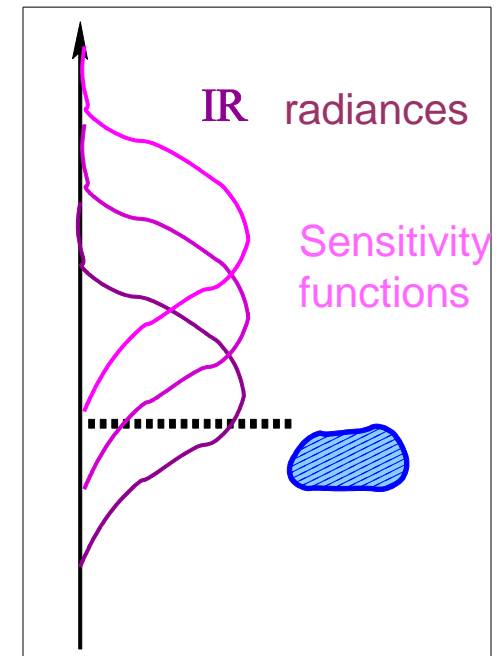


# A probabilistic tool for the cross validation of observations

Olaf Stiller, Deutscher Wetterdienst

*Are the observations consistent*

- *with the background given*
  - *assumed errors*
  - *observation operator ?*
- *with the other observations ?*



*Does the observation operator (properly) deal with the cloud???*

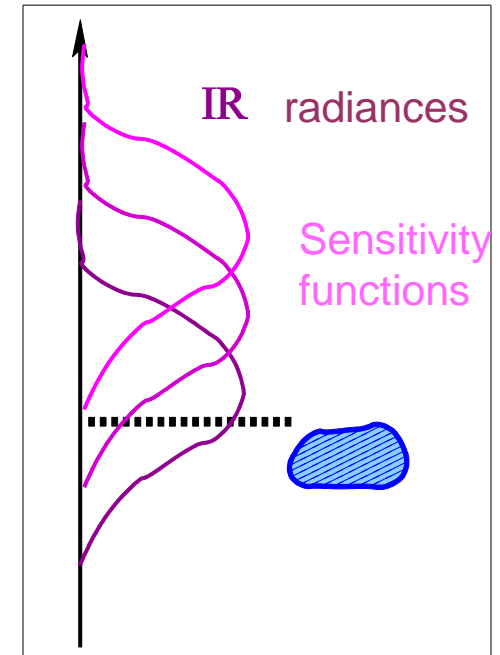
Aim: identify observations which are not consistent with the assumptions made in the DA system

### First Guess checks

- Check consistency of observation with first guess
- Only works if inconsistencies are **very strong**

#### *Are the observations consistent*

- *with the background given*
  - *assumed errors*
  - *observation operator ?*
- *with the other observations ?*



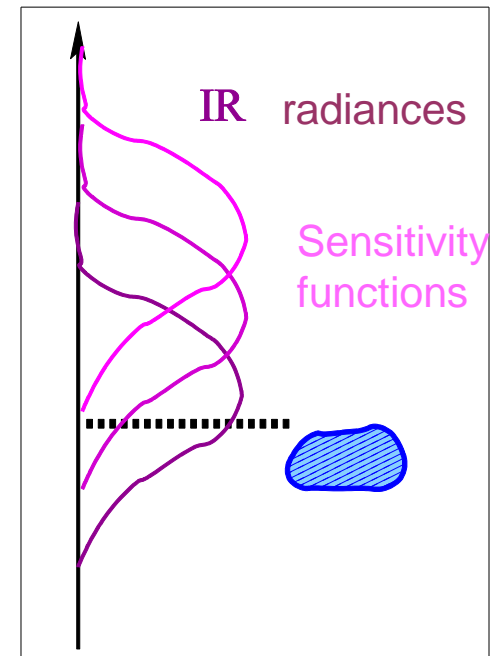
*Does the observation operator (properly) deal with the cloud???*

Aim: identify observations which are not consistent with the assumptions made in the DA system

- Q. : Can we check the consistency of observations
- with other observations
  - using the probabilistic framework of the DA system?

*Are the observations consistent*

- *with the background given*
  - *assumed errors*
  - *observation operator ?*
- *with the other observations ?*



*Does the observation operator (properly) deal with the cloud???*

# Assumed uncertainties in data assimilation

Most DA schemes minimise a quadratic costfunction

$$J(\mathbf{x}) = \frac{1}{2} [\mathbf{x}^T \mathbf{B}^{-1} \mathbf{x} + (\mathbf{y}^o - \mathbf{H}\mathbf{x})^T \mathbf{R}^{-1} (\mathbf{y}^o - \mathbf{H}\mathbf{x})]$$

$$\mathbf{x} = \mathbf{X} - \mathbf{X}^b$$

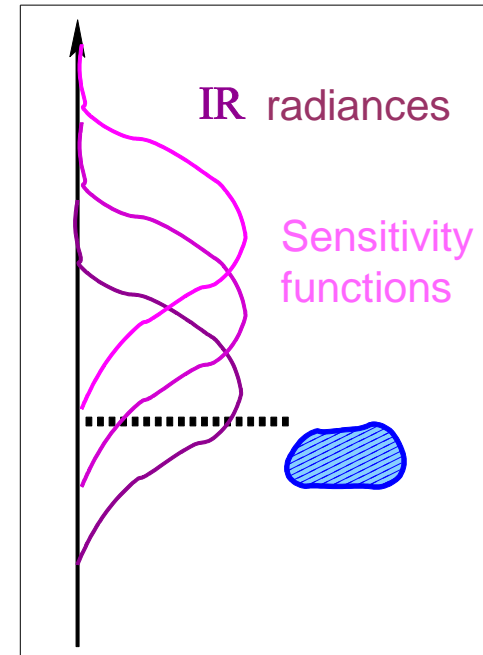
$$\mathbf{y}^o = \mathbf{Y}^o - \mathbf{Y}^b$$

$\mathbf{H}$  : linearised observation operator

Assumed Gaussian error statistic:

Covariance matrix of

- Observation error  $\mathbf{R} = \langle (\mathbf{Y} - \mathbf{Y}^o)^T (\mathbf{Y} - \mathbf{Y}^o) \rangle$
- background error  $\mathbf{B} = \langle (\mathbf{X} - \mathbf{X}^b)^T (\mathbf{X} - \mathbf{X}^b) \rangle$
- background error in observation space  $\mathbf{H}^T \mathbf{B} \mathbf{H} = \langle (\mathbf{H}\mathbf{x})^T (\mathbf{H}\mathbf{x}) \rangle$
- $\mathbf{y}^o = \mathbf{Y}^o - \mathbf{Y}^b$   
obs - first guess  $\langle (\mathbf{y}^o)^T \mathbf{y}^o \rangle = \mathbf{H}^T \mathbf{B} \mathbf{H} + \mathbf{R}$





Assumed Gaussian error statistic:

- $\mathbf{y}^o = \mathbf{Y}^o - \mathbf{Y}^b$   
obs - first guess

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

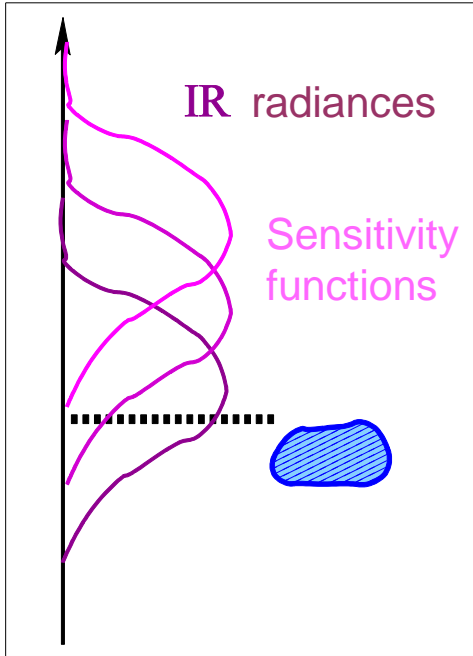
$$\langle (\mathbf{y}_k^o)^2 \rangle = [\mathbf{H}^T \mathbf{B} \mathbf{H} + \mathbf{R}]_{kk} = \sigma_k^2$$

Conditional probability of the observations  $\mathbf{y}_k^o$  (given the background):

$$P(\mathbf{y}_k^o | \mathbf{X}^b) \propto \exp -\frac{1}{2} \left( \frac{\mathbf{y}_k^o}{\sigma_k} \right)^2$$

Cross-Validation with background (standard Quality Control check):

$$n \text{ sigma check: } \left| \frac{\mathbf{y}_k^o}{\sigma_k} \right| < n$$





Assumed Gaussian error statistic:

- $\mathbf{y}^o = \mathbf{Y}^o - \mathbf{Y}^b$   
obs - first guess

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

## Cross-Validation with background and observations $\mathbf{y}_{\tau^C}^o$ :

decompose observations:  $\mathbf{y}^o = \{\mathbf{y}_{\tau^C}^o, \mathbf{y}_{\tau}^o\}$

Conditional probability of observations  $\mathbf{y}_{\tau}^o$  (given the background and observations  $\mathbf{y}_{\tau^C}^o$ ):

$$P(\mathbf{y}_{\tau}^o | \mathbf{y}_{\tau^C}^o, \mathbf{X}^b) \propto \exp -\frac{1}{2} \left\{ (\mathbf{y}_{\tau}^o - \bar{\mathbf{y}}_{\tau})^T \mathbf{D}_{\tau} (\mathbf{y}_{\tau}^o - \bar{\mathbf{y}}_{\tau}) \right\}$$

$$[\mathbf{H}^T \mathbf{B} \mathbf{H} + \mathbf{R}]^{-1} = \begin{pmatrix} \mathbf{D}_{\tau^C} & \mathbf{C}_{\tau}^T \\ \mathbf{C}_{\tau} & \mathbf{D}_{\tau} \end{pmatrix}$$

$$\bar{\mathbf{y}}_{\tau} \equiv -\mathbf{D}_{\tau}^{-1} \mathbf{C}_{\tau} \mathbf{y}_{\tau^C}^o$$

If R matrix is diagonal:

$$\bar{\mathbf{y}}_{\tau} = \mathbf{y}_{\tau}^{a\{\tau^C\}} = \mathbf{H}_{\tau} \left[ \mathbf{x}^{a\{\tau^C\}} \right]$$

(Analysis using only  $\mathbf{y}_{\tau^C}^o$ )



# Application: Identifying the Impact of Localized Features



## Testing: *Can the observation operator properly deal with clouds?*

Radiance measurements can be **ordered** (at least roughly) according to their **likeliness** to be affected by clouds

$$P(\mathbf{y}_k | \mathbf{y}_{\{l < k\}}, \mathbf{x}^b) = N^{-1} \exp -\frac{1}{2} \{ \mathbf{Y}_k^2 \}$$

$$\mathbf{Y} = \mathbf{T}_L^{-1} \mathbf{y}$$

$$[\mathbf{R} + \mathbf{H}\mathbf{B}\mathbf{H}^T] = \mathbf{T}_L \mathbf{T}_U$$

$$[\mathbf{R} + \mathbf{H}\mathbf{B}\mathbf{H}^T]^{-1} = \mathbf{T}_U^{-1} \mathbf{T}_L^{-1}$$

Cholesky decomposition

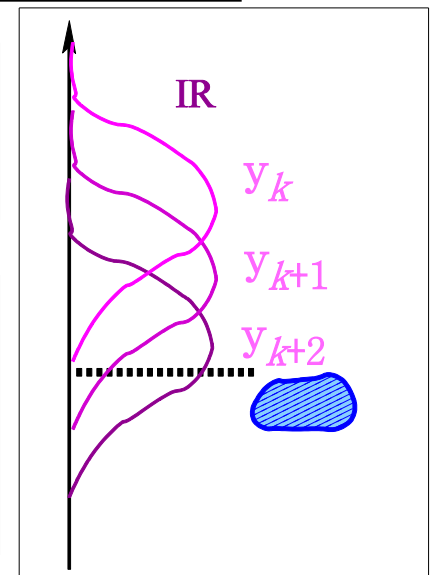
$$\mathbf{T}_U = \mathbf{T}_L^T$$

$$\mathbf{T}_L \mathbf{T}_U = \begin{pmatrix} \begin{bmatrix} t_{11} & 0 \\ t_{21} & t_{22} & 0 \\ \vdots & \vdots & \vdots & 0 \\ t_{k1} & t_{k2} & t_{kk} & 0 \end{bmatrix} & 0 \\ \vdots & \vdots & \vdots & \vdots & 0 \\ t_{p1} & \vdots & \vdots & \vdots & t_{pp} \end{pmatrix} = [\mathbf{R} + \mathbf{H}\mathbf{B}\mathbf{H}^T]$$

$$\mathbf{T}_L \mathbf{Y} = \begin{pmatrix} \begin{bmatrix} t_{11} & 0 \\ t_{21} & t_{22} \\ \vdots & \vdots & \vdots & 0 \\ t_{k1} & t_{k2} & t_{kk} & 0 \end{bmatrix} & 0 \\ \vdots & \vdots & \vdots & \vdots & 0 \\ t_{p1} & \vdots & \vdots & \vdots & t_{pp} \end{pmatrix} \begin{pmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \\ \vdots \\ \mathbf{Y}_k \\ \vdots \\ \mathbf{Y}_P \end{pmatrix} = \begin{pmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_k \\ \vdots \\ \mathbf{y}_P \end{pmatrix}$$

Stratospheric channels are never affected by clouds

Vulnerability increases the deeper weighting functions enter into the troposphere



# Application: 1D Var for

## dealing with Localized Features



$$\begin{aligned} \mathbf{x}^a &= \mathbf{B}\mathbf{H}^T [\mathbf{R} + \mathbf{H}\mathbf{B}\mathbf{H}^T]^{-1} \mathbf{y} \\ &= \mathbf{B}\mathbf{H}^T \mathbf{T}_U^{-1} \mathbf{T}_L^{-1} \mathbf{y} \\ &= \mathbf{B}\mathbf{H}^T \mathbf{T}_U^{-1} \mathbf{Y} \end{aligned}$$

- Order observations according to their vulnerability

- Do outer\_loop=1, Nmax

Compute first  $\mathbf{Y} = \mathbf{T}_L^{-1} \mathbf{y}$

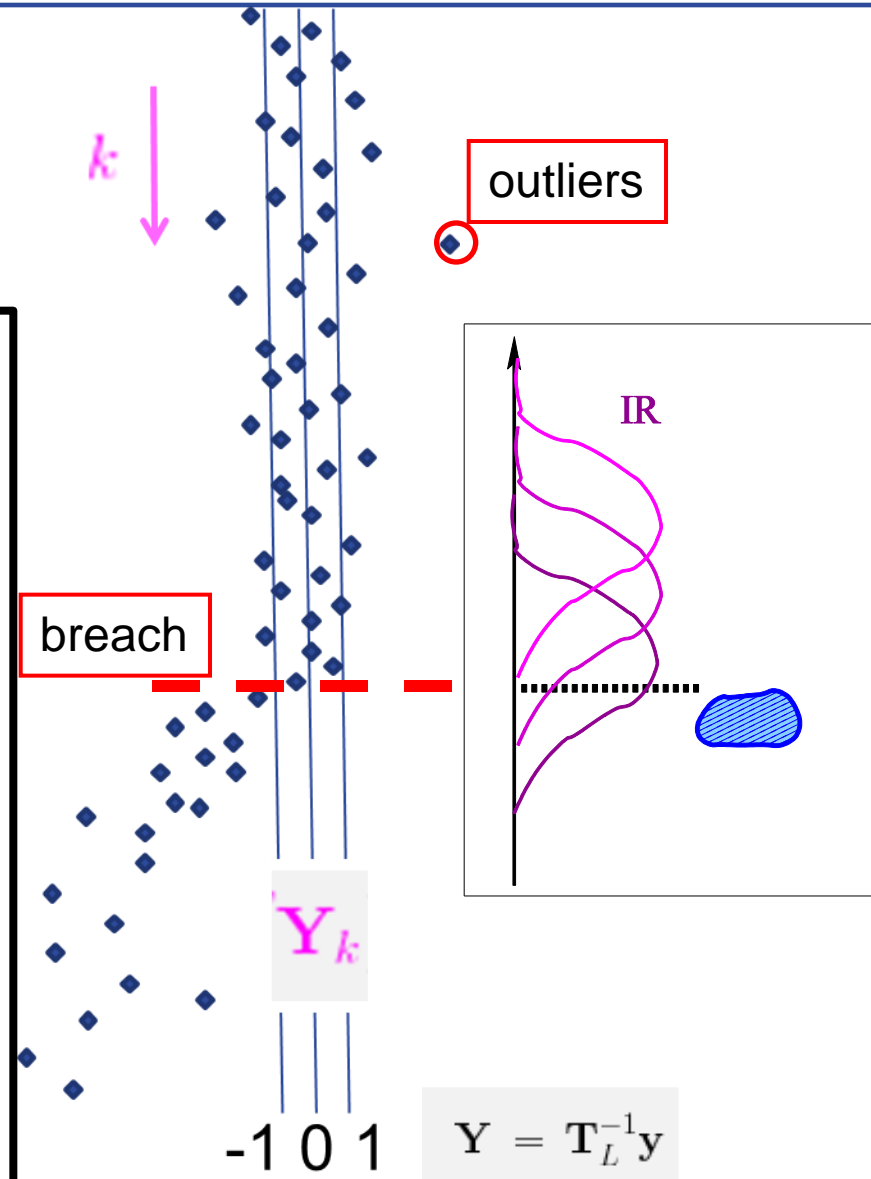
- Do  $k=1$ , numb.of observations

- Compute  $\mathbf{Y}_k$
- Flag (reject) outliers
- Test for breaches
  - ✓ Reject all observations after breach

End Do

Compute  $\mathbf{x}^a = \mathbf{B}\mathbf{H}^T \mathbf{T}_U^{-1} \mathbf{Y}$   
only from *good* observations

- End Do ! outer loops

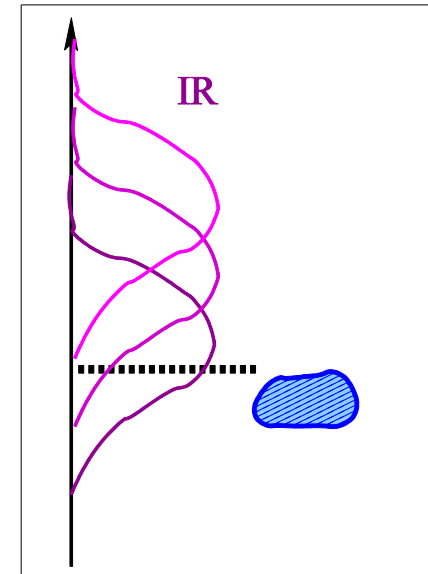




# Some applications of the 1D Var system



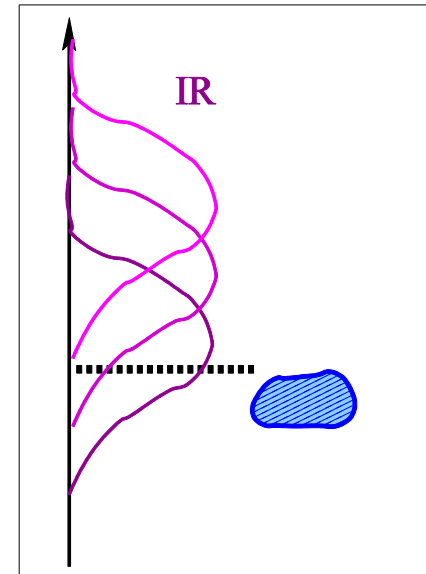
- **Stand alone:**
  - Testing of observation operators dealing with strong nonlinearities related to
    - clouds
    - landsurfaces
    - any localised feature or perturbation
- **Inline with full DA system:**
  - Preprocessing (Quality Control) of satellite radiances: Flagging channels inconsistent with
    - the channels above
    - the linearised form of the observation operator **used at a given outer loop**



# Summary and Conclusions



- A cross validation method for observations has been developed which
  - works within the probabilistic framework of the DA system
  - puts a powerful constraint on observations if
    - observation operators sufficiently overlap
    - observation errors are sufficiently small
- The design of a 1D Var system has been outlined which
  - allows
    - observation cross validation at **almost no additional cost**
    - the detection of outliers
    - the detection of breaches
    - the flagging of bad observation **before** they enter into the analysis
  - can be used for
    - Stand alone: E.g., testing of observation operators
    - Inline with the full DA system: Preprocessing of observations
    -





Thank you for listening



**Probability** given background and observations  $\mathbf{y}_{\tau}^o$ :

$$P(\mathbf{y}_{\tau}^o | \mathbf{y}_{\tau}^o, \mathbf{X}^b) \propto \exp -\frac{1}{2} \left\{ (\mathbf{y}_{\tau}^o - \bar{\mathbf{y}}_{\tau})^T \mathbf{D}_{\tau} (\mathbf{y}_{\tau}^o - \bar{\mathbf{y}}_{\tau}) \right\}$$

$$\propto \exp -\frac{1}{2} \left\{ \mathbf{z}_{\tau}^T \mathbf{D}_{\tau}^{-1} \mathbf{z}_{\tau} \right\}$$

$$\mathbf{z} = [\mathbf{H}^T \mathbf{B} \mathbf{H} + \mathbf{R}]^{-1} \mathbf{y}^o$$

$$[\mathbf{H}^T \mathbf{B} \mathbf{H} + \mathbf{R}]^{-1} = \begin{pmatrix} \mathbf{D}_{\tau} & \mathbf{C}_{\tau}^T \\ \mathbf{C}_{\tau} & \mathbf{D}_{\tau} \end{pmatrix}$$

**Expectation value**  $\bar{\mathbf{y}}_{\tau}$  given background and observations  $\mathbf{y}_{\tau}^o$ :

$$(\mathbf{y}_{\tau}^o - \bar{\mathbf{y}}_{\tau}) = \mathbf{D}_{\tau}^{-1} \mathbf{z}_{\tau}$$

$$\bar{\mathbf{y}}_{\tau} = \mathbf{y}_{\tau}^a \{ \tau^C \} + \mathbf{R}_{\tau, \tau^C} \mathbf{R}_{\tau^C}^{-1} (\mathbf{y}_{\tau}^o - \mathbf{y}_{\tau^C}^a \{ \tau^C \})$$

$$\mathbf{y}_{\tau}^a \{ \tau^C \} = \mathbf{H}_{\tau} [\mathbf{x}^a \{ \tau^C \}] \quad (\text{Analysis using only } \mathbf{y}_{\tau}^o)$$

$$\text{if } \mathbf{R}_{\tau, \tau^C} = 0$$

$$\mathbf{R}_{\tau, \tau^C} = \langle (\mathbf{y}_{\tau}^o - \mathbf{y}_{\tau}^t) (\mathbf{y}_{\tau^C}^o - \mathbf{y}_{\tau^C}^t) \rangle$$

error cross correlations:

$$(\mathbf{y}_{\tau}^o - \bar{\mathbf{y}}_{\tau}) = \{ [\mathbf{R}^{-1} (\mathbf{1} - \mathbf{S})]_{\tau} \}^{-1} \mathbf{R}_{\tau}^{-1} (\mathbf{y}_{\tau}^o - \mathbf{y}_{\tau}^a)$$

$$\text{if } \mathbf{R}_{\tau, \tau^C} = 0$$

$$= (\mathbf{1}_{\tau} - \mathbf{S}_{\tau})^{-1} (\mathbf{y}_{\tau}^o - \mathbf{y}_{\tau}^a)$$

self sensitivity matrix:

$$\mathbf{S} = \mathbf{H} \mathbf{K}$$

Kalman gain matrix

compare: Liu, Kalnay, Miyoshi and Cardinali, QJ 2009 : Analysis sensitivity calculation in an ensemble Kalman filter

