Assimilation of transformed retrievals applied to MTG-IRS

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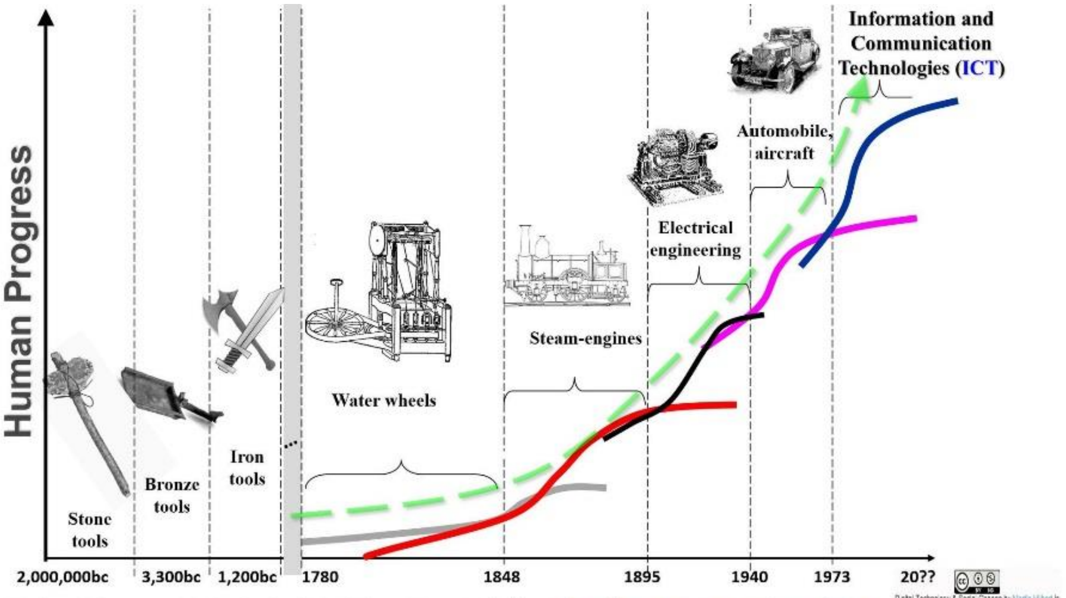
Laura Stewart, David Davies

Outline

- Motivation
- Transformed retrievals: definition and significance
- Results with simulated data
- DFS weighting function
- First results with real IASI data (new!)
- Discussion and future work

E-volution

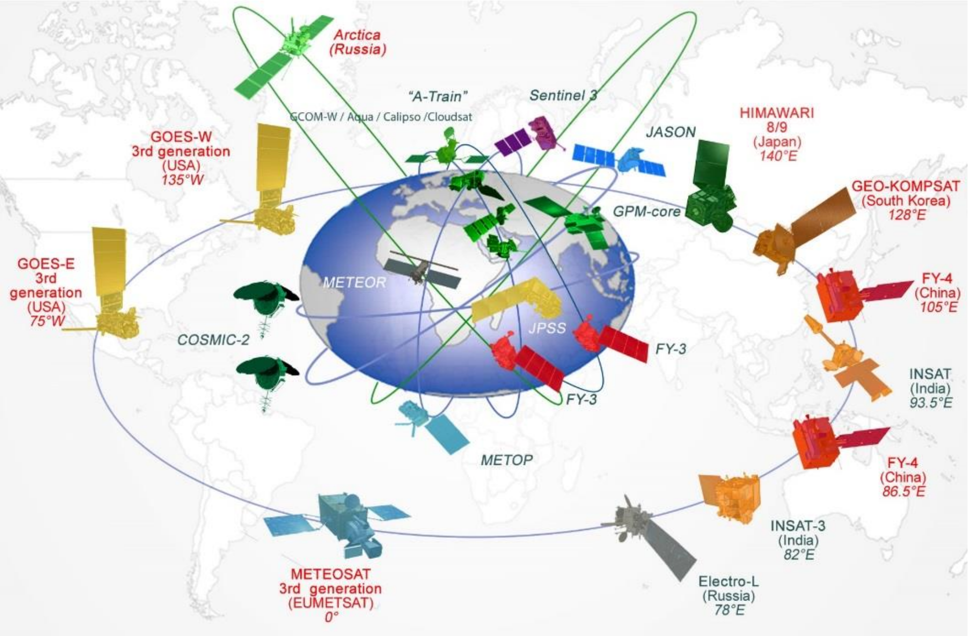
- Since the beginning of the Information Age, marked by the Digital Revolution, humanity has been processing, transmitting/receiving and storing data represented in form of binary digits or bits
- Data proliferation (Big Data), including from satellite platforms



M. Hilbert, Online Course *Digital Technology & Social Change*, University of California: https://canvas.instructure.com/courses/949415

The new generation of Meteorological satellites

- planned to enter operations in the 2015-2020 period



From WMO-CGMS Satellite User Readiness Navigator (SATURN)

Valuable information

- When observations are used to update an already available estimate of a set of parameters we can say that they generate Information
- First described mathematically by Claude Shannon
- The value we give to information depends on how we use it.
- Here the purpose of information from satellite measurements is improving numerical weather predictions.

Assimilation of satellite data

- Satellite radiances are currently assimilated by major operational NWP centres
- It can be shown (Migliorini 2012, Prates et al. 2016) that an equivalent strategy is to assimilate transformed retrieval components using their own jacobians (linearized obs operators)
- If reasonable (and conservative) knowledge of prior pdf used by NWP centres is available, transformed retrievals can be produced and disseminated by external data providers

Transformed retrievals

- Linearized and normalized measurements

$$\mathbf{y}^o \cong \mathbf{H}\mathbf{x}^t + \varepsilon^o \qquad \mathbf{y}' \cong \mathbf{R}^{-1/2}\mathbf{H}\mathbf{x}^t + \mathbf{R}^{-1/2}\varepsilon \equiv \mathbf{H}'\mathbf{x}^t + \varepsilon'$$

$$\mathrm{cov}(\varepsilon^o) = \mathbf{R} \qquad \mathrm{cov}(\varepsilon') = \mathbf{I}$$

- Projection onto signal-to-noise basis (in obs space)

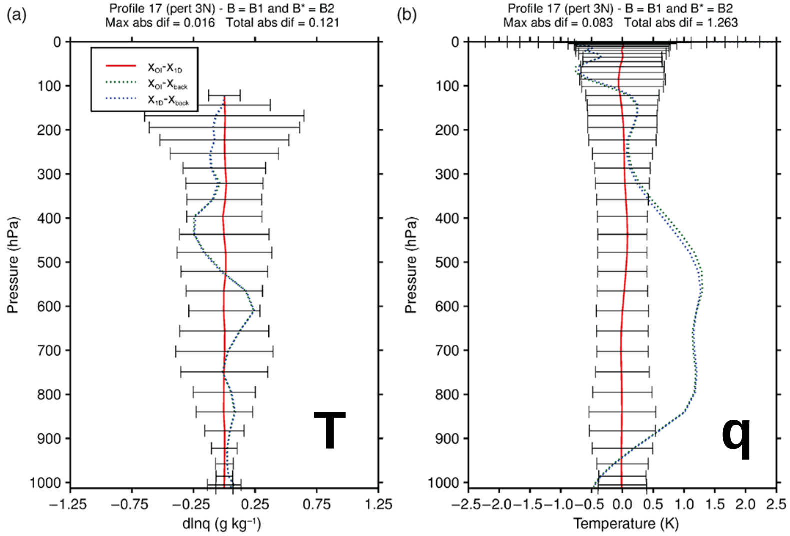
$$\mathbf{S} = \mathbf{R}^{-1/2}\mathbf{H}\mathbf{B}^{1/2} = \mathbf{H}'\mathbf{B}^{1/2} = \mathbf{U}\Lambda\mathbf{V}^T$$

$$\mathbf{y}_{ret} = \mathbf{U}_r^T\mathbf{y}' \qquad \mathbf{H}_{ret} = \mathbf{U}_r^T\mathbf{H}' = \Lambda\mathbf{V}^T\mathbf{B}^{-1/2}$$

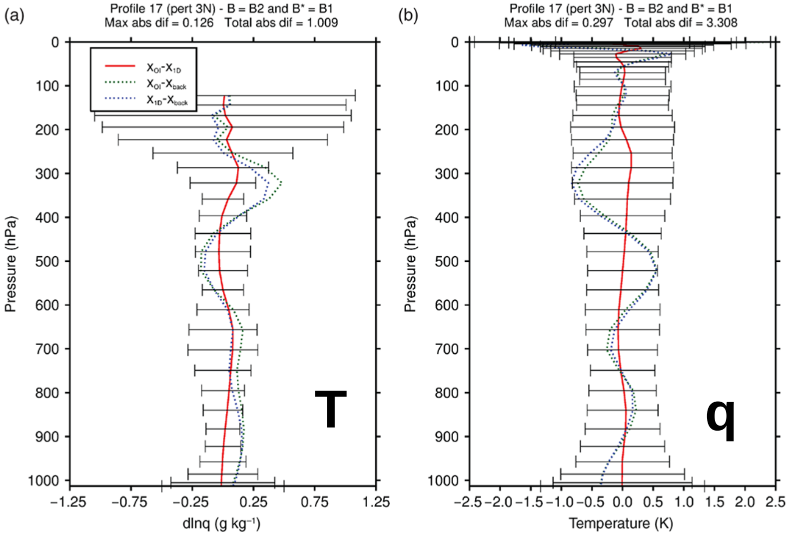
- signal-to-noise matrix **S**, with r = rank(**S**) ≤ min(m,n)
- $\mathbf{y}_{ret}$ is assimilated with $\mathbf{H}_{ret}$

Transformed retrievals from simulated radiances

$B = B_1$; $B^* = B_2$



$B = B_2$; $B^* = B_1$



Prates et al. (2016)

- TransRet with **B** assimilated with $\mathbf{B}^*$
- Best results when $\det(\mathbf{B}_1) > \det(\mathbf{B}_2)$

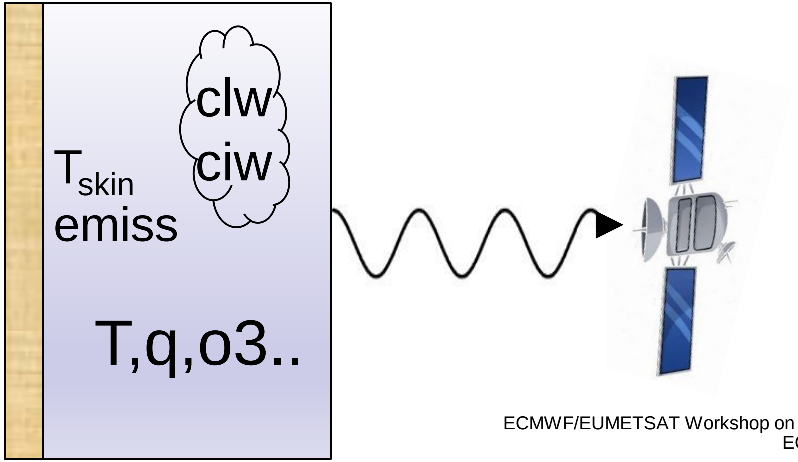
Sources of information from satellite data

- Signal-to-noise matrix **S** is non-dimensional and its singular values are directly linked to information

$$\mathbf{S} = \mathbf{R}^{-1/2}\mathbf{H}\mathbf{B}^{1/2} \qquad \mathbf{y}' \cong \mathbf{R}^{-1/2}\mathbf{H}\mathbf{x}^{t} + \varepsilon' \equiv \mathbf{S}\mathbf{B}^{-1/2}\mathbf{x}^{t} + \varepsilon' = \mathbf{S}\mathbf{x}' + \varepsilon'$$

$$\mathbf{x} = (\mathbf{T}, \mathbf{q}, \mathbf{o3}, \mathbf{clw}, \mathbf{ciw}, T_{skin}, e)^{T} \qquad E(\mathbf{x}) = -\int_{S} p(\mathbf{x}) \log_2 p(\mathbf{x}) d\mathbf{x}$$

$$I(\mathbf{x};\mathbf{y}) = E(\mathbf{x}) - E(\mathbf{x} \mid \mathbf{y}) \qquad E(T,q) = E(T) + E(q \mid T) \leq E(T) + E(q)$$



- Information about the full state not equal to sum of information on its parts (true only if independent)
- Information is on rotated state, not on vertical levels

DFS weighting function

$$\mathbf{S} = \mathbf{R}^{-1/2}\mathbf{H}\mathbf{B}^{1/2} = \mathbf{H}'\mathbf{B}^{1/2} = \mathbf{U}\Lambda\mathbf{V}^T$$

$$d_s = \sum_{i=1}^{r} \frac{\lambda_i^2}{1+\lambda_i^2} = \sum_{i=1}^{r} d_{si}$$

When **B** = ∑ = diag(**B**)

$$\mathbf{s}_i = d_{si}\left(v_{1i}^2, \cdots, v_{ni}^2\right) = d_{si}\mathbf{v}_i \circ \mathbf{v}_i$$

See Migliorini 2015; Prates et al., 2016

- Cumulative DFS weighting function

$$\mathbf{s} = \sum_{i=1}^{r} \mathbf{s}_i = \sum_{i=1}^{r} d_{si}\left(v_{1i}^2, \cdots, v_{ni}^2\right) = \sum_{i=1}^{r} d_{si}\mathbf{v}_i \circ \mathbf{v}_i$$

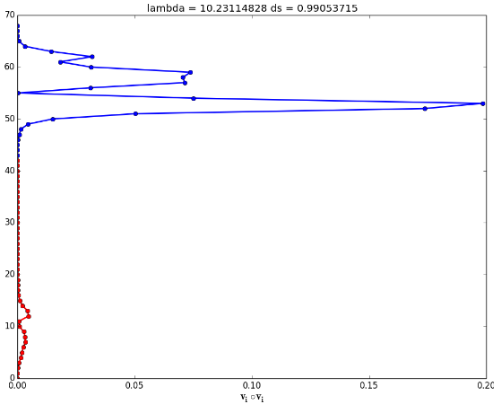
DFS weighting function

- Differential measure of information

i=3; λ=10.2

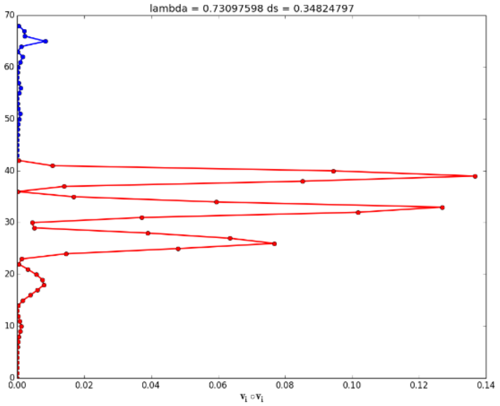
q

T



$v_i \circ v_i$

i=10; λ=0.73

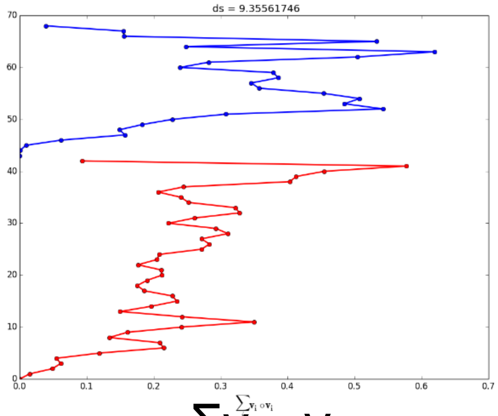


$v_i \circ v_i$

cumulative; ds=9.36

q

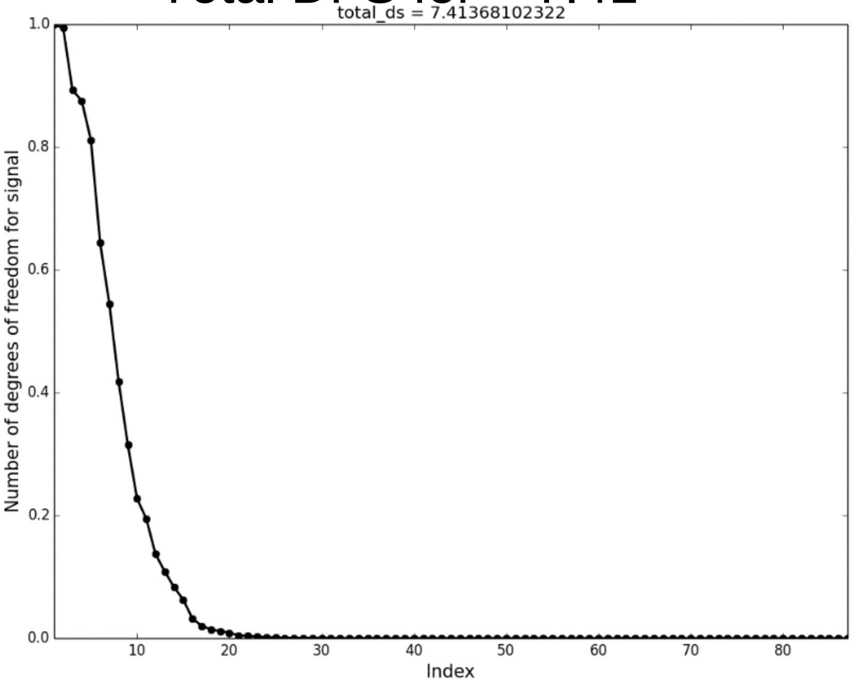
T



$\Sigma v_i \circ v_i$

Total number of DFS

Total DFS for = 7.41

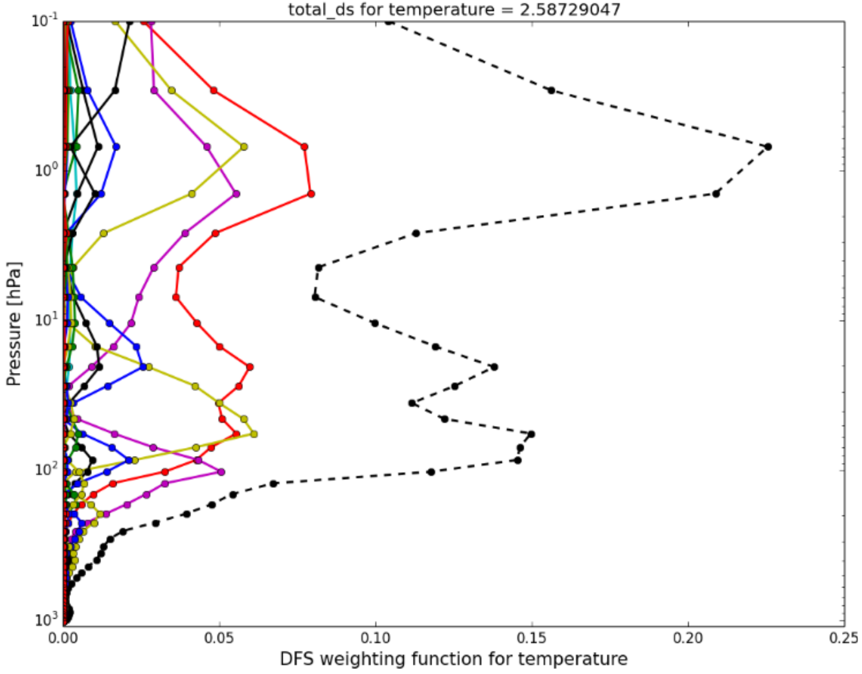


$$d_s = \sum_{i=1}^{r} \frac{\lambda_i^2}{1+\lambda_i^2} = \sum_{i=1}^{r} d_{si}$$

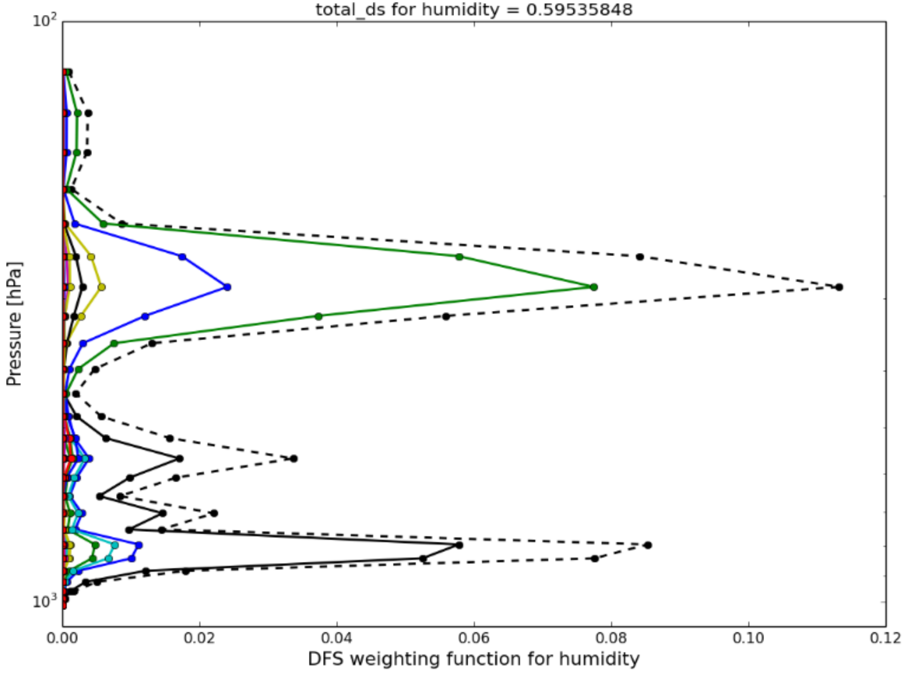
- Only ~10 components with “large” DFS

DFS wf for T and q

Total DFS for T = 2.59

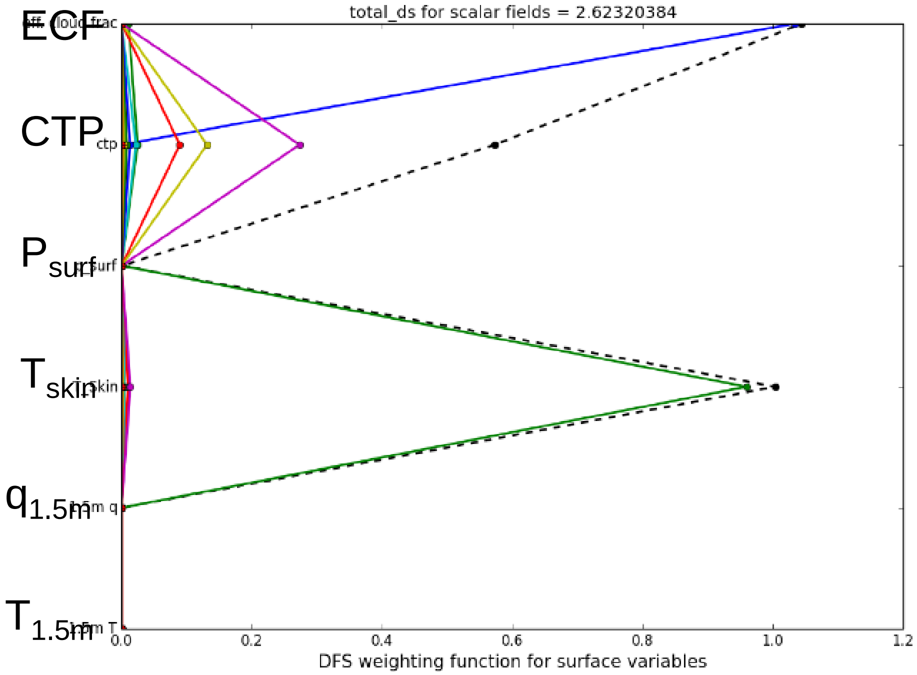


Total DFS for q = 0.60

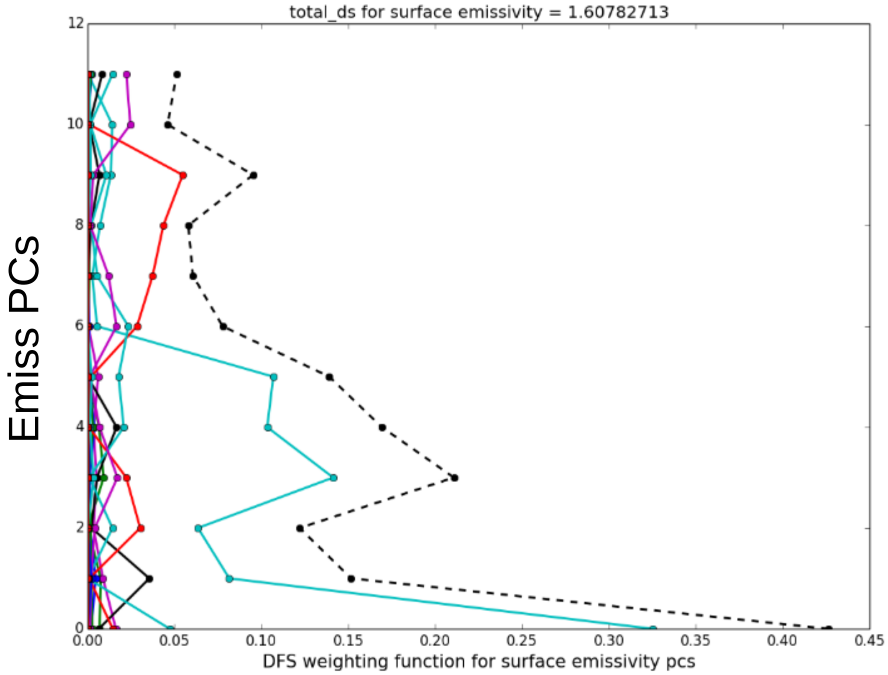


DFS wf for surface fields

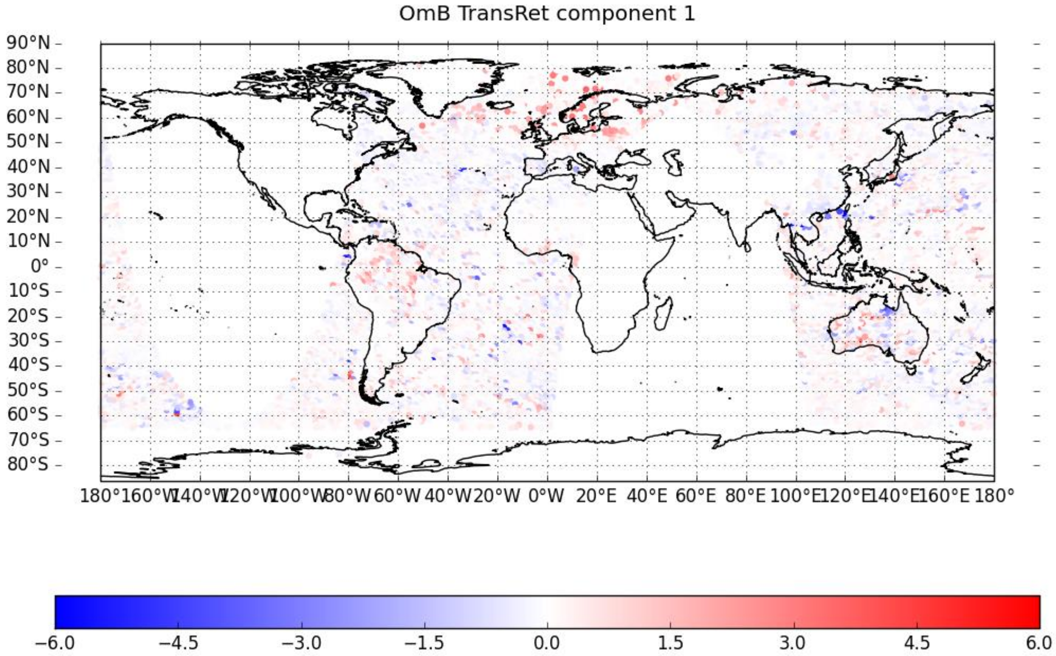
Total DFS for surface = 2.62



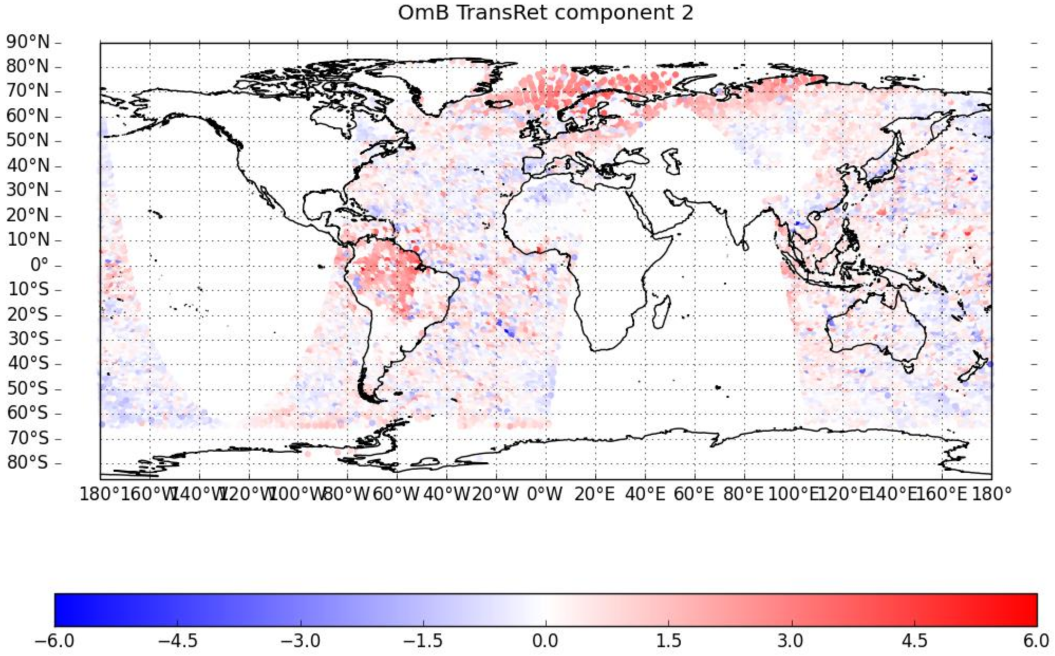
Total DFS for emiss = 1.61



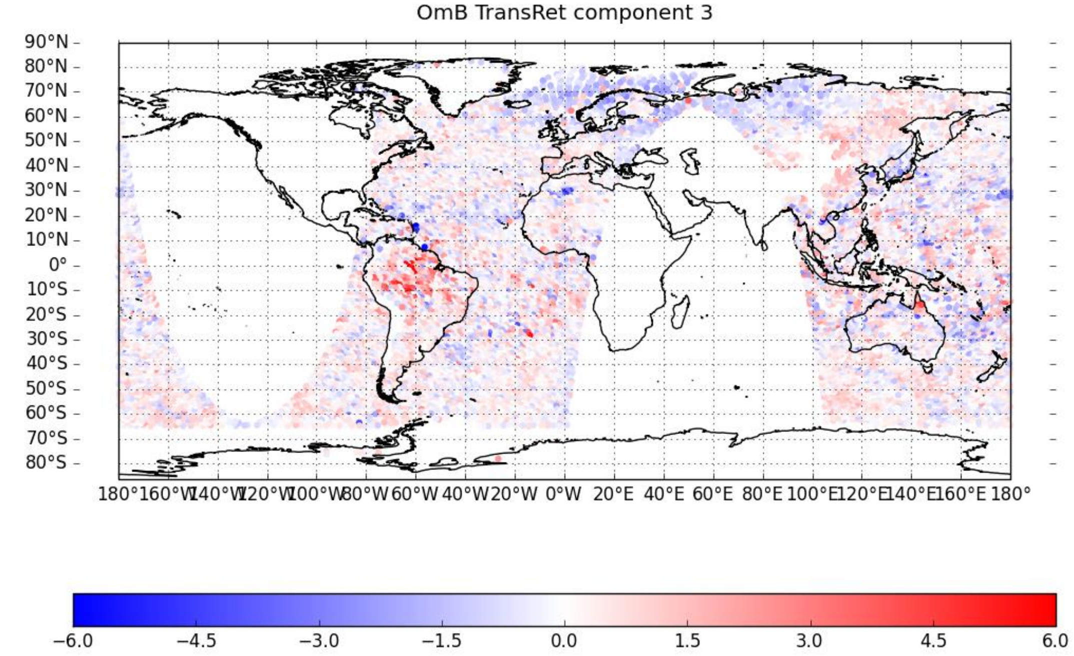
TransRet OmB: component 1



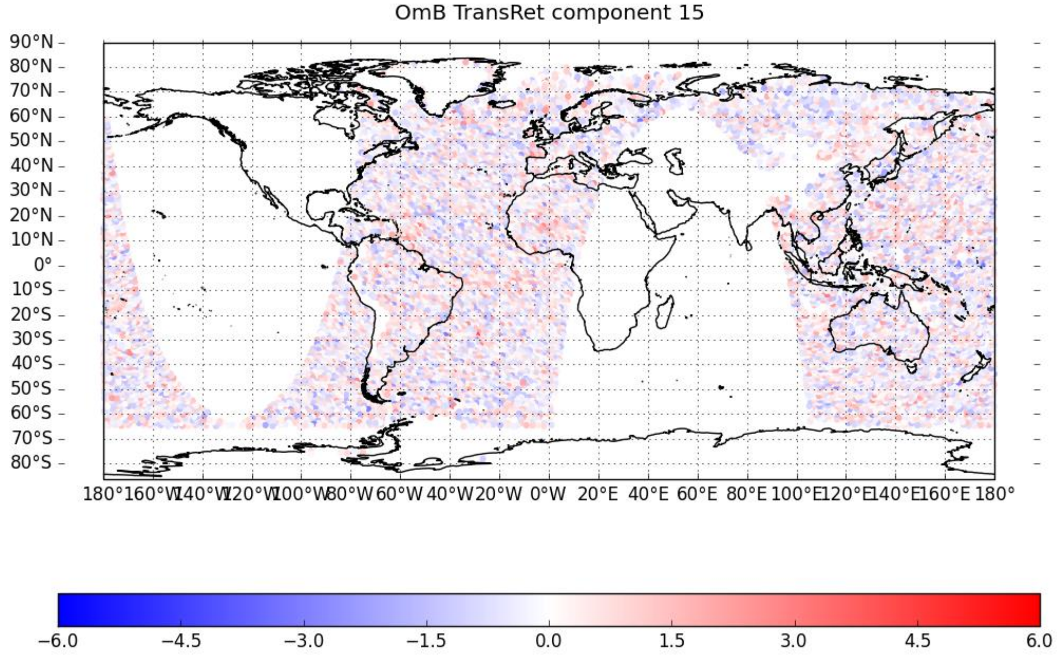
TransRet OmB: component 2



TransRet OmB: component 3



TransRet OmB: component 15

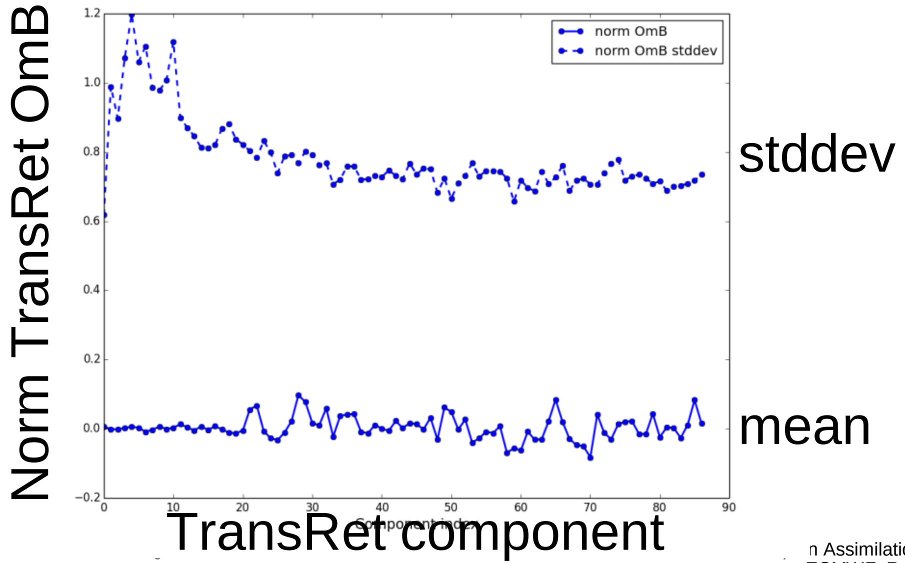


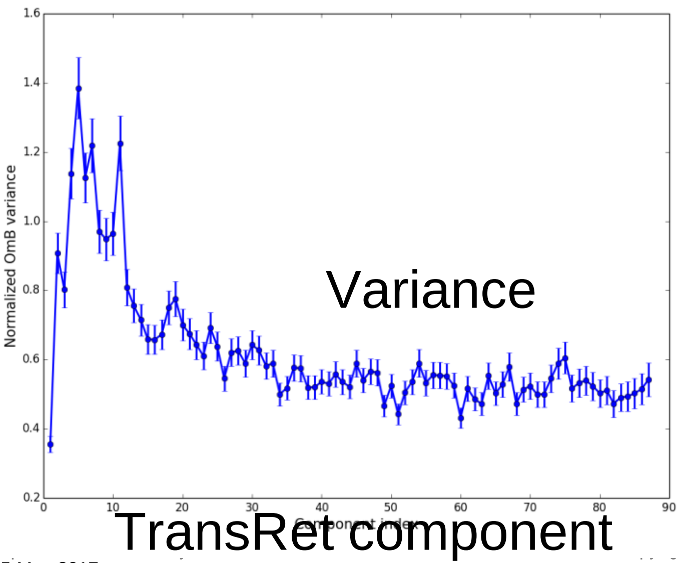
OmB TransRet stats

$$\mathrm{cov}(\mathbf{y}_{ret} - \mathbf{H}_{ret}\mathbf{x}^f) = \boldsymbol{\Lambda}_r^2 + \mathbf{I}_r \quad \mathrm{cov}\left(\left(\boldsymbol{\Lambda}_r^2 + \mathbf{I}_r\right)^{-1/2}\left(\mathbf{y}_{ret} - \mathbf{H}_{ret}\mathbf{x}^f\right)\right) = \mathbf{I}_r$$

- When real B = α B and real R = β R:

$$\mathrm{cov}\left(\left(\boldsymbol{\Lambda}_r^2 + \mathbf{I}_r\right)^{-1/2}\left(\mathbf{y}_{ret} - \mathbf{H}_{ret}\mathbf{x}^f\right)\right) = \left(\boldsymbol{\Lambda}_r^2 + \mathbf{I}_r\right)^{-1}\left(\alpha\boldsymbol{\Lambda}_r^2 + \beta\mathbf{I}_r\right) \xrightarrow[\lambda \to 0]{} \beta, \quad \xrightarrow[\lambda >> 1]{} \alpha$$





Critical issues: bias correction

- Eigenvectors direction well defined, not their sign
- Not an issue in the absence of bias

$$\mathbf{y}_{ret} = \mathbf{U}_r^T \mathbf{y}' \cong \mathbf{U}_r^T \mathbf{H}' \mathbf{x}^t + \mathbf{U}_r^T \varepsilon' + \mathbf{U}_r^T \mathbf{b}$$

- We need consistent choice of eigenvector signs
- Possible choices: ensuring positive peak; ensuring positive integral

Critical issues: data reduction

- When TransRet are from a data provider, can we achieve savings wrt dissemination of *m* radiances?

$$\dim(\mathbf{y}_{ret}) = r \le \min(m, n) \qquad \dim(\mathbf{H}_{ret}) = rn$$

- Typically r = O(10), n = O(100)
- For each ob we need to disseminate O(10^3) floats
- Advantages when $m \gg rn$ = O(10^3) and for centres not using radiance assimlation

Critical issues: channel and state selection

- Production/dissemination of transformed retrievals need to be consistent with ability of data user to represent the same state vector (e.g. ozone, surface…)

- We need to avoid/minimise contamination from parts of the state users can't model: channel selection

- Parts of the retrieved state that are not present in DA state should be discarded and their variability should add to TranRet uncertainty

Conclusions

- Transformed retrievals conserve information contained in satellite radiances
- DFS wf can be used to explore their information content
- At the Met Office TransRet can now be produced from real remote sounding data (namely from IASI)
- First results are encouraging (reasonable OmB stats, done directly on TransRet components)
- Future work: assimilation in VAR; applications to MTG-IRS/GIIRS; evaluation in all-sky conditions