Int J Appl Earth Obs Geoinformation 72 (2018) 109–121

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

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

A model for downscaling SMOS soil moisture using Sentinel-1 SAR data

Junhua Li[a,*], Shusen Wang[a], Grant Gunn[b], Pamela Joosse[c], Hazen A.J. Russell[d]

[a] Canada Centre for Mapping and Earth Observation, Natural Resources Canada, 560 Rochester Street, Ottawa, Ontario, K1A 0E4, Canada
[b] Department of Geography, Environment and Spatial Sciences, Michigan State University, 673 Auditorium Rd, East Lansing, MI, 48823, USA
[c] Science and Technology Branch, Agriculture and Agri-Food Canada, 174 Stone Road West, Guelph, Ontario, N1G 4S9, Canada
[d] Geology Survey of Canada, Natural Resources Canada, 601 Booth Street, Ottawa, Ontario, K1A 0E8, Canada

A R T I C L E I N F O

Keywords:
Soil moisture
Downscaling
SAR
Sentinel
SMOS

A B S T R A C T

A model for downscaling SMOS (Soil Moisture Ocean Salinity) soil moisture products is developed by using multi-temporal dual-polarized (HH + HV) C-band SAR data. In this model, the effect of vegetation on soil moisture retrieval from SAR data is minimized by using the water-cloud model (WCM), in which vegetation contribution is quantified using the backscatter coefficient of HV polarization. The wavelet transform is used to fuse high resolution Sentinel-1A SAR backscatter with low resolution SMOS soil moisture, where the difference in spatial heterogeneity between scales is also accounted for. The influence of soil surface roughness is eliminated by using multi-temporal data. The multi-temporal SMOS soil moisture and dual-pol Sentinel-1/SAR data are the only inputs of this downscaling model. The model is tested in southern Ontario, Canada to downscale 40 km resolution SMOS soil moisture to 1.25 km and 2.5 km resolutions. The downscaled results show good agreements with the in-situ soil moisture collected in May and July of 2016 with an unbiased root-mean-square-error (*RMSE*) of 0.045 m^3/m^3 and 0.047 m^3/m^3 and a coefficient of determination (R^2) of 0.54 and 0.70 at 1.25 km and 2.5 km resolutions respectively. The results suggest that the model can be applied for C-band at regional scales to provide continuous soil moisture mapping at higher resolutions. The high revisit frequency of the up-coming Radarsat Constellation Mission (RCM) combined with its large areal coverage characteristics are ideal for the generation of downscaled products.

1. Introduction

Soil moisture is a key component in the water cycle. The retrieval of continuous soil moisture over a large area is important in the understanding and modelling of various applications such as hydrology, agriculture, meteorology, climatology, and flood forecasting (Baghdadi et al., 2008; Wagner et al., 2007; Wang et al., 2007; Wang, 2008; Munoz-Sabater et al., 2016). With high temporal and spatial variations, reliable soil moisture data over large areas is difficult to obtain from a sparse network of ground-based in-situ measurements. Although the problem is being addressed with the development of passive microwave remote sensing techniques, which can be used to obtain soil moisture from regional to global scales and at a temporal resolution of days, current passive microwave satellites in orbit, such as Soil Moisture Ocean Salinity (SMOS) and Soil Moisture Active Passive (SMAP), have coarse spatial resolutions (~40 km), which limit their soil moisture products in applications such as crop management, localized drought monitoring, and fine-scale water budget assessment and ecological modelling (Hanesiak et al., 2011; Wang et al., 2014a,b).

A number of studies have made attempts to downscale the coarse resolution of passive microwave soil moisture products by using optical/thermal data (Merlin et al., 2008; Srivastava et al., 2013; Piles et al., 2014). These studies developed several downscaling methods and have generated reliable soil moisture products at high spatial resolution. A characteristic of these methods is that they utilize multiple data sources and long-term records of the optical/thermal data (Peng et al., 2017). Because of the nature of optical sensors, however, these methods are constrained by several environmental factors, such as cloudy sky conditions, cloud shadows, haze, and smoke from wildfires, etc. An alternative approach for downscaling passive microwave soil moisture is through the use of high resolution Synthetic Aperture Radar (SAR) imagery. The greatest advantage of the SAR data is the high sensitivity to soil moisture with large contrast of the microwave relative permittivity between dry soil ($\varepsilon = 2–3$) and water ($\varepsilon = 80$) (Ulaby et al., 1986), and the ability of SAR signals to penetrate cloud, haze, and smoke; therefore, SAR is able to observe the earth's surface in all

* Corresponding author.
E-mail addresses: Junhua.Li@canada.ca (J. Li), Shusen.Wang@canada.ca (S. Wang), gunng@msu.edu (G. Gunn), Pamela.Joosse@agr.gc.ca (P. Joosse), Hazen.russell@canada.ca (H.A.J. Russell).

https://doi.org/10.1016/j.jag.2018.07.012
Received 7 May 2018; Received in revised form 5 July 2018; Accepted 6 July 2018
0303-2434/

weather conditions, day and night. The soil moisture retrieval from SAR, however, is highly affected by vegetation cover, soil surface roughness, and SAR parameters including wavelength, incidence angle, and polarization. In order to overcome these limitations of SAR observations on soil moisture retrieval, several algorithms, such as change detection methods (Njoku et al., 2002; Piles et al., 2009; Das et al., 2011; van der Velde et al., 2015) and a Bayesian merging method (Zhan et al., 2006), have been proposed to combine passive microwave data and SAR data to generate reliable high resolution soil moisture data.

Among various active-passive combined methods, the most often-used is the change detection algorithm. Change detection is based on the near linear relationship between SAR backscatter and volumetric soil moisture. It assumes the effect of vegetation and surface roughness on observed backscatter are consistent between acquisitions. The change detection method was first proposed by Njoku et al. (2002) for the retrieval of soil moisture from passive and active L-band system (PALS) imagery collected during the Southern Great Plains Experiment in 1999. Narayan et al. (2006) expanded the method to retrieve high resolution soil moisture by using the L-band PALS system passive data and airborne SAR (AIRSAR) data obtained from the Soil Moisture Experiment 2002 (SMEX02) over agricultural landscapes. Piles et al. (2009) further expanded the method by using it in an observation system simulation experiment (OSSE) to obtain significantly higher resolution soil moisture values with reduced retrieval uncertainties in comparison to using the passive microwave-only method. Das et al. (2011) continued in the development of the change detection algorithm and developed a new method, which was proposed as the baseline algorithm for the SMAP 9-km combined active/passive soil moisture product. The advantage of this baseline method is that it provides an absolute soil moisture rather than relative soil moisture change obtained by previous change detection methods.

The change detection algorithms either assume scale-invariance of spatial heterogeneity (Piles et al., 2009) or introduces new scale-invariant parameters for describing spatial heterogeneity (Das et al., 2011, 2014). However, natural homogeneity within a passive microwave image pixel (e.g. SMOS/SMAP) rarely exists and the heterogeneity changes as the image's resolution changes. The heterogeneity of backscatter variability at a specific resolution cannot be inferred to similarly represent other resolutions. Therefore, it is very important to account for the spatial heterogeneity in the downscaling process. The issue of heterogeneity at variable scales could be resolved by using wavelet transform in the downscaling process. Wavelet transform is a powerful technique for fusing one image of high spatial resolution with another of lower spatial resolution in remote sensing discipline, to adequately characterize spatial heterogeneity across scales.

Most of these change detection algorithms were developed using L-band SAR data since the low frequency penetrates further through vegetation/soil than C-band and X-band, and can minimize the effect of vegetation canopy and surface roughness. The L-band SAR that was deployed in SMAP, however, stopped transmitting in July 2015. Currently, ALOS-2/PALSAR is the only long wavelength (L-band) SAR sensor in orbit. Since its data is less frequently acquired especially for regions outside Japan, the use of ALOS-2/PALSAR is considerably restricted for operational soil moisture retrieval, especially in North America. Sentinel-1A, Sentinel-1B and Radarsat-2, which are C-band SAR satellites currently in orbit, can provide routine observations of Earth's surface over large areas, especially in Canada. Radarsat Constellation Mission (RCM) will further expand the availability of current C-band SAR satellite observations, and significantly improve revisit capabilities. C-band has a short wavelength (~ 5.6 cm wavelength) that exhibits backscatter signal interaction from both the vegetation canopy and soil. Soil moisture retrieval using C-band needs accurate characterization of vegetation and surface roughness (Gherboudj et al., 2011). Therefore, the existing change detection algorithms may be problematic when C-band SAR is used, especially considering these algorithms assume vegetation is unchanged between acquisitions. This may invalidate change detection algorithms (even with L-band SAR data) for cropland regions where the land surface vegetation varies rapidly over periods as short as several days (i.e. during the growing season).

A number of SAR backscatter models have been proposed to separate the backscattering contributions of soil and vegetation (Ulaby et al., 1986; Oh, 2004; Zribi et al., 2005; Bai and He, 2015). These models are generally categorised into three groups: theoretical, empirical, and semi-empirical. The theoretical models, such as the Integral Equation Model (IEM) and the advanced IEM model (Fung and Chen, 1992; Fung, 1994), are complicated and require a large number of parameters. On the other hand, the empirical models are simple to develop but may have limitations in applicability for other sites due to their data and site dependency (Zribi et al., 2005; Gorrab et al., 2014). The semi-empirical models begin with a physical basis and then use simulated or experimental datasets to simplify the theoretical backscattering models (Petropoulos et al., 2015). The semi-empirical Water Cloud Model (WCM), which simulates the backscattering coefficient (HH or VV polarizations) as a function of soil properties (moisture and roughness) and vegetation properties (e.g. biomass, leaf area index), is often used to separate vegetation from soil backscatter contributions due to its simplicity. However, WCM's performance relies on the characterization of surface roughness and vegetation. Various vegetation descriptors such as plant height, leaf area index (LAI), vegetation water mass, and normalized difference vegetation index (NDVI) have been used in quantifying vegetation parameters in the WCM (Bai and He, 2015). These vegetation descriptors either come from in-situ measurement or optical satellite sensors. The use of in-situ measured vegetation parameters, however, makes it difficult for operational purposes due to the cost and logistic constraints, especially in remote areas. On the other hand, the use of remote sensing vegetation parameters from optical satellite sensors is limited by the weather conditions such as cloud and haze. Our recent study showed that C-band SAR HV backscatter can be used as an alternative to optical image derived vegetation parameters in the WCM for soil moisture retrieval. This makes it possible to use parameters derived from SAR data alone to characterize vegetation in the WCM.

The objective of this study is to produce high resolution soil moisture by downscaling coarse resolution SMOS soil moisture using high resolution C-band Sentinel-1 SAR data. In this study, we propose a downscaling model, in which WCM is used to minimize the influence of vegetation on soil moisture retrieval for C-band SAR data and wavelet transform is used to account for spatial heterogeneity across scales. The downscaling model is a further development of the change detection algorithm, assuming that surface roughness remains stable for a specific period of time. The downscaling model also addresses the aforementioned problems of existing downscaling algorithms including that they are: 1) not applicable to C-band SAR with respect to soil moisture retrieval, and 2) not suitable for crop lands where vegetation changes rapidly. This study would provide a practical tool for operational mapping of soil moisture at high resolution over large areas by using SMOS/SMAP satellites and future SAR missions such as RCM.

2. Methodology

In this section, we first briefly introduce a simplified WCM and the wavelet transform, which are used in the downscaling model, and provide details about the downscaling model. This is followed by the brief description of the methods for model validation.

2.1. Simplified water-cloud model (WCM)

The water-cloud model, initially developed by Attema and Ulaby (1978), considers the vegetation canopy as a cloud containing water droplets randomly distributed within the canopy. It provides solutions for the backscattering coefficients for the vegetation canopy as well as