PCA based information content studies from high spectral resolution infrared observations

P. Antonelli, H. Revercomb, R. Knuteson,

Larry Sromovsky, A. Huang, Ray Garcia, Ben Howell

D, Tobin, F. Best

CIMSS/SSEC, UW-Madison

R. Episcopo, L. Galdi,

M. di Bisceglie

University of Sannio, Italy

W. Smith

NASA Langley (retired)

Langley Research Center

Questions we are trying to answer

- What is the impact of PCA on hyperspectral IR data?
  - Estimation of the Information Loss
  - Noise reduction
- What do the Principal Components represent?
  - Statistical meaning
  - Physical meaning
- What are the benefits and risks in applying PCA to hyperspectral IR data for noise filtering?
  - How should it be applied?
  - When should it be applied?

Outline

- PCA used to Filter out random component of instrument Noise (PNF)
  - Theory
- Application of PNF to simulated data
  - Aircraft FTS data
- Application of PNF to real data
  - Airborne FTS and Spaceborne Grating observations
- Conclusions

Noise Filter Problem

$$L_{obs}(\nu)=L_{atm}(\nu)+\eta(\nu)$$

Find F such that: $L_{est}(\nu)=F(L_{obs}(\nu))$

With minimal Estimation Errors: $EE(\nu)=L_{est}(\nu)-L_{atm}(\nu)$

MMSE

If $S=cov(\eta)$ and $R=cov(L_{atm})$ are known,
the optimal linear filter in the least square sense is
$F=R(R+S)^{-1}$

PCA

$$L_{est}(\nu)=P(L_{obs}(\nu))$$

Useful Quantities

Estimation Error (EE): difference between noise free and filtered signals

Atmospheric Information Loss (AIL): difference between noise free signal before and after filtering

Reconstructed Noise (RN): noise signal after filtering

Reconstruction Residuals (RR): difference between observed signal before and after filtering

PCA Noise Filter: Implementation Strategy

- Normalize each spectrum L_{obs} by estimated Noise Equivalent Radiance
- Derive the Principal Components from observations (Eigenfunctions of Covariance Matrix of dependent L_{obs})
- Project each L_{obs} onto PCs
- Estimate noise normalized signal (L_{est}) by retaining only N_t PCs
- Remove normalization

Noise Reduction Factor (NRF)

After Noise Normalization data: $\sigma_i = 1 \ \forall \ i$

Original space: $\Phi^2 = \Sigma \ \sigma_j^2 = N$ $\quad j=1,\ldots.,N$

Reduced space: $\Gamma^2 = \Sigma \ \sigma_j^2 = N_t$ $\quad j=1,\ldots.,N_t$

Noise Reduction Factor (NRF)

$NRF = sqrt(\Phi^2 / \Gamma^2) = sqrt(N/N_t)$

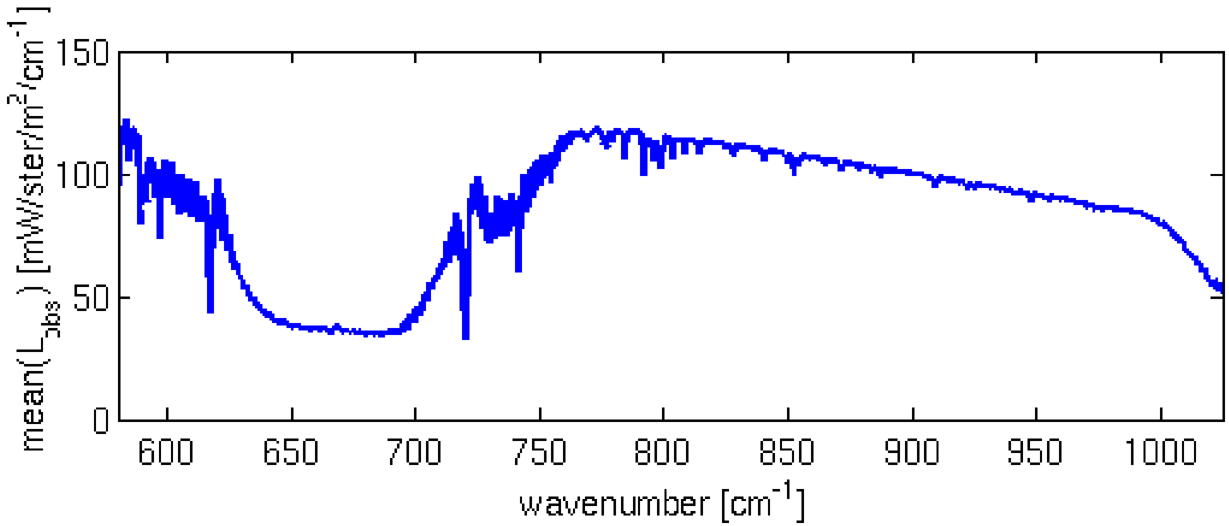
PNF on Simulated Data

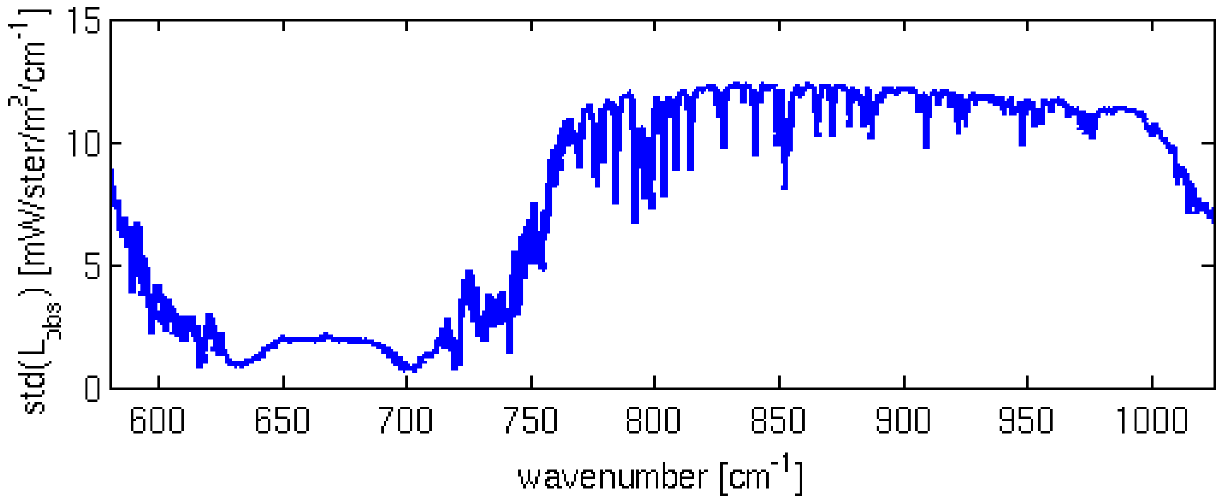
- Quantification of:
  - Atmospheric Information Loss (AIL)
  - Reconstructed instrument Noise (RN)
- Comparison between:
  - Accuracy of PNF (PCA Noise Filter)
  - Accuracy of MMSE (Minimum Mean Square Error from Estimation Theory)
- Verification importance of:
  - Noise normalization
  - Importance of large training sets

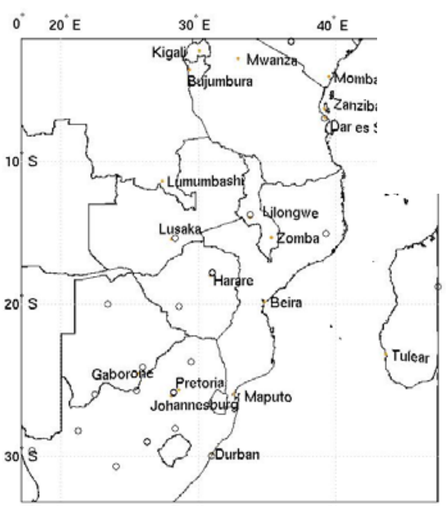
Training Set

- 10000 raob profiles collected over South Africa (REGIONAL or Local DATASET)
- Clear Sky radiances only, simulated with LBLRTM 8.1 and convoluted at Scanning-HIS resolution (.5 cm^{-1})
- Noise RMS estimated from observed instrument noise (Scanning-HIS, 7 Sep 2000)

Training Set Simulated Data

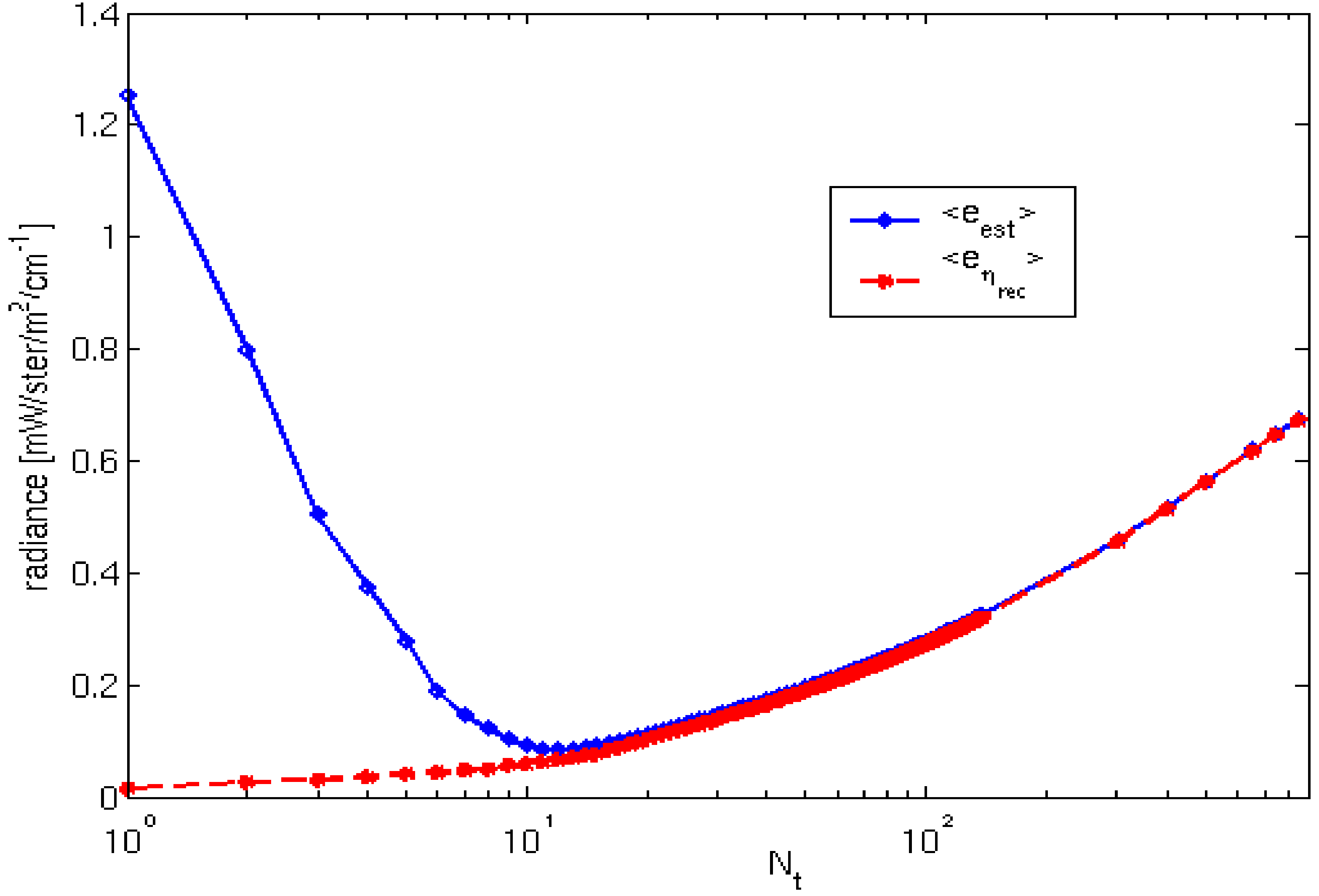






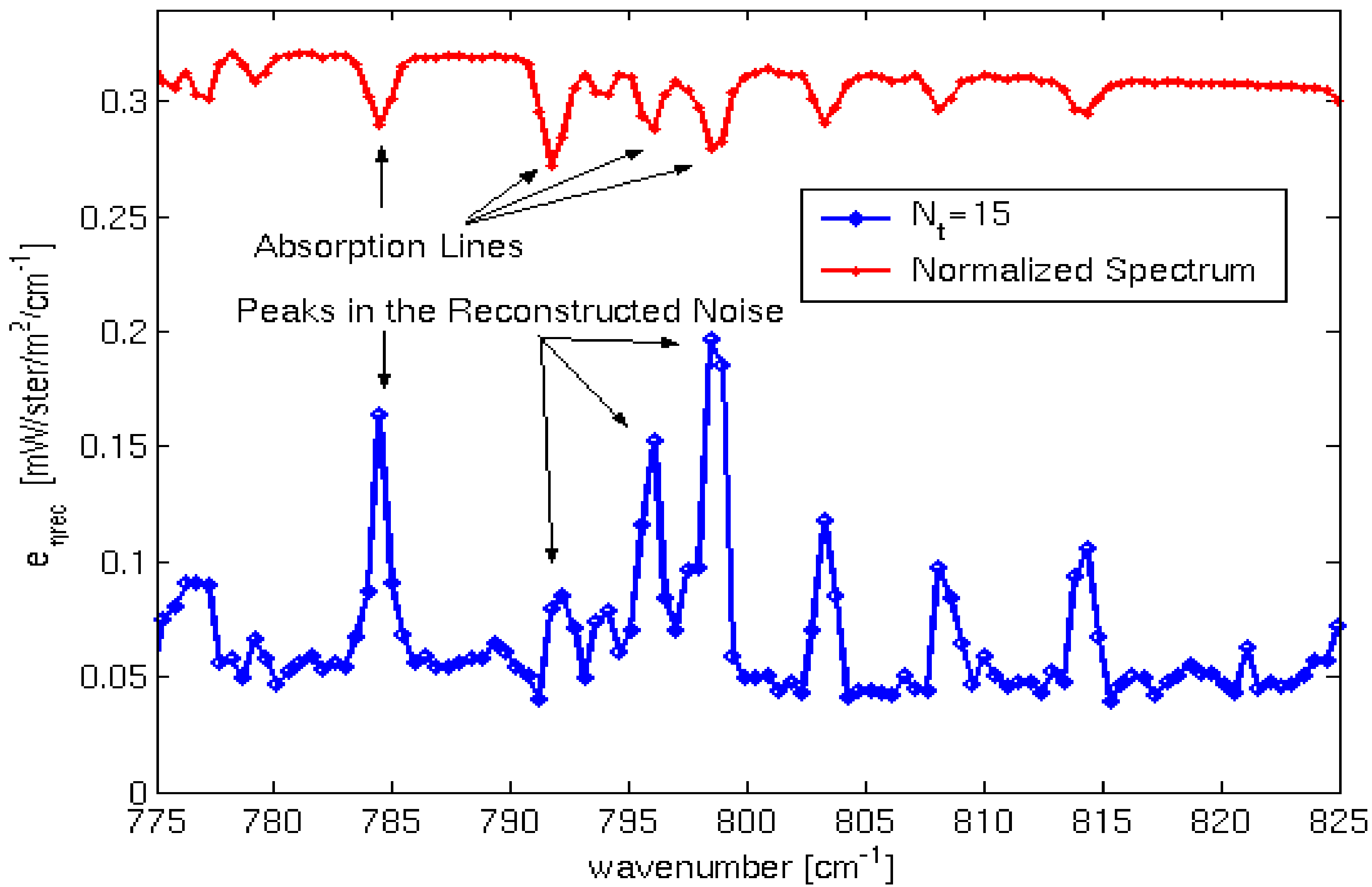
REGIONAL TRAINING SET
July-October / 1990-2000
Over South-East African Countries

EE vs RN

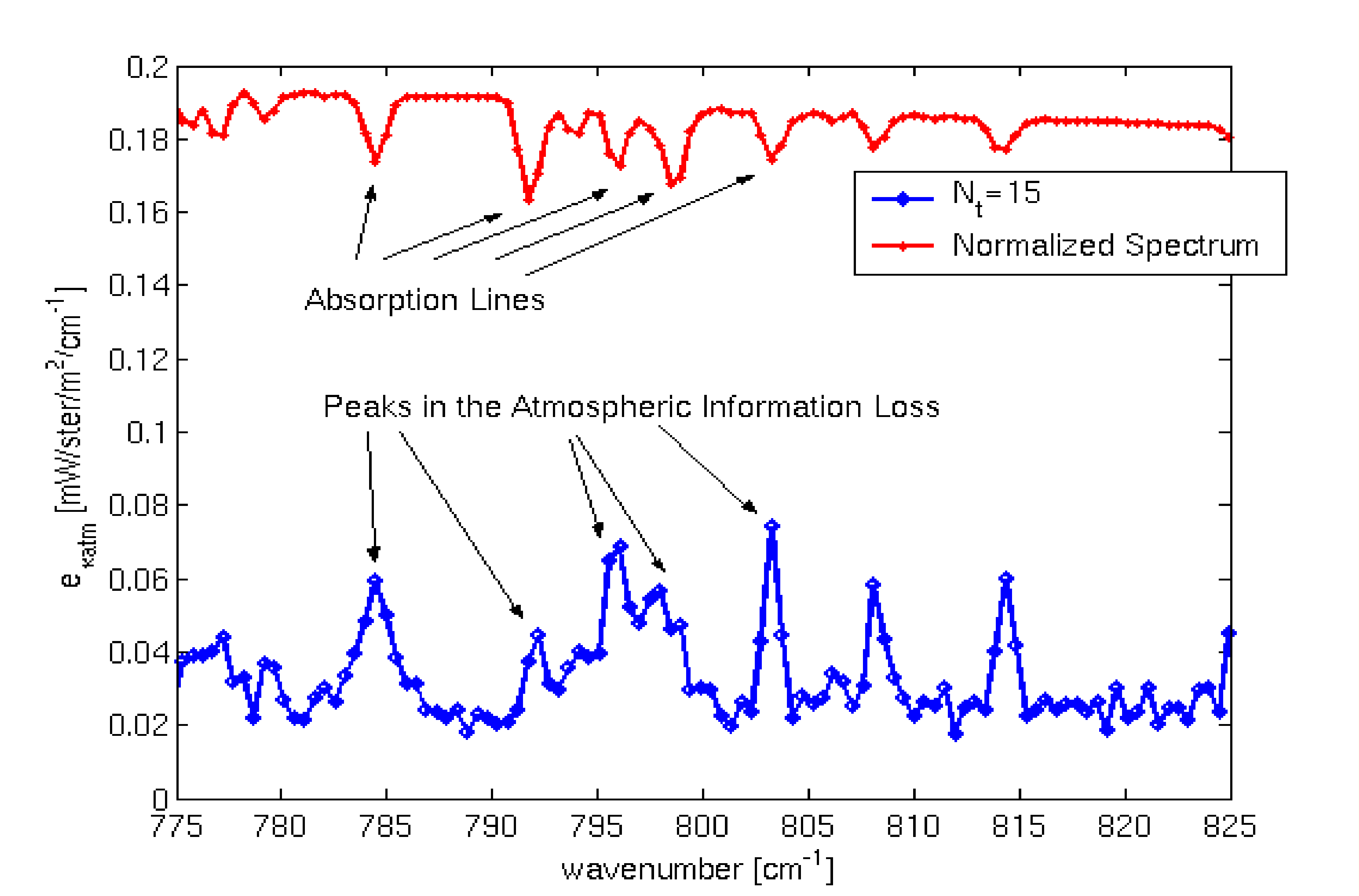


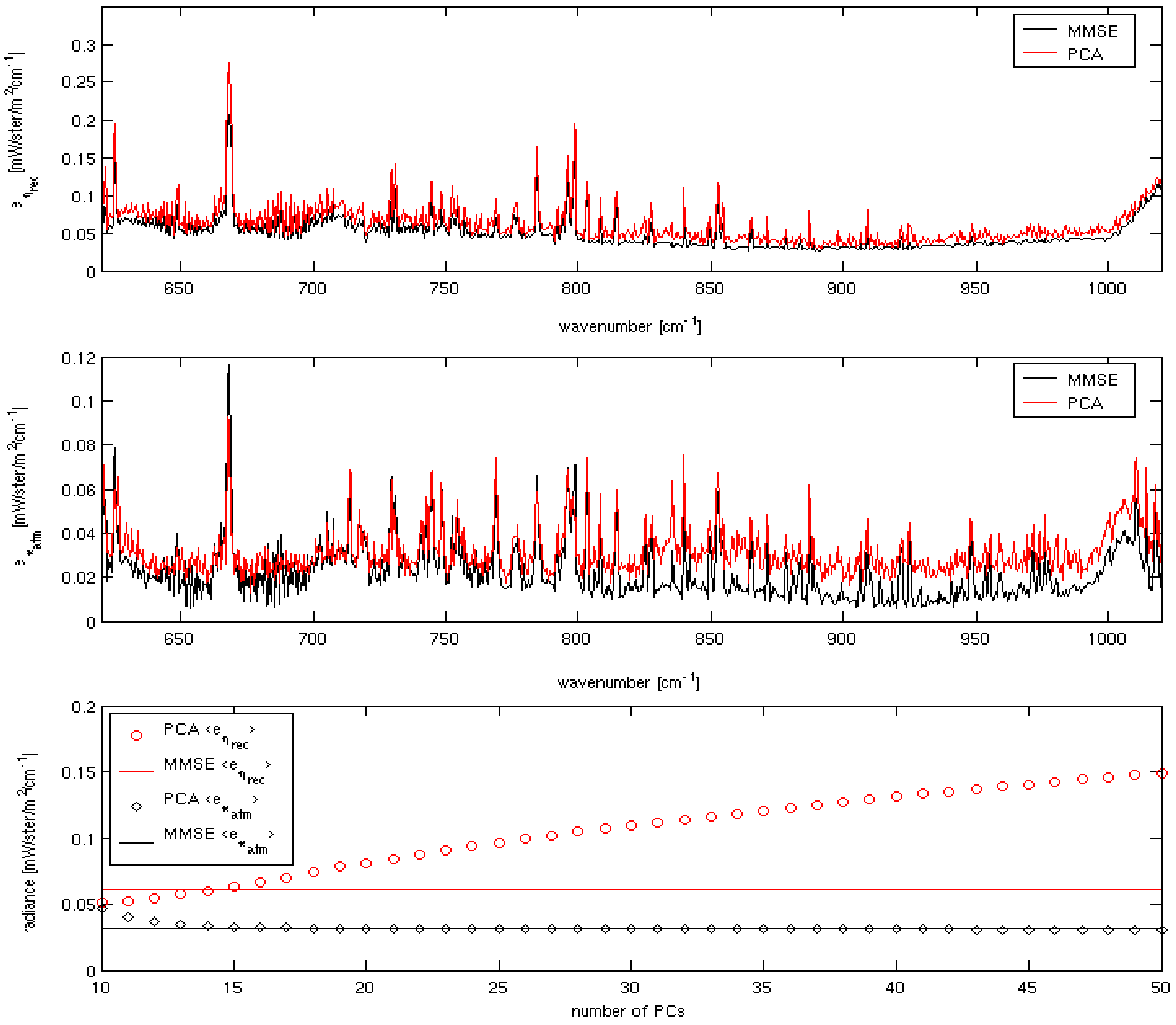
1.4
1.2
1
0.8
0.6
0.4
0.2
0
radiance [mW/ster/m2/cm-1]
10^0
10^1
10^2
Nt
<eest>
<eηrec>

Correlation in RN



Correlation in AIL





PCA Rms(RN)

PCA Rms(RN)

PCA Rms(AIL)

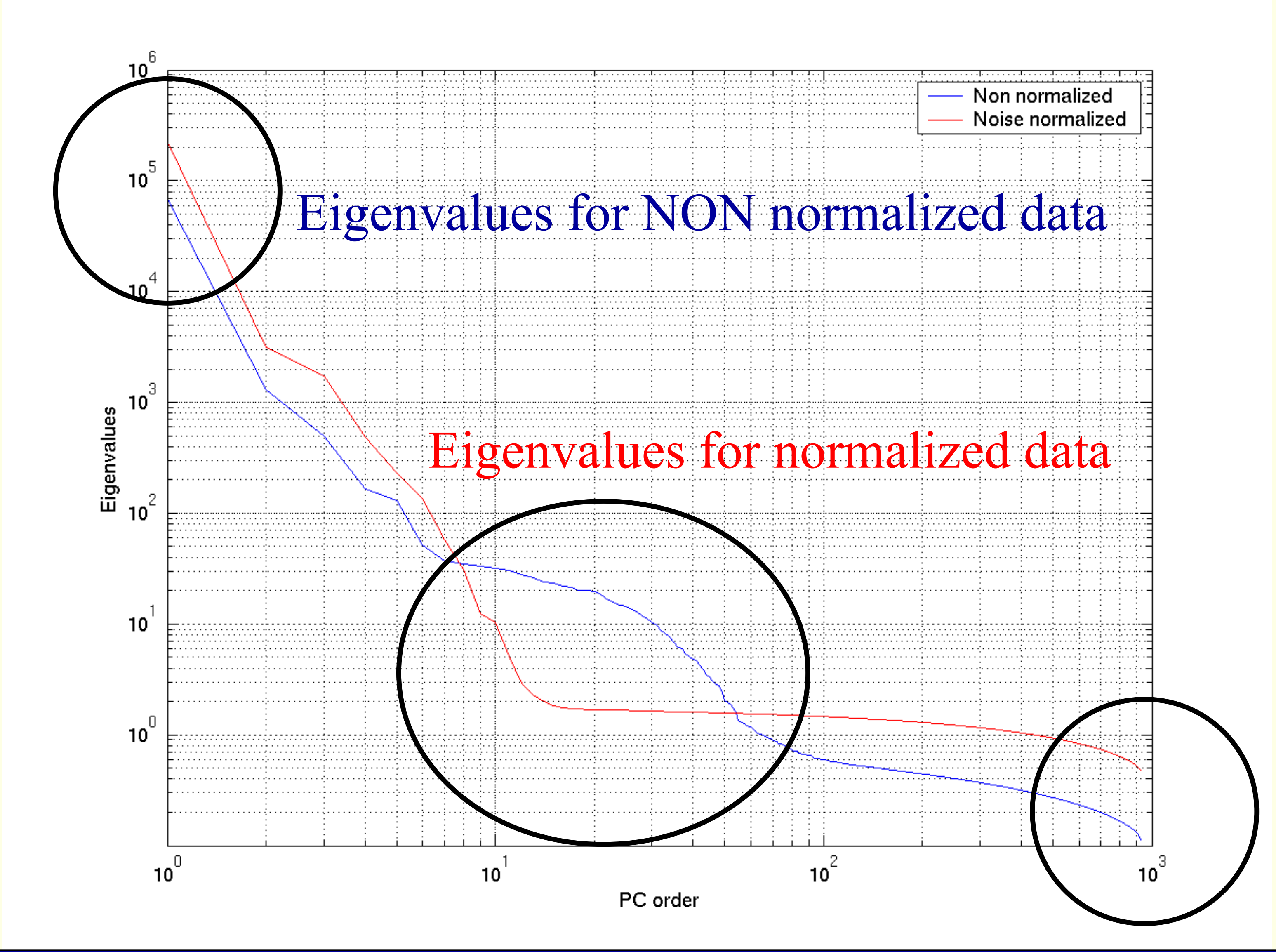
PCA Rms(AIL)

<Rms(AIL)>

<Rms(RN)>

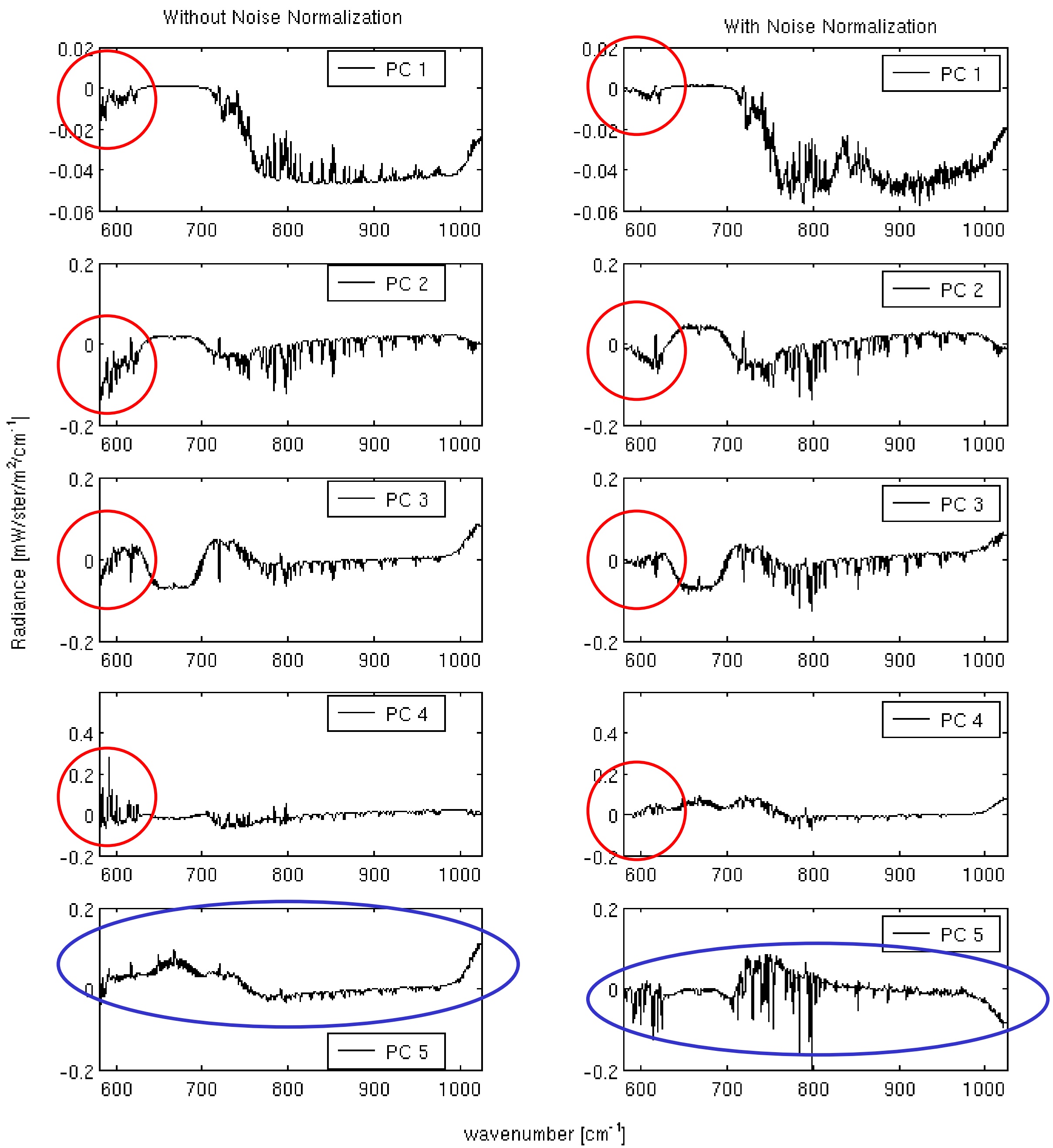
PNF approaches theoretical limits defined Linear Estimation Theory

Importance of Noise Normalization



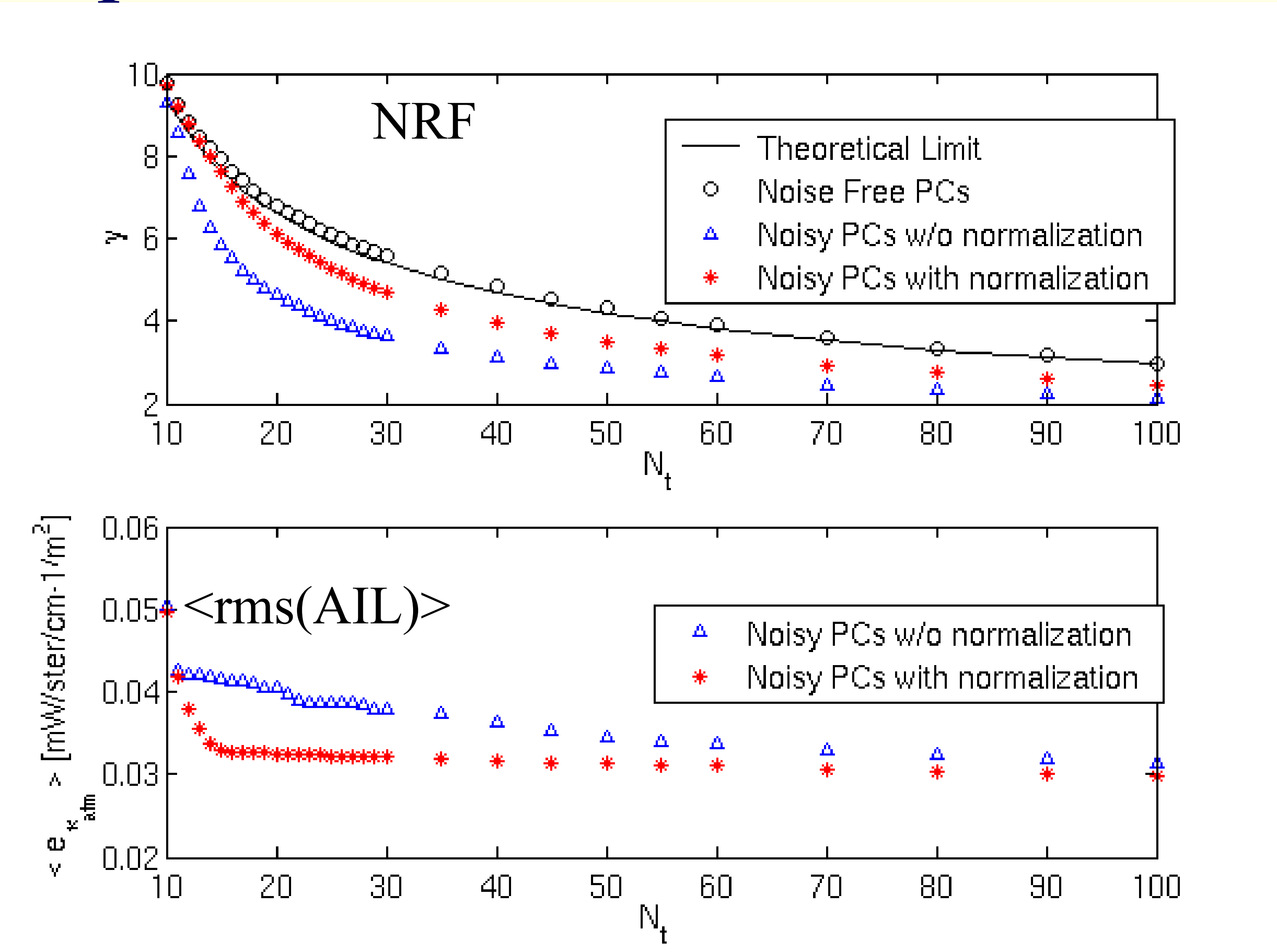
Noise Normalization changes noise distribution along different PCs

PCs Without Noise Normalization



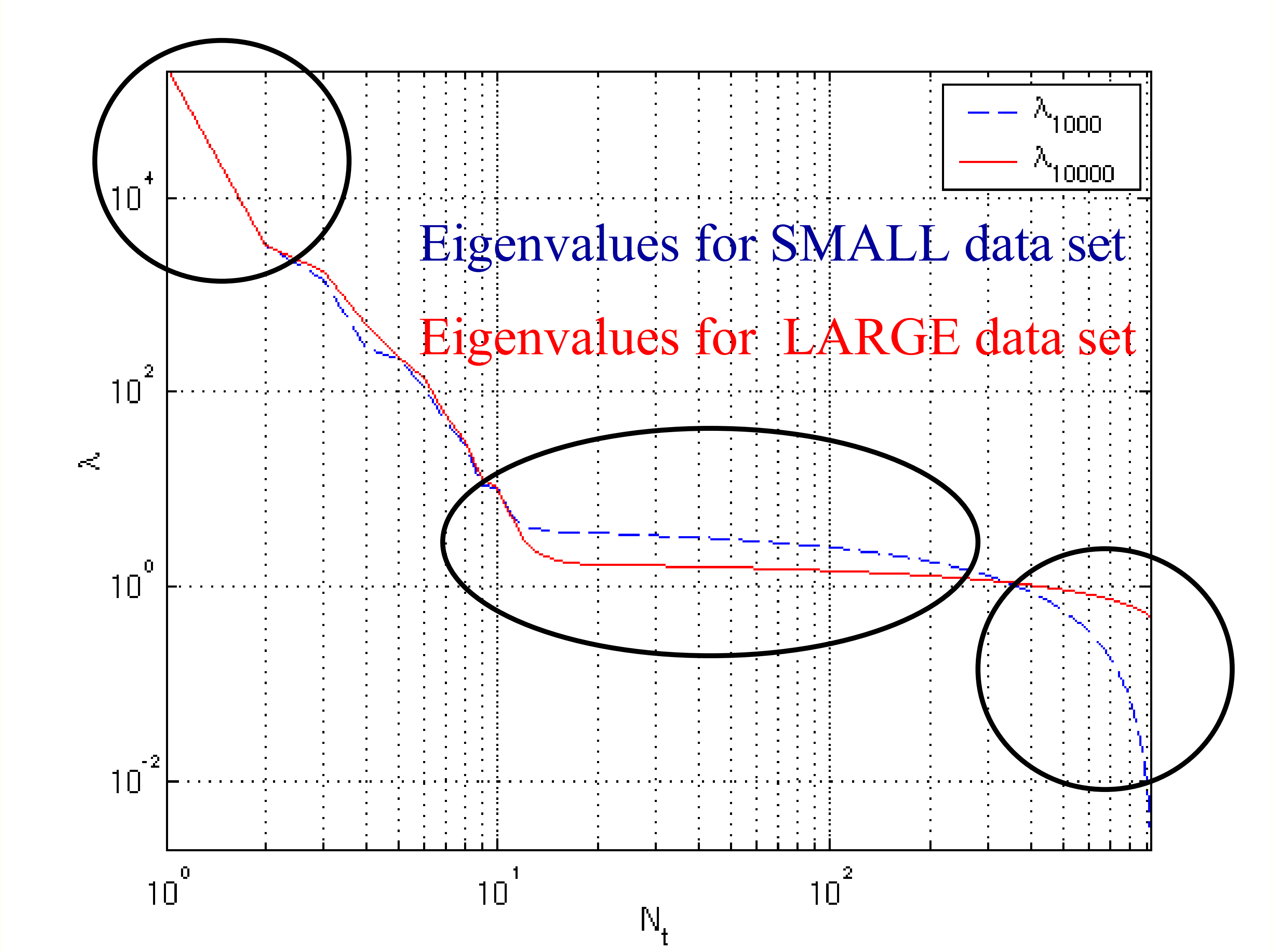
PCs With Noise Normalization

Importance of Noise Normalization



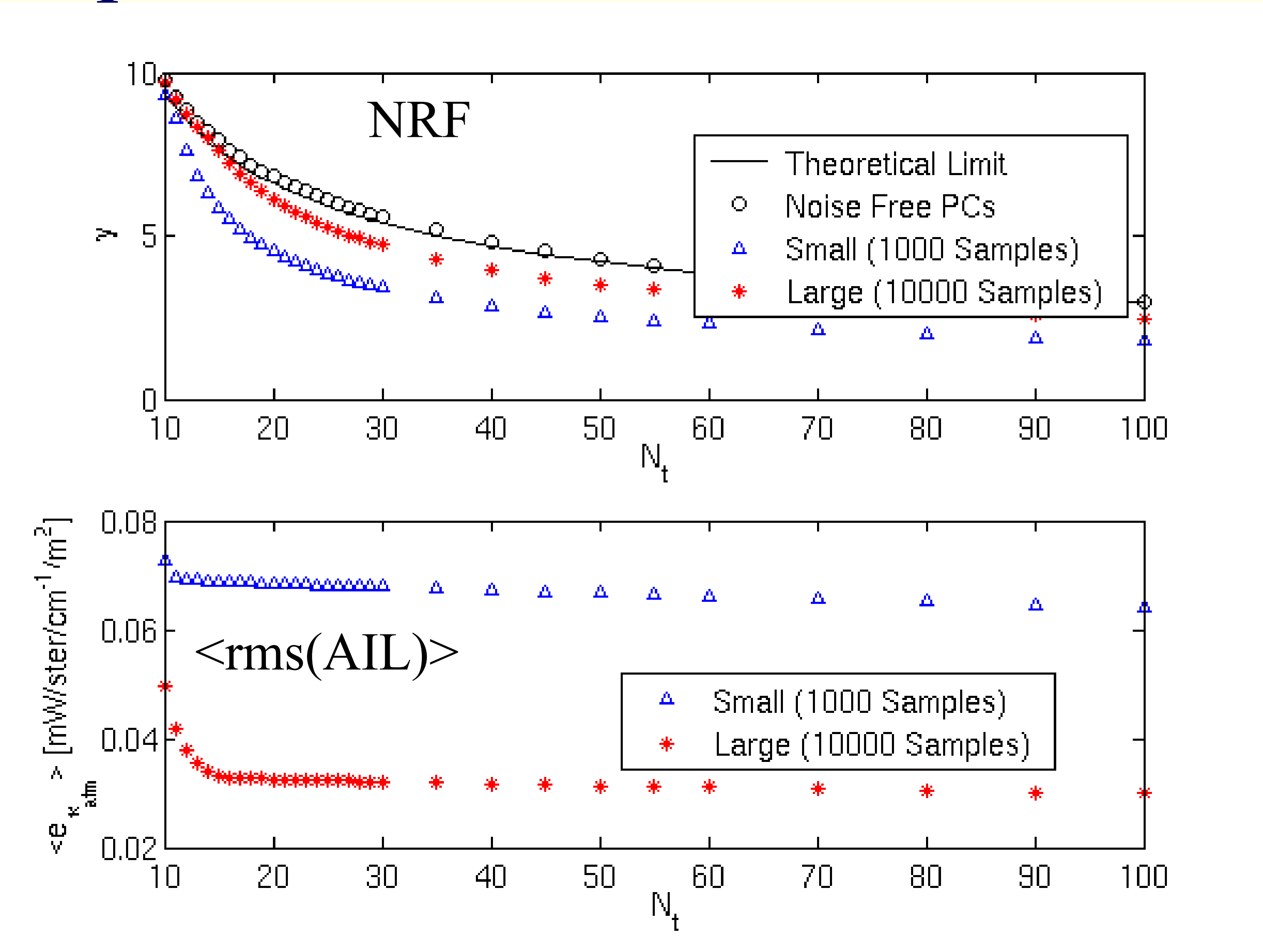
Noise Normalization increases NRF and decreases Atm. Info Loss

Training Set Size



More Noise Variance explained by high order PCs (large values of N_t)

Importance of Noise Normalization



Large Training Sets* increase NRF and decrease Atm. Info Loss

Conclusions on PNF impact on Simulated Data

- In RMS sense PNF approaches optimal values defined by Linear Estimation Theory for both AIL and RN

- RMS of AIL and RN are about 7 times* smaller that RMS of Original Noise

- Noise normalization and Large Training Sets improve filter efficiency and accuracy

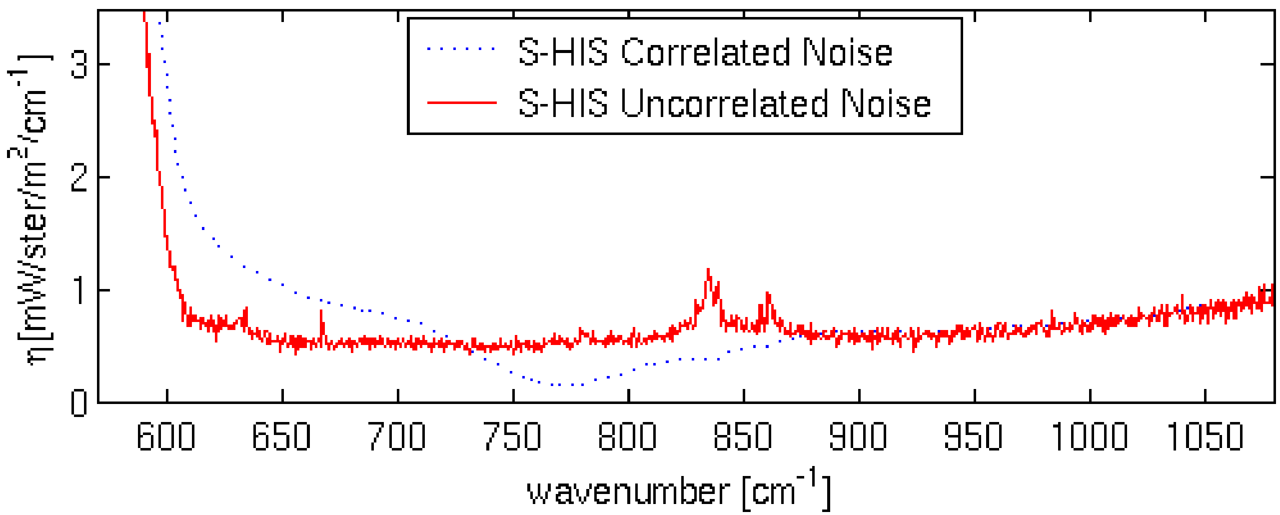
* This Value depends on the specific instrument used

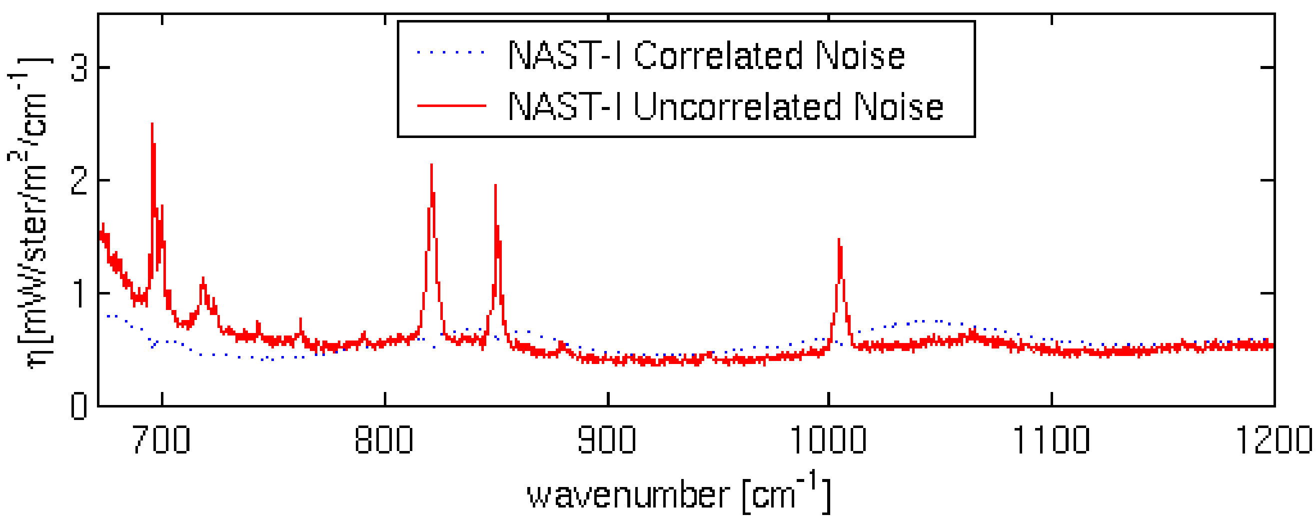
Real Data: Platforms & Instruments

- ER-2 (cruise altitude: 20 km), its instruments are above 94% of the earth's atmosphere
  - NAST-I (FTS, 3.7-16 microns @ .25 cm^{-1})
  - S-HIS (FTS, 3.3-18 microns @ .5 cm^{-1})

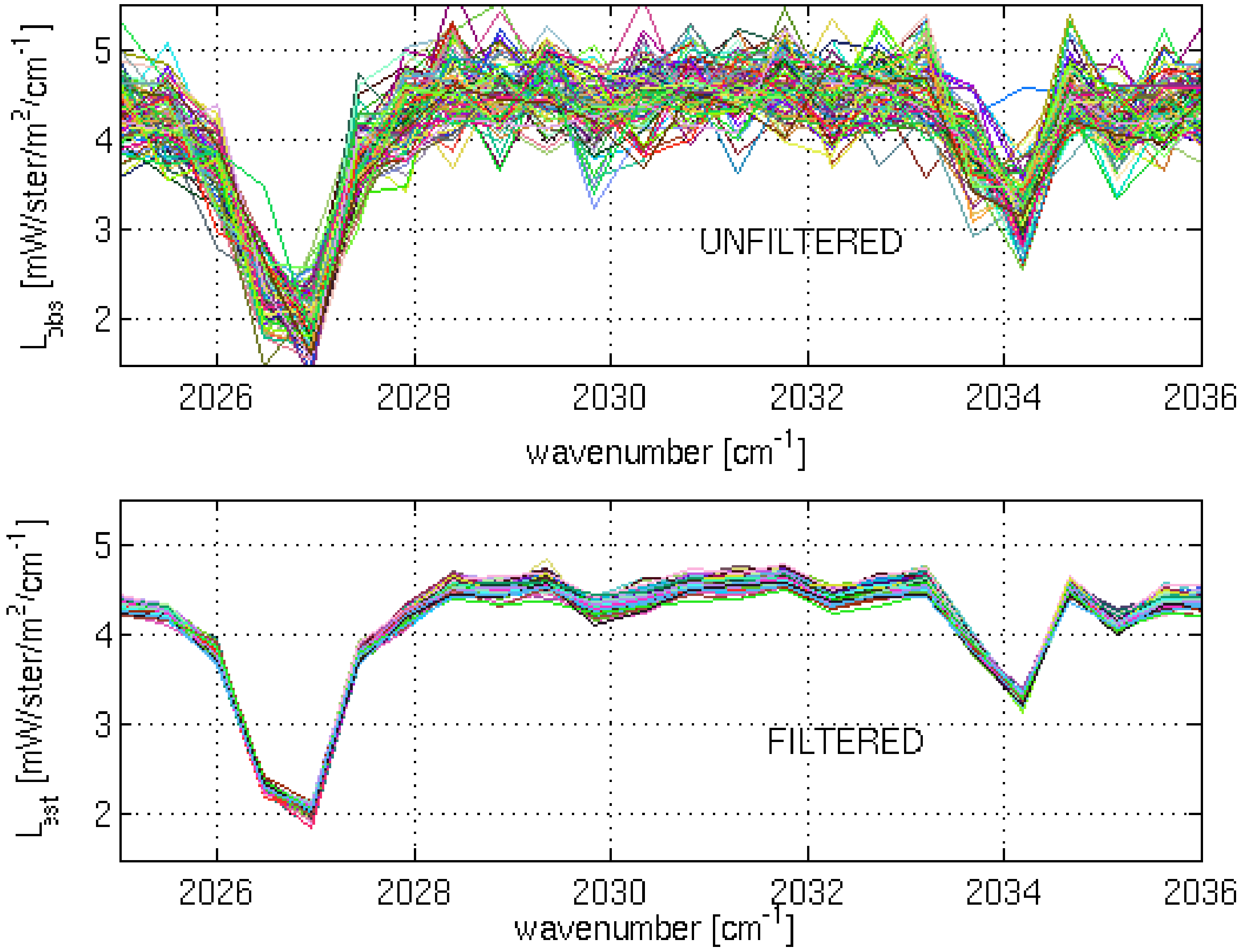
- AQUA (Orbit altitude 705 km)
  - AIRS (Grating, 3.7-15.4 microns, resolving power 1200)

Training Set:
S-HIS from SAFARI 2000

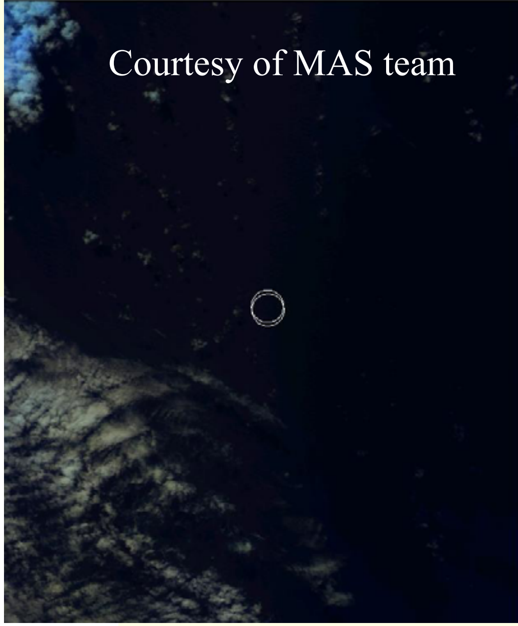


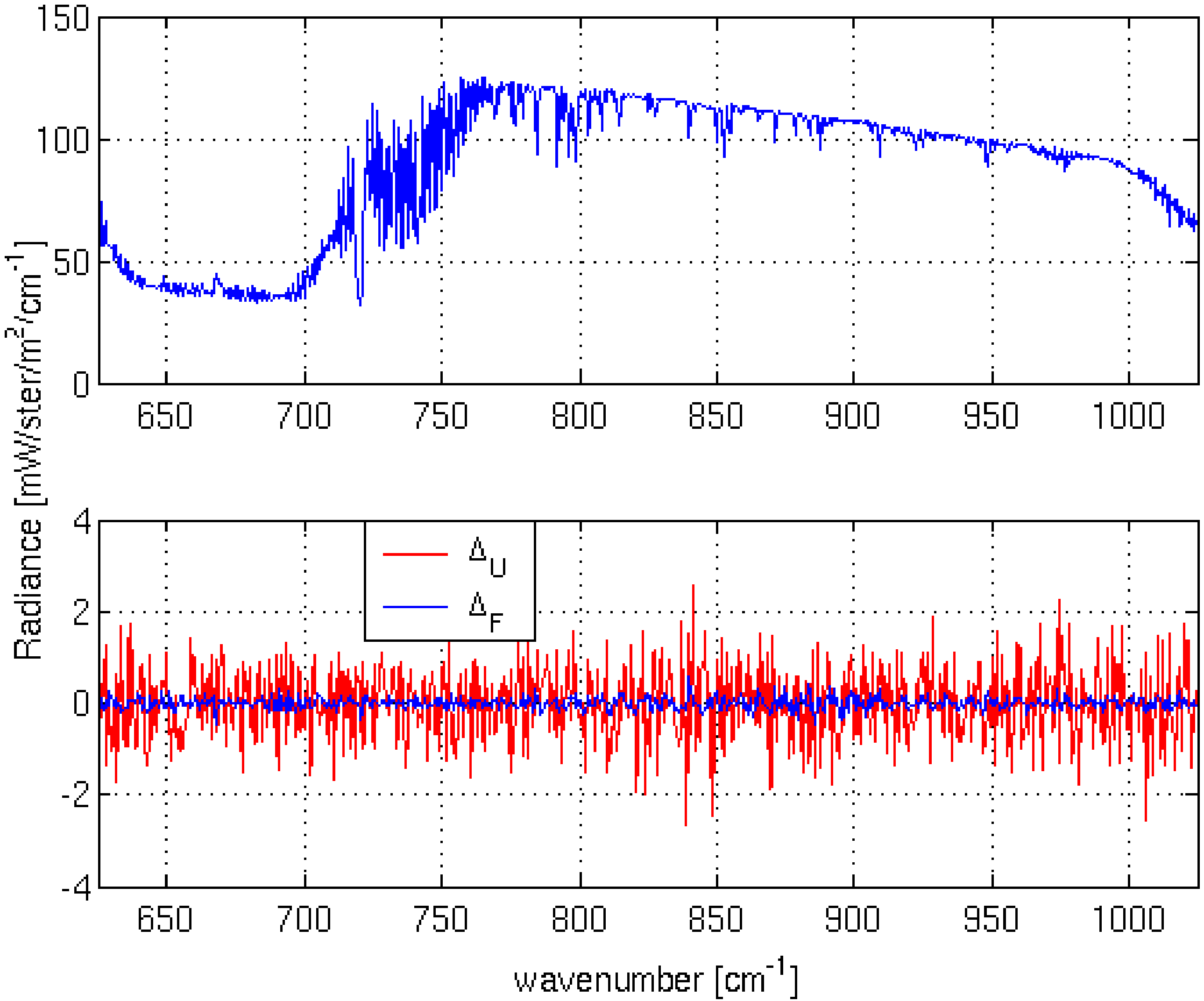


The Noise Filter Effect



Filtered-Unfiltered for almost overlapping FOVs over Ocean

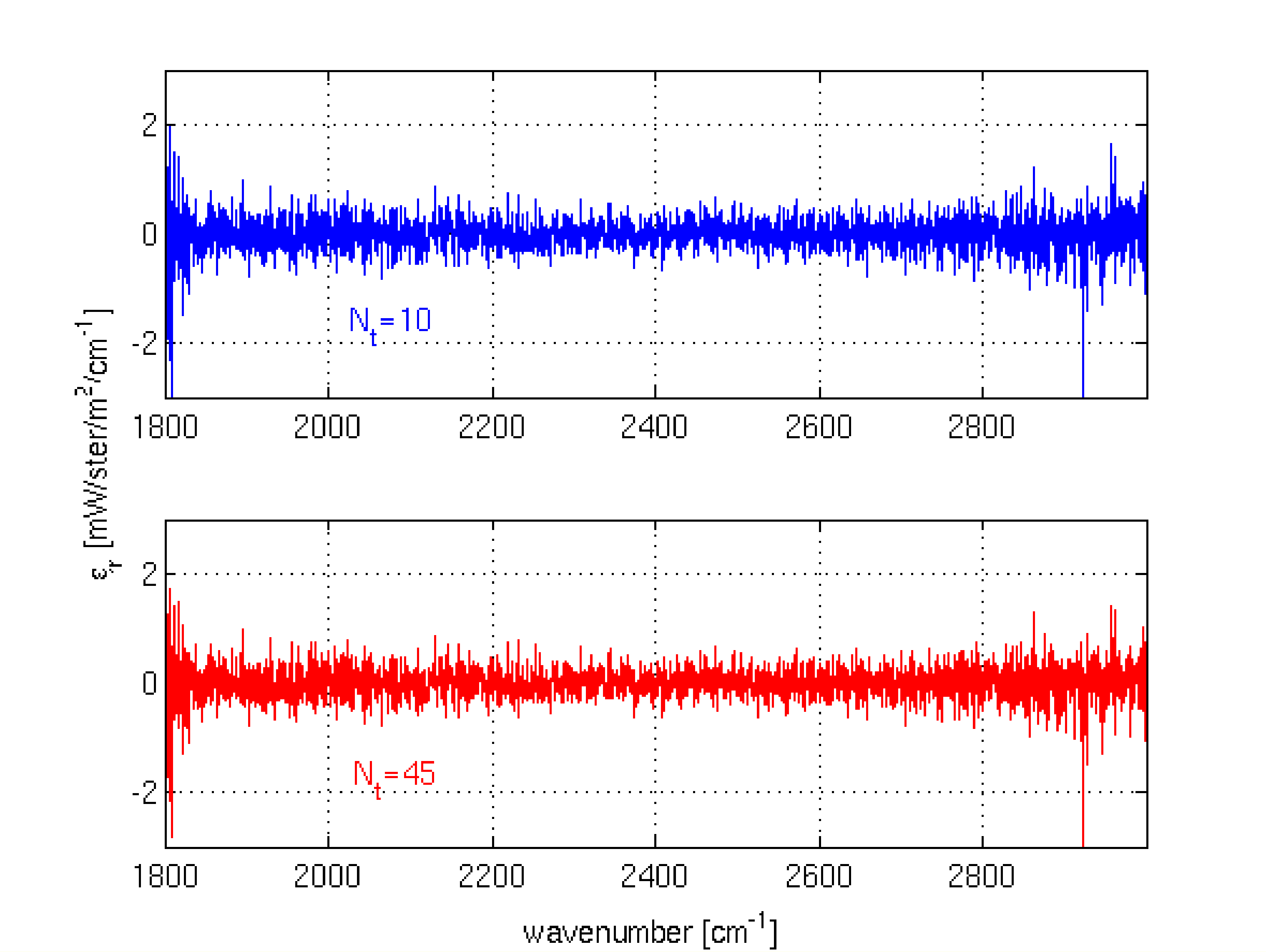




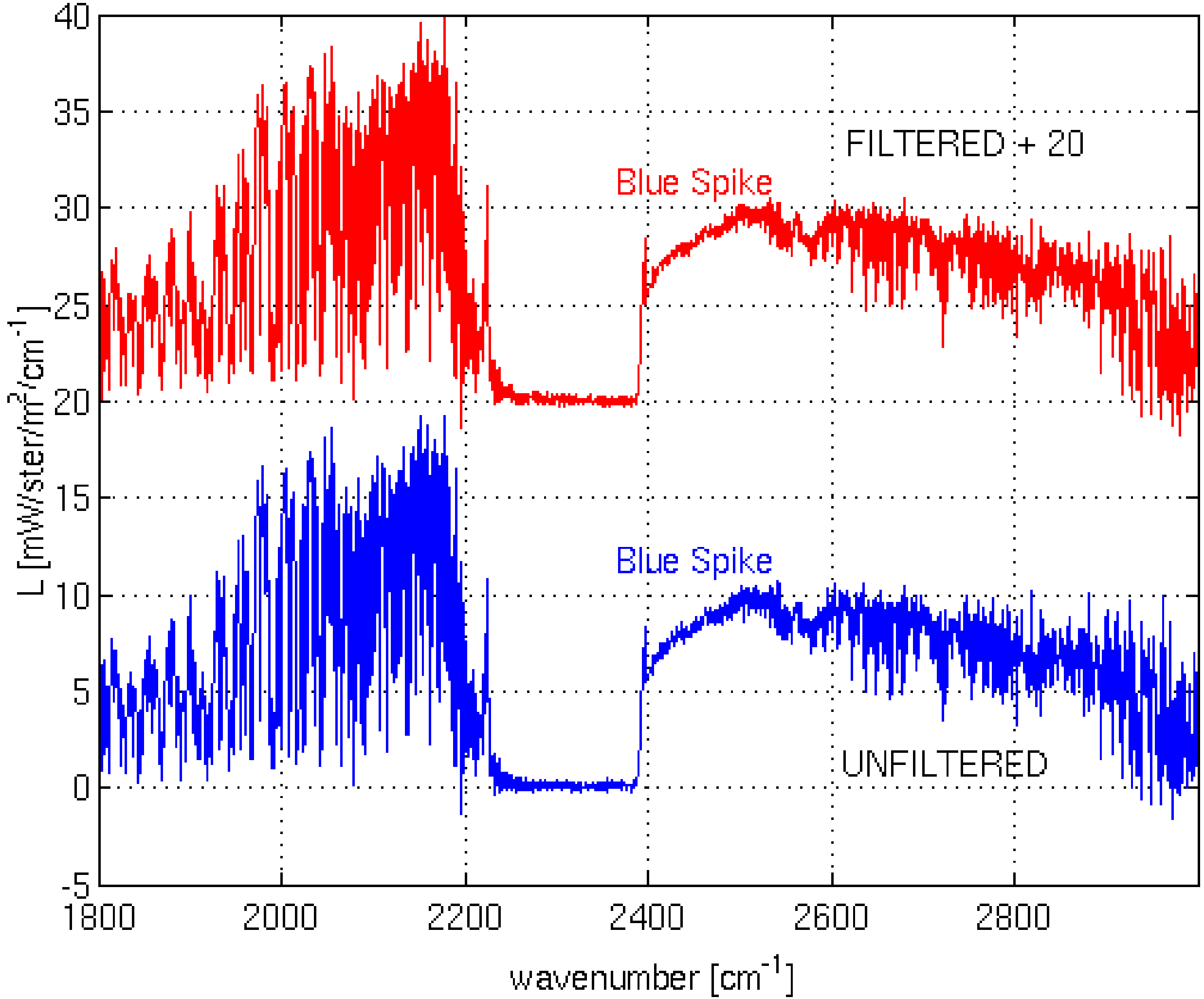
Unfiltered

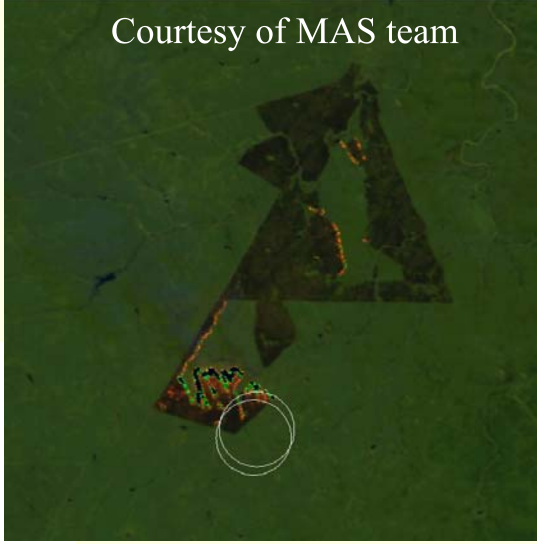
Filtered

Filtered-Unfiltered single FOV over Ocean

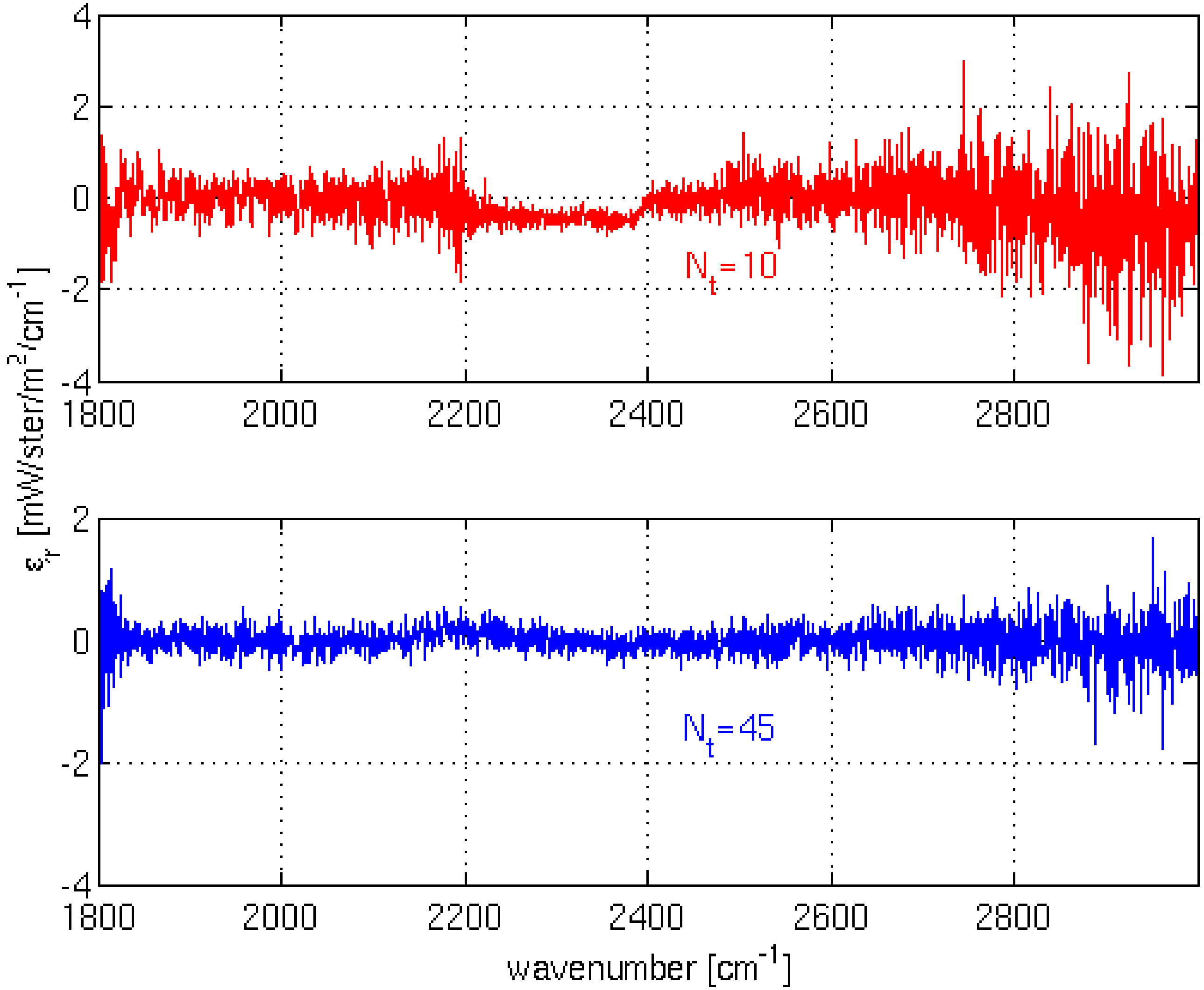


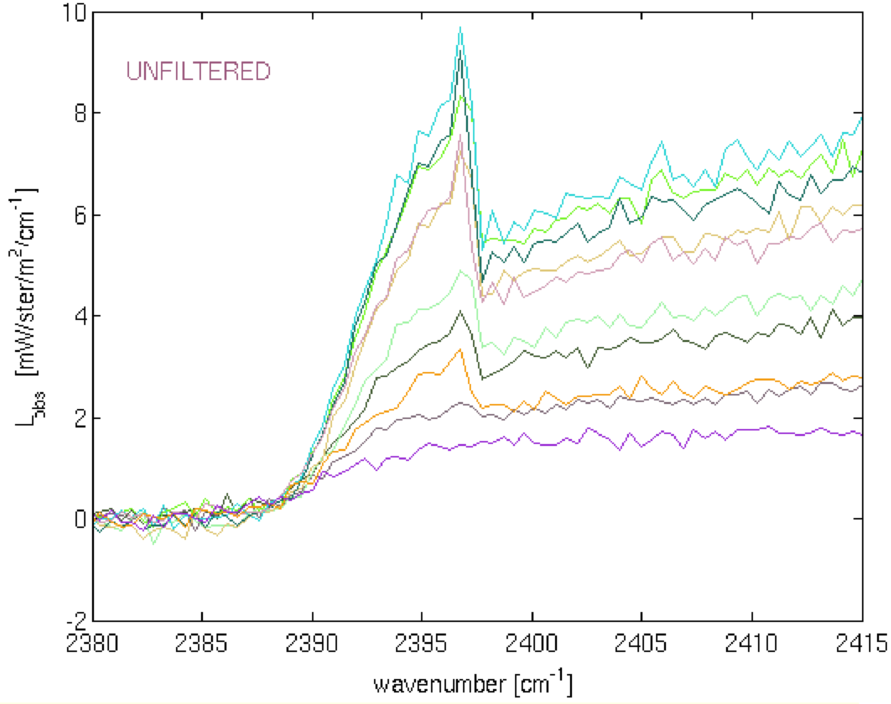
Filtered and Unfiltered data for almost overlapping FOVs over Fire





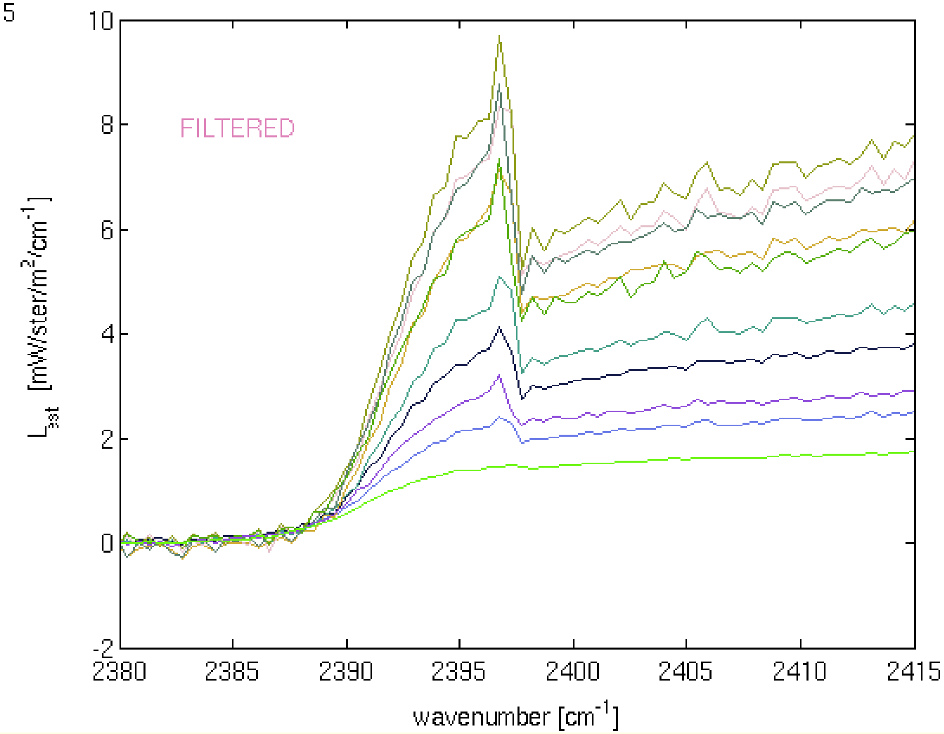
Filtered-Unfiltered for almost overlapping FOVs over Fire

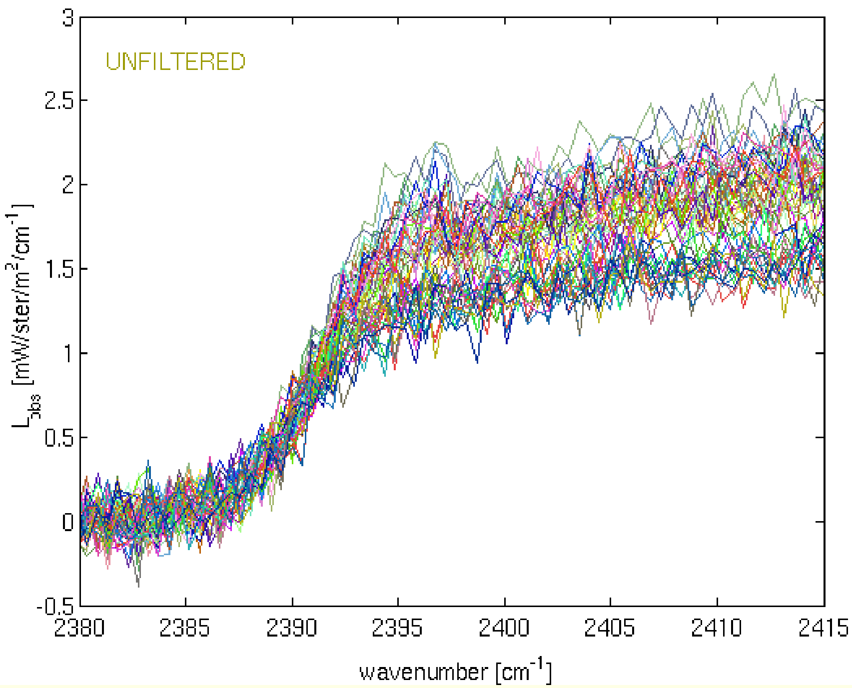




Unfiltered data for 10 FOVs over Fire

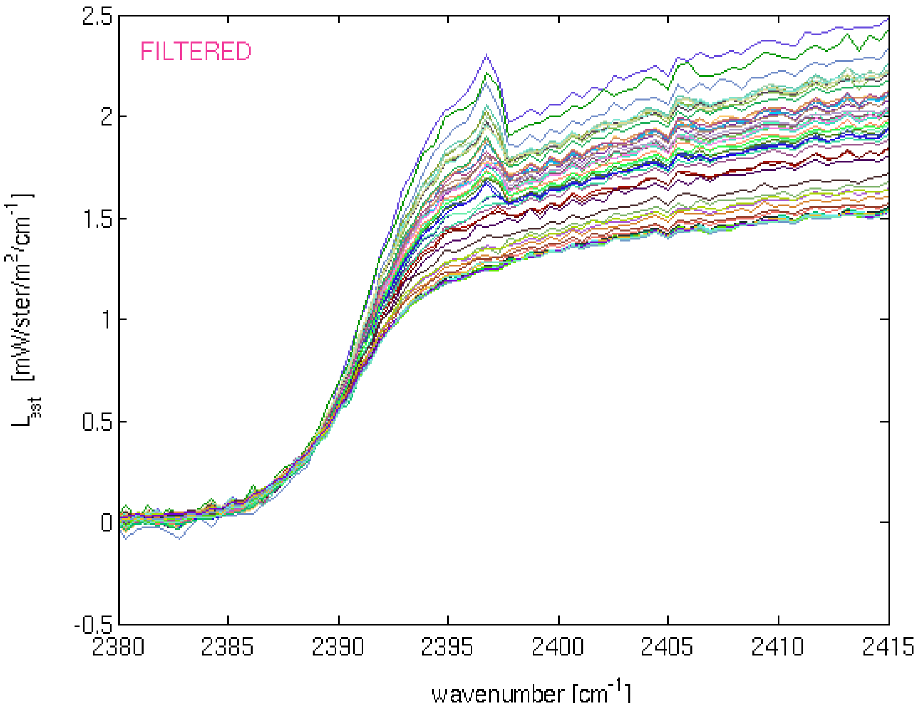
Filtered data for 10 FOVs over Fire

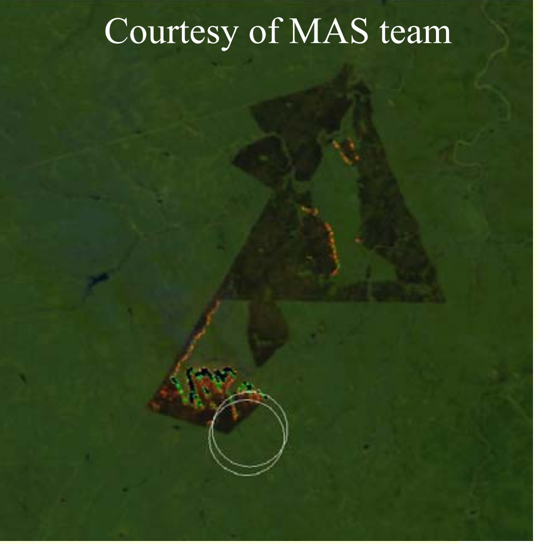




Unfiltered data for 10 FOVs after Fire

Filtered data for 10 FOVs after Fire

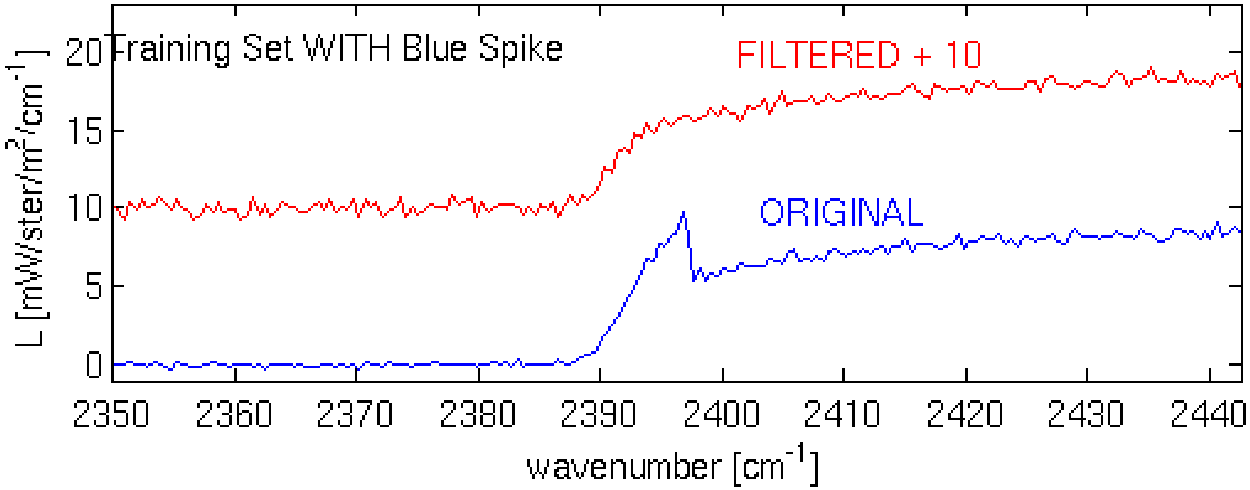


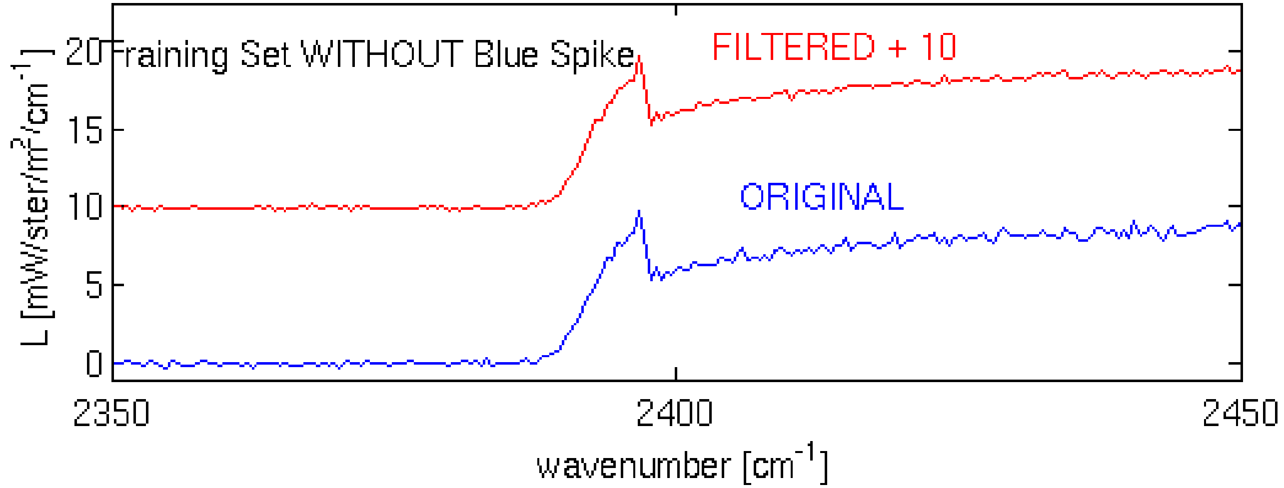


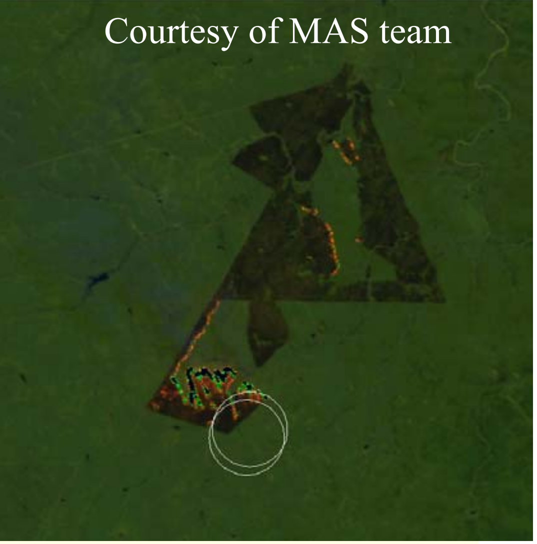
Importance Dependent Training

Poorly Estimated

Properly Estimated

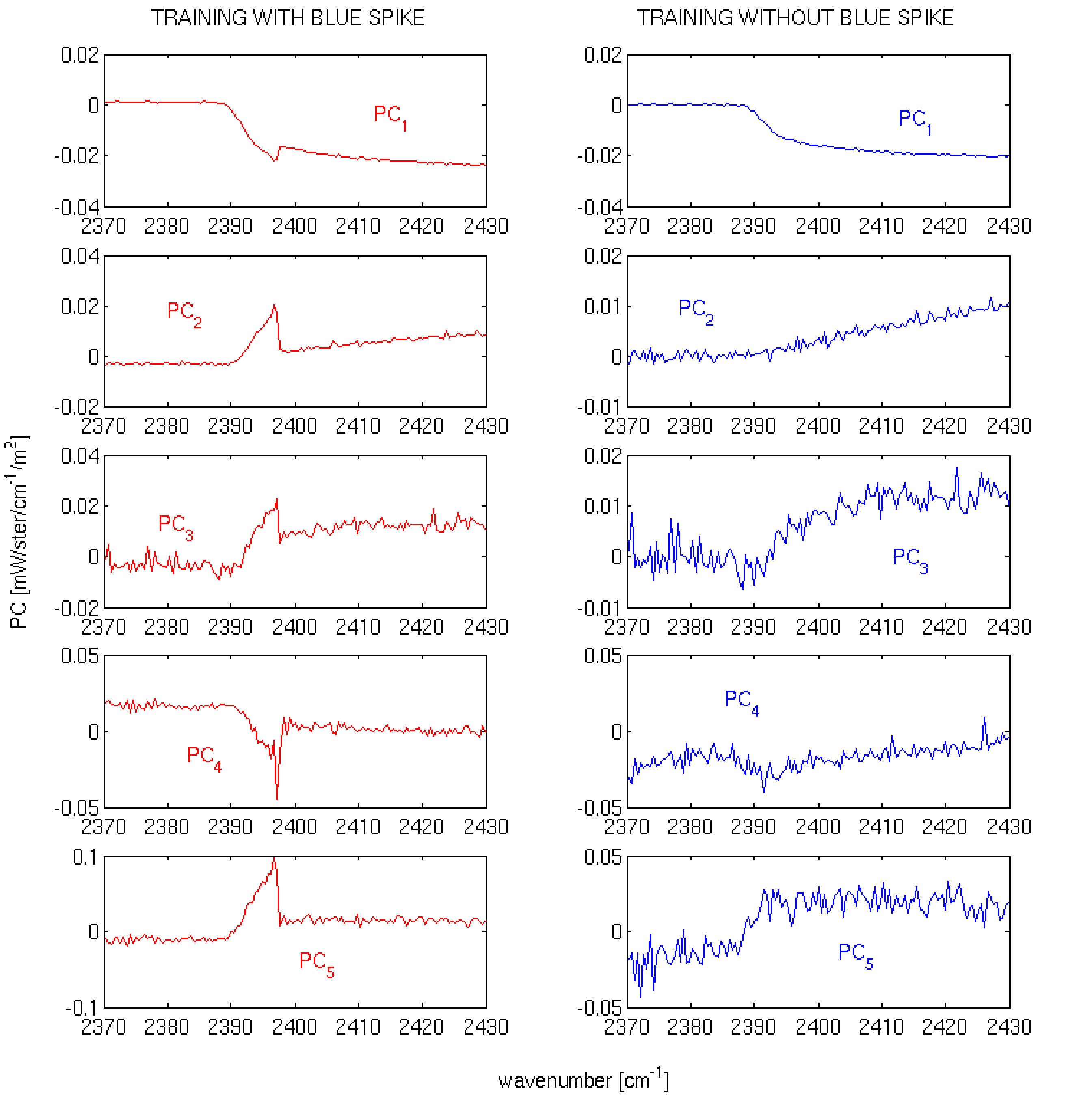




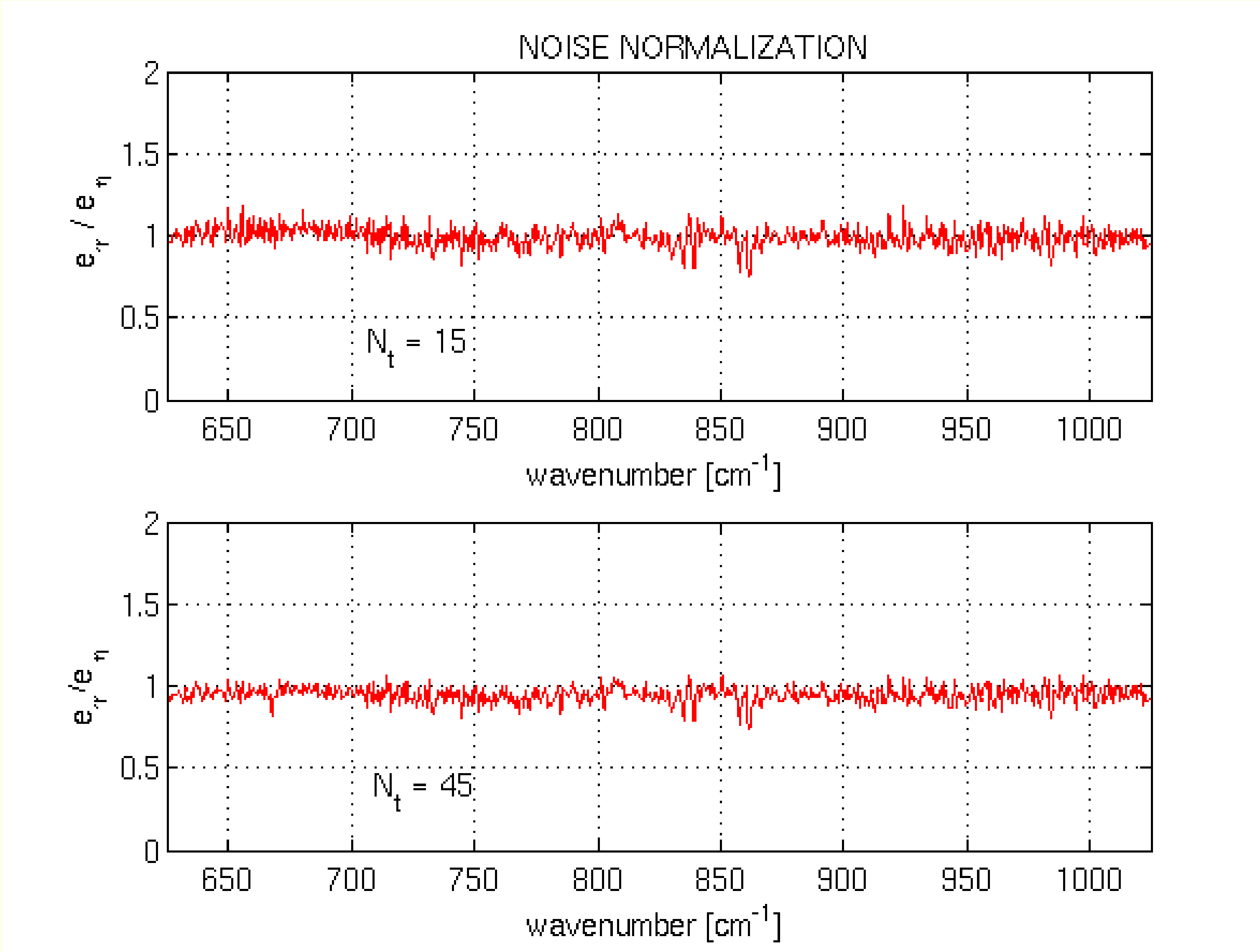


Training Set with Blue Spike

Training Set without Blue Spike



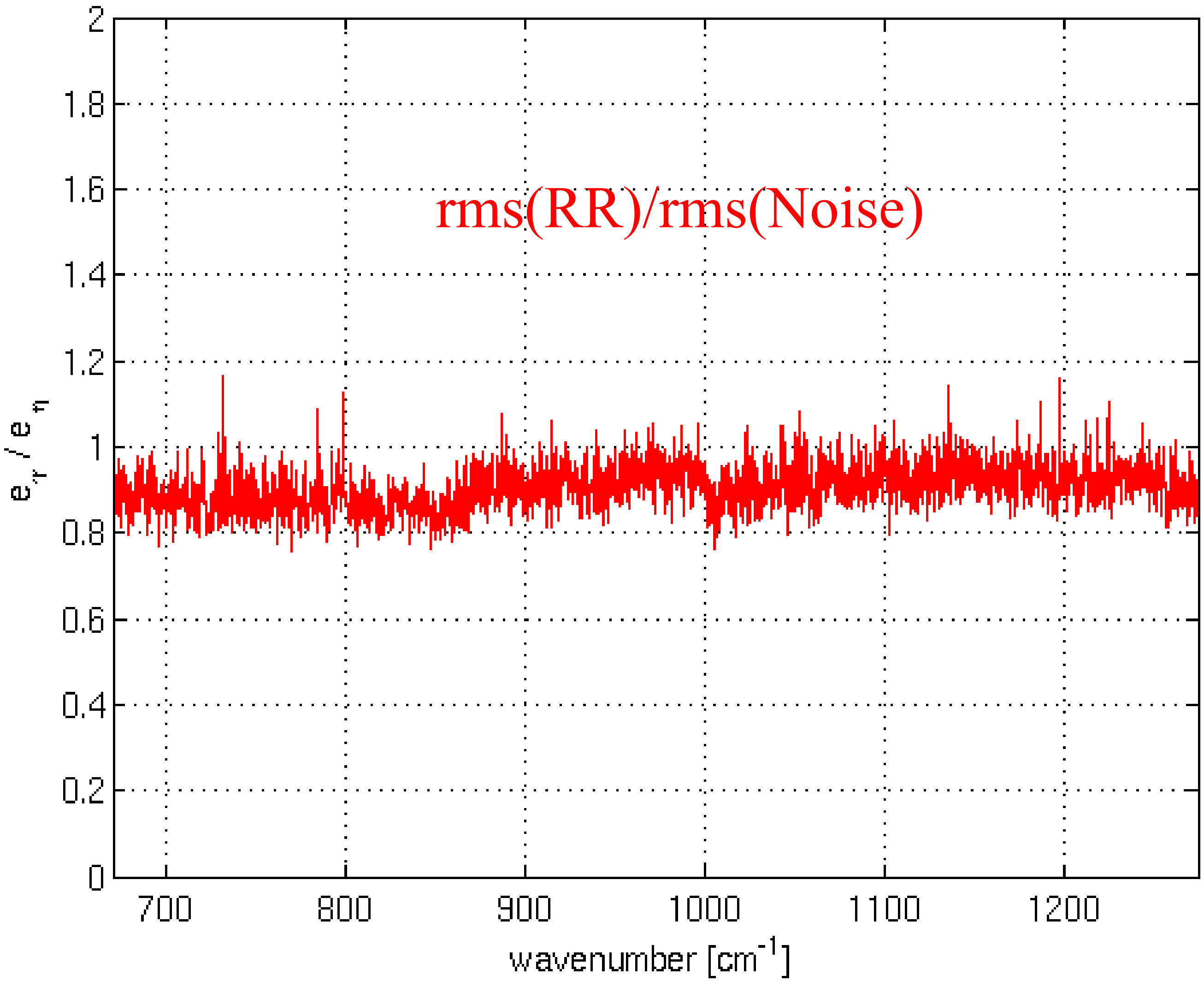
Importance of Noise Normalization



rms(RR)/rms(Noise)

Noise normalization avoids fitting noise where noise level is high

PNF used for noise estimation

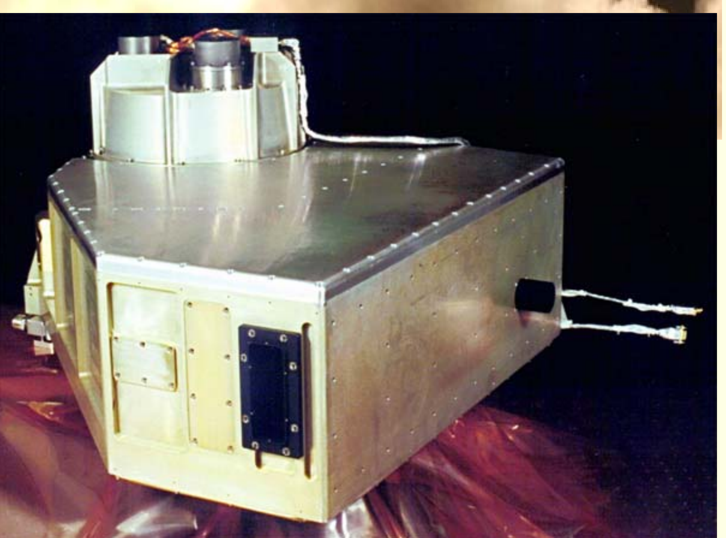


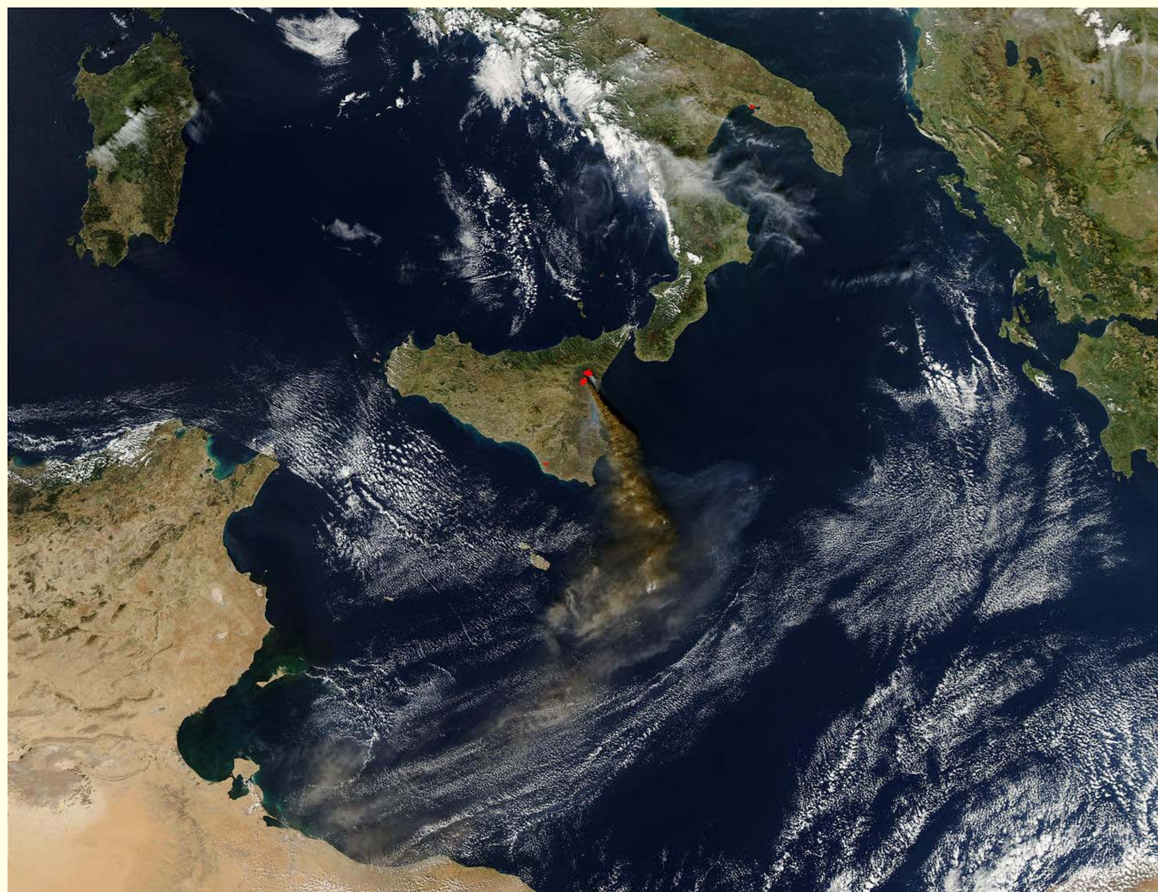
<rms(RR)>

$\partial\langle rms(RR)\rangle / \partial N_t$

Noise estimation with PNF still not objective!

AIRS
on Mount Etna



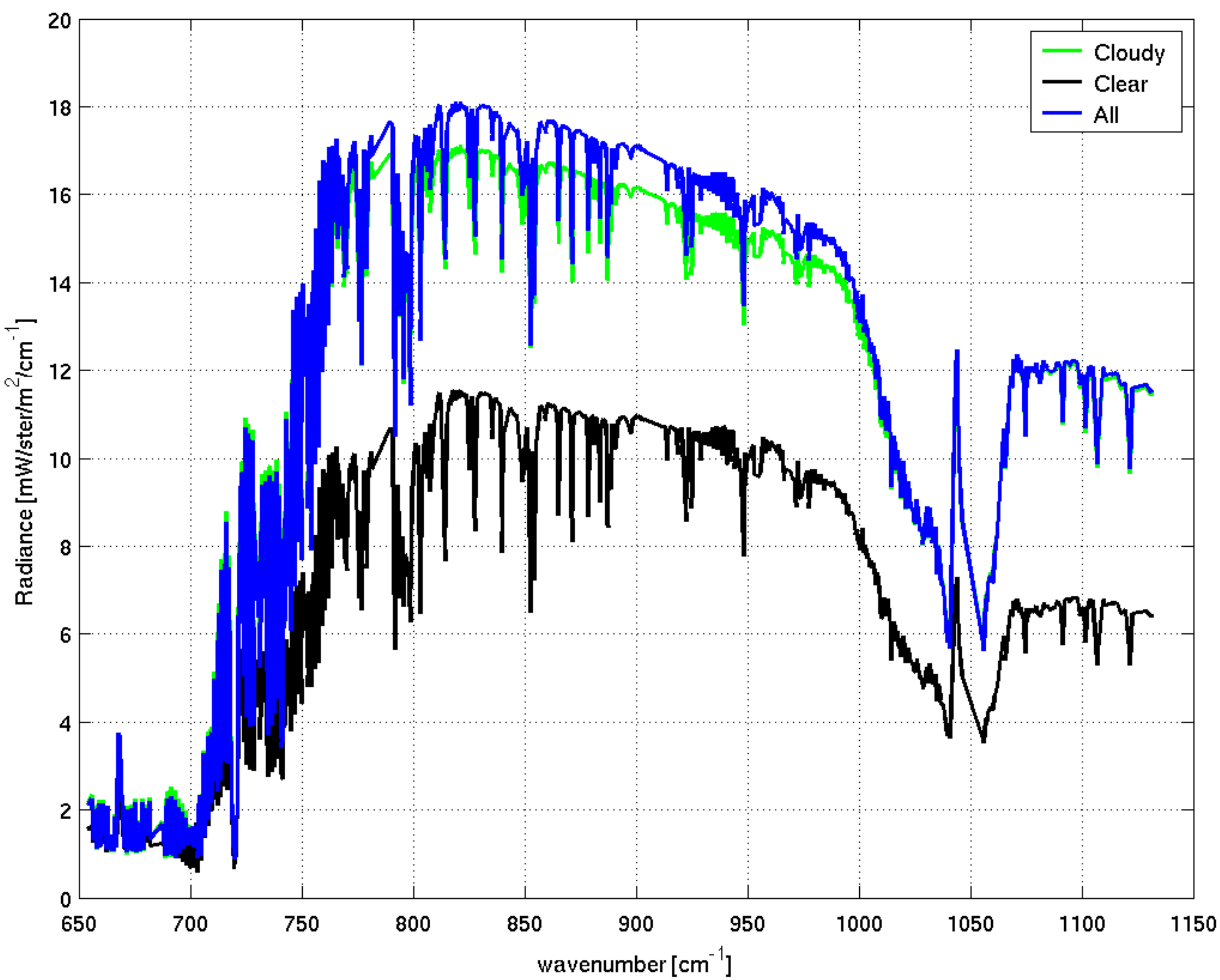


Signal Variance
Granule 123, 28 Oct 2002

Cloudy

Clear

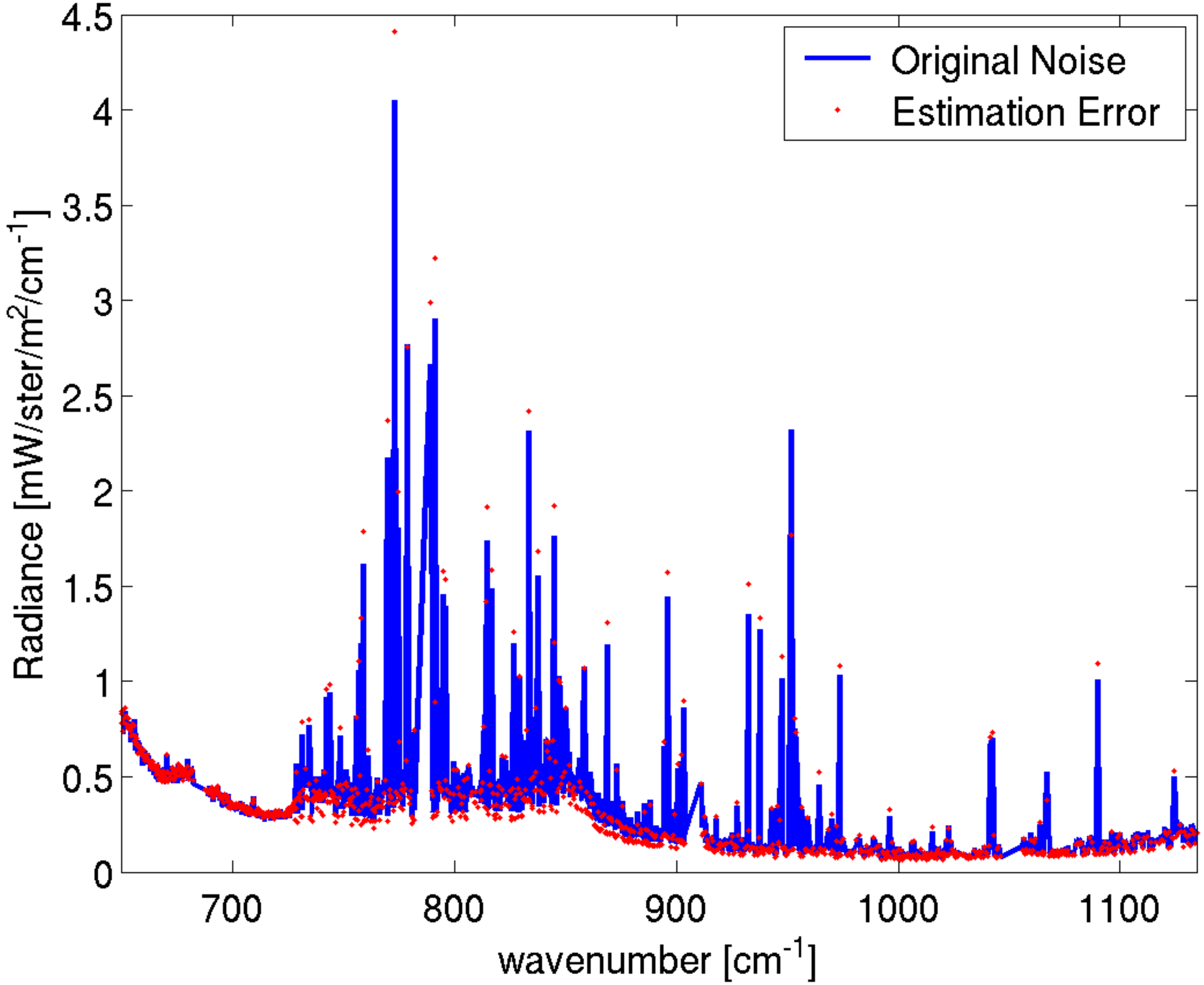
All



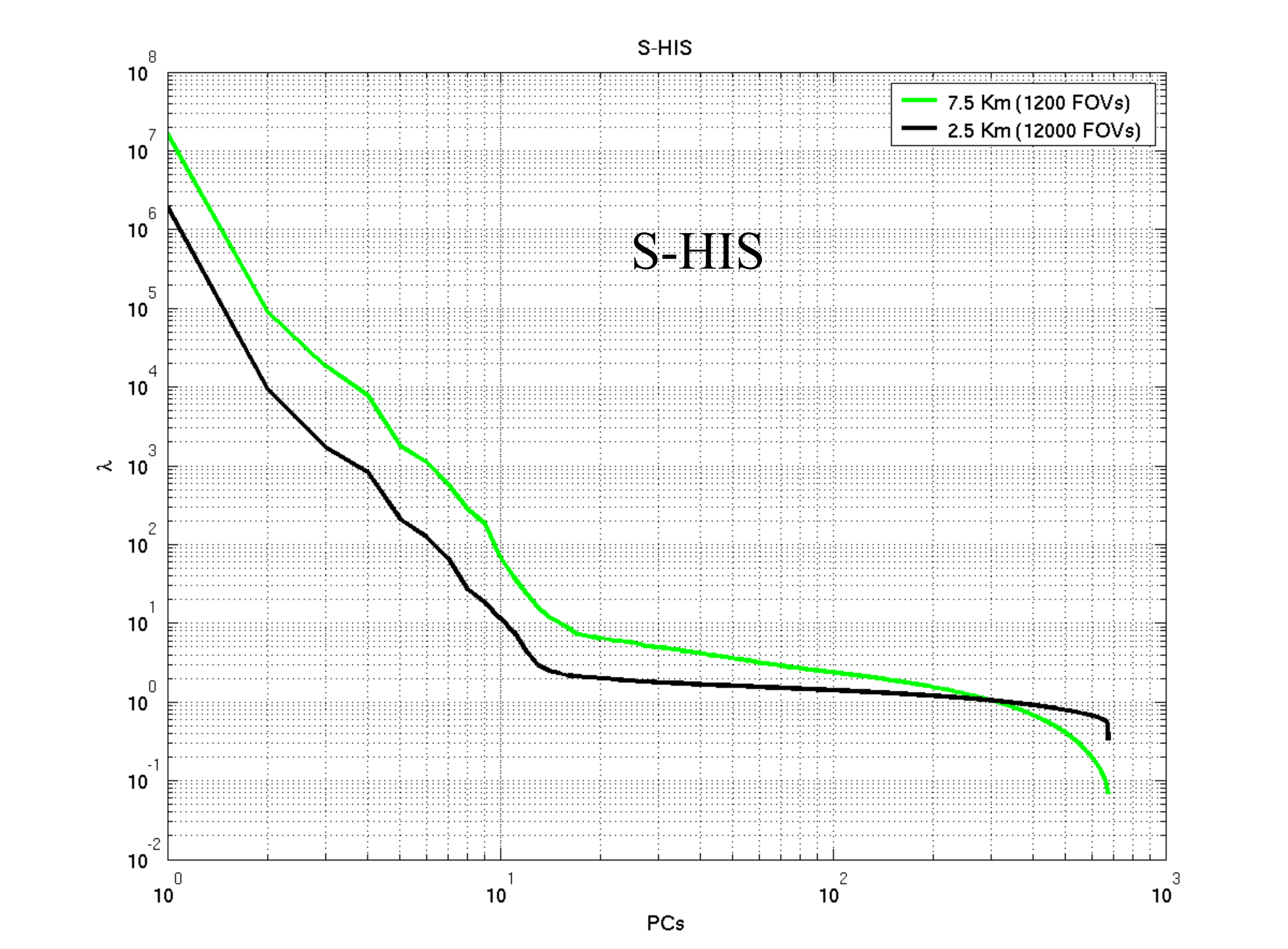
AIRS noise

From Granule

Estimated Noise

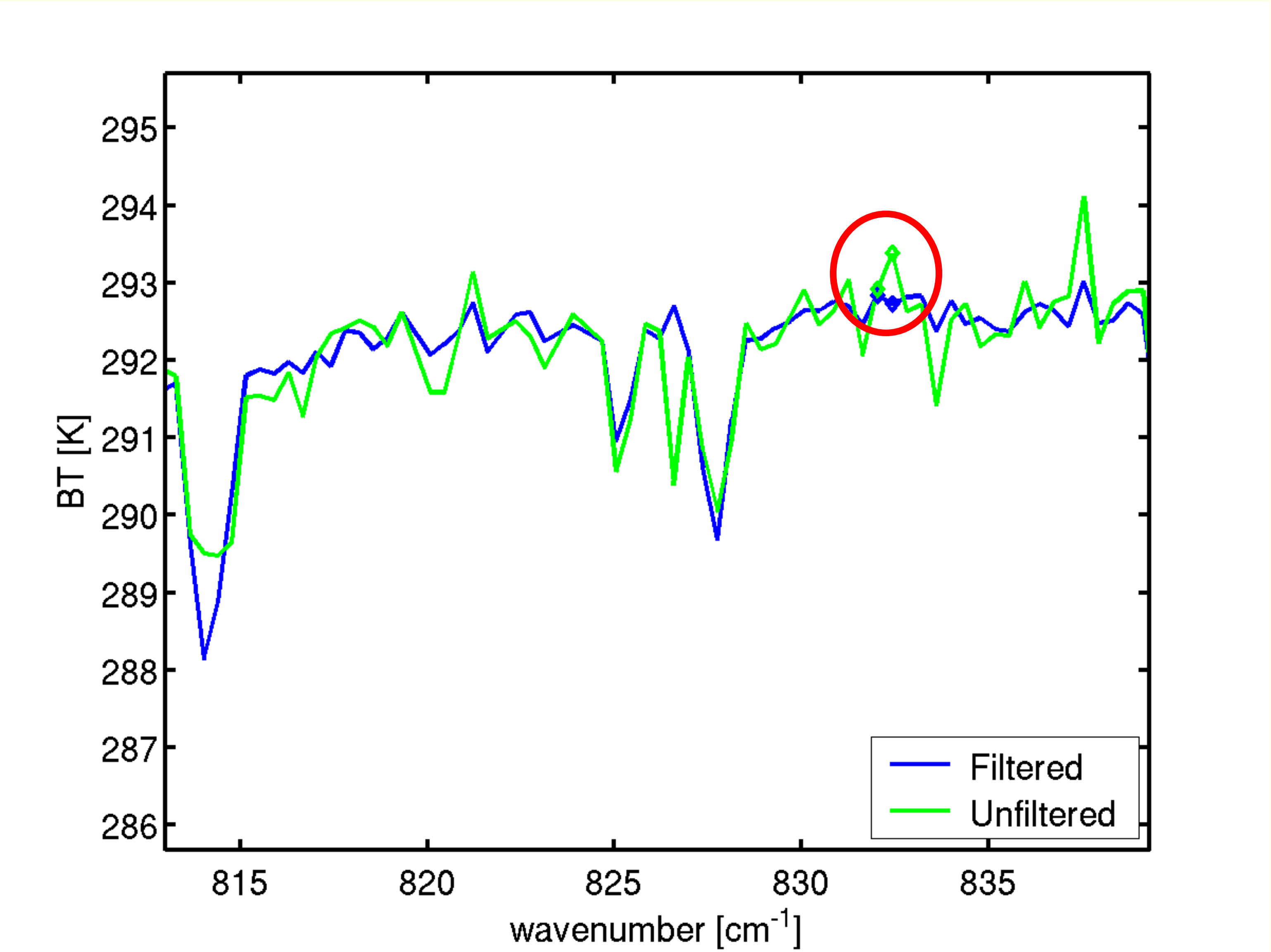


Eigenvalues of Obs covariance Matrix

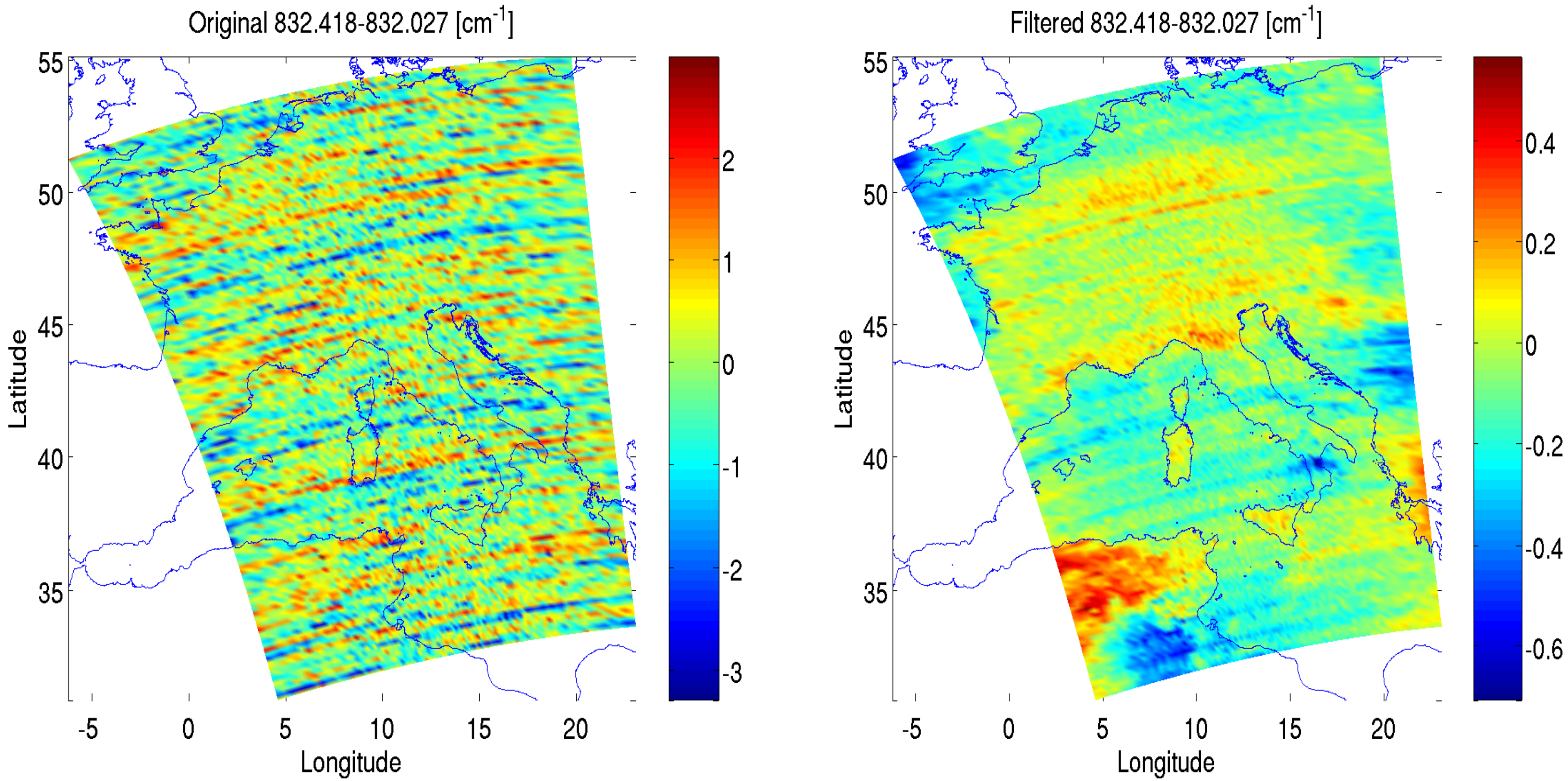


Larger Training with more redundant observation == Smaller FOVs

AIRS channel differences

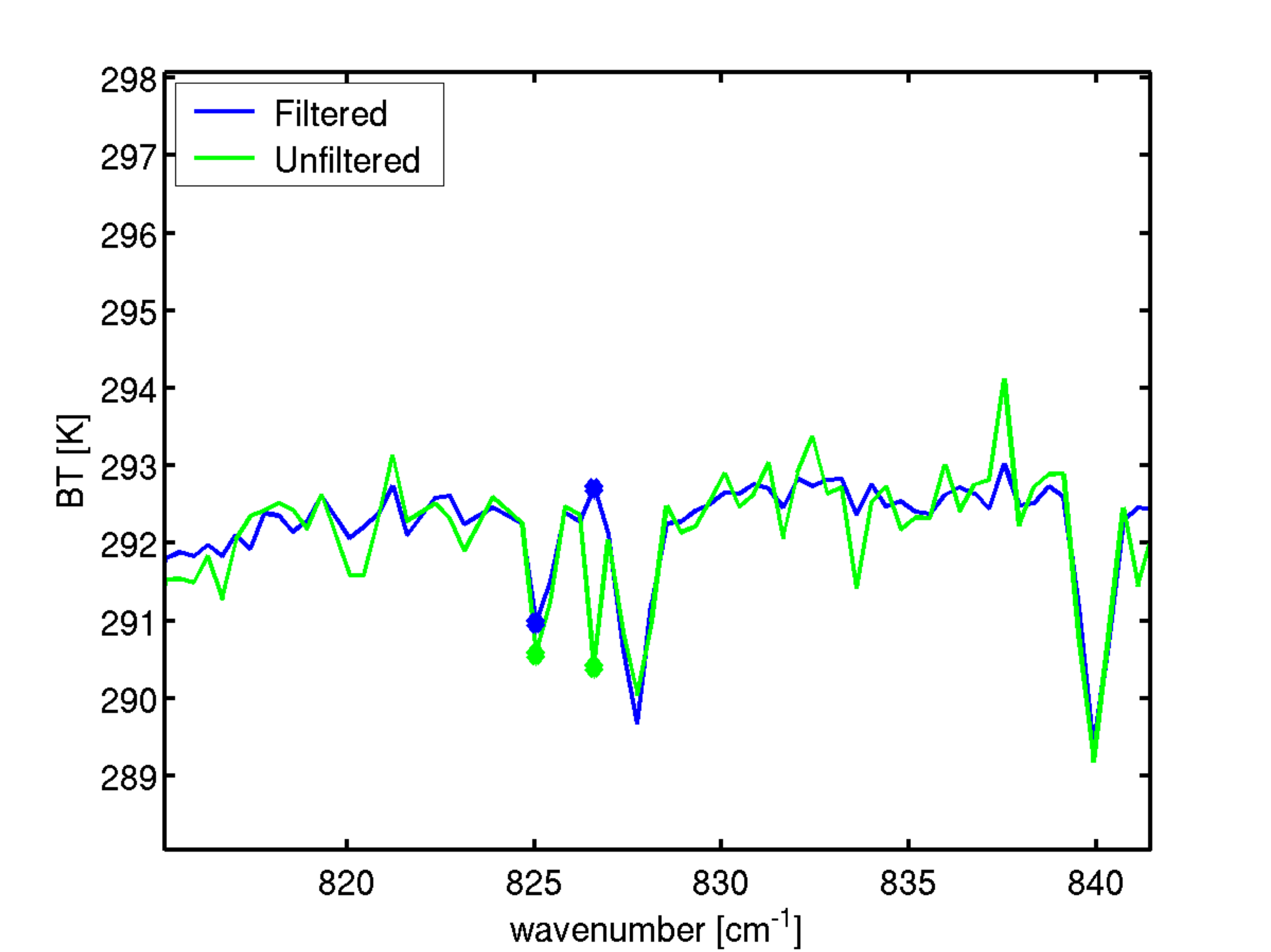


Filter vs Unfiltered

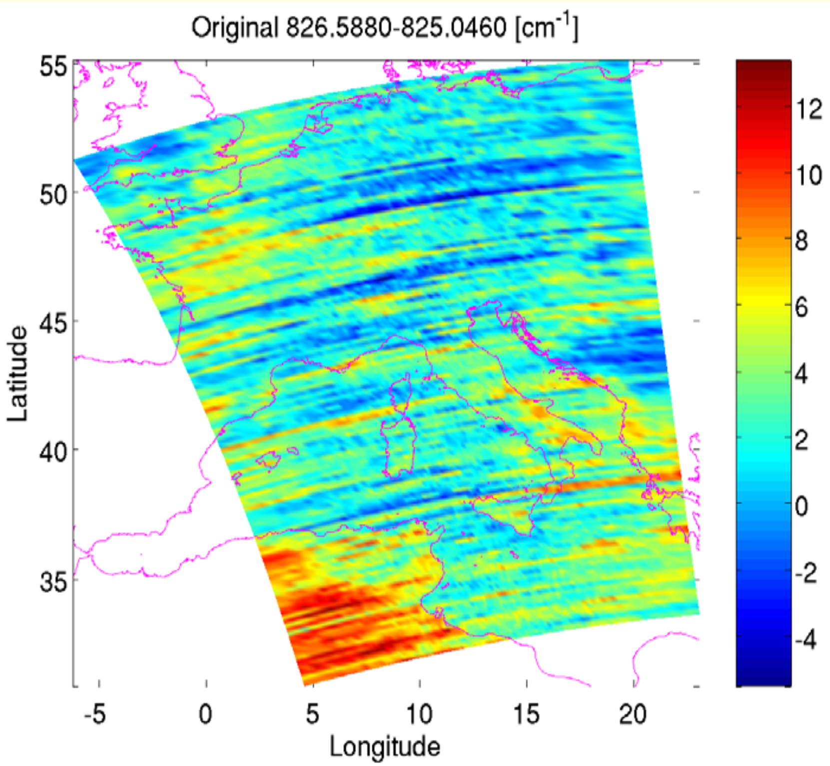


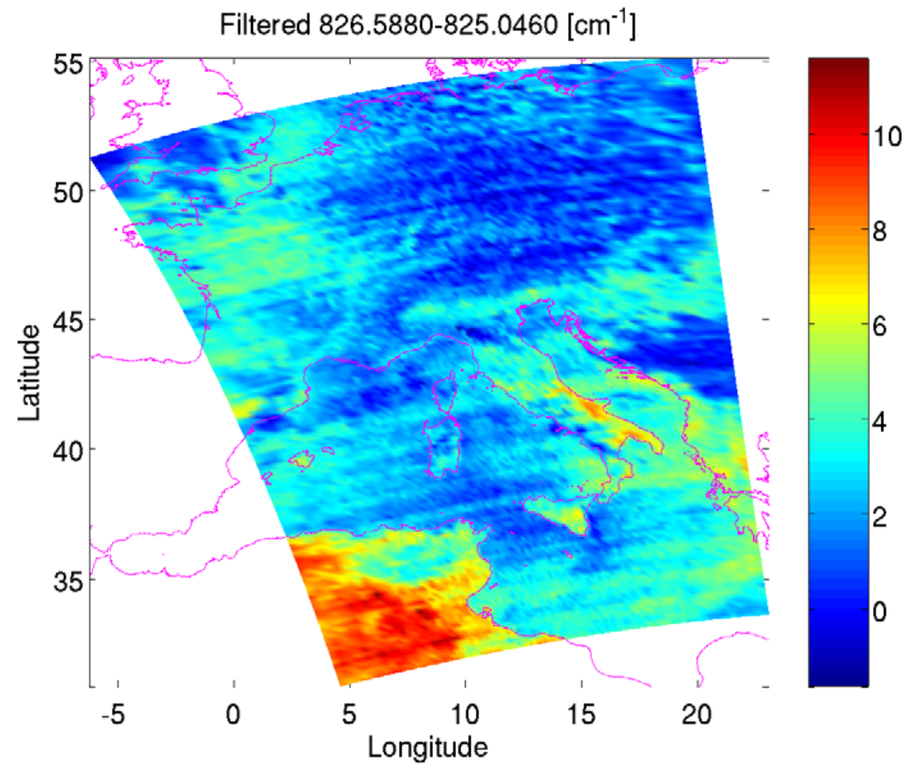
Features over Northern Africa and Southern Italy are visible after filtering

AIRS channel differences



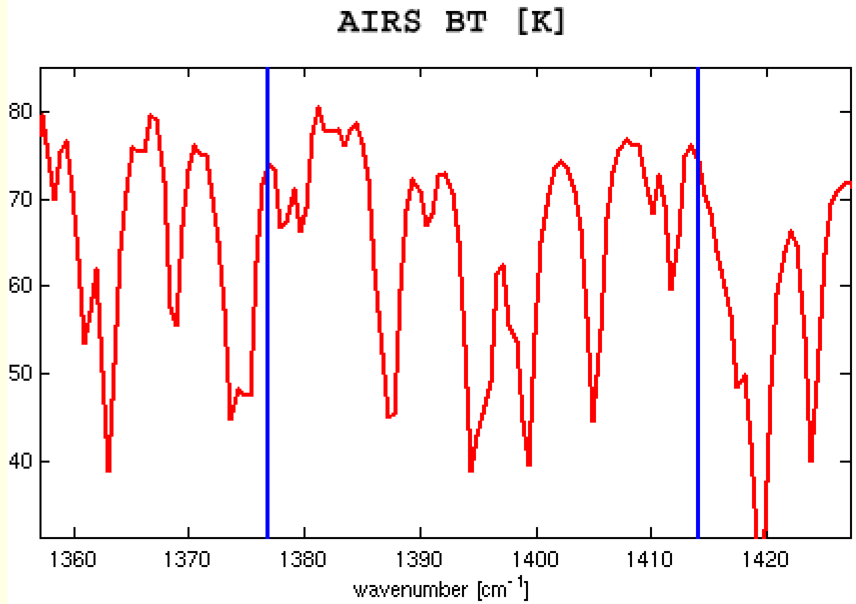
Filter vs Unfiltered

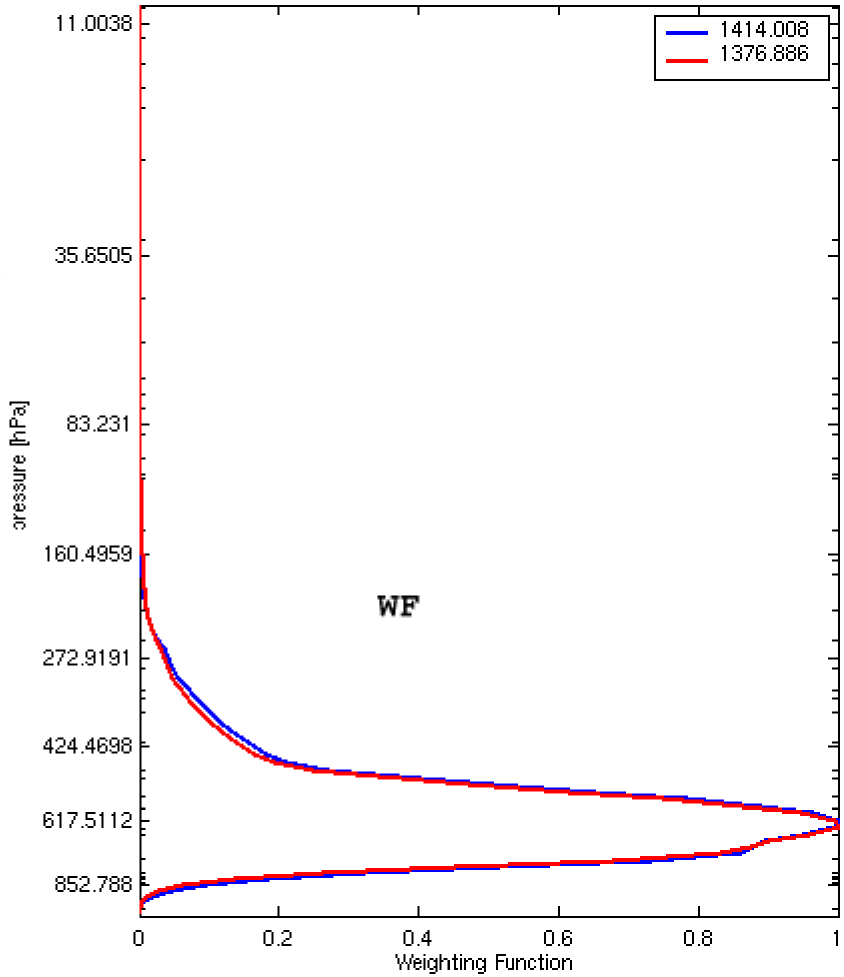




Striping is removed and features over Northern Africa are visible after filtering

Sensitivity to SO_2

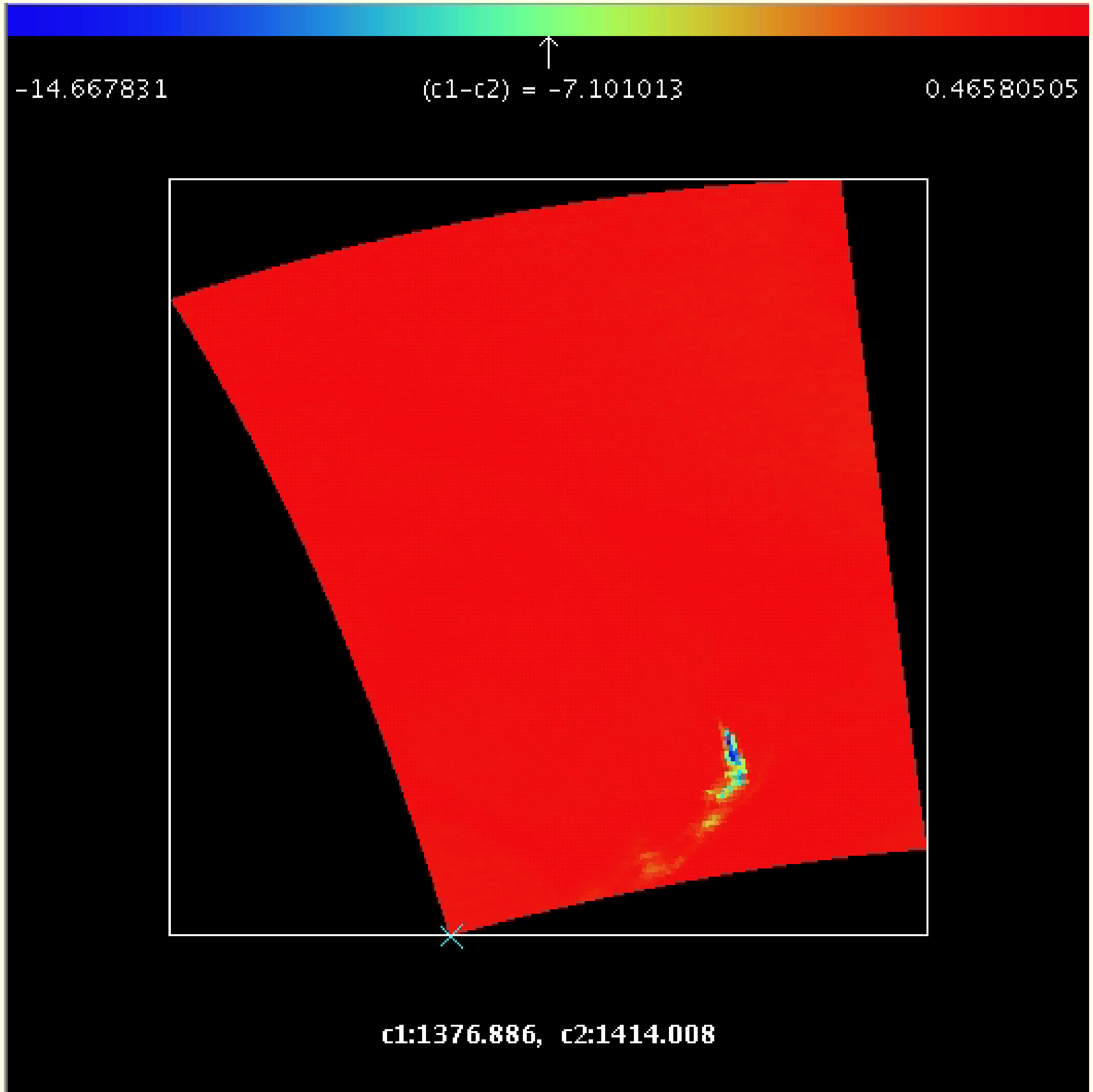




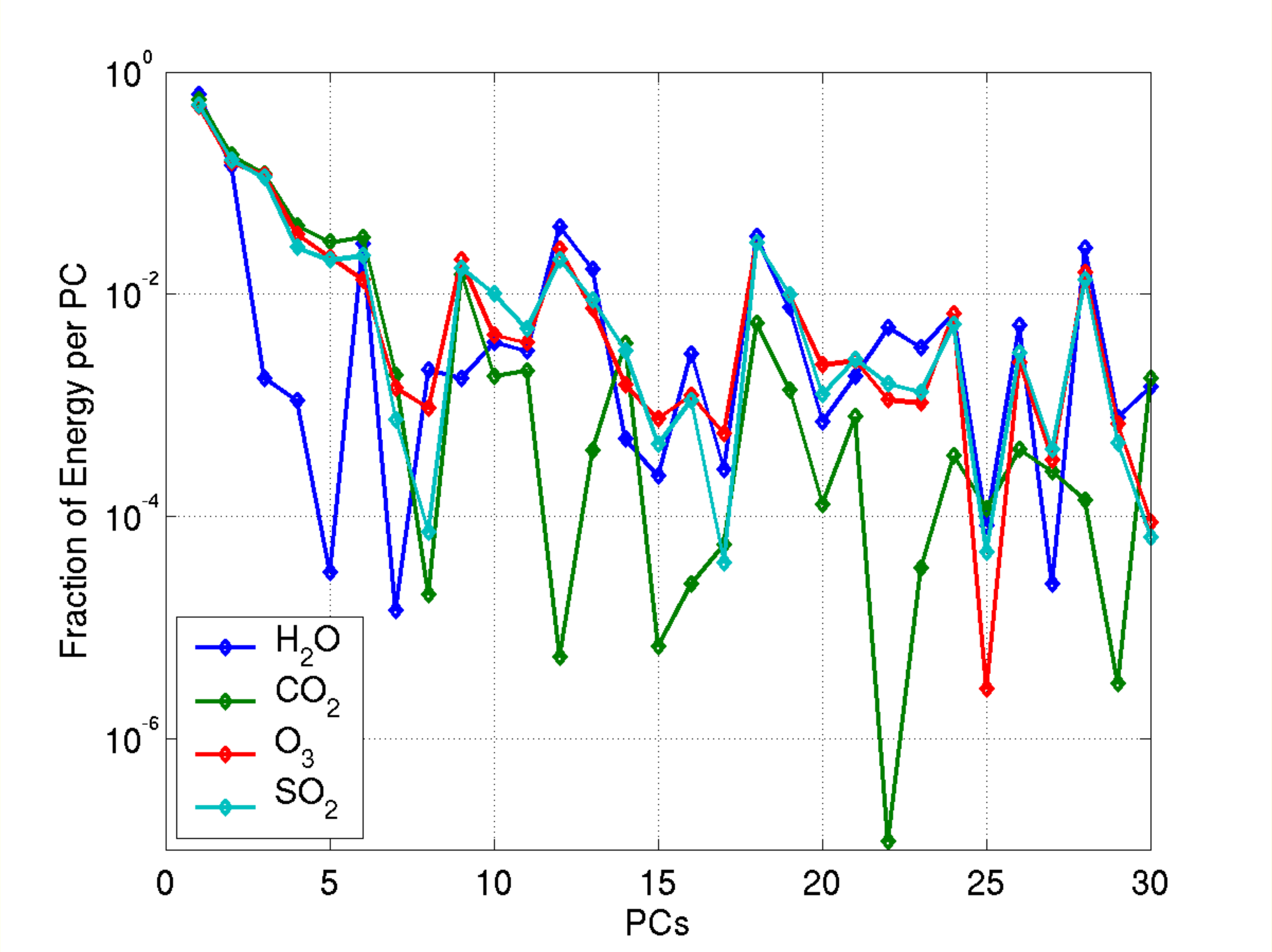
Work initiated by
Larrabee Straw
And Dave Tobin

SO_2 emitted by Mount Etna

1414.008-1376.886 cm^{-1}

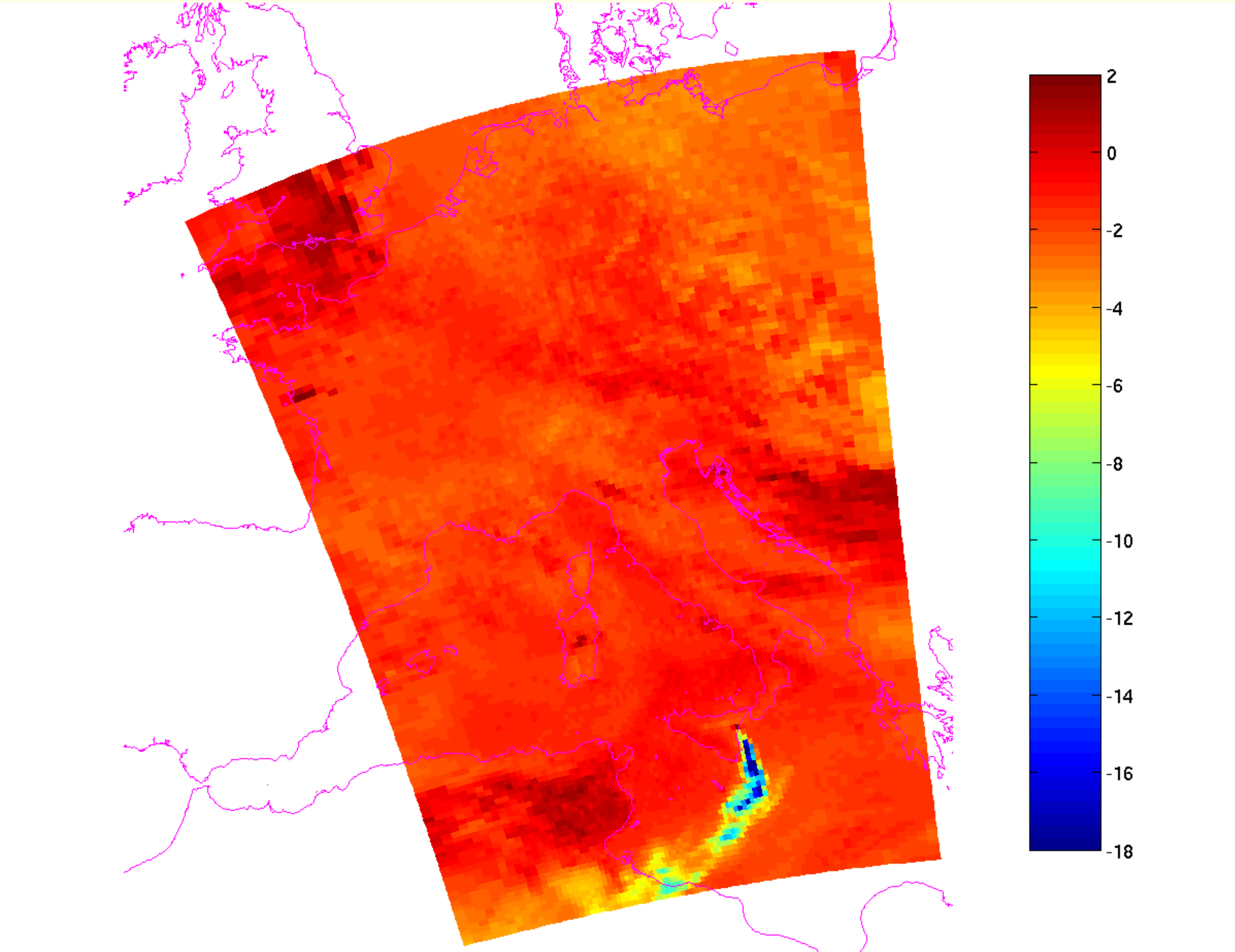


Fraction of Energy per PCs



SO_2 Concentration

PCC8-PCC11



Conclusions

- PCA by taking advantage of redundancy reduces random component of Instrument noise (PNF)
- Both AIL and RN approach the optimal value defined by Linear Estimation Theory
- For simulated data (presented case) AIL and RN are 7 times smaller that original noise
- Both AIL and RN are correlated in wavenumber space
- Most difficult cases, observation highly deviant from mean, are properly treated if PCs are derived in Dependent Mode

Conclusions

- Noise normalization and large training set enhance accuracy and efficiency of PNF
- If not available, estimate of random component of instrument noise can be obtained by applying PCA to observations
- With real data (AIRS) achieved NR factor is between 4 and 5
- PNF is not quite ready to be used as Black Box, it requires tuning and monitoring of Reconstruction Residuals

Ongoing Work

- Characterization of AIL and RN spectral correlation
- Investigation of physical meaning of PCs

Thanks!

Questions?