Error Consistency Analysis Scheme (ECAS) for Retrieval Error Budget Estimation

Daniel Zhou
NASA Langley Research Center
Hampton, VA 23681

and

Allen Larar and Xu Liu (NASA LaRC)
William Smith (HU & UW)
L. Larrabee Strow (UMBC)

Current Methods for Retrieval Evaluation

Tobin et al. (*J. Geophys. Res.*, 111, D09S02, 2006) used a multi-instrument/platform correlative measurement dataset to build the best-estimated atmospheric state for each individual satellite measurement for validation.

Pougatchev et al. (*Atmos. Chem. Phys.*, 9, 6453–6458, 2009) developed a linear statistical Validation Assessment Model (VAM) providing the best estimated atmospheric state and corresponding nominal satellite measurement using the correlative data per se.

1. These validation methods are accurate, they depend on other independent measurements, such as radiosondes, and the accuracy of these independent "**coincident**" measurements. These data usually are collected during dedicated field campaigns and/or matchup soundings (e.g., radiosonde and Raman Lidar data).

2. In practice, these validation studies are more complex in considering that "**coincident**" measurements or that measurement-derived "**truth**" is at the same location and time.

3. In addition, the vertical and horizontal resolutions of other independent measurements have to be taken into account as well. The instrumental averaging kernels are typically used to resolve the difference in vertical resolution. However, the difference of horizontal resolution and the effect of spatial variations in atmospheric properties are too complex to consider and is often neglected.

4. These validation methods do not validate all retrieval parameters (such as land surface skin temperature and emissivity).

Motivation & Approach

Our motivation for this work is to understand and estimate the retrieval error contributed by major error sources in obtaining a link between the retrieved-geophysical-parameters and the radiometric accuracies. For example, we would like to answer questions such as how the radiometric random noise in the measurement propagates to the retrieval error (or retrieval noise) in the retrieved parameters, e.g., temperature and moisture profiles, and what is the magnitude of retrieval error introduced by an ill-posed retrieval model.

What is achieved retrieval accuracy?

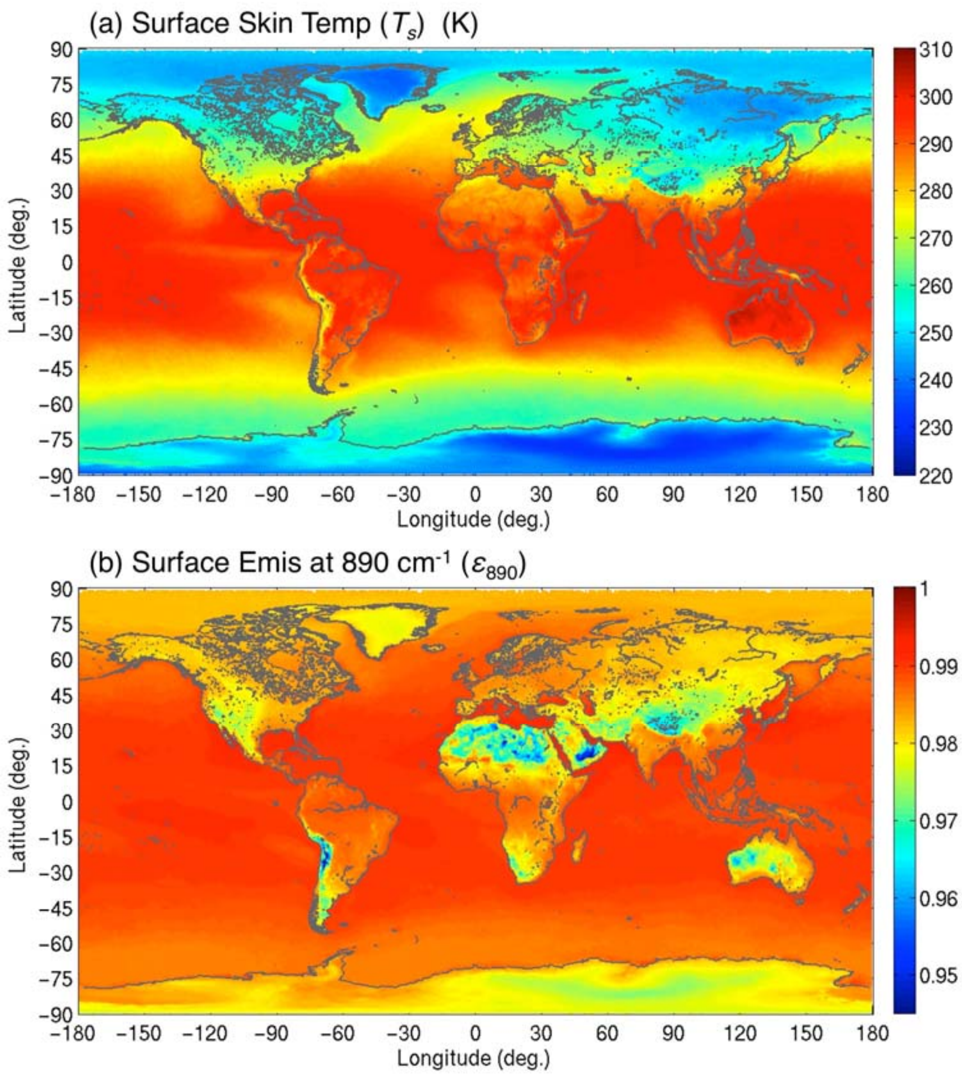
Our approach:

1. Develop a statistical **E**rror **C**onsistency **A**nalysis **S**cheme (**ECAS**) through fast RTM forward and inverse (RTM^{-1}) calculations.
2. Estimate the error budget in terms of mean difference (bias) and standard deviation of difference (STDE) in both spectral radiance domain and retrieved-geophysical-parameter domain for major error sources.
3. Provide an internal consistency check with RTM and RTM^{-1} calculations to establish a reliable link between radiometric error in the spectral radiance domain and retrieval error in the geophysical-parameter domain.
4. Limits the uncertainty introduced by the different time and space in other validation studies (e.g., using radiosonde measurements); and provides error estimation on all retrieved parameters.

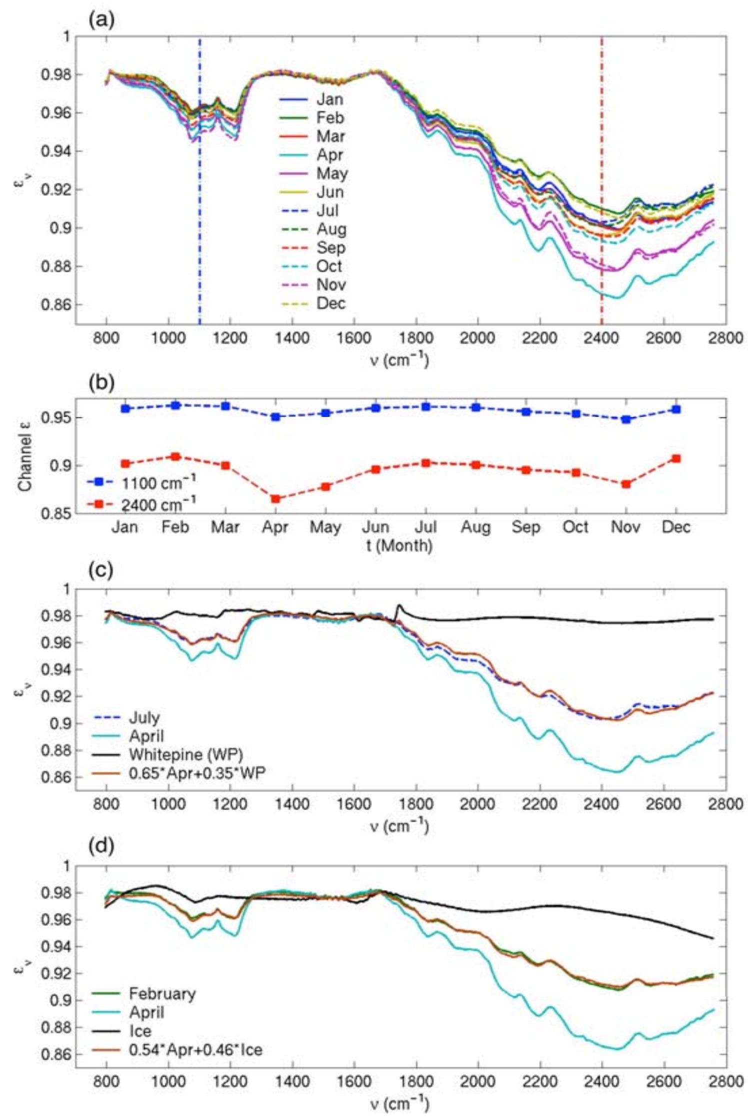
These errors are from (1) an ill-posed retrieval system, (2) the instrument random noise, and (3) the discrepancy between measured radiances and the RTM "truth" simulated radiances added with instrument noise (hereafter denoted as "un-modeled" errors).

Langley Research Center

Climate Data Record: T_s & ε_ν



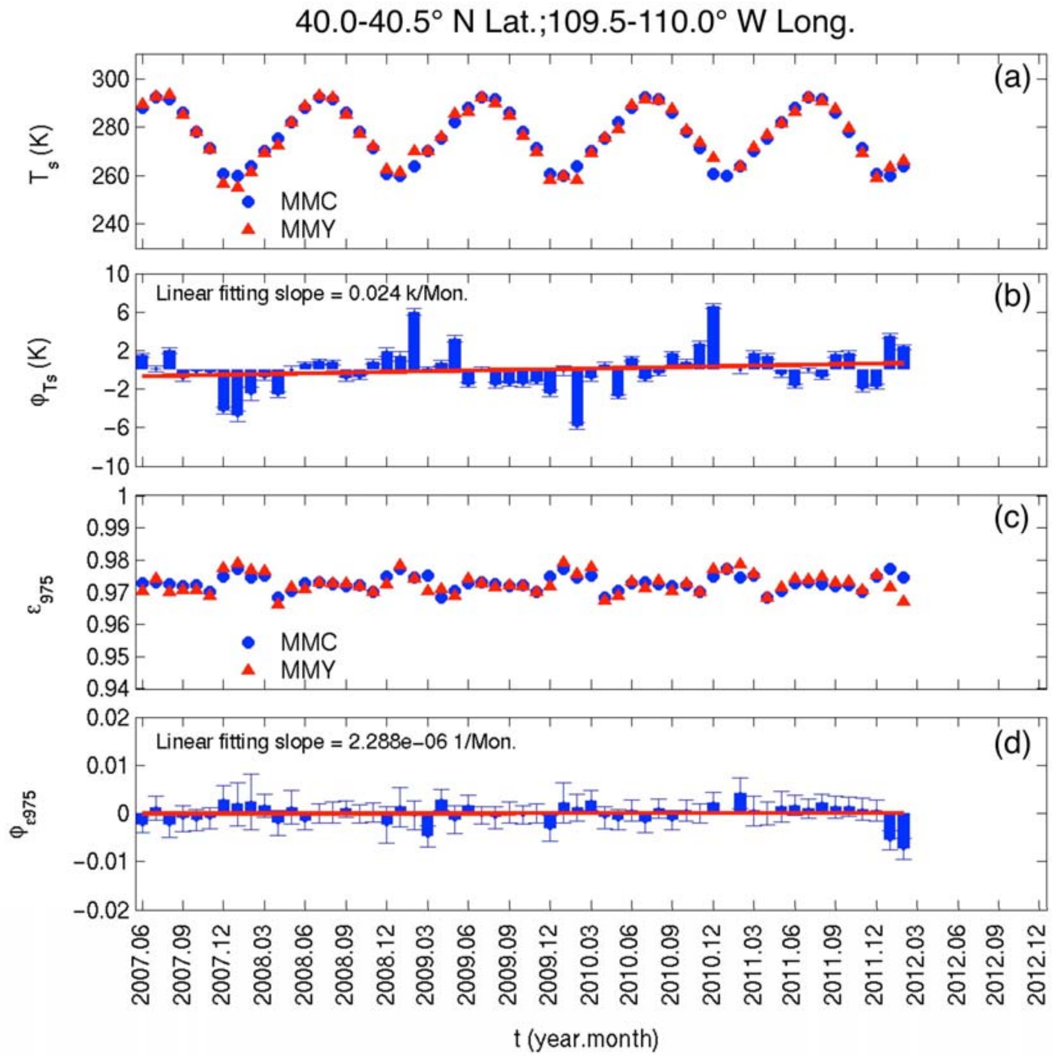
IASI monthly mean climatology based on 5-year measurements: December nighttime (a) surface skin temperature (T_s) and (b) emissivity at 890 cm^{-1} (ε_{890}).



Emissivity seasonal variation: Monthly mean climatology ε_ν measured from 40.0-40.5° N Latitude and 109.5-110.0° W Longitude.

Langley Research Center

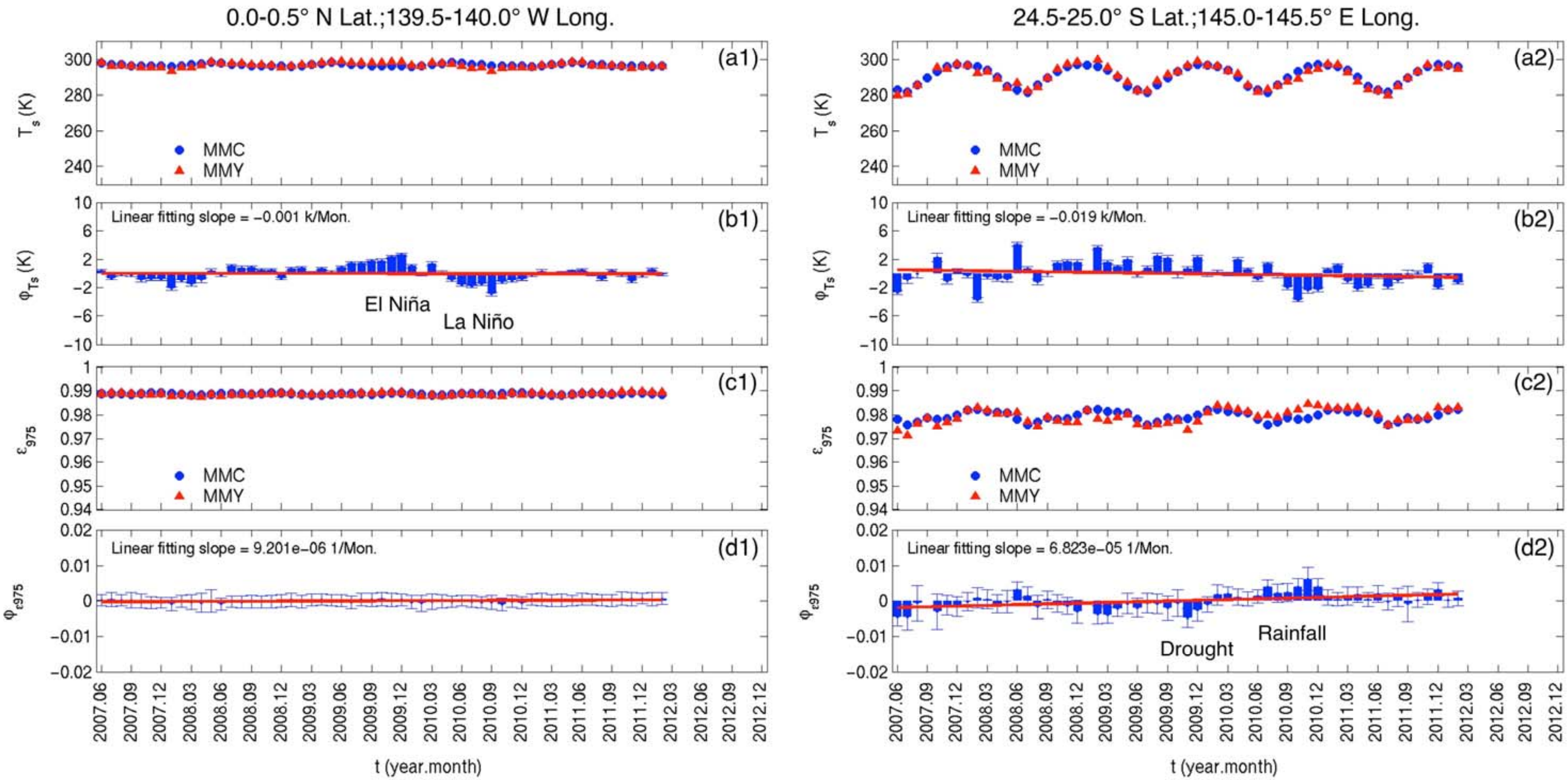
Climate Data Record: T_s & ε_v



Sample from 40.0-40.5° N Latitude and 109.5-110.0° W Longitude: Illustration of monthly mean (a) T_s and (c) ε_{975} against their monthly mean climatology, (b) T_s anomalies and (d) ε_{975} anomalies plotted to derive their trends.

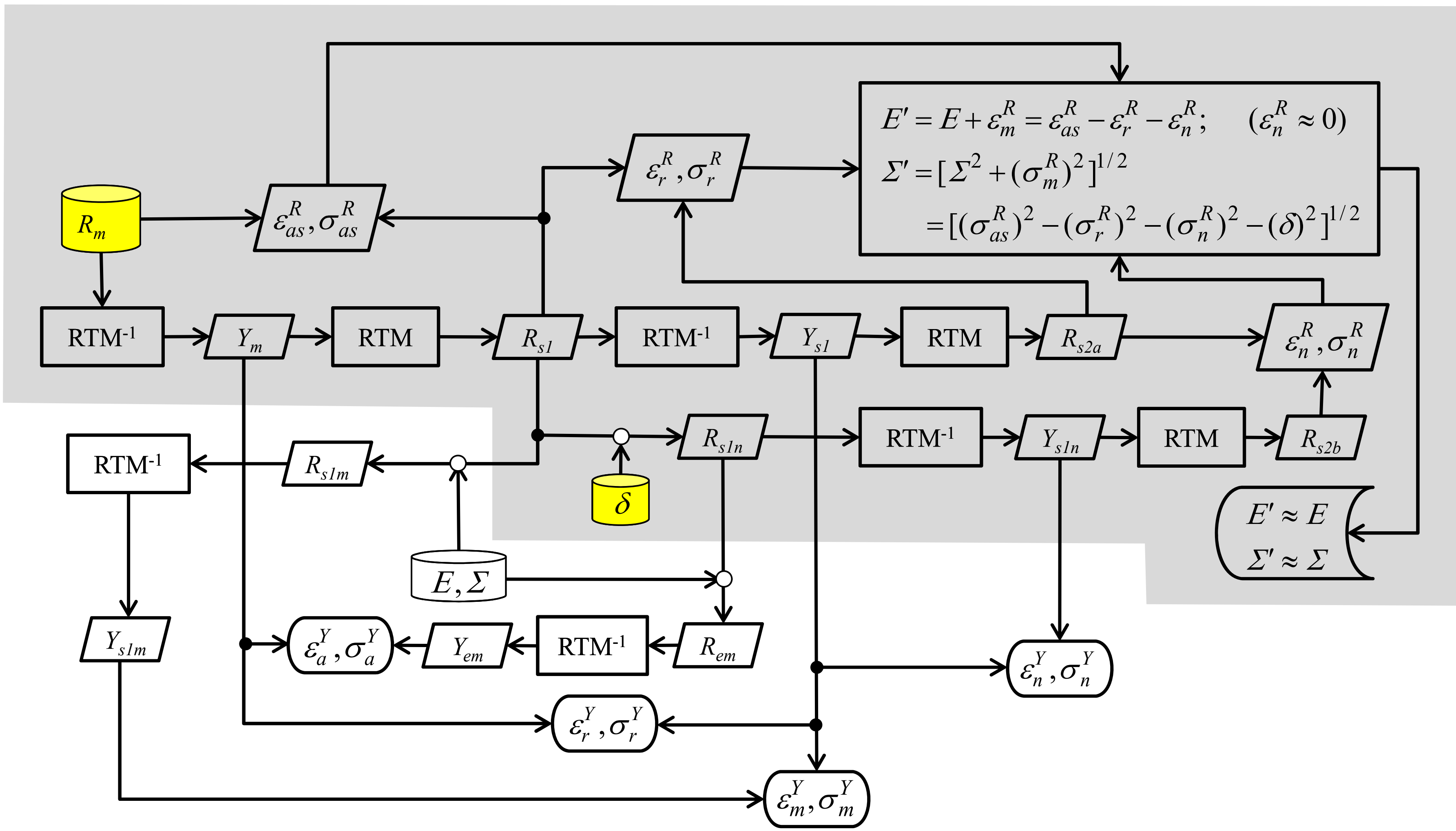
Langley Research Center

Climate Data Record: T_s & ε_ν



At other 2 locations: As El Nino plays the largest role in tropical drought occurrence, one location in Australia is chosen (right-column of Fig. 5: 24.5-25.0° S Latitude; 145.0-145.5° E Longitude) to illustrate ε_ν variation associated with the drought during the El Niño years and greater rainfall during La Niña events

Error Consistency Analysis Scheme (ECAS)



ECAS and analysis flowchart. The "un-modeled" radiance errors $[E, \Sigma]$ in the shaded area are first estimated starting with measured radiances R_m. Then the "un-modeled" radiance errors and instrument random noise are used to estimate retrieval errors in the rest of the flowchart

Error Consistency Analysis Scheme (ECAS) - 2

Notation:

R_m = measured radiances

δ = instrument random noise

E = "un-modeled" radiance bias

Σ = "un-modeled" radiance STDE

Y_m = retrievals from R_m

R_{s1} = simulated radiances from Y_m

R_{s1n} = R_{s1} with instrument noise

R_{s1m} = R_{s1} with "un-modeled" error

Y_{s1} = retrievals from R_{s1}

Y_{s1n} = retrievals from R_{s1n}

Y_{s1m} = retrievals from R_{s1m}

R_{s2a} = simulated radiance from Y_{s1}

R_{s2b} = simulated radiance from Y_{s1n}

R_{em} = emulated radiance

Y_{em} = retrievals from R_{em}

ε^R = bias in radiance domain

σ^R = STDE in radiance domain

ε^Y = bias in retrieval domain

σ^Y = STDE in retrieval domain

subscription for ε and σ:

a = all error sources with R_m

as = all error sources with R_m and δ_a

r = ill-posed inversion

n = random noise ret.-induced

m = "un-modeled" error ret.-induced

Data and RTM (RTM^{-1}) Used for Demo.

Data: IASI data from JAIVEx campaign covering the continental US and the Gulf of Mexico using 11871 identified "clear" cases out of a total 21600 observations. Only retrievals identified as "clear-sky" measurements are used to represent error budget estimations under "clear-sky" conditions.

RMT: The fast transmittance model used herein is a combination of the Stand-alone AIRS Radiative Transfer Algorithm (SARTA) Version 1.07 and the physically-based cloud RTM based on the DIScrete Ordinate Radiative Transfer (DISORT) calculations performed for a wide variety of cloud microphysical properties.

1. Strow et al., "An overview of the AIRS radiative transfer model," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 2, pp. 303–313, Feb. 2003.
2. Stamnes et al., "Numerically stable algorithm for discrete-ordinate-method radiative transfer in multiple scattering and emitting media," *App. Opt.*, 27, no. 12, pp. 2502–2509, Jun. 1988.
3. Yang et al., "Radiative Properties of cirrus clouds in the infrared (8-13 μm) spectral region," *J. Quant. Spectros. Radiat. Transfer*, vol. 70, no. 4, pp. 473–504, Aug. 2001.

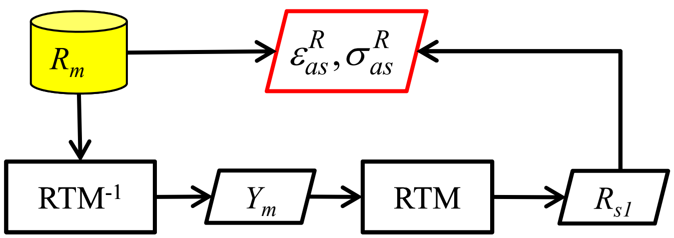
RTM^{-1} An iterative 1-D Var. multi-variable inversion using the minimum-information regularization method is used for obtaining the final retrieval (i.e., cloud, surface, and atmospheric parameters). An all-season, global EOF regression database is used to obtain the initial profile for the 1-D Var. physical retrieval.

The retrieval algorithm used here only uses measured radiance and instrument noise; no other "truth" data from satellite or surface-based instruments or from numerical weather analysis/prediction models are utilized in assisting or constraining the retrieval products.

1. Zhou et al., "All weather IASI single field-of-view retrievals: Case study - Validation with JAIVEx data," *Atmos. Chem. Phys.*, vol. 9, pp. 2241–2255, Mar. 2009.
2. Zhou et al., "Physically retrieving cloud and thermodynamic parameters from ultraspectral IR measurements," *J. Atmos. Sci.*, vol. 64, no. 3, pp. 969–982, Mar. 2007.

Langley Research Center

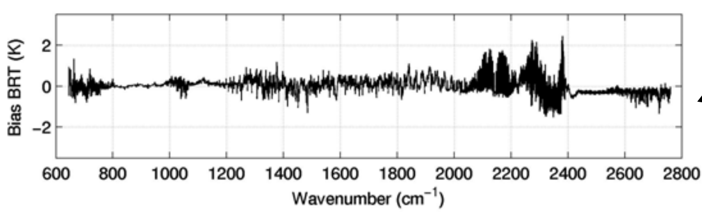
ECAS: Radiance Domain -1



Note:

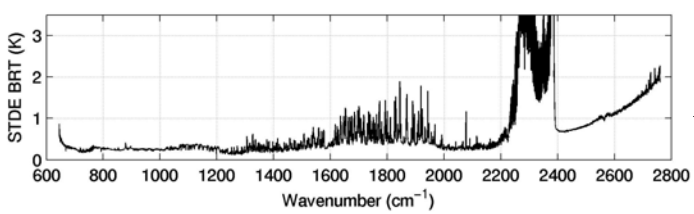
*1. **Primary errors: "un-modeled" error and instrument random noise**.*

*2. **Secondary errors: retrieval-induced error**.*



1. "um-modeled" bias
2. ill-posed retrieval bias
3. "un-modeled" error retrieval-induced bias
4. random noise retrieval-induced bias ≈ 0

$$\varepsilon_{as}^R = E + \varepsilon_r^R + \varepsilon_m^R + \varepsilon_n^R; \quad (\varepsilon_n^R \approx 0)$$

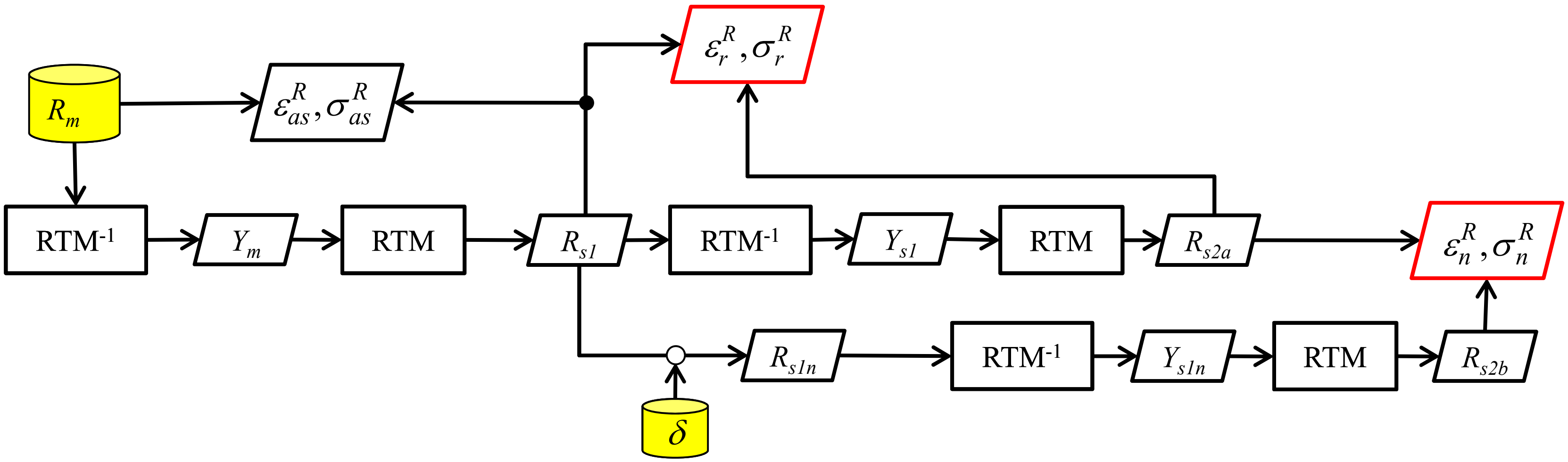


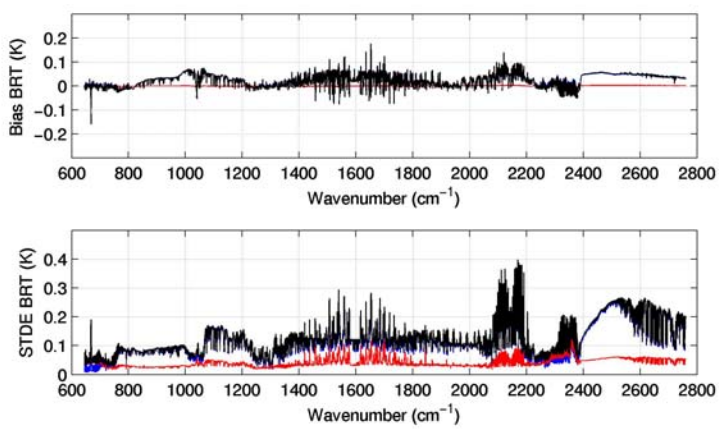
1. instrument random noise
2. "um-modeled" STDE
3. ill-posed retrieval STDE
4. "un-modeled" error retrieval-induced STDE
5. random noise retrieval-induced STDE

$$(\sigma_{as}^R)^2 = (\delta_a)^2 + \Sigma^2 + (\sigma_m^R)^2 + (\sigma_r^R)^2 + (\sigma_n^R)^2$$

Langley Research Center

ECAS: Radiance Domain -2



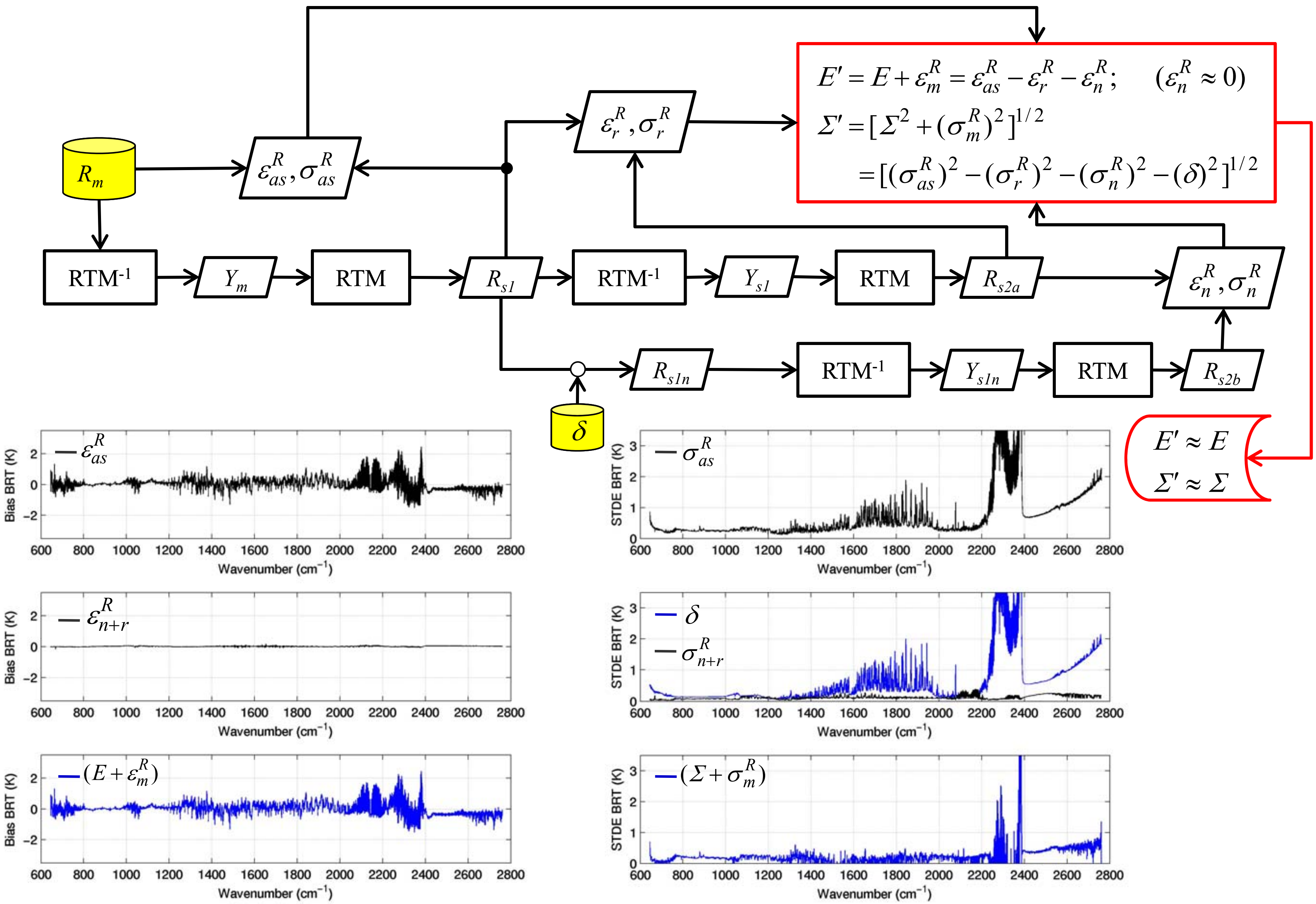


“ill-posed” retrieval-induced error $[\varepsilon_r^R, \sigma_r^R]$

random noise retrieval-induced error $[\varepsilon_n^R, \sigma_n^R]$

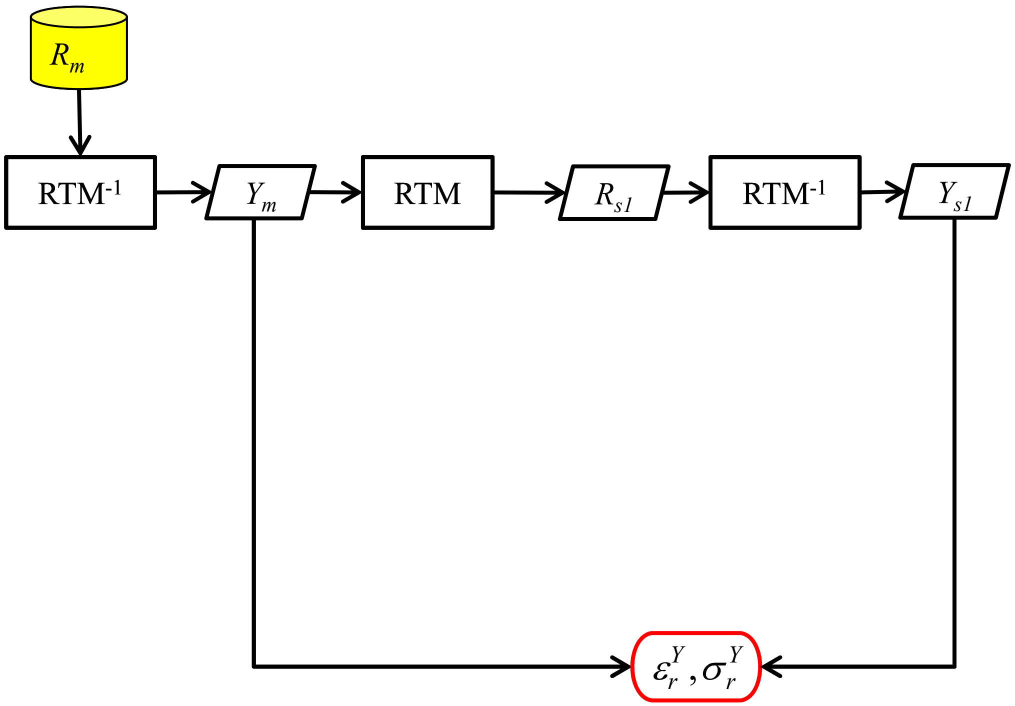
ill-posed and noise retrieval-induced error $[\varepsilon_{r+n}^R, \sigma_{r+n}^R]$

ECAS: Radiance Domain - 3



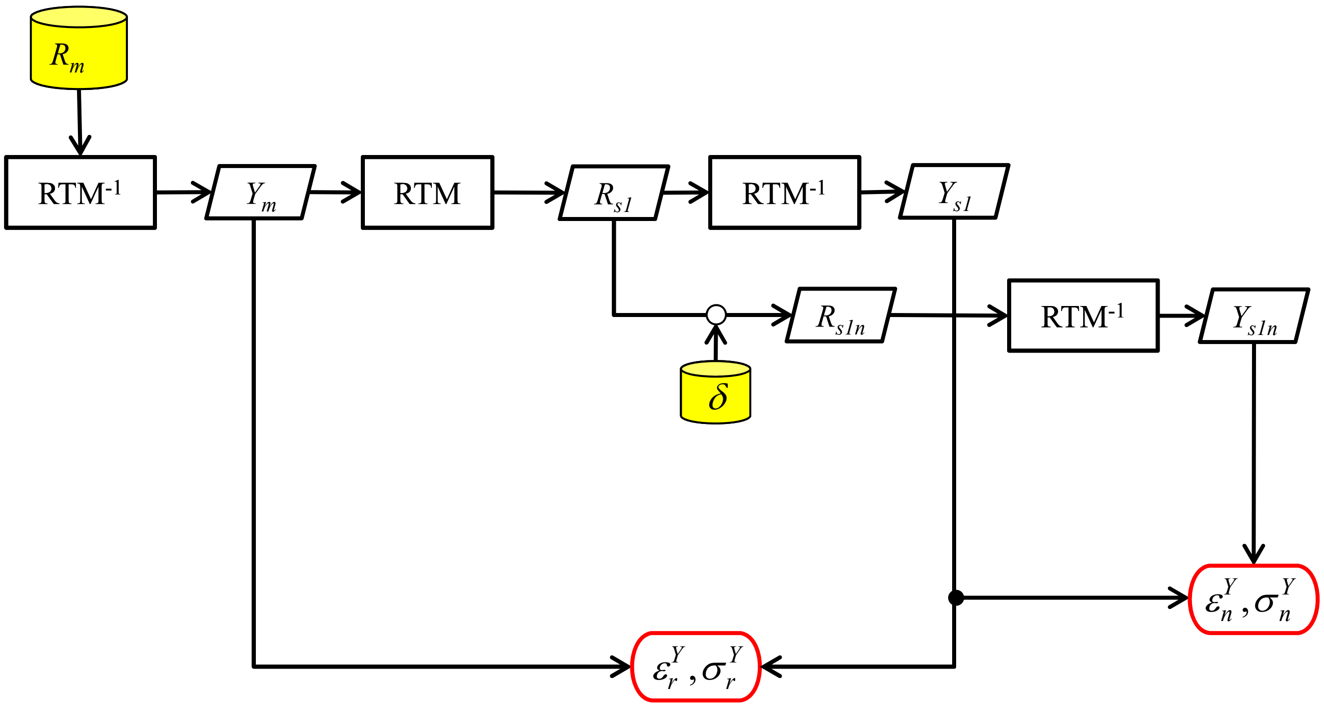
Langley Research Center

ECAS: Retrieval Domain

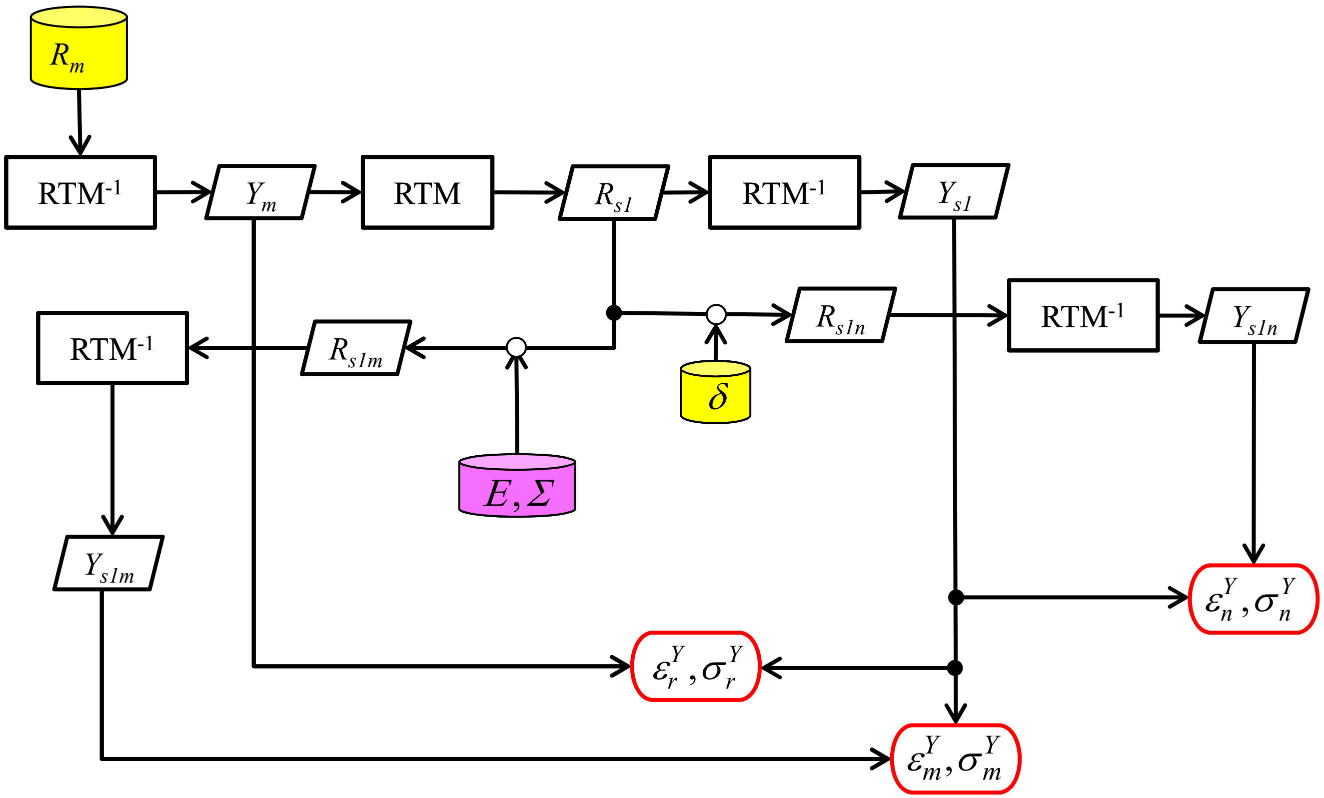


Langley Research Center

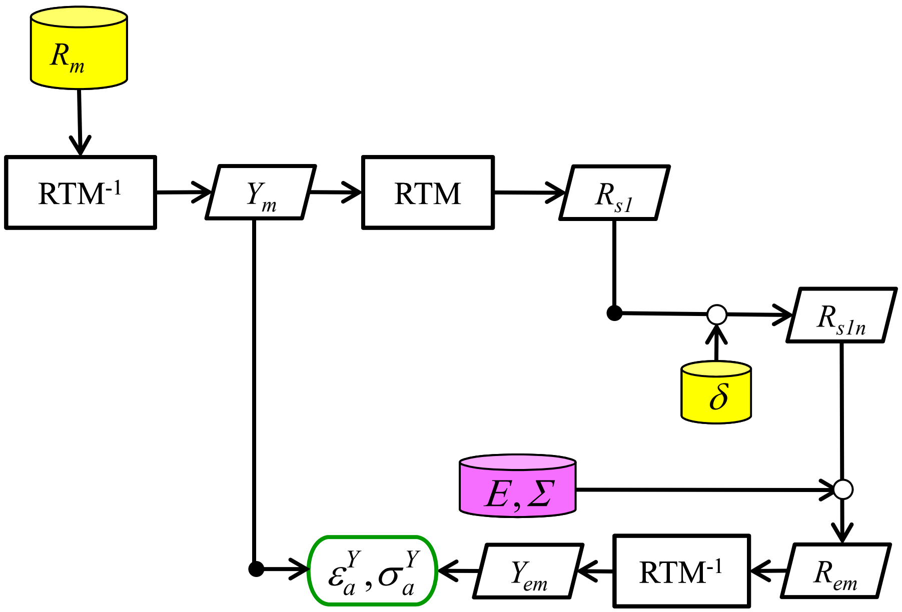
ECAS: Retrieval Domain



ECAS: Retrieval Domain

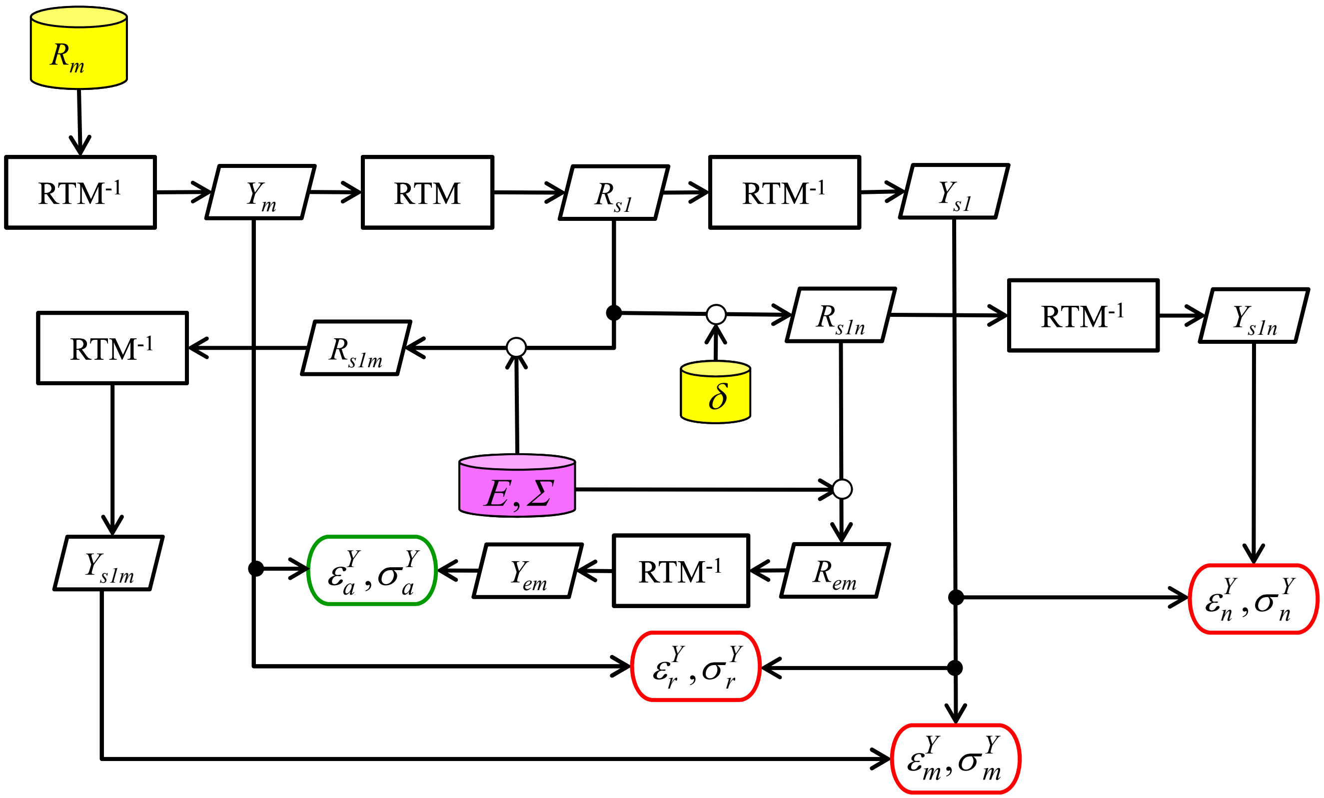


ECAS: Retrieval Domain

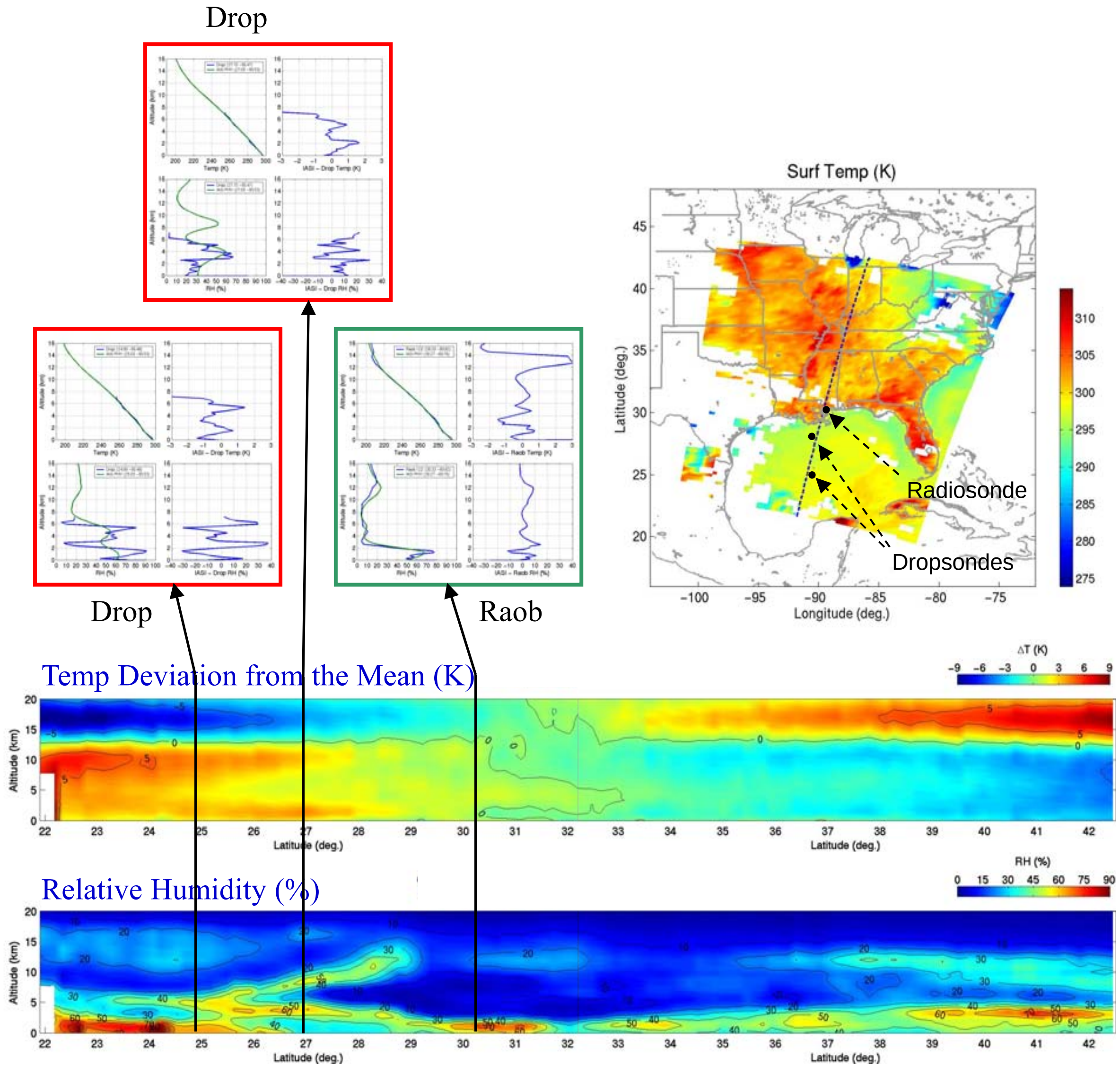


ECAS: Retrieval Domain

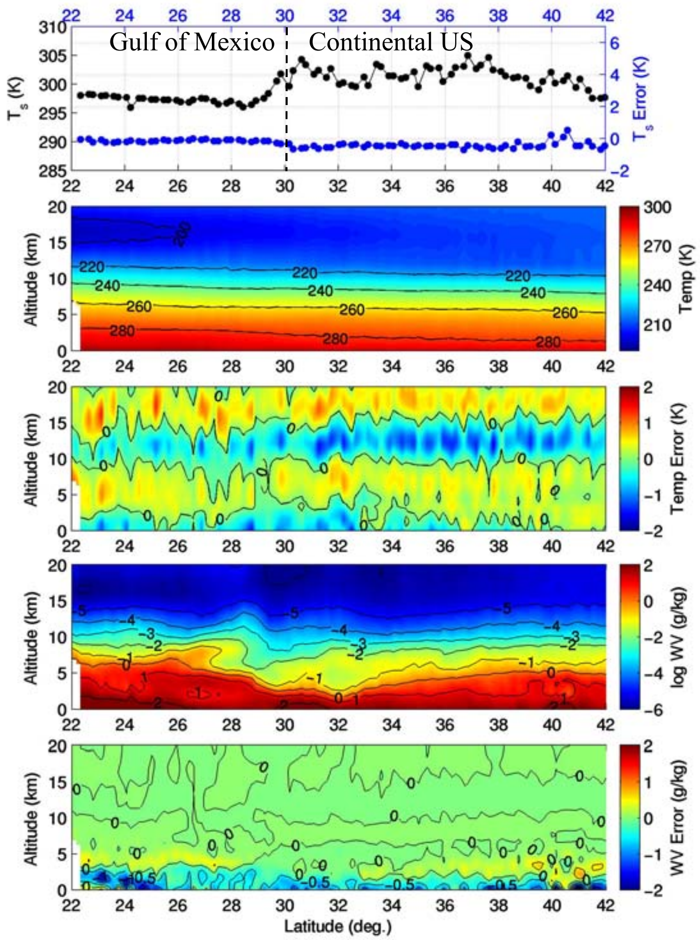
This $[\varepsilon_a^Y, \sigma_a^Y]$ can also be estimated by $\varepsilon_{ax}^Y = \varepsilon_r^Y + \varepsilon_n^Y + \varepsilon_m^Y$ and $\sigma_{ax}^Y = [(\sigma_r^Y)^2 + (\sigma_n^Y)^2 + (\sigma_m^Y)^2]^{1/2}$. Two approaches for total retrieval error estimation have given nearly the same results (i.e., $[\varepsilon_a^Y, \sigma_a^Y] \approx [\varepsilon_{ax}^Y, \sigma_{ax}^Y]$), indicating our early assumption of independent error sources is suitable for the analyses.



ECAS: Retrieval Error Estimated - 1



Retrieval error estimated by ECAS



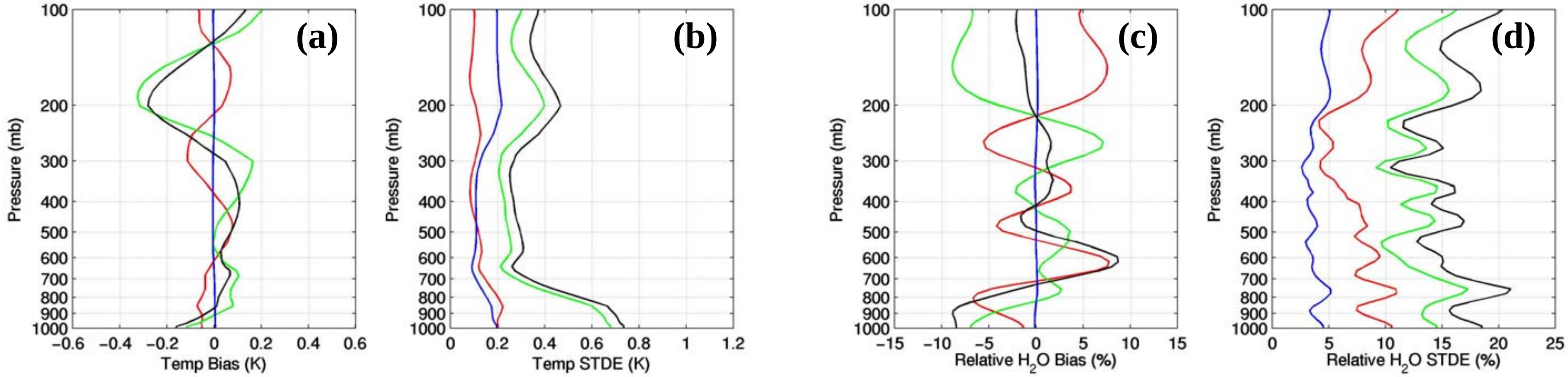
$$[\ Error = Y_{em} - Y_m\ ]$$

Langley Research Center

ECAS: Retrieval Error Estimated - 2

Temperature Profile Errors

Water Vapor Profile Errors



(a) Bias and (b) STED for temperature profile error budget estimation; (c) bias and (d) STDE for water vapor profile error budget estimation in a relative value (%) of water vapor mixing ratio in g/kg. "***Un-modeled***", ***ill-posed retrieval***, ***instrument noise***, and ***total error*** are in red, green, blue, and black, respectively.

Surface Skin Temperature Errors

	Bias (K)	STDE (K)
"un-modeled"	**-0.127**	**0.131**
ill-posed Ret	**-0.093**	**0.276**
ins. noise	**0.0**	**0.153**
total	**-0.220**	**0.342**

	Bias (K)	STDE (K)
Over water	**-0.134**	**0.362**
Over land	**-0.270**	**0.349**

Discussion and Summary

1. **The "un-modeled" error is estimated:** "un-modeled" is measurement dependent, it can be different from time to time and depends on atmospheric conditions (e.g., aerosol, dust, and some trace species not modeled in current RTM).
2. **There is no time and space difference:** since the iteration between radiance simulations and retrievals starts with measured radiance spectra, the horizontal footprint size of a retrieved profile obtained from its associated-measured spectrum is the same as the one it compares with to produce the final retrieval error. These retrievals, at difference stages of the analysis, have an almost identical vertical resolution. This provides a critical advantage of limiting the uncertainty or so-called "artificial smoothing error" caused by a different time and space of the "truth" in retrieval validation or error estimation.
3. **Error estimation is meaningful only if that parameter is retrieval sensitive:** for instance, error for the moisture profile above the tropopause (~18 km) is not meaningful as the moisture above the tropopause is not sensitive to measured radiances.
4. **ECAS contains an "ill-posed" problem:** given the retrieval parameters and their errors compensating to a certain minimal degree among themselves, although constraints are used in the retrieval to minimize such cross talk among retrieved parameters. For example, the retrieval errors estimated herein for surface skin temperature and emissivity spectra could compensate each other to satisfy a minimal radiance fitting in the retrieval process.
5. **The challenge is that the retrieval error is dominant:** retrieval error is algorithm dependent, it is larger than other errors introduced by "un-modeled" and instrument noise errors.