

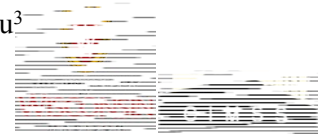
# The Physical Derivation of Emissivity Spectrum and Its Impact on Hyperspectrum Infrared Sounding Retrieval

Jinlong Li<sup>1</sup>, Jun Li<sup>1</sup>, Elisabeth Weisz<sup>1</sup>, Timothy J. Schmit<sup>2</sup>, and Daniel K. Zhou<sup>3</sup>

<sup>1</sup>Cooperative Institute for Meteorological Satellite Studies (CIMSS), University of Wisconsin – Madison

<sup>2</sup>NOAA/NESDIS/STAR

<sup>3</sup>NASA Langley Research Center



## 1. Introduction

Retrieval of temperature, moisture profiles and surface skin temperature from infrared (IR) radiances requires the spectral information of surface emissivity. Using constant or inaccurate surface emissivity typically results in the large retrieval errors, particularly over the semi-arid or arid area where the variation of emissivity spectrum is large spectrally and spatially. In this research, a physically based algorithm (Li et al. 2007) has been developed to retrieve hyperspectral IR emissivity spectrum simultaneously with the temperature and moisture profiles from AIRS.

## 2. Retrieval algorithm

In general, atmospheric measurement equation is written as

$$y = F(x) + e$$

$$y = (R_1, R_2, \dots, R_n)^T; \quad F: \text{forward model operator};$$

$$x = (t(p); w(p); o(p); t_s; \varepsilon_1; \dots; \varepsilon_n)^T; \quad e: \text{measurement and model error}$$

$$x: \text{retrieved parameters}; \quad y: \text{measured radiance}$$

Retrieval process is based on the regularization and discrepancy principle developed by J. Li and H.L. Huang (1999). To get the optimum solution, we need to construct a cost function as:

$$J(x) = (y_m - y_c(x))^T E^{-1} (y_m - y_c(x)) + (x - x_0)^T \gamma S^{-1} (x - x_0)$$

$y_m$ : satellite measurement  
 $y_c$ : forward model calculated radiance  
 $x_0$ : initial guess  
 $E$ : measurement error covariance matrix  
 $S$ : background error covariance matrix  
 $\gamma$ : dynamical factor to balance measurement and background contribution

Because surface emissivity is channel related, there are too many parameters to be retrieved if including all channels' emissivities !!! However, retrieving emissivity spectrum is still possible if the eigenvector expansion is used:

$$x = \sum_i a_i \phi_i = a \phi; \quad \begin{cases} \phi: \text{eigenvector matrix}; \\ a: \text{eigenvector coefficients} \end{cases}$$

$$J(x) = J(a\phi) = (y_m - y_c(a\phi))^T E^{-1} (y_m - y_c(a\phi)) + ((a - a_0)\phi)^T \gamma S^{-1} ((a - a_0)\phi)$$

By minimizing cost function and using quasi-nonlinear Gauss-Newton iteration

Define:  $c = a - a_0$

$$c_{i+1} = (\gamma \tilde{S}^{-1} + \tilde{K}^T E^{-1} \tilde{K})^{-1} \tilde{K}^T E^{-1} [(y_m - y_c(c_i + a_0)) + \tilde{K} c_i]$$

$$\tilde{K} = K \phi; \quad \tilde{S} = S \phi;$$

$K$  is the jacob matrix:  $k_{ij} = \partial F_i(x) / \partial x_j$

After transformation, retrieval variables have been reduced from a couple thousands to a few tens for AIRS application.

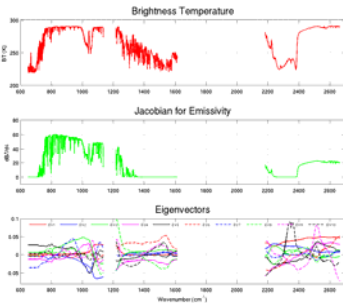


Figure 1: To make the computation more efficient, an analytical Jacob calculation was used in the retrieval. A calculated surface emissivity Jacob along with the brightness temperature and the first 10 eigenvectors of surface emissivity for AIRS spectrum are shown in the figure.

## 3. Simulation study

In simulation study, a global training profiles and associated physically meaningful surface emissivities have been used. 90% of about 12000 training sets are used to create regression coefficients, another independent 10% of training sets are used for algorithm validation. To test our algorithm, the following experiment results have been shown and compared:

- Regression retrieval: T, W, O3 profiles, Ts, Emissivity
- Three types of physical retrieval by using regression retrieval as first guess and different handlings of surface emissivity:
  - Setting initial emissivities as a constant 0.98 and keeping them unchanged during physical retrieval process (constant).
  - Using regression emissivities as initial and keeping them unchanged during physical retrieval process (fixed).
  - Using regression emissivities as initial and updating them during physical retrieval process (retrieval).

## Global cases

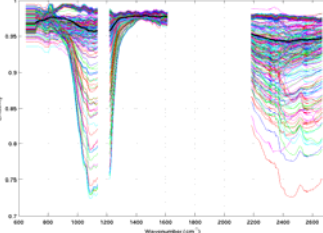


Figure 2: A subset of surface emissivities spectrum (about 450 cases) chosen from global training sets.

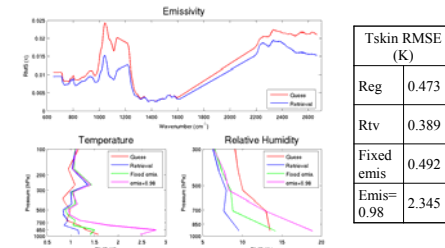


Figure 3: The root mean square errors (RMSE) of retrievals for designed experiment schemes from selected subset of global training data: Surface emissivity (top panel); Temperature and moisture profiles (low panel); Surface skin temperature (right table).

## Regional cases

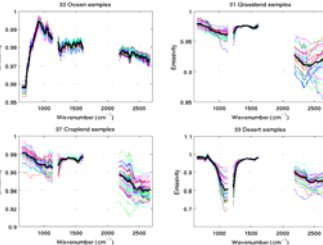


Figure 4: The selected emissivity spectra assigned to ocean (top left), grassland (top right), cropland (bottom left), and desert (bottom right) regions from the training data set. The dark black lines are the means for each regional data set.

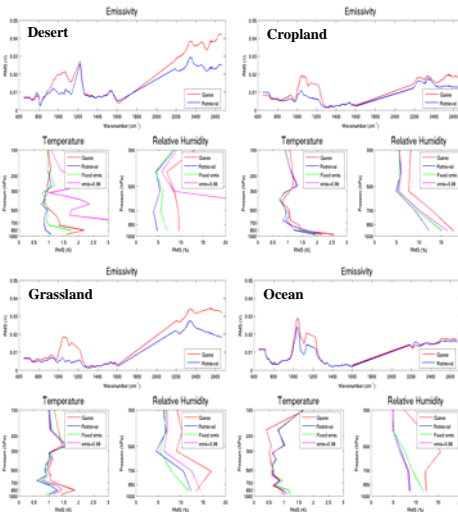


Figure 5: The RMSE of retrievals of surface emissivity, temperature and moisture profiles for three configurations described along with the first guess (from regression) results from four subsets of data: desert region (top left); cropland region (top right); grassland region (low left); ocean region (low right).

## 4. AIRS data application

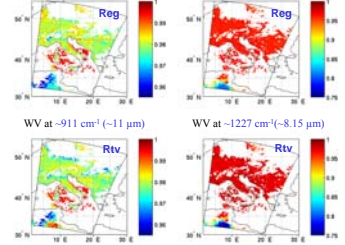


Figure 6: The emissivity retrieval from the regression (top panels) and physical (low panels) approaches at ~11 um (left) and ~8.15 um. (right).

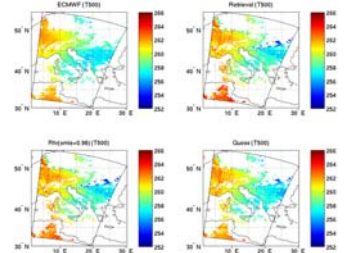


Figure 7: Temperature retrievals around 500mb from the regression (bottom right), physical retrieval with surface emissivity as a constant of 0.98 (bottom left) and simultaneous physical retrieval (top right), along with ECMWF analyses (top left).

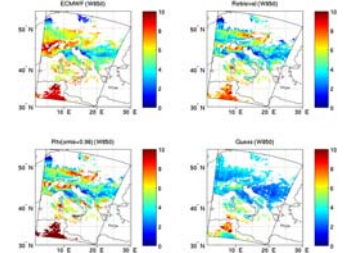


Figure 8: Moisture retrievals around 850mb from the regression (bottom right), physical retrieval with surface emissivity as a constant of 0.98 (bottom left) and simultaneous physical retrieval (top right), along with ECMWF analyses (top left).

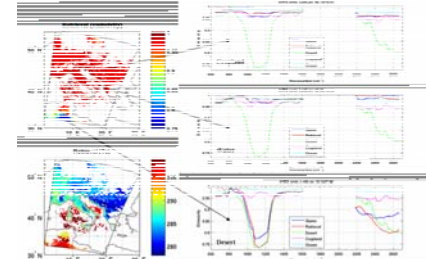


Figure 9: Retrieved surface emissivity at ~8.15 um (top left) and surface skin temperature (low left). Examples of emissivity spectrum retrieval over the cropland, water and desert regions along with three reference emissivity spectra from laboratory data corresponding to cropland, water, and desert surface types, respectively.

## 5. Summary

Handling surface IR emissivity is very important for sounding retrieval and radiance assimilation. The emissivity uncertainty has a significant impact on the retrieval of boundary layer temperature and moisture, particularly over desert regions where surface IR emissivity has large variations both spectrally and spatially. This study shows that simultaneous retrieval of hyperspectral IR emissivity spectrum and sounding is helpful in the sounding retrieval. The emissivity spectrum can be retrieved together with the profile through an eigenvector representation of the spectrum.

**ACKNOWLEDGEMENT:** This program is supported by NOAA GOES-R project at CIMSS. Suzanne Seemann and Eva Borbas developed the global training data set.

**REFERENCES**  
 Li, J., J. Li, E. Weisz, and D.K. Zhou, 2007: Physical retrieval of surface emissivity spectrum from hyperspectral infrared radiances. *Geophys. Res. Lett.*, 34, L16682, doi:10.1029/2007GL030543.

Li, J., and H.-L. Huang, 1999: Retrieval of atmospheric profiles from satellite sounder measurements by use of the discrepancy principle. *Appl. Optics*, Vol. 38, No. 6, 916-923.

Li, J., 1994: Temperature and water vapor weighting functions from radiative transfer equation with surface emissivity and solar reflectivity. *Adv. Atmos. Sci.*, 11, 421-426

**Contact:** Jinlong.Li@ssec.wisc.edu; Jun.Li@ssec.wisc.edu