

# **A Deterministic Inverse Method for SST Retrieval from VIIRS: Incorporating Aerosol in the Retrieval Vector**

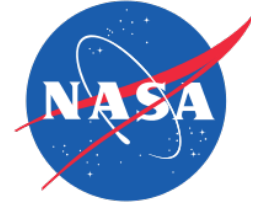
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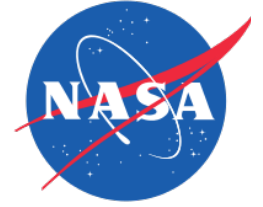
# Physical Retrieval - Recap



- **Reduces the problem to a local linearization**
  - Dependent on ancillary data (NWP) for an initial guess
  - More compute-intensive than regression – not an issue nowadays
    - Especially with fast RTM (e.g. CRTM)
- **Widely used for satellite sounding**
  - More channels, generally fewer (larger) footprints
- **Initially, started with a simple reduced state vector**
  - $\mathbf{x} = [\text{SST}, \text{TCWV}]^T$
  - *N.B.* Implicitly assumes NWP profile shape is more or less correct
- **Selection of an appropriate inverse method**
  - Ensure that satellite measurements are contributing to signal
  - Avoid excessive error propagation from measurement space to parameter space
    - If problem is ill-conditioned



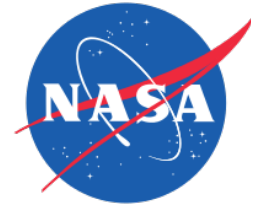
# History of Inverse Model



- **Forward model:**  $\mathbf{Y} = \mathbf{K}\mathbf{X}$
- **Simple Inverse:**  $\mathbf{X} = \mathbf{K}^{-1}\mathbf{Y}$  (measurement error)
- **Legendre (1805) Least Squares:**  
$$\mathbf{X} = \mathbf{X}_{ig} + (\mathbf{K}^T \mathbf{K})^{-1} \mathbf{K}^T (\mathbf{Y}_\delta - \mathbf{Y}_{ig})$$
- **MTLS:**  $\mathbf{X} = \mathbf{X}_{ig} + (\mathbf{K}^T \mathbf{K} + \lambda \mathbf{R})^{-1} \mathbf{K}^T (\mathbf{Y}_\delta - \mathbf{Y}_{ig})$
- **OEM:**  $\mathbf{X} = \mathbf{X}_a + (\mathbf{K}^T \mathbf{S}_e^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1} \mathbf{K}^T \mathbf{S}_e^{-1} (\mathbf{Y}_\delta - \mathbf{Y}_a)$



# Uncertainty Estimation



## Physical retrieval

Normal LSQ Eqn:  $\Delta x = (\mathbf{K}^T \mathbf{K})^{-1} \mathbf{K}^T \Delta y$  [=  $\mathbf{G} \Delta y$ ]

MTLS modifies gain:  $\mathbf{G}' = (\mathbf{K}^T \mathbf{K} + \lambda \mathbf{I})^{-1} \mathbf{K}^T$

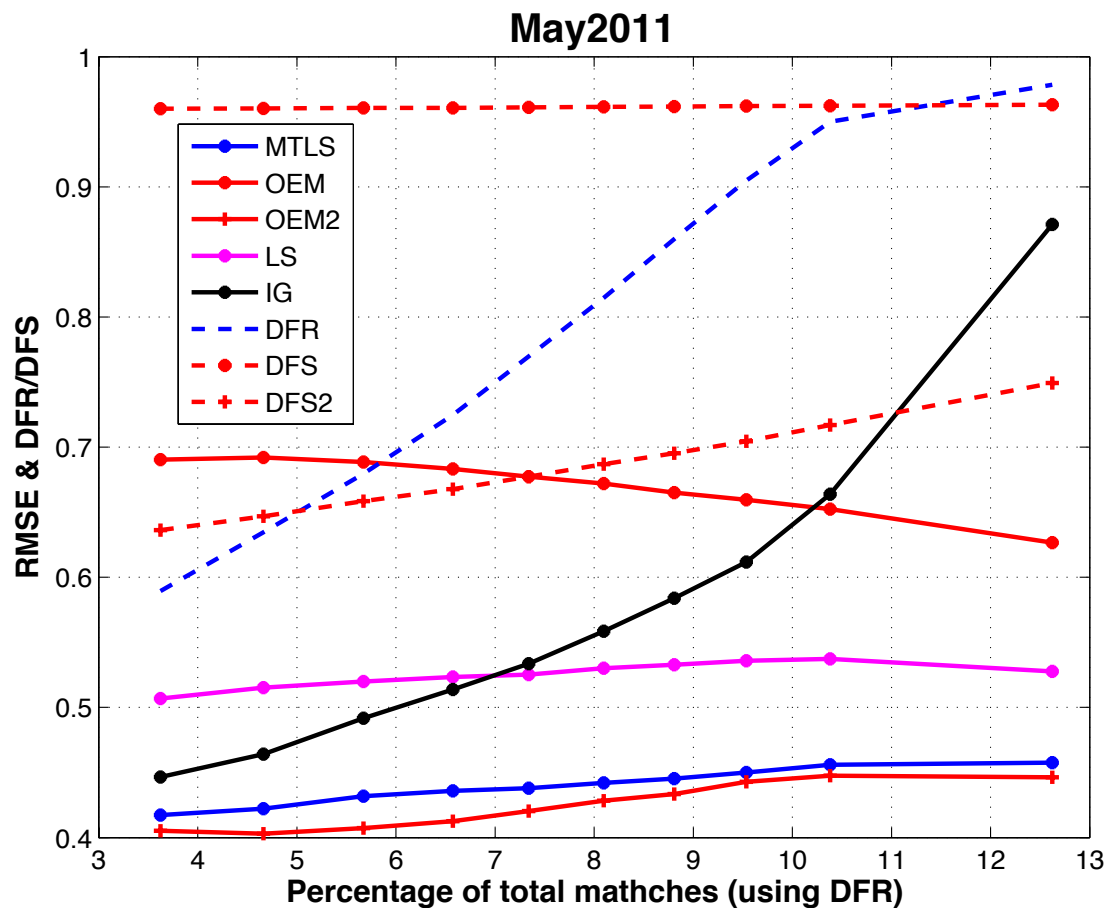
Regularization strength:  $\lambda = (2 \log(\kappa) / \|\Delta y\|) \sigma_{\text{end}}^2$

( $\sigma_{\text{end}}^2$  = lowest singular value of  $[\mathbf{K} \ \Delta y]$ )

## Total Error

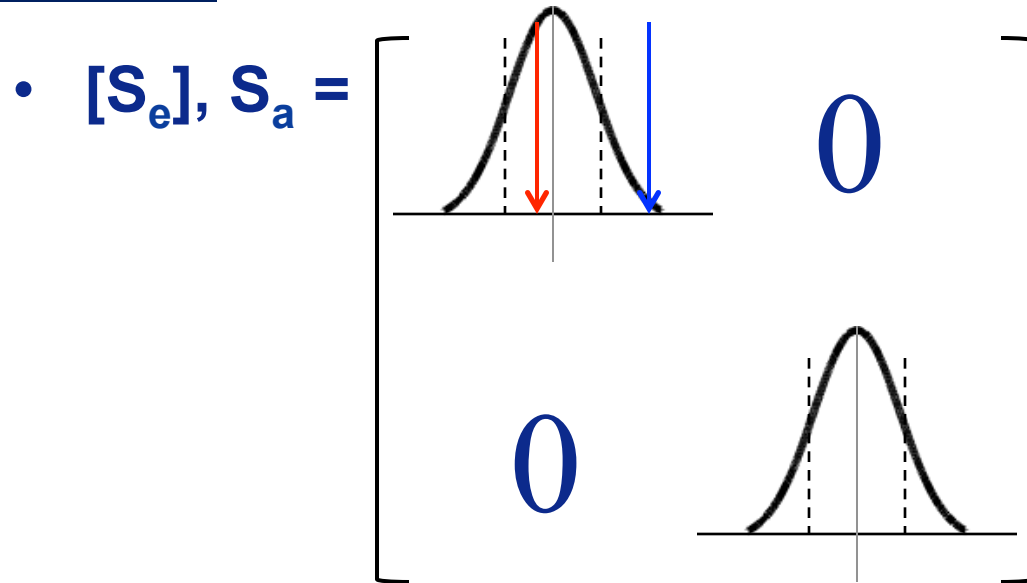
$$\|e\| = \|(\mathbf{MRM} - \mathbf{I})\Delta x\| + \|\mathbf{G}'\| \langle \|\Delta y - \mathbf{K}\Delta x\| \rangle$$

**N.B.** Includes TCWV as well as SST



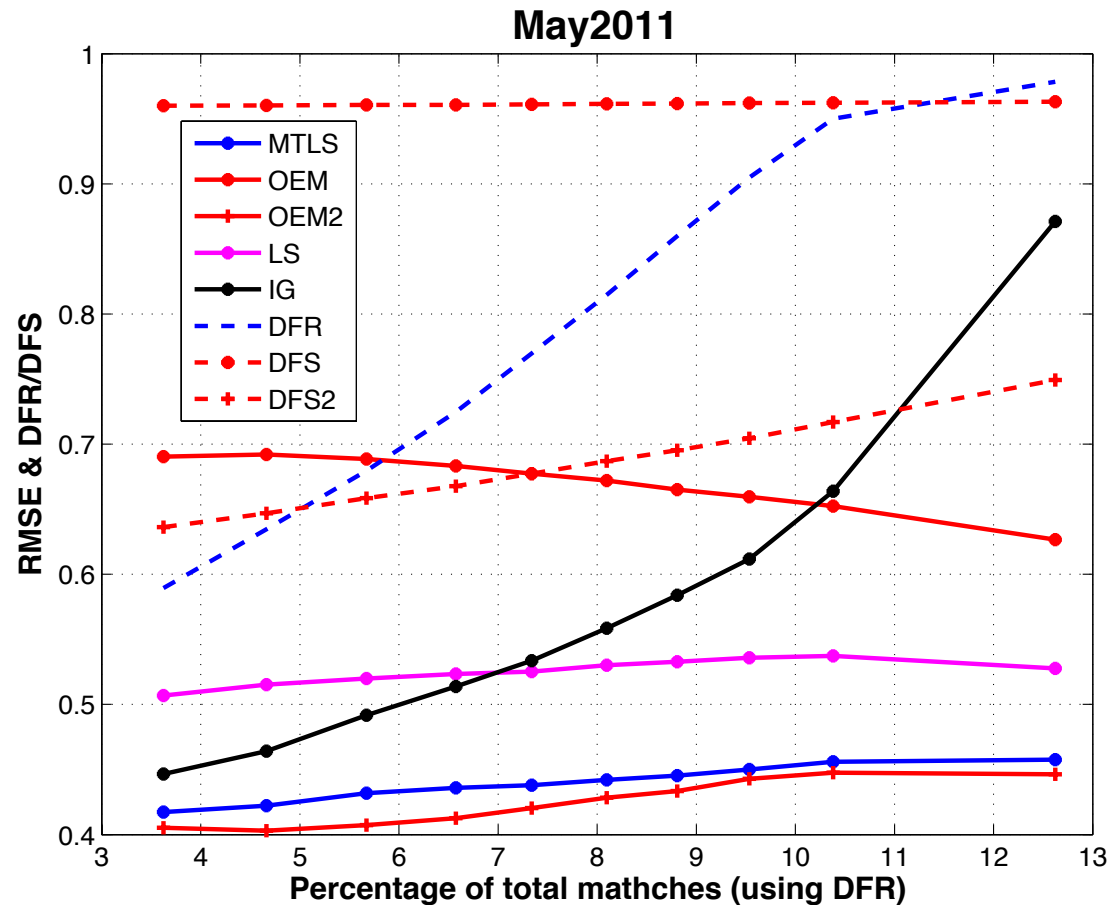
- Retrieval error of OEM higher than LS
- More than 75% OEM retrievals are degraded w.r.t. *a priori* error
- DFR of MTLs is high when *a priori* error is high

# “Optimized” OE



$\sigma^2$  is an overestimate...  
...or an underestimate

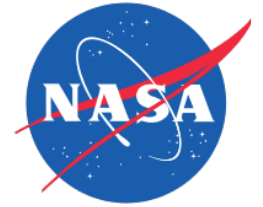
- **Perform experiment – insert “true” SST error into  $S_a^{-1}$** 
  - Can only be done when truth is known, e.g. with matchup data



- Retrieval error of OEM higher than LS
- More than 75% OEM retrievals are degraded w.r.t. *a priori* error
- DFR of MTLs is high when *a priori* error is high
- The retrieval error of OEM is good when a *priori* SST is perfectly known, but DFS of OEM is much lower than for MTLs



# Improved cloud detection

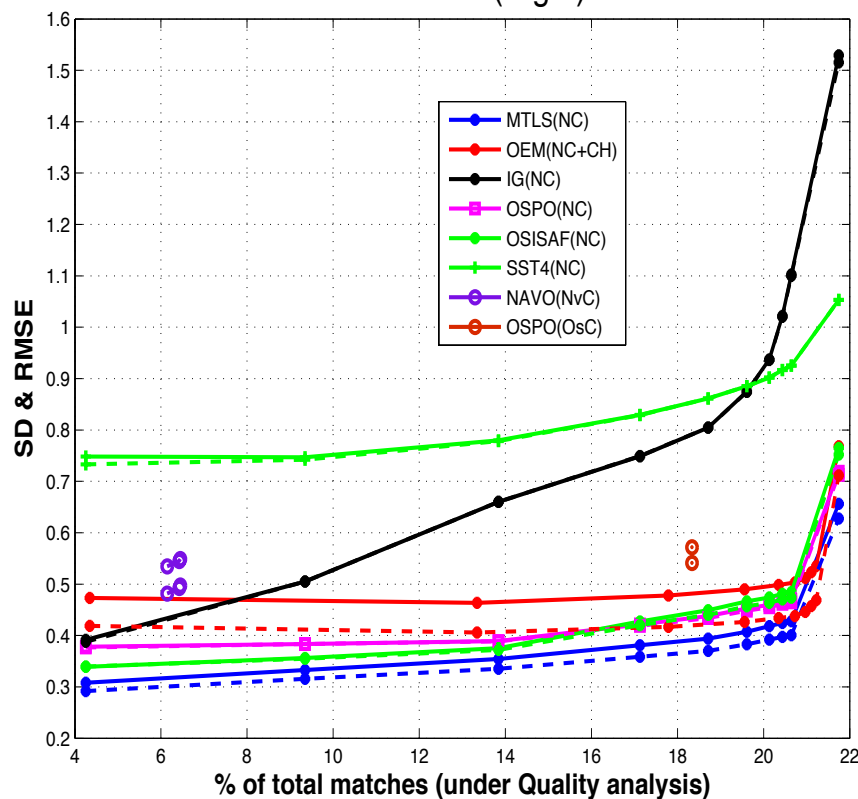


- **Use a combination of spectral differences and RT**
  - Envelope of physically reasonable clear-sky conditions
- **Spatial coherence (3×3)**
- **Also check consistency of single-channel retrievals**
- **Flag excessive TCWV adjustment & large MTLs error**
- **Increased coverage w.r.t. GHRSSST QL3+, but with reduced cloud leakage**
  - Prabhat's talk in yesterday's Oceans Breakout
  - ~50% increase in coverage & ~50% reduction in error

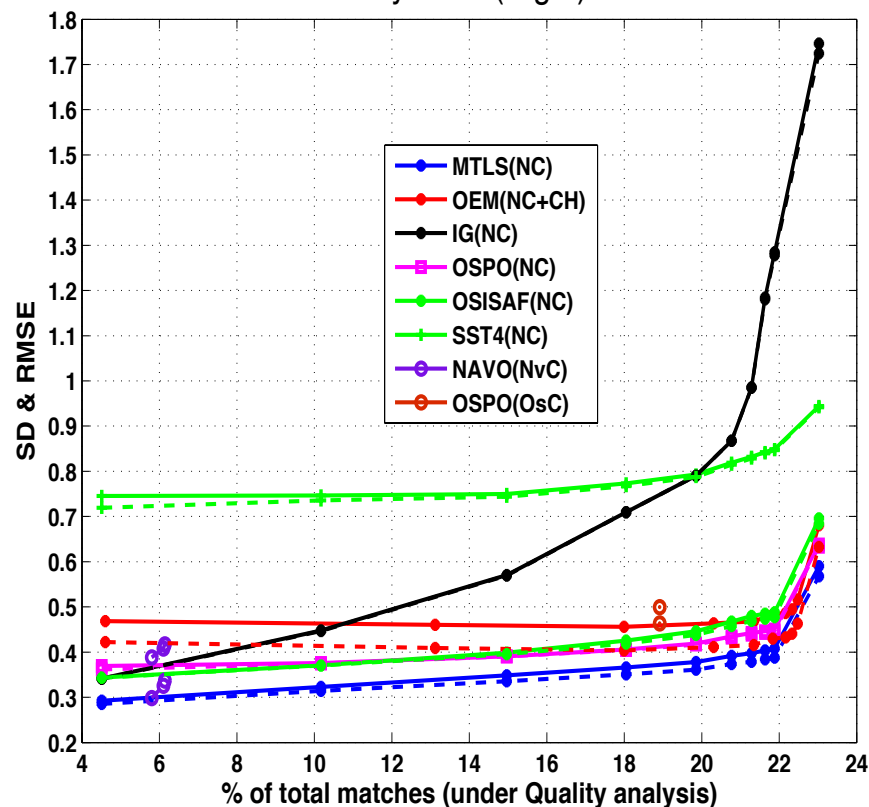


# VIIRS Initial Results

June 2014 (Night)



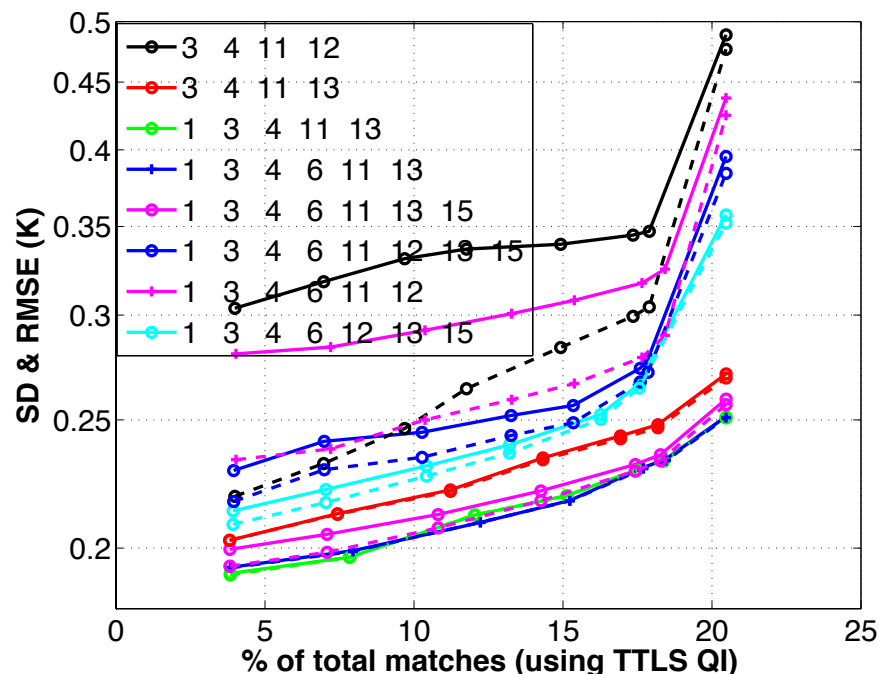
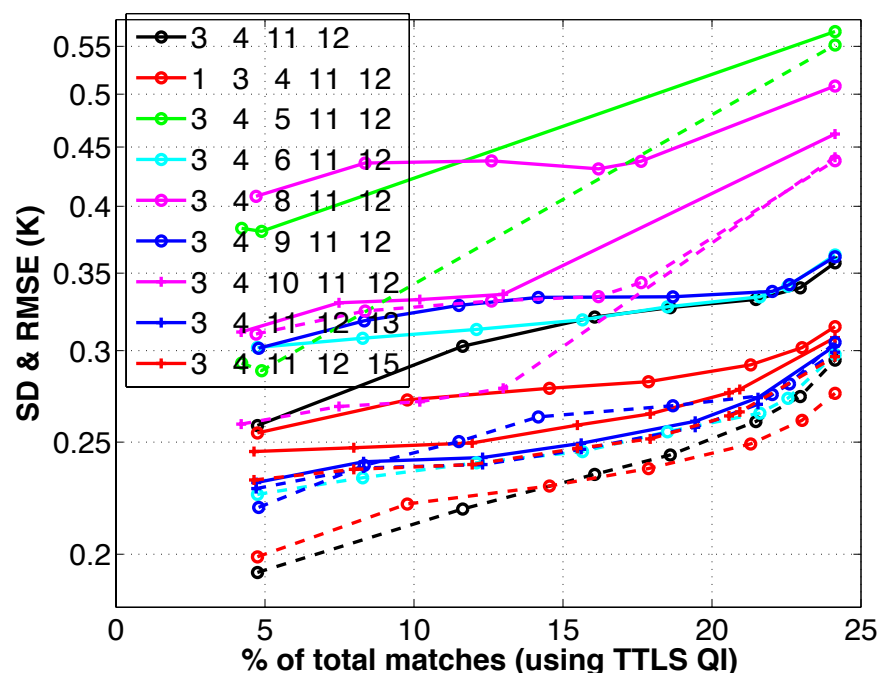
July 2014 (Night)



- **Data are ordered according to MTLs error**
  - Reliable guide for regression as well as MTLs
  - Trend of initial guess error is expected

- Channel selection**

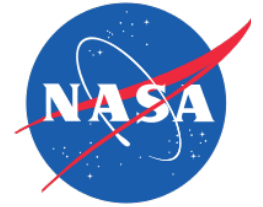
- Test various combinations and look at accuracy of retrieval



- RTM may be inadequate for some channels → bias
- Channels 1, 3, & 13 are particularly useful



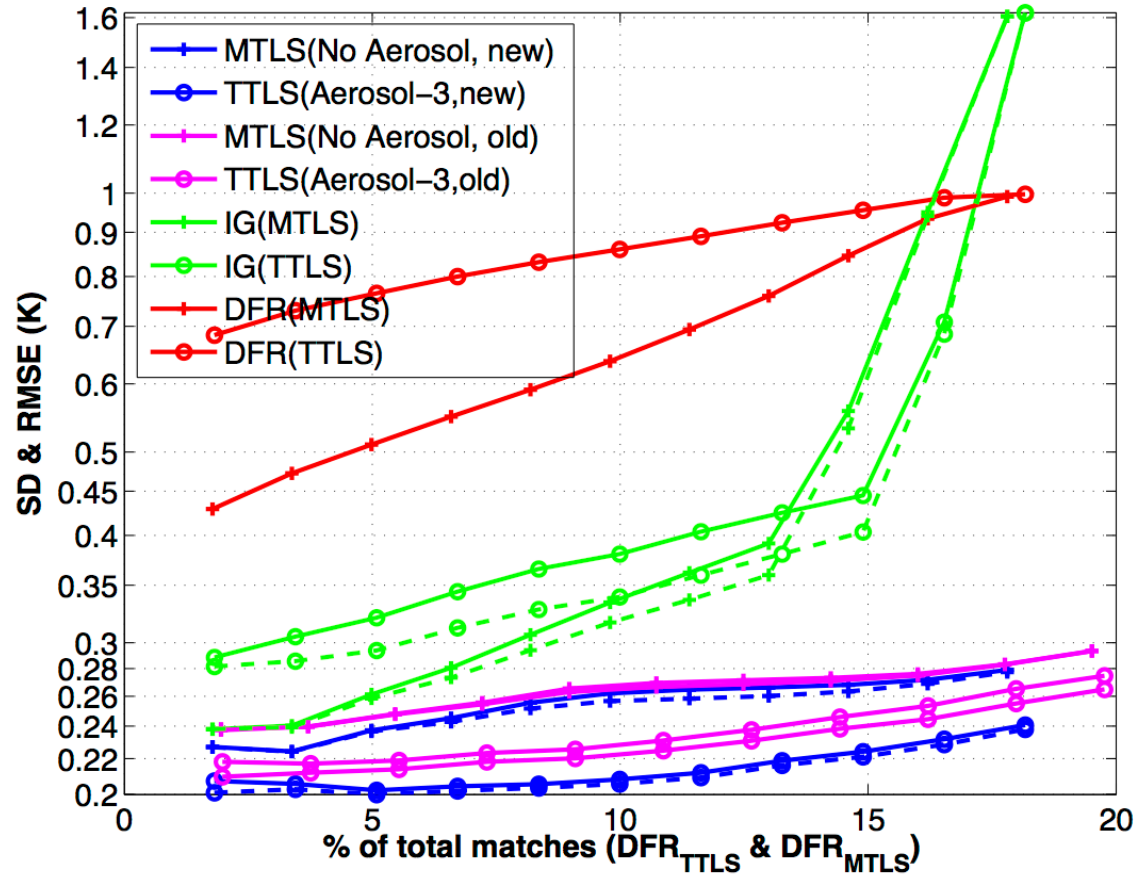
# Addition of aerosol



- **Put aerosol information in the CRTM**
  - NGAC profiles, multiple species (dust, salt, sulfate, soot)
  - Improve match of RTM to observation
  - Does this improve retrieval?
- **Put aerosol in the retrieval vector**
  - Allow Total Column Aerosol to vary
  - $\mathbf{x} = [\text{SST}, \text{WV}, \text{TCA}]^T$
  - Jacobian now includes  $\partial T / \partial \text{TCA}$  for each channel
  - Does this improve retrieval?
- **MTLS developed for 2-parameter retrieval**
  - Try different regularization operator since problem is now more ill-conditioned: **Truncated Total Least Squares (TTLS)**

$$|\Delta \mathbf{y}| \leq 1: \lambda = (\sigma_{\text{end}-1})^2 \quad |\Delta \mathbf{y}| > 1: \lambda = (\sigma_{\text{end}-1} / \log(|\Delta \mathbf{y}|))^2$$

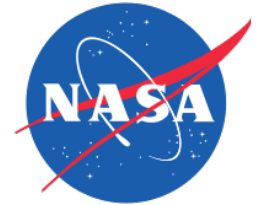
# Inclusion of aerosol



- Accuracy with TTLS & joint [SST, WV, TCA] ~0.2 K
- Algorithm sensitivity is also improved *cf.* MTLs



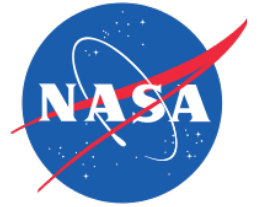
# Summary

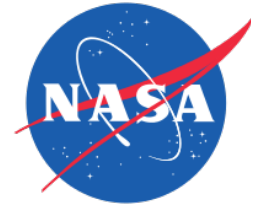


- **Addition of aerosol has significant benefit**
  - Most of all when included in retrieval vector as well as CRTM
- **Better partitioning of brightness temperature residuals**
  - No longer forcing delta-BTs caused by aerosol into the SST and/or WV retrieval space
  - Also improves algorithm sensitivity to SST (better overall fit to model)
- **TTLS better choice for 3-parameter retrieval**
  - Initial “tuning” with MODIS works well
  - Adaptation to VIIRS channels underway
- **Validation results are approaching buoy accuracy limit**
  - Best ~50% of retrievals at 0.2 K
  - Implies actual retrieval accuracy is better than this
- **Need to consider what might be needed @SIPS**
  - Full aerosol profiles as well as NWP



# Backup slides





# Improvements

- **It seems “obvious” that a sensitivity of 1 is desirable**
  - *E.g.* if there is diurnal warming of 5 K, it will be observed in the data, and strong upwellings will be accurately observed, *etc.*
- **However, there is a penalty to be paid**
  - Ill-conditioned problem → noise propagates from measurement space to parameter space
  - Compromise is usually struck (*e.g.* minimum least squares result for training data in a regression algorithm)
- **Regression algorithms may have sensitivity <1 for large regions**
  - *E.g.* daytime algorithms in the tropics (diurnal warming!)
  - Causes bias if local atmospheric conditions are different from the ensemble mean for the training data

Fig. 1a

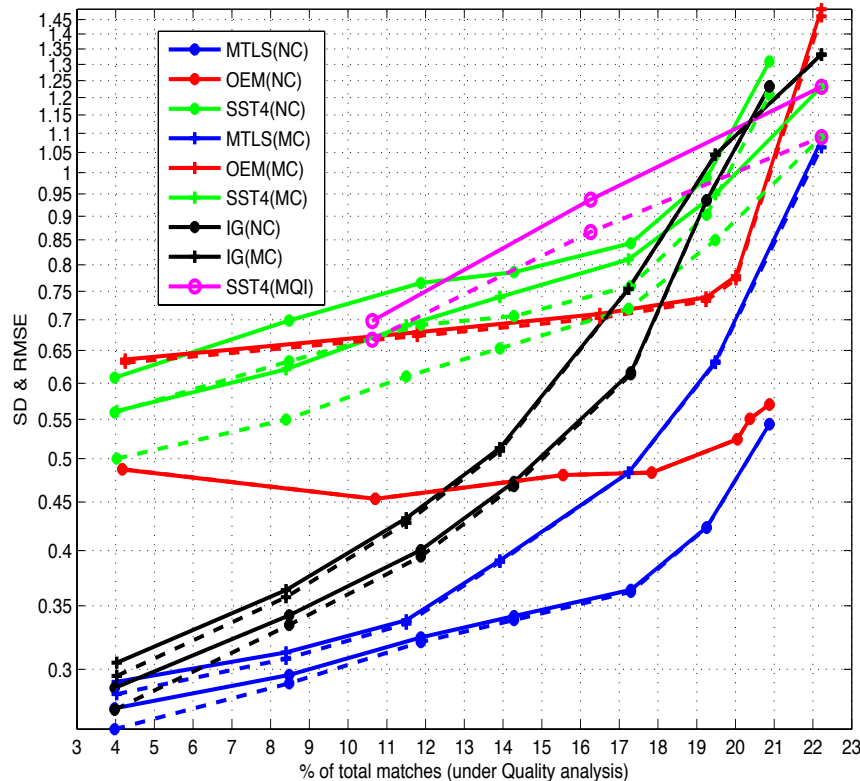
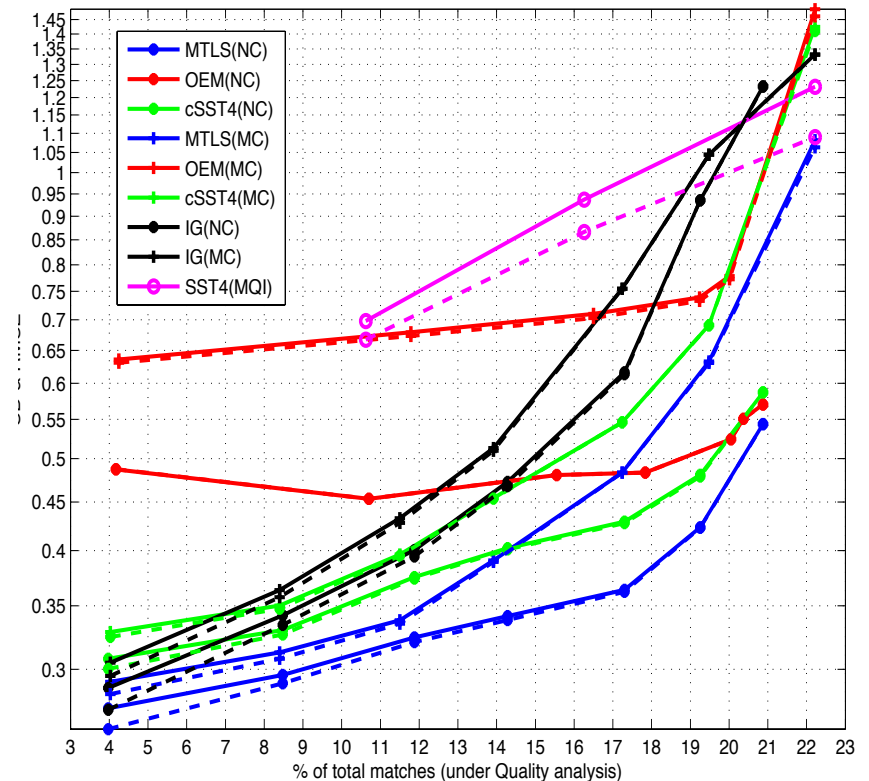


Fig. 1b



- **Note improvement from discarding MTLs error “last bin”**
  - Irrespective, MTLs is quite tolerant of cloud scheme
- **Recalculated SST4 coefficients produce quite good results**