Active Passive Remote Sensing of Soil Moisture

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1.0 INTRODUCTION

Numerous studies have shown the influence of soil moisture on the feedbacks between land-surface and climate, which in turn affect the dynamics of the atmosphere boundary layer and have a direct relationship to weather and global climate (Shukla and Mintz, 1982). Chang, et al., 1991 have shown the influence of spatial variations of soil moisture and vegetation on the development and intensity of severe storms, whereas Engman, 1997, has demonstrated the ability of soil moisture to influence surface moisture gradients, and to partition incoming radiative energy into sensible and latent heat. Better understanding of the processes involved in the forcing of, and responses to, Earth's changing environment is needed in order to accurately assess, predict and evaluate the global hydrologic cycle and weather and climate change. In order for this to be accomplished, it is necessary to intimately understand the relationship of soil moisture to these phenomena on small and large-scales. Unfortunately, complicating these overall goals is our inability to completely observe large-scale hydrologic land-surface interactions. Remote sensing enables us to estimate large-scale soil moisture for the purpose of modeling the two-way interaction between land and atmosphere, making it possible to understand the nature of global climate. This paper examines a multiple techniques used to retrieve land surface parameters using microwave remote sensing. In general, past studies (Li and Islam, 1999, Mattikalli et al., 1998; Laymon et al. 1999; Jackson et al. 1995 and Schmugge et al. 1988) have focused on either regression between observed remotely sensed observations and surface soil moisture or limited comparisons between aircraft/ satellite retrievals and in-situ observations. However, in general, field experiments gather limited data, and exhaustive comparisons are generally not possible. Therefore, in this paper we attempt to combine; a) observations from PALS, b) statistical regressions c) physically based forward modeling of the sensor and d) retrievals using combinations of b and c. The above has been accomplished in three vegetation regimes; low(<0.25 kg m^{-2}), med(0.25-3.0 kg m^{-2}), high(>3.0 kg m^{-2}). The dataset used in this study is derived from the Southern Great Plains (SGP) 1999 experiment. This wide spectrum of land surface conditions helps to recognize the advantages and disadvantages of carrying out passive and active remote sensing under varying vegetation, soil moisture and roughness conditions.

In the present study, data from an airborne Passive/Active L and S-band sensor (PALS) were used to detect soil moisture in the Southern Great Plains Little Washita, Oklahoma region. PALS was developed to study the utilization of dual-frequency, dualpolarization, passive and active measurements for remote sensing of ocean salinity and soil moisture. The active component of the instrument provides radar backscatter data that contain added information on surface roughness and vegetation for soil moisture sensing. The instrument operates at 1.4 and 2.69 GHz in the radiometer channels and 1.26 and 3.15 GHz in the radar channels. PALS utilizes a multi-frequency, multi-polarized design, and capable of acquiring simultaneous radar and radiometric signatures of land and ocean surfaces. The radiometer receives coincidental vertical and horizontal emission and the radar transmits vertical or horizontal polarization and receives these two linearly polarized radar echoes simultaneously; a more thorough description of the PALS specifications and applications can be found in (Wilson et al, 2001).

The land conditions and time of study of the Little Washita Basin are ideal for evaluating new sensor systems and algorithms. The basin consists mostly of rolling hills (maximum relief is less than 200m), rangeland and pasture. For purposes of this paper, the representative texture for the surface layer soil is taken to be 20% sand, 60% clay, 20% silt. Land use in the floodplain of the western regions of the watershed area consists of has selected field sites including winter wheat, corn and other crops. Within the watershed, the ground truth effort consisted of 42 Agricultural Research Service (ARS) Micronet stations recording rainfall, relative humidity, air temperature at 1.5 m, solar radiation, and soil temperature at 5, 10, 15 and 30 cm below the surface. Additional gravimetric soil moisture and soil and surface temperatures were measured as well as vegetation and land cover mapping, soil bulk density, surface roughness, ground penetrating radar and surface heat fluxes.

The PALS instrument flew over the SGP99 field area at a nominal altitude of 3,000 feet for a total of 6 days between July 9 and July 14, 1999. Selected flight lines over the field sites and in incremental latitude steps were flown to provide flanking coverage of the Little Washita region. Data were gathered over a wide range of vegetation covers including bare soil, pasture, crops, and trees (pasture and crops had vegetation water content ranging from 0-7.18 kg/m^2). The PALS instrument acquired data before and after a significant rain event on the third day of the study, enabling observation of soil wetting and drying patterns.

R^2	Channels
.904	lh
.908	lh, lv
.92	lh, lv, sh
.92	lh, lv, sh, sv

Table I- Best subset regression models were performed to compute the optimum combination of passive PALS channels for soil moisture retrieval. Listed are the channels that provided the highest correlation with in-situ soil moisture in the 0-5.0 cm range using 1,2,3 and 4 channels.

2.0 SOIL MOISTURE ESTIMATION

Emphasis was placed in the previous section on verifying the relative sensitivities of L- and S-band passive and active measurements to surface soil moisture. The effectiveness of the passive/active sensing is evaluated in the following sections using a series of comparisons between the PALS data and in-situ/ ancillary data collected during SGP99. Three techniques are examined in this paper for retrieving soil moisture from PALS microwave emissions and backscatter of the ground-canopy system; (a) Regression analysis, (b) Passive physical model, (c)Active physical model. No attempt has been made to create a combined passive active algorithm, rather, the analyses (for passive radiometer and active radar) have been carried out separately.

2.1 Regression Analysis

Multiple linear regression analyses were performed on the collected PALS/in-situ data to investigate the sensitivity of the individual channels to varying moisture content. An equation of the form

$$m_j^* = a_0 + \sum_{i=1}^{N} a_i d_{i,j} \qquad (1)$$

was used, where $d_{i,j}$ are the radiometer or radar data (brightness temperatures or backscattering coefficients) in channel i and data point j, N is the number of channels included in the regression, a_0 and a_i are the derived regression coefficients, and m_j^* are the regression fit estimates of soil moisture. Assuming a uniform temperature gradient, (thermal equilibrium) throughout the system, the microwave brightness temperature $T_b(\theta_i)$ can be expressed as

$$T_{bq}(\theta_i) = e_q(\theta_i)T \qquad (2)$$

Where θ_i is the incidence or view angle of the sensor, and q = {v, h} refers to the horizontal and vertical polarizations of the emitted radiation and T is the surface temperature. Here, for a given T, the emissivity $e_q(\theta_i)$ of the surface is proportional to the brightness temperature. The active instrument has been shown to have a less linear relationship to soil moisture than the passive instrument.

Using the five days of collocated data, two (three) days were regressed and predictions were performed on the remaining three (two) days of data. Figure 1 shows the regression result over all the fields using the four passive channels noted in Table I. The plot shows the predicted and in-situ soil moisture values for July 12th and July 14th. The regression estimate has an R^2 value of 0.954, with predictions accurate within 1.92 % of observed gravimetric soil moisture. A number of additional combinations were performed for all vegetation ranges and days. Caution must be used when interpreting the regression results, for example, the limited number of flight lines and sampled fields allow for only 36 co-located (within 300m of each other) data points to be used in

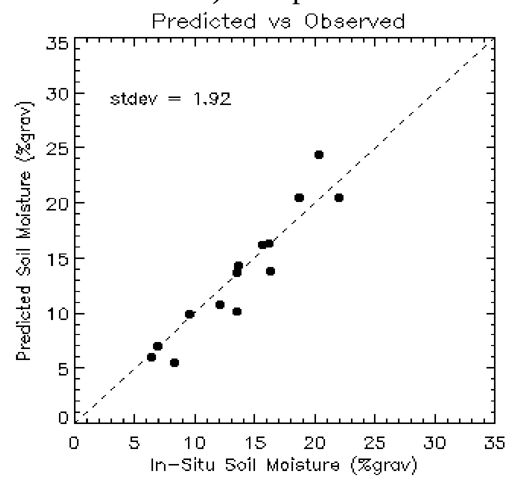

Figure 1. Predicted vs. In-Situ soil moisture using the statistical regression technique (on days July 9th, 11th, 13th) to predict soil moisture for July 12th and 14th over all fields.

the study. Given this small data set, the correlation of the predicted points weigh heavily on those used for the initial regression.

2.2 *Forward Model for Passive Radiation Transfer*

A physically based microwave emission model was used to provide verification of the relative sensitivities of L- and S- band passive measurements to surface soil moisture. The algorithms developed for this paper are based on a physical model of microwave emission from a layered soil-vegetation-atmosphere. All parameters were fixed in the model with the exception of those collected during the SGP99 study; volumetric soil moisture, vegetation water content, surface temperature and bulk density. Surface parameters collected during the study were input into the model collocated by field type and day of study (Figure 2). All the variables were collected daily, except for vegetation water content, bulk density and surface roughness, whose values were assumed to remain constant for the duration of the study. The model assumes homogeneous surface conditions giving averaged effective values over the radiometer footprint, based on returns of real and imaginary parts of the dielectric constant of the soil, for a given bulk density, frequency, volumetric moisture content, sand and clay fractions, and temperature (Using empirical relations taken from Dobson et al. 1985).

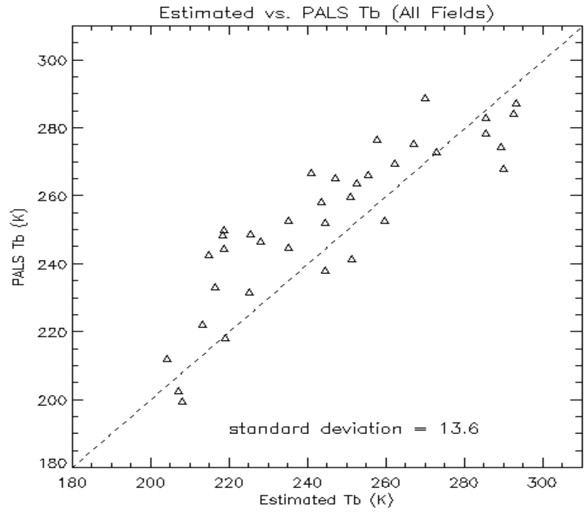

Figure 2. Simulated brightness temperatures computed at frequency (1.4 GHz) plotted against observed PALS brightness temperatures.

A combination forward model-statistical regression-inverse physical model technique was used to retrieve soil moisture over all the fields. Using this method, two(three) days of surface parameter data were input in the model and the resulting brightness temperatures were regressed against the corresponding PALS brightness temperatures (as the two are not exact). The resulting regression coefficients were then applied to the remaining three(two) days of observed PALS brightness temperature to derive a set of model brightness temperature. An iterative least-squares minimization algorithm was performed on the modeled and computed brightness temperatures, with soil moisture adjusted iteratively (spanning the dynamic range: m_g = 0.03 to 0.35 g cm^{-3}) until the difference between the modeled and computed brightness temperatures was minimized. The next step in the soil moisture retrieval scheme was to apply the regression coefficients to the remaining three(two) days of field data in the model inversion. The results of

2.3 Forward Model for Active Backscatter

Prior investigations utilizing microwave scatterometers for retrieval of surface variables have shown long wavelength, co-polarized backscatter possible benefits when applied to surface roughness and land-cover separability (Chauhan et al. 1994; O'Neill et al. 1996 and Chauhan, 1997). These studies have demonstrated the strong degree to which σ^0 is a function of surface roughness, vegetation and near surface soil moisture. Having explored the PALS passive channels for soil moisture sensitivity, the active channels were examined to analyze the possible information retrievable using the active channels.

This paper utilizes scattering models developed by Dobson et al. 1986 and Dubois et al. 1995. From the σ^0_{hh} and σ^0_{vv} measurements and the Dubois empirical model, we are able to interpret the response of the backscatter coefficients to increased soil moisture. Figure 6 presents the σ_{hh}^{0} response of the model verses the in-situ measurements from the PALS data over the low vegetated fields. This model has a better correlation (R^2=0.6) with the PALS backscatter compared with the Dobson model, possibly a result of the robustness of the empirical model (applicable to a wider range of conditions). This is surprising, given that the Dobson model has inputs of vegetation parameters, whereas the Dubois excludes all vegetation inputs.

3.0 CONCLUSION AND DISCUSSION

A combination of multiple regression analysis and contrasting evaluations with physical active and passive models were used in this study for the evaluation of the PALS instrument's sensitivity to near surface soil moisture. The soil moisture signal was found to be well received for bare as well as high vegetated fields. Aside from soil moisture retrievals, the purpose of this paper is to:

1) Illustrate the sensitivity of remote sensing measurements (active and passive) with soil moisture.
2) Demonstrate our (complete) knowledge of the emission (passive) and scattering (active) physics on ancillary variables such as vegetation water content, surface roughness and temperature.

All three prediction techniques exhibited varying soil moisture retrieval potential. On average, over half of the predictions were within 2% in-situ gravimetric soil moisture. Interestingly, the passive model proved to give the best results for the low vegetated fields, (average standard deviations of 2.13% m_g) vs. 2.27, 2.7 and 13.2 using the regression technique, active Dubois and Dobson models respectively. The present paper attempts to provide a unique framework for studying the active/passive observation of the land surface under diverse conditions. It starts with a statistically-based regression which is of limited scope (considering the limitation of the data set). The prediction of soil moisture based on a physically-based forward problem is motivated by our desire to ensure a full understanding of the radiative transfer and backscatter process. It is seen that such (a physically-based) method coupled with regression analysis serves as a good tool for this and other studies. The physically based emission algorithm is found to correlate well with the PALS data collected over bare and low vegetated (biomass < 0.25 kg m^{-2}), medium (0.25-3.0 kg m^{-2}), and high(>3.0 kg m^{-2}) vegetated fields, with LH-band brightness temperature standard deviations of 6.6K, 9.9K, and 6.17K respectively. The active model was found to provide additional information, however, the regression and inverse passive model technique were found to be more reliable. . In this study, we do not make an attempt to merge the active and passive components into a single retrieval technique. Such a single technique could serve as a method to retrieve all the surface variables involved, viz., soil moisture, surface temperature, surface roughness, vegetation biomass and water content. However, given the limited extent of the data, we do not carry out such a combined retrieval, but, hold hope for such a method (and algorithm) through a future field experiment.

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