Information content of radiance climatologies

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- Sean Healy, ECMWF
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- Fiona Hilton, Met Office

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Outline

- Motivation
- Optimal estimation of radiances
- Consequences for retrieval accuracy
- Conclusions

Motivation (1)

- Assimilation of radiances in NWP:
  - normally 2 sources of information:
    - measured radiances
    - NWP background
- Now we have 3rd source - “radiance climatology”:
  - a large ensemble of “historical” radiances from the same instrument, used to compute the PCs

→ Question: What are the implications of this, for information content, analysis error, etc.?

Motivation (2)

- The “engineering” properties of the PCs of spectra from advanced IR sounders have been demonstrated:
  - More compact representation of information in full spectrum
  - Faster computations for forward and inverse problems
  - Noise reduction – cleans up the spectrum – potentially important when carefully selected small spectral windows must be used

- … but do the “radiance climatologies” used to compute these PCs also contain information to improve the retrieval, when all/most channels are used?

Optimal estimation of radiances (1)

radiance information

observation:	$\mathbf{y^o}$	error cov, $\mathbf{N}$
radiance climatology:	mean, $\mathbf{y^m}$	covariance, $\mathbf{C}$

definitions

$\mathbf{C_o} = \mathbf{C} + \mathbf{N}$ = climatological covariance including noise

$\mathbf{N^{-1/2} C_o N^{-1/2}} = \mathbf{E \Lambda E^T}$; eigenvector rep. in noise-normalised space

Change space: – noise-normalise, rotate, truncate

observation:	$\mathbf{E_{tr}^T N^{-1/2} (y^o - y^m)}$	error cov, $\mathbf{I_{tr}}$
radiance climatology:	$\mathbf{0}$	covariance, $\mathbf{\Lambda_{tr} - I_{tr}}$

Optimal estimation of radiances (2)

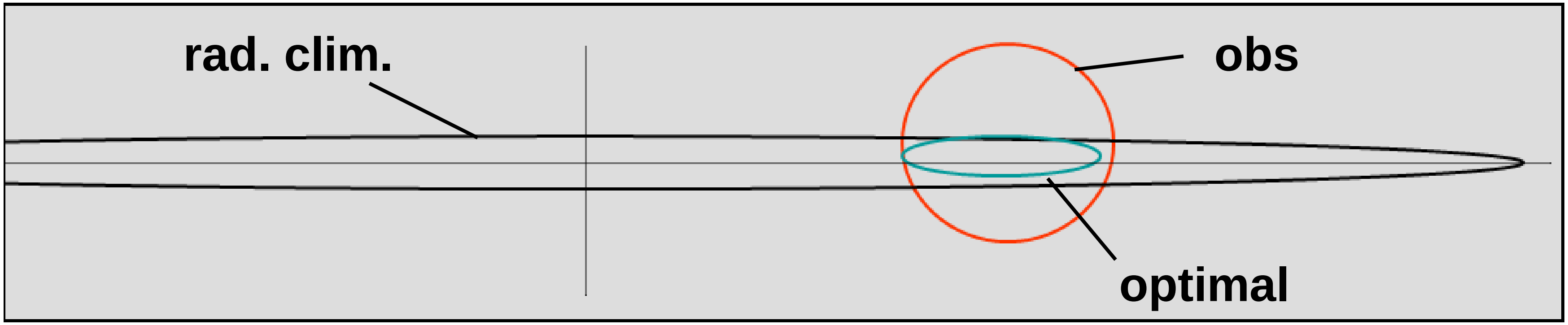
observation: $\mathbf{E_{tr}}^T \mathbf{N}^{-½} (\mathbf{y}^o\text{-}\mathbf{y}^m)$ error cov, $\mathbf{I_{tr}}$

radiance climatology: **0** covariance, $\mathbf{\Lambda_{tr}}\text{-}\mathbf{I_{tr}}$

→ optimal estimate: $\mathbf{y_{tr}}'$ error cov, $\mathbf{Q_{tr}}$

- $\mathbf{y_{tr}}' = \mathbf{Q}\,\mathbf{E_{tr}}^T \mathbf{N}^{-½} (\mathbf{y}^o\text{-}\mathbf{y}^m)$
- $\mathbf{Q_{tr}} = (\mathbf{\Lambda_{tr}}\text{-}\mathbf{I_{tr}})\,\mathbf{\Lambda_{tr}}^{-1}$ $q_i = (\lambda_i\text{-}1) / \lambda_i$ = "pc weight"

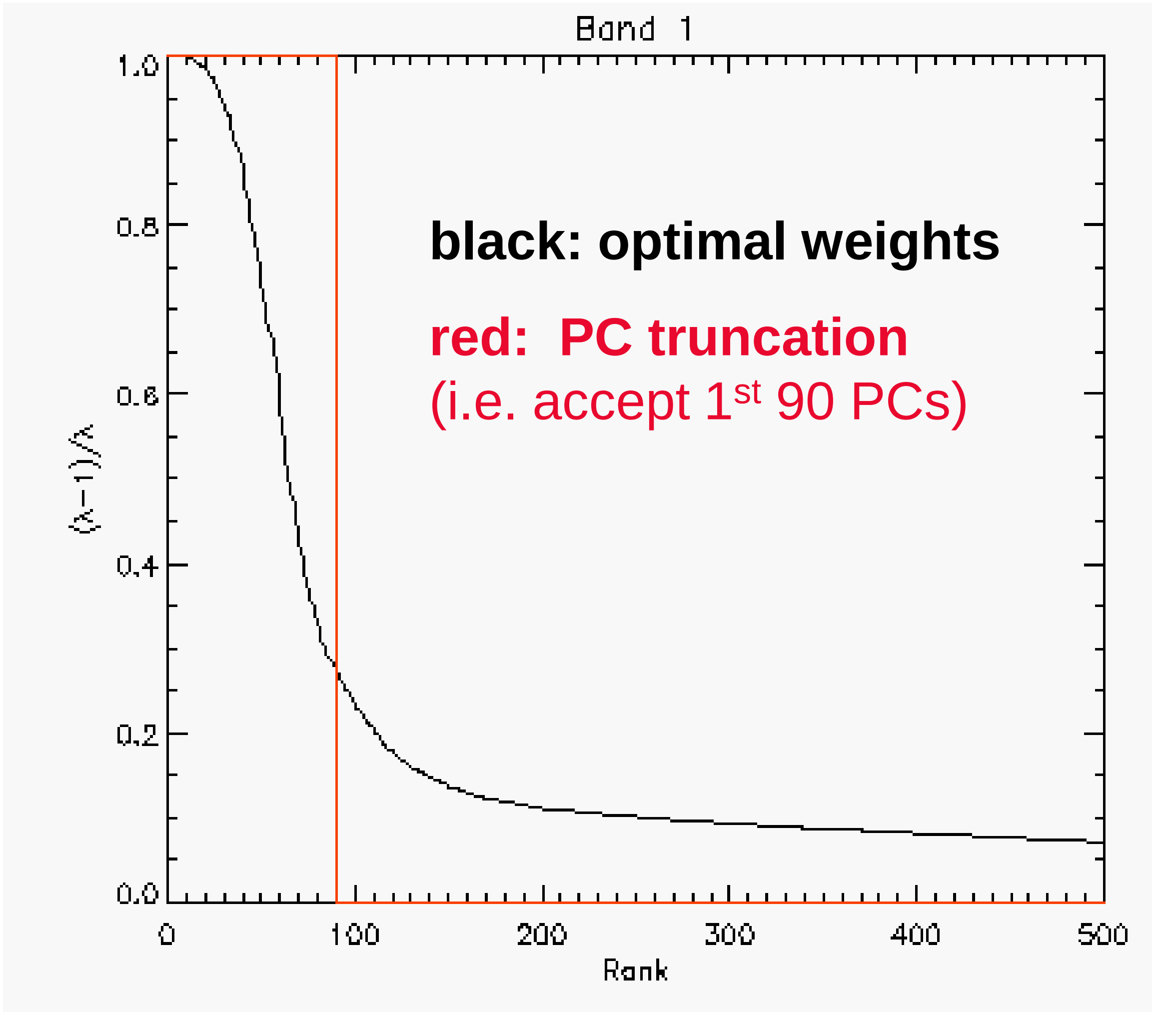
Note: normal "PC truncation" just gives "observation"



Relationship to PC truncation: IASI band 1

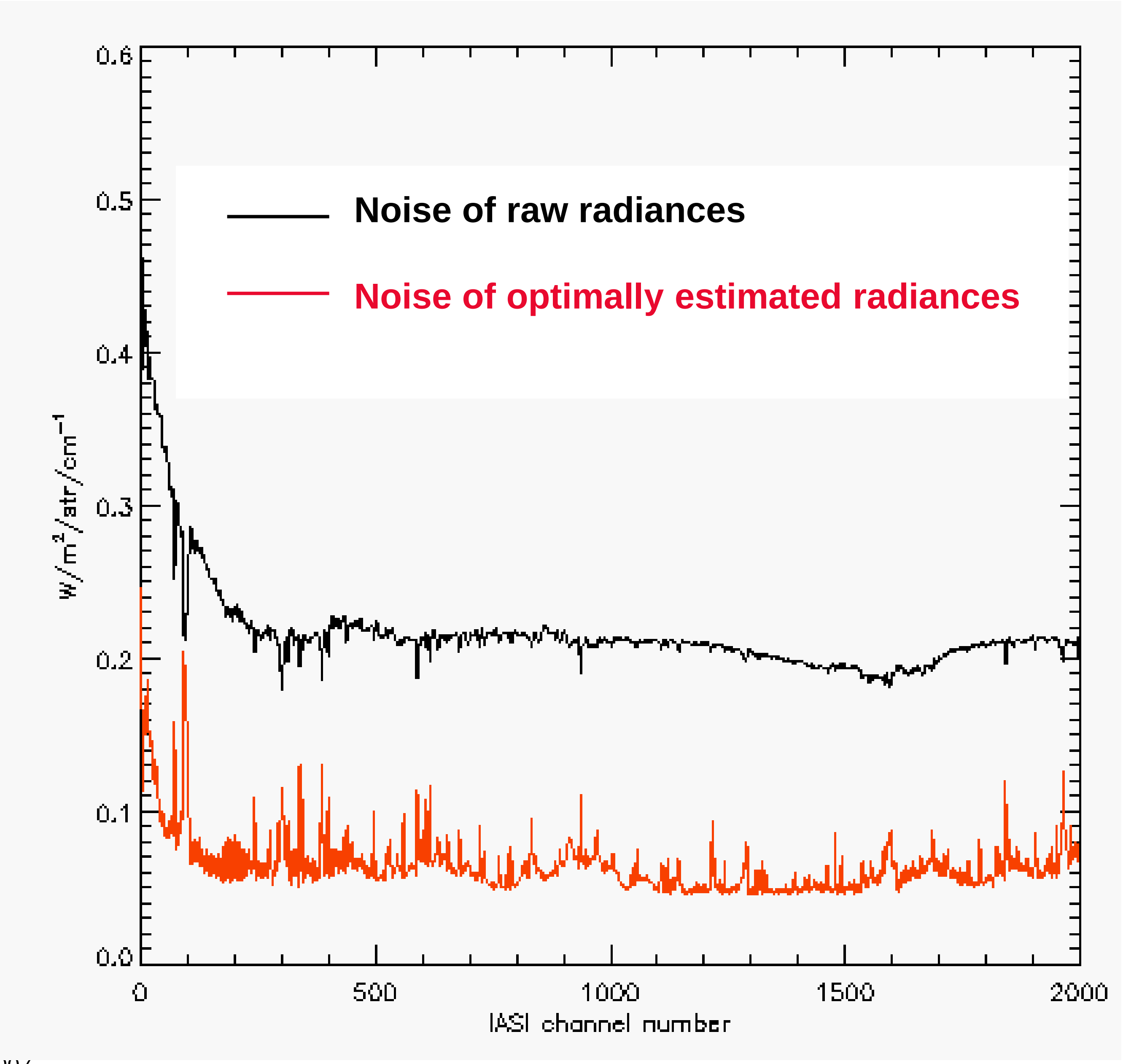
pc weight:

$q = (\lambda-1) / \lambda$



pc rank

Noise reduction – IASI band 1

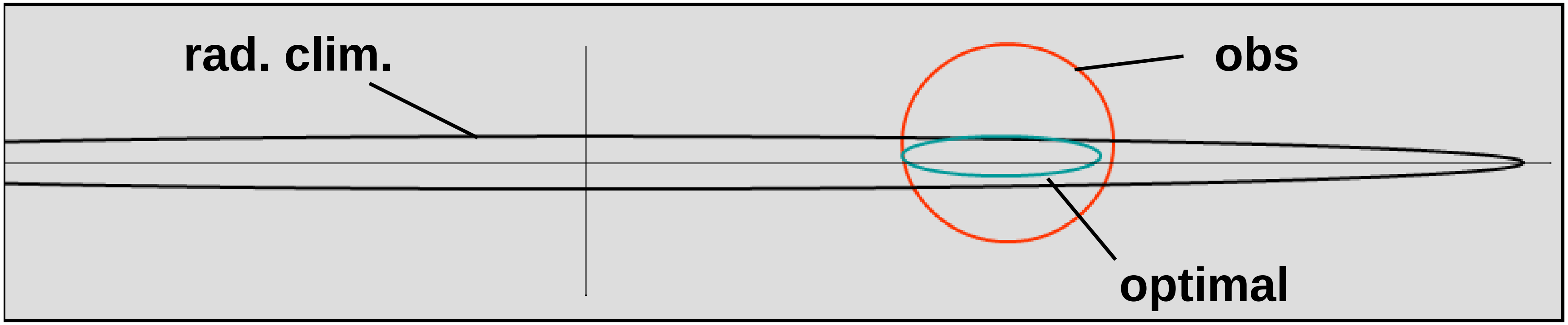


Optimal estimation of radiances (3)

Conclusions:

- Optimal radiance estimation gives **large** reductions in noise
- … **but** noise is removed mainly in “directions” containing no atmospheric information
- … and so it is **not** expected to lead to large reductions in retrieval error.

- But does it lead to **any** improvement?



Retrieval error analysis (linear)

radiances: $Q\,E_{tr}^{T}\,N^{-½}\,(y^{o}-y^{m})$ error cov: $Q = (\Lambda_{tr}-I_{tr})\,\Lambda_{tr}^{-1}$

background: x_b error cov: B

analysis: x_a error cov: A

$$H = \nabla_x\, y(x) \quad ; \quad H_{PC} = E^{T}\,N^{-½}\,H$$

$$A^{-1} = B^{-1} + H^{T}\,N^{-1}\,H = B^{-1} + H_{PC}^{T}\,I^{-1}\,H_{PC}$$ **all PCs, all channels**

$$A^{-1} = B^{-1} + (H_{PC}^{T})_{tr}\,I_{tr}^{-1}\,(H_{PC})_{tr}$$ **PC truncation**

$$A^{-1} = B^{-1} + (H_{PC}^{T})_{tr}\,Q_{tr}^{-1}\,(H_{PC})_{tr}$$ **optimal**

[Note assumption here: forward model error = 0]

Retrieval errors – IASI band 1 (1)

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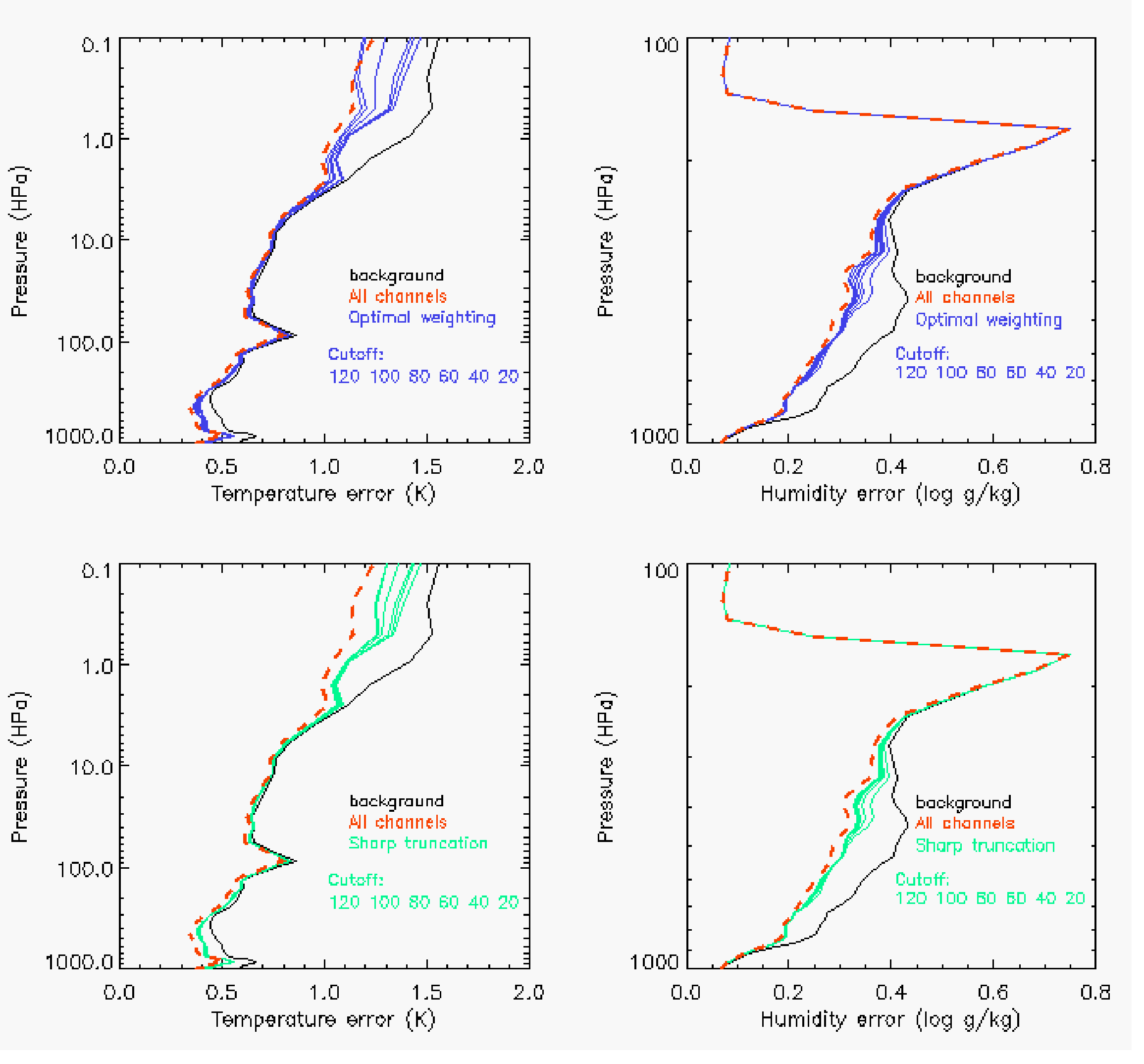
temperature | **ln(spec.hum)**

optimal weighting

PCs (normal truncation)



black: prior error

red: all PCs

blue: optimal, at various truncations

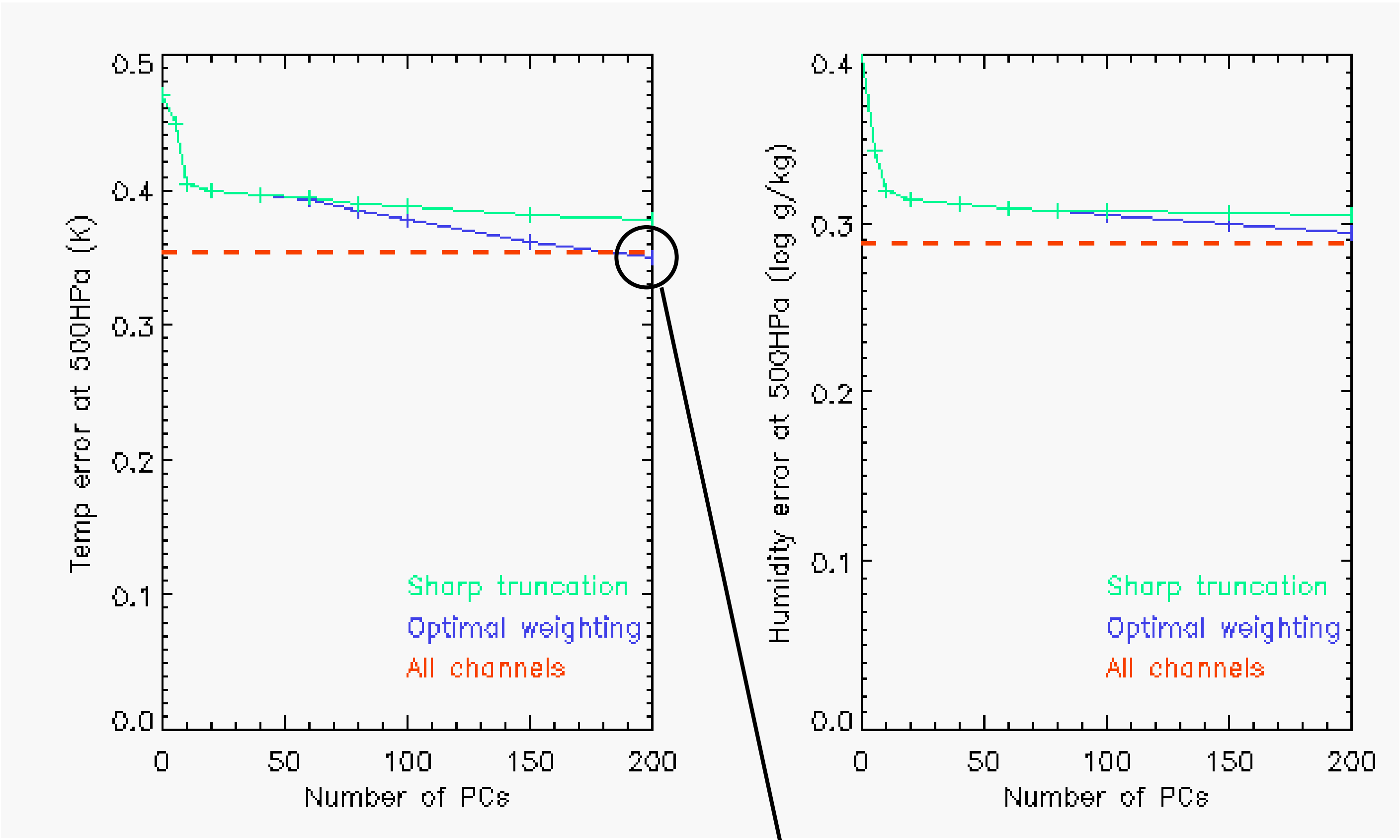
green: PCs, at same truncations

truncations: 20, 40, 60, 80, 100, 120 PCs

Retrieval errors – IASI band 1 (2)

PRELIMINARY

temperature   500 hPa   ln(spec.hum)



__ **all channels**

__ **PCs**

__ **optimal**

better than all channels?

Note: No forward model error !!

Retrieval errors - results so far

- PC truncation – as expected:
  - Increasing the number of PCs gives decreasing retrieval error
  - … but gain is small above a relatively low number of PCs
  - Retrieval error never reduces below the level for all channels / all PCs

- Optimal radiance estimation:
  - Theory suggests that, for a given PC truncation, optimally estimated radiances can give lower retrieval error than PC truncation
  - Results confirm this in the range 50-150 PCs for IASI band 1
  - Caution. At large number of PCs, as $q_i \rightarrow 0$, results become unstable, through mismatches between RTTOV Jacobians for IASI and IASI PCs computed from real data (acknowledgment.: A.Collard)

Conclusions

- PC of radiance climatologies have demonstrated "engineering" advantages
- …but do they have additional scientific advantages, in terms of reduced retrieval error?

- Expected conclusions (when this study is finished):
  - PC truncation gives higher retrieval error than all channels
    - …but information gain is small above a well-chosen truncation
  - Optimal radiance estimation can give lower retrieval error than all channels
    - …but insignificantly lower??? – more work needed

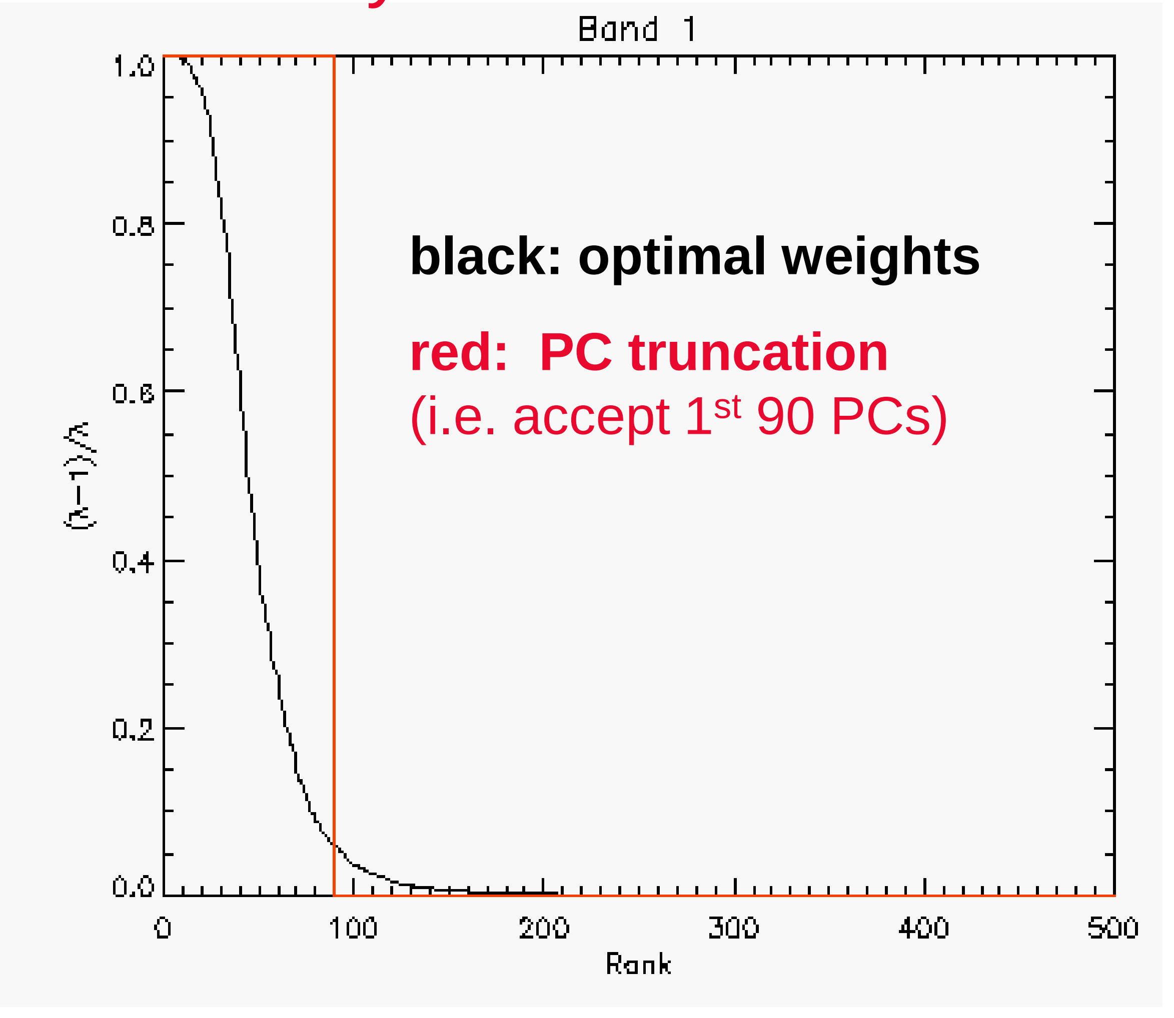
Thank you! Questions?

Relationship to PC truncation: IASI band 1

PCs from synthetic cloud-free data

pc weight:

$q = (\lambda-1) / \lambda$



pc rank

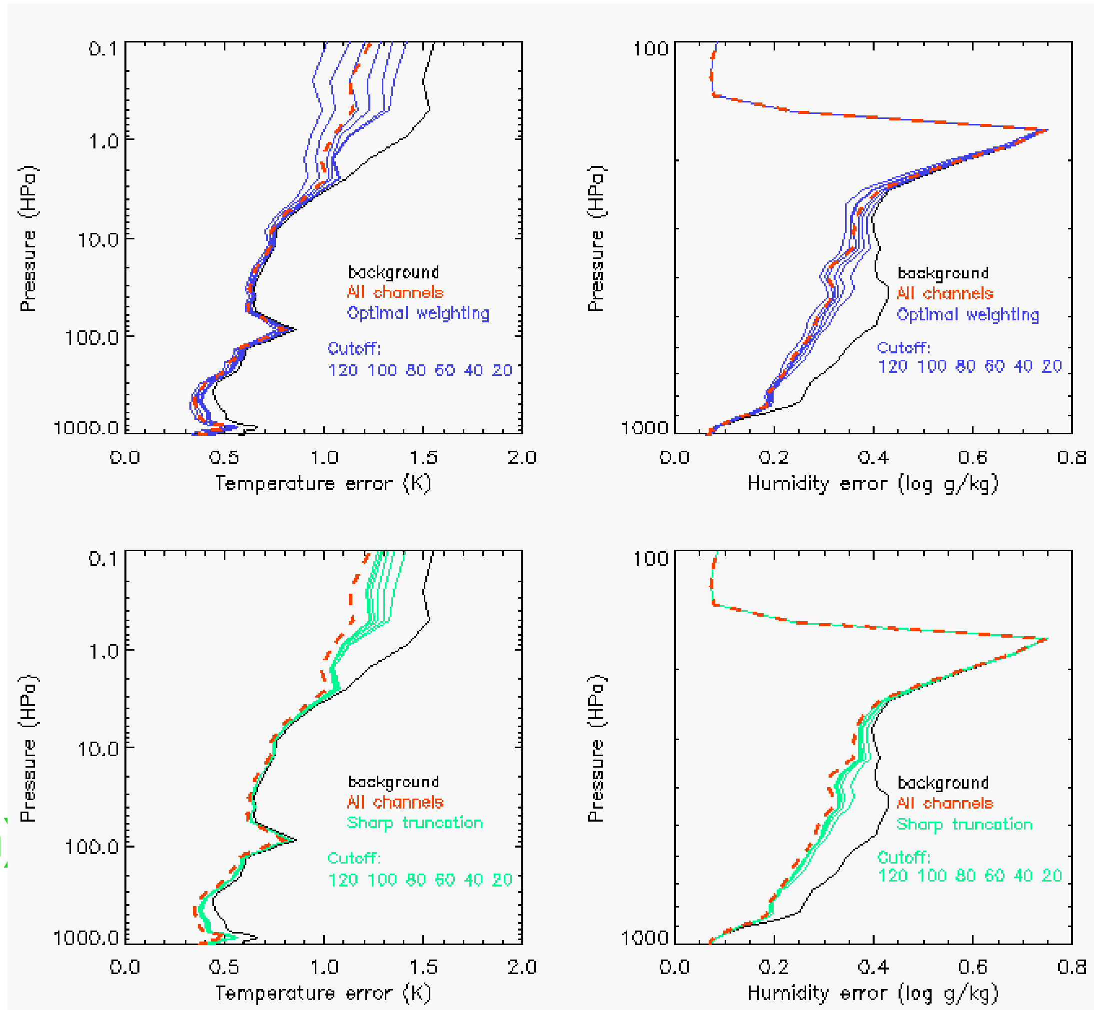
Retrieval errors – IASI band 1 (1)

PCs from synthetic cloud-free data

T **ln(q)**

optimal weighting

PCs (normal truncation)



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Retrieval errors – IASI band 1 (2)

PCs from synthetic cloud-free data

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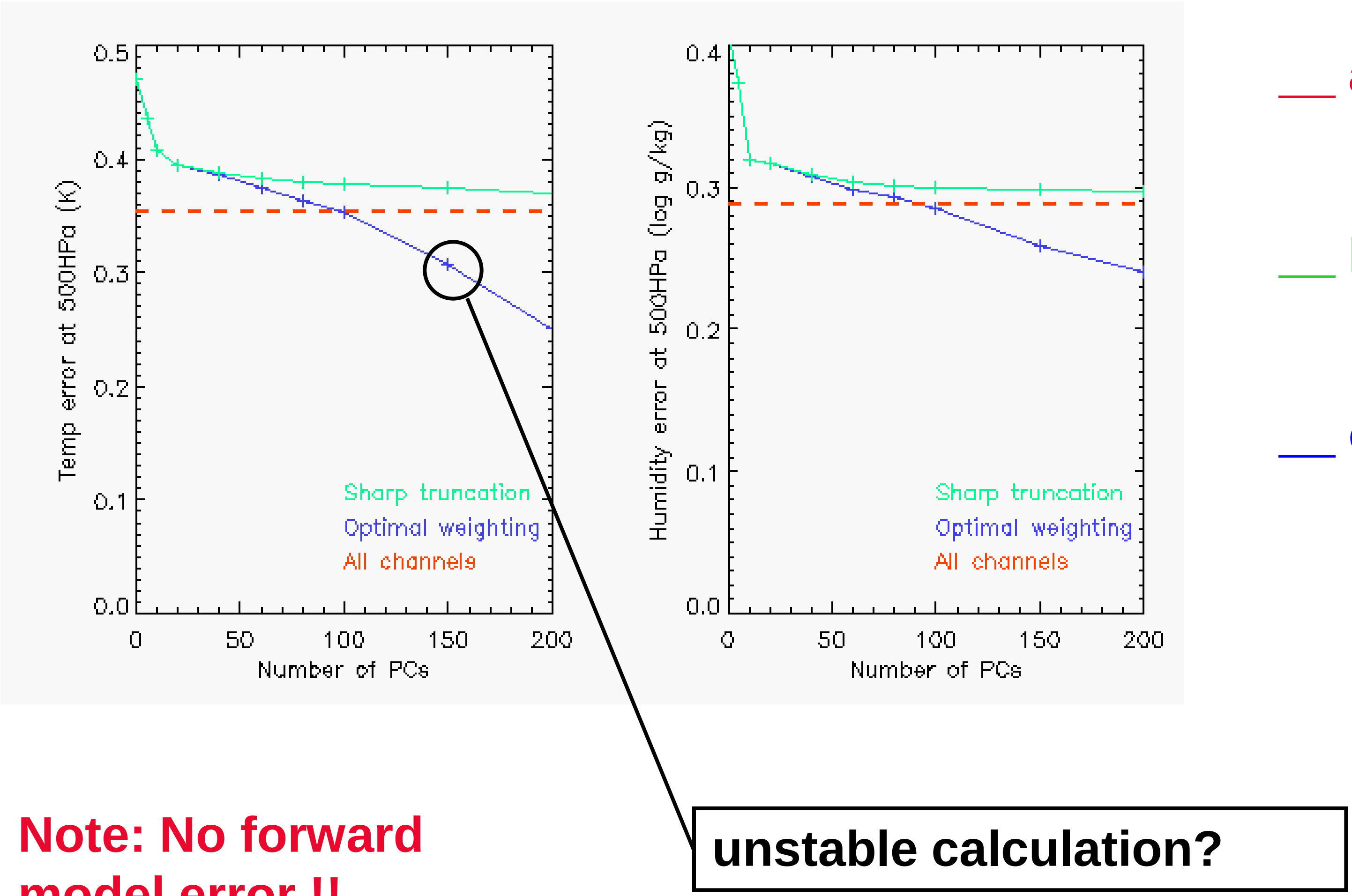

__ **all channels**

__ **PCs**

__ **optimal**

Note: No forward model error !!

A Bayesian perspective (1)

Conditional probability of state **x** given observations $\mathbf{y^o}$ (Rodgers 1976):

$$P(\mathbf{x}|\mathbf{y^o}) = P(\mathbf{y^o}|\mathbf{x})\; P(\mathbf{x}) / P(\mathbf{y^o})$$

To find most probable **x**:

- maximise $P(\mathbf{x}|\mathbf{y^o})$ with respect to **x** …
- equivalent to maximising $\ln\{P(\mathbf{x}|\mathbf{y^o})\}$ …
- giving usual "cost function" J(**x**) used in variational analysis (Lorenc 1988):

$$J(\mathbf{x}) = k_1 - \ln\{P(\mathbf{x}|\mathbf{y^o})\} = k_1 - \ln\{P(\mathbf{y^o}|\mathbf{x})\} - \ln\{P(\mathbf{x})\} + \ln\{P(\mathbf{y^o})\}$$

$$(\mathbf{y^o}-\mathbf{y}(\mathbf{x}))^T \mathbf{R}^{-1} (\mathbf{y^o}-\mathbf{y}(\mathbf{x})) \qquad (\mathbf{x}-\mathbf{x_b})^T \mathbf{B}^{-1} (\mathbf{x}-\mathbf{x_b}) \ldots$$

…if PDFs are Gaussian → cost function takes normal quadratic form.

A Bayesian perspective (2)

$$J(\mathbf{x}) = k_1 - \ln\{P(\mathbf{x}|\mathbf{y^o})\} = k_1 - \ln\{P(\mathbf{y^o}|\mathbf{x})\} - \ln\{P(\mathbf{x})\} + \ln\{P(\mathbf{y^o})\}$$

- The final term is usually absorbed into the constant and ignored
- …because $P(\mathbf{y_o})$ usually assumed constant (over the range of physically possible observed values)

- If we have prior knowledge of y^o through a radiance climatology, we can replace the constant $P(\mathbf{y^o})$ by a Gaussian of the form:

$$\ln\{P(\mathbf{y^o})\} = k_2 - (\mathbf{y^o} - \mathbf{y^m})^T.(\mathbf{C_o})^{-1}.(\mathbf{y^o} - \mathbf{y^m})$$

where $\mathbf{y^m}$ and $\mathbf{C_o}$ are the mean and covariance of the radiance climatology

- This clearly changes the form of the cost function, and hence the value of $J(\mathbf{x})$ for a given $\mathbf{y^o}$.

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A Bayesian perspective (3)

HOWEVER

- ln{P(yo)} is **not** a function of x →
- when we differentiate

  $J(\mathbf{x}) = k_1 - \ln\{P(\mathbf{x}|\mathbf{y^o})\} = k_1 - \ln\{P(\mathbf{y^o}|\mathbf{x})\} - \ln\{P(\mathbf{x})\} + \ln\{P(\mathbf{y^o})\}$,

  with respect to **x**, then $\ln\{P(\mathbf{y^o})\}$ disappears !!!
- Therefore, it can have no effect on the optimal value of x.

Therefore, from this perspective - i.e. radiance climatology as prior information on $\mathbf{y^o}$ - it does not allow us to improve our estimate of x.

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