Derived infrared surface emissivity from satellite hyperspectral sounders

Daniel K. Zhou[1], Allen M. Larar[1], Xu Liu[1], William L. Smith[2,3], L. Larrabee Strow[4], P. Yang[5], and Peter Schlüssel[6]

[1]NASA Langley Research Center, Hampton, VA, USA
[2]Hampton University, Hampton, VA, USA
[3]University of Wisconsin-Madison, Madison, WI, USA
[4]University of Maryland Baltimore County, Baltimore, MD, USA
[5]Texas A&M University, Collage Station, TX, USA
[6]EUMETSAT, Darmstadt, Germany

NASA Sounding Science Team Meeting
May 4-6, 2009; Pasadena, CA

Outline

- Motivation & Goal
- Retrieval Algorithms
- Retrieval Analysis
- Cloud Detection and Quality Filter
- Spectral Emissivity Retrieval Demonstration - preliminary
- Emissivity Temporal/Seasonal Variation
- Summary and Future Work

Motivation & Goal

Study Earth from space to improve our scientific understanding of global climate change; derive seasonal-global IR spectral emissivity with operational satellite hyperspectral IR measurements.

- This will help to understand the nature of radiative transfer process for the Earth and atmospheric environment, and the radiation budget for the Earth system.

- Accurate surface emissivity retrieved from satellite measurements are greatly beneficial but not limit to
  1) improving retrieval accuracy for other thermodynamic parameters (e.g., T_s, CO, O_3, H_2O…),
  2) helping surface skin temperature retrieval from other satellite broad-band measurements,
  3) assisting assimilation of hyperspectral IR radiances in NWP models, and
  4) climate simulation.

- Retrieval algorithm evaluation/validation through retrieval products.

- Long-term and large-scale observations, needed for global change monitoring and other research, can only be supplied by satellite remote sensing.

- Surface emissivity and skin temperature from the current and future operational satellites can and will reveal critical information on the Earth's land surface type properties and Earth's ecosystem.

IR-only Cloudy Retrieval Algorithm

Part A: Regression Retrieval (*Zhou et al*., GRL 2005)

Using an all-seasonal-globally representative training database to diagnose 0-2 cloud layers from training relative humidity profile:

A single cloud layer is inserted into the input training profile. Approximate lower level cloud using opaque cloud representation.

Use parameterization of balloon and aircraft cloud microphysical data base to specify cloud effective particle diameter and cloud optical depth:

Different cloud microphysical properties are simulated for same training profile using random number generator to specify visible cloud optical depth within a reasonable range. Different habitats can be specified (Hexagonal columns assumed here).

Use LBLRTM/DISORT "lookup table" to specify cloud radiative properties:

Spectral transmittance and reflectance for ice and liquid clouds interpolated from multi-dimensional look-up table based on DISORT multiple scattering calculations.

Compute EOFs and Regressions from clear, cloudy, and mixed radiance data base:

Regress cloud, surface properties & atmospheric profile parameters against radiance EOFs.

Part B: 1-D Var. Physical Retrieval (*Zhou et al*., JAS 2007)

A one-dimensional (1-d) variational solution with the regularization algorithm (i.e., the minimum information method) is chosen for physical retrieval methodology which uses the regression solution as the initial guess.

Cloud optical/microphysical parameters, namely effective particle diameter and visible optical thickness, are further refined with the radiances observed within the 10.4 to 12.5 μm window.

Retrieval Algorithm Involved with ε_ν

Emissivity EOF Regression (*Zhou et al.*, AO 2002)

A surface emissivity function is used instead of emissivity in the retrieval in order to constrain retrieved emissivity spectrum (ε_ν) within a boundary between ε^{min} and ε^{max};

$$\mathbf{F}(\boldsymbol{\varepsilon}) = \log[\log(\varepsilon^{min})-\log(\varepsilon^{max}-\boldsymbol{\varepsilon})], \quad (1)$$

← **New approach**

$$\mathbf{A}_F = \mathbf{F}\,\boldsymbol{\Phi}, \quad (2)$$

where $\mathbf{A}_F$ is a set of EOF amplitudes of $\mathbf{F}(\boldsymbol{\varepsilon})$ and $\boldsymbol{\Phi}$ is the eigenvector matrix generated with a set of lab measured emissivity spectra in the form of the emissivity function $\mathbf{F}(\boldsymbol{\varepsilon})$.

A set of 10 $\mathbf{F}(\boldsymbol{\varepsilon})$ EOF amplitudes is used together with other retrieved parameters (e.g., T_s, $\mathbf{T}$, $\mathbf{q}$) as a state vector to be retrieved against a set of radiance EOF amplitudes representing measured radiance spectrum.

Emissivity Physical Retrieval (*Li et al.*, GRL 2008)

Physical iteration retrieval, using the regression solution as the initial guess, with the regularization methodology can be performed with a penalty function,

$$\mathbf{J}(\mathbf{x}) = [\mathbf{Y}^m-\mathbf{Y}^c(\mathbf{x})]^T\,\mathbf{E}^{-1}\,[\mathbf{Y}^m-\mathbf{Y}^c(\mathbf{x})] + (\mathbf{x}-\mathbf{x}_0)^T\,\gamma\mathbf{I}\,(\mathbf{x}-\mathbf{x}_0), \quad (3)$$

and the Newtonian iteration, where $\mathbf{x}$, $\mathbf{Y}$, $\mathbf{E}$, and γ are a state vector, radiance, measured error covariance matrix, and Lagrangian multiplier, respectively; m, c, and T represent measured, calculated, and transpose, respectively.

Emissivity Jacobian matrix (i.e., weighting functions) of the radiance with respect to the channel emissivity ($\mathbf{W}_{chan}$) is compressed to the Jacobian matrix of the radiance with respect to the emissivity function eigenvector amplitudes ($\mathbf{W}_F$) using the eigenvector matrix $\boldsymbol{\Phi}$.

$$\mathbf{W}_F = \mathbf{W}_{chan}\,\boldsymbol{\Phi} \quad (4)$$

Emissivity (ε_ν) is linear to Radiance (I_ν)

$$I_\nu = \int_0^z B_\nu[T(z)]\cdot\frac{\partial\tau_\nu(z,\ z^s)}{\partial z}\cdot dz + \rho_\nu\cdot\tau_\nu(0,\ z^s)\cdot\int_\infty^0 B_\nu[T(z)]\frac{\partial\tau_\nu(z,\ z^s)}{\partial z}\cdot dz +$$

$$\varepsilon_\nu\cdot B_\nu(T_s)\cdot\tau_\nu(0,\ z^s) + \rho_\nu^{solar}\cdot H\cdot\tau_\nu^b(0,\ z^s,\ \theta)\cdot\cos(\theta)$$

$$= \left[\int_0^z B_\nu[T(z)]\cdot\frac{\partial\tau_\nu(z,\ z^s)}{\partial z}\cdot dz + \tau_\nu(0,\ z^s)\cdot\int_\infty^0 B_\nu[T(z)]\frac{\partial\tau_\nu(z,\ z^s)}{\partial z}\cdot dz + \frac{H\cdot\tau_\nu^b(0,\ z^s,\ \theta)\cdot\cos(\theta)}{\pi}\right] +$$

$$\left[B_\nu(T_s)\cdot\tau_\nu(0,\ z^s) - \tau_\nu(0,\ z^s)\cdot\int_\infty^0 B_\nu[T(z)]\frac{\partial\tau_\nu(z,\ z^s)}{\partial z}\cdot dz - \frac{H\cdot\tau_\nu^b(0,\ z^s,\ \theta)\cdot\cos(\theta)}{\pi}\right]\cdot\varepsilon_\nu$$

$$= K_1 + K_2\cdot\varepsilon_\nu,$$

where we assume that $\rho_\nu = (1-\varepsilon_\nu)$, and $\rho_\nu^{solar} = \dfrac{(1-\varepsilon_\nu)}{\pi}$

$I_\nu =$ observed spectral radiance

$\varepsilon_\nu =$ spectral emissivity

$B_\nu =$ spectral Planck function

$T_s =$ surface skin temperature

$\tau_\nu(z_1,\ z_2) =$ spectral transmittance from altitude z_1 to z_2

$z^s =$ sensor altitude

$T(z) =$ temperature at altitude z

$\rho_\nu =$ spectral surface reflectivity

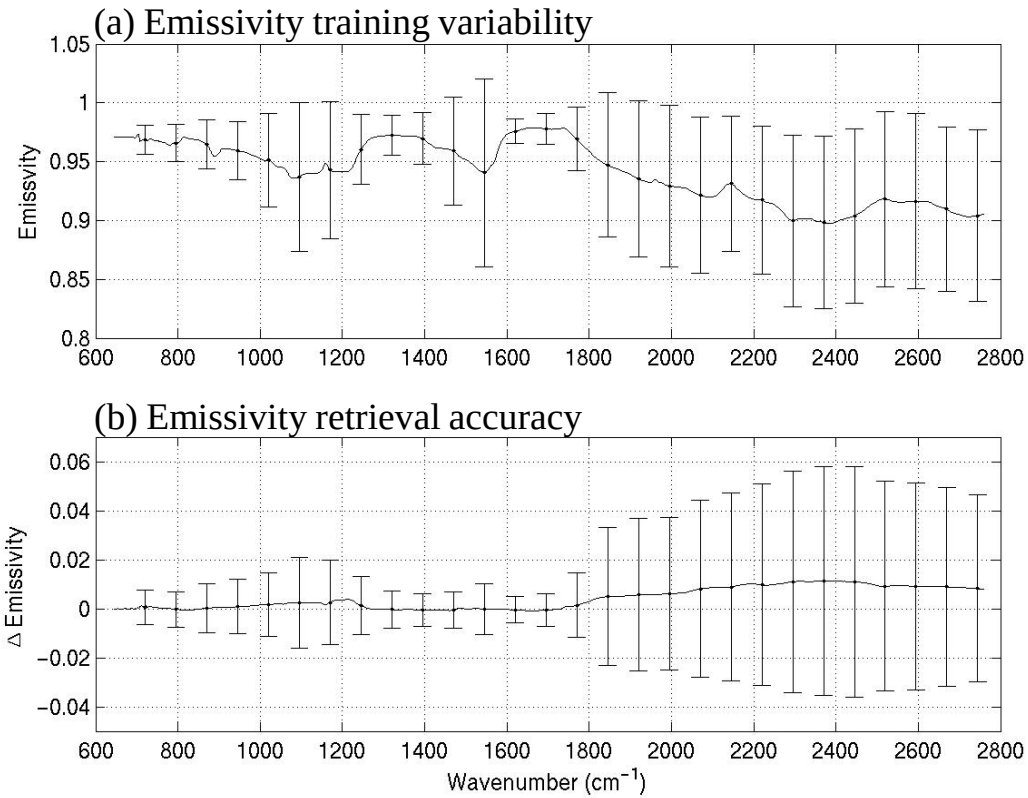
$\rho_\nu^{solar} =$ spectral solar reflectivity

$H =$ solar irradiance

$\theta =$ solar zenith angle

$\tau_\nu^b =$ two-path transmittance from the Sun to the surface then to the satellite

Reg. Emis. Ret. Accuracy Estimation

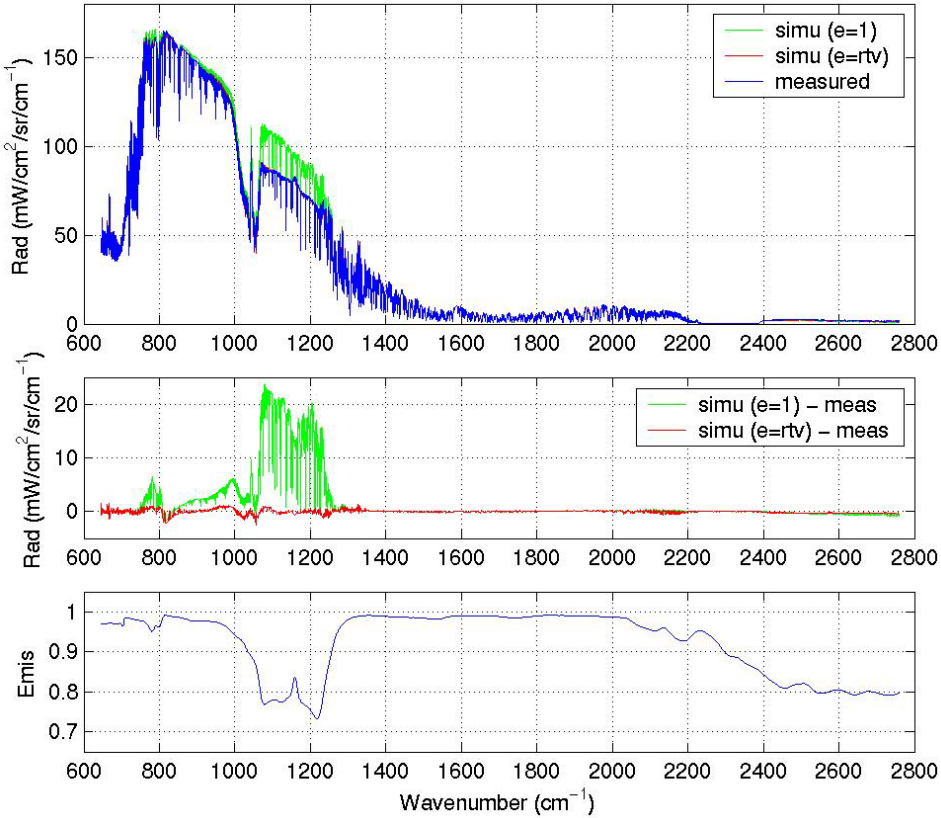


- The emissivity assigned to each training profile is randomly selected from a laboratory measured emissivity database, indicated in panel **a**, and has a wide variety of surface types suitable for different geographical locations. The vertical bars show the emissivity STD for this dataset.
- Estimated surface emissivity retrieval accuracy, the mean difference (or bias) in curve and the STDE in vertical bars shown in panel **b**, is training data dependent.
- Surface skin temperature is one of the most "coupled" parameters with emissivity, it is necessary to mention that skin temperature retrieval accuracy has a -0.07 K bias with a 0.84 K STDE from the same analysis

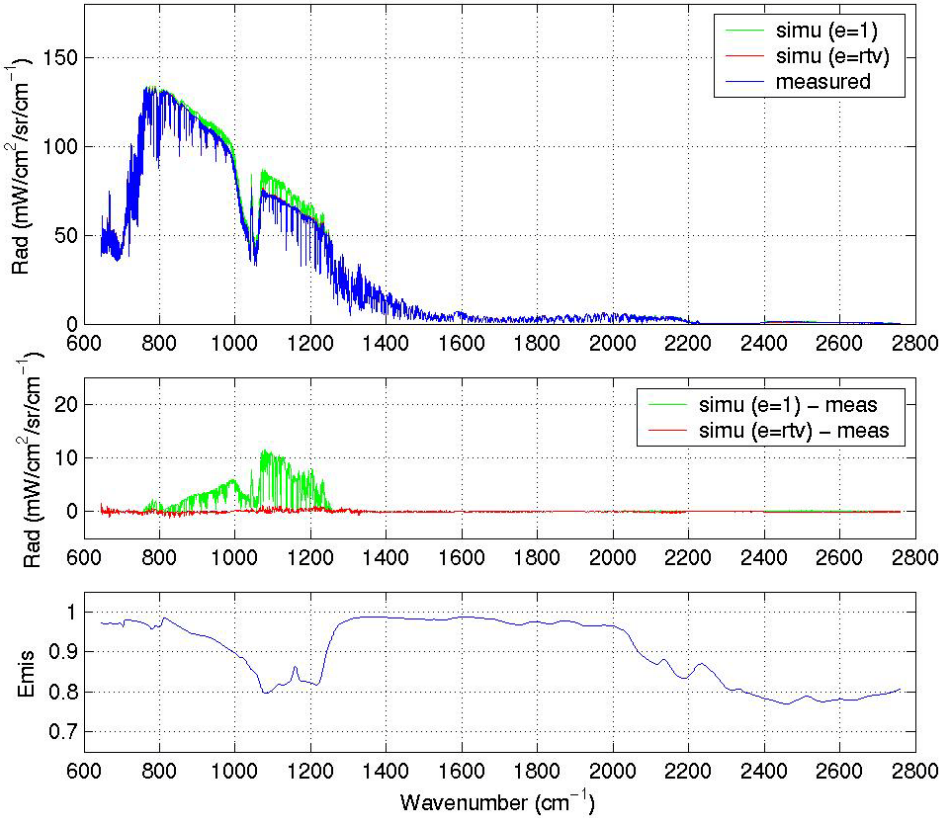
Note: since the emissivity is linear to channel radiances, we chose to use retrieved emissivity from linear EOF regression, not further retrieved in physical iteration. However, if the physical retrieval is performed for other parameters, emissivity will be further refined through physical iteration.

Emis. Ret. and Rad. Fitting Samples

Over Sahara (Lat.=26.43°N; Lon.=18.45°E);
Daytime (SZA=36.72°), 2007.08.01



Over Sahara (Lat.=23.23°N; Lon.=18.37°E);
Nighttime (SZA=116.1°), 2007.08.01



Samples shown are for both day and night observations over the Sahara Desert. Simulated spectral radiances from the retrieved parameters (i.e., atmospheric profiles, surface skin temperature and emissivity) are plotted (in top panels) in red curves in comparison with the measurements in blue curves. Retrieved surface emissivity spectra are plotted in the bottom panels with IASI day and night observations, respectively.

"ACP Commercial…"

Atmos. Chem. Phys., 9, 2241–2255, 2009
www.atmos-chem-phys.net/9/2241/2009/
© Author(s) 2009. This work is distributed under
the Creative Commons Attribution 3.0 License.

Atmospheric Chemistry and Physics

All weather IASI single field-of-view retrievals: case study – validation with JAIVEx data

D. K. Zhou[1], W. L. Smith[2,3], A. M. Larar[1], X. Liu[1], J. P. Taylor[4], P. Schlüssel[5], L. L. Strow[6], and S. A. Mango[7]

[1]NASA Langley Research Center, Hampton, VA, USA
[2]Hampton University, Hampton, VA, USA
[3]University of Wisconsin-Madison, Madison, WI, USA
[4]Met Office, Exeter, Devon, UK
[5]EUMETSAT, Darmstadt, Germany
[6]University of Maryland Baltimore County, Baltimore, MD, USA
[7]NPOESS Integrated Program Office, Silver Spring, MD, USA

Received: 7 October 2008 – Published in Atmos. Chem. Phys. Discuss.: 16 December 2008
Revised: 17 February 2009 – Accepted: 16 March 2009 – Published: 27 March 2009

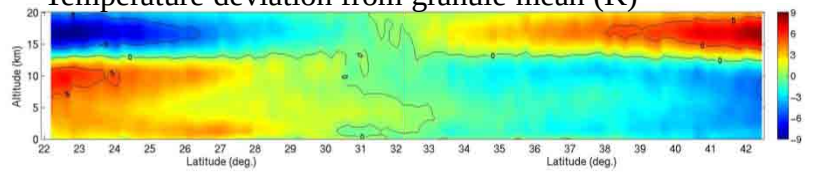
Abstract. Atmospheric thermodynamic parameters, such as atmospheric temperature and moisture profiles, cloud optical/microphysical properties, and surface properties are basic meteorological variables for weather forecasting. In ad-

IASI examples presented here demonstrate the ability to retrieve fine-scale horizontal features with high vertical resolution from satellite ultraspectral sounder radiance spectra.

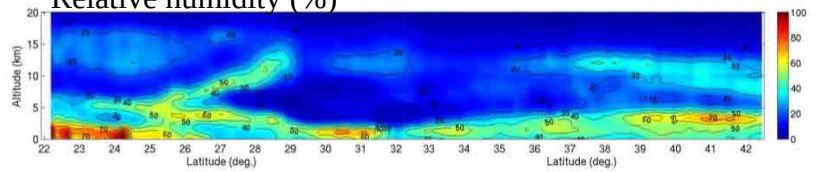
APC paper: AIRS vs. IASI (4/29/2007)

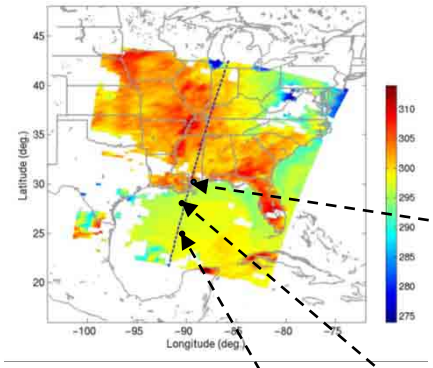
IASI at 15:48 UTC

Temperature deviation from granule mean (K)



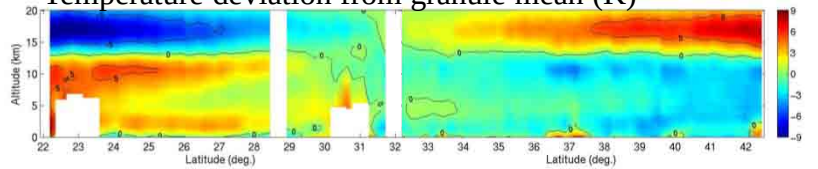
Relative humidity (%)



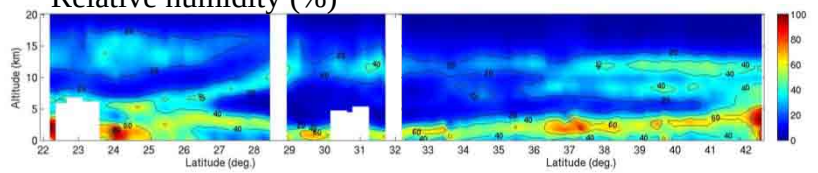


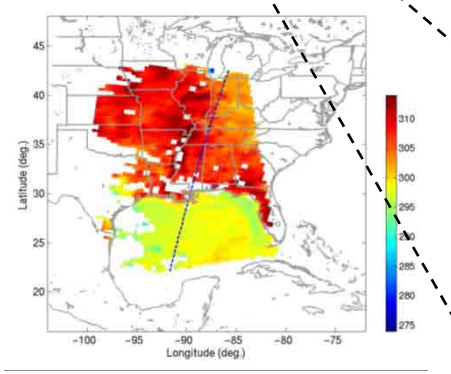
AIRS at 19:30 UTC

Temperature deviation from granule mean (K)



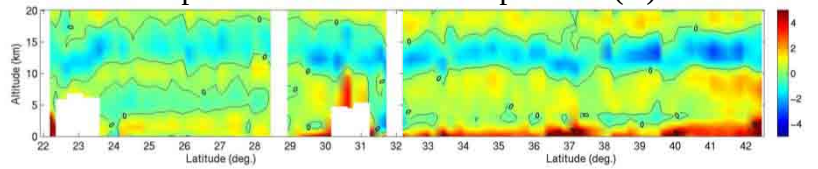
Relative humidity (%)



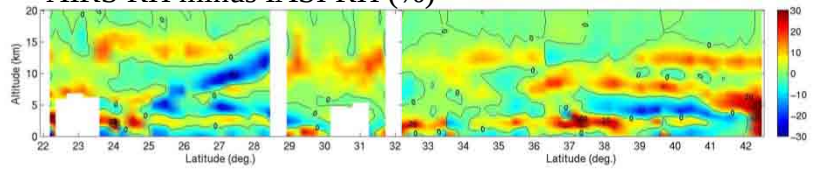


AIRS minus IASI

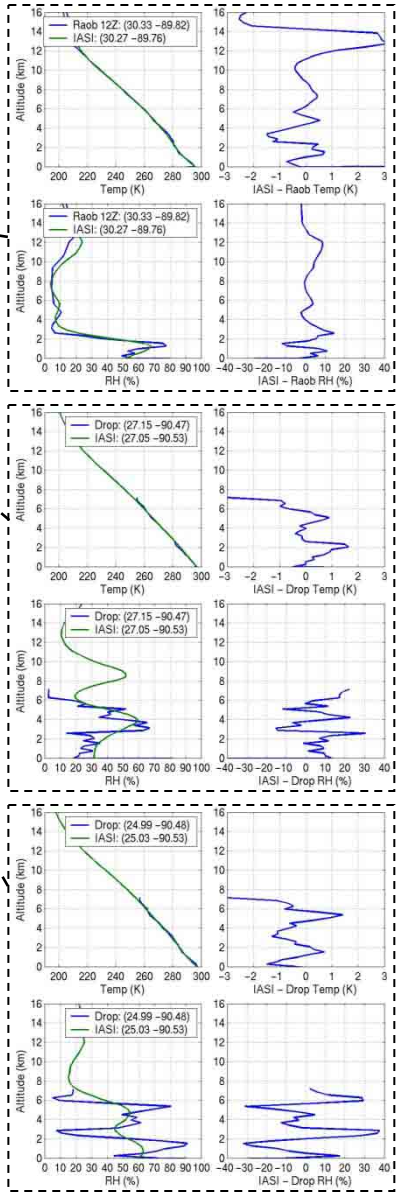
AIRS temperature minus IASI temperature (K)



AIRS RH minus IASI RH (%)

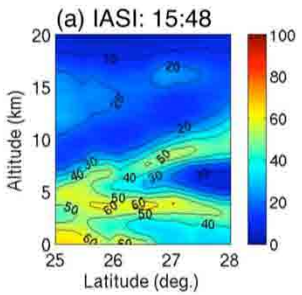


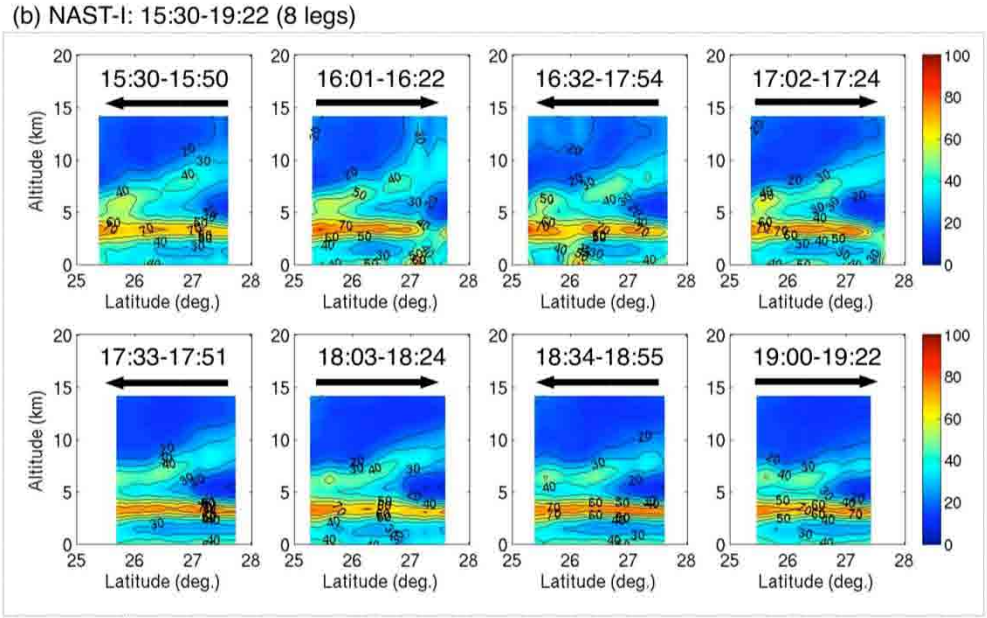
IASI vs. Sonde

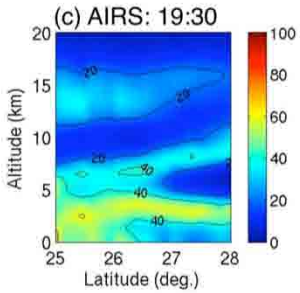


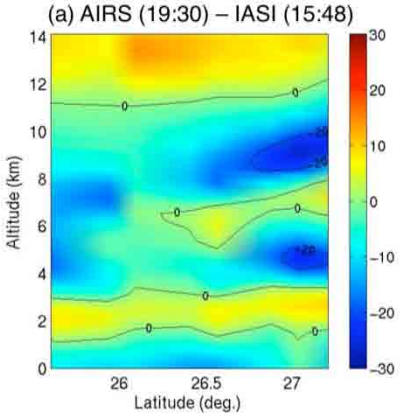
The field evolution is subtle while the atmospheric variation from location to location is strong.

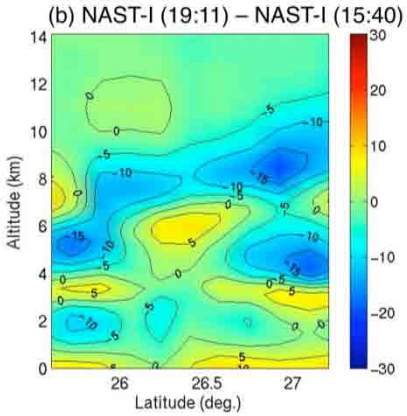
ACP paper: RH Field Evolution (4/29/2007)









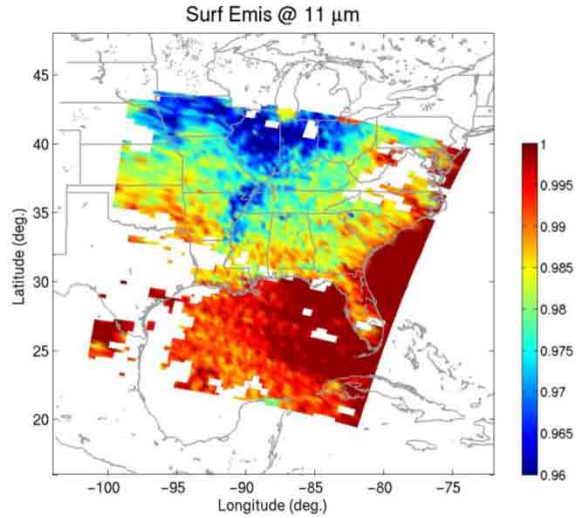


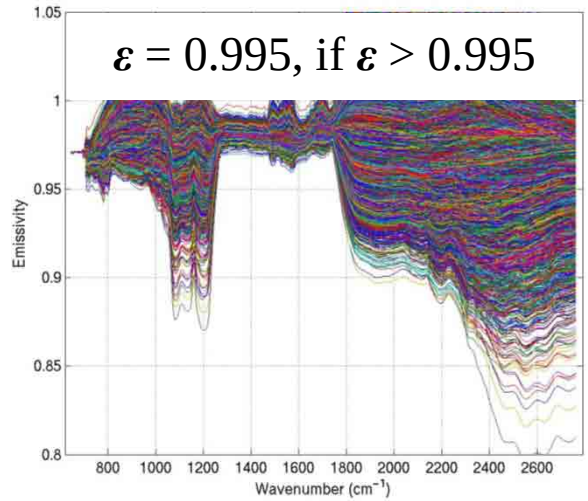
RH evolution characteristic between AIRS and IASI measurements observed by (**a**) AIRS at 19:30UTC and IASI at 15:48 UTC, and (**b**) by NAST-I at 19:11 UTC and 15:40 UTC.

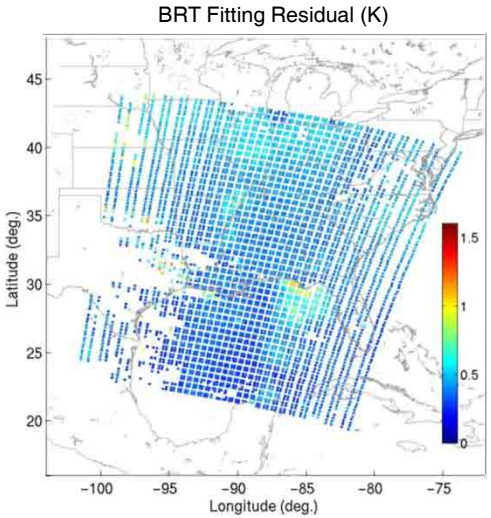
Can we improve these retrievals? **YES WE CAN**

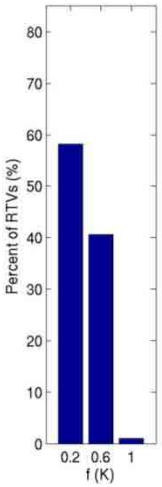
Improved Retrievals?

Emissivity retrieved with ε EOF amplitudes (in ACP paper)

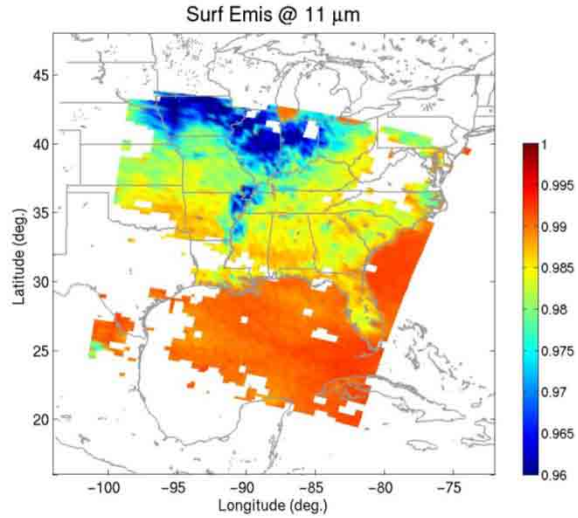


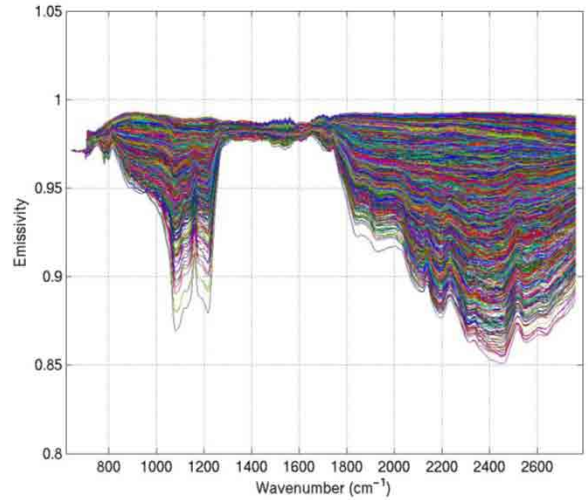


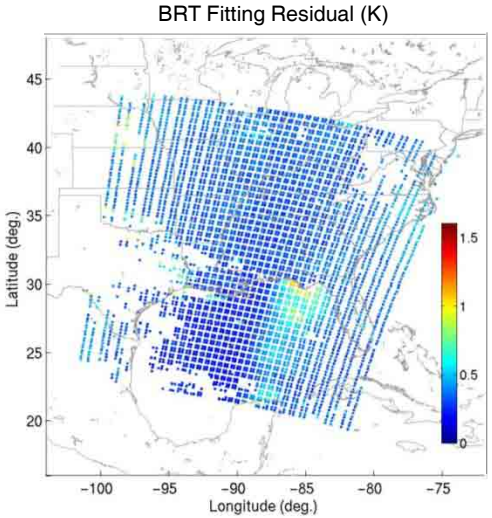


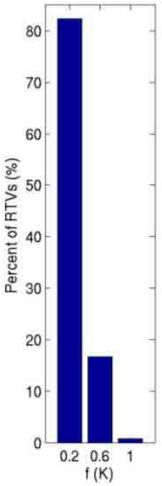


Emissivity retrieved with $\boldsymbol{F}(\varepsilon)$ EOF amplitudes (new approach) and other minor changes



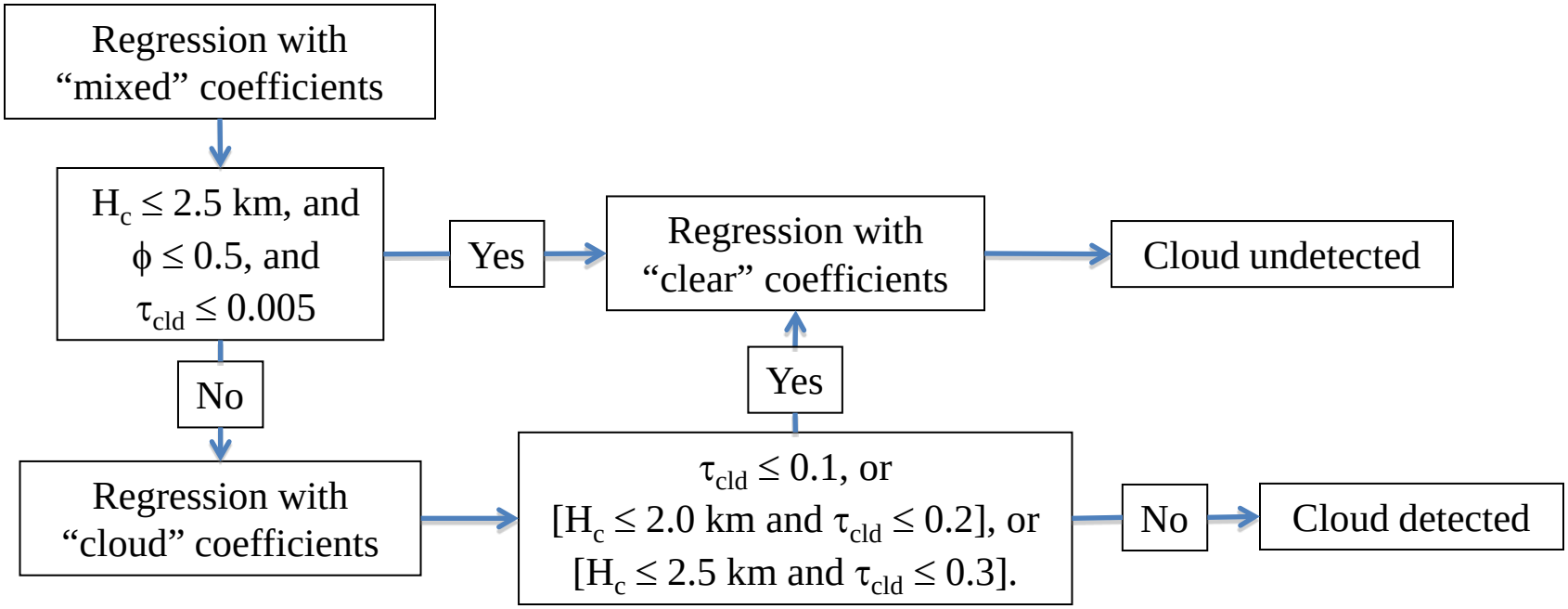






Cloud Detection with Regression

Multi-stage regression retrievals are performed. The first-stage involves mixed (i.e., clear and cloudy) regression. The second-stage (e.g., either clear or cloudy) depends on the cloud detection criteria that are based on first-stage retrieved cloud parameters.



where ϕ = 0, 1, and 2 are for clear sky, ice cloud, and water clouds, respectively; and H_c is cloud top height relative to surface, ϕ is cloud phase, and τ_{cld} is cloud visible optical depth.

Quality Filter for Global Assembled Mean

Since the cloud parameters, atmospheric and surface parameters are simultaneously retrieved. Cloud parameters are used for cloud filter.

Due to cloud coverage, not every measurement can provide surface parameters; however, the surface parameters can be retrieved under optically thin clouds with a relatively poor accuracy in comparison with that retrieved under clear-sky conditions.

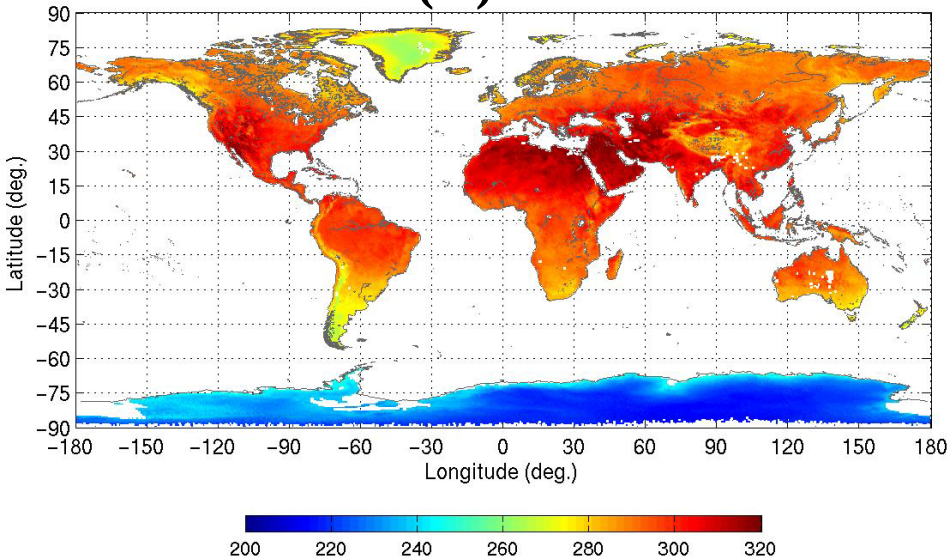
The surface emissivity composition can be assembled over a period of time and area. A set of retrievals is used to generate a mean surface emissivity. Single retrievals within a spatial grid (area) meeting the following criteria will be taken to generate a convoluted emissivity. These criteria are

1. $\tau_{cld} \leq 0.5$,
2. $|T_s - T_{sm}| < \sigma_t$,
3. $|A_{F1} - A_{F1m}| < \sigma_{F1}$, and
4. $N > 6$,

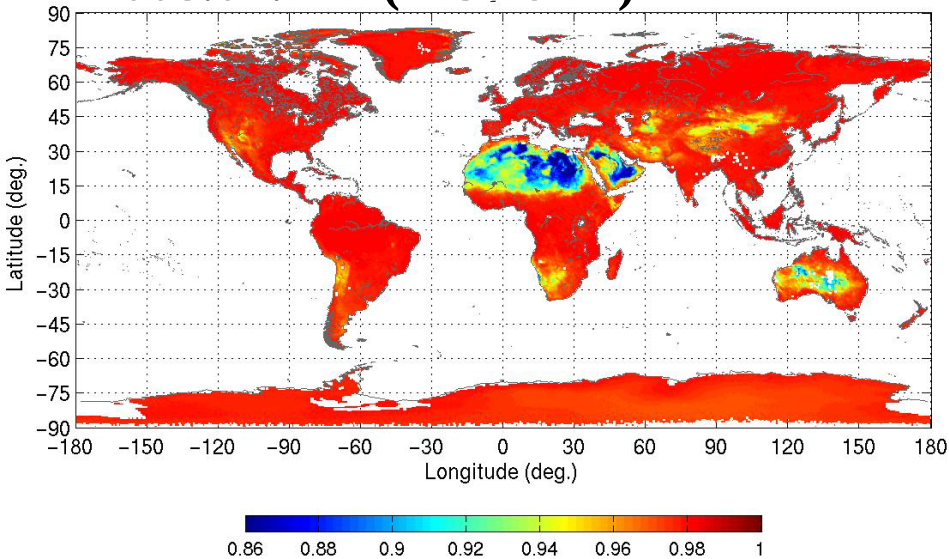
where T_{sm}, σ_t, A_{F1}, A_{F1m}, σ_{F1}, and N are T_s mean, T_s STD, first EOF amplitude of $F(\varepsilon)$, A_{F1} mean, A_{F1} STD, and the number of SFOV measurements satisfying criteria 1-3, respectively.

Monthly Mean LST and LE_{1250} (0.5-deg scale)

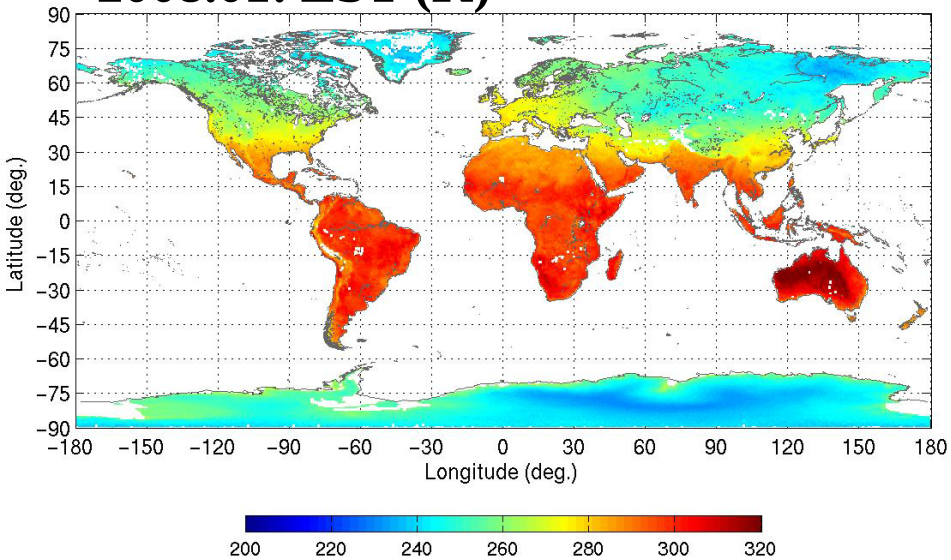
2007.07: LST (K)



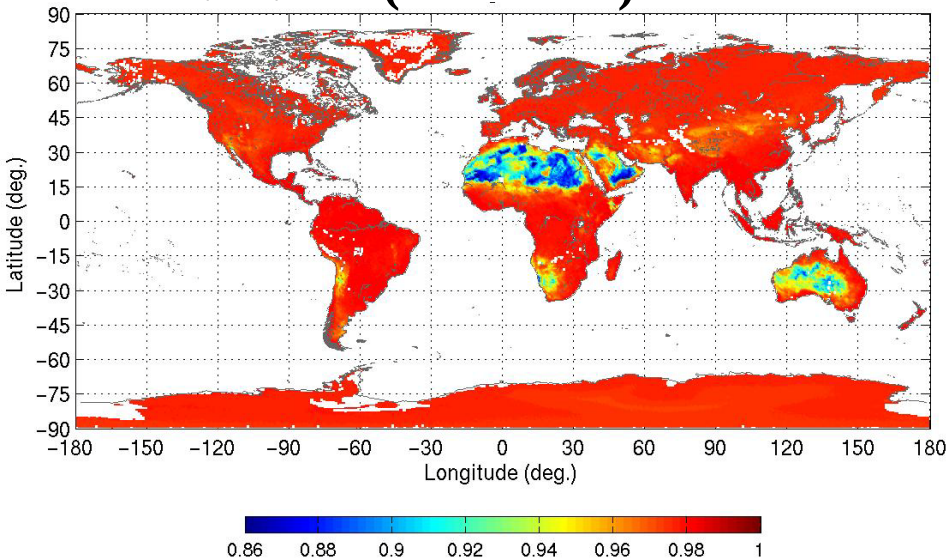
2008.07: LE (1250 cm^{-1})



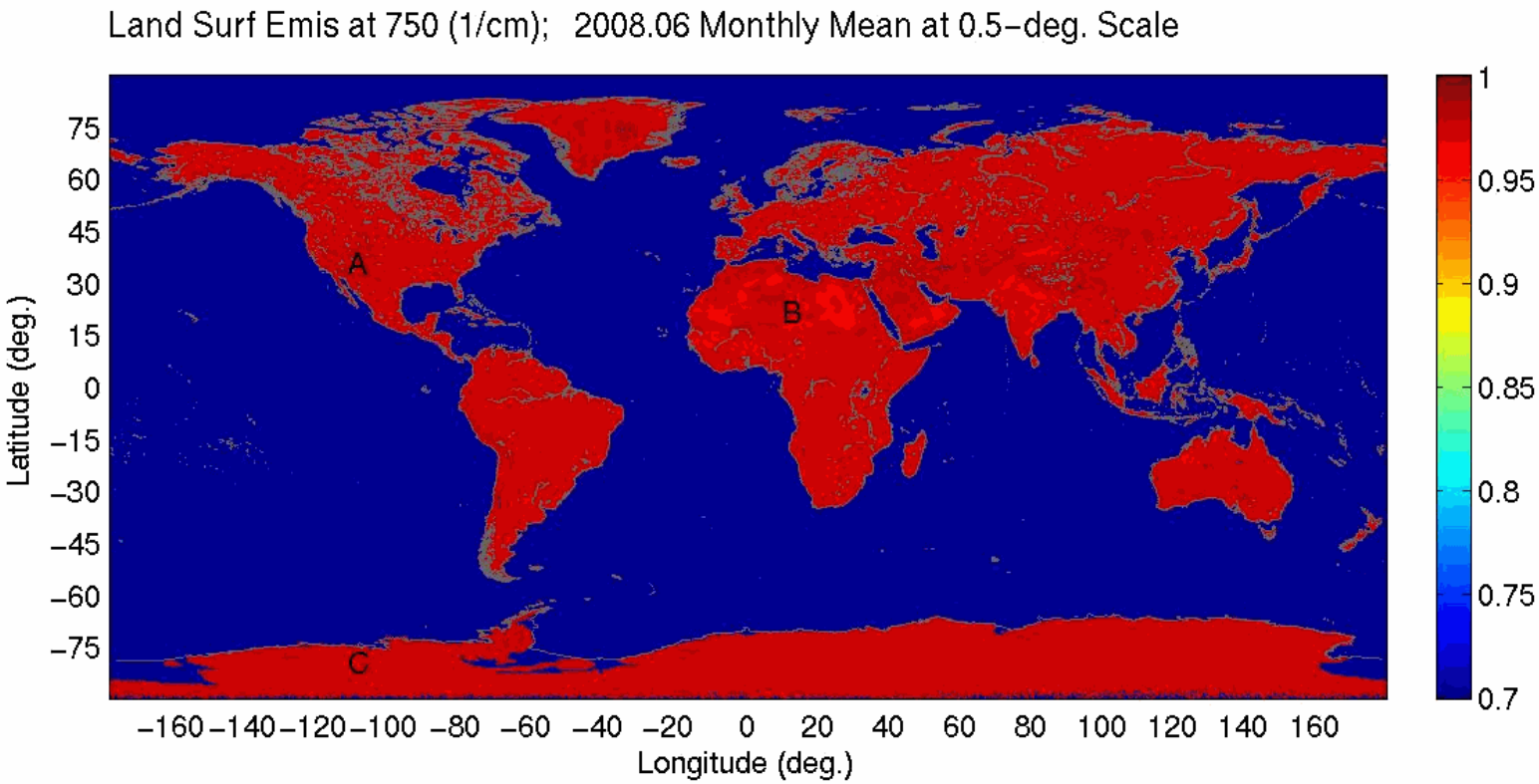
2008.01: LST (K)

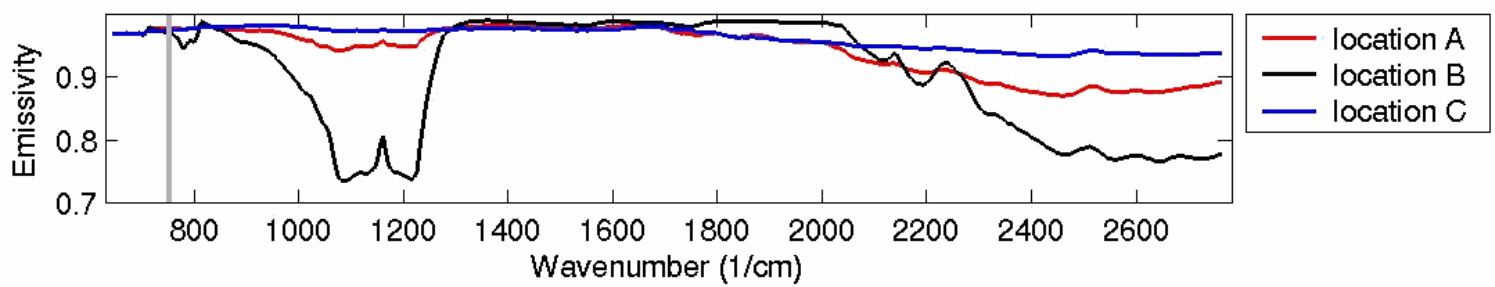


2008.01: LE (1250 cm^{-1})



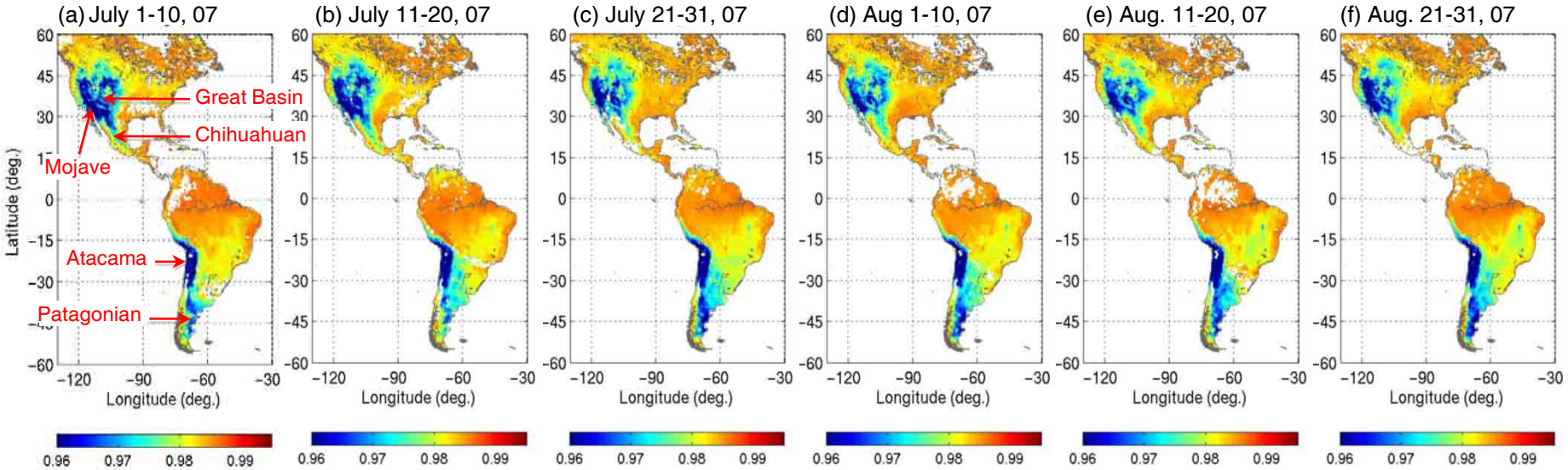
June 2008 Monthly Mean LE(v)





LE Temporal Variation: July-August

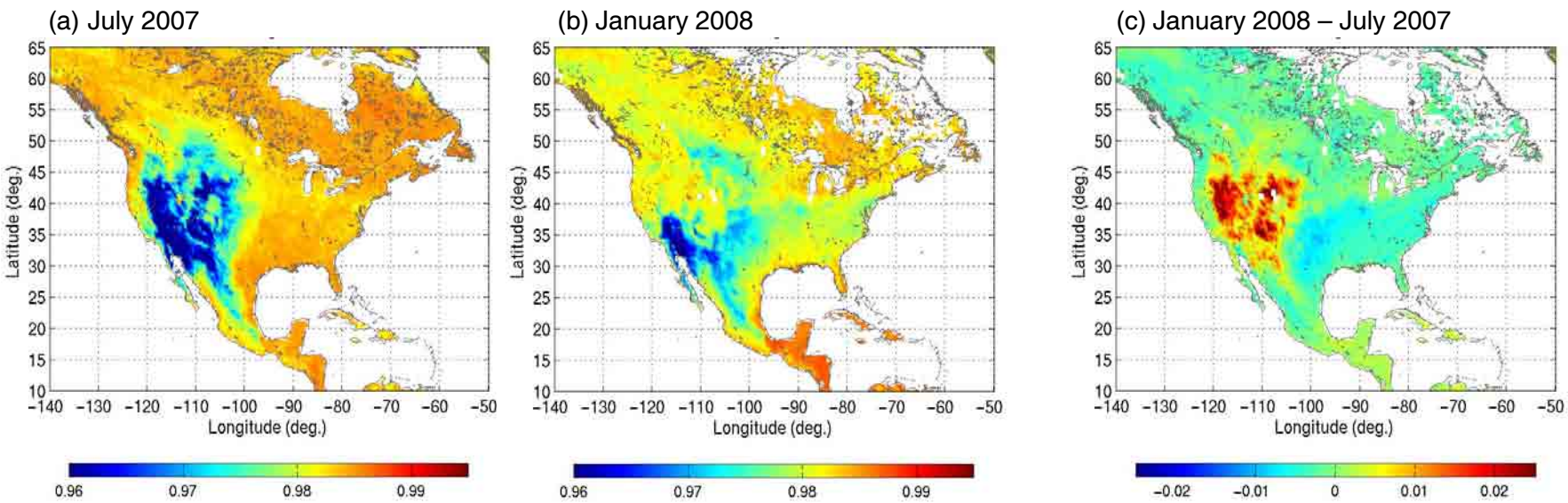
Emissivity at 950 cm^{-1} (~10.5 μm)



The changes of surface emissivity are noticed. These changes, through a 2-month period, are mainly due to seasonal variation and weather conditions (e.g., temperature and rainfall).

LE Temporal Variation: Semi-annual

Emissivity at 950 cm^{-1} (~10.5 μm)



Semi-annual variation is shown to demonstrate the emissivity contrast between summer and winter. This shows the monthly-convoluted emissivities from July 2007, January 2008, and their differences at a selected frequency. Relatively speaking, the smaller or larger effective emissivity denotes more or less barren land during the winter or summer.

A higher or lower emissivity over the Great Basin or the Great Plains is expected because of the snow/ice or barren land during the winter season.

Summary and Future Work

- A state-of-the-art retrieval algorithm, dealing with all-weather conditions, has been developed and applied to IASI radiance measurements. **Surface emissivity is rapidly retrieved using multi-stage linear EOF regressions**.
- **This retrieval process is so fast that it can provide near-real-time result** that is desired by the numerical weather prediction (NWP) model analysis using IR hyperspectral simulations.
- The seasonal variation of global land surface emissivity derived from satellite IR ultraspectral data is evident. Results from IASI retrievals indicate that **surface emissivity is retrieved with satellite IR ultraspectral data to capture different land surface type properties** that contain useful information on the terrestrial ecosystem health and reflect on the biosphere's response to proximal climatic factors (such as temperature and rainfall) and human activities.
- **Operational satellite data can provide information for monitoring the Earth's environment and global change** as well as the study of ecosystem health that plays an important role in understanding the impact of climate change and human activity on altered degradation, biodiversity, and ecosystem sustainability.
- **Focus on emissivity validation** for providing more-definitive accuracy of the emissivity products. Algorithm improvements, along with its product validation, will be made and applied to current and future satellite instruments to provide data for long-term monitoring of the Earth's environment and global change.
- **Produce AIRS emissivity** (from the beginning) to current and future operational IASI and CrIS for monitoring global change.
- **Use IASI data to produce CrIS proxy data for emissivity retrieval analysis.**