Andrew S. Jones<sup>\*</sup>, J. M. Forsythe, and T. H. Vonder Haar

DoD Center for Geosciences / Atmospheric Research (CG/AR) Cooperative Institute for Research in the Atmosphere (CIRA) Colorado State University Fort Collins, CO

# 1. INTRODUCTION

Microwave remote sensing from satellites has proven to be a valuable tool for observing Earth. Microwave products showing such varied parameters as total precipitable water, precipitation, and sea ice are routinely produced and used by forecasters worldwide.

The reason many satellite microwave retrievals are possible over ocean and not over land is due to the complex, variable, and poorly known microwave emissivity of land (and snow and ice) surfaces (Prigent et al., 2002; Bennartz et al., 2002). Modern weather satellites measure passive microwave radiation in the range from 6 to 183 GHz. Physical models have existed for decades which specify the dielectric properties of seawater in this frequency range as a function of a few variables such as sea surface temperature, wind speed. and salinity. Knowledge of the viewing angle allows the dielectric properties to be converted into emissivity at vertical and horizontal polarizations. Over oceans, the surface emissivity ranges from about 0.5 to 0.7. Over land and ice, the surface is more complex due to variable surface types and vegetation. A typical emissivity value over land might be 0.95, much higher than over ocean. The higher emissivity itself makes it more difficult to sense atmospheric phenomena over land, since the surface appears radiometrically brighter. In addition, time-dependent changes in the surface, such as the seasonal cycle of vegetation, affect the emissivity. Soil moisture changes in the upper few mm of the surface are a large source of variability of the microwave emissivity at 6 to 183 GHz on a timescale of hours to days. In contrast, infrared surface emissivity is much closer to about 0.98 over land and oceans, with a reduced dynamic range. While the surface emissivity in the infrared requires characterization, particularly over desert regions, it is a more tractable problem than in the microwave.

### 2. RESEARCH GOALS

NOAA has developed a microwave land surface emissivity model which shows promise in enhancing assimilation of satellite microwave data. The NESDIS Microwave Land Emissivity Model (MEM) (Weng et al., 2001) is used within the NOAA Global Data Assimilation System (GDAS) to determine important surface behaviors for microwave sensors. This includes sensors such as the NOAA Advanced Microwave Sounding Unit (AMSU) and other microwave sensors. The MEM allows the GDAS system to account for background variability of the land surface, and to obtain a clearer view of Earth's atmosphere. This results in improved NOAA weather forecasts. Our research focuses on the observational validation of the NESDIS MEM using fairly sophisticated cross-sensor satellite data analysis to verify the integrity of the MEM output.

Our goals are to:

- Conduct an error analysis of the MEM model via creation of a Global Microwave Surface Emissivity Validation Atlas (GMSEVA)
- 2. Generalize the error characterization approach to future NESDIS/NWS Observational Operator (OO) needs.
- 3. A parallel goal is to develop a microwave water vapor, cloud and temperature profiling algorithm (please see P8.13 in this conference Forsythe et al., 2004).

A related collaborative effort which blends infrared and microwave measurements is underway at the Naval Research Laboratory in Monterey, CA. A multisensor approach has shown promise in the past (Jones and Vonder Haar, 1997). In this paper, we show our approach and initial results, and compare them to the MEM model. Further work planned with the method is outlined, and its application to future sensors is discussed.

#### 3. 1DVAR EMISSIVITY RETRIEVAL METHOD

In order to make progress on the measurement of microwave land surface emissivity from space, we have chosen to retrieve land emissivity simultaneously with the atmospheric profile. By using radiances from the Advanced Microwave Sounding Unit (AMSU) A and B

<sup>&</sup>lt;sup>\*</sup> Corresponding author address: Andrew S. Jones, Colorado State University / Cooperative Institute for Research in the Atmosphere (CIRA), Fort Collins, CO 80523-1375; e-mail: jones@cira.colostate.edu.

instruments, 20 channels are available to retrieve atmospheric profiles and surface properties.

The work underway at CIRA, a 1-dimensional variational assimilation (1DVAR) of microwave radiances, is one component of several efforts to make headway on the difficult land emissivity problem. We call our retrieval "MOE" (Microwave Optimal Estimation). This work is supported by the Joint Center for Satellite Data Assimilation, an effort of NOAA, NASA and the Department of Defense to better utilize satellite data in weather prediction.

The retrieval algorithm is a physically based iterative optimal-estimation scheme (OE algorithm) adapted from the method of Engelen and Stephens (1999). The algorithm takes combined data from AMSU-A and AMSU-B. Since it is a physical retrieval, it is flexible to allow insertion of future sensors, only the channelization and instrument must be specified. The SSMIS, SSM/T-2, and upcoming ATMS instruments on NPP can all be used as well. A variety of parameters are retrieved including profiles of water vapor mixing ratio, joint water vapor and temperature profiles (including surface temperature), and water vapor and temperature profiles along with microwave surface emissivities. The retrieval scheme requires a first guess of the water vapor and temperature profiles as well surface emissivities at the relevant microwave frequencies. This first guess for moisture can come from climatology, or from global model output such as from GDAS. An a priori distribution of the retrieval parameters is used to constrain a non-linear iterative optimal-estimation scheme which uses the method of Rogers (1976) to minimize the cost function to find the optimal solution x, where:

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

where x is the vector of parameters to be retrieved, xa is the a priori vector, y is the set of observations, F(x) is a forward radiative transfer model used to compute radiances given x, and Sa and Sy are the error covariance matrixes of the a priori data and the observations, respectively. 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. One of the objectives of this work is to refine the knowledge of the correlation matrix between emissivities at various frequencies. Currently, we use a loose correlation constraint to allow the retrieval to iterate to a solution. A maximum of 12 iterations is currently specified, which is exceed only 1 - 2% of the time. Causes for this include inadequate precipitation detection. The error covariance matrix of the observations includes forward model errors and uncertainty in the observed radiances.

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 model of microwave atmospheric attenuation. Only liquid clouds currently are included. An analytic Jacobian has been developed for the radiative transfer model, resulting in an order of magnitude speed increase.

### 4. GLOBAL EMISSIVITY RESULTS

A comparison of the MEM and MOE retrievals of 89 GHz emissivity over CONUS is shown in Figure 1. The use of AGRMET surface temperature as a first guess has a strong impact on the solution. This is an initial result showing the types of comparisons between MOE and MEM which we will perform. Further improvements in the MOE first guess should yield even more robust solutions. The MOE emissivities will be validated via proxy by comparing the water vapor and temperature retrievals to radiosondes and GPS TPW. Errors in the surface emissivity will propagate into retrievals of these fields and make themselves evident.

Figure 2 shows the sensitivity of the retrieved emissivity to the error covariance specification of temperature and moisture profiles and emissivity. The initial loose constraint (control run) is tightened by a factor of 10 and then 1000 (i.e. "over-constrained"). The results remain roughly similar for a factor of 10, which is a large reduction, indicating that the retrieval is fairly stable. The over-constrained specifications begin to cause more unrealistic results.







Figure 2. Sensitivity of the retrieval to covariance between moisture profile, temperature profile, and emissivity. The emissivities at 89 GHz are shown for the control run, covariance reduced by a factor of 10, and extremely constrained by a factor of 1000

# 5. CONCLUSIONS

The MOE 1DVAR retrieval of microwave emissivity from AMSU shows promise as an approach to create useful fields of this key physical variable. The retrieval is stable and behaves as expected. Comparisons are underway at present with the NESDIS MEM emissivity fields. A real-time system to create emissivity fields using both methods is being developed at CIRA and will be implemented by the end of 2004. Obtaining an improved first guess of moisture is a major goal at present.

Continued collaborations with the data assimilation and modeling communities will encourage more utilization of the plethora of passive microwave measurements now available. This work has applications to future platforms such as NPP and NPOESS, each of which carry passive microwave imagers and sounders. In particular, improved knowledge of global land surface emissivity values and their variance and covariance will be needed before these measurements can achieve their full potential in weather prediction.

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