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Extending Satellite Microwave Humidity Retrievals from Ocean to Land

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1. INTRODUCTION

In their study of the impact of various satellite data sources on the Eta model Data Assimilation System (EDAS), Zapotocny et al (2005) found that the impact of polar orbiter satellite data on moisture fields over land was very limited. Moisture fields are historically the most difficult fields to forecast for mesoscale models, and this remains true today.

Synoptic analysis of water vapor and clouds from satellite would fill an important gap in our characterization of the atmosphere. Better depiction of water vapor and clouds, which satellites promise, would address needs such as analyzing cloud base, detecting aircraft icing regions, and assisting short-term forecasts of clouds and moisture. Moisture profiles and products measured from space could propagate into data assimilation systems and weather forecast models and potentially yield gains on critical forecast needs like improved quantitative precipitation forecasts (QPF). This is especially true for high-impact moisture events such as atmospheric rivers affecting the western U.S> and return flow from the Gulf of Mexico.

The impact of meteorological satellites on moisture analysis has been limited due to different physical limitations. Infrared instruments, such as the GOES sounder and the NASA Atmospheric Infrared Sounder (AIRS) instrument, can measure total precipitable water (TPW) and moisture profiles in clear skies, but are limited by clouds. Passive microwave measurements from 20 – 200 GHZ are much less affect by clouds, especially cirrus, and hold promise for moisture retrievals. The Advanced Microwave Sounding Unit (AMSU) instruments onboard the NOAA operational satellites and the Special Sensor Microwave Imager / Sounder (SSMIS) instrument onboard the Defense Meteorological Satellite Program (DMSP) satellites are current examples of operational passive microwave sounders. The exploitation of the passive microwave data has been hindered by the challenges in using the radiance over land. In the microwave spectrum, a basic distinction is between atmospheric remote sensing over land and over ocean. This is due to the higher emissivity of land (~ 0.95) versus ocean (~ 0.5) surfaces. In addition, ocean emissivity is more readily modeled and is a function of fewer and better understood variables (windspeed, viewing angle, temperature) versus land (soil moisture, vegetation type, soil type, radiometric roughness). Our lack of knowledge of land emissivity has hindered passive microwave atmospheric remote sensing applications, except for precipitation detection.

Progress in extracting the atmospheric signal above land surfaces from passive microwave observations depends on characterizing the land surface emissivity, which determines the radiometric brightness of the surface. This challenge is being approached by using combined infrared and microwave measurements (Ruston and Vonder Haar, 2004; Prigent et al. 2005; Karbou et al. 2005) and by modeling the surface emissivity through a Microwave Emissivity Model (Weng et al. 2001). Figure 1 shows a composite emissivity map from the summer months during 2000 – 2002 (Ruston and Vonder Haar 2004). Notice the lower emissivity in moist, vegetated areas such as the Mississippi River Valley. Deserts also have lower emissivity. Seasonal composites such as in Fig. 1 can help in retrieving moisture by accounting for the surface emission. But microwave land surface emissivity is also influenced by phenomena which vary on shorter timescales, such as wet ground from precipitation and snow cover.

In this paper we focus on the development of a retrieval to obtain water vapor profiles and TPW over land from AMSU measurements. Heritage techniques to measure TPW over ocean from AMSU exist (Ferraro et a. 2003) and the network of roughly 300 Global Positioning System (GPS) sites over the CONUS allows an independent comparison of TPW. The retrieval is named the CIRA 1-Dimensional Variational Optimal Estimator, or C1DOE.

2. DATA

AMSU is a set of instruments onboard the NOAA series of spacecraft with 20 channels from 23 to 183

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GHz. The frequencies and instrument noise are shown in Table 1. AMSU is a cross-track scanning instrument with spatial resolutions of 16 km at nadir for the 183 GHz moisture sounding channels and 50 km at nadir for the 50-60 GHz temperature sounding channels. The Advanced Technology Microwave Sounder (ATMS) in the NPOESS system now under development is similar to AMSU in a general sense. Beginning with NOAA-18, AMSU-B has been replaced with the Microwave Humidity Sounder (MHS), which is quite similar but with some small channel placement differences. This paper presents only AMSU-B results.

To test the performance of the C1DOE retrieval, a global matchup dataset of collocated radiosondes and AMSU overpasses was created for September, 2003 from NOAA-16 and NOAA-17. The dataset was filtered so only small (< ~ 5 x 5 km) islands were used, so that the retrievals were essentially over ocean only.

	Channel	**Frequency (GHz)**	**NEDT (K)**
AMSU-A	1	23.8	0.3
	2	31.4	0.3
	3	50.3	0.4
	4	52.8	0.25
	5	53.596 ± . 115	0.25
	6	54.4	0.25
	7	54.94	0.25
	8	55.5	0.25
	9	57.290344 = f_0	0.25
	10	f_0 ± . 217	0.4
	11	f_0 ± . 3222 ± .048	0.4
	12	F_0 ± . 3222 ± . 022	0.6
	13	f_0 ± . 3222 ± . 010	0.8
	14	F_0 ± . 3222 ± . 0045	1.2
	15	89.0	0.5
AMSU-B	1	89.0	0.37
	2	150.0	0.84
	3	183.31 ± 1.0	1.06
	4	183.31 ± 3.0	0.70
	5	183.31 ± 7.0	0.60

Table 1: AMSU channel characteristics.

A prototype near real-time C1DOE system has been developed at CIRA and is functioning with several data feeds. Figure 2 shows the data flow through the system. Historical runs of C1DOE are also possible. In Fig. 2, GDAS is the NOAA Global Data Assimilation System, a 6-hour, 1-degree global analysis used as a first guess. AGRMET is a land surface model run at the Air Force Weather Agency which provides land boundary condition first guesses every three hours. C1DOE is hosted within the Data Processing and Error Analysis System (DPEAS), a computing environment described in Jones and Vonder Haar (2002).

3. THE C1DOE ALGORITHM

The C1DOE algorithm uses the method of Engelen and Stephens (1999) to simultaneously retrieve profiles of temperature and water vapor as well as cloud water path and surface emissivity. It can be considered a 1-dimensional variational data assimilation retrieval, or 1DVAR. The retrieval method is quite general, making it flexible in terms of data used and parameters retrieved. The retrieval is structured in a modular fashion, so new data sources, updates on instrument noise and channel failures, and retrieval parameters can be added easily. Our primary test data source is AMSU, although the SSMIS data from the DMSP satellites can be used in the future.

The retrieval scheme requires a first guess of the water vapor and temperature profiles as well as surface emissivities at the relevant microwave frequencies. An *a priori* distribution of the retrieval parameters is used to constrain a non-linear iterative optimal-estimation scheme which minimizes the cost function Φ to find the optimal solution x, where:

$$\Phi=(x-x_a)^T S_a^{-1}(x-x_a)+\{y-F(x)\}^T S_y^{-1}\{y-F(x)\}$$

(Equation 1)

where x is the vector of parameters to be retrieved, x_a is the a priori vector, y is the set of observations (Tb's), F(x) is a forward observational operator model used to compute radiances given x, and S_a and S_y are the error covariance matrixes of the a priori data and the observations, respectively. The vector of retrieval parameters consists of the temperature and moisture profiles at seven levels, surface temperature, surface emissivity in 6 bands from 23 to 183 GHz, and cloud liquid water in cloudy cases. For the initial test of the retrieval, we focus on clear cases. The presence of cloud as a constraint would best be added from another infrared or visible sensor. The *a priori* error covariance matrix includes the variances of and correlations between the retrieval parameters, thus providing a constraint on the solution from a priori knowledge. The formulation of and sensitivity of the results to this matrix is currently under research.

For the forward radiative transfer, monochromatic microwave brightness temperatures are computed using numerical integration of the radiative transfer equation for a plane parallel, absorbing atmosphere together with Liebe's MPM92 (Liebe and Hufford 1993) model of microwave atmospheric attenuation. Only liquid clouds are currently included. An analytic Jacobian, which calculates the sensitivity of the radiances to state variables, is used in the radiative transfer model for speed. The method is modular so that an alternative RTM can be added if desired.

4. RETRIEVAL DEVELOPMENT

The initial testing of C1DOE has been performed with the clear ocean rawinsonde sites from the

September 2003 matchup dataset (Donofrio, 2006). This approach was chosen to examine retrieval performance with good knowledge of required model parameters. Among the questions which must be addressed before C1DOE can be run are:

- What is the emissivity first guess and standard deviation?
- What is the surface temperature first guess and error?
- What is the atmospheric temperature profile first guess and error?
- What is the atmospheric moisture profile first guess and error?
- How many levels will be retrieved (currently set at 7 levels)?
- What is the error (random and systematic) in the radiances versus the radiative transfer model?

By choosing an ocean case, we have more control over the specification of the surface. In particular, the emissivity at the 6 bands from 23 to 183 GHZ can be estimated using the ocean emissivity model from the NOAA Community Radiative Transfer Model (CRTM). Sea surface temperature is also a more uniform field over ocean as compared to land. And by using AMSU radiances which are collocated with the radiosonde, the temperature and moisture profiles can be considered closer to truth. By specifying the error of the retrieved variables, C1DOE adjusts them more or less depending on the error specification. In this case, the temperature profile error is specified at 1 K (very good knowledge), so the retrieval essentially keeps the initial guess temperature profile. The emissivity error is specified at 0.01. For land profiling, similar knowledge of emissivity to ~ 0.01 will be required. The moisture error is set to a large value of 50 %. This gives C1DOE the freedom to adjust the moisture profile to match the measured radiances, while only small adjustments to the other fields are possible.

Figure 3 shows a comparison of C1DOE TPW to TPW calculated by integration of the adjacent sounding. It should be noted that the TPW calculated by the C1DOE is arrived at in a fundamentally different manner than the NOAA operational product described in Ferraro et al. 2003. The C1DOE TPW is calculated by an integration of a sounding which is iteratively retrieved, versus by a total column-only retrieval. In Fig. 3, the C1DOE and radiosonde TPW are well correlated, but the C1DOE results have a positive bias. Fig. 3 was created without a bias correction term for the radiances, which accounts for differences between the radiative transfer model and the measurements. With AMSU, this can be a complex function since the zenith angle varies across the scene. A simple, non-zenith dependent bias correction was applied which reduced the TPW bias (Donofrio, 2006). Further study of the bias correction is in progress. All of the results presented here have no bias correction applied.

An attractive feature of C1DOE is the numerous diagnostics generated automatically from the optimal estimation framework. In particular, C1DOE reports how much impact the observations and *a priori* constraint had on the solution. For each retrieval, C1DOE stores over 500 fields. These fields are being evaluated and show the innovation provided from AMSU data.

Since the ultimate goal of passive microwave water vapor profiling is to yield information on the vertical structure of moisture over both land and ocean in clear skies and clouds, the impact of clouds on the retrieval must be considered. One approach is to show the sensitivity of AMSU radiances to moisture in the presence of clouds. Figure 4 presents the change in brightness temperature for a 1 g / kg change in mixing ratio at 700 hPa with a cloud from 700 to 850 hPa. This is for a nadir view in a midlatitude atmosphere. The sensitivity varies with atmospheric type and viewing geometry. Results are presented for “ocean” (emissivity = 0.5) and “land” (emissivity = 0.95). Notice that the ocean sensitivities are greater than the sensitivity over land. This is another way to indicate the challenge of retrieving water vapor over land from AMSU. Notice also that the sensitivities asymptote towards zero at high integrated cloud liguid water. In practice, most microwave retrievals use a threshold greater than ~ 0.4 mm as a cutoff to indicate precipitating cloud. In spite of the challenge posed by clouds, there should still be a radiometric response to moisture in AMSU given the low noise (Table 1) of this sensor.

5. LAND RETRIEVAL EXAMPLE

Using the dataflow in Fig. 2, C1DOE has been exercised over the CONUS from a NOAA-16 overpass on June 8, 2006 at 2030 UTC. An example of the first guess land emissivity at 89 GHz for this case from the NOAA MEM model is show in Figure 5. The results are only shown within the AMSU swath, since the MEM requires AMSU radiances as input.

Infrared cloud imagery and independent TPW calculations are shown in Figure 6. TPW is shown from the GDAS analysis, which is represents the integration of the moisture profile first guess used by C1DOE, and from an experimental CIRA blended AMSU / SSM/I product (Kidder and Jones, 2006). GPS TPW data from roughly 300 stations over CONUS has also been blended in to the satellite TPW product to provide information over land. GPS TPW measurements are highly accurate and provide an excellent validation source. Note the missing values outside of CONUS due to lack of GPS TPW data and the fact that the AMSU and SSM/I products are ocean only.

The GOES imagery shows mostly clear skies over the Gulf of Mexico and southern U.S. This is important since C1DOE is not yet ingesting infrared data for cloud information and cloud physics are not activated in this version of the retrieval. So a correct C1DOE retrieval in a cloudy region is non-convergence and no retrieval.

Figure 7 shows the C1DOE retrievals of TPW for this case for a variety of experimental configurations. In particular, results are shown for various choices of emissivity variance (error) and instrument noise. The instrument noise is set at either 3.5 or 7 K, and the emissivity variance is set at either 0.5 or 0.01. In practice for a debiased perfect radiative transfer model, the instrument noise would be set at the values shown in Table 1. The bias is larger than this because of approximations in the radiative transfer model, such as the number of vertical levels. There are several noteworthy features in Fig. 7. First, by setting the emissivity variance to 0.5, a solution is obtained over most of the domain. There are some non-retrieved areas within the swath (across Cuba and adjacent waters, Mexico into New Mexico, Mid-Atlantic States) where no retrieval is performed, this is due to precipitation masking. The fact that a solution is obtained when the emissivity error is set to be very large is important. It means that, unless the emissivity can be specified with low error, the retrieval can deposit atmospheric errors into the emissivity and not provide new atmospheric information. Comparison of Fig. 7a with the GDAS TPW in Fig. 6 shows that they are essentially the same fields. In other words, without adequate emissivity constraints, C1DOE can perform a moisture retrieval but provide no new moisture information. In Fig. 7b, the instrument noise is halved to 3.5 K, and a large number of land retrievals become non-convergent. In Fig. 7c, the emissivity variance is reduced to 0.01 while the noise is left at 3.5 K. It is promising that C1DOE maintains a number of retrievals over the Gulf of Mexico, and also retrieves the spatial structure seen in the blended product in Fig. 6.

6. CONCLUSIONS

The CIRA 1-Dimensional Variational Optimal Estimator (C1DOE) retrieval is being used to explore passive microwave retrievals of water vapor and clouds over land. All of the necessary data is flowing into the system, and a near real-time demonstration has been completed.

Initial results suggest that C1DOE is behaving as expected. A study of the biases in the radiative model transfer set up is underway and should enable greater impact of the AMSU radiances on the moisture solution. Progress is needed to provide first guess fields with low error, particularly for land emissivity and land surface temperature. The GPS TPW fields provide an excellent new comparison source for the retrieval. Future work will focus on:

- Testing the performance of various land emissivity formulations compared to the MEM.
- Analyzing the bias in the radiative transfer model
- Adding infrared data as a cloud constraint and to provide a cloud mask
- Adding dynamic creation of cloud liquid water in the retrieval.
- Validation using new datasets such as the NASA CloudSat sensor and GPS occultation soundings.

The C1DOE system is a step towards analyzing atmospheric moisture globally and eventually having a positive impact on forecast models.

7. ACKNOWLEDGMENTS

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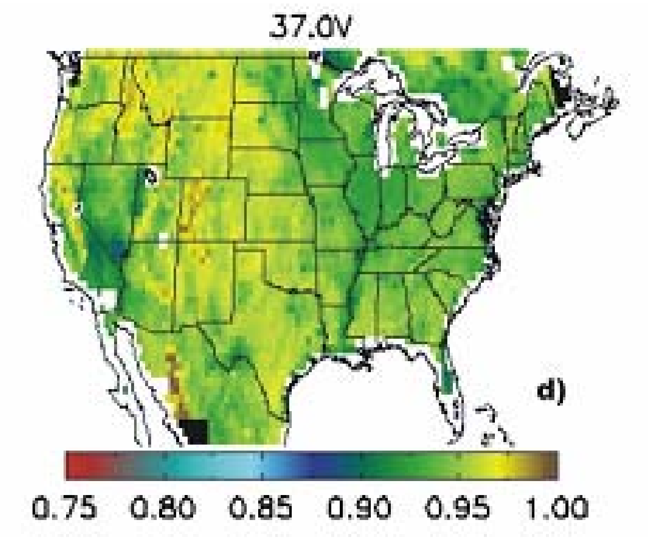
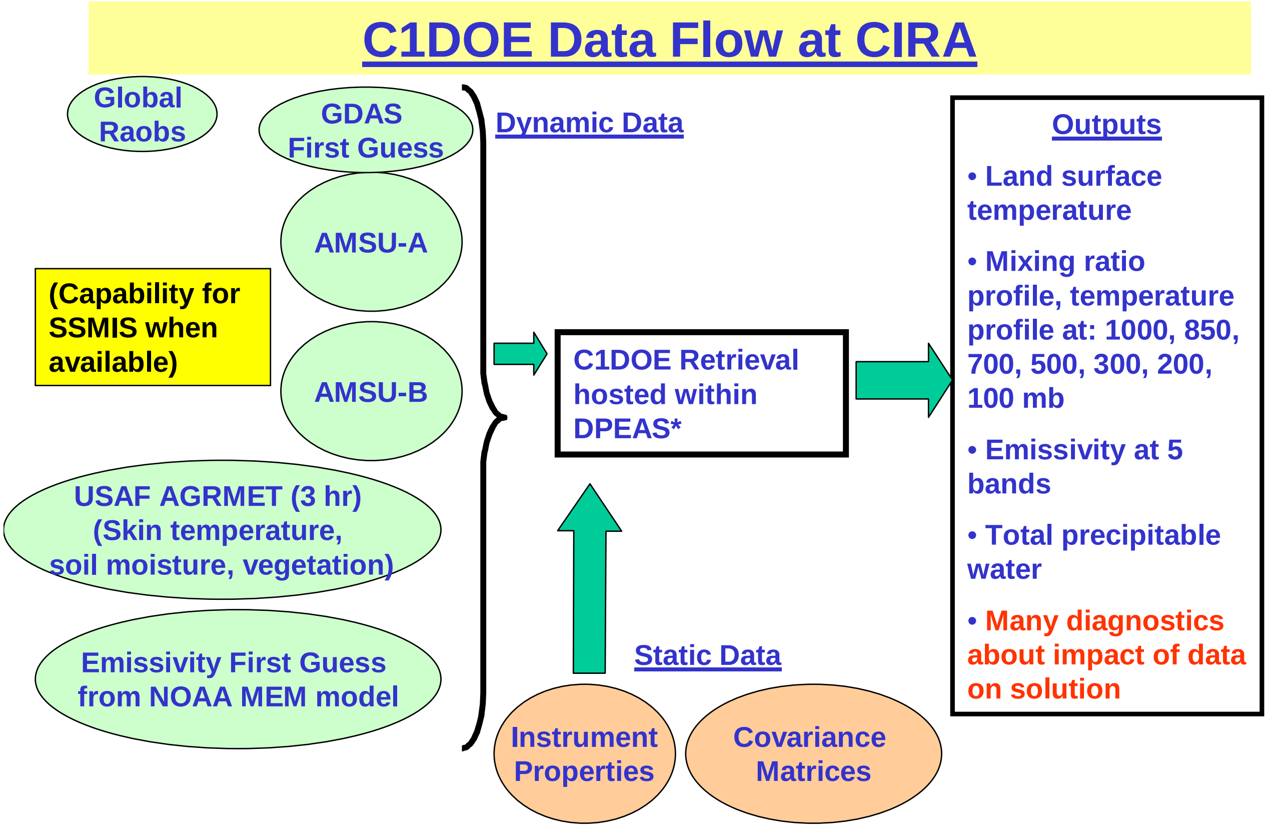


Figure 1: Composite SSM/I emissivity 37 GHz (V-pol) for summer months (2000-2002) (Ruston and Vonder Haar, 2004).



C1DOE Data Flow at CIRA

Global Raobs

GDAS First Guess

AMSU-A

AMSU-B

(Capability for SSMIS when available)

USAF AGRMET (3 hr) (Skin temperature, soil moisture, vegetation)

Emissivity First Guess from NOAA MEM model

Dynamic Data

C1DOE Retrieval hosted within DPEAS*

Static Data

Instrument Properties

Covariance Matrices

Outputs

- Land surface temperature
- Mixing ratio profile, temperature profile at: 1000, 850, 700, 500, 300, 200, 100 mb
- Emissivity at 5 bands
- Total precipitable water
- Many diagnostics about impact of data on solution

DPEAS = Data Processing and Error Analysis System (J. Atm. Ocean Tech, 19, pp. 1307-1317; 2002)

Figure 2: C1DOE data flow at CIRA.

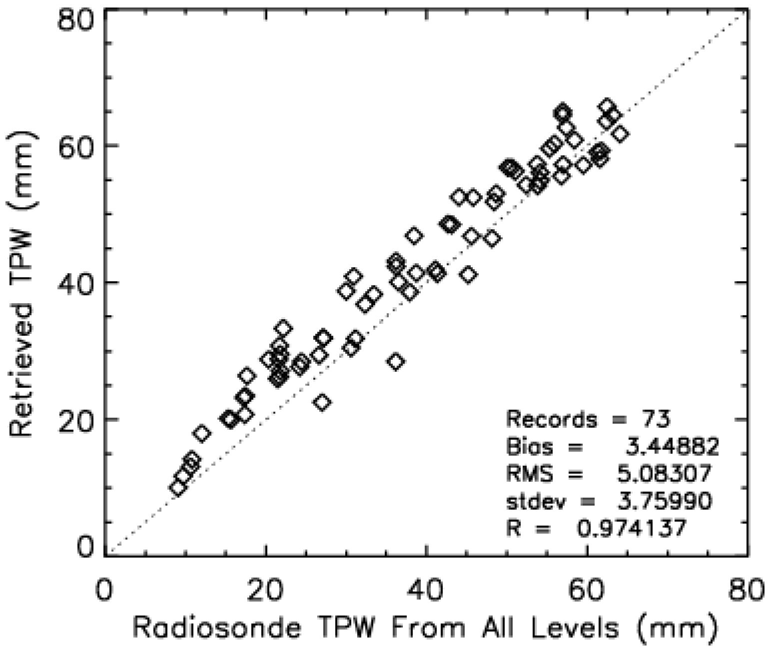


Figure 3: Retrieved TPW calculated using the 7 C1DOE pressure levels versus radiosonde TPW calculated using all available levels (73 clear cases, island rawinsondes, no debiasing).

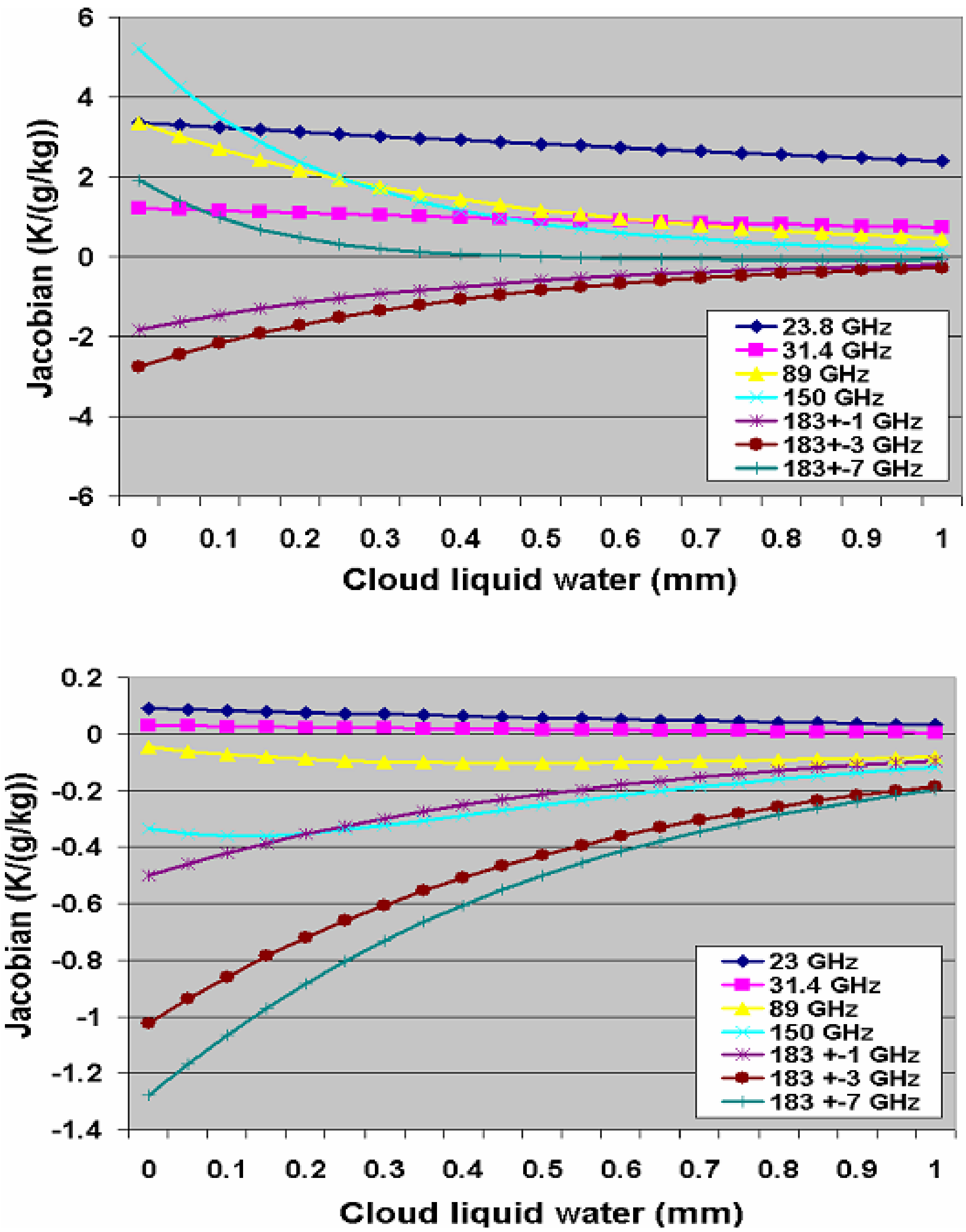


Figure 4: Sensitivity to 1 g/kg of water vapor at 700 hPa as cloud liquid water (mm) is added to the retrieval at 700 hPa over ocean (emissivity = 0.5), top and land (emissivity = 0.95), bottom.

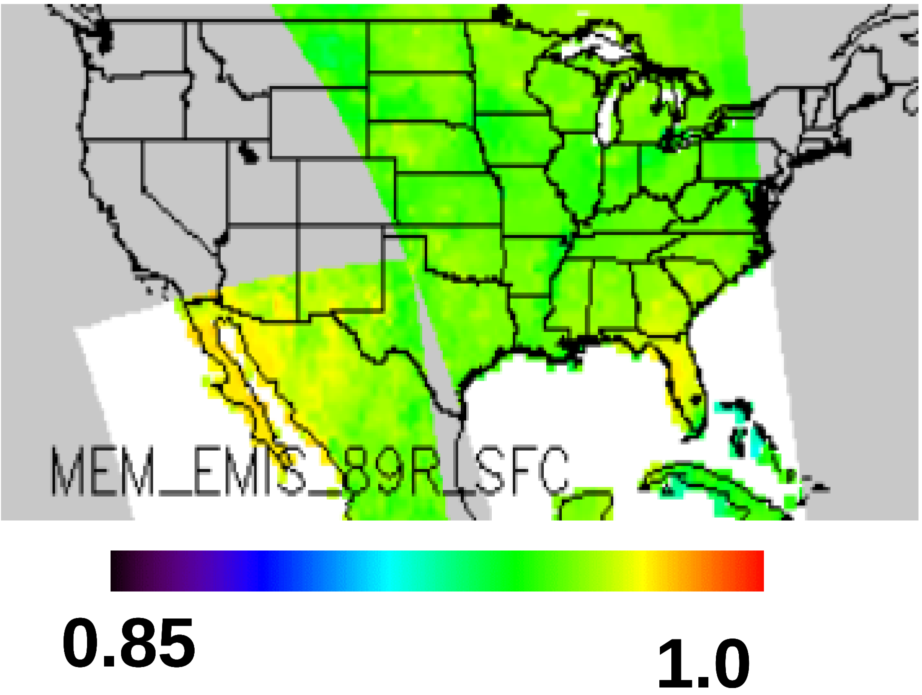


Figure 5: Microwave Emissivity Model (MEM) land emissivity at 89 GHz over CONUS for NOAA-16 AMSU. June 8, 2006, 2030 UTC.

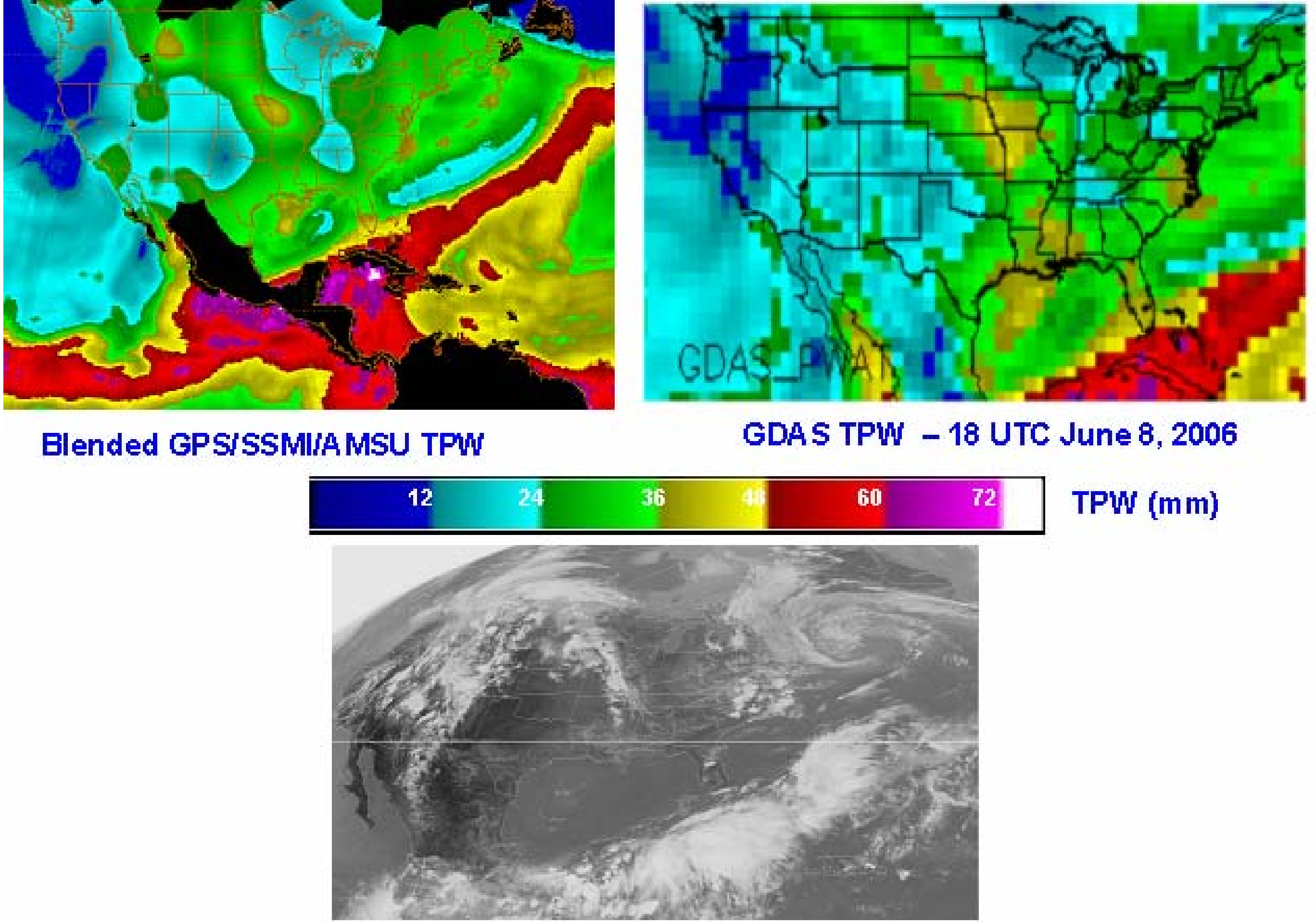
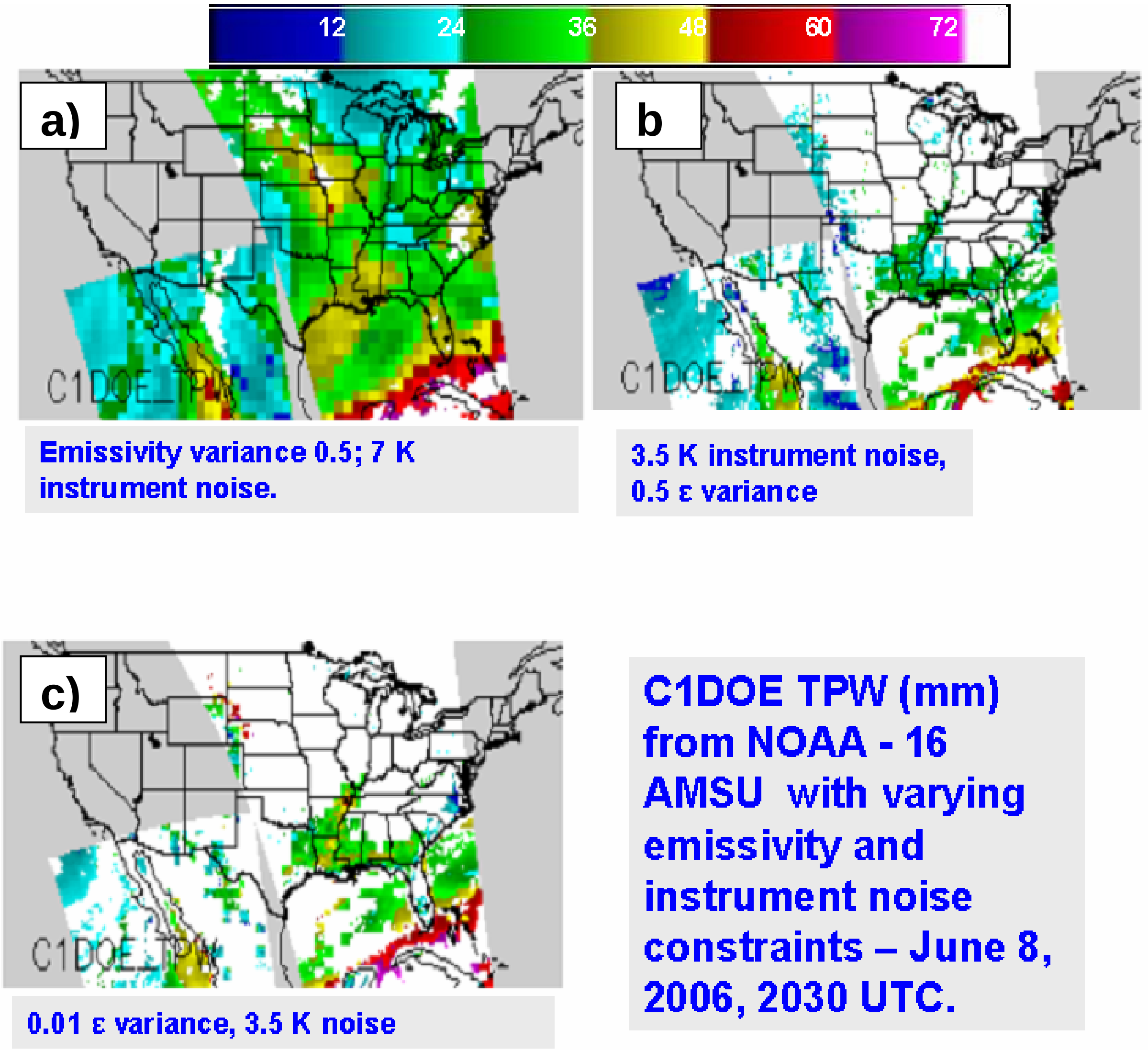


Figure 6: CIRA experimental blended GPS / AMSU / SSMI TPW product over CONUS, compared with GDAS TPW analysis. June 8, 2006, 2030 UTC GOES channel 4 infrared image also shown.



Emissivity variance 0.5; 7 K instrument noise.

3.5 K instrument noise, 0.5 ε variance

0.01 ε variance, 3.5 K noise

C1DOE TPW (mm) from NOAA - 16 AMSU with varying emissivity and instrument noise constraints – June 8, 2006, 2030 UTC.

Figure 7: C1DOE retrieved TPW over land and ocean, June 8, 2006, 2030 UTC for a variety of emissivity variances and assumed AMSU-A/B instrument noise.