EVALUATION OF RADAR VEGETATION INDICES FOR VEGETATION WATER CONTENT ESTIMATION USING DATA FROM A GROUND-BASED SMAP SIMULATOR

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ABSTRACT

Vegetation water content (VWC) is an important component of microwave soil moisture retrieval algorithms. This paper aims to estimate VWC using L band active and passive radar/radiometer datasets obtained from a NASA ground-based Soil Moisture Active Passive (SMAP) simulator known as ComRAD (Combined Radar/Radiometer). Several approaches to derive vegetation information from radar and radiometer data such as HH, HV, VV, Microwave Polarization Difference Index (MPDI), HH/VV ratio, HV/(HH+VV), HV/(HH+HV+VV) and Radar Vegetation Index (RVI) are tested for VWC estimation through a generalized linear model (GLM). The overall analysis indicates that HV radar backscattering could be used for VWC content estimation with highest performance followed by HH, VV, MPDI, RVI, and other ratios.

Keywords: Vegetation Water Content, Microwave Polarization Difference Index, Radar, Radiometer, Vegetation Indices

1. INTRODUCTION

Microwave remote sensing has great potential in the monitoring and assessment of crop growth [1]. Among all frequencies, L band has been found to be found sensitive to vegetation growth and provides information on the entire canopy [2]. However, characterizing crop growth using a radar or radiometer for a range of system configurations is still a challenging problem requiring additional study.

In the past, the vegetation canopy has been characterized by biophysical variables such as vegetation water content (VWC) and biomass as well as indices based on optical remote sensing such as the normalized difference vegetation index (NDVI) and leaf area index (LAI) [3-5]. In this investigation, the relationship between L band radar and radiometer data for estimation of VWC is examined. The data utilized in this study were obtained from NASA's ground-based Soil Moisture Active Passive (SMAP) simulator known as ComRAD (Combined Radar/Radiometer) [6]. Several parameters, ratios, and indices are investigated in this study for estimation of VWC.

2. VEGETATION INDICES AND RATIOS

Several active and passive radar and radiometer parameters such as HH, HV, VV, Microwave Polarization Difference Index (MPDI), HH/VV ratio, HV/(HH+VV), HV/(HH+HV+VV) and Radar Vegetation Index (RVI) are used in the study to estimate VWC based on ComRAD radar and radiometer measurements. MPDI is computed following the equation given by Owe et al., in 2001 [7] (Eq.1):

$$MPDI = \frac{T_{bV} - T_{bH}}{T_{bV} + T_{bH}} \qquad (1)$$

where T_{bV} and T_{bH} are brightness temperatures for V and H polarizations, respectively. RVI can be calculated using the relationship (Eq.2) given by Kim et al., in 2012 [8]:

$$RVI = \frac{8\sigma_{HV}}{\sigma_{HH} + \sigma_{VV} + 2\sigma_{HV}} \qquad (2)$$

where σ_{HV} = cross-polarization backscattering cross section, and σ_{HH} and σ_{VV} = co-polarization backscattering cross sections represented in power units. RVI generally ranges between 0 and 1 and is a measure of the randomness of the scattering.

3. GENERALIZED LINEAR MODEL

The Generalized Linear Model (GLM) is used to build empirical relationships between radar/radiometer indices and VWC. It attempts to model the relationship between two variables by fitting a linear equation to the observed data. One variable is considered to be an explanatory or independent variable ($\boldsymbol{x}_i$), and the other is considered to be a dependent variable ($\boldsymbol{y}_i$). They are represented as

$$\boldsymbol{y}_i = \boldsymbol{x}_i\boldsymbol{b} + \boldsymbol{e}_i, \qquad (3)$$

where $i = 1, \ldots, n$,; y_i = dependent variable, $\boldsymbol{x}_i$ = vector of k independent predictors, $\boldsymbol{b}$ = vector of unknown parameters, and the e_i = stochastic disturbances. For a normal linear model there is an identity function ($\boldsymbol{x}_i\boldsymbol{b}$) of the mean parameter, while GLM is governed by some *link* function which is in this case *"identity"*.

4. 2012 FIELD EXPERIMENTS

The ComRAD system [9] is used in this study for L band active radar and passive radiometer datasets (Figure 1). It was developed by NASA GSFC in collaboration with George Washington University [10]. The main features of this instrument include a quad-polarized 1.25 GHz radar and a dual-polarized 1.4 GHz radiometer sharing the same 1.22-m parabolic dish antenna.

In 2012, a ComRAD field experiment was conducted over a growing season near NASA/GSFC in Greenbelt, Maryland at a USDA test site. In this detailed experiment, both radar and radiometer observations were measured over adjacent fields of corn and soybeans at a single incidence angle of 40° from nadir at both horizontal & vertical polarization (passive) and co-pol and cross-pol (active). Periodic measurements of VWC were also made during this experiment, which are used here for development of all the relationships and testing over the corn crop. Data from the soybean fields are not included in this study.

5. RESULTS AND DISCUSSION

5.1 Temporal trends and correlation in the datasets

The comparisons between VWC, radar backscatter and ratios, MPDI, and RVI are indicated in Figure 2. The time series of all the indices and ratios exhibit a high temporal variability with vegetation growth and follow closely the measured VWC. A minimum VWC was obtained during the period of June (very early stage of crop growth) whereas high VWC content was observed during the period of July and August months (time of peak biomass). A very close temporal pattern to measured VWC is exhibited by the HV radar channel followed by HH and VV radar backscatter. The temporal pattern revealed by MPDI and RVI also shows a similar trend to measured VWC. The backscatter ratios display a bit lower relationship with measured VWC than the vegetation indices and co-

Fig. 1. The ComRAD Microwave Instrument System

and cross-polarization backscatter. A poor trend is obtained in the case of HV/(HH+VV) followed by HH/VV and HV/(HH+HV+VV) ratios. Similar relationships were also confirmed from Pearson's correlation analysis. The highest correlation is obtained with HV backscatter (R = 0.73) followed by HH (R = 0.67) and VV backscatter (R = 0.63). In the case of RVI and MPDI, correlations of 0.58 and -0.63 respectively with the measured VWC were obtained. The other backscatter ratios -- HH/VV, HV/(HH+VV), and HV/(HH+HV+VV) -- had correlations of -0.43, 0.38 and -0.49, respectively, which are lower than the others.

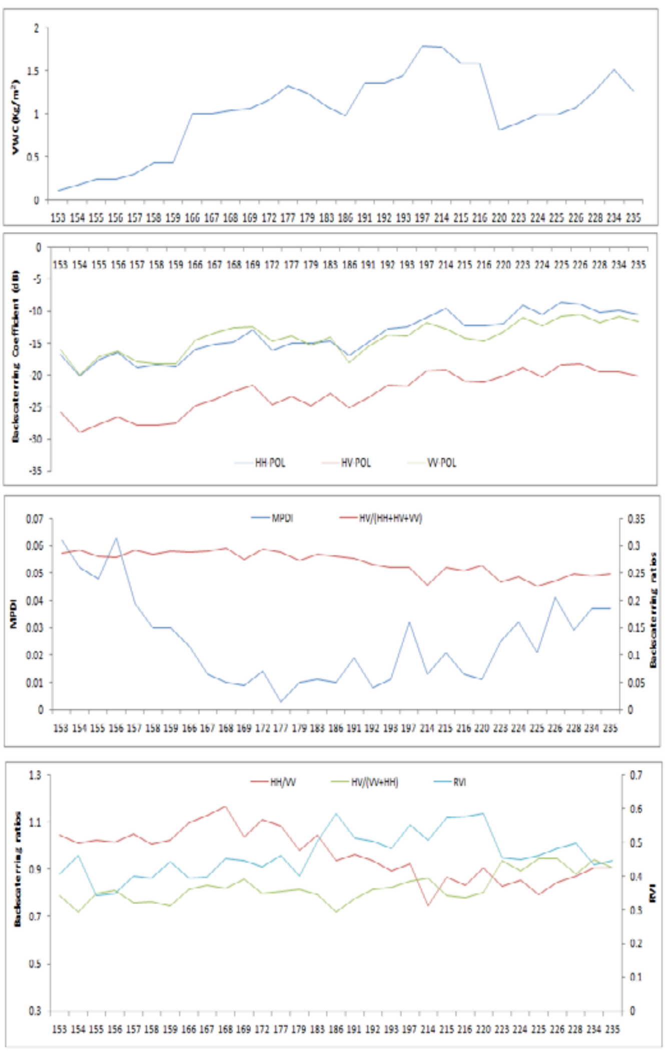

Fig. 2. Temporal variations in VWC, vegetation indices, radar backscatter, and ratios

5.2 Performance of the Generalized Linear Model

The Taylor diagram [11] is used here to show the ability of the GLM model for prediction of VWC through the vegetation indices and ratios obtained from the radar/radiometer datasets. The performance during validation is depicted in Figure 3. For estimating the performance of the GLM model, datasets are divided into two lots in which one is used for calibration while the other is used for the validation of the model. The circle mark on the *x*-axis, called the reference point, represents the perfect fit between algorithm results and data. The position of the other symbols, representing the results of the different runs, is determined by the values of the correlation *R* and of the standard deviation *(SD)* estimated from the measured and predicted VWC. The closer a symbol is to the reference point, the better is the performance of the given GLM model. The over/under estimation in the GLM model can be also indicated by the Taylor diagram: when the standard deviation of the simulated data is higher than that of the observed values, an overestimation can be predicted and vice versa.

The data in Figure 3 show that HV backscatter is giving high correlation and low standard deviation and root mean square deviation (RMSD), which indicate a better performance for predicting VWC than the other ratios or indices. The other two -- HH and MPDI -- are also found suitable for predicting VWC with some lower performance as compared to HV. The lowest performance is given by the HH/VV ratio. RVI and VV give a moderate performance for predicting VWC. Overall, this analysis indicates that radar backscatter is a promising approach for VWC estimation. However, additional research and analysis is needed to refine the approach to the point where radar-derived VWC is accurate enough to be used for soil moisture retrievals with the radiometer datasets.

Currently, baseline soil moisture retrieval algorithms for the SMAP mission utilize ancillary information for VWC derived from NDVI (Normalized Difference Vegetation Indices) from visible-infrared satellite sensors. The ability to eventually estimate VWC from the SMAP radar to the same level of accuracy as NDVI estimates would lessen the mission's reliance on ancillary data in the generation of its routine soil moisture products.

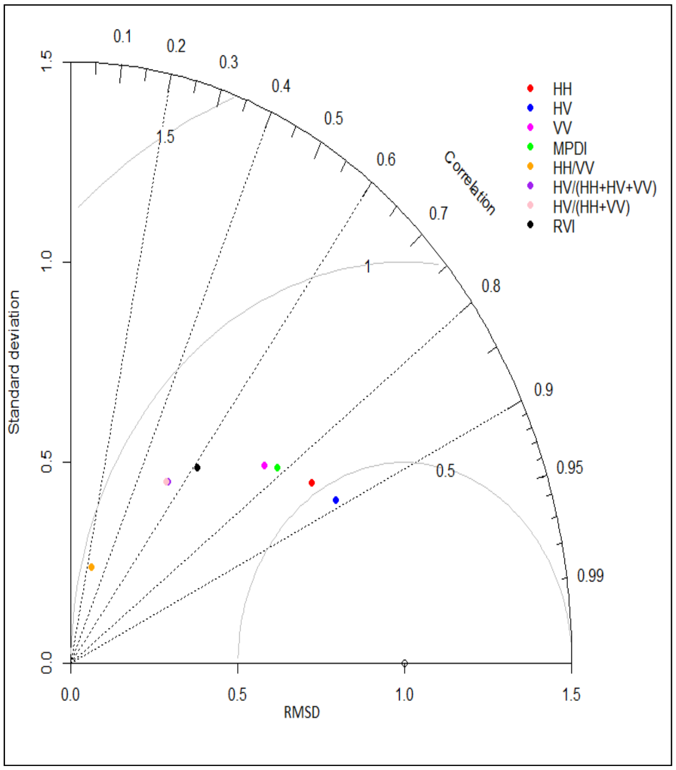

Fig. 3. Taylor diagram indicating performance during the validation

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