Remote Sensing of Environment 206 (2018) 123–138

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Quantifying the relative contributions of vegetation and soil moisture conditions to polarimetric C-Band SAR response in a temperate peatland

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ARTICLE INFO

Keywords:
Radar
LiDAR
Surface roughness
Wetlands
Volumetric soil moisture
Monitoring

ABSTRACT

Effective modeling of many hydrological and climatological processes requires accurate spatial characterization of soil moisture, often over large regions and across different spatial scales. Synthetic Aperture Radar (SAR) has been shown to be sensitive to surface soil moisture, and is therefore a promising alternative to field data campaigns. However, the presence of spatially-variable vegetation and surface roughness also affect SAR backscatter. In this research, empirical models were developed to both predict soil moisture from SAR and assess the relationship between LiDAR-derived vegetation and surface conditions, and polarimetric SAR parameters in a vegetated peatland environment. Importantly, the low predictive strength of soil moisture models was only evident through a process of model cross-validation (bivariate regression R^2 ranged from 0.14 to 0.66 for fitted models and 0.05 to 0.41 for independently cross-validated models). The LiDAR-derived vegetation density was found to explain a large amount of variance in the SAR data, and models to predict soil moisture from SAR from only the least vegetated sites within the peatland demonstrated much higher predictive strength (R^2 = 0.11 to 0.71). Soil moisture within the vegetated and least-vegetated sites was not significantly different. Therefore, non-vegetated areas may be useful as representative imaging locations for remotely monitoring surface moisture conditions in large peatland complexes with heterogeneous vegetation.

1. Introduction

Effective modeling of many hydrological and climatological processes depends on accurate spatial characterization of soil moisture (Seneviratne et al., 2010). Peatland surface soil moisture conditions have been linked to greenhouse-gas (GHG) exchange from peatland surface and hence their potential role as net-GHG sources or sinks (Bubier et al., 2003). Due to their high organic content, dry surface conditions in peatlands are prone to wildfire, and monitoring of peatland soil moisture is becoming increasingly important as a way to reduce the loss of carbon stocks over large land areas (Turetsky et al., 2015). Moreover, current climatological models are parameterized using very limited observations of peatland soil moisture based on sparse, global monitoring networks. Thus, there is a critical need for synoptic, soil moisture datasets for peatland landscapes, derived from remote sensed imagery. Since remote peatlands are typically inaccessible areas with challenging terrain detailed, however, ground-based soil moisture datasets required to test remotely sensed soil moisture monitoring methods are difficult and expensive to acquire.

In general, the literature encourages the use of Synthetic Aperture Radar (SAR) for remote soil moisture monition due to its sensitivity to dielectric permittivity, which is directly related to the water content of a target (Ulaby and Batlivala, 1976; Ulaby et al., 1996). Extensive work has been conducted by Baghdadi, Zribi, Srivastava, among others and is well-documented in a review by Kornleson and Coulibaly (2013) with many examples of additional contributions since that publication (e.g. Wang et al., 2004; Zhang et al., 2016; Zribi et al., 2016; Baghdadi et al., 2016a). Throughout the literature many different sensors, wavelengths and techniques have been used. Importantly, most methods are being actively developed for agricultural landscapes (Merzouki et al., 2011; Paloscia et al., 2013) and have not been successfully operationalized for natural environments such as peatlands.

There are three main types of methods used to retrieve estimates of soil moisture from SAR: empirical, semi-empirical, physically-based models. Physically-based models are based on theoretical and approximate solutions of electromagnetic scattering from rough surfaces. Semi-empirical models are based on physics theory and model parameters are derived from experimental data (e.g. Oh, Dubois and IEM). These are commonly used in inversion of soil moisture from SAR data, but recently Chocker et al. (2017) and Baghdadi et al. (2011) found that these common models produced higher bias and lower predictive power in forward estimation of SAR backscatter from soil conditions than

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https://doi.org/10.1016/j.rse.2017.12.011
Received 17 August 2016; Received in revised form 12 October 2017; Accepted 8 December 2017

recently proposed, improved versions of these methods (e.g. IEM_B put forth by Baghdadi). Baghdadi et al. (2012a, 2012b) found that X band SAR resulted in a better relationship with soil moisture than C-Band SAR in bare agricultural fields, but numerous authors have also tested C, L and X band for soil moisture retrieval. For estimating soil moisture in vegetated environments, the semi-empirical Water-Cloud model has been used experimentally for decades (Beriaux et al., 2013). The model requires calibration measurements of vegetation and soil parameters (surface roughness and moisture content) and models the vegetation canopy as a "cloud" containing the vegetation's water content per unit volume (Ulaby, 1978). While advances have been made in using this technique to predict soil moisture in crop-specific agricultural landscapes, extending the Water-Cloud model to natural environments such as peatlands would require extensive calibration, which may be landscape or peatland-specific (Beriaux et al., 2013) and may require specific radar wavelengths.

Empirical modeling approaches involve the derivation of statistical relations between radar backscatter and soil moisture (Gala et al., 2011; Baghdadi et al., 2016a). It is commonly found that the relations derived at one location (or from one set of SAR images) must be recalibrated for other locations, due to differences in soil and vegetation characteristics between different sites (e.g. Merzouki et al., 2011). Empirical relations between SAR backscatter and field measured soil moisture have been analyzed in many landscapes, but data collection, modeling methods and reported results vary considerably (Table 1).

Several authors have reported strong relationships between SAR backscatter and measured soil moisture (see Table 1), including moderately strong relations in vegetated environments (e.g. Bourgeau-Chavez et al., 2007 reported correlation coefficients (r) of 0.7 to 0.8 in burned boreal forest). Others have applied machine learning techniques with variable results. Baghdadi et al. (2016b) used neural networks and found HH to be the most useful in estimating soil moisture within grasslands (maximum $R^2 = 0.43$), whereas Pasolli et al., 2011 used Support Vector Regression to predict soil moisture with good results (maximum $R^2 = 0.81$) in an alpine environment. However, most empirical analyses reported in the literature do not describe independent validation procedures, which are required to assess model transferability and to provide honest assessment of predictive strength when the model is applied outside of the spatial or temporal domain used for model fitting (i.e. predict soil moisture at new locations or through time; Table 1). Additionally, most studies have focused on the use of SAR intensity to estimate soil moisture (Table 1) but many SAR polarimetric parameters are easily produced from polarimetric SAR imagery and may provide information about vegetation and surface roughness (dependent on radar wavelength; Nolan and Fatland, 2003). Many SAR parameters have been tested empirically for there ability to predict soil moisture but these studies have been almost exclusively applied to unvegetated agricultural areas.

Vegetation strongly influences SAR backscatter and introduces major challenges for soil moisture retrieval in both agricultural and natural environments (Dubois et al., 1995; Ulaby, 1978; Shi et al., 1997; Moran et al., 2000; Salgado et al., 2001; Hajnsek et al., 2009; Jagdhuber et al., 2012; Di Martino, 2016; El Hajj et al., 2016). SAR systems are sensitive to vegetation, partly due to the geometrical properties of vegetation (e.g. distribution of scatterers within the vegetation canopy) and partly due to the vegetation water content. Vegetation structure and vegetation water content vary spatially as well as temporally. Surface roughness also affects the SAR signal, and as with vegetation, varies spatially and temporally. Typically, surface roughness in agricultural areas is measured in the field as the root mean square surface height (Mattia et al., 1997). Unlike agricultural fields where tillage and soil texture can vary greatly within a field and over time, in peatlands surface roughness temporally varies slowly (within one growing season there will be little to no change in surface roughness) and spatially surface roughness is rather homogenous within the different peatland classes.

Additionally, penetration into peat may reduce our ability to measure surface soil moisture with SAR. Depending on the wavelength (Nolan and Fatland, 2003), SAR may be sensing the surface of its target (i.e. the peatland) or, under the correct conditions, may be penetrating several decimeters. Longer wavelengths such as L-Band and P-Band allow penetration further into sediments than C-Band (Zribi et al., 2016) but this has not been examined in peat soils.

In vegetated environments, such as peatlands, accurate representations of vegetation and surface roughness are required in physical models, but to our knowledge have not been used in empirical models to aid in understanding the components that affect SAR backscatter. Many attempts to model soil moisture using SAR (empirically, semi-empirically or physically) have required extensive field calibration values which cannot be realistically repeated over large expanses (e.g. the large expanse of peatland in the James Bay Lowlands). Additionally, many methods rely on extensive measurements of vegetation height, density, structure and water content for calibration. While these methods have been shown to produce good results (e.g. Beriaux et al., 2013) they are often restricted to study areas where sites are easily accessible so that the true variability in soil moisture and vegetation can be captured, or where somewhat uniform vegetation exists (such as crops), neither of which are not the case of most of the peatlands in the world. Methods that do not rely on extensive field calibration are required to improve operational monitoring of soil moisture over large areas. In order to control for the effects of vegetation and surface roughness, such methods will most likely require use of ancillary remote sensing information such as high resolution topographic and vegetation derivatives from airborne Light Detection and Ranging (LiDAR) and aerial photogrammetry.

Discrete-return LiDAR provides high resolution information about topography, vegetation height and structure, and these data are now widely used for many applications including forestry, hydrologic modeling and wetland ecosystem classification. Due to the multiple returns recorded by most LiDAR systems, vegetation and ground returns are separable, and are easily manipulated to produce many different aspects of vegetation and surface characteristics such as surface roughness. LiDAR has been used extensively for mapping wetlands and peatlands and has been shown to accurately capture vegetation height (Hopkinson et al., 2005), leaf area index (Luo et al., 2015) and biomass (Boehm et al., 2013). However, LiDAR datasets normally represent static vegetation conditions from a single acquisition date which cannot capture vegetation changes throughout the growing season. Multispectral imagery such as Landsat provides moderate spatial and temporal resolution but, like all optical imagery, is affected by cloud cover. Moderate Resolution Imaging Spectroradiometer (MODIS) provides lower spatial resolution but higher temporal resolution, and therefore provides more chance to obtain a cloud free image. Vegetation indices can be computed from MODIS as composites over a defined time-period.

In this study, we tested whether LiDAR derivatives of vegetation and surface roughness as well as times series of MODIS vegetation indices may aid in understanding the influence of spatially variable vegetation and surface conditions in the SAR signal and could be integrated into empirical models to predict soil moisture model from SAR data. We used C-Band SAR to model soil moisture across a variety of peatland vegetation conditions in combination with single-date LiDAR and coarse-resolution, multi-date MODIS-derived vegetation information. Our methods focus on the use of empirical models (i.e. linear regression and CART) to model soil moisture from a variety of SAR parameters. First, we assessed several different polarimetric parameters for their usefulness in predicting soil moisture at sites with a variety of vegetation conditions. Next, using CART, we inverted our models and used a selection of LiDAR derivatives (vegetation and terrain roughness derivatives) to determine which vegetation and surface characteristics explained the most variability in the SAR data, and their potential interactions. In general, peatlands exhibit significantly more sparse