

# Newly developed impact diagnostics for cross-validating satellite radiances with conventional observations

Deutscher Wetterdienst  
Wetter und Klima aus einer Hand



Olaf Stiller, DWD, German Meteorological Service, Data assimilation section

## 1. Introduction:

The established impact diagnostic originally introduced by Langland and Baker (2004) have been further partitioned into **two components** related to different aspects of the observations and their use in the data assimilation (DA) system. Following largely Kalnay et al (2012), these components can be computed from the *model error covariances in observation space* which we estimate using the ensemble of our LETKF. This poster focuses on the **first component** (displayed below by the blue curves) which can be regarded as a **cross-validation diagnostic**, indicating the consistency between first guess departures (o-fg) of an observation type and those of the verifying data. Here we use observations for verification and restrict to the case of forecast time  $t=0$  (impact on the analysis) which allows us to focus on issues related to the DA- rather than the forecast-system.

## 2a. Partitioning EFSOI type statistics in 2 components

- Forecast Sensitivity to Observation Impact (FSOI) diagnostics are computed from a verification function  $J$  which reflects the impact of assimilated observations  $y_{\alpha}^o$  on the fit to some verifying data  $y_v^v$ .
- For this  $J$  is written as a sum over contributions  $J_{\alpha}$  which are linked to the individual observations  $y_{\alpha}^o$ .
- In this work the terms  $J_{\alpha}$  are further partitioned into 2 components.

using obs -- not using obs

$$J = \frac{1}{2} \left( \|y^v - y^{v|a}\|_C^2 - \|y^v - y^{v|b}\|_C^2 \right)$$

$$J = - \sum_{\alpha \in \text{Obs}} J_{\alpha}$$

$$J_{\alpha} = 2 J_{\alpha}^{lb} - J_{\alpha}^{la}$$

$(y_{\alpha}^o - y_{\alpha}^b)$	(obs - fg) of analysis obs $\alpha$
$(y_v^v - y_v^{v b})$	(obs - fc(fg)) of verifying obs $v$
$(y_v^v - y_v^{v a})$	(fc(a) - fc(fg)) of verifying obs $v$
$\bar{P}_{en[v,\alpha]}^a$	analysis error covariance matrix in obs space between: analysis obs $\alpha$ & verifying obs $v$

Verifying against observations and using the diagonal R-matrix (elements:  $R_{vv}$  and  $R_{\alpha\alpha}$ ) as metric, these components can be written in the form:

i. (blue curves)

$$J_{\alpha}^{lb} = \sum_v \bar{P}_{en[v,\alpha]}^a(t) \frac{(y_v^v - y_v^{v|b})(y_{\alpha}^o - y_{\alpha}^b)}{R_{vv} R_{\alpha\alpha}}$$

ii. (red curves)

$$J_{\alpha}^{la} = \sum_v \bar{P}_{en[v,\alpha]}^a(t) \frac{(y_v^v - y_v^{v|a})(y_{\alpha}^o - y_{\alpha}^b)}{R_{vv} R_{\alpha\alpha}}$$

## 2b. Interpretation of $J_{\alpha}^{lb}$ and $J_{\alpha}^{la}$

i. Consider  $J^{lb} = \sum_v \frac{(y_v^v - y_v^{v|b})(y_{\alpha}^o - y_{\alpha}^b)}{R_{vv}}$  which can be written as the sum  $J^{lb} = \sum_{\alpha \in \text{Obs}} J_{\alpha}^{lb}$

Note that  $\langle J^{lb} \rangle > 0$  has to hold if analysis pulls model towards verifying data

$$\langle J_{\alpha}^{lb} \rangle > 0$$

Q: Are  $(y_{\alpha}^o - y_{\alpha}^b)$ ,  $(y_v^v - y_v^{v|b})$  and  $\bar{P}_{en[v,\alpha]}^a$  consistent?

ii. One can show that **if either**

- analysis increments  $(y_v^v - y_v^{v|b})$  are optimal w.r.t. the verification function  $J$
- or covariances used in Kalman gain matrix are all correct

then

$$\langle J_{\alpha}^{la} \rangle \approx \langle J_{\alpha}^{lb} \rangle$$

Q: Do the ana increments contain obs info "optimally"?

## 2c. Reference curves and normalisation

(green curves)

$$\langle J_{\alpha}^{lb} \rangle_{estim} = \sum_v \bar{P}_{en[v,\alpha]}^a(t) \frac{\bar{P}_{en[v,\alpha]}^b}{R_{vv} R_{\alpha\alpha}}$$

: Noise indicator for blue curves

(Here: noise estimate for a sum  $\sum_j A_j$  is  $\sqrt{\sum_j A_j^2}$ )

(bound of shaded areas)

$$J_{\alpha} = 2 J_{\alpha}^{lb} - J_{\alpha}^{la} \quad (\sim \text{"total EFSOI"})$$

If  $\bar{P}_{en[v,\alpha]}^a$  (ensemble background covariance in obs space) was the correct background error covariances, then:

$$\langle (y_v^v - y_v^{v|b})(y_{\alpha}^o - y_{\alpha}^b) \rangle = \bar{P}_{en[v,\alpha]}^a \quad \text{so that}$$

blue curves = green curves

Normalization:

Orig. Idea: normalize with  $\langle J_{\alpha}^{lb} \rangle_{estim}$  directly (i.e., divide by green curve - theoretical reference).

Problem:  $\bar{P}_{en[v,\alpha]}^a$  computed from ensemble+localization function  $\eta_{loc}$

$$\bar{P}_{en[v,\alpha]}^a = \text{model spread} * \eta_{loc} \rightarrow \text{large noise where } \eta_{loc} \text{ is small}$$

Chosen method

n: normalized graphs all curves divided by  $\langle J_{\alpha}^{lb} \rangle_{estim} / \eta_{loc}$

## 4. Application to satellite radiances:

### a) determination of localization height "plevel"

The first trials to apply the method to satellite radiances emphasized the importance of a good plevel assignment

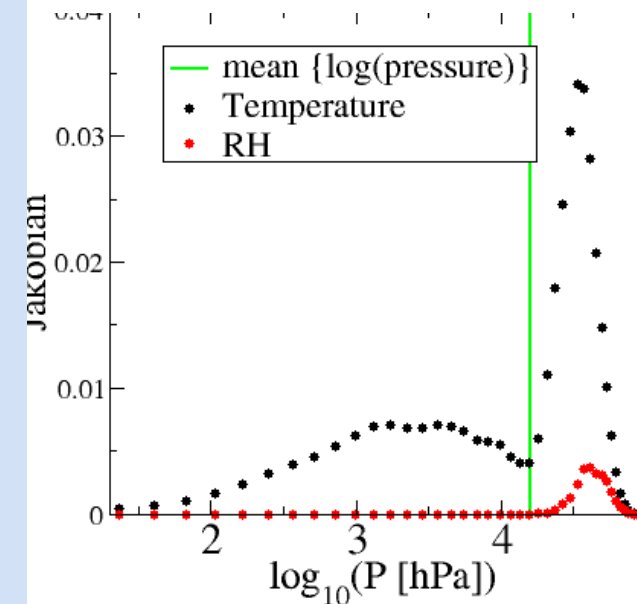
3 Methods to compute plevel (from the Jacobian  $H$ ) have been tested:

- centre of mass of  $|H|$
- Take the maximum of  $|H|$
- Take  $BH^T$  instead of  $H$

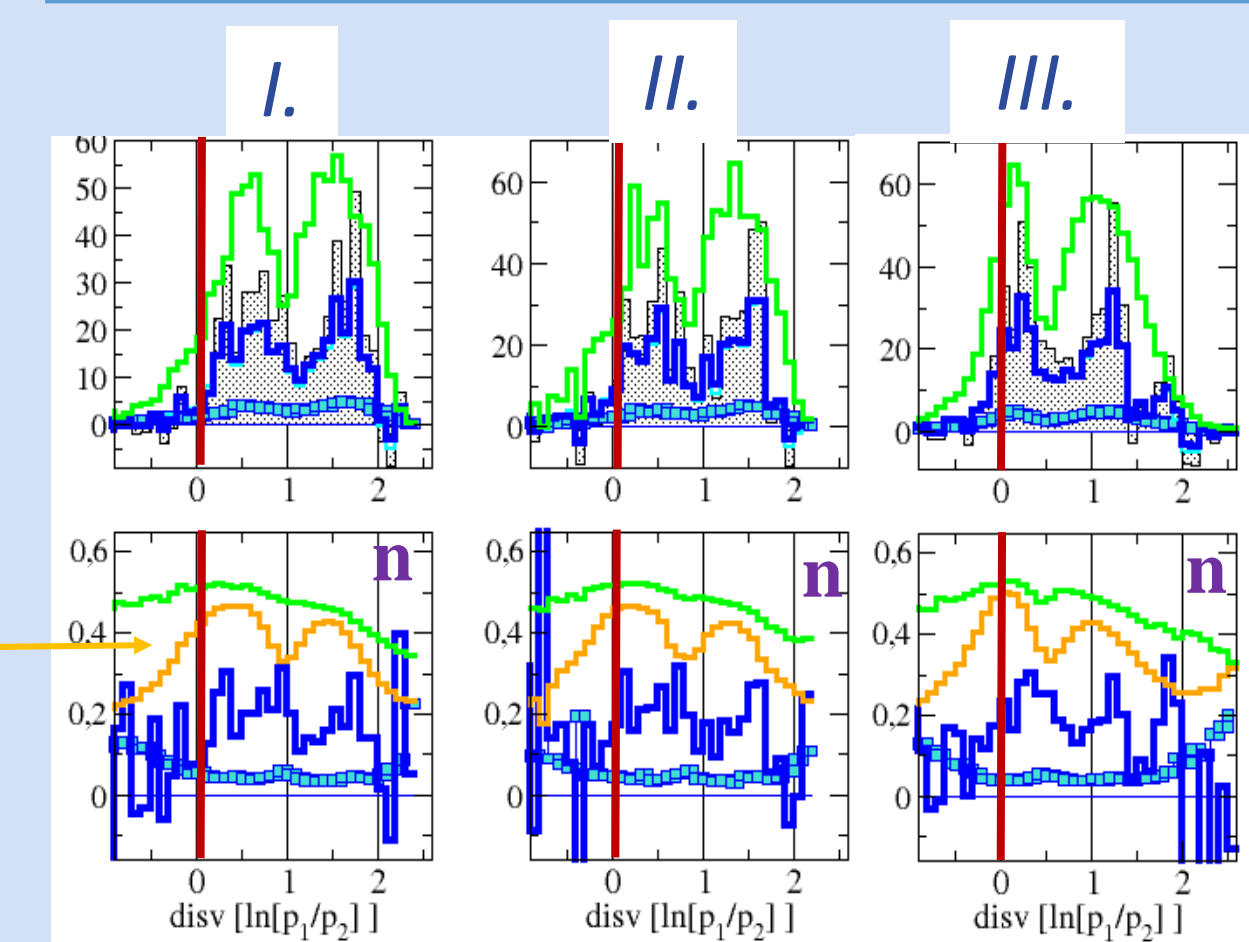
Here: Statistics are collected with vertical localization "switched off"

(orange curves) weighted mean of ensemble correlation

Jacobian of IASI ch. 262:

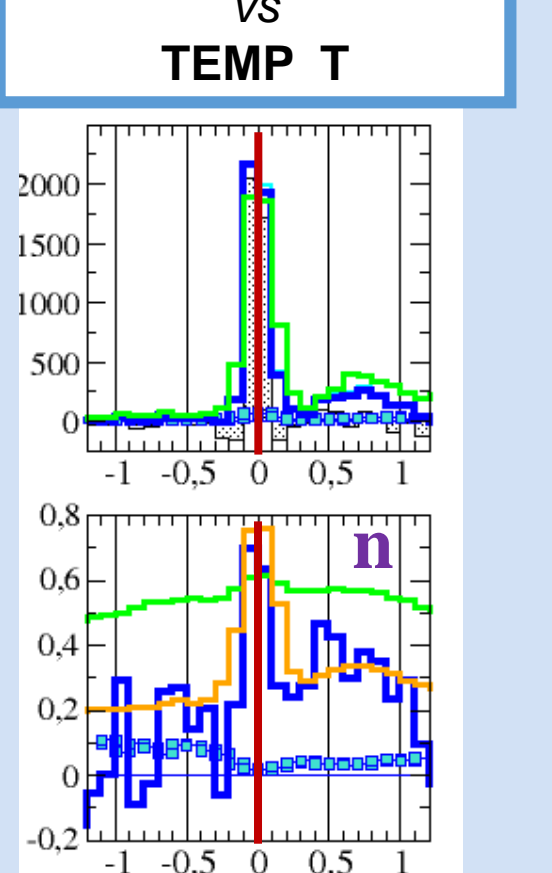


AMSU A ch 8 vs TEMP T

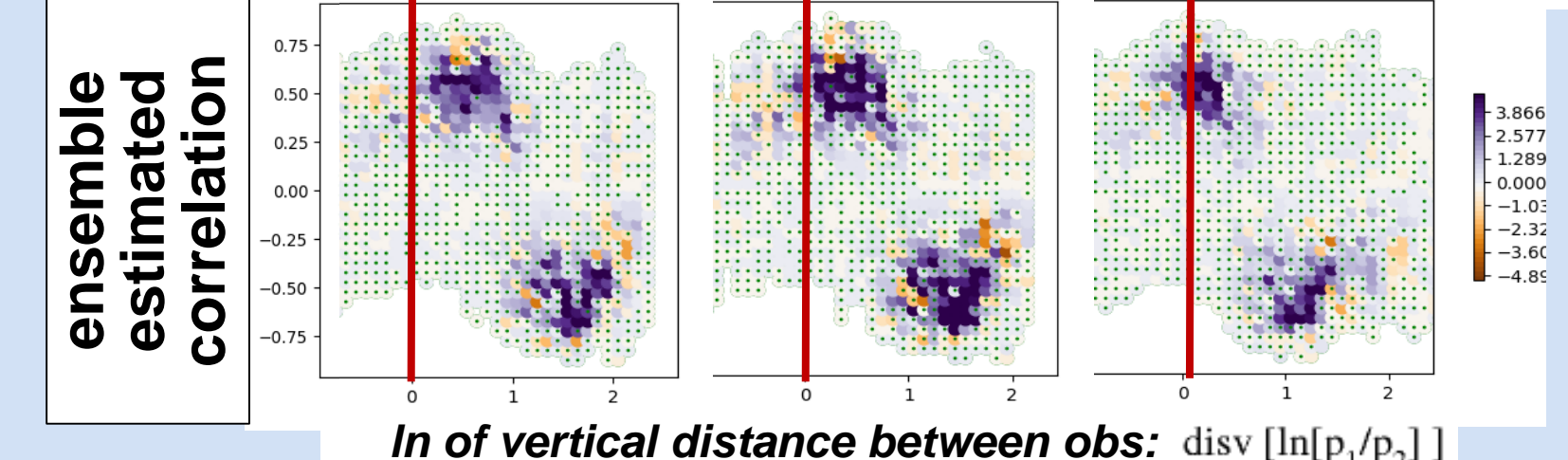


Secondary peak with neg. correlations also for:

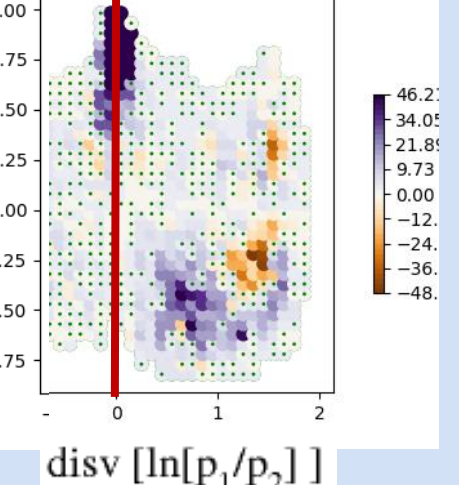
AIREP T vs TEMP T



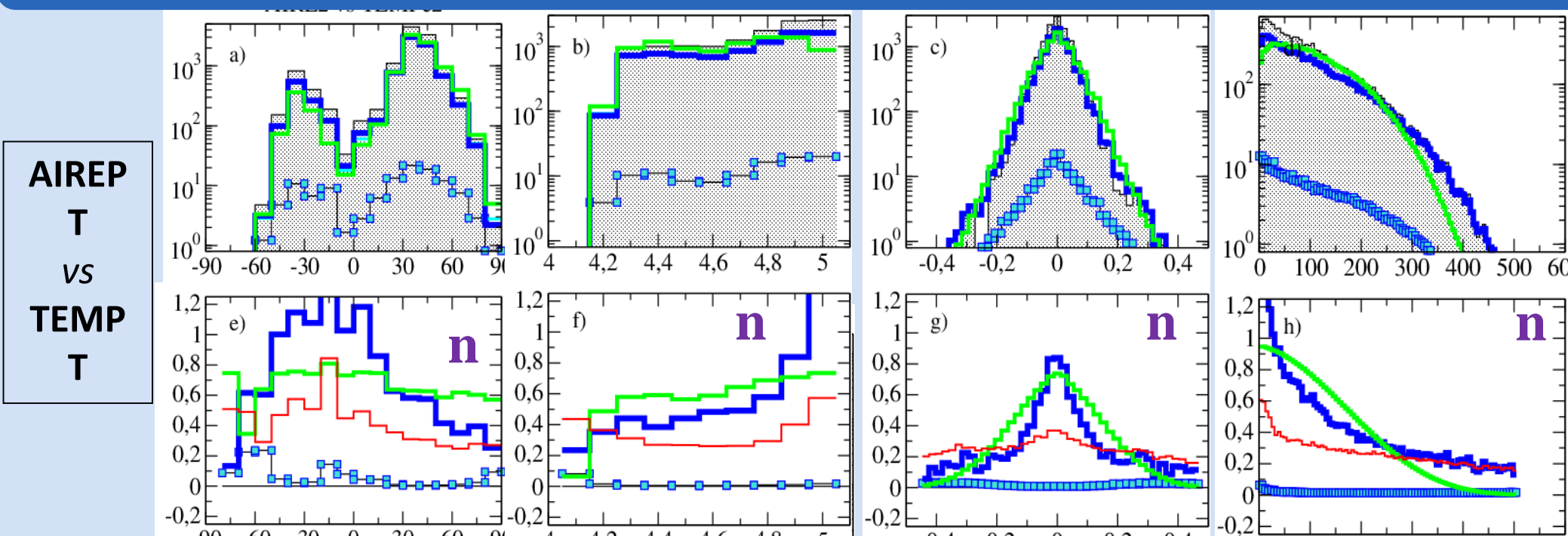
Contributions to the blue curves from different sub-bins



In of vertical distance between obs:  $\text{div}[\ln(p_1/p_2)]$



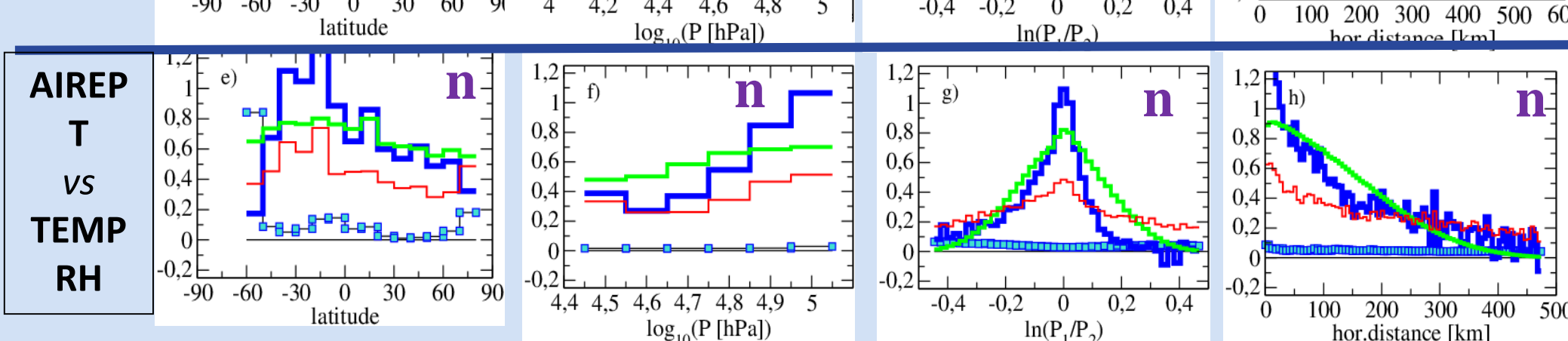
## 3. Applied to local („in situ“) measurements (t=0)



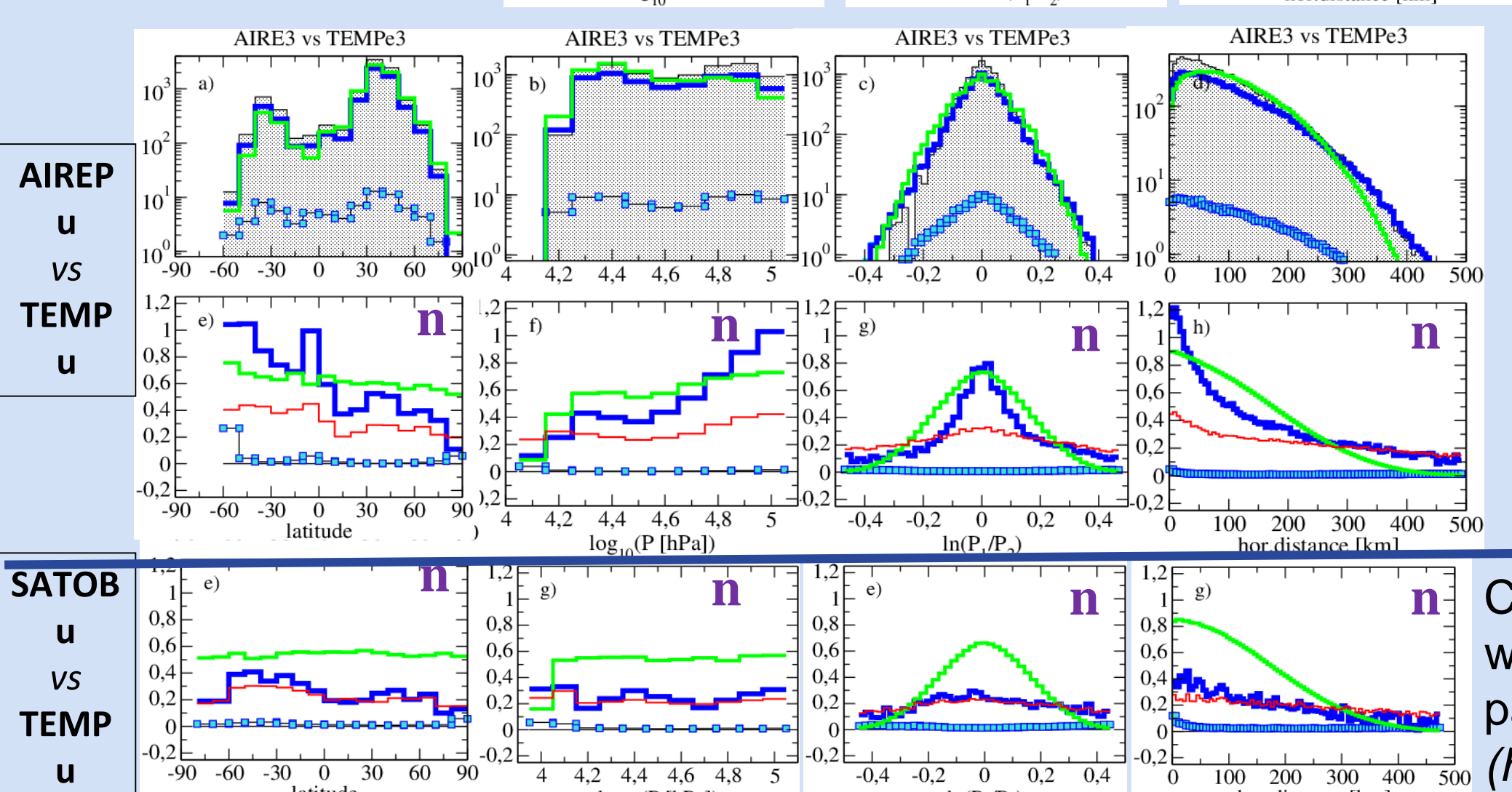
Blue curves always:  
(i)  $> 0$ ,  
(ii) mostly similar magnitude as green curves

I.e., in situ measurements generally show good agreement between (o-fg) departures and ensemble covariances.

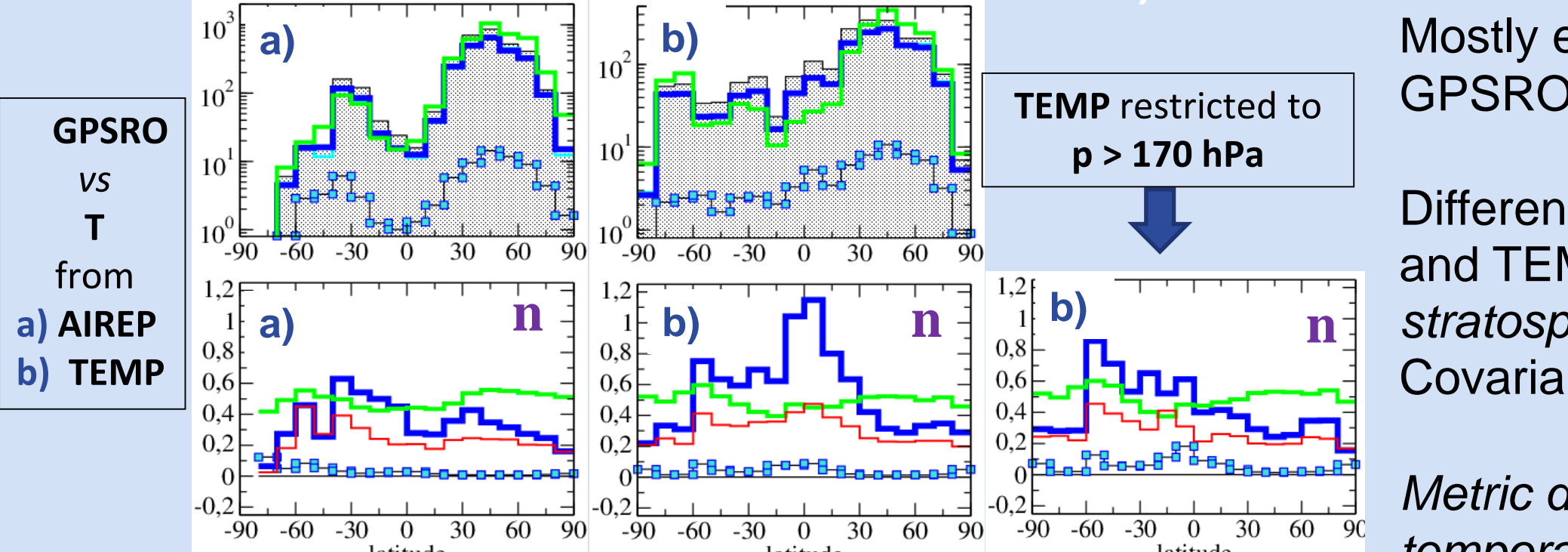
Unless for large separation distances, ana incs contain less obs-info than "optimal" (red lines clearly below blue lines).  
EnVar ana incs substantially more optimal (not shown).  
Probable explanation: LETKF of global system is less able to capture small scale information than EnVar



Correspondance substantially worse for AMVs (SATOB) particularly at small scales (height assignment problems!!)



Bending Angles (GPSRO):

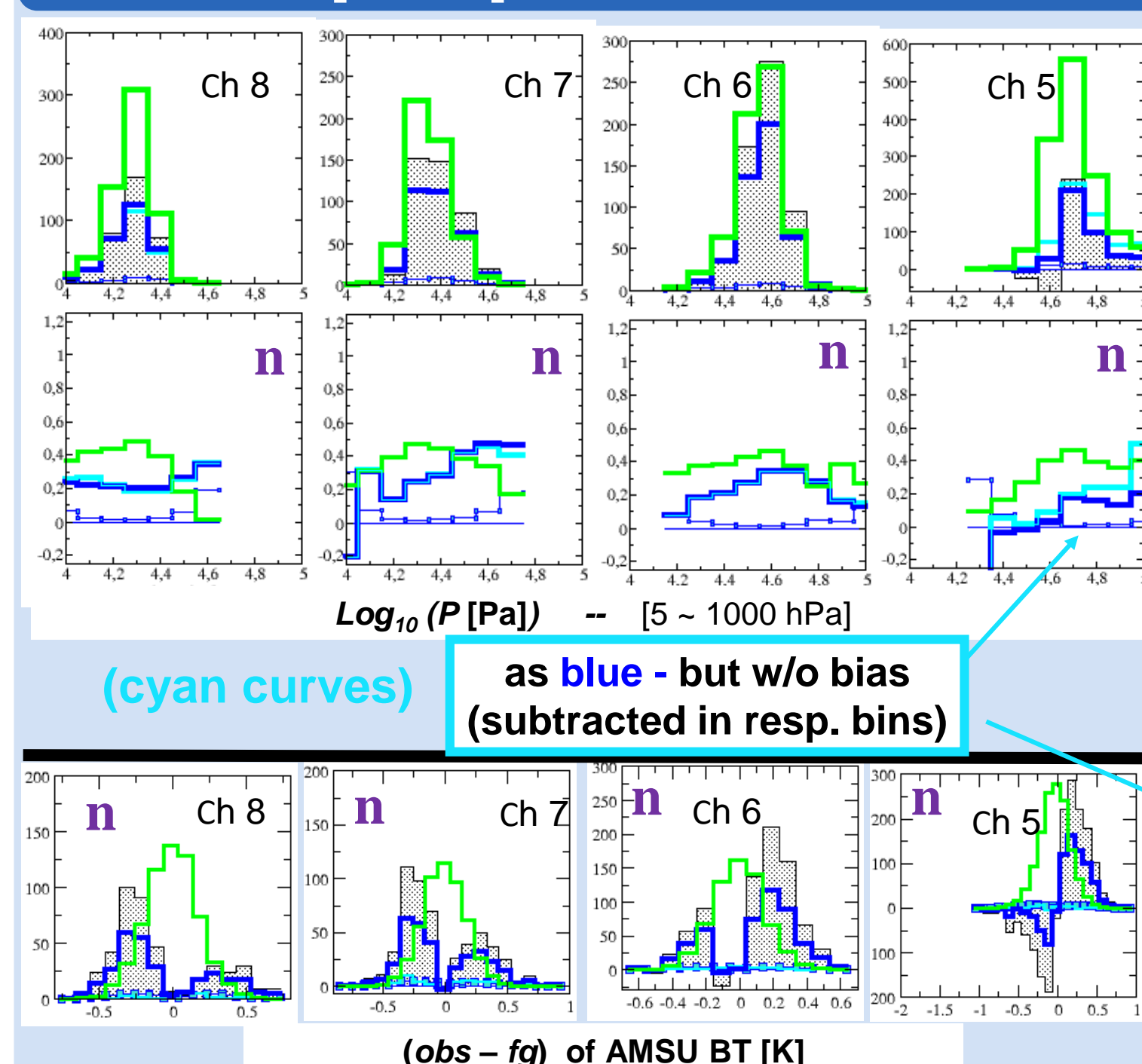


Mostly excellent agreement also for GPSRO (bending angles).

Differences of verification vs AIREPs and TEMPs are largely due to stratospheric TEMPs. Covariances in stratosphere are larger

Metric depends on spatial and temporal distribution of verifying obs

## 4b. Tropospheric Channels of AMSU A



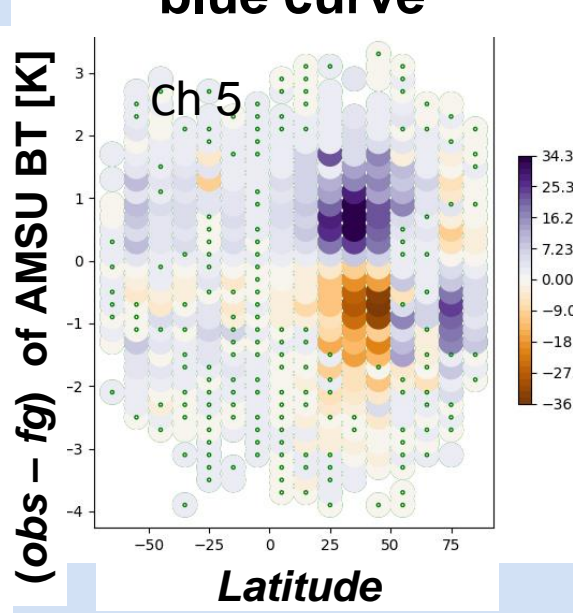
AMSU A shows clearly beneficial impact (though less ideal than in situ obs)

Channel 5: bias problems (obs-fg) bias opposite sign as for TEMPs or GPSRO (not shown)

Bias (particular model bias) strongly varies with:

- > location (e.g. latitude),
- > season,
- > weather regime,
- > other conditions.

Contributions to the blue curve



## 5. Concluding Remarks

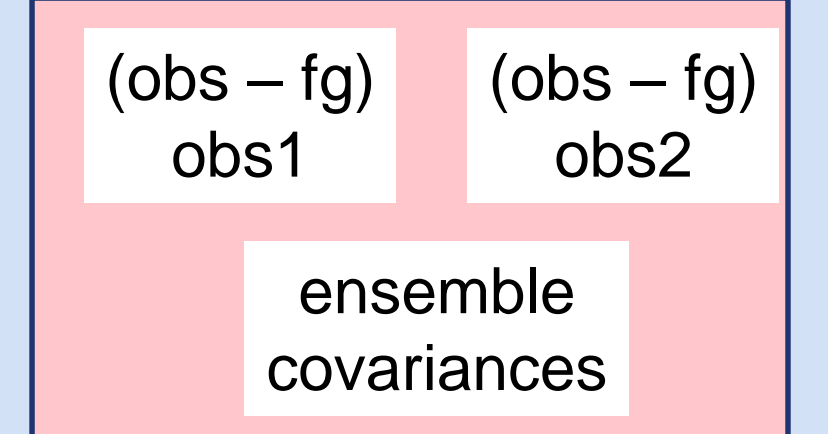
A new verification method has been introduced

- for testing the consistency of obs types (i.e., individual channel)
- under predefined conditions (latitude, height, etc.)
- which is very sensitive to impact of biases
- and directly related to an impact measure
- it divides established impact measure into parts related to different aspects of the data usage/quality
- most suitable for testing new methods / tuning parameters.

Interpreting statistics requires some experience / comparisons. Starting with in situ observations permitted:

- testing of method
- Benchmark for more complex observations

Testing consistency of:



Further work:  $t > 0$

Check for ensemble covariances at different times. Involves impact of dynamics (balances, spin up/down)



DWD, German Meteorological Service, Data assimilation section  
Author: Olaf Stiller, [Olaf.Stiller@dwd.de](mailto:Olaf.Stiller@dwd.de)

