Vegetation Effects on Soil Moisture Estimation

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ABSTRACT

Several successful algorithms have been developed to estimate soil moisture of bare surfaces. We previously reported a new algorithm using the tilted Bragg approximation. However, these algorithms are only applicable to bare surfaces. When vegetation is present, soil moisture is typically underestimated by bare surface algorithms. In order to derive soil moisture under vegetation, we have to understand the complex scattering process due to vegetation. Our main interest is to retrieve the global soil moisture information using Hydros L-band polarimetric radar data. The Hydros mission will provide the first global view of land soil moisture using L-band radar and radiometer. The unique characteristics of the Hydros data are the availability of the low resolution soil moisture information from radiometer data and the continuous time series radar data collected at the same incidence angle. In this paper, we will examine a potential inversion algorithm to retrieve soil moisture under vegetation canopies using Hydros L-band polarimetric radar data.

I. INTRODUCTION

Soil moisture is a key parameter to understand the global water and energy cycle. The Hydros mission will use a combined radar/radiometer L-band instrument to measure the land hydrosphere state globally from space. Hydros will provide measurements with a global revisit of 2 to 3 days over a mission duration of 2 years. The baseline resolution of the final soil moisture product is 10 km for radar and 40 km for radiometer. Therefore, the baseline soil moisture algorithm should take advantage of the simultaneous radar/radiometer measurement and the continuous time series data.

For bare surfaces, several successful algorithms can be used to estimate soil moisture using polarimetric radar data by separating roughness and soil moisture effects [1,2,3]. Using the lower resolution soil moisture information from the Hydros radiometer, the radar soil moisture accuracy can be improved. The temporal variation can also be used to enhance the retrieved soil moisture accuracy.

For vegetated surfaces, we have to consider much more complex scattering mechanisms with numerous input parameters on the vegetation structure and dielectric constant [4,5]. In this paper, we study a vegetation model that includes four scattering components: 1) surface backscattering attenuated by vegetation, 2) branch scattering, 3) trunk-ground double bounce scattering, and 4) branch-ground double bounce scattering [6]. The soil moisture inversion algorithm depends on the level of biomass. We estimate the biomass level using a polarimetric parameter known as the radar vegetation index. For the low biomass case, soil moisture should be retrieved from the attenuated surface scattering component. For the high biomass case, the attenuated surface scattering component can be ignored. To measure soil moisture directly, the forward ground reflection component must be derived from the double bounce scattering by removing the branch scattering component. The lower resolution soil moisture information derived from the Hydros radiometer can be used to enhance the soil moisture estimation under vegetation canopies. The time variation in polarimetric radar measurements should also be used to improve the soil moisture estimation accuracy even further. Two external components that must be included in the time series analysis are precipitation and the diurnal effect.

In this paper, we first introduce a vegetation model that includes four scattering mechanisms. Then, we consider a potential soil moisture algorithms using the proposed vegetation model. The assumptions used in the algorithm will be briefly discussed. Finally, we conclude this paper by summarizing the results of our study.

II. A VEGETATION MODEL FOR SOIL MOISTURE ESTIMATION

A vegetation model that we propose in this paper is suitable for the L-band vegetation scattering and it is composed of four components: 1) surface backscattering attenuated by vegetation, 2) branch scattering, 3) trunk-ground double bounce scattering, and 4) branch-ground double bounce scattering. The attenuated surface scattering component is given by

$$\sigma_{hh}(1) = \exp(-2\alpha_h)\sigma_{hh}(s) \quad (1)$$

$$\sigma_{vv}(1) = \exp(-2\alpha_v)\sigma_{vv}(s) \quad (2)$$

$$\sigma_{hv}(1) = \exp(-\alpha_v - \alpha_h)\sigma_{hv}(s) \quad (3)$$

where S denotes surface scattering and α_p is the p-polarization one-way attenuation by a canopy layer.

The branch scattering is modeled by scattering from randomly oriented thin cylinders. The polarimetric response is determined by the branch orientation as shown in equations (4), (5), and (6).

$$\sigma_{hh}(2) = P_B \exp(-\alpha_h) \int_{-\pi/2}^{\pi/2} \sin^4 \phi\, f(\phi)\, d\phi \quad (4)$$

$$\sigma_{vv}(2) = P_B \exp(-\alpha_v) \int_{-\pi/2}^{\pi/2} \cos^4 \phi\, f(\phi)\, d\phi \quad (5)$$

$$\sigma_{hv}(2) = P_B \exp\left[-\frac{1}{2}(\alpha_h + \alpha_v)\right] \int_{-\pi/2}^{\pi/2} \cos^2 \phi \sin^2 \phi\, f(\phi)\, d\phi \quad (6)$$

where $f(\phi)$ is the branch orientation angle probability density function and P_B represents the branch scattering strength.

The trunk-ground double bounce scattering can be written as

$$\sigma_{hh}(3) = P_{TG} \exp(-2\alpha_h)|R_h(G)|^2|R_h(T)|^2 \quad (7)$$

$$\sigma_{vv}(3) = P_{TG} \exp(-2\alpha_v)|R_v(G)|^2|R_v(T)|^2 \quad (8)$$

where P_{TG} represents the trunk-ground scattering strength, $|R_p(G)|^2$ is the p-polarization (p=h or v) ground reflectance, and $|R_p(T)|^2$ is the p-polarization trunk reflectance. The ground reflectance includes the surface roughness attenuation and the ground tilt. The surface roughness attenuation is given by $\exp(-4k^2\langle h^2\rangle\cos^2\theta)$ where k is the wavenumber ($=\frac{2\pi}{\lambda}$) and $\langle h^2\rangle$ is the rough surface height variance.

The branch-ground double bounce scattering is given by

$$\sigma_{hh}(4) = 4P_{BG} \exp(-2\alpha_h)|R_h(G)|^2|R_{hh}(B)|^2 \quad (9)$$

$$\sigma_{vv}(4) = 4P_{BG} \exp(-2\alpha_v)|R_v(G)|^2|R_{vv}(B)|^2 \quad (10)$$

$$\sigma_{hv}(4) = P_{BG}|R_{hv}(B)|^2 < |\exp[j(a\gamma_h + b\gamma_v)]R_v(G) + \exp[j(a\gamma_v + b\gamma_h)]R_h(G)|^2 > \quad (11)$$

where P_{BG} represents the branch-ground scattering strength, $|R_{pq}(B)|^2$ is the p-polarization transmit, q-polarization receive branch bistatic reflectance ($p,q = h$ or v), γ_p is the p-polarization complex wavenumber ($= k_p + j\alpha_p$), and a+b=2 to represent the two-way canopy attenuation.

III. A SOIL MOISTURE RETRIEVAL ALGORITHM IN THE PRESENCE OF VEGETATION

The first step of the soil moisture estimation is a segmentation process based on the amount of biomass presented in each pixel. The parameter used for this segmentation is the radar vegetation index given by

$$RVI = \frac{8\sigma_{hv}}{\sigma_{hh} + \sigma_{vv} + 2\sigma_{hv}} \quad (12)$$

When the vegetation scattering is dominated by randomly oriented thin cylinders, the radar vegetation index becomes one. A pixel can include bare surfaces and various vegetation types. This is particularly true for Hydros since its final pixel size is 10km. For this inhomogeneous pixel case, the polarimetric covariance matrix can be written as

$$[C] = f[C]_{Surface} + (1-f)[C]_{Vegetation} \tag{13}$$

where f is the fraction of bare surfaces in a pixel. In this paper, we consider a homogeneous pixel (f=1 or 0) only.

For a bare surface pixel, we will use a bare surface algorithm. The low resolution soil moisture information from the Hydros radiometer can provide the additional constraint to improve higher resolution soil moisture derived from polarimetric radar data. For a pixel with modest vegetation that satisfies

$$0.2 < RVI < 0.4 \text{ and } \sigma_{vv} > \sigma_{hh}, \tag{14}$$

the vegetation attenuation must be estimated to apply the bare surface algorithm. For a pixel with significant vegetation (RVI> 0.4), the attenuated surface scattering component can be ignored. When the branch scattering component is a dominant cross-polarization source, σ_{hv} can be used to estimate the branch scattering strength. For Hydros, there are 16 radar pixels within one radiometer pixel. If we assume that 16 neighboring pixels have similar forest structures such as $f(\phi)$, the higher resolution soil moisture variation using radar data can be estimated under the constraint that the average soil moisture within 16 radar pixels must be the same as the radiometer soil moisture. This approach is only possible if there is sufficient double bounce scattering that interacts with the ground soil. If there is no double bounce component, we cannot measure soil moisture directly.

In order to improve the soil moisture accuracy, both temporal and spatial changes must be considered simultaneously. For the temporal variation, we must consider two external factors: precipitation and diurnal effect. To reduce the diurnal effect, soil moisture measurements will be made at the same local time. Precipitation events will be identified using radar data and other data sources. Except the precipitation effect on the tree dielectric constant, the main source of temporal variation of radar data is the soil moisture change. Therefore, the soil moisture variation can be estimated for each radar pixel. The retrieved soil moisture using time series data must be consistent with the soil moisture value derived from the spatial variation. This will provide an additional constraint to enhance the retrieved soil moisture accuracy.

IV. CONCLUSIONS

In this paper, we presented a vegetation model to estimate soil moisture under vegetation canopy. A potential soil moisture algorithm was discussed under several assumptions. We also considered additional constraints using radiometer measurements and time series data to enhance the soil moisture retrieval accuracy. The proposed method will be evaluated using numerical and experimental radar data.

ACKNOWLEDGMENT

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