Overview of Hydros Radar Soil Moisture Algorithm

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ABSTRACT

In this paper, we will describe the Hydros algorithms to derive soil moisture from L-band polarimetric radar measurements. The baseline Hydros radar algorithm to estimate soil moisture is composed of three steps: land classification, preliminary soil moisture estimation, and final time-series improvement. Before soil moisture is estimated using Hydros radar data, each pixel will be classified in order to apply a suitable soil moisture algorithm. Land cover types for this classification include bare surfaces, low vegetation areas, medium vegetation areas, forests, urban areas, water bodies, and mountain areas. We will also include a RFI (RF Interference) indicator to identify RFI contaminated areas. Then, a polarimetric soil moisture algorithm is applied to estimate preliminary soil moisture with the constraint imposed by Hydros radiometer data at lower resolution. Using time-series data, the preliminary soil moisture information will be improved for the final science product.

I. INTRODUCTION

The Hydros State Mission (Hydros) is a NASA (National Aeronautics and Space Administration) ESSP (Earth System Science Pathfinder) mission to provide exploratory global measurements of the earth's soil moisture and land freeze/thaw conditions. The mission data will be used for understanding processes that link the water, energy, and carbon cycles. The Hydros instrument is an integrated radiometer/radar instrument at L-band. The soil moisture information derived from L-band radar measurements will be used to derive the global soil moisture product at 10km resolution. The current Hydros launch date is September 2010.

The Hydros radar provides three polarimetric backscattering cross sections (σ_{hh}, σ_{vv}, and σ_{hv}). It is not a fully polarimetric radar since H- and V- polarization transmit signals do not have the same frequency in order to minimize the range ambiguity contamination. The bandwidth of the Hydros transmit signal is 1 MHz and two polarization transmit frequencies do not overlap. The exact radar frequencies will be determined later after we study RFI (Radio Frequency Interference) frequencies and the radar architecture.

The Hydros raw radar data will be processed to produce calibrated backscattering cross sections sampled at 1 km. This radar processing will be performed at the Hydros Radar Processing Facility provided by CSA (Canadian Space Agency). These backscattering data and the associate supporting data will be used to generate a global soil moisture map sampled at 3 km. Since we have to use a soil moisture estimation algorithm suitable for a specific land type, each pixel will be classified before soil moisture is retrieved from radar measurements. A snapshot algorithm is applied to estimate soil moisture using a single radar measurement. After Hydros radar data are accumulated for three months, we will start a time-series analysis. The amount of data to be accumulated for a time-series analysis depends on land types even though one-year data should be sufficient. In this paper, we describe three steps to retrieve soil moisture from Hydros polarimetric radar data.

II. LAND CLASSIFICATION

The Hydros Radar Processing Facility will produce Level 1C calibrated radar backscattering data. A typical single-look resolution of the Hydros radar data is 250m in the ground range direction and 400m – 1200m in the azimuth direction. Due to the relatively large pixel size, a usual SAR calibration process cannot be used. As an example, a corner reflector is too small to be used to calibrate the Hydros polarimetric data. Therefore, we will use distributed targets such as rain forests to calibrate the radar data. Since we do not have to measure the phase relationship between polarimetric channels, the calibration process is simpler than a typical polarimetric SAR system. For the calibration purpose, we can collect both σ_{hv} and σ_{vh}. Even though the H- and V- polarization transmit frequency is slightly different, we can use the reciprocity ($\sigma_{hv} = \sigma_{vh}$). Other airborne and space-borne polarimetric data over large homogeneous areas will be used to calibrate the Hydros data.

The first step in the soil moisture estimation process is the land classification. Land cover types considered for the Hydros classification process are bare surfaces, low vegetation areas, medium vegetation areas, forests, urban areas, water bodies, and mountain areas. The objective of this classification process is to identify an algorithm suitable for a specific land type. Low vegetation areas have biomass less than 0.2 kg/m^2. Medium vegetation areas have biomass higher than 0.2 kg/m^2 and the vegetation water content is less than 5 kg/m^2. For forest areas, the biomass is often too high to retrieve soil moisture reliably. However, time-series data can be used to estimate soil moisture especially when the double bounce scattering component dominates [1]. Using Hydros data, the biomass level will be estimated using *RVI* (Radar Vegetation Index) defined as

$$RVI = \frac{8\sigma_{hv}}{\sigma_{hh} + \sigma_{vv} + 2\sigma_{hv}} \tag{1}$$

Prior to the Hydros launch, all land areas will be classified at 1 km resolution using the MODIS/Terra land cover data, the SRTM data, and other data sets such as PALSAR and RADARSAT II data. Urban areas, permanent water bodies, and mountain areas are predetermined without using Hydros data. During the Hydros mission, water bodies are verified since the retrieved soil moisture for water bodies must be high. Transitory water bodies can be identified by large changes in soil moisture, the total backscattering cross section, and the co-polarization ratio (σ_{hh}/σ_{vv}). If the retrieved soil moisture value sharply increases or the total backscattering cross section decreases significantly in time, we can classify the area as potential transitory water bodies. If the area is covered by vegetation, the co-polarization ratio (σ_{hh}/σ_{vv}) becomes high due to the increased double bounce component when the area is inundated. It is difficult to estimate soil moisture of mountainous areas since local incidence angles within a pixel change significantly. The mountainous area will be identified using the SRTM data.

The Hydros radar instrument will measure the noise power by averaging the received power over the small frequency band outside of the transmit bandwidth. This noise bandwidth is close to the radar transmit frequency. If the measured noise power is much higher than the predetermined value, we will identify the pixel as a RFI contaminated pixel. Soil moisture will not be estimated if a pixel is identified as a RFI contaminated pixel.

III. SNAPSHOT SOIL MOISTURE ALGORITHMS

If a pixel is identified as bare surfaces or low/medium vegetation areas, we will estimate soil moisture using a single Hydros measurement to produce a snapshot soil moisture map. For bare surfaces and low vegetation areas (less than 0.2 kg/m^2), we will use a bare surface soil moisture algorithm. The current Hydros baseline is the algorithm developed by Dubois, van Zyl, and Engman [2]. Various algorithms [3,4] will be tested using experimental and simulated data sets to select the best bare surface algorithm before the Hydros soil moisture processor is finalized.

For medium vegetation areas, the soil moisture information from the Hydros radiometer will be used as a constraint at 40km resolution. Within a 40 km radiometer pixel, 1600 radar pixels exist. An algorithm will be developed using simulated vegetation scattering data [5,6] to derive soil moisture under vegetation. To retrieve soil moisture accurately, we need to separate two scattering components: vegetation scattering and surface (or vegetation-surface interaction) scattering. The vegetation dielectric constant change after a precipitation event is also an important factor. Therefore, the vegetation water content information can be used to understand the vegetation dielectric constant variation. Relative soil moisture will be estimated using co-polarization backscattering cross sections for a given biomass level. The biomass level will be estimated using the cross-polarization backscattering cross section. The proposed constraint is that the average value of estimated soil moisture using radar data over a radiometer pixel (40km x 40km) must be the same as the corresponding radiometer-based soil moisture. Mathematically,

$$\frac{1}{N_1}\sum_{n=1}^{N_1} m_v(n) + a\frac{1}{N_2}\sum_{m=1}^{N_2} m_v(m) = m_v(R) \tag{2}$$

where N_1 is the number of pixels that belong to bare surfaces and low vegetation areas and N_2 is the number of pixels for medium vegetation areas. After we estimate relative soil moisture for medium vegetation areas, the scale factor a is determined to satisfy equation (2). The radiometer soil moisture value is denoted by $m_v(R)$.

IV. TIME SERIES SOIL MOISTURE ESTIMATION

After the Hydros radar data are accumulated for three months, we will start a time-series analysis [7]. That is, using the knowledge on the time variation of backscattering cross sections, we can characterize the soil moisture effect on backscattering cross sections of each pixel in order to improve the retrieval accuracy. As an outcome of the time-series analysis, we will derive an expression for each pixel to related the backscattering cross section to soil moisture as

$$m_v = f(\sigma_{hh}, \sigma_{vv}) \quad (3)$$

Since this expression depends on the biomass level, the cross-polarization will be used to compensate the biomass variation over time. One obvious choice for f is given by

$$f(\sigma_{hh}, \sigma_{vv}) = C_1 + C_2 \frac{(\sigma_{hh} + \sigma_{vv})}{2} \quad (4)$$

Here, the co-polarization backscattering cross sections are expressed in dB. Two coefficients (C_1 and C_2) for each pixel will be determined using the expected minimum and maximum values for soil moisture and the time series backscattering cross section data. In order to include the nonlinear effect observed from simulated backscattering data, the second order term can be added to (4). Using ground radar data and numerical simulations, we will derive the final expression for the function $f(\sigma_{hh}, \sigma_{vv})$. The slowly varying backscattering cross section component due to the biomass variation must be estimated and compensated using the cross-polarization backscattering cross section. An example of a time-series processing will be presented.

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