LASP CLARREO Science Definition Team Studies

Using measurements of scattered spectral shortwave radiation to define requirements and to develop methods for climate change detection and attribution.

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SDT Tasks

1. Trend Detection in SCIAMACHY Spectral Radiances

<u>Task Summary</u>

Objective: Extract trends in TOA outgoing shortwave spectral radiance.

Method: PCA, examining PC score time series, and SSA/MSSA for trend extraction.

Data: SCIAMACHY shortwave spectral radiance; radiative transfer simulations of TOA outgoing spectral radiance.

Models: PCA implemented through IDL/ENVI; SSA from published algorithms; MODTRAN.

Expected outcomes: Validation of trend detection methods using measured shortwave radiances and tested with modeled simulations with known forcings; improved quantification and refinement of CLARREO requirements.

SDT Tasks

2. Intersection of Spectrally Decomposed Subspaces

<u>Task Summary</u>

Objective: Find intersection of eigenvector subspaces in measured and modeled radiance data sets. Use to separate the underlying physical variables that explain the variance in the measurements.

Method: Numerical methods of determining the angles between the complementary linear subspaces. Look-up tables to match model input to variance as depicted by measurement eigenvectors.

Data: SCIAMACHY shortwave spectral radiance; radiative transfer simulations of TOA outgoing spectral radiance from Langley and UC Berkeley groups.

Models: PCA implemented through IDL/ENVI; MODTRAN; numerical model to derive angles between principle axes.

Expected outcome: Improved attribution techniques through identification of physical variables responsible for spectral variability; improved quantification and refinement of CLARREO requirements.

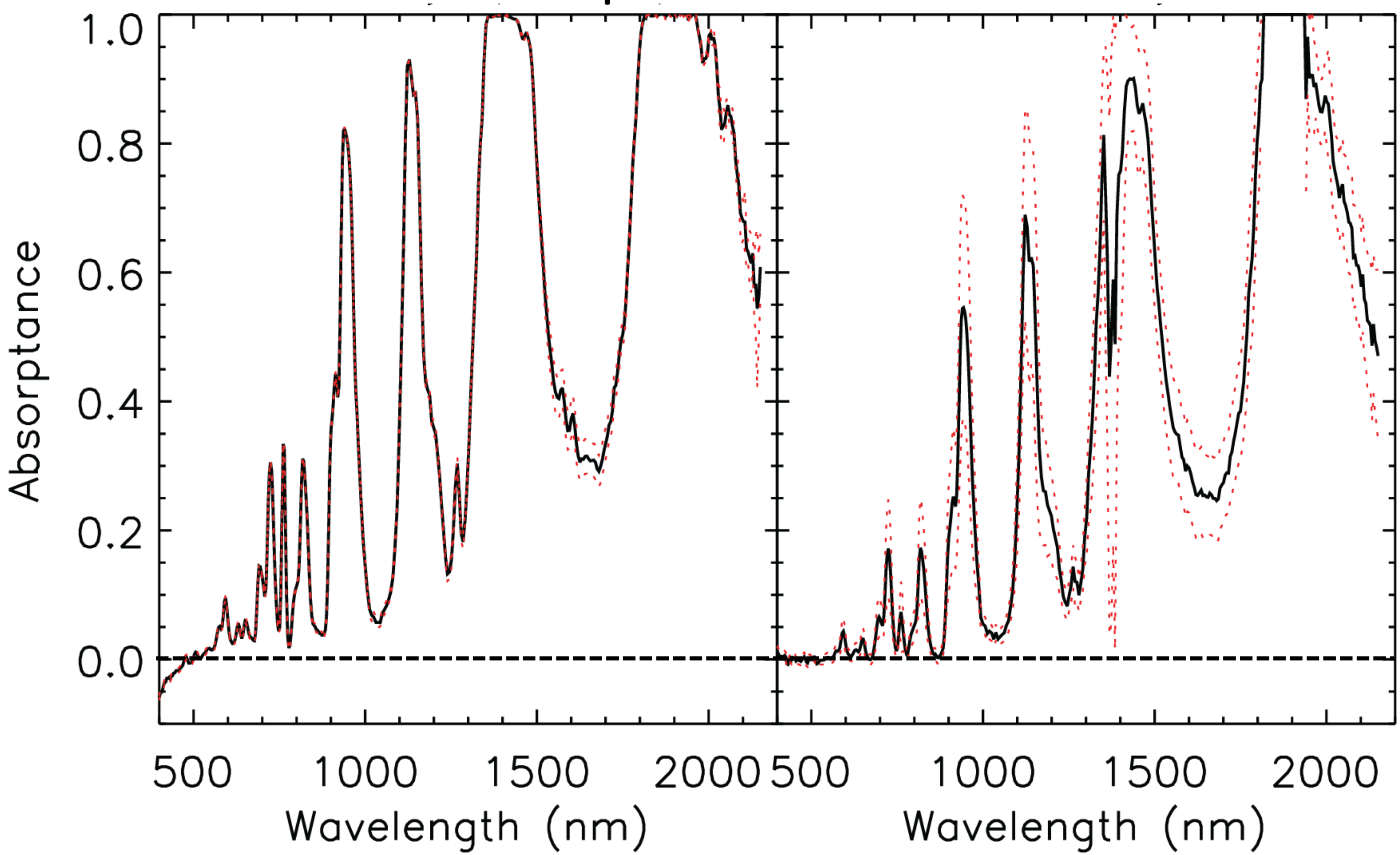
Summary of Prior Studies

- Continuous near-full spectrum is required for shortwave climate benchmarking.
  - Energy arguments: 50% absorption > 1400 nm
  - Increased information content over discrete band sampling
- Approximately 0.5-1%/decade change in reflectance based on various climate change predictions.
- For both a full-global case and a subset single SCIA orbit, 99% of the variance is explained by 5-6 components.
- Spectral resolution makes little difference in distributed variance in SCIA spectra.
  - Recommendation: 10 nm for cloud phase discrimination, surface characterization.
- Directional sampling:
  - Little change in variance contribution between nadir and full-swath.
  - Nadir bias < inter-annual variability.

Summary of Prior Studies

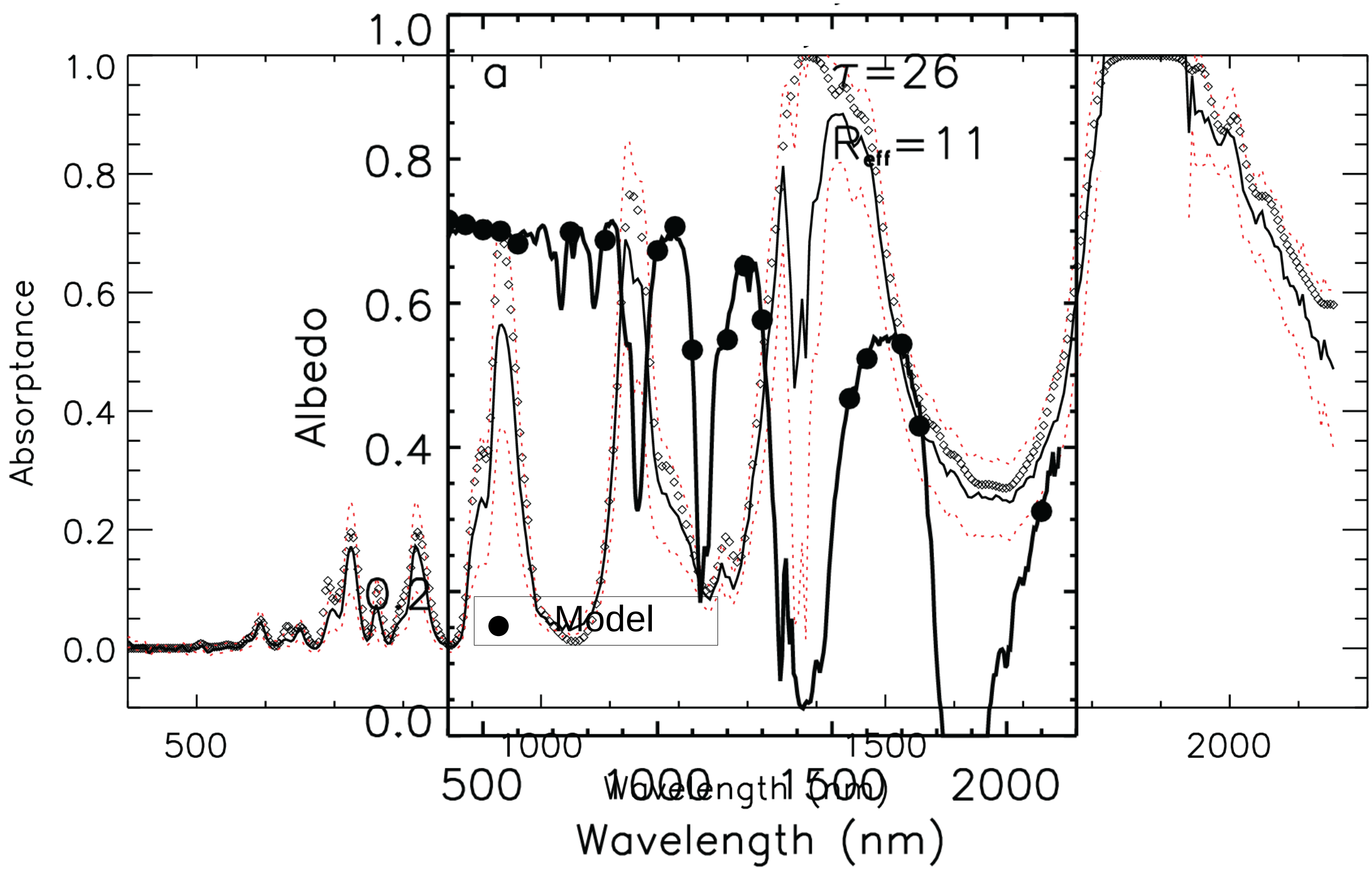
- Seasonal variability is evident, but PC order is conserved.
- Recommended spatial resolution based on cloud resolving arguments:
  - Tradeoff between IPA and PP assumptions.
- Interpretation of physical causality:
  - First component: clouds/water vapor; fourth: molecular scattering; fifth: vegetated surface albedo.
  - PCA very effective in separating surface and atmospheric variability.
- Trend detection in PC time series.
  - Arctic PC2 is ice albedo and follows trend with sea ice extent.

A new method for deriving spectral shortwave cloud absorption from aircraft …

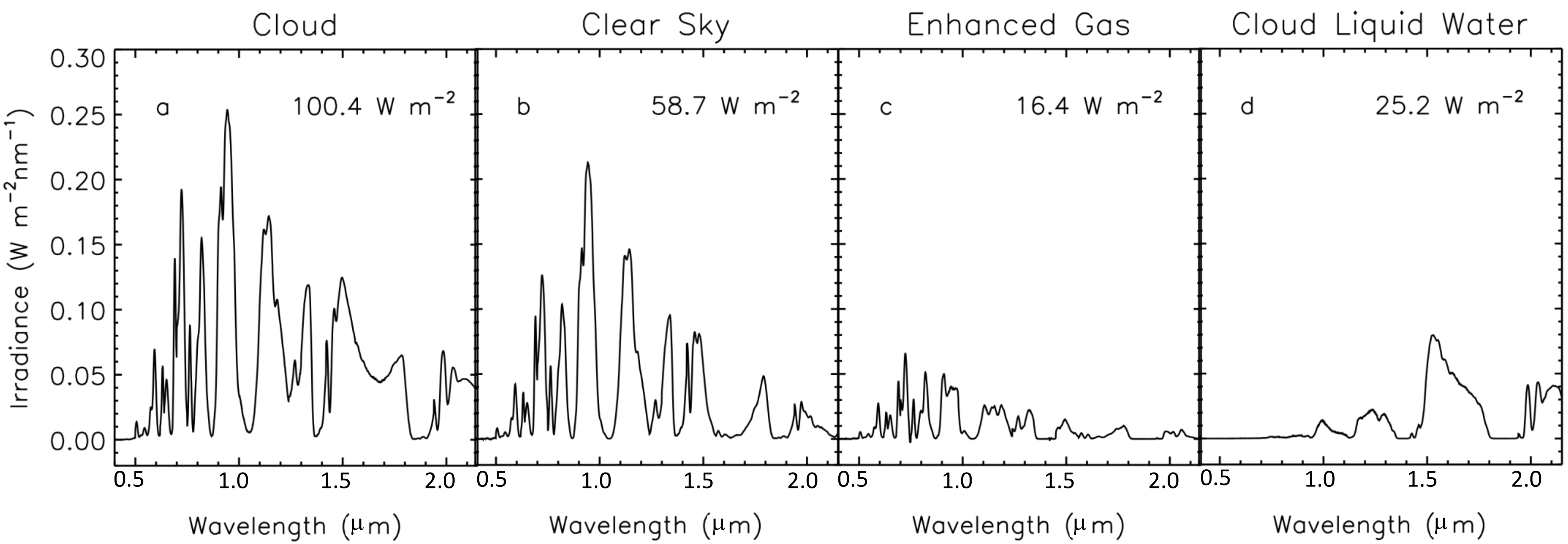


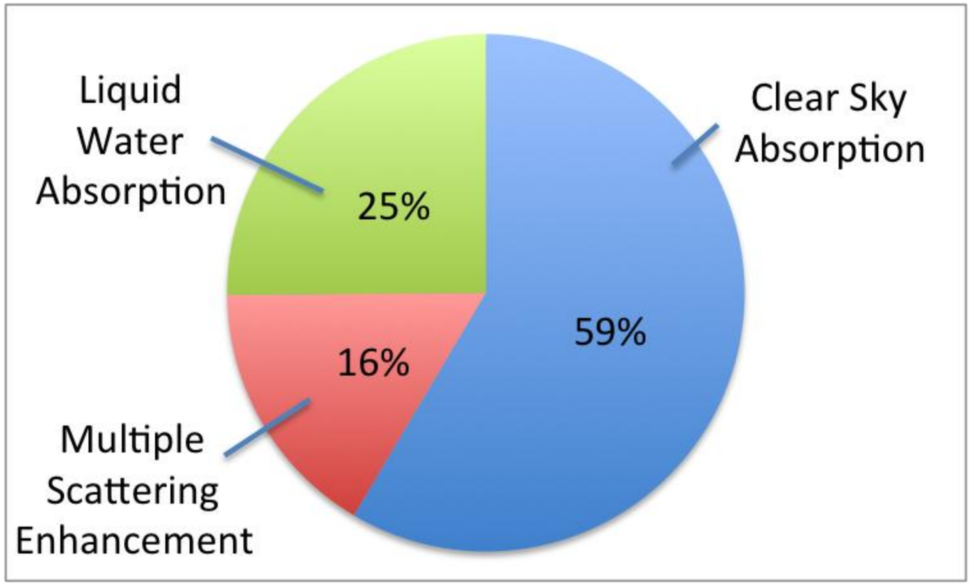
Kindel et al., 2011

… that agrees well with modeled absorption



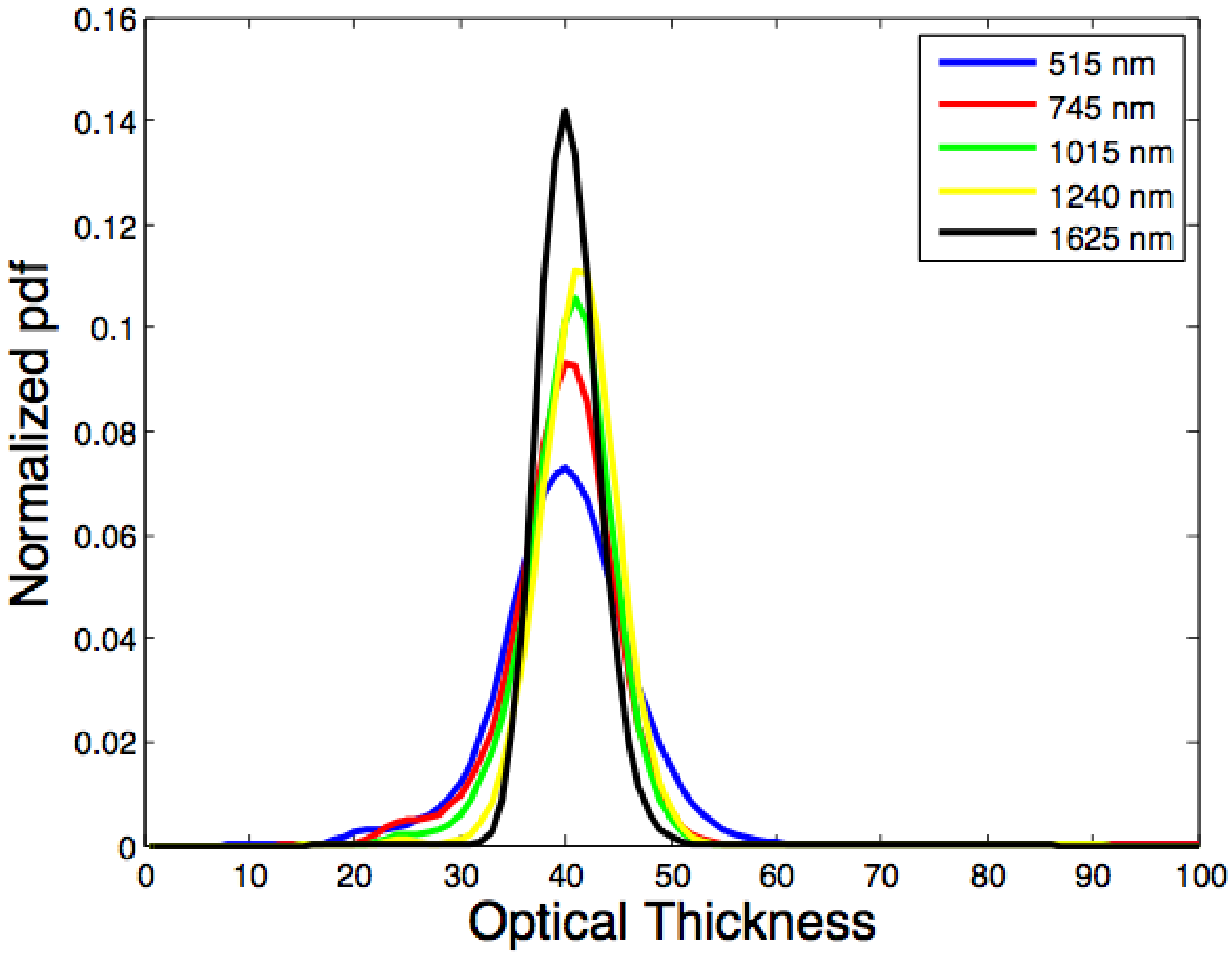
Contributions to Absorbed Irradiance In Cloud





Kindel, et al., 2011; Schmidt & Pilewskie, 2011

Retrieval Accuracy Improves With Added Spectral Coverage

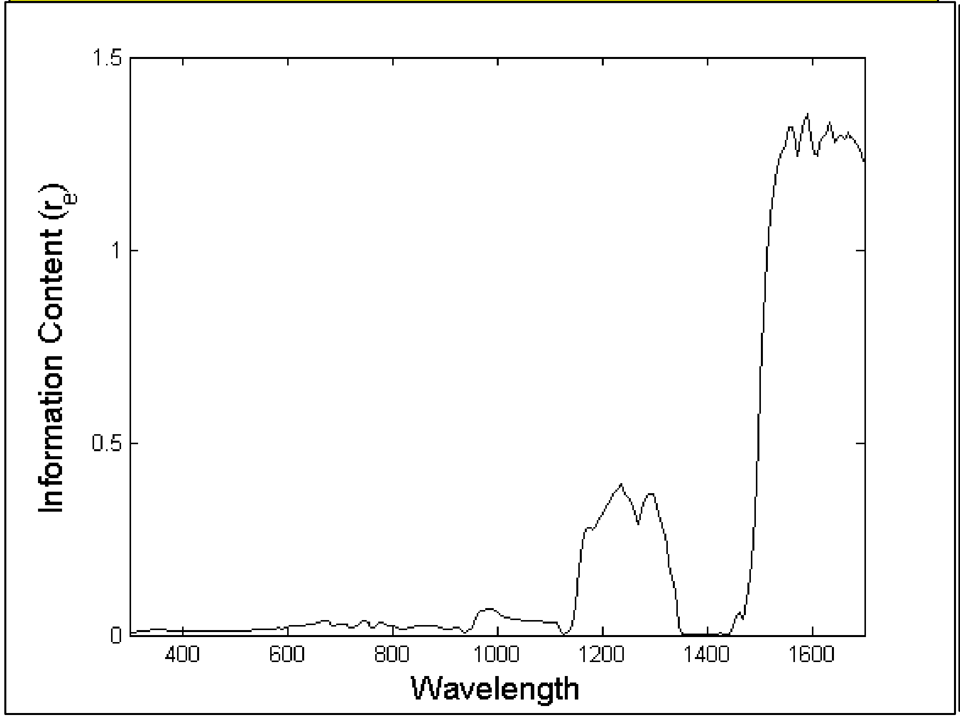


Coddington , Pilewskie, Vukicevic ,2011

GEneralized Nonlinear Retrieval Analysis (GENRA; *Vukicevic et al*., 2010)

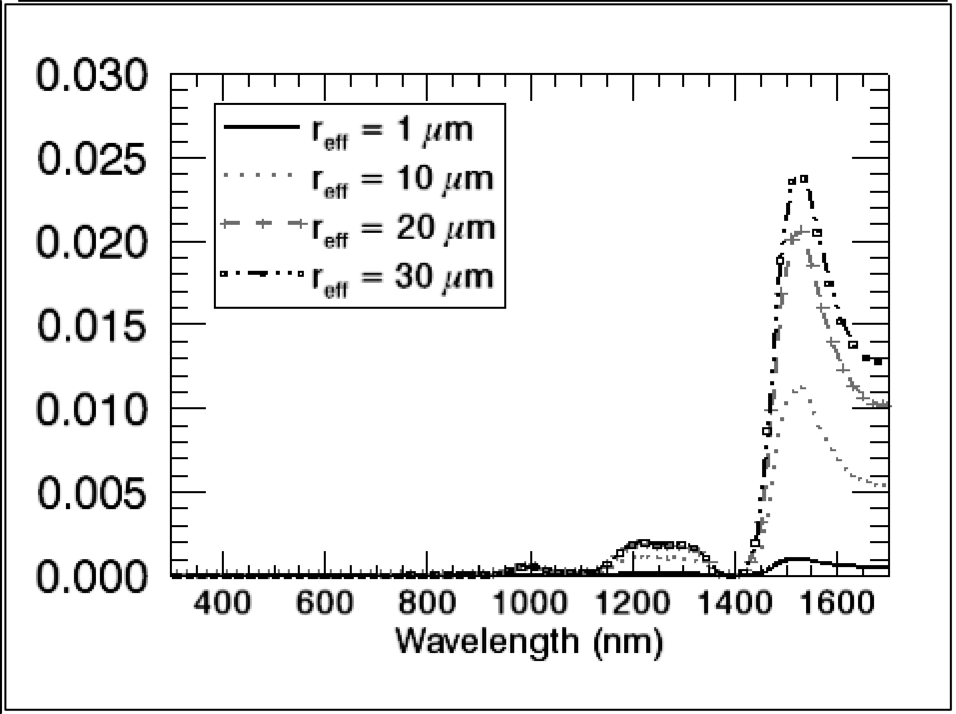
Information Content supports the physical basis for retrievals of droplet effective radius

Information Content for Effective Radius



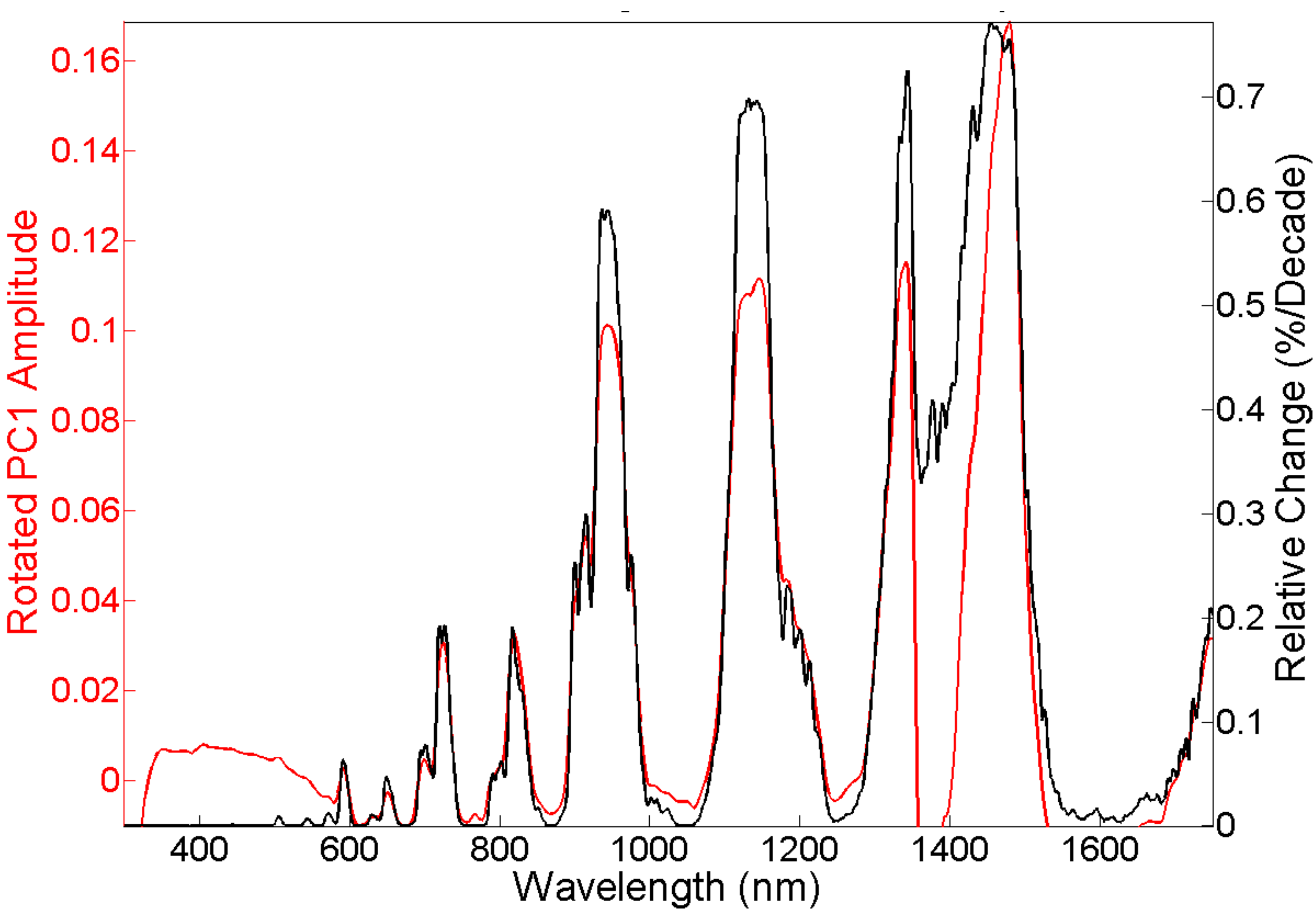
Co-albedo of water

multiplied by Transmission of main absorbing species (primarily water)



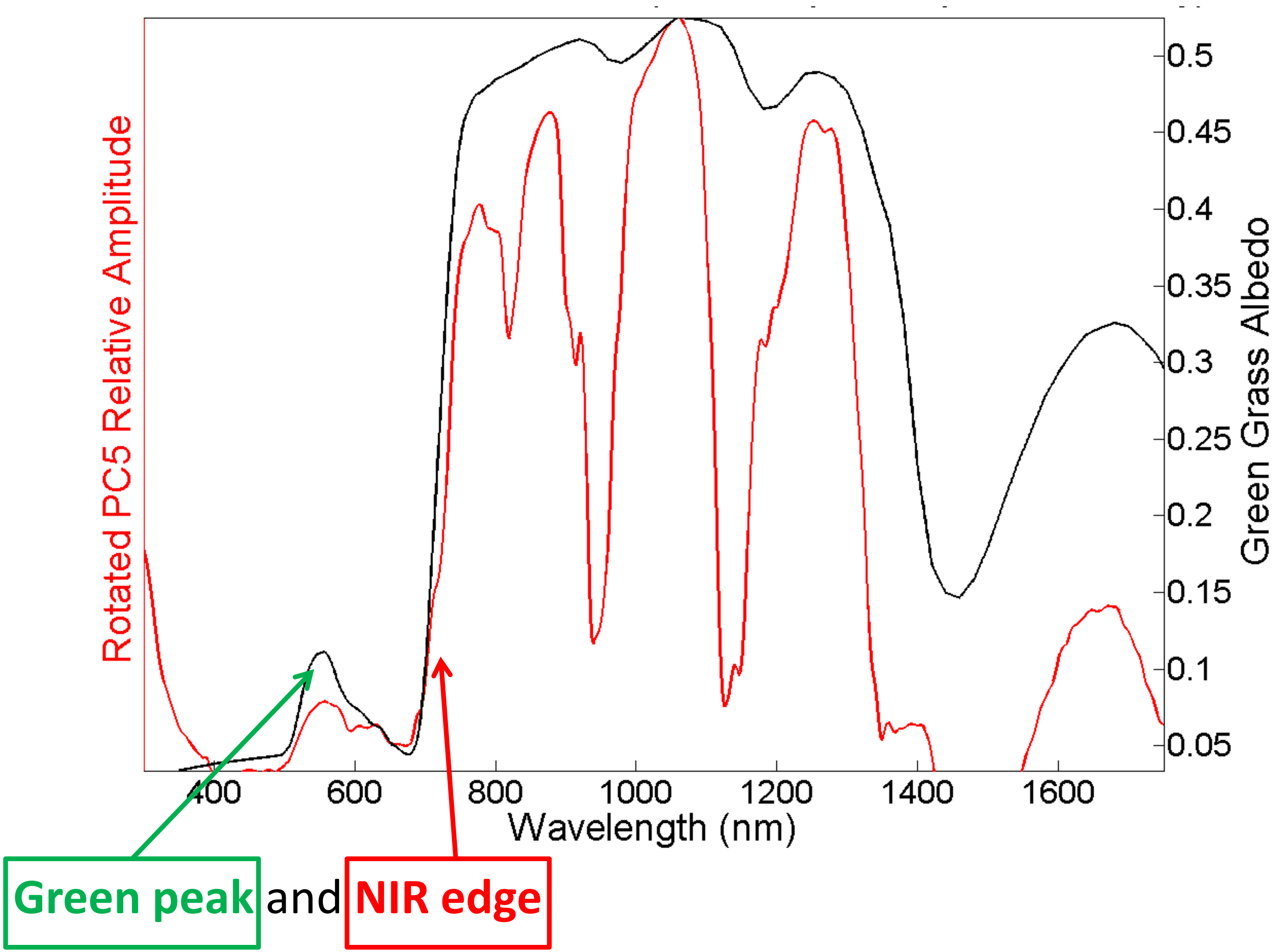
Information content increases at wavelengths where water absorbs.

SCIAMACHY Global PCA



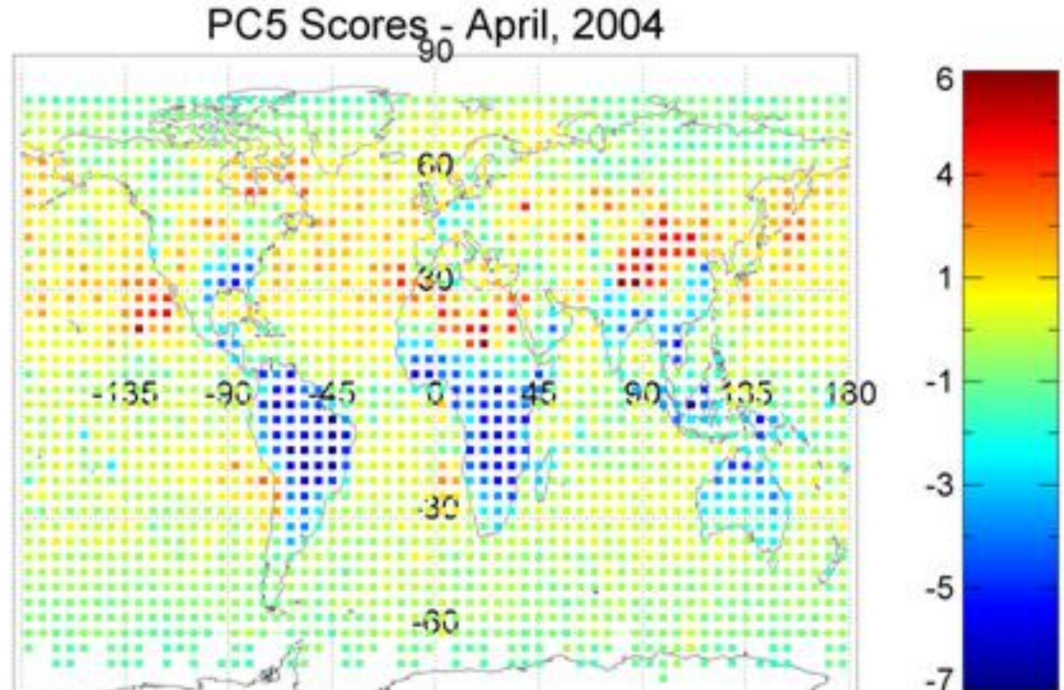
Roberts and Pilewskie, 2011

SCIAMACHY Global PCA



Roberts and Pilewskie, 2011

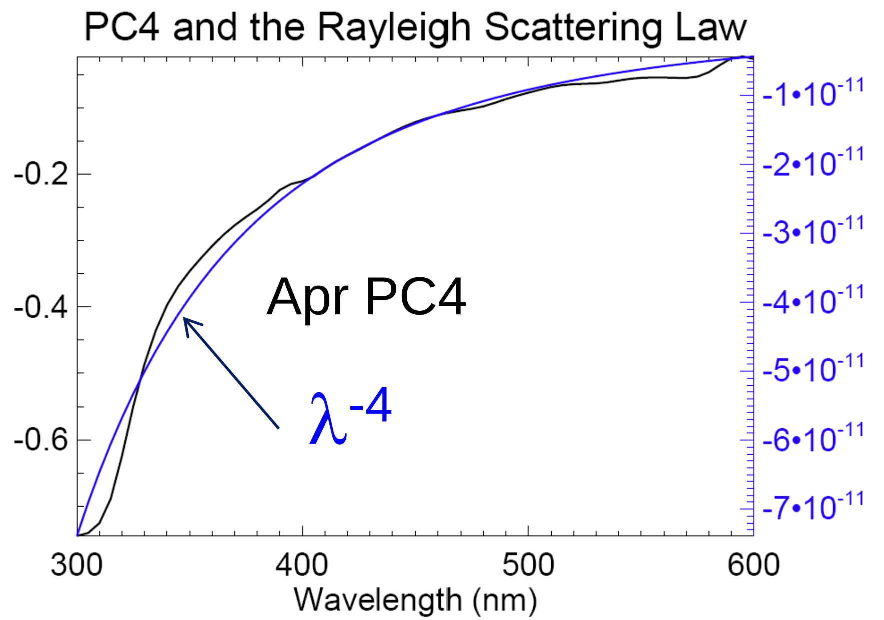
Spatial distribution of component scores track global MODIS VI patterns

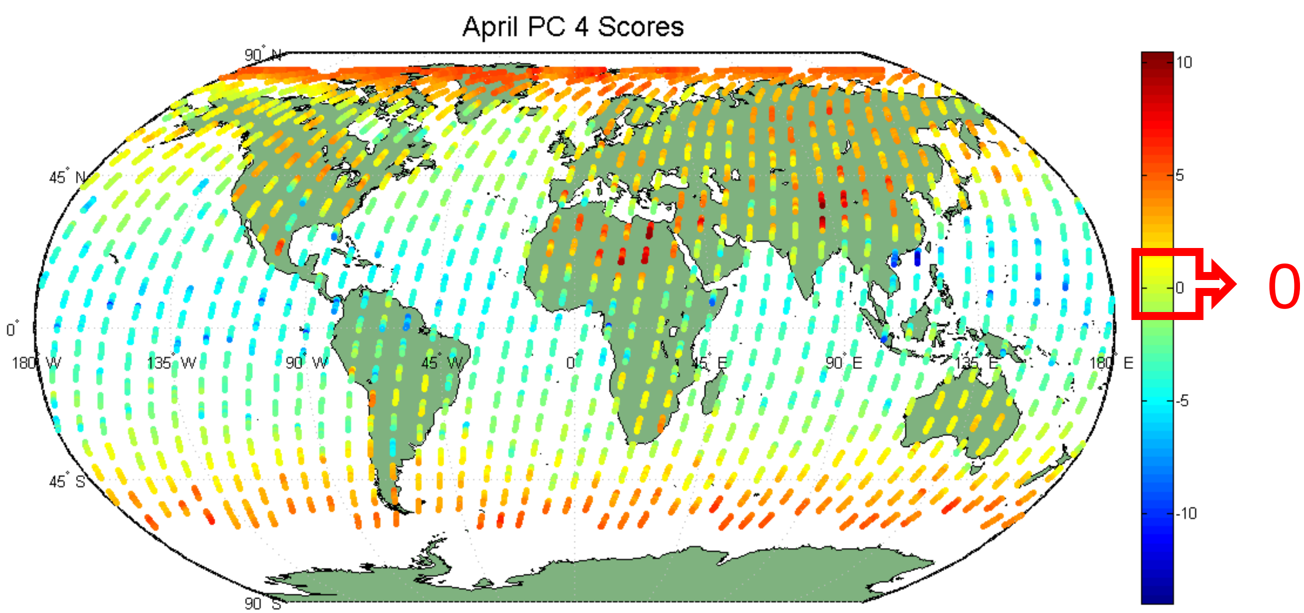


Roberts and Pilewskie, 2011

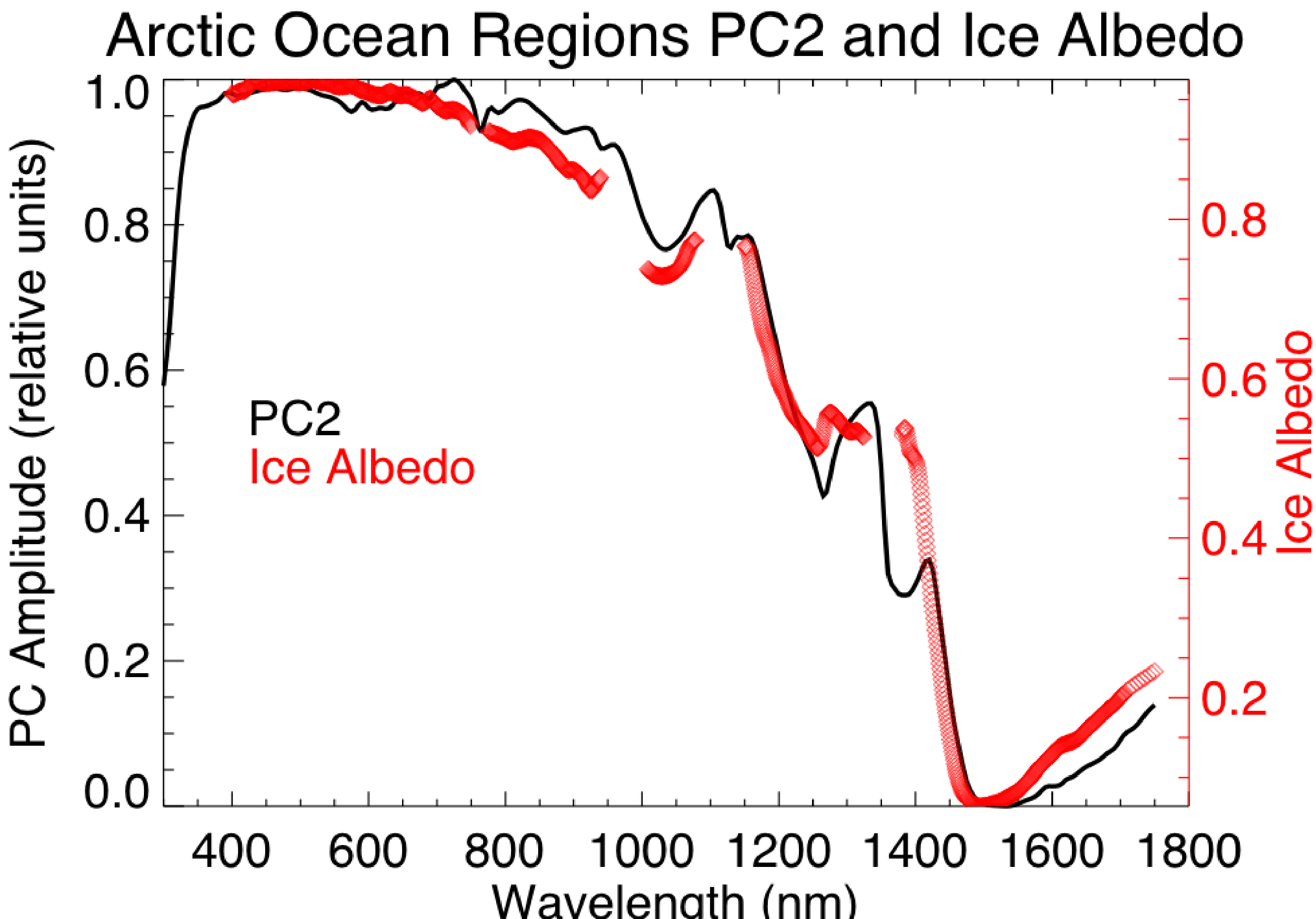
PC4: Molecular Scattering

PC4 follows a -4 power law in wavelength: Rayleigh's scattering law.



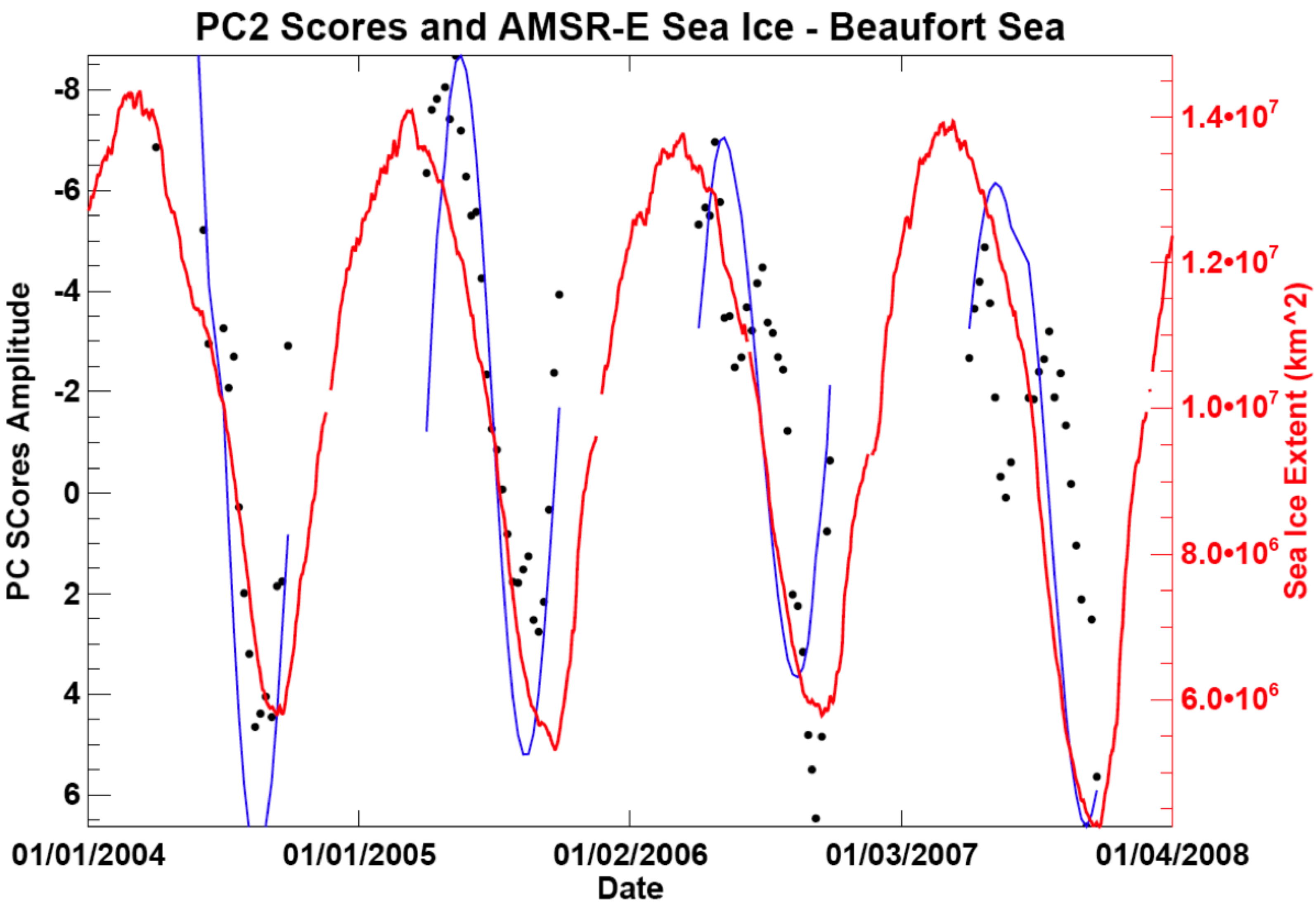


Can the contributions from sea ice and clouds be separated in the top-of-atmosphere outgoing shortwave radiation?



Roberts et al., 2011

Singular Spectrum Analysis tracks trends in sea ice extent



Roberts et al., 2011

Intersection of Spectrally Decomposed Subspaces

- Standardized PCs shows a close comparison between the SCIA data and OSSEs output
- Common practice to compare the structure of PCs that have not be standardized
  - Unstandardized PCA results
  - Transformation of sets of PCs and measures of their similarity
  - What does this method help us to understand about how the two data sets compare?
- What's next?

Comparable spatial sampling

- Averaged SCIAMACHY radiances
  - Resulting in monthly averaged, spatially gridded, 15nm fwhm spectra
- Also spatially averaged and spectrally resampled OSSEs radiances over the same spatial grid and spectral resolution
  - Only used locations present in SCIAMACHY data
- Spatial grid 4°(lat) x 6°(lon)
- Examples shown here are from October 2004 for both data sets

Quantitative Comparison of Subspaces

- Decompose the covariance matrix of the intersection of two subspaces (two sets of PCs)
- What do the results say about the similarity of subspaces?
  - The eigenvalues of this decomposition gives measure of contribution of each pair of new vectors to the similarity between the two.
  - The sum of these eigenvalues lies between 0 and # of dimensions included. Measure of total subspace similarity.
  - The new eigenvectors can be studied to understand the spectral nature of the similarity.

Quantitative Comparison of Subspaces

A = Radiance Data A

B = Radiance Data B

L= Eigenvectors_A

$S = LM^TML^T$
Intersection

M= Eigenvectors_B

Decompose $S = Y_A \; C \; Y_B$

Y_A and Y_B contain weightings representing the contribution of each PC to each shared dimension

C – the correlations between the newly transformed eigenvectors

Y_A

Y_B

$C = \cos(\theta)$
Correlations between each eigenvector in U_A and U_B.

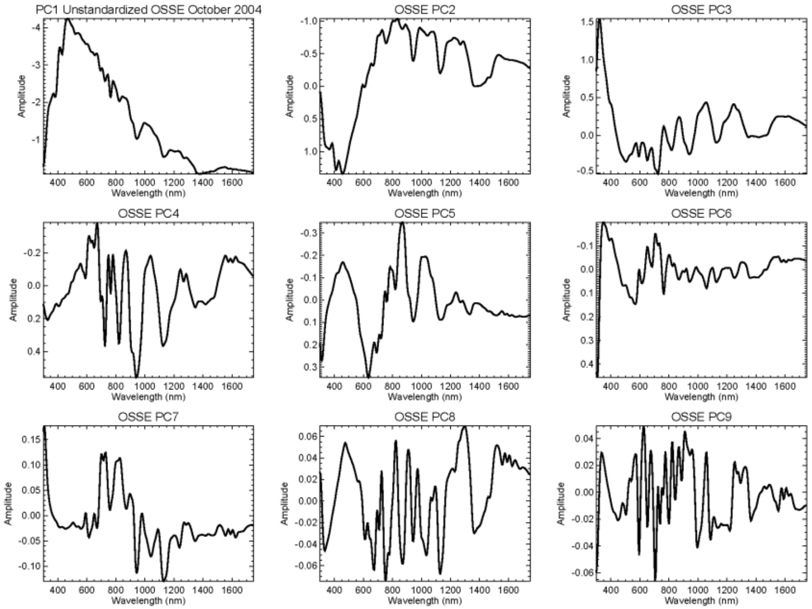
$U_A = LY_A$

$U_B = MY_B$

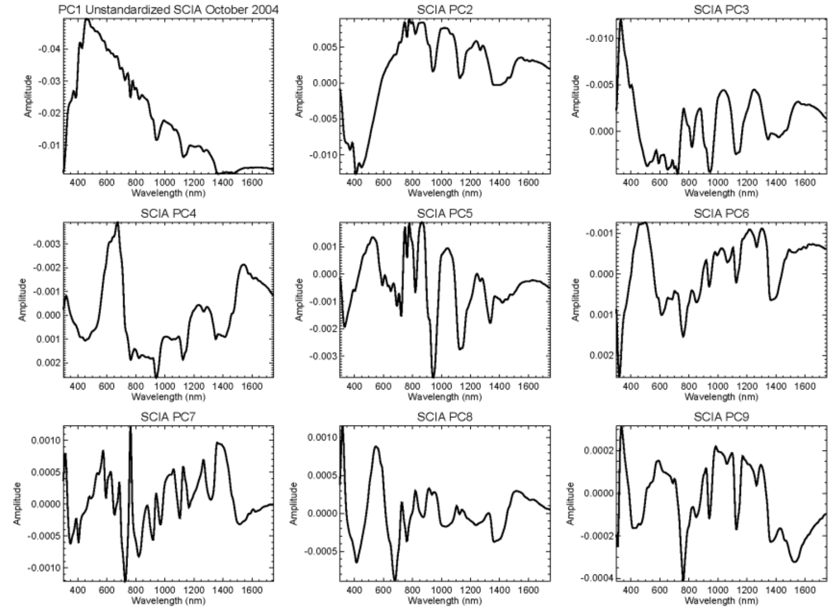
U, the original PCs projected onto the weightings vectors (Y_A and Y_B), are the newly transformed eigenvectors.

Unstandardized PCs

OSSES

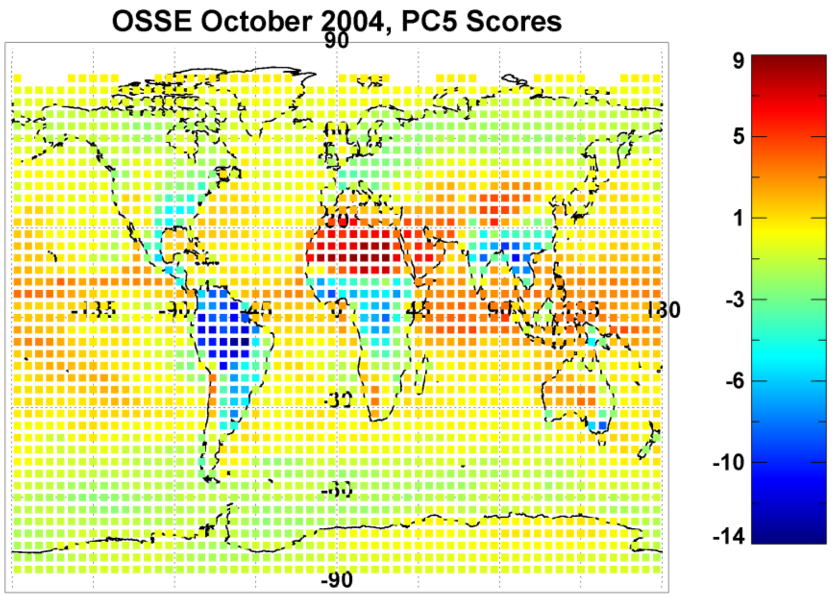


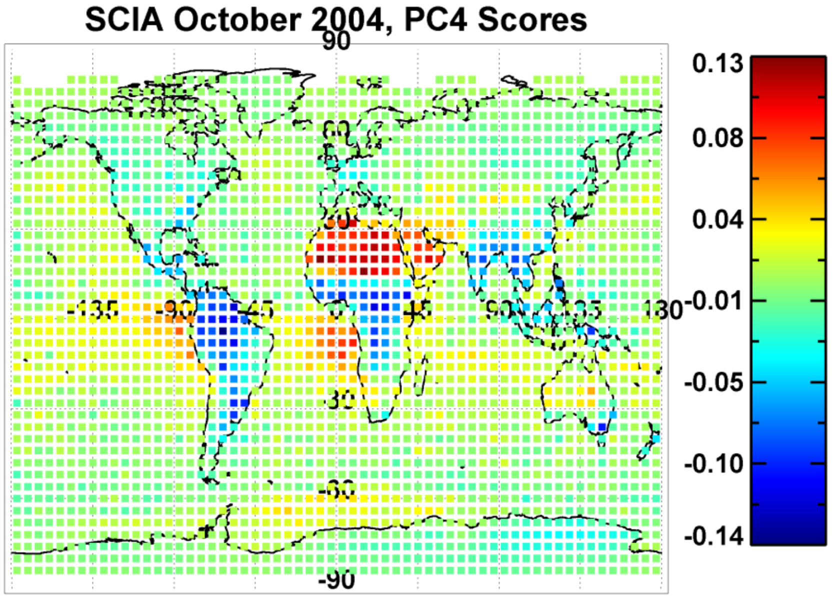
SCIAMACHY

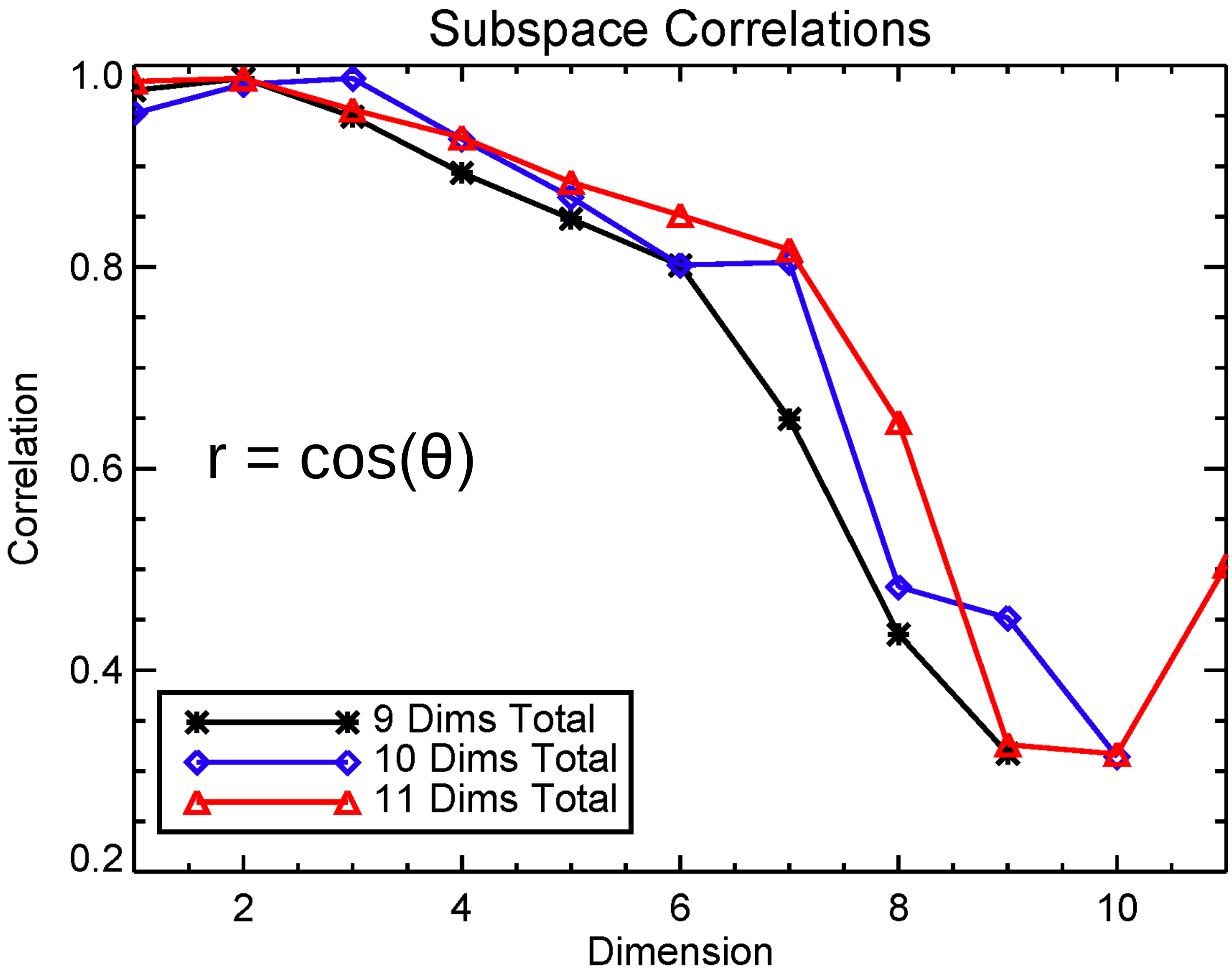


Nine eigenvectors from the principal component transformation of the measured SCIA radiance spectra (left) and OSSE MODTRAN spectra (right).

Unstandardized PCs

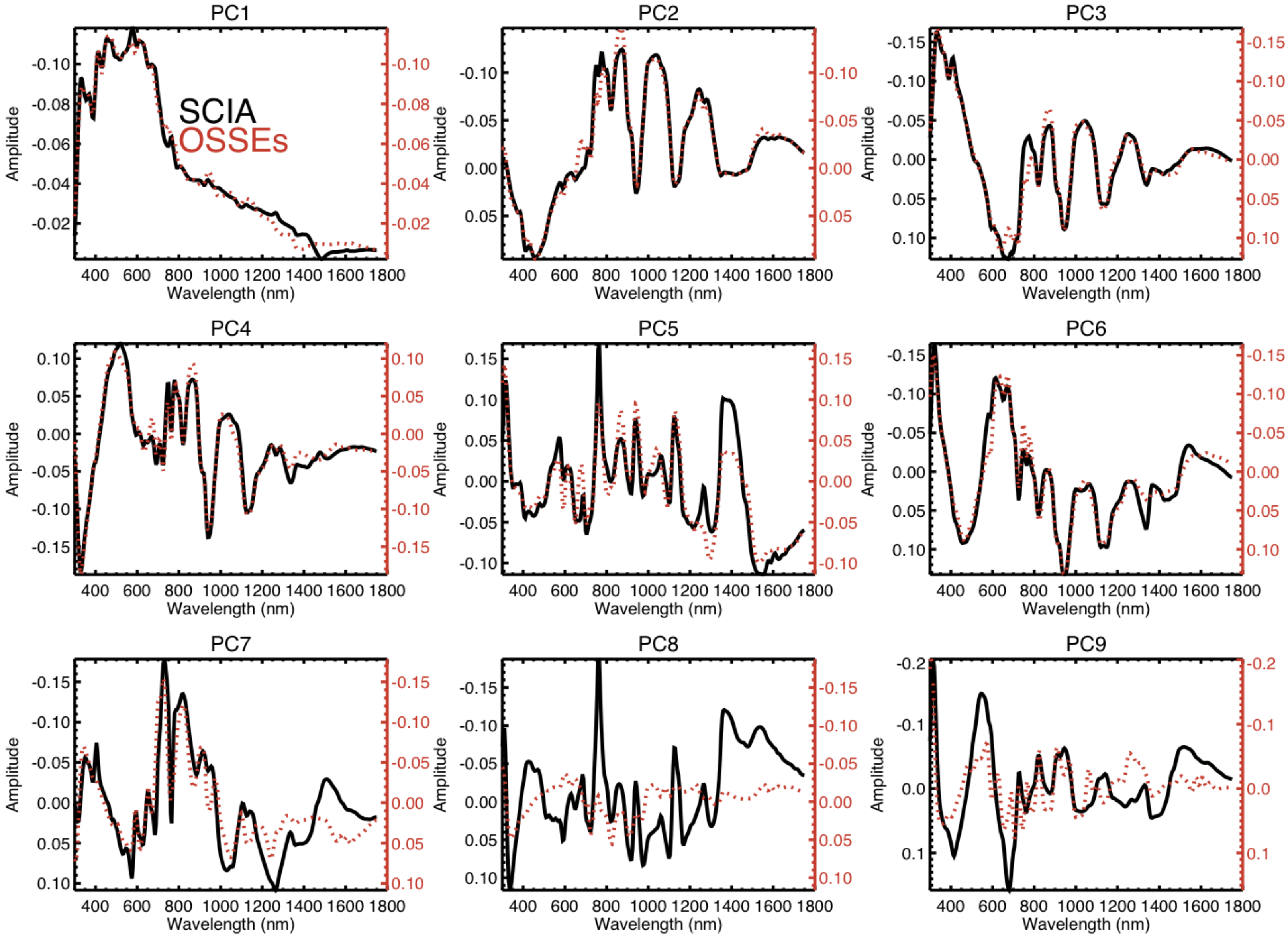






Quality of overlap in SCIA and OSSE radiances measured by the angle between subspaces.

Transformations of the Intersecting Data



Nine eigenvectors for the transformed databases.

What's Next?

- Statistical significance of correlations
- Gives good quantitative measure of similarities, but is there a way to identify the differences?
- Comparisons over longer periods of time.
- How does the OSSEs variability change over the century?