Estimating observation errors: diagnostics, possibilities, and pitfalls

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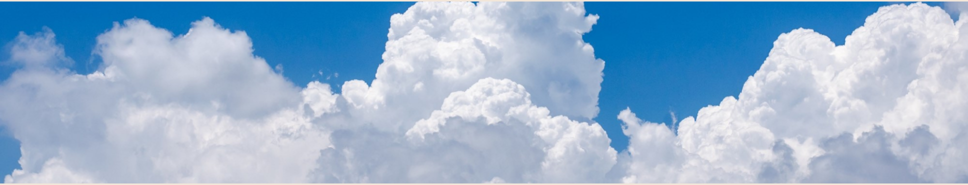

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Outline

Why estimate observation uncertainty?

How can we estimate observation uncertainty?

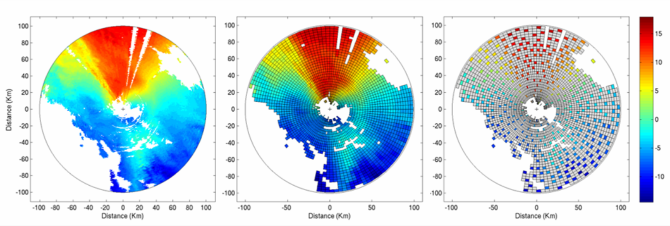
What are the pitfalls?

What are the possibilities?

Conclusions

Why do we want to estimate observation uncertainty?

- Only use 5% of some obs types due to thinning



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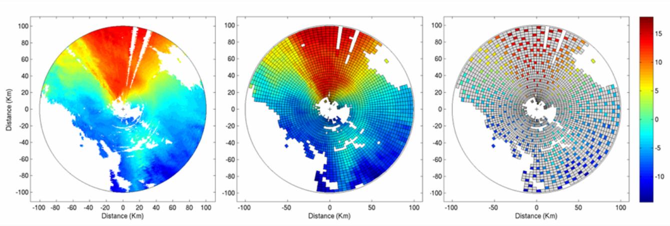

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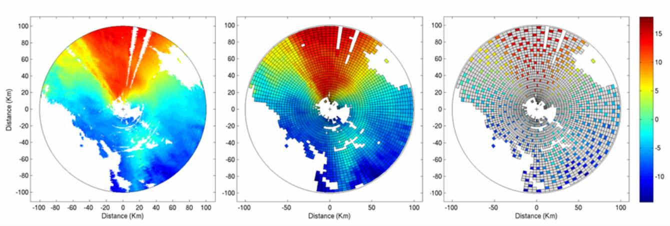

- Improve analysis accuracy and forecast skill (e.g., Stewart et al. 2013; Weston et al., 2014)
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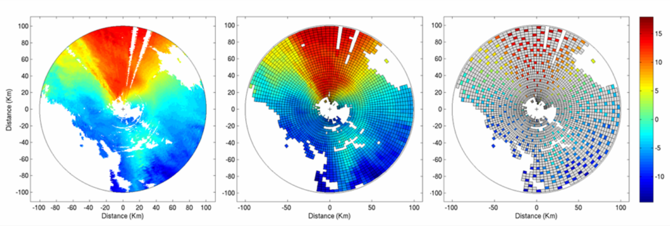

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Estimating observation uncertainty

- In DA, observation uncertainty depends on YOUR observation operator, model resolution etc and is state dependent (Waller et al., 2014; Janjić et al, 2018)
- Approximations are still useful and can give improved forecast skill (Healy and White, 2005; Stewart et al, 2013)

How can we estimate observation uncertainty?

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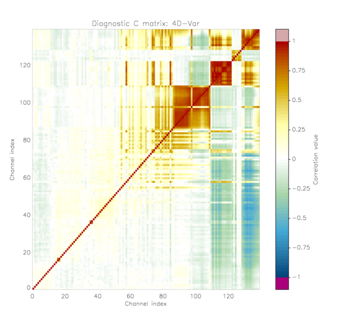
- Collocation with other observations (but rep. error?)
- Diagnosis from assimilation (review by Tandeo et al, 2020)
  - Moment based methods (e.g., using innovation and residual statistics, Desroziers et al, 2005)
  - Likelihood based methods (e.g., expectation maximization, Pulido et al, 2018)

Focus of talk

Focus on DBCP diagnostic (Desroziers et al 2005)

- Easy to compute from standard innovations and analysis residuals
- Proven useful in NWP

Early IASI example (Stewart et al., 2009, 2014.)



- Non-symmetric structure

DBCP diagnostic, Desroziers et al., (2005)

Use the background innovations and analysis residuals:

$$\mathbf{d}_b^o = \mathbf{y} - \mathcal{H}(\mathbf{x}^b),$$

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Taking the statistical expectation, and after some calculations...

$$E[\mathbf{d}_a^o \mathbf{d}_b^{o\,T}] = \widetilde{\mathbf{R}}(\mathbf{H}\widetilde{\mathbf{B}}\mathbf{H}^{\mathbf{T}} + \widetilde{\mathbf{R}})^{-1}(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R}) = \mathbf{R}^e,$$

where

- $\mathbf{R}^e$ is the estimated observation error covariance matrix

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- **B** and **R** are the exact background and observation covariance matrices.

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- $\widetilde{\mathbf{R}}$ and $\widetilde{\mathbf{B}}$ are the assumed statistics used in the assimilation.

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- $\mathbf{B}$ and $\mathbf{R}$ are the exact background and observation covariance matrices.
- $\widetilde{\mathbf{R}}$ and $\widetilde{\mathbf{B}}$ are the assumed statistics used in the assimilation.

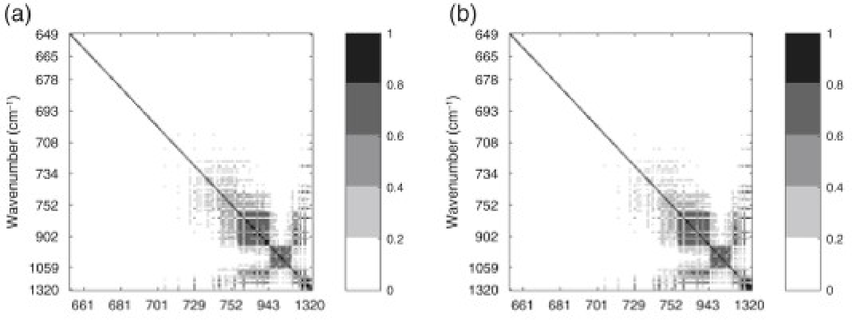
If $\widetilde{\mathbf{R}} = \mathbf{R}$ and $\widetilde{\mathbf{B}} = \mathbf{B}$, then

$$E[\mathbf{d}_a^o \mathbf{d}_b^{o\,T}] = \mathbf{R}.$$

Pitfalls

Aside on iteration

- Iteration converges to the correct estimate only when assumed $\widetilde{\mathbf{B}}$ is correct (Menard, 2016; Bathmann, 2018)
- More often, the first iterate is used. Experience shows little difference between iterates.



Bathmann(2018) a) First iterate b) Sixth iterate correlation matrix for IASI with NCEP global system

Beware the assumptions used in the calculation!

Assumption: optimal DA system

Experiment to estimate spatial correlations: Use a (much) higher density of observations than usual in order to estimate spatial error-correlation lengths.

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Assumption: optimal DA system

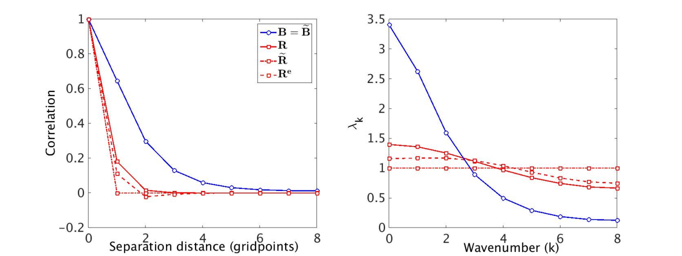
Experiment to estimate spatial correlations: Use a (much) higher density of observations than usual in order to estimate spatial error-correlation lengths.

Analysis overfits the observations and results (esp. variances) are suboptimal. (Waller et al, 2016 Remote Sensing)

Sensitivity to Assumed Statistics (Waller et al, 2016 QJ)

$$E[\mathbf{d}_a^o \mathbf{d}_b^{o\,T}] = \widetilde{\mathbf{R}}(\mathbf{H}\widetilde{\mathbf{B}}\mathbf{H}^{\mathbf{T}} + \widetilde{\mathbf{R}})^{-1}(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R}) = \mathbf{R}^e,$$

Example: True background error stats, $\widetilde{\mathbf{B}} = \mathbf{B}$; diagonal $\widetilde{\mathbf{R}}$

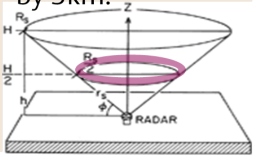


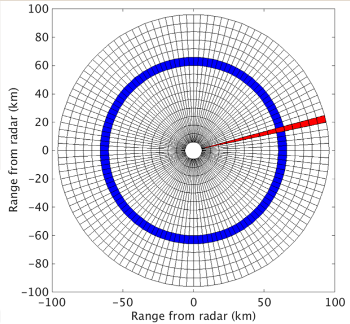
$\mathbf{R}^e$ has an underestimated variance and correlation lengthscale, but is a better approximation than $\widetilde{\mathbf{R}}$.

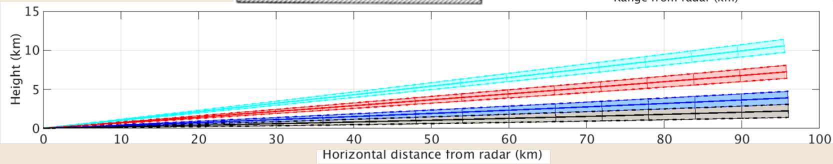
Doppler radar winds and Met Office UKV

Each radar beam produces observations of radial velocity out to a range of 100km with measurements taken:

- Every 75m along the beam.
- Every degree.
- At five different elevation angles.
- Superobbed to 3° by 3km.
- Thinned to 6km.



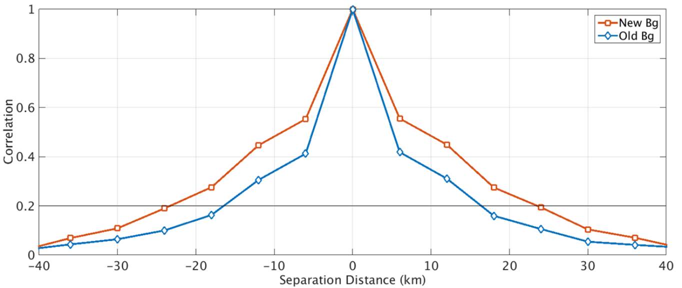




Horizontal Correlations, sensitivity to $\widetilde{\mathbf{B}}$

Waller et al. (2016) MWR

Case	B statistics	Superobs	Observation operator	Standard deviation (m/s)
New Bg	New	Yes	Old	1.97
Old Bg	Old	Yes	Old	1.57



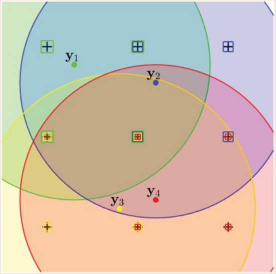
- Increasing variance and lengthscale in $\widetilde{\mathbf{B}}$ reduces variance and lengthscale in diagnosed $\mathbf{R}^e$.
- Consistent with Waller et al (2016) QJ theory.

DBCP and Local DA (Waller et al, 2017)

- DBCP does not always give the right answers. Must only calculate with the right set of points.

Regions of observation influence
The region of influence of an observation is the set of analysis states that are updated in the assimilation using the observation.

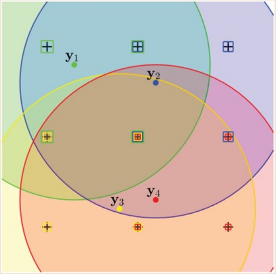
Grid points (pluses) and observations (dots), with observations coloured with corresponding regions of observation influence (shaded coloured circles).



DBCP and Local DA Cont(Waller et al, 2017)

The domain of dependence of an observation y_i is the set of elements of the model state that are used to calculate the model equivalent of y_i

Example: The coloured squares around grid points select the points that would be utilized by the observation operator for the observation of the corresponding colour.

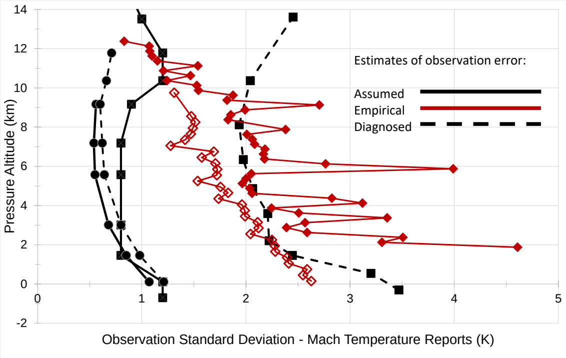


The correlation between the errors of observations y_i and y_j can be estimated using the DBCP diagnostic only if the domain of dependence for observation y_i lies within the region of influence of observation y_j.

Possibilities

Comparison of approaches (Mirza et al, 2020)

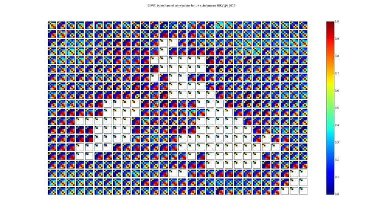
- Mode-S EHS temperatures - errors from lack of precision in Mach number
- Diagnosed std (black-dashed-squares) compare well with metrological estimates (red diamonds)



Identifying sources of error - Examples

Waller et al (2016) Rem. sens.

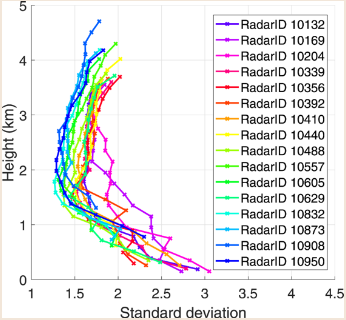
SEVIRI interchannel error covariances over different subdomains



Land-sea QC issue

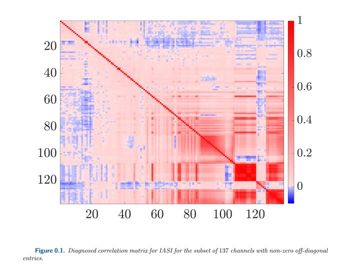
Bauernschubert et al (2019)

Doppler radar wind error std



Radars 10169 and 10204 contaminated by wind turbines and ship tracks

Using diagnosed covariances in operations



Diagnosed interchannel observation error correlations for IASI (for the Met Office global model)

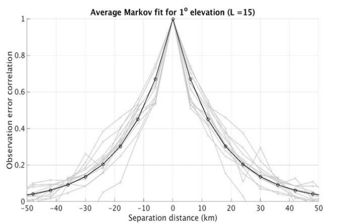
Diagnosed covariances typically

- Not symmetric
- Not positive definite
- Variances too small
- Ill-conditioned

- Can prevent convergence of variational minimization (Weston et al. 2014, Tabeart et al 2018, 2020 submitted)
- Can be overcome by reconditioning (Tabeart et al 2020a,b - see poster)
- Many centres have improved NWP skill (Met Office, ECMWF, NRL, ECCC, Meteo France, JCSDA...).

Using more observations (Simonin et al, 2019)

- Reduce spatial thinning and assimilate 4x number of Doppler radar wind observations by taking account of spatial correlations
- **R** is derived on-the-fly (different observations each assimilation)
- Correlation lengthscale determined by fitting to diagnosed horizontal correlations



- Clever load balancing leads to improved NWP skill without increase in wall-clock time. (See also Guannan Hu's poster!)

Conclusions

- Diagnosis of **R** requires care!
  - Careful experimental design
  - Sensitivity to assumed statistics
  - Local DA - diagnosis only valid for some observation pairs
  - Sampling error- could this change correlation lengths?

Conclusions

- Diagnosis of **R** requires care!
  - Careful experimental design
  - Sensitivity to assumed statistics
  - Local DA - diagnosis only valid for some observation pairs
  - Sampling error- could this change correlation lengths?
- But many benefits to be gained !
  - Good estimates of uncertainty (some limited evidence)
  - Identification of error sources (that could be corrected)
  - Using diagnosed estimates improves NWP skill
  - Reduce thinning (high resolution forecasting) improving skill without increasing wall-clock time (some evidence)

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