Atmospheric Profiles Over Land and Ocean from AMSU

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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. Figure 1 shows the impact of rawinsonde versus polar orbiter satellite data on the initial 850 hPa relative humidity field in EDAS. Note the dominance of the radiosonde moisture field in the analysis, even though the radiosonde data is only taken twice a day and is from a sparse network with average spacing of ~ 500 km between stations.

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 satisfy critical needs of aviation users such as analyzing cloud base, detecting aircraft icing regions, and assisting short-term forecasts of clouds and moisture. Techniques to profile moisture from passive microwave sensors could propagate into data assimilation systems and weather forecast models and potentially yield gains on critical forecast needs like improved quantitative precipitation forecasts (QPF).

Several meteorological satellites have the capability to greatly improve the analysis of moisture fields over land. While infrared-based sensors such as the GOES imager and sounder do make a contribution in clear skies, the passive microwave sensors onboard the NOAA and DMSP satellites have not been fully exploited for providing water vapor information over land. In the passive microwave spectrum from 20 - 200 GHZ, 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. Figure 2 shows a recent global blended total precipitable water vapor (TPW) passive microwave product from NOAA, which has no coverage over land.

In this paper we show our results to date on performing simultaneous retrievals of the water vapor and temperature profile, and surface emissivity from the Advanced Microwave Sounding Unit (AMSU) –A and –B instruments onboard the NOAA-15 and NOAA-16 satellites. The retrieval is named the CIRA 1-Dimensional variational Optimal Estimation, or C1DOE.

2. DATA

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

In order to minimize a cold bias in the AMSU-B due to use of antenna temperatures in the retrieval as opposed to brightness temperatures (Tb's), we developed an antenna pattern correction (APC) for the AMSU-B radiances. The APC has the effect of warming the Tb's by a few Kelvin, depending on scan position. The APC has been shown to have an impact of up to 10 % on upper tropospheric moisture retrievals (Nielsen et al. 2005 (submitted)).

To test the performance of the C1DOE retrieval, two global matchup datasets of collocated radiosondes and AMSU overpasses have been created. The NOAA-15 dataset is from coastal and island stations from year 2000, and the NOAA-16 and NOAA-17 matchup dataset is from September 2003.

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| | 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 \pm .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 | $f_0\pm$. 217 | 0.4 |
| | 11 | $f_0\pm$. 3222 \pm .048 | 0.4 |
| | 12 | $F_0 \pm .3222 \pm .022$ | 0.6 |
| | 13 | $f_0\pm$. 3222 \pm . 010 | 0.8 |
| | 14 | F₀±.3222±. 0045 | 1.2 |
| | 15 | 89.0 | 0.5 |
| AMSU-B | 1 | 89.0 | 2.0 |
| | 2 | 150.0 | 2.0 |
| | 3 | 183.31±1.0 | 2.0 |
| | 4 | 183.31±3.0 | 2.0 |
| | 5 | 183.31 ± 7.0 | 2.0 |

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 3 shows the data flow through the system. Historical runs of C1DOE are also possible. We have assembled all required data to use September 2003 as a test month. In Fig. 3, 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 and 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 1dimensional variational data assimilation retrieval, or 1DVAR. Because of the highly coupled nature of the atmosphere and the sensitivity of microwave measurements to the desired retrieval parameters, more accurate retrievals of each can be achieved through a simultaneous retrieval. Furthermore, the retrieval method is guite 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 at some point in the future.

The retrieval scheme requires a first guess of the water vapor and temperature profiles as well 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 radiative transfer model used to compute radiances given x, and S_a and S_v 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, surface emissivity in 5 bands from 23 to 183 GHz, and cloud liquid water is available in cloudy cases, although cloud liquid water is currently disabled. 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 sensor, such as infrared or visible radiances. 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 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 RESULTS

It is instructive to determine the expected radiometric response of the AMSU channels to water vapor over various highly emissive land surfaces. If the change in Tb due to changing water vapor is below the instrument noise in Table 1, it is fruitless to attempt to retrieve these changes in water vapor. Figure 4 shows the derivative (or analytic Jacobian) of brightness temperature for four channels sensitive to water vapor for a 1 g/kg change in water vapor at 500 hPa. The 183 GHz channels have a Tb change of several K, while the 150 and 89 GHz channels show a smaller response. So for detecting moisture at 500 hPa the 183 GHz channels do possess signal above the instrument noise, for all surface emissivities. This indicates that theoretically

there is signal to be extracted in a moisture profiling retrieval from AMSU over land.

The performance of C1DOE over scenes dominated by ocean is shown in Figure 5 for 500 hPa mixing ratio and temperature. 255 matchups between NOAA-15 and radiosonde are shown. The temperature first guess was from the NESDIS statistical retrieval (Mitch Goldberg of NESDIS) and the moisture first guess was from climatology. Initial work showed significant biases in these retrievals, because the model C1DOE atmosphere was capped at 100 hPa and no antenna pattern correction was applied. The results in Fig. 5 are much improved, although temperature has a slight cold bias.

An attractive feature of C1DOE is the numerous diagnostics generated automatically from the mathematical framework. In particular, C1DOE reports how much impact the observations and *a priori* constraint had on the solution. This is presented as percent variance due to observations. In Figure 6, an example of the C1DOE moisture retrieval over the U.S. is shown which includes this diagnostic. The date is October 4, 2005, 1945 UTC. C1DOE retrieved mixing ratio for 300, 500 and 850 hPa are shown, along with the variance due to the AMSU observations at each level.

The black areas (within the AMSU swath) are where C1DOE did not converge in this experimental configuration. This is typically due to precipitating clouds and also liquid clouds, which are not currently included in the physics of the retrieval. Work is underway to add non-precipitating liquid clouds as a term in the cost function. It is also important to note that the surface emissivity guess in this case is from the NOAA Microwave Emissivity Model (MEM, Weng et al. 2001), which is expected to have some differences from true emissivity and is the subject of related CIRA research. The results are encouraging because they show more impact from the data at 300 hPa, where the influence of surface emissivity is less. There is also more impact over the ocean at 850 hPa, where the signal is greater. The main point of Fig. 6 is that C1DOE provides diagnostics which can be used to determine whether the data are affecting the solution. This is extremely useful when adjusting the constraints of the retrieval, for instance the first guess and error for emissivity and the first guess and error of the atmosphere.

GPS-derived TPW values are a rich source of comparison for satellite retrievals. There are roughly 200 observations per hour available over CONUS, and the networks have been expanding. Unlike traditional rawinsonde networks, GPS TPW values are taken at a frequency of hourly or greater. The GPS TPW retrievals are quite accurate, to within a couple of mm. Figure 7 shows an initial comparison of C1DOE TPW (formed by integrating the 6 retrieved layers) versus GPS TPW. The retrieval seems to be biased a bit high in this initial comparison.

5. WORK IN PROGRESS AND FUTURE WORK

An algorithm for the retrieval of water vapor profiles from passive microwave satellite observations has been presented. The retrieval shows encouraging performance over oceans. Theoretical results indicate that there is signal available for retrievals over land. Better characterization of the microwave land emissivity is the key to realizing the potential of passive microwave measurements. Related work at CIRA (see Jones et al. Poster 5.8 this conference) aims to improve our understanding of microwave land emissivity.

Current work in progress focuses on these topics:

- Test the hypothesis that land performance can be improved using a retrieved emissivity database. Assess baseline performance using the NOAA MEM.
- Measure sensitivity to a priori covariance matrix. Does it need refinement?
- Add dynamic creation of cloud liquid water in the retrieval.
- Add infrared data as a cloud constraint?
- Explore cloud performance with NASA CloudSat data as verification.

From our initial results with C1DOE over land, it appears we are making progress toward increasing the impact of passive satellite microwave observations on water vapor and clouds over land.

6. ACKNOWLEDGMENTS

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REFERENCES

- Engelen, R. J. and G. L. Stephens, 1999: Characterization of water-vapour retrievals from TOVS/HIRS and SSM/T-2 measurements. *Q. J. R. Meteor. Soc.*, **125**, 331-351.
- Jones, A. S., and T. H. Vonder Haar, 2002: A dynamic parallel data-computing environment for cross-sensor satellite data merger and scientific analysis. *J. Atmos. and Oceanic Technol.*, **19**, 1307-1317.
- Liebe, H. J. and G. A. Hufford, 1993: Models for atmospheric refractivity and radio-wave propagation at frequencies below 1 THz. *Int. J. Infrared and Millimeter Waves*, **77**, 437-471.
- Nielsen, M. J., P. J. Stephens, A. S. Jones, J. M. Forsythe, R. W. Kessler, and T. H. Vonder Haar, 2006: Impact of AMSU-B antenna pattern corrections on physical profile retrieval methods. *Submitted to J. Atmos. and Oceanic Technol.*
- Weng, F,., B. Yan, and N.C. Grody, 2001: A microwave land emissivity model. *J. Geophys. Res.*, **D17**, 20115-20123.
- Zapotocny, T. H., W. P. Menzel, J. A. Jung, and J. P. Nelson, 2005: A four-season impact study of rawinsonde, GOES, and POES data in the Eta data assimilation system. Part II: Contribution of the components. *Wea. Forecasting*, **20**, 178-198.



Radiosonde still dominates moisture field impact in mesoscale forecast models

Polar Orbiter Satellite Impact (%)

Figure 1: Distributions of the four-season, time-averaged 00-h sensitivity (%) for 850-hPa relative humidity from Eta model. Polar orbiter impact includes AMSU-B. Contour interval 2%. (after Zapotocny et al. 2005).



Figure 2: NESDIS blended total precipitable water product (mm) for October 2, 2005. Three AMSU and three SSM/I instruments are blended. Note that there are no fields over land.



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

Figure 3: C1DOE data flow at CIRA.



Figure 4: The derivative of AMSU brightness temperature for a 1 g / kg change in 500 mb mixing ratio as emissivity ranges from 0.5 to 1.0. The magnitude of the change decreases as emissivity increases, but is mostly above the AMSU sensor noise. This indicates that there should be a signal to extract in a retrieval.









Figure 5: Comparison of C1DOE retrievals of 500 hPa temperature and mixing ratio for 255 coastal and island radiosonde sites. Results are from NOAA-15 in year 2000.



Figure 6: C1DOE moisture results over the United States from a NOAA-16 pass at 1945 UTC, October 4, 2005. Upper row is mixing ratio at 300, 500 and 850 mb. Lower row is percent variance in solution due to observations. Black areas indicate non-convergent retrievals, often due to clouds and precipitation. See text for



Figure 7: Comparison of C1DOE retrieved total precipitable water (TPW) with GPS-derived (TPW) from September 2003 over CONUS for 26 collocated retrievals.