# Adding Liquid Clouds to CIRA's Passive Microwave Profiling Retrieval


**Kevin M. Donofrio, John M. Forsythe, Matthew J. Nielsen, Andrew S. Jones, Ron W. Kessler, and Thomas H. Vonder Haar**

*DoD Center for Geosciences/Atmospheric Research*

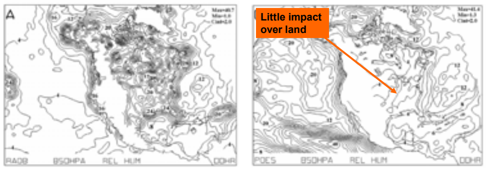
*Cooperative Institute for Research in the Atmosphere*

*Colorado State University, Fort Collins, CO*


## The Challenge

**"By virtue of the very tight vertical and horizontal gradients that develop… Moisture-related fields have historically been the most difficult to forecast… this remains true in modern high-resolution models" (Zapotocny et al. 2005).**

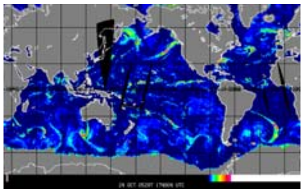
**Radiosonde still dominates moisture field impact in mesoscale forecast models**




**Raob Impact (%)** **Polar Orbiter Satellite Impact (%)**

**Distributions of the four-season, time-averaged 00-h sensitivity (%) for 850-hPa relative humidity from in Eta model from raob and Polar Orbiting Satellite, including AMSU. Contour interval is 2%. (Zapotocny et al. 2005).**

**Current satellite microwave products over land (ε ~ 0.95) are lacking due to complex surface emissivity**



**This work aims to extend microwave water vapor, cloud and temperature retrievals to profiles over land**

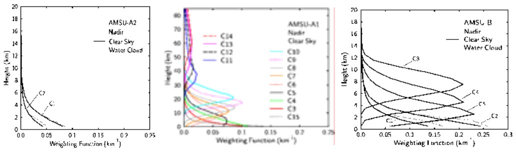
NESDIS blended cloud liquid water product, Oct. 24, 2005. Note lack of retrievals over land, and only total column values

**Objectives of Research**

- **Develop cloud and moisture profile retrievals over land to enable products of value to military users (target obscuration, aircraft icing, cloud base…)**
- **Testbed and preparation for new sensors (e.g. NPOESS instruments)**

## The AMSU Instrument

AMSU is a low noise, cross-track passive microwave sensor with spatial resolution of ~ 50 km at nadir (16 km for moisture). An antenna pattern correction for AMSU-B was developed at CIRA to remove angular brightness temperature biases (Nielsen et al. 2005, submitted to *J. Atmos. Oceanic Tech.*) It has a ~ 10 % impact on upper tropospheric humidity retrievals.




AMSU-A and AMSU-B weighing functions better sample the atmosphere then previous microwave sensors.. The purpose of the AMSU-B instrument is to receive and measure radiation from a number of different layers of the atmosphere in order to obtain global data on humidity profiles. It works in conjunction with the AMSU-A instrument to provide a 20 channel microwave radiometer. The following table is for AMSU-B:

| Channel number | Center freq. of channel (GHz) | No. of pass bands | Bandwidth per passband (MHz) | NEΔT (see Note 1) (K) | Polarization angle (see Note 2) |
|---|---|---|---|---|---|
| 16 | 89.0±0.9 | 2 | 1000 | 0.37 | 90-θ |
| 17 | 150.0±0.9 | 2 | 1000 | 0.84 | 90-θ |
| 18 | 183.31±1.00 | 2 | 500 | 1.06 | 90-θ |
| 19 | 183.31±3.00 | 2 | 1000 | 0.70 | 90-θ |
| 20 | 183.31±7.00 | 2 | 2000 | 0.60 | 90-θ |

## The C1DOE* Algorithm

*C1DOE = CIRA 1-Dimensional Variational Optimal Estimator

- Physical Basis: Minimize cost function
- Retrieval iterates fast radiative transfer model to minimize cost. Analytic Jacobian implemented for speed.
- Physical retrieval allows new instruments to be added easily

$$\Phi = \underbrace{(x-x_a)^T S_a^{-1}(x-x_a)}_{\text{Cost of retrieved atmosphere versus background atmosphere}} + \underbrace{\{y-F(x)\}^T S_y^{-1}\{y-F(x)\}}_{\text{Cost of satellite measurements versus calculated radiances}}$$

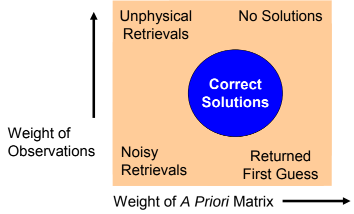
**Key Feature: Accommodates a Variety of Sensors**

**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) are radiances computed from a forward radiative transfer model given x, and $S_a$ and $S_y$ are the error covariance matrixes of the *a priori* data and the observations, respectively.**

- **Physically based iterative retrieval**
- **Simultaneous retrieval of temperature and water vapor profile, liquid clouds, and emissivity**
- **Flexible sensor inputs (AMSU, SSM/T-2). {SSMIS, ATMS, CMIS in future}**
- **Liebe MPM92 radiative transfer model for gaseous microwave absorption; modular so other models may be applied**
- **A priori error covariance currently from NOAA-88 sounding dataset**
- **Many diagnostics calculated automatically**
- **Near real-time performance demonstrated**

## Constraining the Retrieval

The retrieval must be constrained by a priori knowledge of temperature and moisture profile correlations and expected error. A balance must be found between these constraints. The retrieval calculates how much influence the data and background data have on the solution.




$$\mathrm{cov}(x,y) = r\sqrt{\sigma_x^2 + \sigma_y^2}$$

27 x 27 matrix — Correlation matrix (from global radiosondes) — Expected errors in first guess, for instance from a forecast model

A single covariance matrix ($\mathbf{S_a}$) is currently used. The $\mathbf{S_a}$ matrix shown here should have both seasonal and spatial dependencies. For instance, the error in sea surface temperature is typically less than land surface temperature.

## Cloud Liquid Water Profile First Guess

The C1DOE retrieval is run in two configurations at CIRA. The retrieval has first guess of water vapor, temperature information from radiosondes in 1-D (GDAS in 2-D). CLW is derived from the RAOB or GDAS data.

1. AMSU / Radiosonde match up files. Two match up datasets have been developed, NOAA-15 from Jan-Dec 2000 over oceans and NOAA-16 from September 2003 over land and oceans.
2. Cloudy soundings are identified where the data has RH>87% at one of the seven C1DOE vertical pressure levels. Note: Blankenship et al. (1999) adds .3 g/m² of CLW where RH>95% to most humid level in each iteration.
3. Adiabatic liquid water mixing ratio values calculated as difference between LCL total water mixing ratio and the saturated mixing ratio at the sounding level. CLW added to all levels with RH>87%. (see Eq. 1 below)
4. An empirical relation derived from observations from Walcek and Taylor (1985) is used to determine actual liquid water mixing ratio apriori profiles for growing, non-precipitating clouds (see Eq. 2 below)

$$(Q_1)_{ad} = Q_{src} - Q_{sat}(T_{ad}, P) \qquad (1)$$

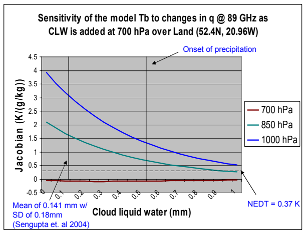
Adiabatic liquid water mixing ratio — Src is the "source level", typically the LCL for non-precipitating clouds — Saturated mixing ratio at the Temperature and Pressure level

$$\frac{Q_{cld}}{(Q_1)_{ad}} = 0.6\exp\left(\frac{P-P_{lcl}}{60.0}\right) + 0.2 \qquad (2)$$

Actual liquid water mixing ratio (g/kg) — P= pressure, $P_{lcl}$ = lcl pressure

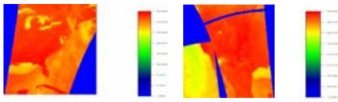
## Results

### Theoretical Basis



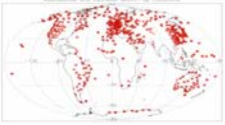

The derivative of AMSU brightness temperature at 89 GHz over land (e=0.95) for water vapor mixing ratio as cloud liquid water changes. The magnitude of the change decreases as cloud liquid water increases.

**There should at least be signal to extract in areas above the sensor noise. (see AMSU-B table)**

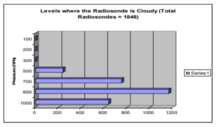


AMSU 89 GHz brightness temperatures. Surface effects reduced allowing for thermal contrast and signal even over land.

### AMSU – Radiosonde match up data set

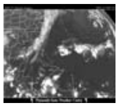


5,053 Radiosondes within 100km and 2hr of AMSU over pass from September 21-30, 2003




Distribution of clouds in the 1,840 cloudy soundings of match up set

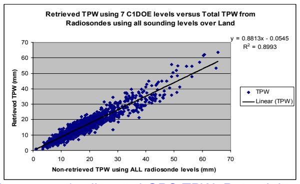
### Upcoming validation methods



September 23, 2005 1215 UTC test case with clear and cloudy gradients

GPS network provides hourly data

Retrieved TPW potential low bias from using 7 pressure levels and using the MEM for emissivity first guess. Radiosonde TPW is calculated using all sounding levels. In both cases, TPW = Σ((q * Δp) / g), where q is the mean q between levels. Retrieved TPW used radiosonde as first guess for q and T from clear and cloudy soundings, and MEM as first guess for emissivity, all parameters iterate:




Validation of liquid water mixing ratio can be done by:

- Validating TPW in clear/cloudy cases w/ collocated GPS TPW. Potential bias due to 7 levels and MEM must be considered in the analysis.
- Comparing Q (g/kg) or T (K) in cloudy environments with radiosonde Q or T and comparing retrieved CLW with MSPPS CLW over ocean.

### Future Work

- **Explore cloud performance with CloudSat verification**
- **Measure sensitivity to *a priori* covariance matrix.**
- **Test hypothesis that land performance can be improved using retrieved emissivity database.**
- **Add infrared data as a cloud constraint.**

References


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.

Walcek, C.J. and Taylor, G.R., 1986: A Theoretical Method for Computing Vertical Distributions of Acidity and Sulfate Production within Cumulus Clouds. *J. Atmos. Sci.*, 43, 339-355.

Blankenship, C.B., A. Al-Khalaf, and T.J. Wilheit, 1999: Retrieval of Water Vapor Profiles Using SSM/T-2 and SSM/I Data. *J. Appl. Meteorol.*, 57, 939-955.

Sengupta, M., E.E. Clothiaux, T.P. Ackerman, 2004: Climatology of Warm Boundary Layer Clouds at the ARM SGP Site and Their Comparison to Models. *J. Climate*, 17, 4760-4782.



*This work was supported by the DoD Center for Geosciences/Atmospheric Research at Colorado State University under the Cooperative Agreement DAAD19-02-2-0005 with the Army Research Laboratory.*