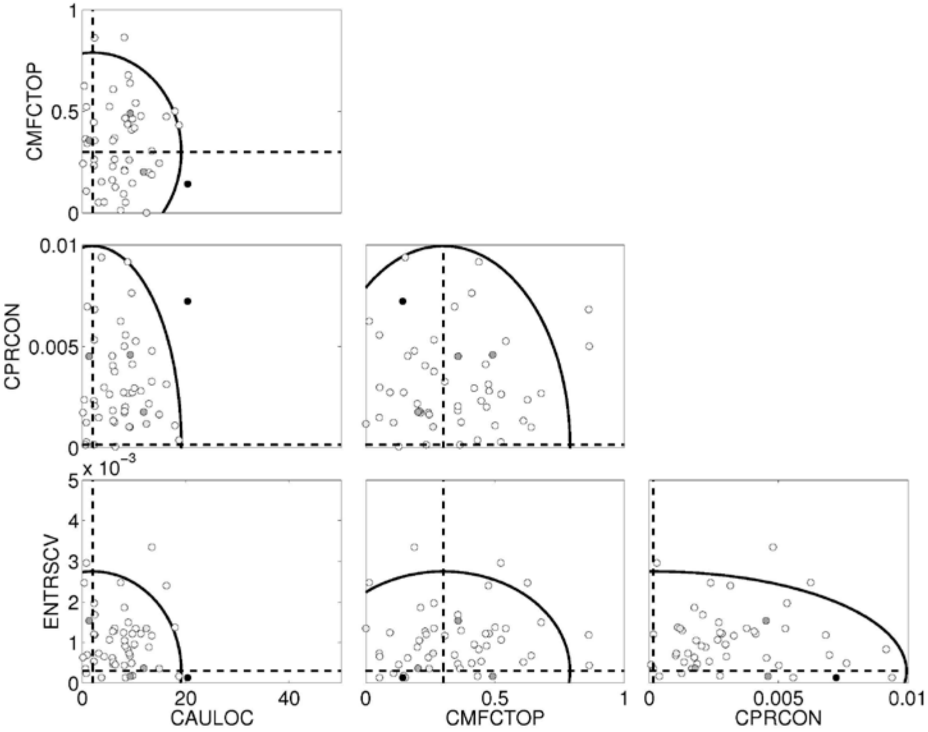
$$J(\theta) = \frac{5}{2}\sum_{A}\left(z_f^{72}(\theta) - z_a\right)^2 dA + \sum_{A}\left(z_f^{240}(\theta) - z_a\right)^2 dA \, ,$$

4-parameter evolution in 180 consecutive ensembles

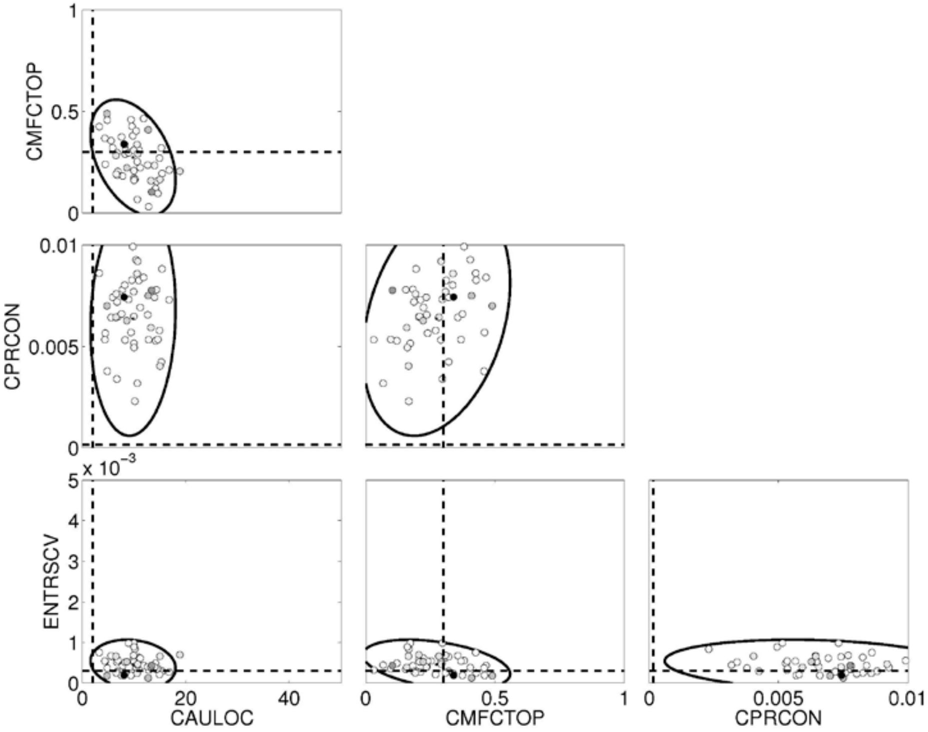


Pair-wise parameter uncertainties $\theta \sim N(\mu, \Sigma)$

As specified intially



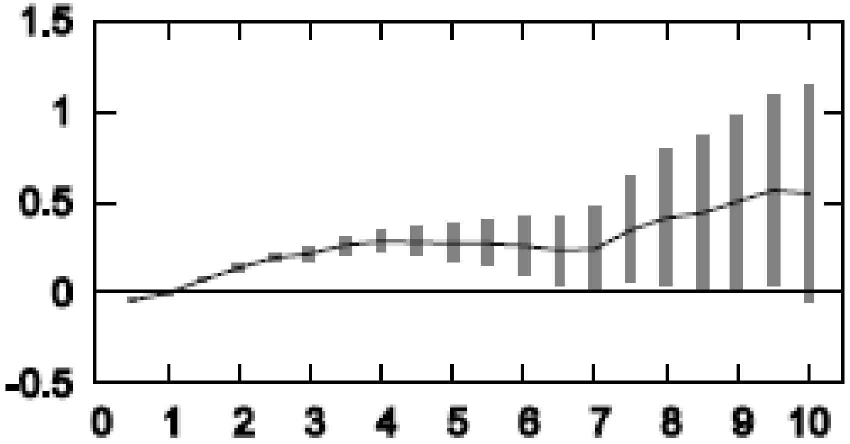
As estimated (180 steps)



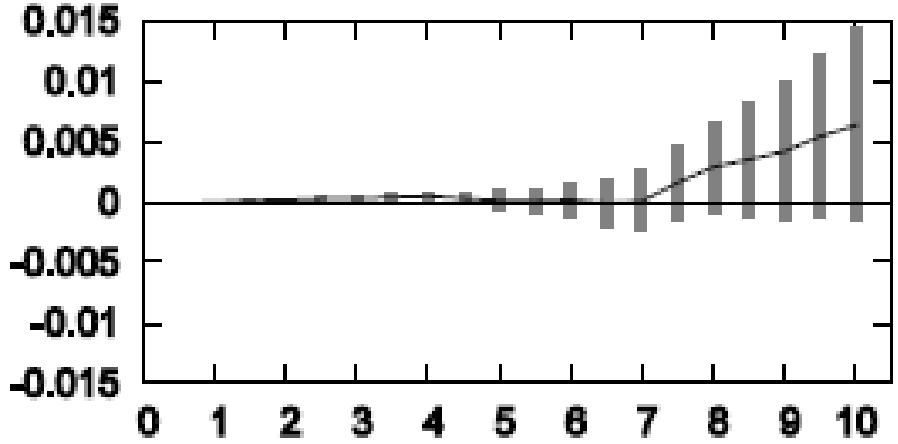
Validation of the 500 hPa height forecast skill

(above zero, good for the optimized model)

RMS ERROR



ANOMALY CORRELATION



Dependent sample

Similar for the independent samples

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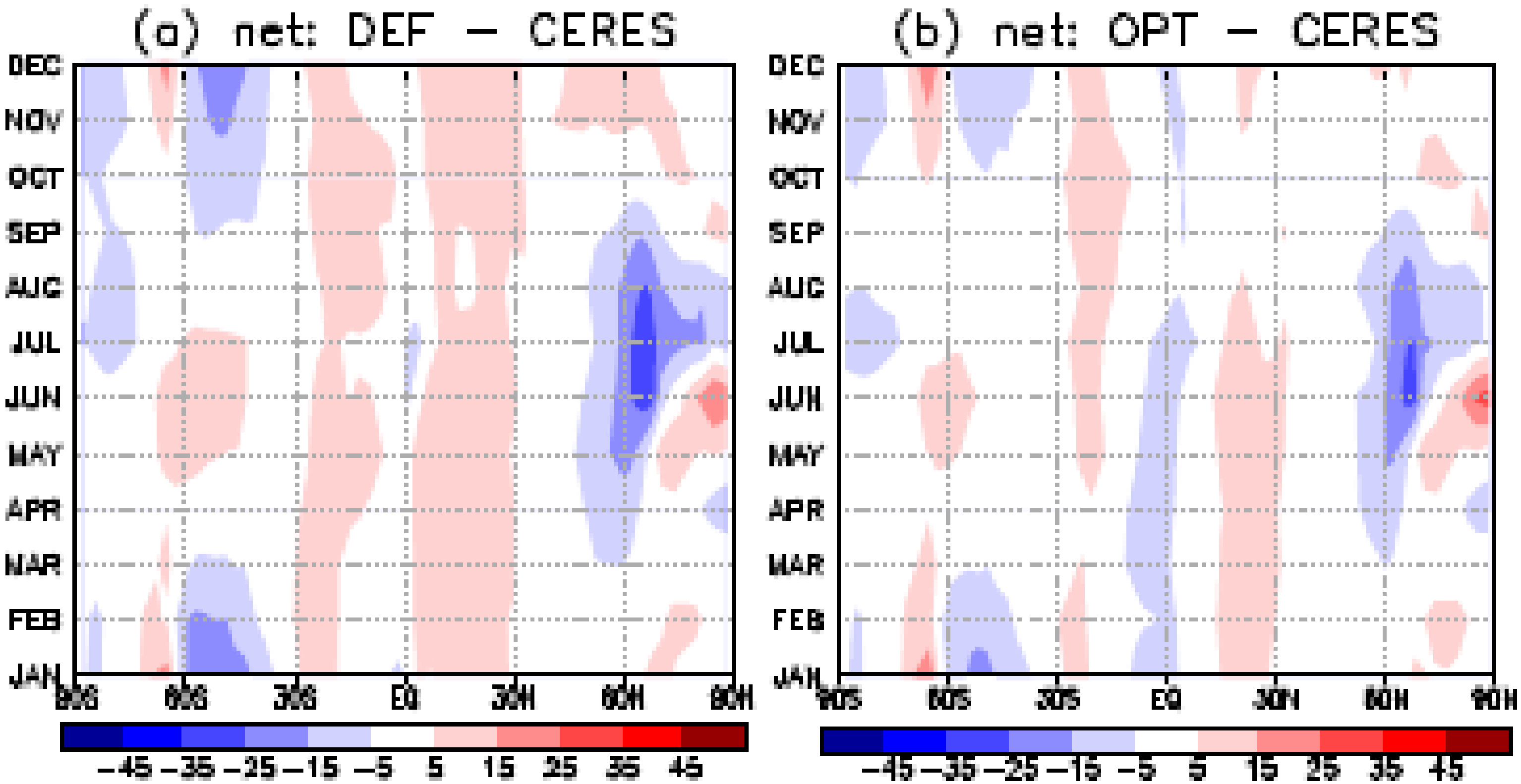
Validation of the model climate
- top-of-atmosphere net radiative flux (5-yr simulation)



Good medium-range prediction skill and good simulation of climate are not a conflicting targets

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ECMWF IFS prediction model

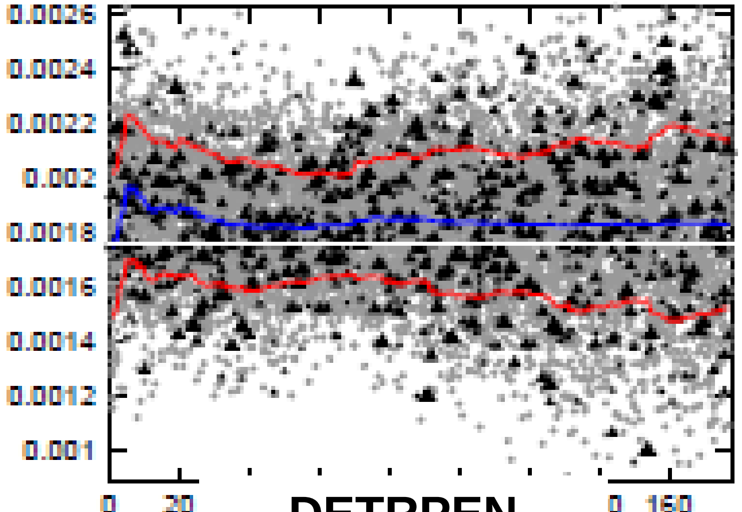
- **ECHAM5 was not tuned to medium-range forecasts**
  - Perhaps ”easy” to tune
  - Large parameter corrections were quite expected
- **IFS is very well tuned + much higher dimensionality**
  - Certaily hard to improve by further tuning
  - Expect small parameter adjustments

- **Acknowledgements: Pirkka Ollinaho was supervised by Peter Bechtold and Martin Leutbecher at ECMWF**

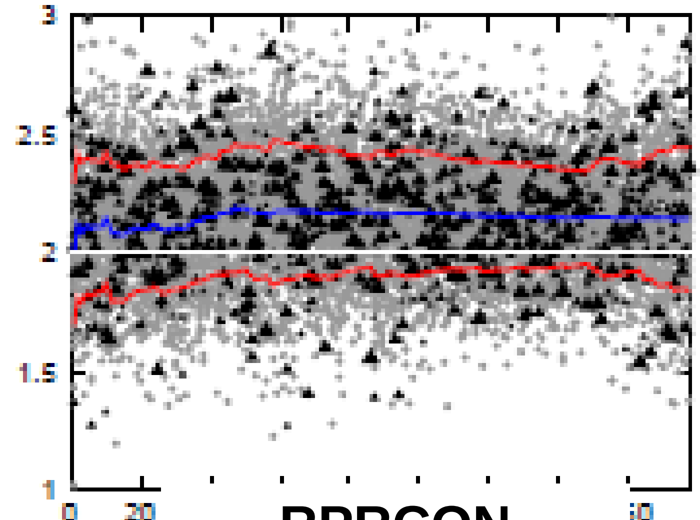
The experiments with the IFS (T159L62)

- **50+1 members, 3 months, twice daily, day 10 forecasts**
- **The parameters**
  - ENTRORG - entrainment for deep convection
  - ENTSHALP - shallow entrainment
  - DETRPEN - detrainment for deep convection
  - RPRCON - conversion from cloud water to rain
- **Cost function as in the ECHAM5 case**
- **Initial state perturbations switched ”ON”**
- **Stochastic physics tendencies switched ”ON”**

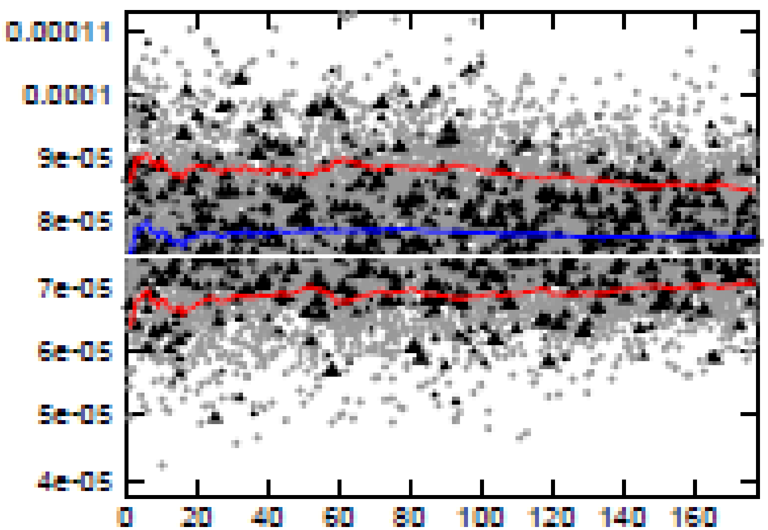
ENTRORG
(entrainment for deep convection)



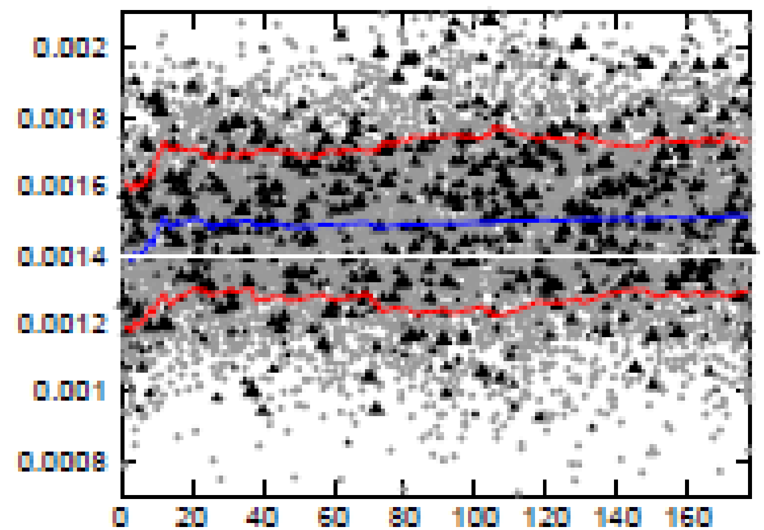
ENTSHALP
(shallow entrainment)



DETRPEN
(detrainment for deep convection)



RPRCON
(conversion from cloud water to rain)



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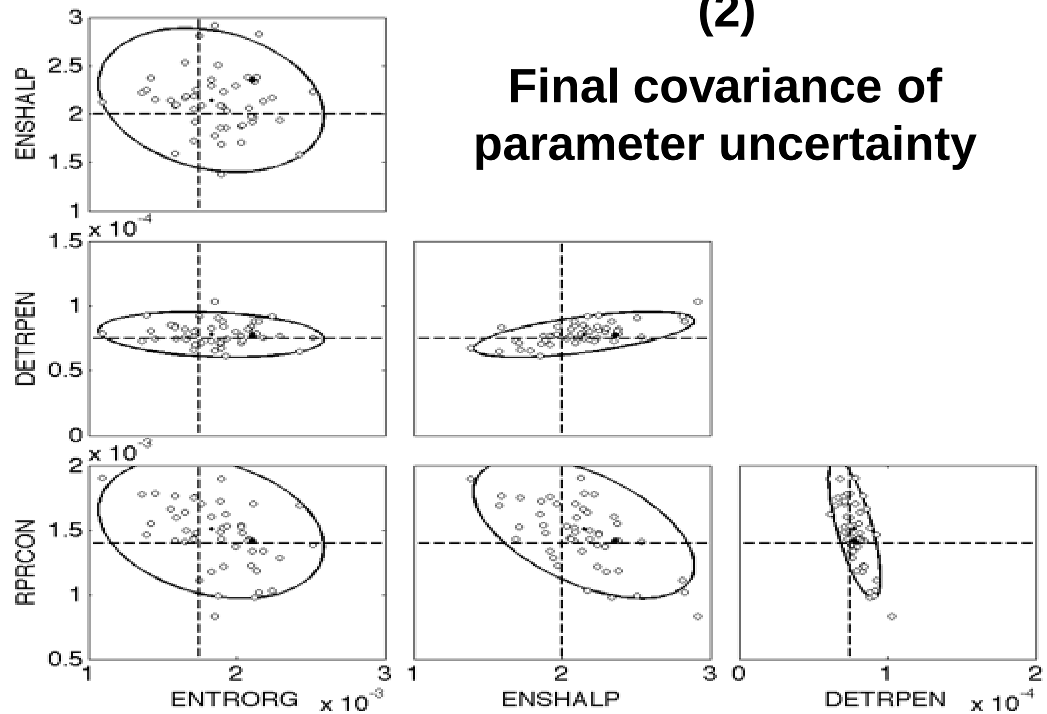
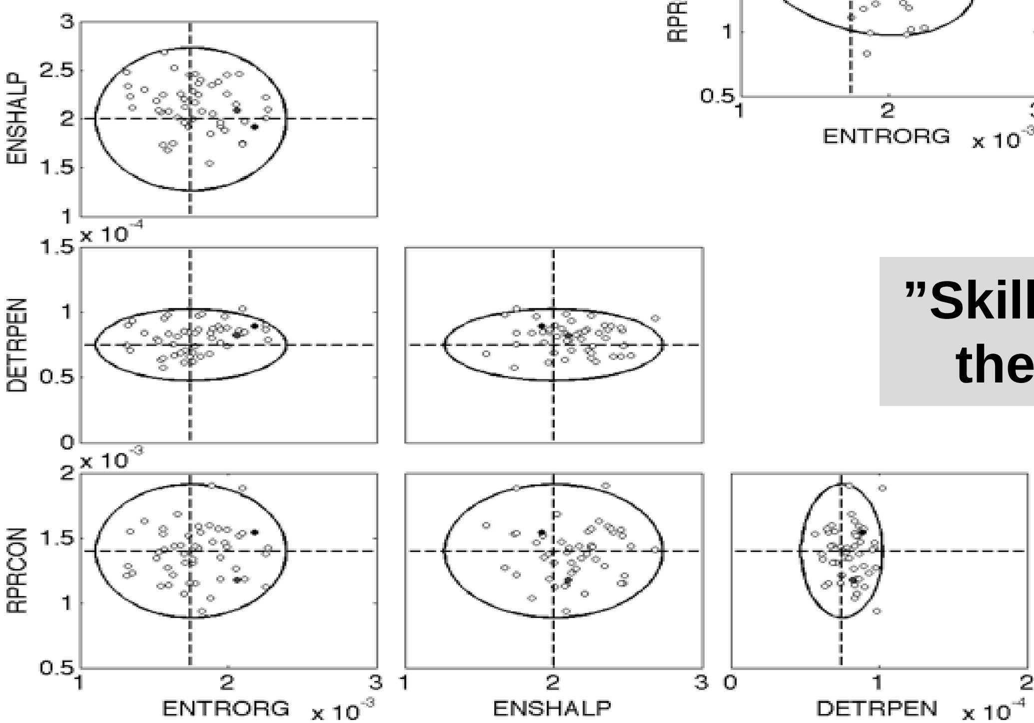
(2)

Final covariance of parameter uncertainty



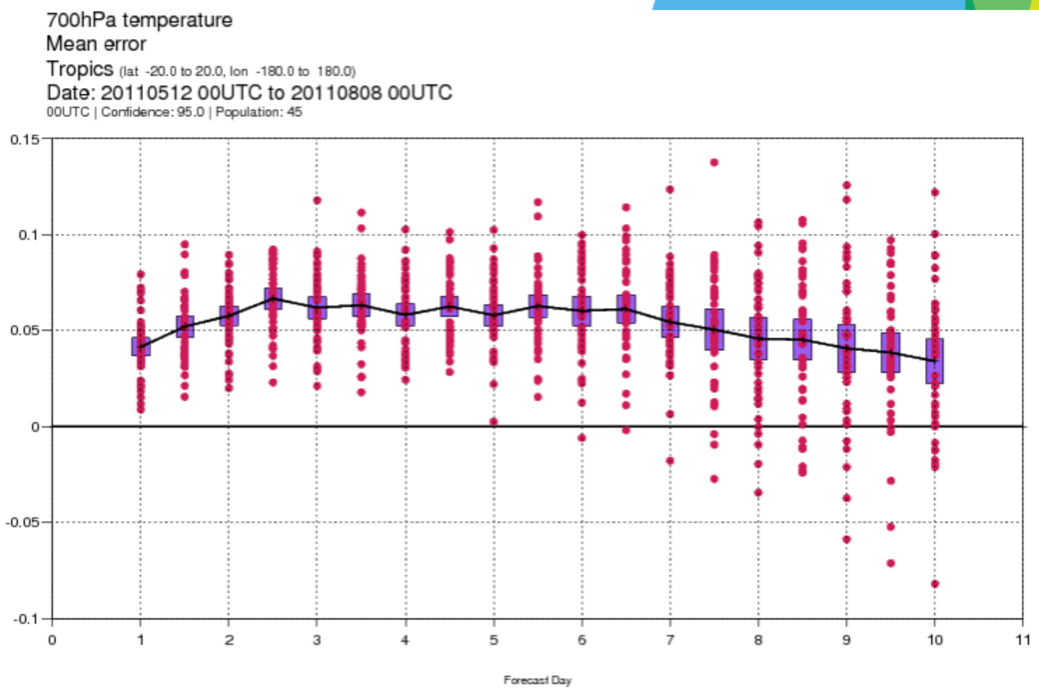
(1)

Initial covariance of parameter uncertainty (expert knowledge)

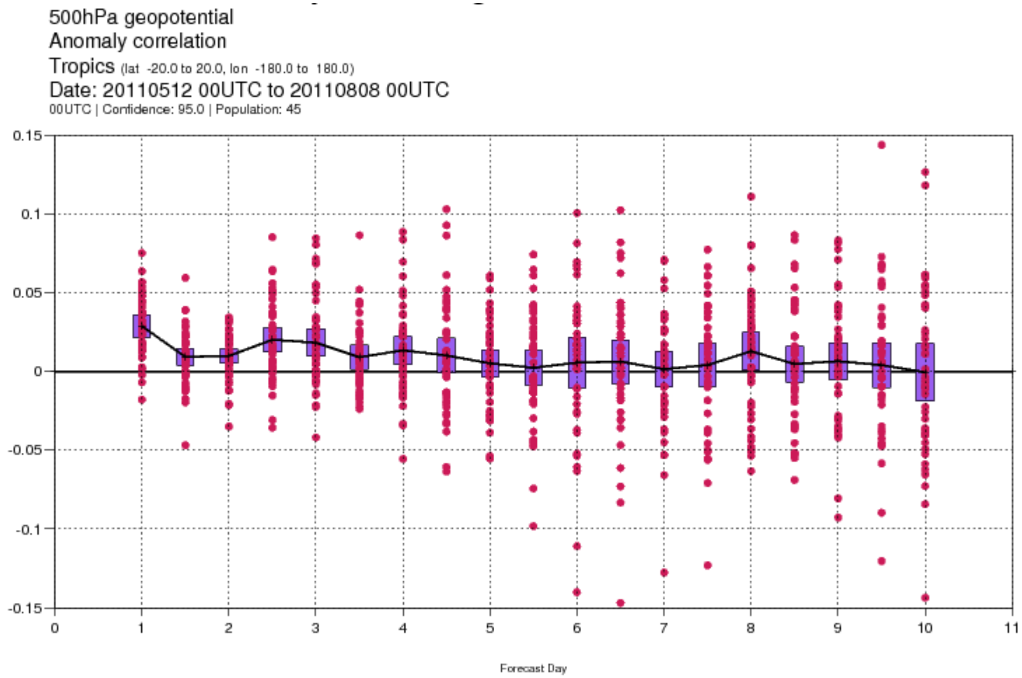


(3)

”Skillful” models are within these final covariances



700 hPa temperature
Mean error
Tropical belt
45 cases



500 hPa geopotential height
Anomaly correlation

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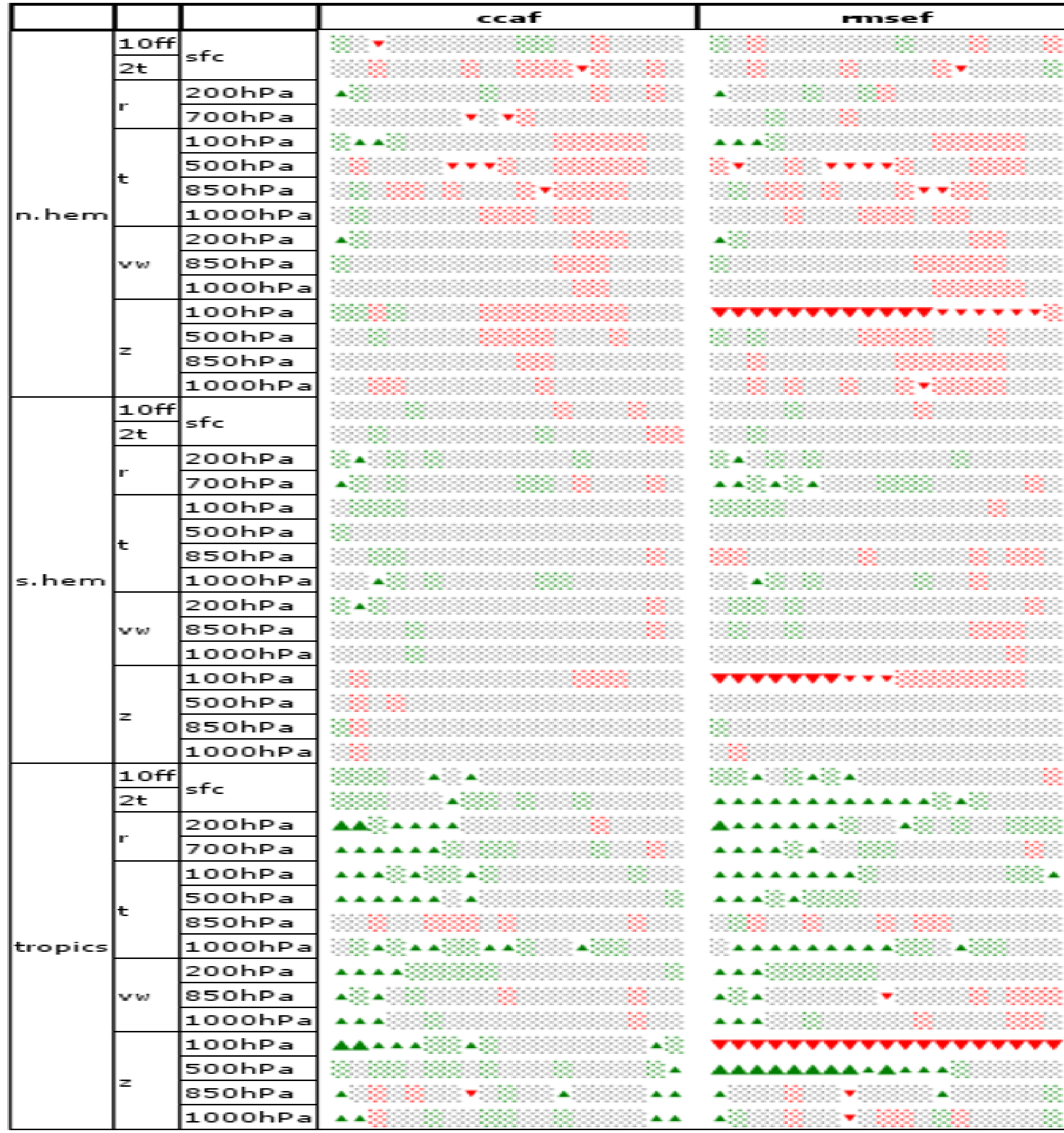
ECMWF ”scorecard”



Symbol legend: for a given forecast step... (d: score difference, s: confidence interval width)

▲ experiment **better** than control **statistically highly significant** (the confidence bar above zero by more than its height)(d/s>3)

▴ experiment **better** than control **statistically significant** (d/s≥1)

experiment better than control, yet not statistically significant (d/s≥0.5)

not really any difference between control and experiment

experiment worse than control, yet not statistically significant (d/s≤-0.5)

▾ experiment **worse** than control **statistically significant** (d/s≤-1)

▼ experiment **worse** than control **statistically highly significant** (the confidence bar below zero by more than its height) (d/s<-3)

Impact on the EPS performance

- **The ECMWF EPS is under-dispersive**
- **Parameter variations increased the spread little**
- **Skill as above**

Conclusion :: An adaptive prediction system

- **Operational EPS added with the parameter estimation functionality**
- **Model parameters / covariances are tuned <u>online</u>**
- **Virtually zero additional cost**
- **”Safety limits” to avoid unrealistic parameter values**

- **EPPES web page:: helios.fmi.fi/~lainema/eppes**

Many thanks

Järvinen, H, Laine, M, Solonen, A and H Haario, 2012: Ensemble prediction and parameter estimation system: the concept. *Q. J. R. Meteorol. Soc.*, 138, 281-288. doi:10.1002/qj.923.

Laine, M, Solonen, A, Haario, H and H Järvinen, 2012: Ensemble prediction and parameter estimation system: the method. *Q. J. R. Meteorol. Soc.*, 138, 289-297. doi:10.1002/qj.922.

Solonen, A, Ollinaho, P, Laine, M, Haario, H, Tamminen, J and H Järvinen, 2012: Efficient MCMC for climate model parameter estimation: parallel adaptive chains and early rejection. *Bayesian analysis*, 7, 715 - 736. DOI:10.1214/12-BA724.

Hakkarainen, J, Ilin, A, Solonen, A, Laine, M, Haario, H, Tamminen, J, Oja, E and H Järvinen, 2012: On closure parameter estimation in chaotic systems. *Nonlin. Processes Geophys.*, 19, 127-143. doi:10.5194/npg-19-127-2012.

Ollinaho, P, Järvinen, H, Laine, M, Solonen, A and H Haario, 2012: NWP model forecast skill optimization via closure parameter variations. *Q. J. R. Meteorol. Soc.* (accepted).