

Fast Forward Modeling in Scattering Atmospheres with Optimum Spectral Sampling

Jean-Luc Moncet, Gennady Uymin, Alan Lipton, Ned Snell

Atmospheric and Environmental Research, Inc.

Topics

- Optimal Spectral Sampling brief overview
- Global training
 - Application to AIRS and IASI
- Use of principal components of radiances
- Treatment of multiple scattering
 - Current training method
 - Minimizing the number of scattering RT operations
 - Application to AIRS and MODIS

Review of the Basic OSS Method

- OSS channel radiances modeled as (Moncet et al. 2003, 2001, 2008)

$$\bar{R} = \int_{\Delta\nu} \phi(\nu) R(\nu) d\nu \cong \sum_{i=1}^N w_i R(\nu_i); \quad \nu_i \in \Delta\nu$$

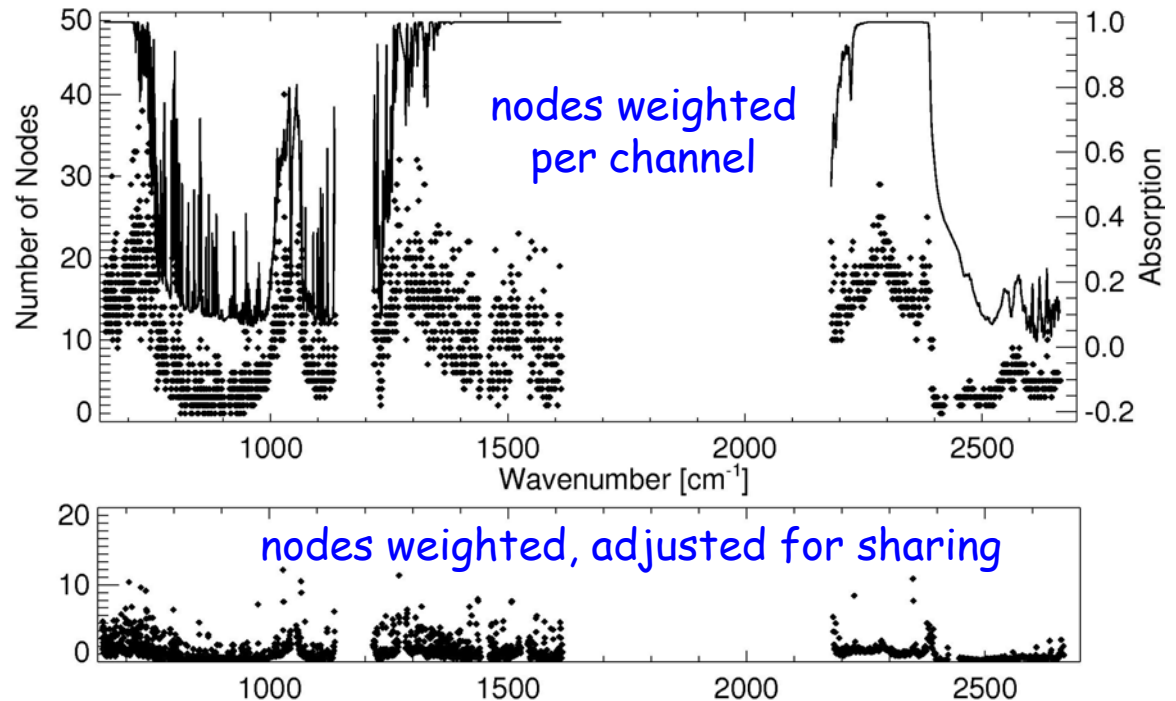
- Channel-average radiance is modeled as weighted average of monochromatic radiances
- Wavenumbers ν_i (nodes) and weights w_i are optimally selected to fit calculations from a reference line-by-line model for a globally representative set of profiles (training set)
- Monochromatic absorption coefficients from look-up tables
- Demonstrated to be generally faster and more accurate than methods that use regression to fit the space-to-level band transmittance (here called total path transmittance regression = TPTR methods)
 - For molecular absorption, non-scattering computations
 - Scattering case is discussed in this presentation

Training Approaches: 1) Local Training

- Operates on individual channels, one at a time
- Nodes for each channel required to be within spectral range of channel response
 - Nodes may be shared between channels with overlapping responses

AIRS (2378 channels):

- Average: 11 nodes weighted per channel
- Average: 1.3 nodes/channel overall (accounts for sharing)



Training Approaches: 2) Global Training

- Operates on groups of channels (up to the full channel set) simultaneously
- Uses clustering of nodes to efficiently account for spectral correlations
 - Condenses the information of the full channel set into a minimal number of nodes
- Monochromatic RT at a relatively few nodes determines radiances for full channel set
- Optionally, can be fit to channel subset, or first X principal components of channel set, or radiances filtered by PC transformation
 - Reduces information relative to full channel set

AIRS Example

	AIRS - full channel set			AIRS - 281 channel subset		
	Local*	Global20	Global	Local	Global20	Global
# channels	2378	2378	2378	281	281	281
# nodes	5340	2323	507	1809	993	328
# nodes / # channels	2.25	0.98	0.21	6.44	3.53	1.17
N'	9.84	35.60	203.63	11.75	30.53	238.43

N' = number of nodes contributing to radiance computation in 1 channel (on average)

Training conditions:

- 0.05 K accuracy requirement
- Extra wide range of incidence angles (0°-70.5°)*
- Variable gases H₂O, O₃

*difference from data
in chart 4

● Global20

- Surface emissivity assumed linear over contiguous 20 cm⁻¹ intervals (needs to be verified with real data)
- Global training applied independently to each interval
- Provides extra robustness by avoiding reliance on correlations from distant spectral points
 - Extra robustness for surfaces whose emissivity spectra are outliers

Application to IASI

● Global and local training results

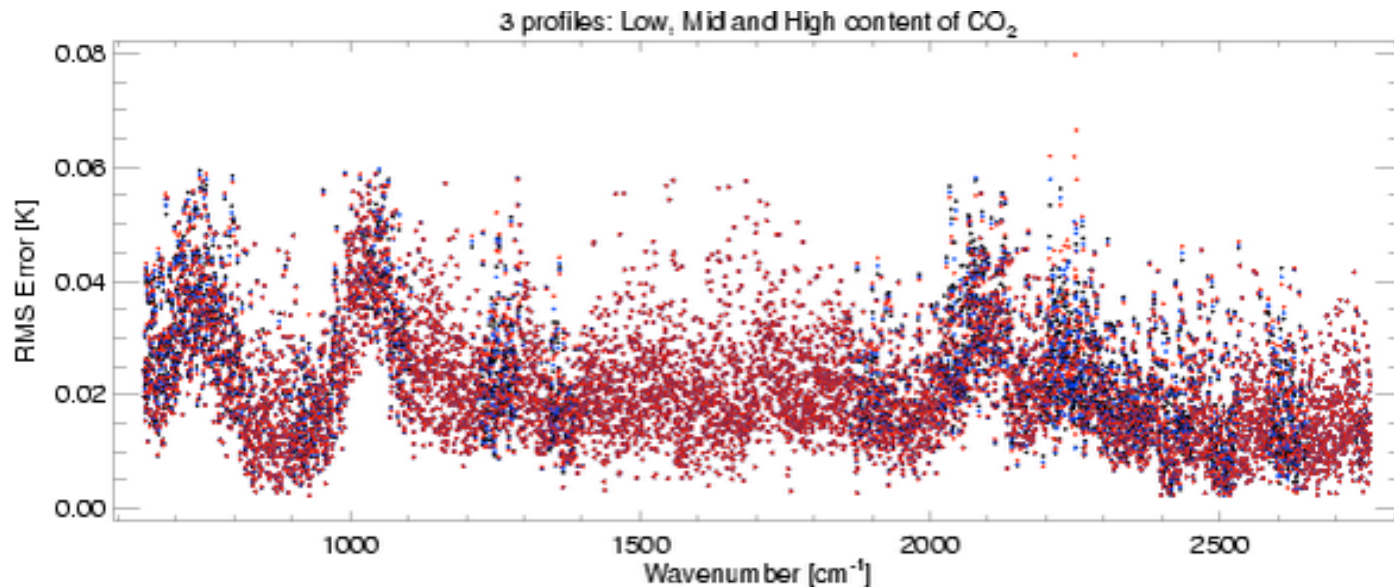
IASI band	Spectral range (cm ⁻¹)	Number of channels	Number of nodes		Global nodes/ channels
			Local	Global	
1	645-1210	2261	1855	220	0.097
2	1210-2000	3160	2927	281	0.089
3	2000-2760	3040	2639	321	0.11
Total		8461	7421	822	

Training conditions:

- 0.05 K accuracy requirement
- 13 variable gases: H₂O, O₃, CO₂, CO, CH₄, N₂O, F11, F12, CCl₄, HNO₃, SO₂, OCS, CF₄
- 5 fixed gases: O₂, NO, NO₂, NH₃, N₂
- Sources: ECMWF for H₂O, O₃; Global Modeling Initiative chem model for CO₂, CO, CH₄, N₂O, F11, M. Matricardi for F12, CCl₄, HNO₃
- 2002-2012 secular trends added for CO₂ and CH₄
- Randomization was applied to all species for robust training
- Emissivity spectra for global training is random walk, with 20-cm⁻¹ steps

IASI Validation

- Validation with 48 independent UMBC profiles
- Each profile assigned 3 CO_2 profiles:
 - Minimum (•), mean (•), maximum (•)
- Validates robustness of training over CO_2 trends



From local training

OSS with Principal Components

- Option may be useful when some information loss is accepted as trade-off for speed
 - When eigenvector truncation goes beyond eliminating redundancy
- Can be done without significant revision to OSS training
 - Filter training-profile radiances with truncated eigenvectors
 - Convert to PCs, then use reverse transformation to recover physical-space radiances
 - OSS training achieves required accuracy for every channel (PC filtered)
 - OSS coefficients project only on retained PCs (within training accuracy)
- Forward model output in terms of PCs efficiently done by combining eigenvectors with OSS coefficients in advance

$$\mathbf{R}_{chan} = \mathbf{W} \mathbf{R}_{node} \quad \mathbf{PC} = \mathbf{U}_m \mathbf{R}_{chan} \quad \text{with } m \text{ retained PCs}$$

$$\mathbf{PC} = \mathbf{U}_m \mathbf{W} \mathbf{R}_{node} = \mathbf{W}_m \mathbf{R}_{node} \quad \text{where} \quad \mathbf{U}_m \mathbf{W} \equiv \mathbf{W}_m$$

Scattering Forward Model

- OSSCAT is single-wavelength version of CHARTS adding-doubling RTM
 - Uses same molecular absorption and weighted monochromatic radiances as non-scattering RTM
 - Cloud module converts from physical properties (e.g., IWP, LWP, D_{eff} , top, thickness, $T(p)$) to optical properties (absorption and scattering optical depths, asymmetry parameter)
 - Look-up table
 - Size distributions based on in-situ aircraft measurements
 - Mie for liquid
 - MADA for ice - with temperature-dependent shape recipes
 - Optical properties linearly interpolated from hinge points to OSS nodes

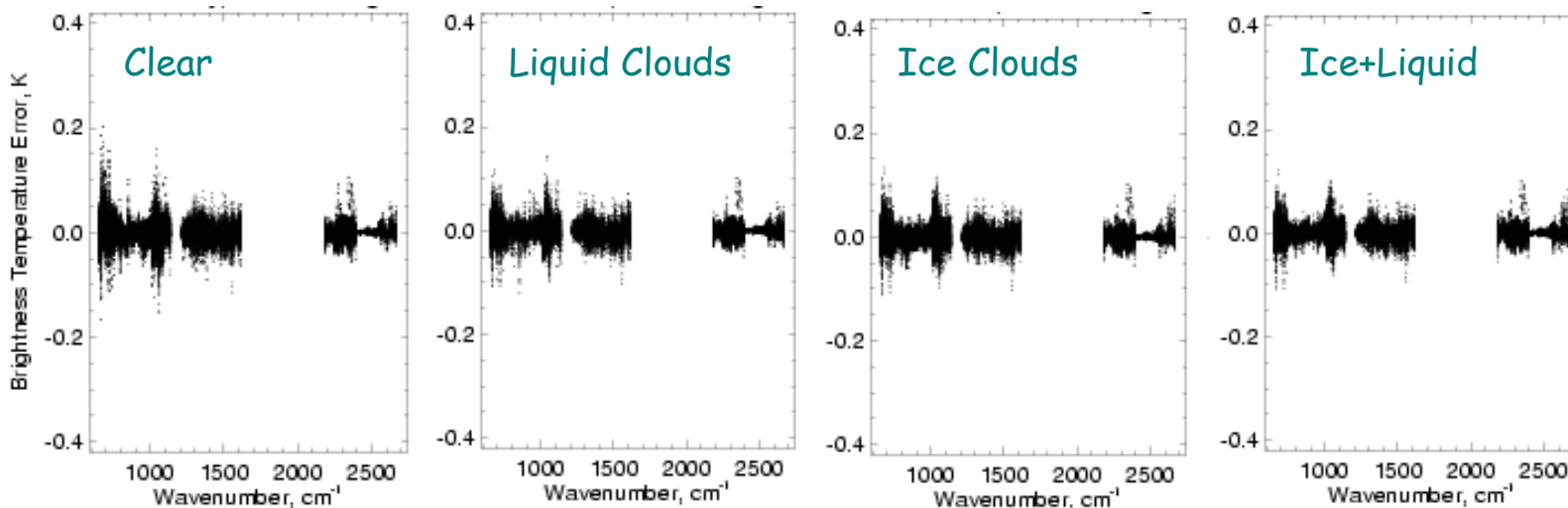
Cloudy Training

- **Must include cloud/aerosol optical properties in training**
 - Over wide bands: training can be done by using a database of cloud/aerosol optical properties
 - More general training obtained by breaking spectrum in intervals of the order of 10 cm^{-1} in width (impact of variations in cloud/aerosol properties on radiances is quasi-linear) and by performing independent training for each interval
 - Lower computational gain but increased robustness
- **Direct cloudy radiance training approach**
 - Clouds tend to mask molecular structure, which makes training less demanding
 - If trained for mixture of clear and cloudy atmospheres in direct training, clear-sky performance degrades
 - Train with clear-sky and several clouds simultaneously, requiring all to meet the accuracy criterion

Cloudy and Clear Fit

- OSS selection requires accuracy threshold be met for each training set individually and simultaneously

AIRS Channel Set
Scattering included
Fit error -- all meet 0.05-K rms requirement
Nadir view shown



Multiple Scattering Acceleration

- With scattering, execution time is dominated by radiative transfer integration
 - Contrasts with non-scattering, where band transmittance calculation may be a bigger factor
 - OSS RT timing ~proportional to number of nodes
 - TPTR RT timing ~proportional to number of channels
 - OSS is faster than TPTR methods only when the number of nodes / number of channels $\ll 1$
- Scattering calculations do not have to be performed for each node
 - Scattering correction may be predicted based on a few nodes only:

$$\bar{R} \cong \sum_{i=1}^N w_i R^{ns}(v_i) + \sum_{k \in S} C_k [R(v_k) - R^{ns}(v_k)]$$

- R is radiance from scattering model
 - R^{ns} is radiance from non-scattering model
 - w are the ordinary OSS weights
 - k are a subset of the set of the OSS nodes (S) for the channel
 - C are regression coefficients
- Number of predictors can be tuned to control balance between cloudy radiance accuracy and computation speed
 - Some relaxation of accuracy may be tolerable in clouds with high optical depth, in proportion to uncertainties in optical properties

In thermal regime

Scattering Prediction Performance for MODIS

MODIS Channel #	Bandpass (μm)	Number of nodes*	Number of predictor nodes [†]
20	3.660 - 3.840	10	4
21	3.929 - 3.989	5	2
22	3.929 - 3.989	3	2
24	4.433 - 4.498	19	2
25	4.482 - 4.549	18	2
27	6.535 - 6.895	14	1
28	7.175 - 7.475	15	2
29	8.400 - 8.700	14	3
31	10.780 - 11.280	4	1
32	11.770 - 12.270	4	1
33	13.185 - 13.485	18	1
34	13.485 - 13.785	21	1
35	13.785 - 14.085	24	1
36	14.085 - 14.385	21	1
Average		13.6	1.7

Selected IR channels

Localized training used
Generalized may require fewer predictors

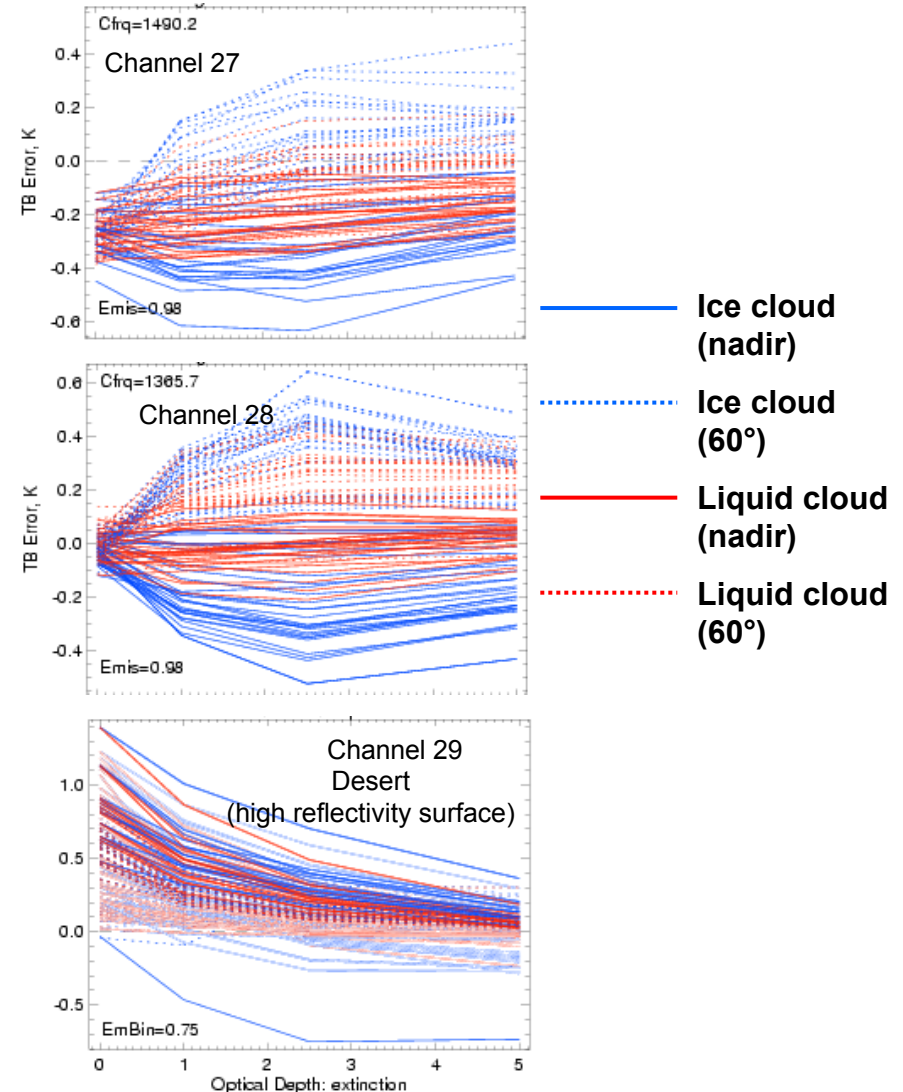
* for error threshold 0.05 K, clear and cloudy training
† for scattering prediction error threshold 0.2 K

Reference for Performance: TPTR Method for MODIS

- Simulated TPTR method
 - Ideal case of no error in transmittance regression
 - Effectively approximates reflected component as product of band-averages

$$\bar{R}_{refl} \approx \bar{r} \bar{T} \bar{R}^{\downarrow}$$

neglects in-band correlations
biggest impact is with low emissivity = high reflectivity r



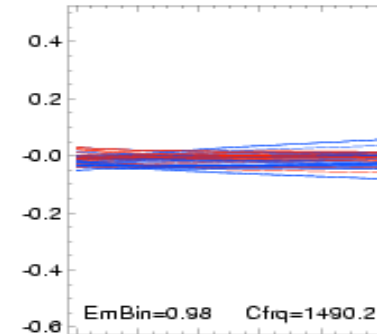
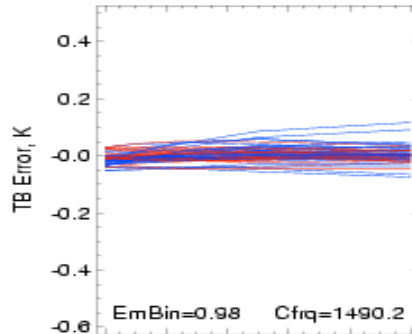
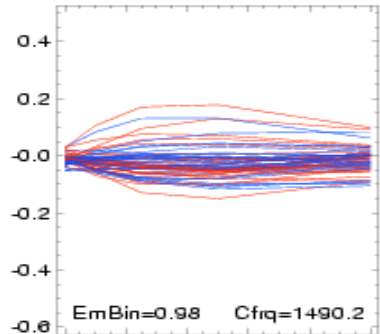
OSS Performance for MODIS Accelerated with Scattering Selection

Scattering: 2 predictor nodes

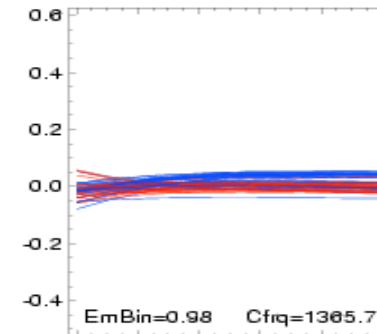
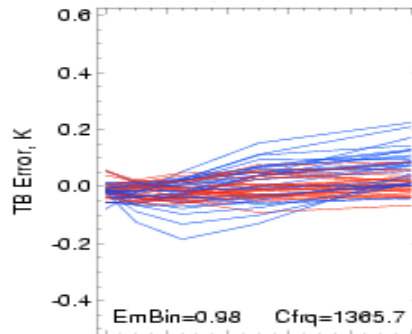
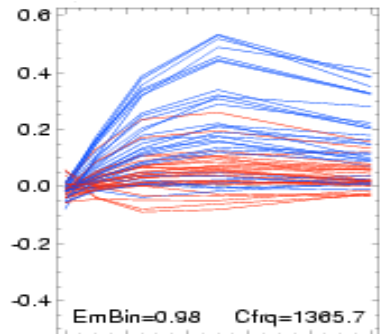
3 predictor nodes

all nodes

Channel
27

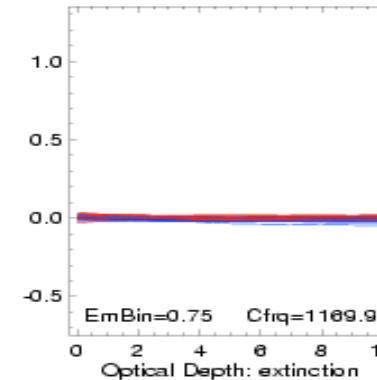
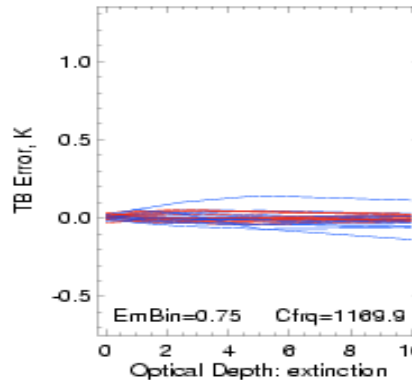
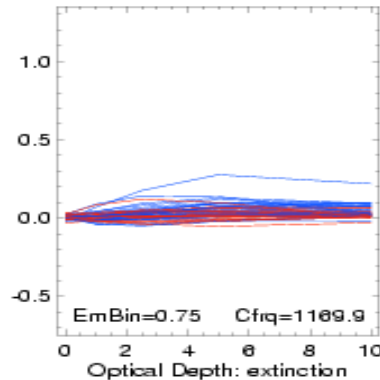


Channel
28



Channel
29

Desert
(high
reflectivity
surface)



- Ice cloud (nadir)
- ⋯ Ice cloud (60°)
- Liquid cloud (nadir)
- ⋯ Liquid cloud (60°)

Generally 1-2 predictor nodes are sufficient to exceed TPTR accuracy

Summary

- Global training with correlated clustering minimizes number of nodes for channel set as a whole
- Flexibility - same monochromatic (physical, general) framework provides options to meet user requirements
 - Produce radiances for full channel set
 - Retrieve/assimilate at OSS nodes
 - Avoids computational cost of mapping from nodes to channels
 - Involves channel → node transformation of measurement error covariance
 - Treatment of scene-dependent noise depends on application
- Scattering version maintains accuracy in clear areas
- Scattering can be accelerated with process to select subset of nodes to do scattering
 - Requires testing with global training

Backup

Inversion

- Variational retrieval methods:
 - Average channel uses ~150 nodes
 - Mapping Jacobians from node to channel space partially offsets speed gain

- Alternatives:
 - (a) PC (reduces first dimension of matrix A)
 - (b) Operate directly in node space

$$\mathbf{y}^m = \mathbf{A}\hat{\mathbf{y}}_0^m \rightarrow \hat{\mathbf{y}}_0^m = \mathbf{H}\mathbf{y}^m$$

Avoids Jacobian transformation altogether and reduce K-matrix size (inversion speed up)

- for AIRS: 2378 channels
→ 250 nodes

$$\delta x_{n+1} = (\mathbf{K}_n^T \mathbf{S}_\varepsilon^{-1} \mathbf{K}_n + \mathbf{S}_x^{-1})^{-1} \mathbf{K}_n^T \mathbf{S}_\varepsilon^{-1} \left[(y_n - y^m) + \mathbf{K}_n \delta x_n \right],$$

where,

$$\mathbf{y} = \mathbf{A}\hat{\mathbf{y}}_0^m \text{ and}$$

$$\mathbf{K} = \mathbf{A}\mathbf{K}_0^m$$

$$\tilde{\mathbf{y}}^m = (\mathbf{A}^T \mathbf{S}_\varepsilon^{-1} \mathbf{A})^{-1} \mathbf{A}^T \mathbf{S}_\varepsilon^{-1} \mathbf{y}^m$$

$$\tilde{\mathbf{S}}_\varepsilon^{-1} = \mathbf{A}^T \mathbf{S}_\varepsilon^{-1} \mathbf{A}$$

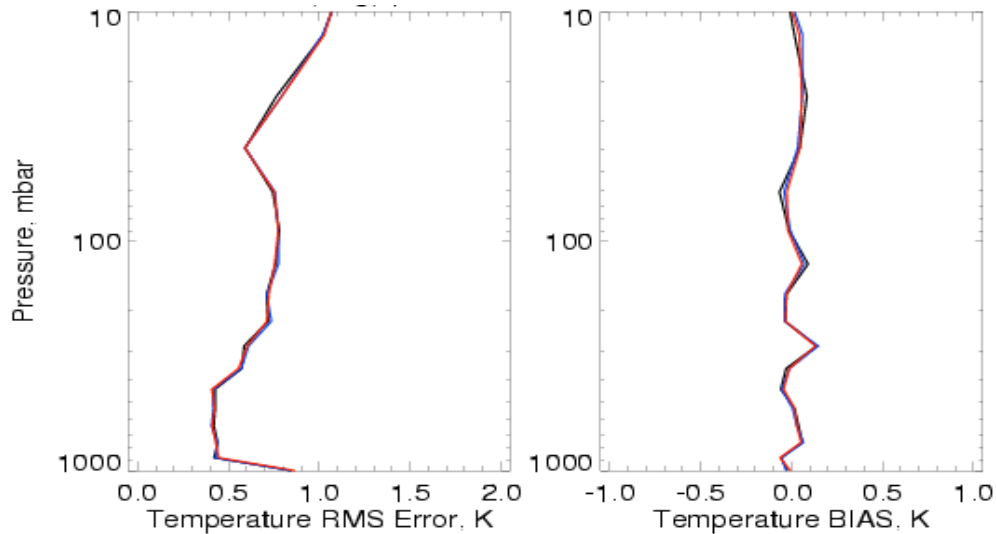
$$\delta \mathbf{x}_{n+1} = (\tilde{\mathbf{K}}_n^T \tilde{\mathbf{S}}_\varepsilon^{-1} \tilde{\mathbf{K}}_n + \mathbf{S}_x^{-1})^{-1} \tilde{\mathbf{K}}_n^T \tilde{\mathbf{S}}_\varepsilon^{-1} \left[(\tilde{y}_n - \tilde{y}^m) + \tilde{\mathbf{K}}_n \delta \mathbf{x}_n \right]$$

****Equivalent to**

$$\delta \mathbf{x}_{n+1} = (\mathbf{K}_n^T \mathbf{S}_\varepsilon^{-1} \mathbf{K}_n + \mathbf{S}_x^{-1})^{-1} \mathbf{K}_n^T \mathbf{S}_\varepsilon^{-1} \left[(y_n - \mathbf{A}\mathbf{H}\mathbf{y}^m) + \mathbf{K}_n \delta \mathbf{x}_n \right]$$

Inversion (continued)

Retrieval performance - constant noise



— Channel space retrieval
— Node space retrieval

Need strategy for handling input -
dependent noise

Scene temperature
dependence (clear/cloudy)
worse in SW band

Cloud clearing noise
amplification

H-transformation not overly sensitive to
noise

For clear retrievals: sufficient to
update noise covariance
regionally