EVALUATION OF SOIL MOISTURE RETRIEVALS FROM ALOS-2, SENTINEL-1 DATA IN GENHE, CHINA

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ABSTRACT

High-resolution soil moisture dataset is crucial for various application such as meteorology, climatology, hydrology and agriculture. Active microwave remote sensing sensors like radar provide earth observations at high spatial resolutions. This study based on physical model simulations (Advanced Integral Equation Method, AIEM, and Water Cloud Model, WCM) combined with the Artificial Neural Networks to investigate the potential of the ALOS-2 and Sentinel-1 radar images for estimating soil moisture at high spatial resolution. The results shows that the statistical parameters of the relationships between estimated and measured soil moisture, expressed in terms of R, bias, and RMSE, are 0.834~0.861, 0.005~0.037m^3m^{-3} and 0.047~0.062m^3m^{-3} for ALOS-2, and 0.733~0.896, 0.018~0.028m^3m^{-3} and 0.032~0.070m^3m^{-3}, for Sentinel-1. In densely vegetated area, RMSE significant increases, due to the limited penetration ability of L and C bands in high vegetation areas.

Index Terms**—** soil moisture, ALOS-2, Sentinel-1, ANN

1. INTRODUCTION

Soil moisture is the key parameter in the processes of water and energy interchange between the atmosphere and land surface [1]. High spatial resolution of soil moisture have a widespread application in meteorological climate forecast, hydrological modeling and agricultural irrigation [2-4]. Microwave remote sensing provides a flexible alternative to capture regional soil moisture. Passive microwave remote sensing with satellite-based retrieval can provide soil moisture data sets for large areas. However, it have coarse spatial resolution (10km~40km) and limited in many applications. Active microwave remote sensing like spaceborne radar provide observations at high spatial resolutions and the backscattering coefficient is sensitivity to soil moisture, especially at low microwave frequencies[1, 5].

The possibility of using radar to obtain soil moisture estimate at high spatial resolution has been widely studied in the past. Several algorithms are available for soil moisture retrievals using radar, including statistical methods [6, 7], Change detection [8, 9] and forward model inversion models (Artificial Neural Network (ANN), Bayes' approach) [10, 11] and so on. However, the retrieval methods mentioned above are mainly applied to bare or sparsely vegetated surfaces. For densely vegetated areas, the retrieval methods need further improvements.

Given the high spatial sampling and the operational configuration of Sentinel-1 (C-band) and Advanced Land Observing Satellite-2 (ALOS-2, L-band), they are expected to make significant contributions to the operational monitoring of dynamic hydrological processes. In this work, the research for the retrieval of soil moisture has been focused on the potentials of Sentinel-1 and ALOS-2. The predictions of the ANN were slightly more suitable than the other methods for generating maps in reasonable time [4]. Therefore, in this paper, firstly, we built the simulated database based on the Advanced Integral Equation Method (AIEM) and Water Cloud Model (WCM). Secondly, with the result of the sensitivity analysis, we selected the simulated data and used the ANN to get optimal training results. Finally, basing on Sentinel-1 and ALOS-2 SAR backscattering coefficient, vegetation index from Sentinel-2 and Landsat-8 and training results, we retrieved the soil moisture on site at 30m resolution. The validation results can be used as a reference for soil moisture inversion methods in the future.

2. STUDY AREA AND DATA

2.1. Location/Environment Conditions

Genhe area has a cold and humid temperate forest climate and a continental monsoon climate at the northernmost and coldest area in Inner Mongolia. An *in situ* measurement experiment was conducted in Genhe area (in Figure 1) and it as part of a network of experiments designed to enhance the dynamic analysis and modeling remotely sensed information for complex land surfaces[12].

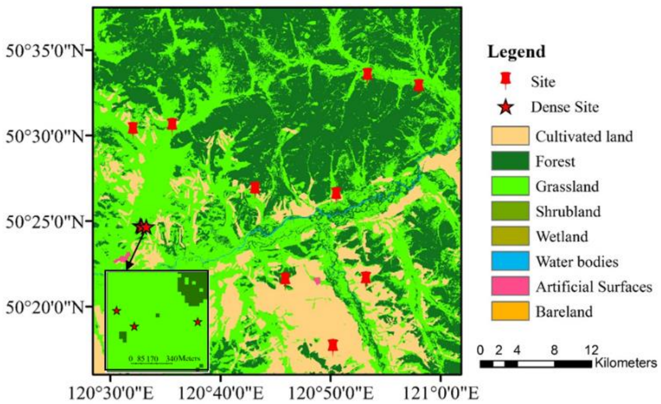


Figure 1. Land cover in Genhe area

2.2. Data

2.2.1. Soil moisture network

As shown in Figure 1, the soil moisture *in situ* sites are located on both sides of Genhe area (50.1°-50.6° N, 120.5°-121.0° E). The land cover data in Figure 1 is from GlobeLand30 (http://glc30.tianditu.com/index.html) with 30m spatial resolution. Soil moisture and soil temperature were continuously measured via Em50 data collection system with EC-5TM probes (Decagon Devices, Inc., Washington, USA) from 15 July 2015 to 23 September 2016. The depth of soil moisture and soil temperature observation is 3 cm, 5 cm and 10 cm with every 30 minutes. Considering the penetration power at C band and L band, we have selected the soil moisture and soil temperature at 0-5 cm soil depth to validate the soil moisture retrievals.

2.2.2. Sentinel-1

The Sentinel-1 mission is the European Radar Observatory for the Copernicus joint initiative of the European Commission and the European Space Agency (ESA). The payload is C band Synthetic Aperture Radar (SAR), the repeat cycle at Equator with one satellite is 12 days[13]. This study used Level 1 ground range detected high-resolution standard products with VV and VH polarization in interferometric wide swath mode from Copernicus Open Access Hub. The details as shown in Table 1. All of the Sentinel-1data was pre-processed using the SNAP and Sentinel-1 Toolbox. Considering the spatial resolution of other satellite data, the last step is resampling to 30m.

2.2.3. ALOS-2

The ALOS-2 follow on mission from the "DAICHI", it was developed by Mitsubishi Electric Corporation under contract to JAXA. ALOS-2 launched on 24 May 2014, revisit time is 14 days. The state of the art Phased Array type L-band Synthetic Aperture Radar-2 (PALSAR-2) aboard ALOS-2, which is an active microwave radar using the 1.2GHz frequency range [14]. This study used Level 1.5 data with fine mode dual polarization (HH, HV) products with right looking from Earth Observation Data Utilization Promotion Platform. All of the ALOS-2 data were pre-processed using ENVI and SNAP Toolbox like Sentinel-1. The date of the selected ALOS-2 data corresponds to Sentinel-1.

2.2.4. Sentinel-2

The Copernicus Sentinel-2 mission comprises a constellation of two polar-orbiting satellites placed in the same sun-synchronous orbit, Sentinel-2A (launched on 23 June 2015) and Sentinel-2B (launched on 07 March 2017). It have high revisit time (10 days) at the equator with one satellite [15]. Sentinel-2 has a high spatial resolution, therefore, this work selected Sentinel-2A Level 1C data (from Copernicus Open Access Hub) to calculate NDVI with formula: (Bnad8-Ban4)/(Band8+Band4). It should be noted that all of the Sentinel-2A data was pre-processed with atmospheric correction and resampling 30m using the Sentinel-2 Toolbox. Details of the data as shown in Table 1.

2.2.4. 5) Landsat 8

Landsat 8 was developed as a collaboration between National Aeronautics and Space Administration (NASA) and the U.S. Geological Survey (USGS), and it was launch on 11 February 2013. The satellite carries the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) and has a 16-day repeat cycle [16]. Sentinel-2 has no data at Genhe area in 2015, therefore, we chose Landsat 8 to calculate vegetation index in 2015. This work used Landsat 8 OLI/TIRS C1 Level 2 data from USGS to calculate 30m NDVI with formula: (Bnad5-Ban4)/(Band5+Band4). Details of the data as shown in Table 1.

Table 1. Satellite data information

Satellite	Acquisition date	Spatial resolution	resampling
Sentinel-1	07/18 2015 09/18 2015 07/12 2016 09/22 2016	10m	30m
ALOS-2	07/172015 09/25 2015 07/15 2016 09/23 2016	10m	30m
Landsat 8 (band5, band4)	07/05 2015 09/07 2015	30m	30m
Sentinel-2 (band8, band4)	07/19 2016 09/30 2016	10m	30m

3. METHODS

ANN can significantly reduce the computational time during the prediction phase provided a sufficiently robust and representative set of samples is used during the training[4]. AIEM improves the calculation accuracy of scattering coefficient by keeping the absolute phase term in Greens function, which was neglected by IEM on bare surface[17]. Water Cloud Model (WCM), which is characterized by a rather simple implementation, simulates the backscattering of vegetated surfaces as a function of the soil backscattering and the vegetation index [18]. In view of these advantages, this study selected the AIEM and WCM models, together with ANN method for estimating surface soil moisture from Sentinel-1 and ALOS-2 images. The flow chart of soil moisture retrieval is represented in Figure 2.

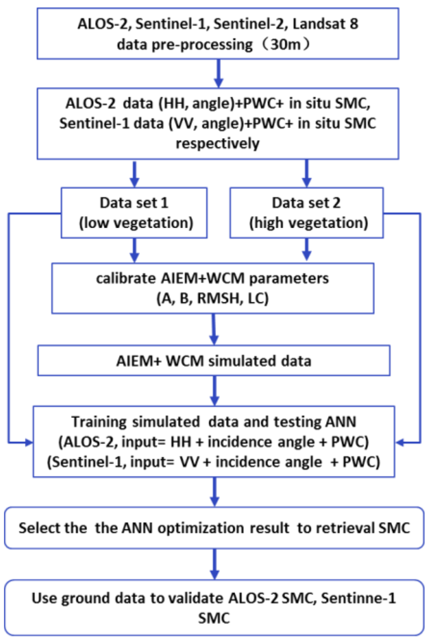


Figure 2. The flow chart of soil moisture retrieval algorithm (RMSH: Root Mean Square Height; LC: correlation length; PWC: Plant Water Content)

As shown in Figure 2, PWC is calculated from NDVI data as follows[19]:

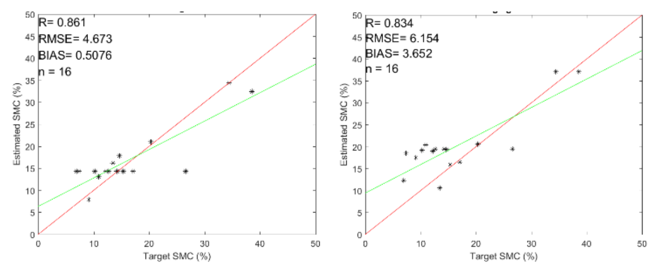
$$PWC = (1.9134 * NDVI^2 - 0.3215 * NDVI) + \text{stem factor} * \frac{NDVI_{\max} - NDVI_{\min}}{1 - NDVI_{\min}} \quad (1)$$

NDVI is derived from Sentinel-2 and Landsat 8; stem factor is associated with different land cover types, the value of stem factor is derived from [19]. NDVImax is the annual maximum NDVI at a given location. NDVImin is to the annual minimum NDVI at a given location [19].

4. RESULTS

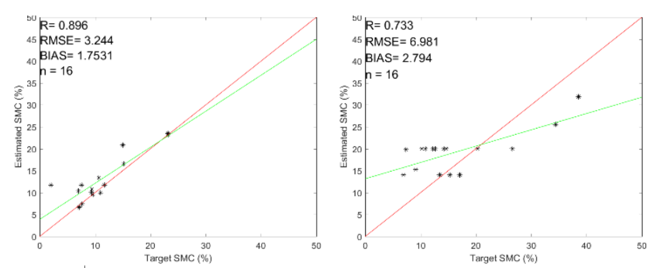
The results of soil moisture retrievals through ALOS-2 and Sentinel-1 data are compared with the in situ soil moisture data in Figure 3 and Figure 4. The results shows that the statistical parameters (R, bias, and RMSE) of ALOS-2 soil moisture retrieval in low and high vegetated areas are 0.861 / 0.005m^3m^{-3} / 0.047m^3m^{-3}, 0.834 / 0.037m^3m^{-3} / 0.047m^3m^{-3}, respectively. The R, bias, and RMSE of Sentinel-1 soil moisture retrieval in low and high vegetated areas are 0.896/0.018m^3m^{-3}/0.032m^3m^{-3}, 0.733/0.028m^3m^{-3}/0.07m^3m^{-3}, respectively.

It can be observed that the accuracy of ALOS-2 and Sentinel-1 soil moisture retrievals in low vegetated area (grass, shrub, crop) is higher than the one retrieved in densely vegetated area (birches and larix gmelinii), and that the accuracy of Sentinel-1 soil moisture retrieval in high vegetated areas is lower than the one of ALOS-2. This is due to the higher frequency of Sentinel-1 (C-band) which is lees able to penetrate the densely vegetated surfaces with respect to the longer wavelength of ALOS-2 (L band). However, the accuracy of Sentinel-1 soil moisture retrieval in low vegetation area is higher than ALOS-2. These results also show that both C band and L band can satisfy the inversion accuracy of surface soil moisture in low vegetated areas and L band does not show significant advantages with respect to Sentinel-1 in Genhe.



(a) Low vegetation (b) High vegetation

Figure 3. Validate the ALOS-2 soil moisture retrievals



(a) Low vegetation (b) High vegetation

Figure 4. Validate the Sentinel-1 soil moisture retrievals

5. CONCLUSION AND DISCUSSION

This paper is based on WCM and AIEM simulations, and applies ANN method to Sentinel-1 and ALOS-2 SAR data and retrieve the on-site soil moisture at 30m spatial resolution. The results indicate that the accuracy of ALOS-2 and Sentinel-1 soil moisture retrievals on low vegetated lands is higher than the one obtained on high vegetated lands, and that the accuracy of ALOS-2 soil moisture retrieval on densely vegetated lands is higher than the one of Sentinel-1. These results are related to the better performance of ALOS-2 wavelength and polarization mode, whereas the penetration ability of Sentinel-1 C-band in forest areas is limited. Actually, forestland is mainly covered by artificial forest farm and the percentage of virgin forest is not very high. Meanwhile, the precision of soil moisture retrieval is affected by the accuracy of the simulated data and by the results of ANN training. Moreover, the fact that Landsat 8 and Sentinel-2 images are not completely cloud-free is also a factor influencing the retrieval results. This paper only inverts the soil moisture of the site; however, in future works, we will plan to optimize the method and the simulated data set to improve the accuracy of soil moisture retrievals and obtain soil moisture maps.

6. ACKNOWLEDGEMENTS

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