P3.15 A PRELIMINARY LOOK INTO SPECTRAL MICROWAVE EMISSIVITIES OVER THE CONTINENTAL US

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1. INTRODUCTION

There is an increasing demand to retrieve surface emissivity from the current suite of passive microwave instruments. This will not only allow for retrieval of atmospheric parameters such as rainfall, water vapor, and cloud water; but will augment climatology of the variation of vegetation and soil wetness. In this study we will undertake a simple linear regression of surface temperature, T_{sfc}, against microwave brightness temperature, T_B, and compare the residuals against vegetation indices. We will then use a simple approximation to estimate land surface emissivity. We find that to a first order the surface temperature can predict the brightness temperature with accuracy decreasing with increasing frequency. We also found the standard deviation of residuals from the linear fit have a pronounced trend compared to vegetation fractional coverage, and vegetation type. Lastly, the simple emissivity calculations we performed were hampered at high frequencies and at 22 GHz due to low transmittance values especially in the south-eastern US.

2. DATA

This study incorporates data from satellite, numerical weather model, and the Land Data Assimilation System (LDAS). The satellite data consists of passive microwave brightness temperatures from three Special Sensor Microwave Imager (SSM/I) instruments, and the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI). The microwave frequencies used are 19.35, 22.235, 37.0, and 85.5 GHz with vertical and horizontal polarization available at 19.35, 37.0, and 85.5 GHz. Both the SSM/I and TMI instruments have a viewing angle of 53.1 degrees. The ground resolution of the instrument is diffraction limited and consequently is a function of frequency. The TMI instrument is in a lower orbit than the SSM/I, so though the antenna is the same, the resolution is improved. The TMI achieves a resolution of ~7 km at 85.5 GHz and ~30 km at 19.35 GHz, while the SSM/I has a resolution of ~15 km at 85.5 GHz and ~60 km at 19.35 GHz.

The numerical weather model used in this study is the Rapid Update Cycle version two (RUC-2). Model analyses reported at 3-hour intervals are used in this study. This model has a resolution of 40 km, with a native isotropic vertical grid with a sigma coordinate surface. The surface air temperature at 2 meters is reported along with a surface soil temperature. The vertical profiles of temperature and moisture are used to generate values of atmospheric transmittance.

The land classification chosen was the Land Data Assimilation System (LDAS) developed at Goddard Space Flight Center. The database is static in time, at one-eighth degree resolution, and gives the fractional coverage of each grid box. The vegetative fractional coverage is then subdivided into fourteen classes. For this study I grouped some of the classes to create four coverage regimes. My first regime was forest and included: two deciduous forest classes, two evergreen forest classes, and the woodland class. My second regime was crop and included only the cropland class. My third regime was grass and included: two classes of grassland, two classes of shrubland, and the mixed cover classification. My final regime was bare ground and included only the bare ground classification.

All data are regridded to one-half degree resolution. The satellite brightness temperatures, T_B, and the RUC-2 model profiles were regridded using a Delauney triangulation procedure, while the vegetation was regridded using bilinear interpolation. The T_B were collocated to the nearest three-hourly RUC-2 analysis. The surface temperatures were then linearly interpolated to the satellite overpass time, while the vertical profiles were left unaltered.

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The temporal regime of this study included the years 1999 – 2001. Only summer months June, July, and August were examined at this time. This is to avoid snowy regions, and reduce vegetative variability.

3. PROCEDURE

The first analysis performed was a simple least-squares linear regression of the surface temperature, T_{sfc}, against the satellite brightness temperature, T_B. The coefficients of the regression were found by using the RUC surface temperature, T_{sfc}, as the predictor variable, x, and the satellite T_B as the response variable, y. The points in the regression where screened for raining pixels using a threshold derived from Ferraro et al. (1998). Rain was assumed when 85.5V GHz dropped below 253 K. Once a preliminary regression was performed a second regression was undertaken, which accepted points within ±13 Kelvin of the first regression estimate. This 13 K threshold is approximately three standard deviations of the residual. This screening attempts to explore a 'base state' which has little cloud cover, average soil moisture, and an average column water vapor. Figure 1 shows as a function of latitude, the number of points included in the regression calculation for August 2000 and 2001. To find the regression coefficient, a_1, can be found by dividing the covariance between x and y, by the variance of x.

$$a_1 = \frac{\overline{x'y'}}{\overline{x'^2}} \quad \text{where} \qquad \text{Eq. 1}$$
$$\overline{x'y'} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})(y_i - \overline{y})$$

The y-intercept, a_o, can be found by determining the mean of the sample x and y, and finding the difference of the mean y with the product of the mean x and the regression coefficient.

$$a_o = \overline{y} - a_1\overline{x} \quad \text{where} \quad \overline{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \qquad \text{Eq. 2}$$

This regression procedure was applied to all the points in the domain over the US. From these regressions a goodness of fit was determined using a student t-statistic. To compute the t-score first the correlation coefficient, r, is needed. This is found by dividing the covariance between x and y by the product of their standard deviations.

$$r = \frac{\overline{x'y'}}{\sqrt{\overline{x'^2}}\sqrt{\overline{y'^2}}} \qquad \text{Eq. 3}$$

From this correlation coefficient a t-score can be found by the product of the correlation coefficient and the square root of the degrees of freedom, divided by the square root of one minus the square of the correlation coefficient.

$$t - \text{score} = \frac{r\sqrt{\nu}}{\sqrt{1 - r^2}} \qquad \text{Eq. 4}$$

The degrees of freedom, ν, for this study were estimated at 15. This is due to the fact that even though there were up to eight samples in a single day, each was not independent. And further a day-to-day correlation was assumed, which dropped the degrees of freedom to days in the month divided by 2, so approximately 15. Using these t-scores, and testing them against a student's t population, relates a confidence in how many times by chance a sample drawn from the population would give a similar result.

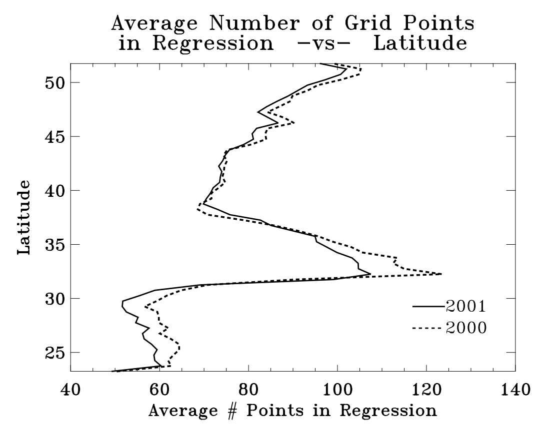

Figure 1: Average number of grid points as a function of latitude used in the regression for the month of August in the years 2000 and 2001.

Next, to compute a simple emissivity we start with an integrated form of the Schwarzchild equation:

$$T_B(\lambda,\mu) = \varepsilon_o(\mu)T_o\tau_o^{\frac{1}{\mu}} + [1-\varepsilon_o(\mu)]T_{space}\tau_o^{\frac{2}{\mu}} + \int_{\tau_o}^{1} TW_\lambda(\tau,\mu)d\tau \qquad \text{Eq. 5}$$

We will ignore the contribution from space (the second term). We also assume an isothermal atmosphere, this approximates the temperature in the last term with the surface temperature. Using an integral constraint the weighting function can be approximated as:

$$\int_{h_o}^{h_T} W_\lambda(h,\mu)dh = 1-\varepsilon_o\tau_o^{\frac{1}{\mu}} - (1-\varepsilon_o)\tau_o^{\frac{2}{\mu}} \quad \text{Eq. 6}$$

This allows us to simplify Eq. 5 as:

$$T_B \approx T_{sfc}\left\{1-[1-\varepsilon_o(\mu)]\tau_o^{\frac{2}{\mu}}\right\} \quad \text{Eq. 7}$$

This allows us to calculate surface emissivities using only T_{sfc}, T_B, and atmospheric transmission. The T_B is taken from either the SSM/I or TMI instrument, T_{sfc} from the temporally and spatially collocated RUC-2 analysis, and atmospheric transmission is calculated from the RUC-2 profiles of temperature and moisture along with an absorption model (Liebe, 1993).

4. RESULTS

We found that the simple linear regression of T_{sfc} against T_B can explain much of the variance seen in the brightness temperatures. The t-score gives an indication of the width of the scatter. A general trend was that the linear fit suffers in mountainous regions where surface variability increases, and temperature contrasts are more pronounced over a one-half degree grid box. The linear fit also has a decreasing confidence with increasing frequency. This is due to the effect of the water vapor continuum effect increasing with frequency, and the sensitivity to sub-pixel storm systems, which contaminate the results.

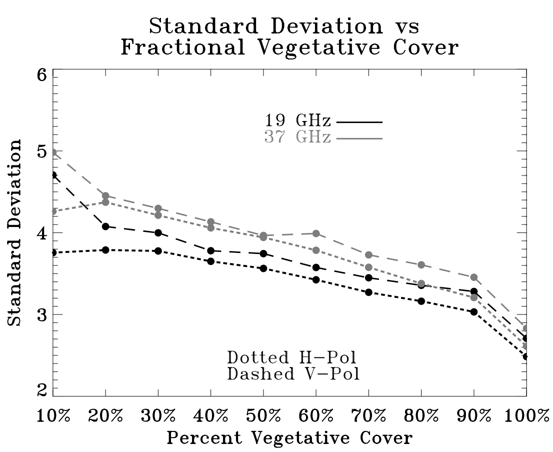

Figure 2: The average value of the residual standard deviation binned by percent vegetative cover, for August 2001.

The residuals, the difference between the actual T_B and the regression estimate of the same value, were found. The standard deviation of these residuals was found as a function of channel. By binning the residual standard deviations by vegetation fractional coverage (see figure 2), and by four categories of vegetation cover strong trends in the magnitude of standard deviation were found. The brightness temperatures have the most variance in bare ground areas with little vegetative cover. In these low vegetation areas the variation in soil moisture can create large changes in the ground emissivity, while the highly vegetated areas the microwave surface emission comes largely from the vegetative canopy. When the values are calculated for a single month, and the vegetation changes are minimal the emission properties of vegetation (especially cropland and forested areas) do not drastically change. The result of a relatively static vegetative canopy, is a much lower variance in the brightness temperature residual over these areas.

The emissivity estimate found produces some well resolved geographic features, along with there expected emissive properties. The depressed emissivity over large landlocked lakes (such as Lake Tahoe), and river basins (such as the Missouri and Mississippi) due to the lower emissivity of the water and the surrounding lands higher soil moisture content. Also desert scattering signals are present in the Great Salt Desert, the Painted Desert, and Death Valley. The greatest errors occur in the south-east US where the atmospheric profile is very warm and moist. This drives the atmospheric transmission down and gives the emissivities a low bias when using the simple approximation shown in Eq. 7.

Histograms of the emissivity values were produced, grouped by the vegetative classification in the LDAS database. Shown in figures 3 and 4 are the bare ground and forest classifications. A larger polarization difference is seen in the bare ground classification. The lower median value seen for the forest classification is quite possibly an effect of our approximation in Eq. 7 (an over correction for atmospheric water vapor due to the isothermal profile).

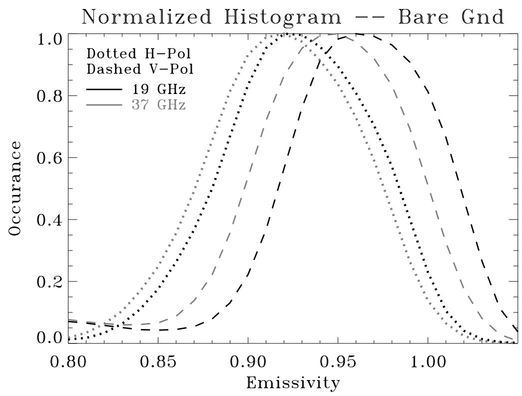

Figure 3: Normalized histogram of emissivity values over bare ground for August 2001.

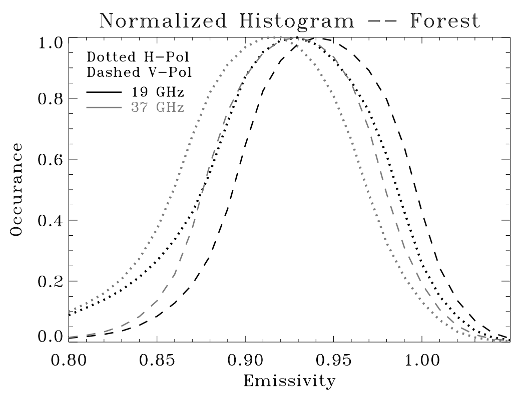

Figure 4: Normalized histogram of emissivity values over forested areas for August 2001.

5. CONCLUSIONS AND FUTURE WORK

The simple linear regression gives a robust result over much of the US with sub-pixel contamination an increasing problem at 85.5 GHz. Such a regression has potential for rainfall monitoring over land on a point-by-point basis. The correlation of the regression residual with rainfall from RADAR is pending. The emissivity calculation must be performed with a layered absorption model, and can include a first guess of Rayleigh scattering clouds (non-raining, small cloud drops relative to frequency). The emissivities from the layered model can be used to generate covariances and correlations binned by vegetation type and frequency. These correlations and covariances can then be used in an optimal estimation retrieval of profiles of temperature, moisture, and cloud liquid water along with a surface emissivity based on the method used by McKague (2001). An independent emissivity calculation can be found from the forward model developed by Weng (2001), and the examination of sensitivities to soil and vegetation properties can be undertaken.

6. ACKNOWLEDGEMENTS

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