

Observation impact diagnostics in an Ensemble Data Assimilation System

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Observation impact diagnostics in an Ensemble Data Assimilation System

Motivation

denial experiments/ observation system experiments (OSE)

 \rightarrow extremely expensive

Aim: Find diagnostic tools to

- indicate impact of observation subsets on analysis/forecast
- identify where observation impact is sub-optimal/negative



Define cost function: "model fit to the truth"

(Langland and Barker, 2004)

Here I follow

Sommer and Weissmann (2014,2016)

and use observations for verification

$$\boldsymbol{y}^{\mathbf{v};t} = \, \boldsymbol{y}^{o;t}_{\mathbf{v}}$$
 observation $\boldsymbol{y}^{o}_{\mathbf{v}}$ at time t

 $oldsymbol{H}_{\mathbf{v}}$: observation operator for $oldsymbol{y}^o_{\mathbf{v}}$

$$C = \boldsymbol{R}_{\mathbf{vv}}^{-1} = \frac{1}{r_{\mathbf{v}}}$$







$$J = \frac{1}{2} \left(\boldsymbol{e}^{t|\boldsymbol{a}} + \boldsymbol{e}^{t|\boldsymbol{b}} \right)^T \boldsymbol{C} \left(\boldsymbol{e}^{t|\boldsymbol{a}} - \boldsymbol{e}^{t|\boldsymbol{b}} \right)$$

$$J = \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{e}^{t|\boldsymbol{a}} + \boldsymbol{e}^{t|\boldsymbol{b}} \right)^T \boldsymbol{C} \boldsymbol{H}_{\boldsymbol{v}} M_{0 \to t} \mathbf{K}_l \left(\boldsymbol{y}_l^o - \boldsymbol{y}_l^b \right)$$
$$= \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{J}_l^{t|\boldsymbol{a}} + \boldsymbol{J}_l^{t|\boldsymbol{b}} \right)$$

 \mathbf{K}_l : column of Kalman gain matrix acting on \boldsymbol{y}_l^o $M_{0 \to t}$: time evolution operator $\boldsymbol{H}_{\mathbf{v}}$: operator computing modelequivalent to $\boldsymbol{y}^{\mathbf{v};t}$ $J \stackrel{\text{def!}}{=} \frac{1}{2} \left(\left\| e^{t|a} \right\|^2 - \left\| e^{t|b} \right\|^2 \right) \qquad \begin{array}{l} e^{t|a} = y^{t|a} - y^{\mathbf{v};t} \\ e^{t|\mathbf{b}} = y^{t|\mathbf{b}} - y^{\mathbf{v};t} \end{array}$ $y^{\mathbf{v};t} : \text{ data used for verification (at time t)}$ $y^{t|a}, y^{t|b} : \text{ modelequivalent to } y^{\mathbf{v};t} \text{ based on forecast from analysis } x^a \to y^{t|a} \\ \text{ background } x^{\mathbf{b}} \to y^{t|b} \end{array}$ $\left\| e^{t|a} \right\| = \left(e^{t|a} \right)^T C \left(e^{t|a} \right) \quad \text{"scalar product with metric } C"$



Time evolution



$$J = \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{e}^{t|\boldsymbol{a}} + \boldsymbol{e}^{t|\boldsymbol{b}} \right)^T \boldsymbol{C} \boldsymbol{H}_{\boldsymbol{v}} \boldsymbol{M}_{0 \to t} \mathbf{K}_l \left(\boldsymbol{y}_l^o - \boldsymbol{y}_l^b \right)$$
$$= \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{J}_l^{t|\boldsymbol{a}} + \boldsymbol{J}_l^{t|\boldsymbol{b}} \right)$$

- \mathbf{K}_l : column of Kalman gain matrix acting on $oldsymbol{y}_l^o$
- $M_{0 \rightarrow t}$: time evolution operator
 - $oldsymbol{H}_{\mathbf{v}}$: operator computing modelequivalent to $oldsymbol{y}^{\mathbf{v};t}$

Different DA systems use different approaches for computing the time evolution $M_{0 \rightarrow t}$

4D Var (Langland and Barker 2004) → use linear (adjoint) model

Ensemble Kalman Filter (EKF) → use ensemble



Optimality Condition



$$J = \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{e}^{t|\boldsymbol{a}} + \boldsymbol{e}^{t|\boldsymbol{b}} \right)^T \boldsymbol{C} \boldsymbol{H}_{\mathbf{v}} M_{0 \to t} \mathbf{K}_l \left(\boldsymbol{y}_l^o - \boldsymbol{y}_l^b \right)$$
$$= \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{J}_l^{t|\boldsymbol{a}} + \boldsymbol{J}_l^{t|\boldsymbol{b}} \right)$$

Choose initial condition:

$$\begin{split} \boldsymbol{x}^{\text{init}}\left(\{\boldsymbol{\lambda}_{\boldsymbol{l}}\}\right) \ &= \ \boldsymbol{x}^{\text{b}} + \sum_{l \in \{obs\}} \mathbf{K}_{l} \boldsymbol{\lambda}_{\boldsymbol{l}} \left(\boldsymbol{y}_{l}^{o} - \boldsymbol{y}_{l}^{b}\right) \\ & \boldsymbol{x}^{a} \ &= \ \boldsymbol{x}^{\text{init}}\left(\{\boldsymbol{\lambda}_{\boldsymbol{l}} = 1\}\right) \end{split}$$

If *J* has a minimum for $x^{\text{init}} = x^a$ one finds

$$\left\langle \boldsymbol{J}_{l}^{t|\boldsymbol{a}} \right\rangle \equiv \left\langle \left(\boldsymbol{e}^{t|\boldsymbol{a}} \right)^{T} \boldsymbol{C} \boldsymbol{H}_{\mathbf{v}} M_{0 \to t} \mathbf{K}_{l} \left(\boldsymbol{y}_{l}^{o} - \boldsymbol{y}_{l}^{b} \right) \right\rangle$$
$$= 0 \quad \text{for all } l \in \{obs\}$$

 $\langle ..\rangle$: statistical mean



Our System



$$J = \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{e}^{t|\boldsymbol{a}} + \boldsymbol{e}^{t|\boldsymbol{b}} \right)^T \boldsymbol{C} \boldsymbol{H}_{\mathbf{v}} M_{0 \to t} \mathbf{K}_l \left(\boldsymbol{y}_l^o - \boldsymbol{y}_l^b \right)$$
$$= \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{J}_l^{t|\boldsymbol{a}} + \boldsymbol{J}_l^{t|\boldsymbol{b}} \right)$$

- LETKF (Hunt et al. 2007) 40 ensemble members
- verification vs obs.

(Sommer and Weissmann 2014)

 time evolution via analysis ensemble (Kalnay et al. 2012)

$$egin{array}{lll} \left(oldsymbol{x}^a-oldsymbol{x}^b
ight) &=& \displaystyle\sum_k \mathbf{w}_k^aoldsymbol{X}^{a(k)} \ M_{0
ightarrow t}\left(oldsymbol{x}^a-oldsymbol{x}^b
ight) &=& \displaystyle\sum_k \mathbf{w}_k^aoldsymbol{X}^{a(k)}(t) \end{array}$$

 $oldsymbol{X}^{a(k)}$: k^{th} incr. analysis ensemble member



Our System



$$J = \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{e}^{t|\boldsymbol{a}} + \boldsymbol{e}^{t|\boldsymbol{b}} \right)^T \boldsymbol{C} \boldsymbol{H}_{\mathbf{v}} M_{0 \to t} \mathbf{K}_l \left(\boldsymbol{y}_l^o - \boldsymbol{y}_l^b \right)$$
$$= \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{J}_l^{t|\boldsymbol{a}} + \boldsymbol{J}_l^{t|\boldsymbol{b}} \right)$$

 time evolution via analysis ensemble (Kalnay et al. 2012)

$$\begin{aligned} (\boldsymbol{x}^{a} - \boldsymbol{x}^{b}) &= \sum_{k} \mathbf{w}_{k}^{a} \boldsymbol{X}^{a(k)} \qquad \mathbf{X}^{a(k)} : \quad k^{th} \text{ incr. analysis} \\ \text{ensemble member} \\ \mathbf{w}_{k}^{a} &= \sum_{\alpha,\beta \in \{obs\}} \mathbf{Y}_{\alpha}^{a(k)} \mathbf{R}_{\alpha\beta}^{-1} \left(\boldsymbol{y}_{\beta}^{o} - \boldsymbol{y}_{\beta}^{b} \right) \\ \mathbf{Y}_{\alpha}^{a(k)} &= \mathbf{H}_{\alpha} \mathbf{X}^{a(k)} : : \quad \mathbf{X}^{a(k)} \text{ in obs space} \\ \mathbf{Y}_{\alpha}^{a(k)} &= \mathbf{H}_{\alpha} \mathbf{X}^{a(k)} : : \quad \mathbf{X}^{a(k)} \text{ in obs space} \\ \mathbf{Y}_{\alpha}^{a(k)} &= \mathbf{H}_{\alpha} \mathbf{X}^{a(k)} : : \quad \mathbf{X}^{a(k)} \text{ in obs space} \\ \mathbf{Y}_{\alpha}^{a(k)} &= \mathbf{H}_{\alpha} \mathbf{X}^{a(k)} : : \quad \mathbf{X}^{a(k)} \text{ in obs space} \\ \mathbf{Y}_{\alpha}^{l(k)} &= -P_{\mathbf{v}l}^{a}(t) \quad \frac{\left(\mathbf{y}_{\mathbf{v}}^{o;t} - \mathbf{y}_{\mathbf{v}}^{t|a}\right) \left(\mathbf{y}_{l}^{o} - \mathbf{y}_{l}^{b}\right)}{\mathbf{R}_{\mathbf{v}\mathbf{v}}\mathbf{R}_{ll}} \\ \mathbf{J}_{l}^{t|b} &= -P_{\mathbf{v}l}^{a}(t) \quad \frac{\left(\mathbf{y}_{\mathbf{v}}^{o;t} - \mathbf{y}_{\mathbf{v}}^{t|b}\right) \left(\mathbf{y}_{l}^{o} - \mathbf{y}_{l}^{b}\right)}{\mathbf{R}_{\mathbf{v}\mathbf{v}}\mathbf{R}_{ll}} \\ \mathbf{J}_{l}^{t|b} &= -P_{\mathbf{v}l}^{a}(t) \quad \frac{\left(\mathbf{y}_{\mathbf{v}}^{o;t} - \mathbf{y}_{\mathbf{v}}^{t|b}\right) \left(\mathbf{y}_{l}^{o} - \mathbf{y}_{l}^{b}\right)}{\mathbf{R}_{\mathbf{v}\mathbf{v}}\mathbf{R}_{ll}} \\ \mathbf{J}_{l}^{t|b} &= -P_{\mathbf{v}l}^{a}(t) \quad \frac{\left(\mathbf{y}_{\mathbf{v}}^{o;t} - \mathbf{y}_{\mathbf{v}}^{t|b}\right) \left(\mathbf{y}_{l}^{o} - \mathbf{y}_{l}^{b}\right)}{\mathbf{R}_{\mathbf{v}\mathbf{v}}\mathbf{R}_{ll}} \\ \mathbf{J}_{l}^{t|b} &= -P_{\mathbf{v}l}^{a}(t) \quad \frac{\left(\mathbf{y}_{\mathbf{v}}^{o;t} - \mathbf{y}_{\mathbf{v}}^{t|b}\right) \left(\mathbf{y}_{l}^{o} - \mathbf{y}_{l}^{b}\right)}{\mathbf{R}_{\mathbf{v}\mathbf{v}}\mathbf{R}_{ll}} \\ \mathbf{J}_{l}^{t|b} &= -P_{\mathbf{v}l}^{a}(t) \quad \frac{\left(\mathbf{y}_{\mathbf{v}}^{o;t} - \mathbf{y}_{\mathbf{v}}^{t|b}\right) \left(\mathbf{y}_{l}^{o} - \mathbf{y}_{l}^{b}\right)}{\mathbf{R}_{\mathbf{v}\mathbf{v}}\mathbf{R}_{ll}} \\ \mathbf{J}_{l}^{t|b} &= -P_{\mathbf{v}l}^{a}(t) \quad \mathbf{J}_{l}^{t|b} = -P_{\mathbf{v}l}^{a}(t) \quad \mathbf{J}_{l}^{t|b} \quad \mathbf{J}_{l}^{t|b} = -P_{\mathbf{v}l}^{a}(t) \quad \mathbf{J}_{l}^{t|b} = -P_{\mathbf{v}l}^{a}(t) \quad \mathbf{J}_{l}^{t|b} \quad \mathbf{J}_{l}^{t|b} \quad \mathbf{J}_{l}^{t|b} \quad \mathbf{J}_{l}^{t|b} \quad \mathbf{J}_{l}^{t|b} \quad \mathbf{J}_{l}^{t|b} \quad \mathbf{J}_{l}^{t|b}$$

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Interpretation for *t=0*



$$\left\langle -\boldsymbol{J}_{l}^{0|a}\right\rangle = P_{\mathbf{v}l}^{a} \frac{\left\langle (\boldsymbol{y}_{\mathbf{v}}^{o} - \boldsymbol{y}_{\mathbf{v}}^{a}) \left(\boldsymbol{y}_{l}^{o} - \boldsymbol{y}_{l}^{b}\right)\right\rangle}{R_{ll}R_{\mathbf{v}\mathbf{v}}} = \frac{P_{\mathbf{v}l}^{a}}{R_{ll}R_{\mathbf{v}\mathbf{v}}} \boldsymbol{R}_{\mathbf{v}l} = 0 \text{ if } \boldsymbol{y}_{\mathbf{v}}^{o}, \, \boldsymbol{y}_{l}^{o} \text{ statistically independent}$$

$$\left\langle -\boldsymbol{J}_{l}^{\boldsymbol{0}|\boldsymbol{b}}\right\rangle = P_{\boldsymbol{v}l}^{a} \frac{\left\langle (\boldsymbol{y}_{\boldsymbol{v}}^{o} - \boldsymbol{y}_{\boldsymbol{v}}^{b})(\boldsymbol{y}_{l}^{o} - \boldsymbol{y}_{l}^{b})\right\rangle}{R_{ll}R_{\boldsymbol{v}\boldsymbol{v}}} = \frac{P_{\boldsymbol{v}l}^{a}}{R_{ll}R_{\boldsymbol{v}\boldsymbol{v}}} P_{\boldsymbol{v}l}^{b} > 0 \text{ if } P_{\boldsymbol{v}l}^{a} \text{ and } P_{\boldsymbol{v}l}^{b} \text{ have the same sign}$$

Results: What is shown?

- So far only results for t=0 ("impact on analysis").
- Statistics have been computed for different cost-function components separately:

 $\sum_{stats} \left(-J_l^{0|a} \right) = \sum_{stats} P_{vl}^a \frac{(y_v^o - y_v^a) (y_l^o - y_l^b)}{R_{ll} R_{vv}} \quad \leftarrow \text{ should be small} \quad --- \text{ "optimality condition"}$ $\sum_{stats} \left(-J_l^{0|b} \right) = \sum_{stats} P_{vl}^a \frac{(y_v^o - y_v^b) (y_l^o - y_l^b)}{R_{ll} R_{vv}} \quad \leftarrow \text{ should be positive (and large)} \quad --- \text{ "potential benefit"}$

Results: Temps verified by GPSRO

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Results: Temps verified by GPSRO



10

10 Excellent correspondence/consistency 10 effective number of pairs between Temps and GPSRO 250 40 200 20 150 100 -20 40 $\sum \left(-J_{l}^{t|b}\right)$: is clearly positive normalised 0.06 normalised everywhere 0.02 0.04 0.01 0.02 -90 -60 -30 0 30 60 30 -90 -60 -30 0 60 90 latitude latitude

 $\sum \left(-J_l^{t|a}\right)$: is

1.) much smaller than $\sum \left(-J_l^{t|b}\right)$

- \rightarrow optimality condition largely fulfilled
- 2.) mostly positive
 - \rightarrow weight on TEMPS in assimilation could be slightly increased in tropical regions

Deutscher Wetterdienst Wetter und Klima aus einer Hand



10 effective number of pairs 3000 2500 -500 2000 1000 1500 -1500 1000 -2000 500 -2500 0.02 3000 normalised 0.015 -0.005 0.01 -0.01 0.005 normalised 0.015 -0.02-90 -60 -30 0 30 60 90 -90 -60 -30 30 60 90 latitude latitude

 $\sum \left(-J_l^{t|b}\right)$: generally positive \rightarrow strong potential

 $\sum \left(-J_{l}^{t|a} \right)$: clearly negative \rightarrow obs have too strong weight

> AMSU-A observation errors are too small (also according to Desroziers diagnostics)

Increased observation errors have been tested for operational implementation.

But: Positive impact on forecast only after reduced thinning of AMSU-A



individual channels

only showing $\sum \left(-J_l^{t|b}\right)$

- normalised

impact variable : bias removed from bins _



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AMSU - GPSRO

individual channels only showing $\sum \left(-J_l^{t|b}\right)$ - normalised

The correspondence between AMSU-A channels and GPSRO is positive or neutral for most channels and most latitudes ($\sum \left(-J_{l}^{t|b}\right)$ is mostly positive).

In some regions

- dark shaded areas are negative or neutral
- green (bias removed a posteriori) clearly positive





individual channels

only showing $\sum \left(-J_l^{t|b}\right)$

- normalised

Bias problems for channels 9 and 10 are stronger over land than over sea

(Channel 11 no significant bias found - neither over land)



data over sea/land only



Outlook: Assessing impact of individual observations



Cost-function J gives impact of all observations assimilated at time t = 0.

Interpretation of different components J_l corresponding to individual observations y_l is suggestive but not rigorous.

$$J = \sum_{l \in \{obs\}} \frac{1}{2} \left(\boldsymbol{J}_{l}^{t|\boldsymbol{a}} + \boldsymbol{J}_{l}^{t|\boldsymbol{b}} \right)$$

More rigorous approach:

Cost-function for data denial experiment. Replace: $x^b \rightarrow x^{a/k}$ (analysis not using y_k^o)

$$J = \frac{1}{2} \left(\left\| \boldsymbol{e}^{t|\boldsymbol{a}} \right\|^2 - \left\| \boldsymbol{e}^{t|\boldsymbol{b}} \right\|^2 \right) \quad \rightarrow \quad \frac{1}{2} \left(\left\| \boldsymbol{e}^{t|\boldsymbol{a}} \right\|^2 - \left\| \boldsymbol{e}^{t|\boldsymbol{a}/\boldsymbol{k}} \right\|^2 \right)$$

$$\begin{split} \boldsymbol{J}_{k}^{\boldsymbol{t}|\boldsymbol{a}} &= -P_{\mathbf{v}k}^{\boldsymbol{a}}(t) \frac{\left(\boldsymbol{y}_{k}^{o} - \boldsymbol{y}_{k}^{\boldsymbol{a}/\boldsymbol{k}}\right) \left(\boldsymbol{y}_{\mathbf{v}}^{o;t} - \boldsymbol{y}_{\mathbf{v}}^{\boldsymbol{t}|\boldsymbol{a}}\right)}{\boldsymbol{R}_{kk} \boldsymbol{R}_{\mathbf{vv}}} & \text{with} \\ \boldsymbol{J} &= \boldsymbol{J}_{k}^{\boldsymbol{t}|\boldsymbol{a}} - \frac{1}{2} \left[P_{\mathbf{v}k}^{\boldsymbol{a}}(t)\right]^{2} \frac{\left(\boldsymbol{y}_{k}^{o} - \boldsymbol{y}_{k}^{\boldsymbol{a}/\boldsymbol{k}}\right)^{2}}{\boldsymbol{R}_{kk}^{2} \boldsymbol{R}_{\mathbf{vv}}} & = (1 - \frac{1}{1 - 1}) \\ \boldsymbol{J} &= \frac{1}{2} \left[P_{\mathbf{v}k}^{\boldsymbol{a}}(t)\right]^{2} \frac{\left(\boldsymbol{y}_{k}^{o} - \boldsymbol{y}_{k}^{\boldsymbol{a}/\boldsymbol{k}}\right)^{2}}{\boldsymbol{R}_{kk}^{2} \boldsymbol{R}_{\mathbf{vv}}} & = (1 - \frac{1}{1 - 1}) \\ \boldsymbol{J} &= \frac{1}{1 - 1} \\$$

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$$egin{aligned} & P_l - oldsymbol{y}_l^{a/k} ig) \,=\, (oldsymbol{1} - oldsymbol{H}_{oldsymbol{v}} \mathbf{K}_k)^{-1} \, (oldsymbol{y}_k^o - oldsymbol{y}_k^o) \ & =\, rac{(oldsymbol{y}_k^o - oldsymbol{y}_k^a)}{1 - P_{kk}^a(t=0)/oldsymbol{R}_{kk}} \end{aligned}$$

Summary and Discussion



Different parts of the cost function $J = \sum_{l \in \{obs\}} \frac{1}{2} \left(J_l^{t|a} + J_l^{t|b} \right)$ should be considered (interpreted) separately.

Examples were given for how the diagnostics could be linked to:

- The use of too small observation errors in the DA system for AMSU-A
- Biases of AMSU-A channels ← → Bias of GPSRO
 [Bias problems only show up if the bias is opposite to the bias which the verifying obs (here GPSRO) have with respect to the model.]
- The interpretation of observation impact diagnostics is often not trivial.
 - Statistical significance/spurious correlations is a big issue (particularly for large forecast lead times).
- A method is under development to show the "denial impact" for individual observations (e.g., a single AMSU channel).





Thank you – any questions?

