Physical retrieval of surface emissivity spectrum from hyperspectral infrared radiances

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Abstract

Retrieval of temperature, moisture profiles and surface skin temperature from hyperspectral infrared (IR) radiances requires spectral information about the surface emissivity. Using constant or inaccurate surface emissivities typically results in large retrieval errors, particularly over semi-arid or arid areas where the variation in emissivity spectrum is large both spectrally and spatially. In this study, a physically based algorithm has been developed to retrieve a hyperspectral IR emissivity spectrum simultaneously with the temperature and moisture profiles, as well as the surface skin temperature. To make the solution stable and efficient, the hyperspectral emissivity spectrum is represented by eigenvectors, derived from the laboratory measured hyperspectral emissivity database, in the retrieval process. Experience with AIRS (Atmospheric InfraRed Sounder) radiances shows that a simultaneous retrieval of the emissivity spectrum and the sounding improves the surface skin temperature as well as temperature and moisture profiles, particularly in the near surface layer.

1. Introduction

Accurate retrieval of atmospheric temperature and moisture profiles, as well as surface skin temperature from hyperspectral infrared (IR) radiance measurements, is needed for climate research, as well as medium range and short-range forecast applications. Hyperspectral IR sounders onboard polar orbiting satellites, such as the Atmospheric InfraRed Sounder (AIRS) (Chahine et al. 2006) on EOS (Earth Observing System) Aqua, the Interferometer Atmospheric Sounding Instrument (IASI) (http://smsc.cnes.fr/IASI/index.htm) on European METOP-A, and the Cross-track Infrared Sounder (CrIS) (http://www.ipo.noaa.gov/Technology/cris_summary.html) on the next generation National Polar-orbiting Operational Environmental Satellite System (NPOESS), are developed for global temperature and moisture sounding observations with high vertical resolution and high accuracy. Although hyperspectral IR radiances have been successfully assimilated in a global forecast model (LeMarshall et al. 2006), challenges remain over land due to the uncertainty in emissivity.

Since the top of atmosphere radiance (TOA) contains a surface IR emissivity (ε) contribution (see Figure 1), especially for a channel within the atmospheric window regions, knowledge of surface emissivity is critical for atmospheric temperature and moisture profile retrieval from radiance measurements. The impact of IR emissivity on sounding or surface temperature retrievals has been studied using the GOES (Geostationary Operational Environmental Satellite) Sounder (Plokhenko and Menzel 2000) and MODIS (Moderate Resolution Imaging Spectroradiometer) (Wan and Li 1997; Ma et al. 2002; Seemann et al. 2003; Wan et al. 2004). Handling IR surface emissivities in the retrieval process is essential for deriving accurate temperature and boundary layer moisture profiles, as well as surface skin temperature, especially over land. This is equally true for IR radiance assimilation in Numerical Weather Prediction (NWP). Surface emissivity (ε) for a given channel is often fixed in the physical retrieval process, for example, using fixed emissivities from a regression approach (Li et al. 2000; Zhou et al. 2006; Zhou et al. 2007).

Some physical algorithms also retrieve emissivities together with the sounding, but only at selected channels and spectral bands. For example, Hayden (1988) retrieved emissivities at two spectral bands (longwave and shortwave IR bands) in GOES sounding processing, Zhou et al. (2007) and Susskind et al. (2003) used approximately 40 channels for emissivity retrieval in AIRS retrieval processing. It is difficult to retrieve emissivities of all channels directly in the sounding step, this is due to a large number of unknowns in the inverse equations and the instability of the solution. Retrieving the whole emissivity spectrum is possible if emissivity eignevectors (EVs) are derived. The hyperspectral emissivity spectrum can be represented in the retrieval process by its EVs derived from laboratory measured hyperspectral emissivity database. Using EVs to represent radiances or parameters to be retrieved has been suggested and attempted by numerous researchers (Smith and Woolf 1976; Huang 1998; Zhou et al. 2006; Liu et al. 2006).

Knowledge of surface IR emissivity is also very important for creating a climate forecasts (Jin and Liang 2006). Data from a satellite based IR imager such as MODIS provide global emissivity distribution at a few IR spectral bands (Wan et al. 2004). With hyperspectral IR data available, a global map of hyperspectral IR emissivity spectra is possible.

Based on a physical iterative approach, this study demonstrates that a hyperspectral emissivity spectrum can be retrieved simultaneously along with temperature and moisture soundings, as well as surface skin temperature from a hyperspectral IR radiance spectrum by using EV representation. This approach has been successfully tested using both simulated and measured AIRS radiances, and is expected to help improve the hyperspectral IR radiance assimilation in forecast models over land. For example, one can use a variational (1DVAR) approach to derive emissivity properties and other atmospheric parameters, and use a four dimensional variational (4DVAR) approach to directly assimilate those derived products in a forecast model (Weng et al. 2007). A further goal of this research is to study the sounding improvement in the physical method over the regression technique in handling surface IR emissivities.

2. Methodology

With pre-determined surface IR emissivities, algorithms for retrieving the atmospheric temperature and moisture profiles, as well as surface skin temperature, have been developed to process single field-of-view radiance measurements (Li and Huang 1999; Ma et al. 1998, Li et al. 2000, Zhou et al. 2003). Since emissivity is wavenumber dependent, it is difficult to retrieve emissivities at all channels together with temperature and moisture profiles due to a large number of unknowns. To take advantage of spectral correlations, the emissivity spectrum can be represented by its EVs (e.g., the first 6 EVs) in the retrieval process, leaving only a few unknowns (emissivity EV coefficients) to be added together with the temperature profile (T(p)), moisture profile (q(p)) and surface skin temperature (Ts) in the 1DVAR process. In addition to the regular unknowns (T(p), q(p), Ts), the emissivity spectrum $\vec{\varepsilon} = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_N)$, where N is the total number of channels used, is expressed by it EVs

$$\vec{\varepsilon} = \sum_{i}^{l} \varphi_i a_i = \phi \vec{a} \quad (1)$$

where φ_i is the ith EV and a_i is the associated EV coefficient, and l is the number of EVs used. ϕ and $\vec{a}$ are the corresponding EV matrix and EV coefficient vector, respectively. Figure 1 (lower panel) shows the first 6 EVs for the AIRS spectrum derived from laboratory measurements of hyperspectral emissivity spectra. Our study shows that the first 6 EVs (6 pieces of independent emissivity information) are representative of the emissivity spectrum information in a simultaneous retrieval process. The Jacobian matrix of the radiance with respect to the eigenvector coefficient can be derived

$$J_a = J_\varepsilon * \phi \quad (2)$$

where J_a is the Jacobian matrix of the radiance with respect to the emissivity EV coefficient, while J_ε is the diagonal matrix with Jacobians corresponding to the emissivity spectrum, and the diagonal values can be calculated approximately by an analytical method (Li et al. 1994). Figure 1 shows the AIRS brightness temperature (BT) spectrum calculated from the U.S. standard atmosphere (top panel) and associated emissivity Jacobian spectrum (middle panel). A Jacobian value of 50 means that a change in emissivity of 0.01 results in a 0.5 K change in BT. The longwave IR window region has a larger emissivity signal than the shortwave IR window region, which is important to note since a good signal-to-noise ratio is required to retrieve emissivity spectrum according to the Jacobian analysis. The convoluted Jacobian from Eq.(2) then can be used in the physical retrieval process.

3. Experiment with simulated AIRS radiances

The algorithm has been tested with both simulated and measured AIRS radiances. In the simulation study, a global set of training profiles (Seemann et al. 2007) was used. Each profile contains a temperature profile, water vapor mixing ratio profile, ozone profile and surface skin temperature; emissivities at 10 spectral points have been assigned to each profile based on the combination of global MODIS emissivity measurements (Wan and Li, 1997; Wan et al., 2004) and laboratory emissivity measurements (http://www.icess.ucsb.edu/modis/EMIS/html/em.html; http://speclib.jpl.nasa.gov/). By using a similar approach and applying emissivity EVs derived from the laboratory, each profile of the training dataset is assigned a hyperspectral emissivity spectrum (e.g., at AIRS full spectral coverage). Figure 2 shows the emissivities assigned to ocean (upper left), grassland (upper right), cropland (lower left) and desert (lower right) regions. In the simulation study, an AIRS radiance spectrum is calculated using the fast and accurate Stand-Alone Radiative Transfer Algorithm (SARTA) developed by University of Maryland Baltimore County (UMBC) for each training profile. The AIRS instrument noise plus 0.2 K forward model errors are added to the simulated radiances. The temperature and moisture retrieval algorithm is a two-step approach: regression followed by a physical iterative approach (Li et al. 2000). The regression technique provides a reasonable hyperspectral emissivity spectrum retrievals. For example, Zhou et al. [2006]

have applied regression for NASTI emissivity retrievals, and Zhou et al. [2007] have used the regression for AIRS emissivity retrievals. Physical retrieval of sounding and surface IR emissivities at the selected channels in a sequential way was performed in the operational AIRS product generation (Susskind et al. 2003). In this study, the simultaneous retrieval of a sounding and the whole emissivity spectrum in a physical iterative approach is developed in an attempt to improve statistical results. The following three configurations are examined:

(1) Use a constant emissivity of 0.98 in the physical retrieval, and the emissivity is not changed in each physical iteration;
(2) Use a regression emissivity spectrum in the physical retrieval, and the emissivity is not changed in physical each iteration;
(3) Use a regression emissivity spectrum as the initial guess in the physical retrieval, and the emissivity is updated in each physical iteration.

In the simulation, 90% of the profiles are used as training for the regression coefficients, while the remaining 10% of the profiles are used as independent testing. The temperature and water vapor relative humidity (RH, 0 – 100%) root mean square errors (RMSE) are calculated for the above configurations; the RMSE is based on the absolute difference between the truth and the retrieval.

Figure 3 shows the retrieved RMSE for the above three configurations along with the first guess (from the regression). The first guess provides a reasonable profile with an accuracy of approximately 10% for water vapor RH and 1 K above 500 hPa; the accuracy for temperature is limited in the boundary layer from the regression. With a fixed constant emissivity, the physical retrieval significantly degrades the first guess for both temperature and water vapor since the assumed emissivity of 0.98 is not accurate. As expected, when the regression based emissivity spectrum is fixed in the physical iterations, the temperature and moisture are improved from the first guess, especially for water vapor, due to the nonlinear contribution of IR radiances to the temperature and water vapor. With a simultaneous retrieval of the sounding and emissivity spectrum, the temperature and moisture retrievals are the best in all three configurations, especially in the boundary layer where emissivity has significant contributions. Configuration 3 improves over configuration 2 significantly. The retrieval simulation illustrates that estimating emissivity in the physical iteration is necessary and helpful for sounding retrievals, especially in desert regions where emissivity variation is large both spectrally and spatially. In addition, the emissivity RMSE from both the regression and the physical retrieval are also shown in the upper panel (from configuration 3), which demonstrates that the physical approach improves the regression. However, the shortwave physical retrieval still has a retrieval error of 0.02 due to the limited emissivity information (see Figure 1). The surface skin temperature retrieval indicates similar results to the boundary layer temperature as shown in Table 1.

4. Experiment with measured AIRS radiances

The algorithm has also been tested with AIRS radiance measurements using granule 011 for 08 September 2004. The MODIS cloud mask is used to identify the AIRS clear footprints (Li et al. 2004). The AIRS granule contains various surface types (cropland, desert, ocean etc.). Figure 4 shows the emissivity spectrum retrieval from the regression (upper left) and physical (upper right) approaches at 1227 cm^{-1} or 8.15 μm. The difference between the physical and first guess (regression) can be seen, especially over the desert region. The lower panel shows one example of an emissivity spectrum retrieval over the desert; the physical approach changes the regression in both longwave and shortwave window region. Three emissivity spectrum references derived from the laboratory database, representing the surface types of desert, cropland, and ocean respectively, are also shown. Accurate surface properties captured by hyperspectral measurements over land, especially in the vicinity of the Sahara Desert, are clearly evident. Sounding in the boundary layer leads to greater improvement in physical retrievals over regression retrievals when compared with the ECMWF analysis (not shown).

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, especially 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 process. The emissivity spectrum can be retrieved together with the profile through an EV representation of the spectrum; a representative laboratory hyperspectral IR emissivity measurement data set containing various ecosystem types are crucial for EVs. With such a technique the global IR emissivity spectrum product can be derived through composite clear hyperspectral IR radiance measurements. The derived hyperspectral IR emissivity product is very useful for processing broad IR spectral band radiances such as from the Advanced Baseline Imager (ABI) (Schmit et al. 2005) onboard the next generation of Geostationary Operational Environmental Satellite (GOES-R) and beyond (e.g., using retrieved emissivity spectra from polar orbiting hyperspectral IR radiances for processing ABI IR radiances). The global emissivity product is also very important for improving the global climate forecast. The algorithm can similarly be applied to process IASI and CrIS.

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Figure captions

Figure 1. The AIRS brightness temperature (BT) spectrum calculated from the U.S. standard atmospheric profile (top panel) and associated emissivity Jacobian spectrum (middle panel). The lower panel shows the first 6 EVs of emissivity spectra derived from hyperspectral laboratory measurements.

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Figure 3. The root mean square errors (RMSE) of retrievals for three configurations described in the text along with the first guess (from regression) results. The first guess provides a reasonable profile with an accuracy of approximately 10% for water vapor RH and 1 K above 500 hPa.

Figure 4. The emissivity retrieval from the regression (upper left) and physical (upper right) approaches at 1227 cm^{-1} or 8.15 μm. The lower panel shows one example of an emissivity spectrum retrieval over the desert region along with three reference emissivity spectra from laboratory data corresponding to ocean, cropland and desert surface types, respectively.

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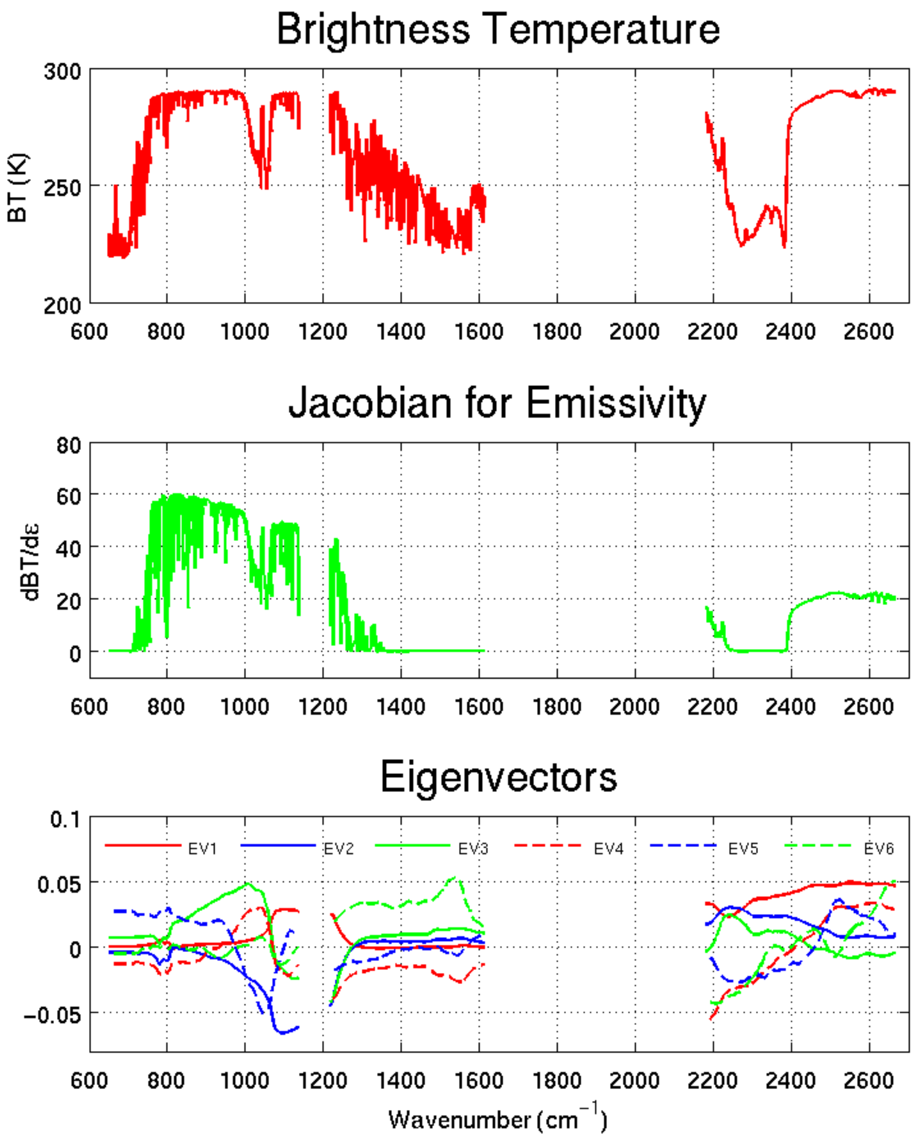

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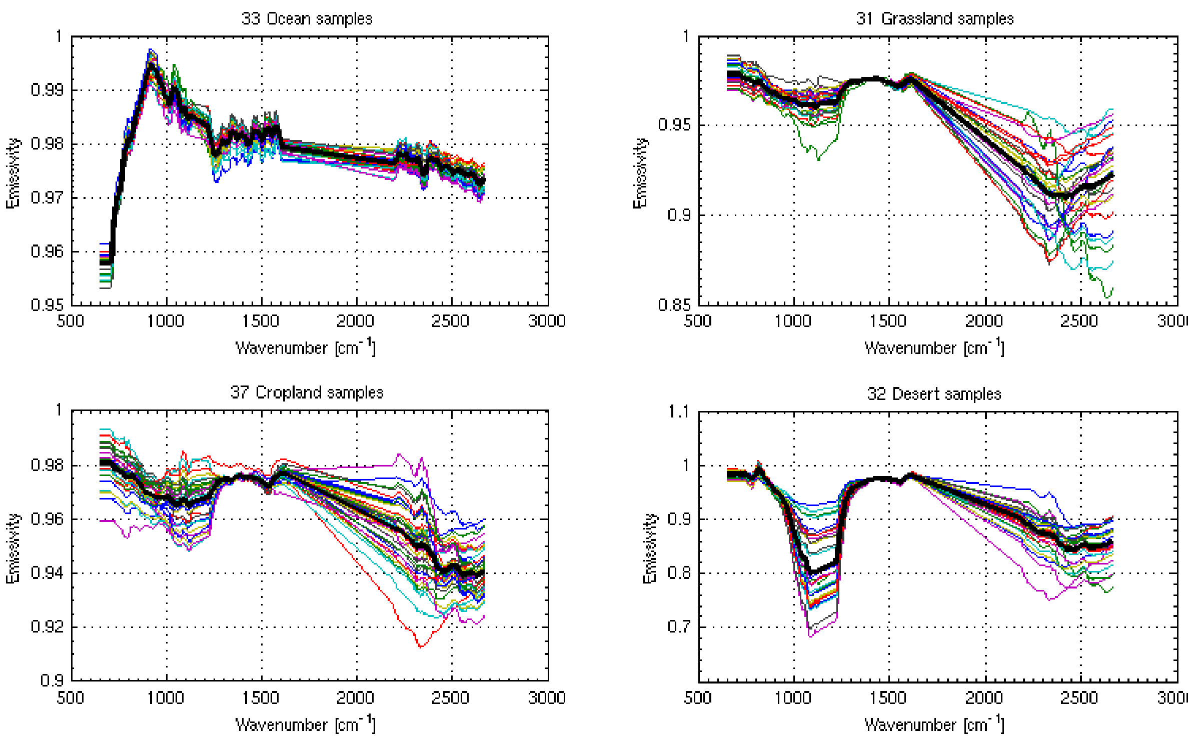

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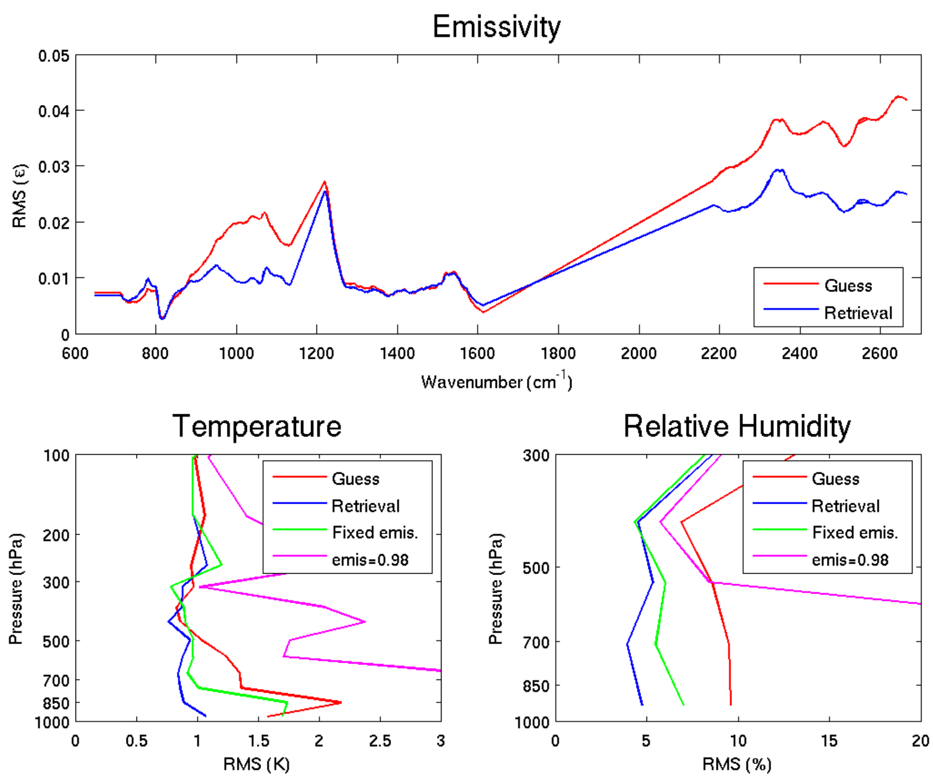

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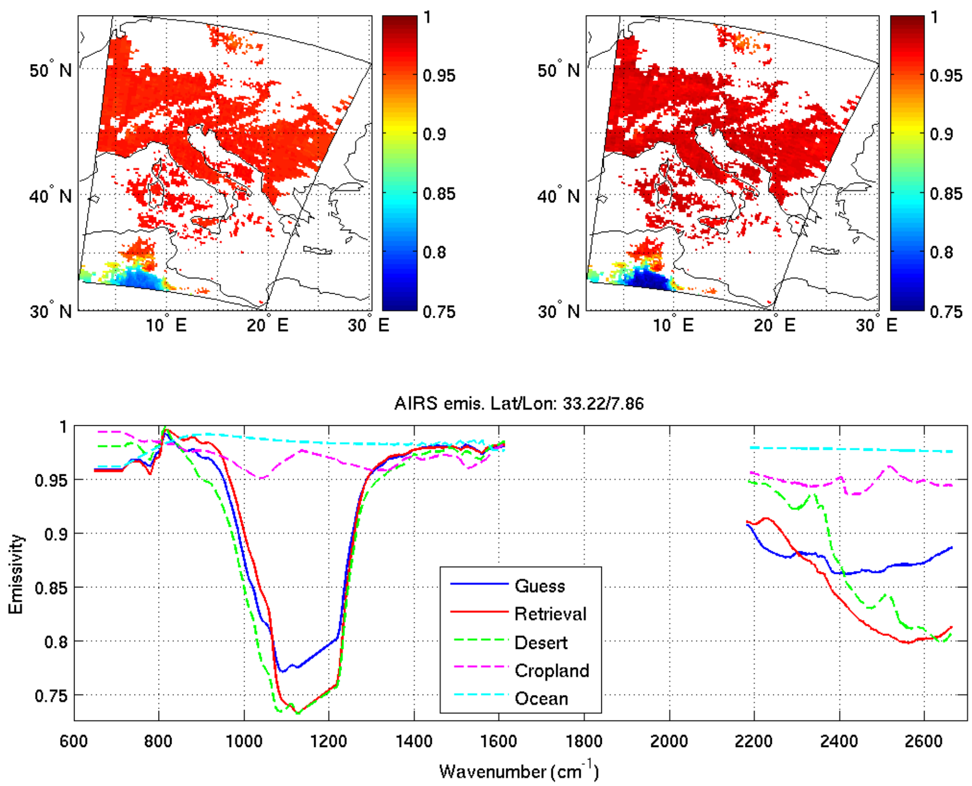

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Method	Cropland RMS (K)	Desert RMS (K)	Grassland RMS (K)	Ocean RMS (K)
Reg	0.485	0.624	0.461	0.703
Rtv (configuration 3)	0.327	0.540	0.316	0.472
Fixed emis (configuration 2)	0.360	0.822	0.421	0.563
Emis=0.98 (configuration 1)	0.686	9.544	0.877	0.409