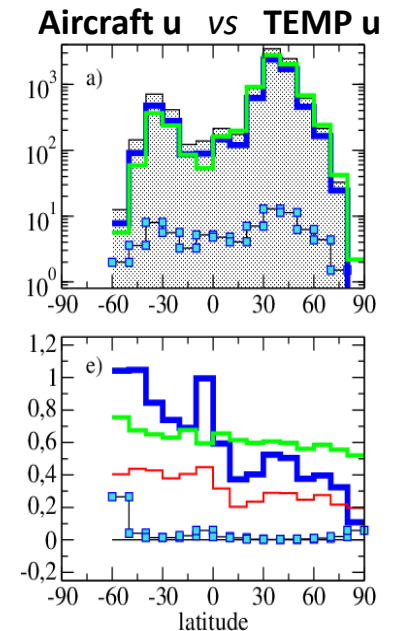


Cross-validating the impact of stochastic physics on ensemble covariances directly with observations

Olaf Stiller and Christoph Schraff

Deutscher Wetterdienst

Using a new diagnostic tool:



Ensembles $\sim\sim$ forecast uncertainty
comprises uncertainty from

- initial conditions
- forecast model

Applications:

- a) Probabilistic forecasting
 - **ensemble variance** (spread) $\sim\sim$ forecast uncertainty
- b) Covariances for data assimilation
 - **ensemble covariance** $\sim\sim$ background error covariance (short term forecast)

Parameter perturbations (e.g. physics parameters):

- improve ensemble spread
- improve ensemble covariances

Background-Error-Covariance → *distributes **obs-info** onto model space*

AIM: Compare ensemble covariances directly with observations:

Applications:

a) Probabilistic forecasting

➤ **ensemble variance** (spread) $\sim\sim$ forecast uncertainty

b) Covariances for data assimilation

➤ **ensemble covariance** $\sim\sim$ background error covariance
(short term forecast)

Parameter perturbations (e.g. physics parameters):

- improve ensemble spread
- improve ensemble covariances

Background-Error-Covariance → distributes *obs-info* onto model space

AIM: Compare ensemble covariances directly with observations:

observations: y_α^o and y_v^o

(obs – fg) : $(y_\alpha^o - y_\alpha^b)$, $(y_v^o - y_v^b)$

background error covariances in observation space:

$$\begin{aligned} P_{ens}^{b,loc}[\alpha, v] &= H_v \mathbf{B} (H_\alpha)^T \\ &= P_{ens}^b[\alpha, v] * f_{loc}[\alpha, v] \end{aligned}$$

$$P_{ens}^{b,loc}[\alpha, v] = \langle (y_{\alpha}^o - y_{\alpha}^b)(y_v^o - y_v^b) \rangle$$

$$\mathbf{H} \mathbf{B} \mathbf{H}^T + \mathbf{R} = \langle (\mathbf{y}^o - \mathbf{y}^b)(\mathbf{y}^o - \mathbf{y}^b)^T \rangle$$

AIM: Compare ensemble covariances directly with observations:

$$\text{(obs - fg)} : y_{\alpha}^o \text{ and } y_v^o$$
$$: (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b)$$

ensemble covariances in observation space:

$$P_{ens}^{b,loc}[\alpha, v] = H_v \mathbf{B} (H_{\alpha})^T$$
$$= P_{ens}^b[\alpha, v] * f_{loc}[\alpha, v]$$

$$P_{ens}^{b,loc}[\alpha, v] = \langle (y_{\alpha}^o - y_{\alpha}^b)(y_v^o - y_v^b) \rangle$$

$$(H \mathbf{B} H^T)_{v\alpha} + \cancel{P_{v\alpha}} = \left\langle (\mathbf{y}^o - \mathbf{y}^b) (\mathbf{y}^o - \mathbf{y}^b)^T \right\rangle_{v\alpha}$$

AIM: Compare ensemble covariances directly with observations:

$$\text{(obs - fg)} : y_{\alpha}^o \text{ and } y_v^o$$
$$: (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b)$$

ensemble covariances in observation space:

$$P_{ens}^{b,loc}[\alpha, v] = H_v \mathbf{B} (H_{\alpha})^T$$
$$= P_{ens}^b[\alpha, v] * f_{loc}[\alpha, v]$$

$$P_{ens}^{b,loc}[\alpha, v] = \langle (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b) \rangle$$

from ensemble

from observations

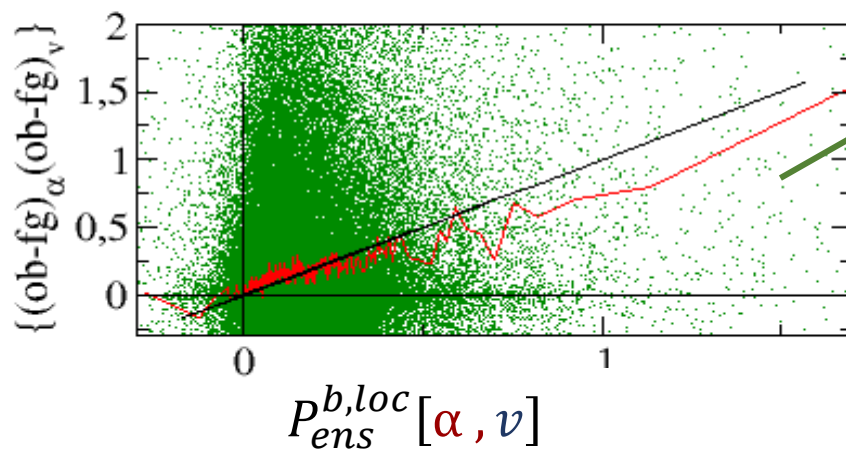
background error covariance

Straight forward test

$$P_{ens}^{b,loc}[\alpha, v] = \langle (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b) \rangle$$

y_{α}^o : aircraft temperature

y_v^o : radiosonde temperature



$$(y_{\alpha}^o - y_{\alpha}^b)(y_v^o - y_v^b)$$

Averaging (data per bin):

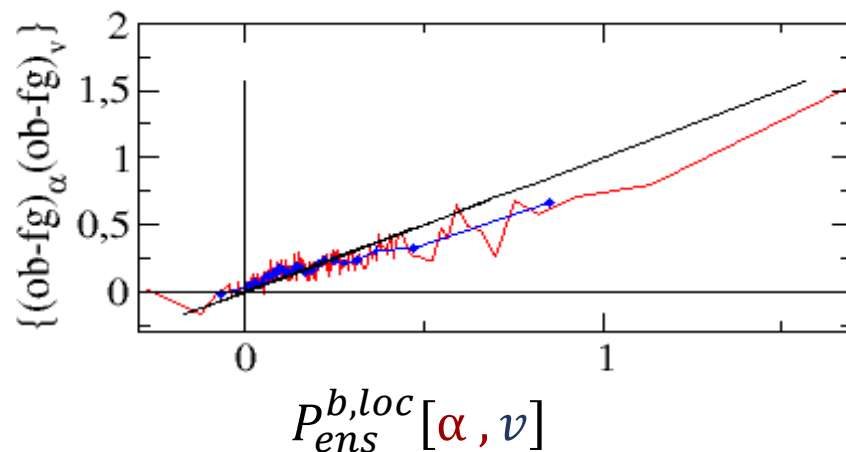
$$N_{bin} = 500$$

Straight forward test

$$P_{ens}^{b,loc}[\alpha, v] = \langle (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b) \rangle$$

y_{α}^o : aircraft temperature

y_v^o : radiosonde temperature



$$(y_{\alpha}^o - y_{\alpha}^b)(y_v^o - y_v^b)$$

Averaging (data per bin):

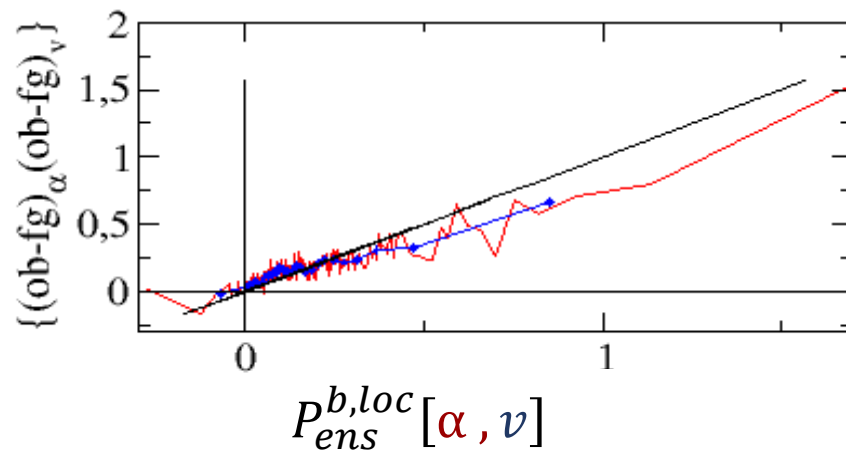
$$N_{bin} = 500$$

$$N_{bin} = 5000$$

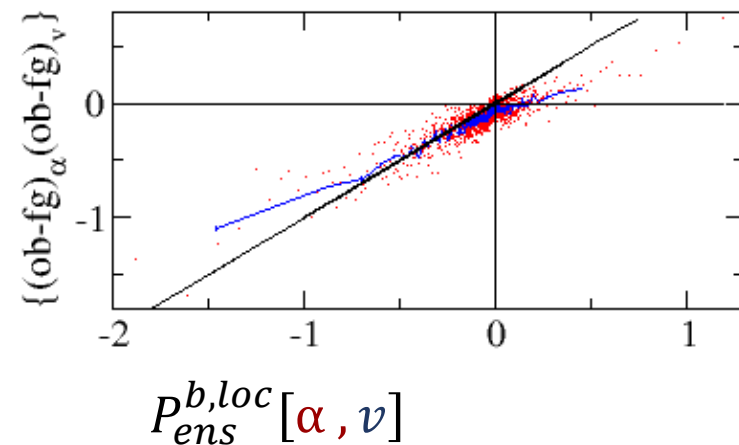
Straight forward test

$$P_{ens}^{b,loc}[\alpha, v] = \langle (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b) \rangle$$

aircraft T vs TEMP T



aircraft T vs TEMP RH



The cross-validation Diagnostic “ J_α^b ”:

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



$$P_{ens}^{b,loc}[\alpha, v] = \langle (y_\alpha^o - y_\alpha^b) (y_v^o - y_v^b) \rangle$$

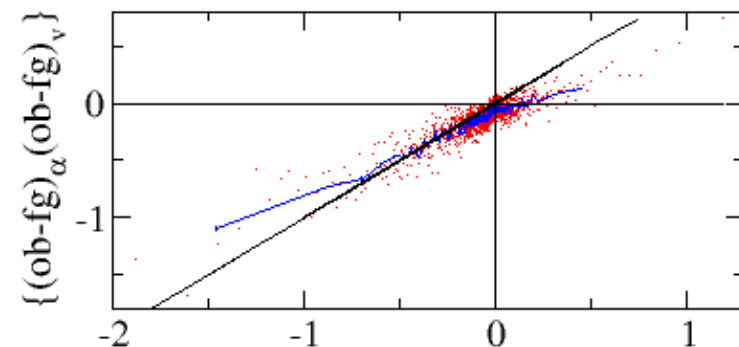
Skill of ensemble “looks good”

But what does that mean for DA?

The new C-V diagnostics “ J_α^b ” is:

- related to impact measure
 - (E)FSOI-type impact function
- more flexible
 - collect data in different kinds of bins

aircraft T vs TEMP RH



$$P_{ens}^{b,loc}[\alpha, v]$$



The cross-validation Diagnostic “ J_{α}^b ”:

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



(obs-fg) assimilation data α :

$$(y_{\alpha}^o - y_{\alpha}^b)$$

good ↓

bad agreement ↘

Verification data v : y_v^o

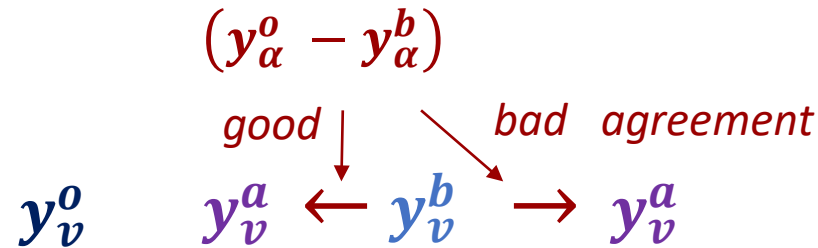
$$y_v^a \leftarrow y_v^b \rightarrow y_v^a$$

(in this talk
observations)

: Model equivalent
based on *background*
(in observations space)



The cross-validation Diagnostic “ $\mathcal{J}_\alpha^b$ ”:

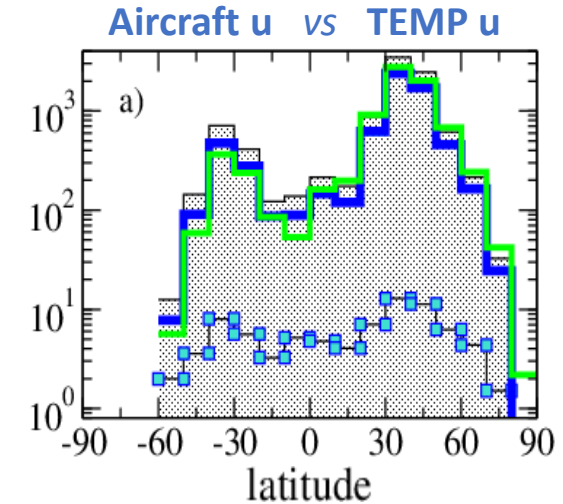
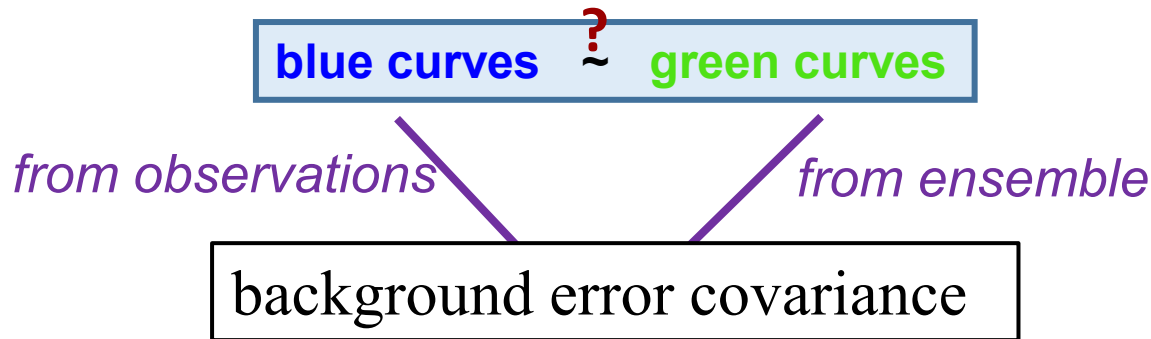


Does the assimilation of $(y_\alpha^o - y_\alpha^b)$

- improve the fit to the verification data y_v^o ? FSOI
- pull the model in the direction of the y_v^o ? Cross-validation

$$\mathcal{J}_\alpha^b = \sum_{\alpha, v} s^{-1} P_{ens}^{a, loc}[\alpha, v] (y_\alpha^o - y_\alpha^b)(y_v^o - y_v^b) > 0$$

The cross-validation Tool



Consistency relation for model covariance:

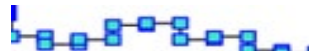
$$P_{ens}^{b,loc}[\alpha, v] \stackrel{!}{=} \langle (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b) \rangle$$

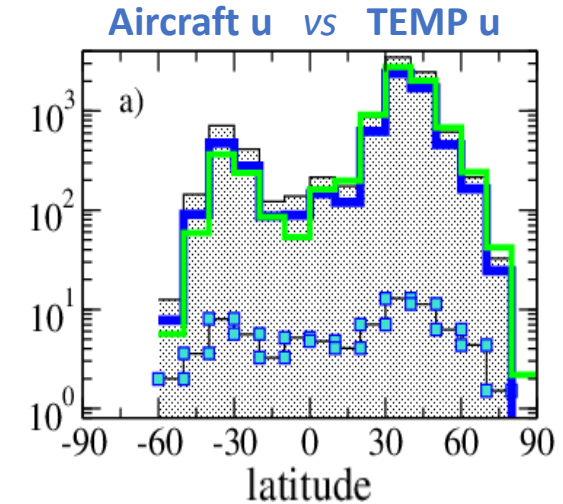
$$\mathcal{J}_{\alpha}^b = \sum_{\alpha, v} s^{-1} P_{ens}^{a,loc}[\alpha, v] (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b) \stackrel{?}{>} 0$$

$$\langle \mathcal{J}_{\alpha}^b \rangle_{est} = \sum_{\alpha, v} s^{-1} P_{ens}^{a,loc}[\alpha, v] P_{ens}^{b,loc}[\alpha, v]$$

The cross-validation Tool

blue curves ? green curves

 : **Noise indicator** for blue curves
(Here: noise estimate for a sum $\sum_j A_j$ is $\sqrt{\sum_j A_j^2}$)



Consistency relation for model covariance:

$$P_{ens}^{b,loc}[\alpha, v] \stackrel{!}{=} \langle (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b) \rangle$$

$$\mathcal{J}_{\alpha}^b = \sum_{\alpha, v} s^{-1} P_{ens}^{a,loc}[\alpha, v] (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b) \stackrel{?}{>} 0$$

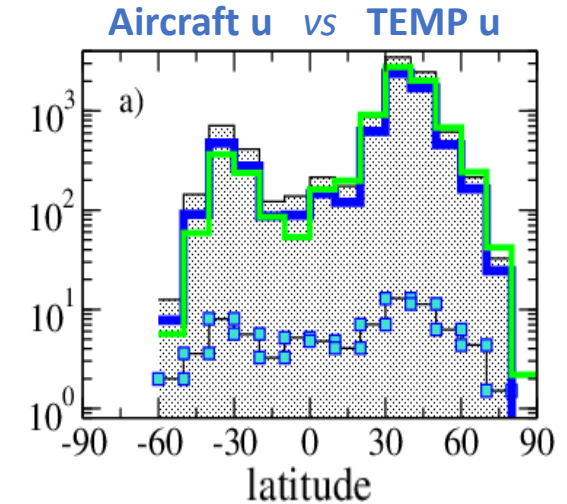
$$\langle \mathcal{J}_{\alpha}^b \rangle_{est} = \sum_{\alpha, v} s^{-1} P_{ens}^{a,loc}[\alpha, v] P_{ens}^{b,loc}[\alpha, v]$$

The cross-validation Tool

Single observation Experiments:

If only y_{α}^o is assimilated

$$P_{ens}^{a,loc}[\alpha, v] = P_{ens}^{b,loc}[\alpha, v] \frac{R'_{\alpha\alpha}}{P_{\alpha\alpha}^b + R'_{\alpha\alpha}}$$



$$\mathcal{J}_{\alpha}^b = \sum_{\alpha, v} s^{-1} P_{ens}^{a,loc}[\alpha, v] (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b)$$

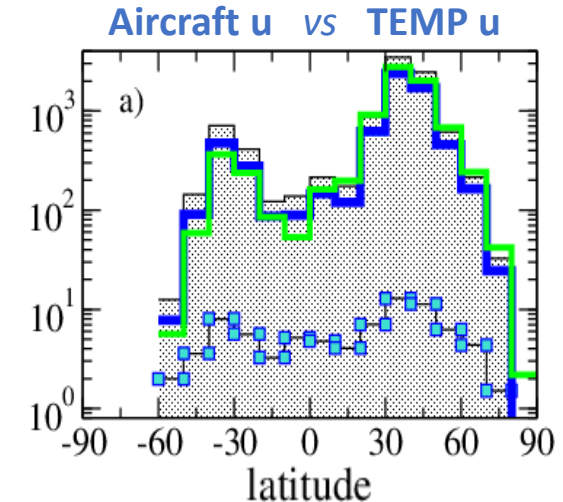
$$\langle \mathcal{J}_{\alpha}^b \rangle_{est} = \sum_{\alpha, v} s^{-1} P_{ens}^{a,loc}[\alpha, v] P_{ens}^{b,loc}[\alpha, v]$$

The cross-validation Tool

Single observation Experiments:

If only y_α^o is assimilated

$$P_{ens}^{a,loc}[\alpha, v] = P_{ens}^{b,loc}[\alpha, v] \frac{R'_{\alpha\alpha}}{P_{\alpha\alpha}^b + R'_{\alpha\alpha}}$$



$$P_{ens}^{b,loc}[\alpha, v] \stackrel{!}{=} \langle (y_\alpha^o - y_\alpha^b)(y_v^o - y_v^b) \rangle$$

$$\mathcal{J}_\alpha^b = \sum_{\alpha, v} ss^{-1} P_{ens}^{b,loc}[\alpha, v] (y_\alpha^o - y_\alpha^b)(y_v^o - y_v^b)$$

$$\langle \mathcal{J}_\alpha^b \rangle_{est} = \sum_{\alpha, v} ss^{-1} P_{ens}^{b,loc}[\alpha, v] P_{ens}^{b,loc}[\alpha, v]$$

The cross-validation Tool

Scaling/Normalizing graphs:

Devide all curves by
the same (bin-dependent) function

Choice may depend on

- type of data and bins
- purpose of statistics

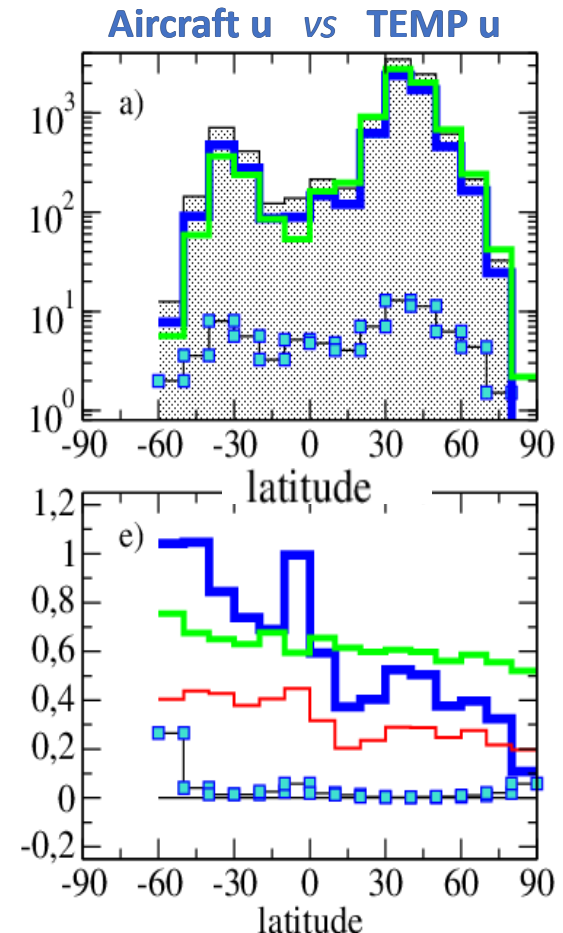
For cross-validating observations:

blue curves ~ green curves

green curves ~ [0, 1]

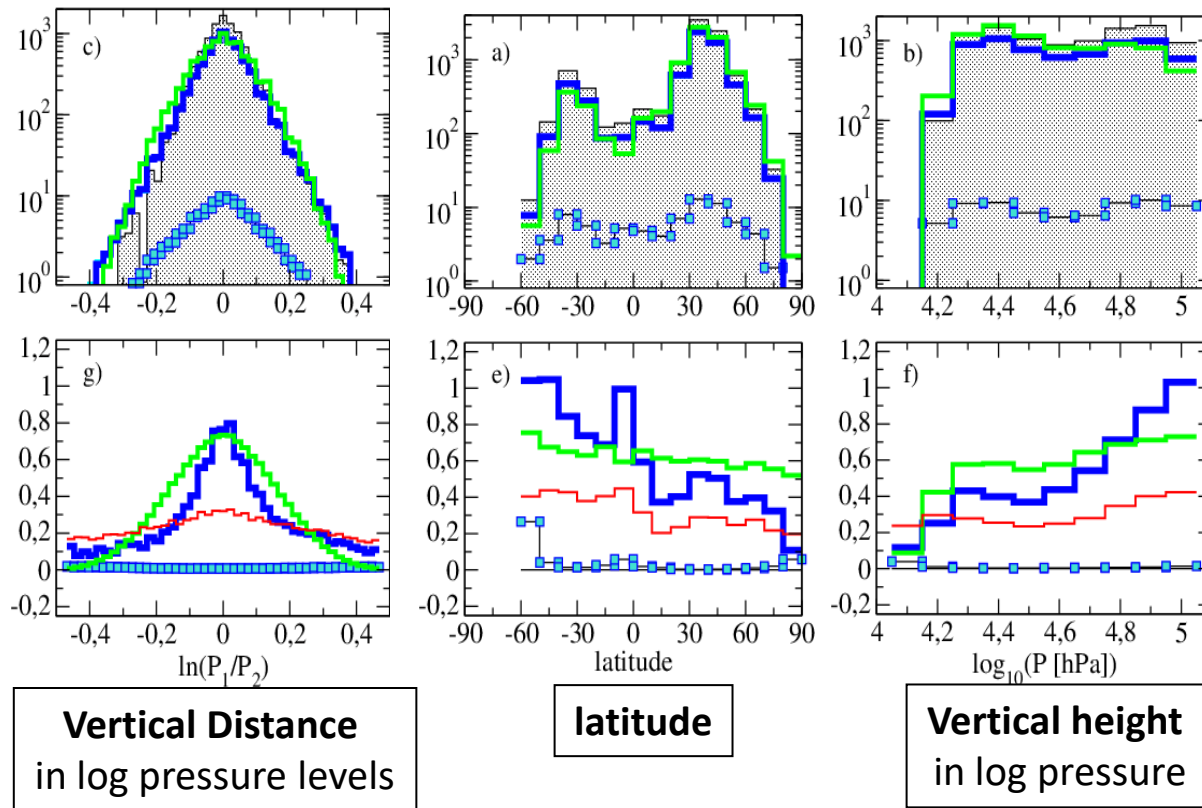
Below for cross-validating covariances

- Scaling with number of observations



The cross-validation strategy for testing observations

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



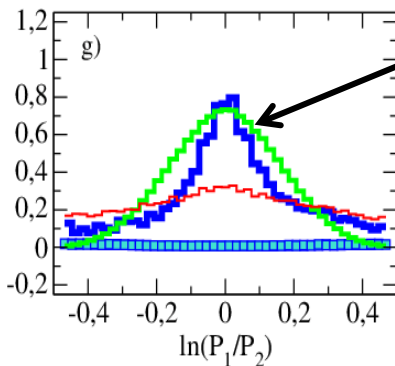
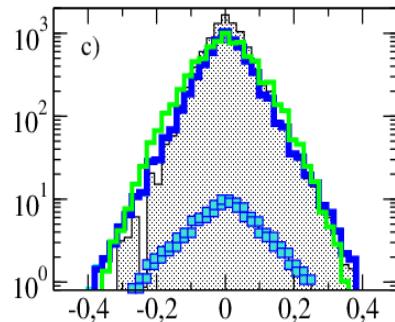
Collect statistics for many different types of bins and observations

Paper is under review
Please ask if interested!!

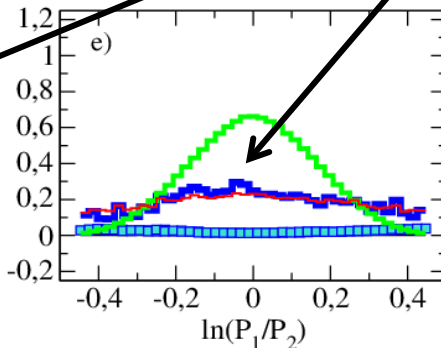
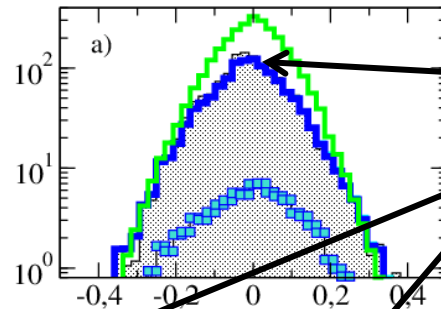


Example: Testing AMVs

Aircraft u vs TEMP u



AMV u vs TEMP u



AMVs (Atmospheric Motion Vectors)

- are clearly “beneficial” ($J_{\alpha}^b > 0$)
- but significantly less optimal than Aircraft or TEMP wind
 - Less skill at small separation distances
 - (consistent with reported “height assignment problems”)

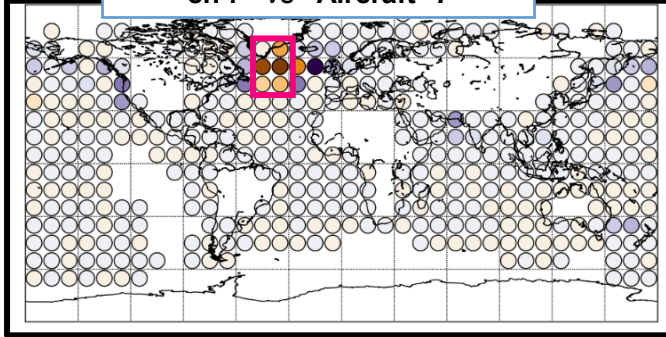
Cross-validation diagnostic useful for
testing/tuning
height assignment methods

Two well established
insitu observations

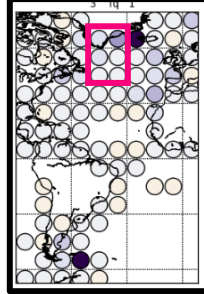
Example: AMSU A channel 7 vs aircraft and TEMP

Contributions to blue curves

June 2020
ch 7 vs Aircraft T



vs TEMP T

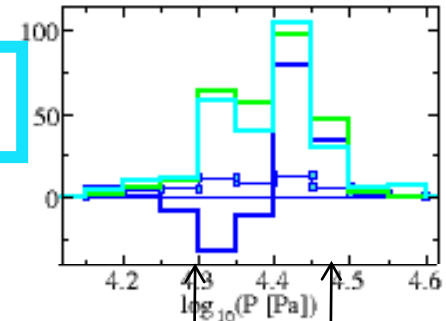


(cyan curves)

as blue - but w/o bias
(subtracted in each bin)

*It's a bias
problem!*

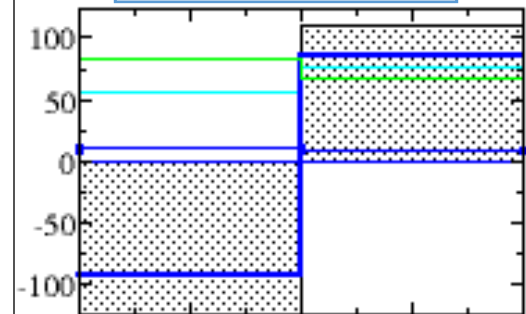
Aircraft T vs TEMP T



200 hPa

300 hPa

Aircraft T vs TEMP T



AIREP

AMDAR

Conflicting results by cross-validating AMSU A channels helped identify region over the N Atlantic where

aircraft T inconsistent with TEMP T

This could be traced back to
aircraft with codetype 141 ("AIREP data")
which had not been bias corrected at DWD

After confirmation with denial experiments

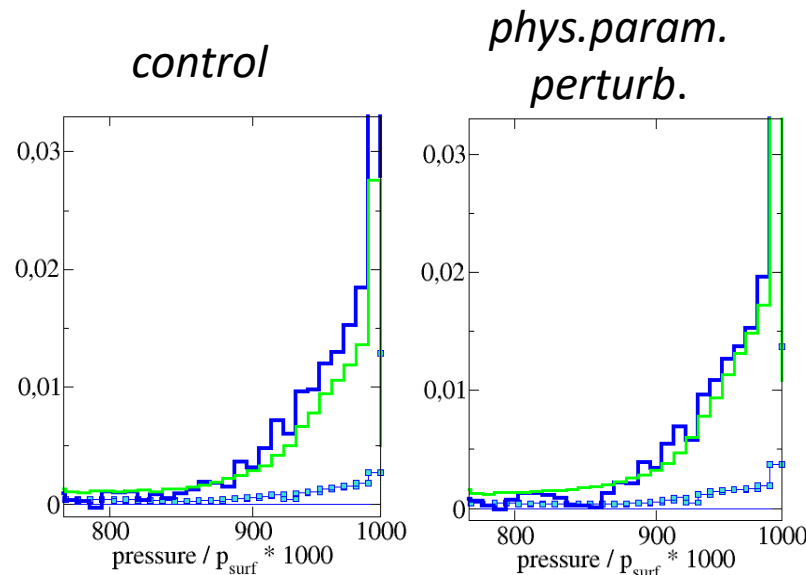
Oct 2021: assimilation of AIREP data stopped at DWD

Cross-validating impact of Param. Pert. on Covariances

$$P_{ens}^{b,loc}[\alpha, v] = \langle (y_{\alpha}^o - y_{\alpha}^b)(y_v^o - y_v^b) \rangle$$

- Use trusted observations y_{α}^o and y_v^o to test $P_{ens}^{b,loc}[\alpha, v]$
- Compare results for perturbed run with control (no perturbations)

radiosonde:
2m T
vs
upper air T



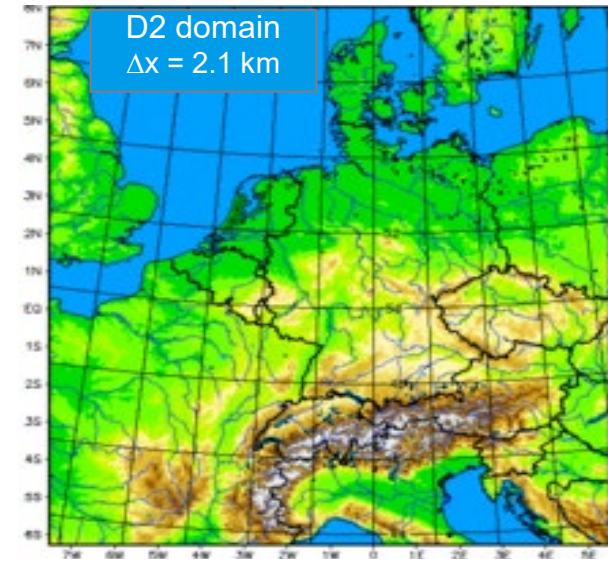
scaling: nb of obs in bin
no vertical localisation

Cross-validating impact of Param. Pert. on Covariances

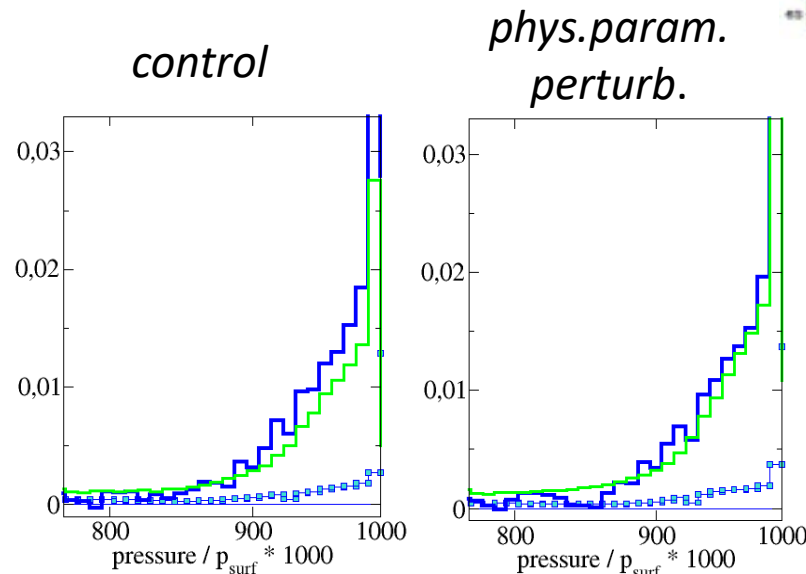
Deutscher Wetterdienst
Wetter und Klima aus einer Hand



- Model: *ICON D2*
- Data assimilation: *KENDA* 40 member ensemble
 - LETKF + latent heat nudging
- Investigating:
 - Parameter Perturbations in DA cycle



radiosonde:
2m T
vs
upper air T



scaling: nb of obs in bin
no vertical localisation

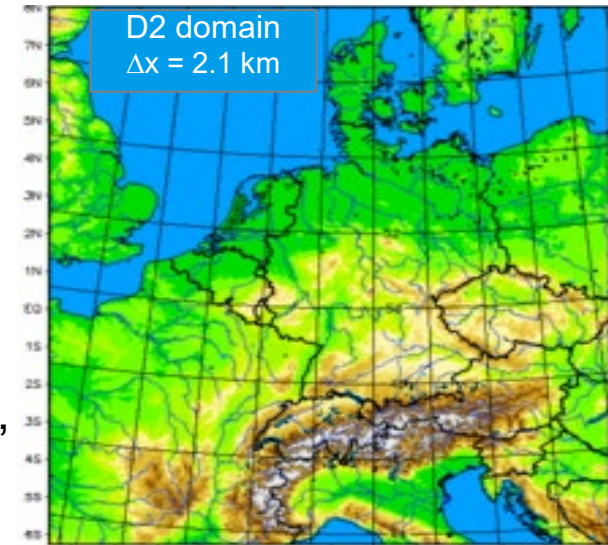


Cross-validating impact of Param. Pert. on Covariances

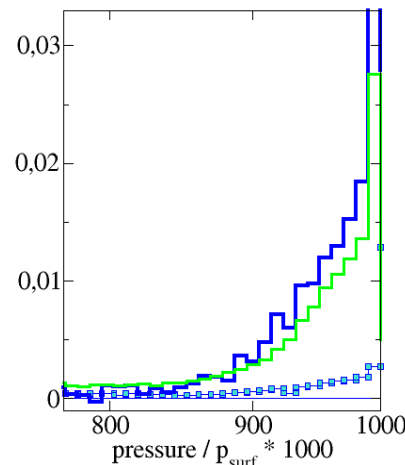
- Parameter Perturbations

- i. 17 physics parameters (as in fc ensemble)
... designed to enhance spread mostly near surface
where underdispersiveness is most severe
- ii. latent heat nudging parameters

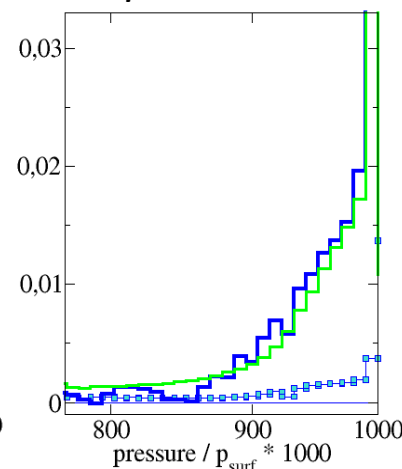
sinusoidal variation in time with period of $\sim 12 - 16$ days,
period / phase depends on member / parameter



control



*phys.param.
perturb.*



radiosonde:
2m T
vs
upper air T

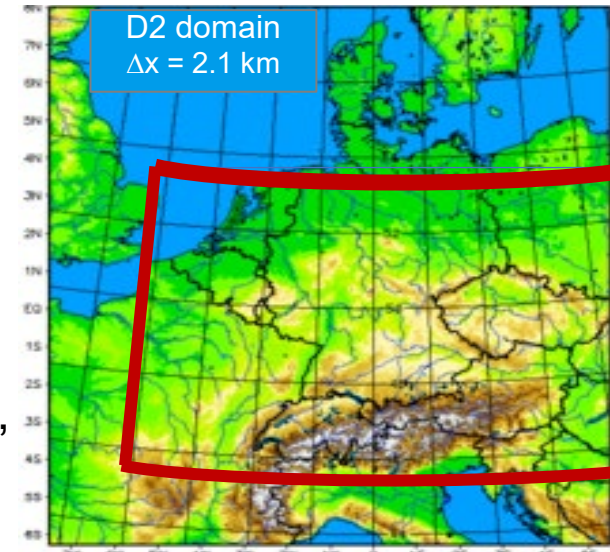
scaling: nb of obs in bin
no vertical localization

Cross-validating impact of Param. Pert. on Covariances

- Parameter Perturbations

- i. 17 physics parameters (as in fc ensemble)
... designed to enhance spread mostly near surface
where underdispersiveness is most severe
- ii. latent heat nudging parameters

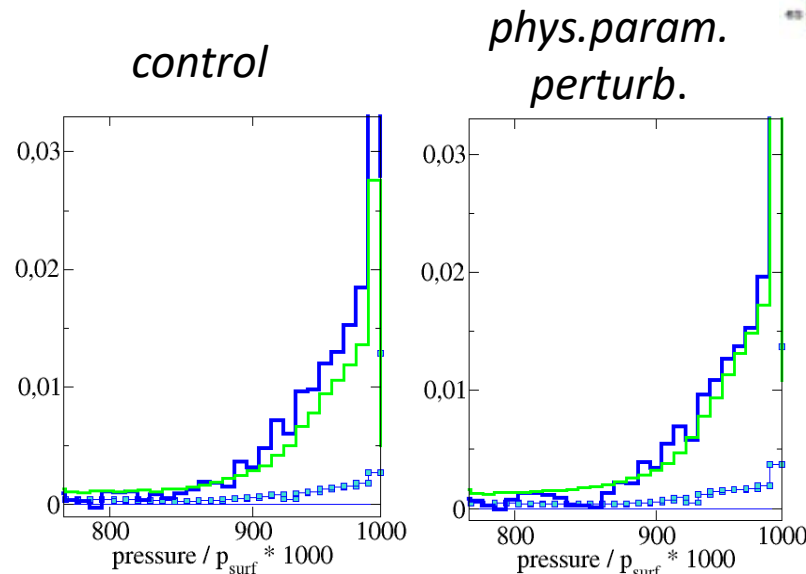
sinusoidal variation in time with period of $\sim 12 - 16$ days,
period / phase depends on member / parameter



June 2021

weeks 1+2
*weakly forced
convection*

weeks 3+4
forced convection



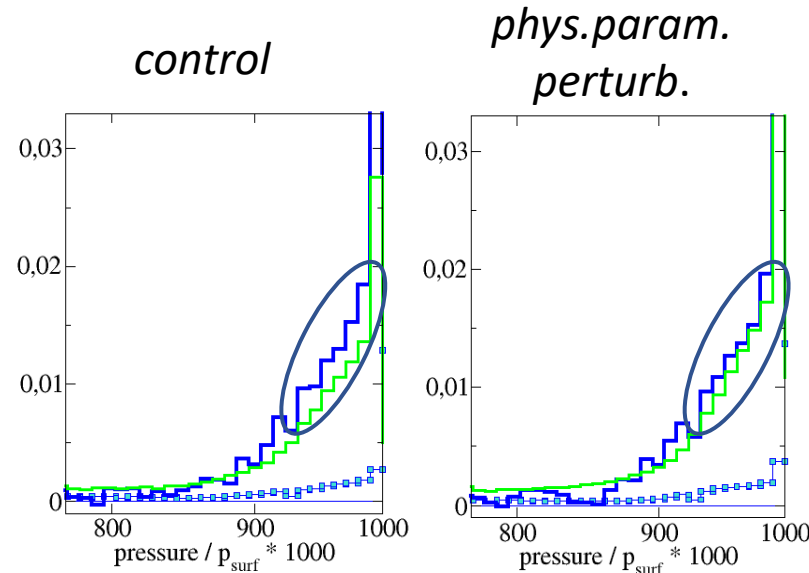
scaling: nb of obs in bin

no vertical localization

only radiosonde data
over land

radiosonde: 2m T vs upper air T

June 2021



In the perturbed run:

green curve higher

blue vs green curves
better agreement

Parameter perturbations seem to slightly improve realism of
covariance between 2m T and upper air T

green curves ~ blue curves

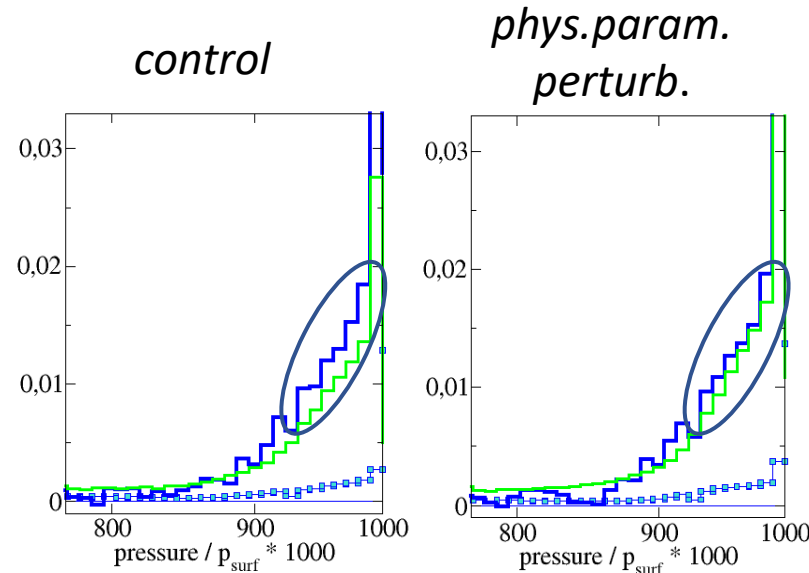
from ensemble

from observations

background error covariance

radiosonde: 2m T vs upper air T

June 2021



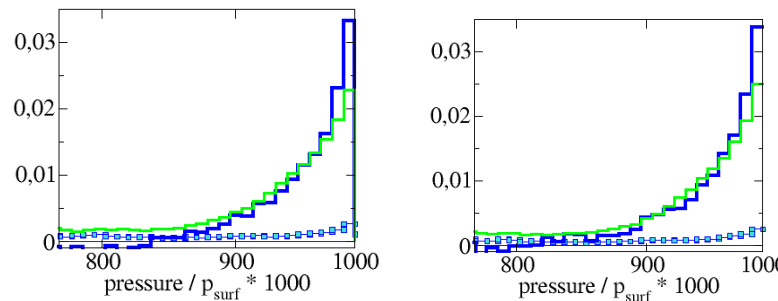
In the perturbed run:

green curve higher

blue vs green curves
better agreement

Parameter perturbations seem to slightly improve realism of
covariance between 2m T and upper air T

2m RH
vs
upper air RH



very small differences
but in the right direction

radiosonde: surface p vs upper air T

June 2021,
weeks 1+2

weakly forced convection

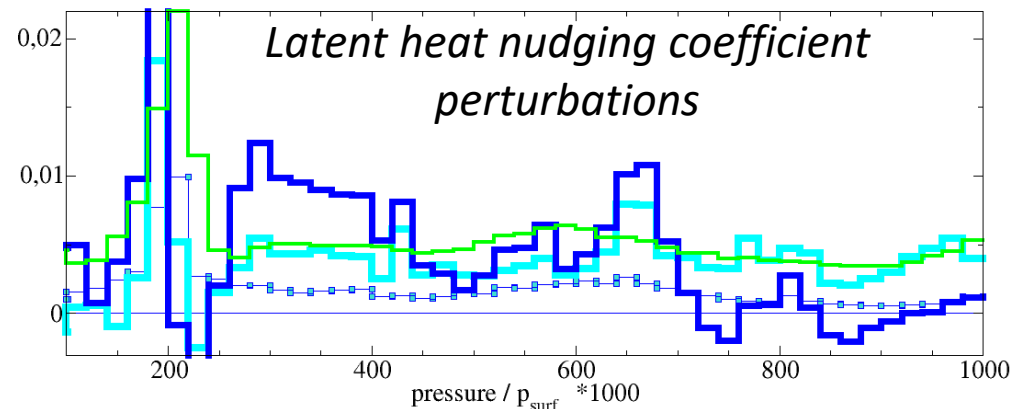
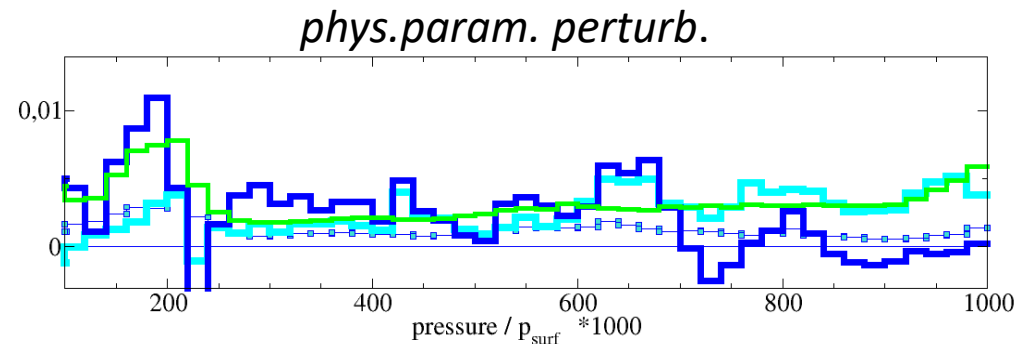
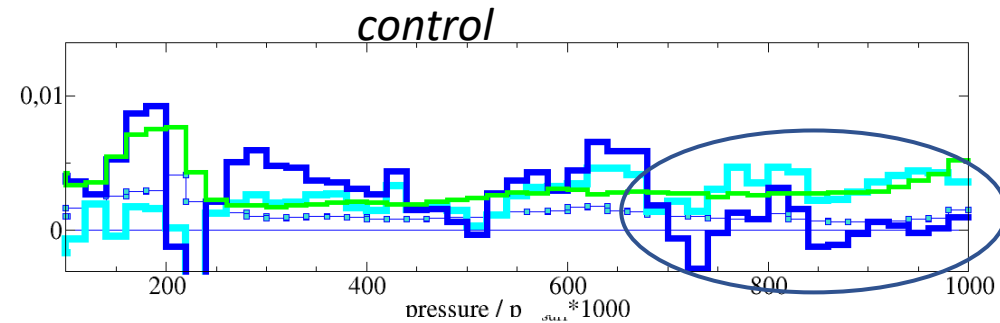
cyan curve : p_{surf} bias subtracted

for $p > 700$ h Pa :

p_{surf} & upper air T agree well
only if p_{surf} bias is subtracted

LHN perturbations

green curve:
ensemble covariances larger



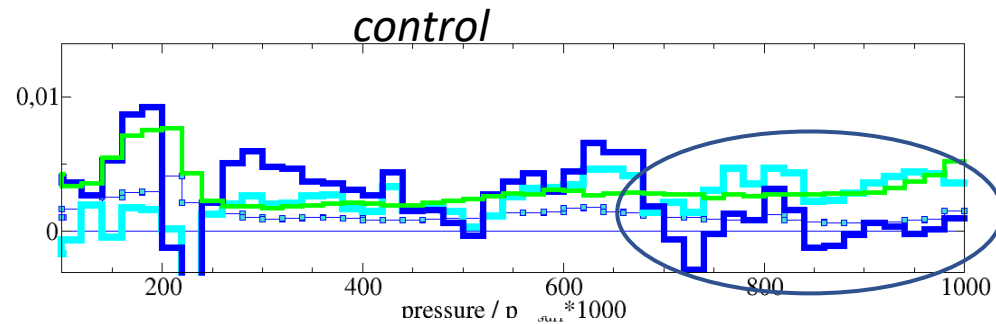
radiosonde: surface p vs upper air T

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



June 2021,
weeks 1+2

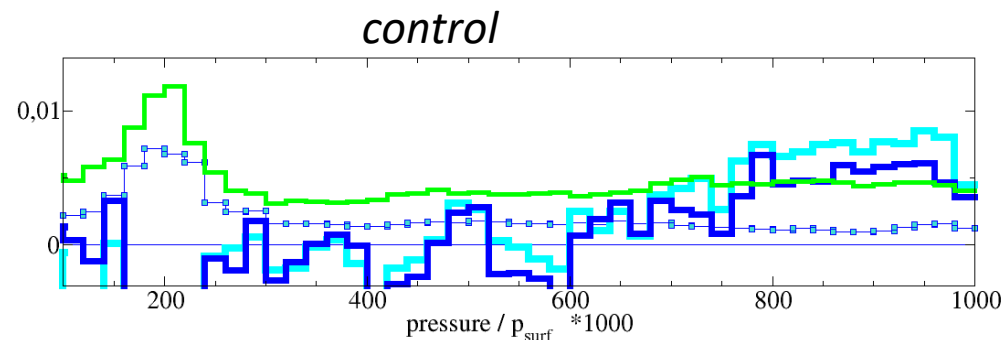
weakly forced convection



weeks 3+4

forced convection

correction of p_{surf} bias
not essential for impact



radiosonde: surface p vs upper air T

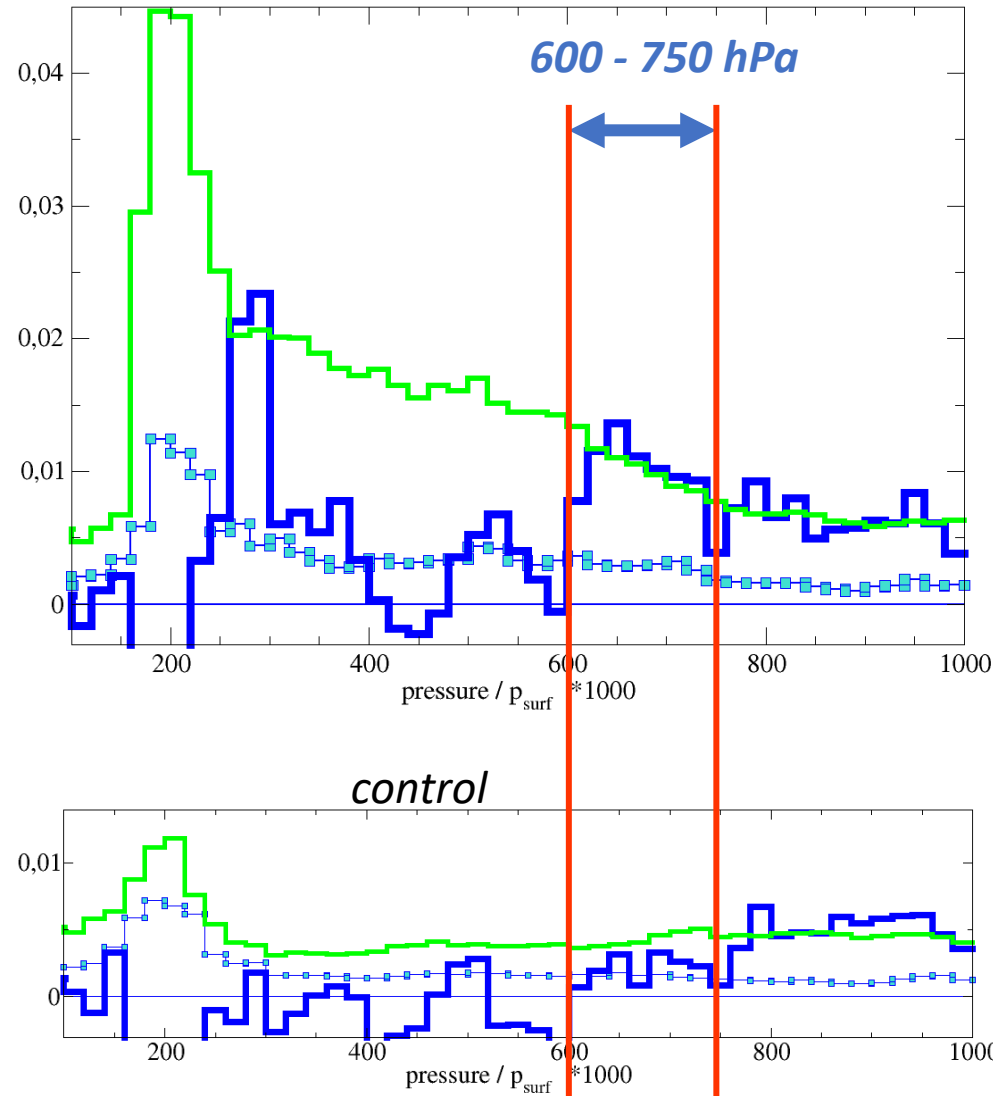
*Experiment with perturbation
of latent heat nudging coeffs*

June 2021

weeks 3+4

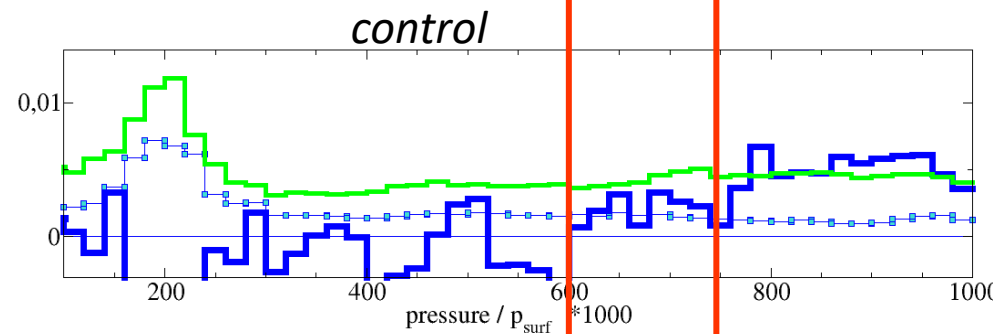
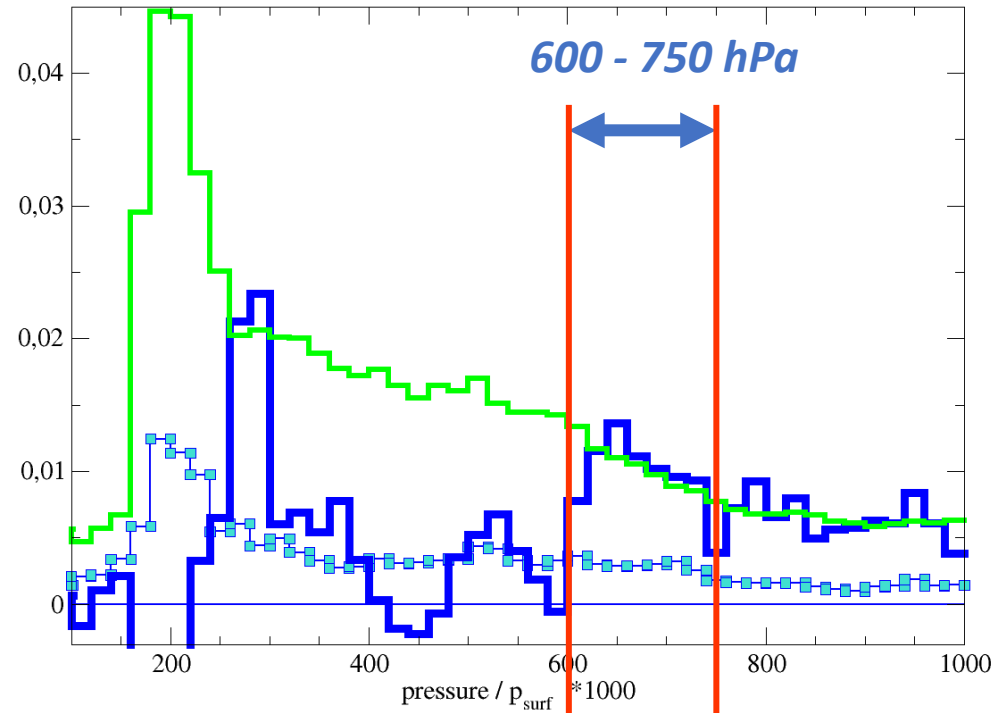
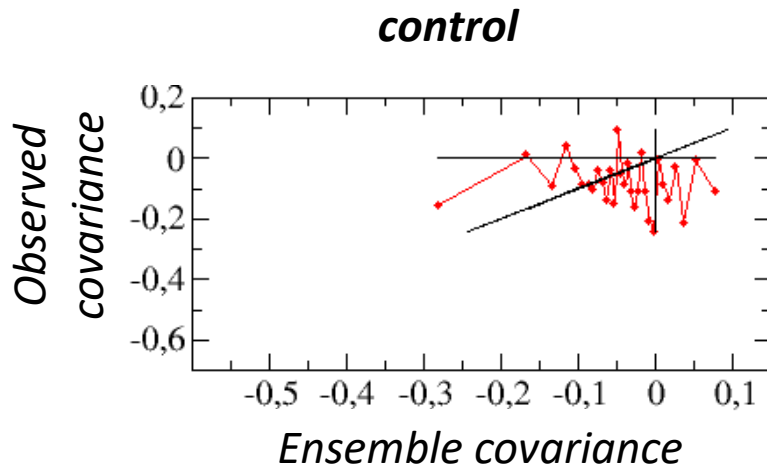
forced convection

correction of p_{surf} bias
not essential for impact



radiosonde: surface p vs upper air T

(600 - 750 hPa)



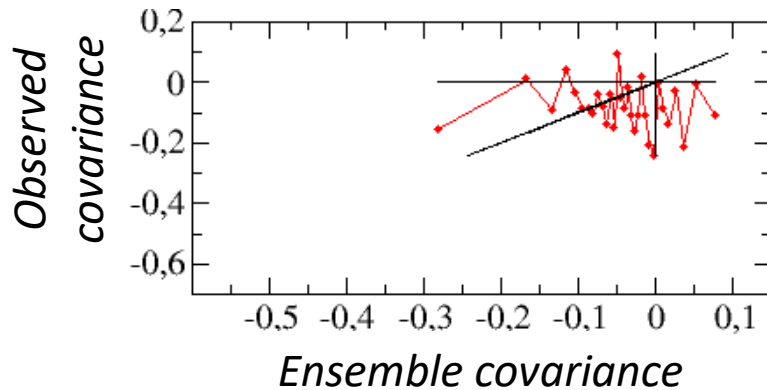
radiosonde: surface p vs upper air T

(600 - 750 hPa)

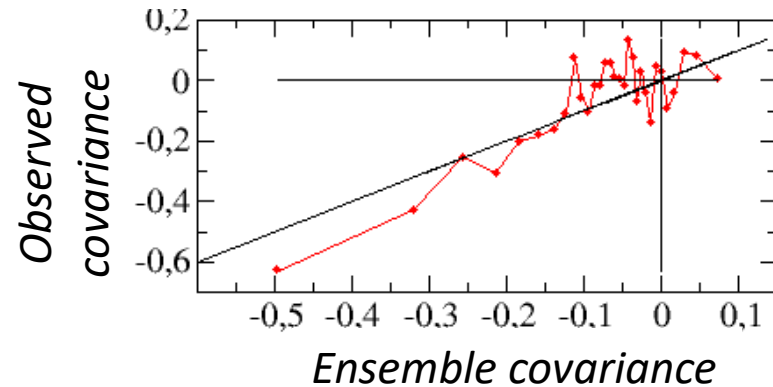
Deutscher Wetterdienst
Wetter und Klima aus einer Hand



control



perturbed



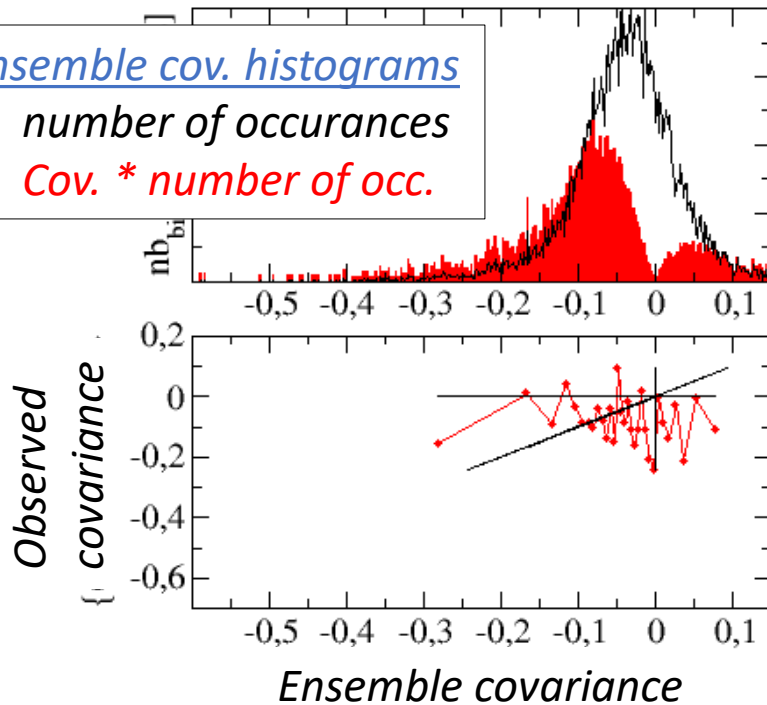
radiosonde: surface p vs upper air T

(600 - 750 hPa)

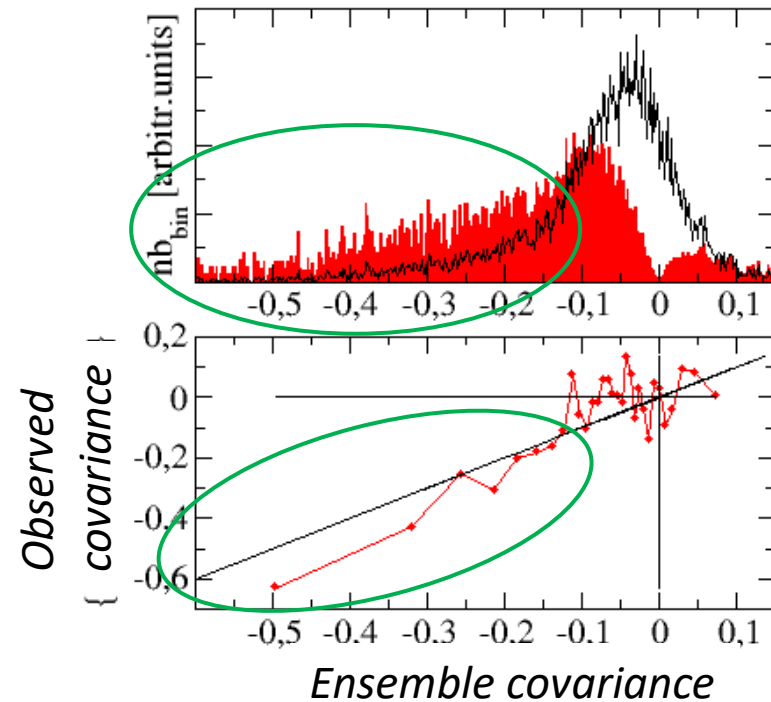
control

Ensemble cov. histograms

- number of occurrences
- Cov. * number of occ.



perturbed



Parameter perturbation induces strong & realistic covariances.

- Parameter perturbations modify ensemble (co-)variances
- Independent observations (with uncorrelated errors) allow testing
 - these covariances
 - the impact related to these covariances
- To evaluate these covariances we used
 - i. a straightforward evaluation of

$$P_{ens}^{b,loc}[\alpha, v] = \langle (y_{\alpha}^o - y_{\alpha}^b) (y_v^o - y_v^b) \rangle$$

from ensemble

from observation

background error covariance

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- ii. a new diagnostic tool with
 - diagnostics related to an impact measure (FSOI type)
 - allows search in different kinds of bins
 - indicates changes to ensemble covariance (“green curves”)
 - and whether the observations agree with this (“blue curves”)
- Examples show: Parameter perturbations can improve
different aspects of covariances and their impact



Thank you for listening

