Postprint: Remote Sensing Retrieval of Surface Soil Moisture Along the Beihei Expressway Using Sentinel-1A and Landsat 8 Data

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Abstract

Soil moisture content is a fundamental parameter affecting hydrological and climate change, and studying its distribution holds important practical significance and scientific value for climate change, water resource distribution, and crop yield estimation. This study, based on dual-polarization synthetic aperture radar imagery from Sentinel-1A (Sentinel-1) acquired on June 21, 2015, combined with concurrent auxiliary optical imagery from Landsat 8, conducts a retrieval study of soil moisture content under complex land surface conditions with different vegetation coverage levels in the area along the Bei' an-Heihe Expressway, and investigates the soil moisture retrieval results of different polarization combination methods under various land use types. The results indicate that the retrieval accuracies of VH polarization and the combination of VH with the auxiliary variable NDVI (Normalized Difference Vegetation Index) are 52.1% and 53.6%, respectively, with overall unsatisfactory performance. VV polarization (VV Polarization) imagery and the dual-polarization VV/VH (VH Polarization) combination demonstrate greater advantages for retrieval in bare and low-vegetation areas, with accuracies of 75.4% and 59.5%, respectively, but are not applicable in high vegetation coverage areas. In the VH polarization retrieval results, the soil moisture content in cropland is 9.37% lower than the actual value; VV polarization yields soil moisture content in low-vegetation areas that is 10.45% lower than the actual value; in shrubland and cropland areas, the VV/VH retrieval results show lower accuracy than single-polarization and its combination retrieval results; the highest-accuracy retrieval is achieved by VV combined with NDVI. The combination of VV with the auxiliary variable NDVI can comprehensively reflect soil moisture content under complex land surface environments, achieving an accuracy of 84% and a root mean square error (RMSE) of 2.07, which represents an 8.8% improvement in retrieval accuracy over VV polarization and a reduction in RMSE of 2.704 compared to VV polarization. The VV and auxiliary variable NDVI combination method demonstrates greater advantages for soil moisture retrieval in moderate vegetation coverage areas and can better exploit the potential and effectiveness of Sentinel-1 C-band synthetic aperture radar in soil moisture research.

Full Text

Preamble

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Soil Water Content Retrieval Based on Sentinel-1A and Landsat 8 Image for Bei' an-Heihe Expressway

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Abstract

Soil water content (SWC) is a fundamental parameter affecting hydrological variability and climate change. Investigating SWC distribution holds important practical significance and scientific value for understanding climate change, water resource distribution, and crop yield estimation. This study analyzed soil moisture conditions of complex surfaces with varying vegetation cover along the Bei' an-Heihe Expressway using Sentinel-1A dual-polarization Synthetic Aperture Radar (SAR) imagery from June 21, 2015, combined with concurrent Landsat 8 optical imagery as auxiliary data. The research explored soil moisture retrieval results under different polarization combinations across various land use types. Results showed that VH polarization alone and VH combined with NDVI (Normalized Difference Vegetation Index) achieved retrieval accuracies of 52.1% and 53.6%, respectively, which were unsatisfactory overall. VV polarization and dual-polarization VV/VH ratio demonstrated advantages in bare and low-vegetation areas, with accuracies of 75.4% and 59.5%, respectively, but proved unsuitable for high-vegetation-cover regions. VH polarization underestimated soil moisture in cultivated land by 9.37% compared to actual values, while VV polarization underestimated soil moisture in low-vegetation areas by 10.45%. In shrub and cultivated land areas, VV/VH dual-polarization performed worse than single-polarization methods. The highest accuracy was achieved by combining VV polarization with NDVI. The VV+NDVI combination comprehensively reflected soil moisture in complex surface environments, achieving an accuracy of 84% with a root mean square error (RMSE) of 2.07. This represented an 8.8% improvement in accuracy over VV polarization alone and a 2.704 reduction in RMSE. The VV+NDVI combination showed particular advantages for soil moisture retrieval in moderately vegetated areas and better leveraged the potential and effectiveness of Sentinel-1A C-band SAR for soil moisture research.

Keywords: Sentinel-1A; Soil water content; Backscattering coefficient; Polarization; Support vector regression

Introduction

Soil water content (SWC) is a fundamental parameter affecting hydrological and climate change processes, serving as a critical link between surface water and groundwater and representing a basic element in surface energy exchange studies. In climatology, variations in SWC influence soil hydrothermal processes, altering surface parameters and consequently affecting climate change. In ecology, SWC plays a vital role in material and energy transformation within the soil-vegetation-atmosphere continuum, directly impacting ecosystem composition. Therefore, investigating SWC distribution holds significant practical and scientific value for climate change analysis, water resource management, ecological degradation processes, and crop yield estimation.

Current remote sensing methods for SWC retrieval primarily include three categories: visible light, thermal infrared, and microwave remote sensing. Microwave remote sensing is widely applied in SWC estimation due to its high sensitivity to soil moisture and its ability to operate unaffected by clouds or darkness. In recent years, bare surfaces have typically been monitored using physical-empirical models such as the Oh model and Dubois model, though these require field measurements for calibration. In low-vegetation-cover areas, semi-empirical models like the Shi model and Water Cloud Model are commonly applied, yet SWC in vegetated areas remains underestimated. For high-vegetation-cover regions, the bidirectional scattering from vegetation canopies attenuates soil backscatter effects, necessitating the use of the Michigan Microwave Canopy Scattering (MIMICS) model and its variants (e.g., Bi-MIMICS). However, these models involve overly complex parameters that limit practical application. Research indicates that combining microwave remote sensing data with optical vegetation indices for SWC retrieval allows optical data to calculate vegetation biophysical parameters, better accounting for vegetation effects. Although domestic and international studies have employed various methods for different vegetation cover conditions, a comprehensive yet simple approach for complex surfaces remains lacking.

This study selected the area along the Bei' an-Heihe Expressway as a case study region. Influenced by global climate change, this area features degrading island permafrost remnants from ancient glacial deposits, resulting in fragmented and complex surface environments. The Water Cloud Model was applied to extract soil backscatter coefficients under different polarization conditions from Sentinel-1A SAR imagery, while optical imagery served as auxiliary data to extract NDVI for complex surfaces. The study compared retrieval accuracies and applicability among different polarization and optical parameter combinations using the Support Vector Regression algorithm, providing new insights for SWC retrieval in various vegetation cover conditions and offering a scientific basis for SWC monitoring in high-latitude permafrost regions.

1.1 Study Area Overview

The study area extends along the Bei' an-Heihe Expressway (127°17 31 E–127°31 24 E, 49°30 57 N–49°41 50 N), located in the northwestern part of the Xiaoxing' anling Mountains in Heilongjiang Province [Figure 1: see original paper]. Situated in the transition zone between high-latitude permafrost and seasonal frozen soil regions, the area exhibits typical periglacial landforms with island permafrost active layer thickness of approximately 1.8 m. Valleys, low-lying river terraces, shady slopes, and wetlands provide suitable conditions for island permafrost development, which reaches maximum depth in May (2.26–2.67 m). The thawing period extends from June to September, with freezing occurring from October to the following May, primarily concentrated in valleys and shady slopes. The terrain consists of river valley sections dominated by hills, floodplains, cultivated land, and marshland. The climate is characterized as alpine mountainous, with mean annual temperature of -2 to 1 °C, annual precipitation of 500–600 mm, annual sunshine of 2,500 hours, and frost-free period of approximately 90 days. The Hongse Bianjiang Farm Second Branch is located within the study area, where cultivated land is distributed on slopes and along river valleys, primarily growing wheat (*Triticum aestivum*). Dominant vegetation types include forest vegetation (coniferous-broadleaf mixed forest) and meadow vegetation (tussock meadow, peat moss), with predominant species being *Betula platyphylla*, *Tilia tuan*, *Xylosma racemosum*, *Larix gmelinii*, and *Populus* spp.

1.2 Data Sources and Processing

The SWC retrieval process involved SAR imagery, MODIS data products, Landsat 8 OLI data, DEM data, and land cover type maps. Data resolution, sources, and applications are summarized in .

TABLE:1 Dataset list of soil water content inversion along the Bei' an-Heihe Expressway

Data Type	Resolution (m)	Application	Data Source
Sentinel-1A SAR image	5 × 20	Extracting backscattering coefficients	European Space Agency
MOD11A1 daily LST product	-	Calculating empirical values of sample points	NASA
DEM	-	Geocode of SAR images	International Scientific Data Service
Landsat 8 OLI image	-	Calculating NDVI	USGS
Land cover map	-	Overlay analysis	Global Land Cover Download Center

1.2.1 Sentinel-1A Imagery and Processing Methods The newly launched Sentinel-1A satellite by the European Space Agency plays a significant role in dynamic SWC monitoring through multiple imaging modes. This study utilized S1 TOPS-mode SLC data in Interferometric Wide (IW) mode, which addresses scalloping effects in wide-swath SAR imaging and enhances radiometric performance, enabling more precise backscatter coefficient extraction. The data were acquired on June 21, 2015, in C-band (0.055466 m) with 250 km swath width, 5 m × 20 m resolution, and dual-polarization (VH and VV). The imagery was right-looking descending orbit, appearing left-right inverted. GAMMA software was employed for preprocessing, geocoding, and backscatter coefficient extraction:

1. **Preprocessing**: The Interferometric SAR Processor (ISP) module performed preprocessing. Radiometric calibration and denoising were applied based on original TIFF files, XML metadata files, calibration files, and noise files to correct phase offsets and interferometric parameter biases [Figure 2a: see original paper]. Multi-look image mosaicking was then conducted by setting range and azimuth looks to generate multi-look images from single-look complex data [Figure 2b: see original paper].

2. **Geocoding**: Differential interferometry and geocoding (DIFF & GEO) were performed, including initial lookup table generation, image registration, and lookup table refinement to obtain geocoded backscatter images and DEM in SAR coordinates. Using SAR echo delay range and Doppler centroid frequency, coordinates (x, y, z) in the inertial coordinate system were derived through the range-Doppler positioning equation. Pixel offset correction was applied using existing DEM imagery [Figure 2c: see orig-

inal paper] to obtain final geocoded SAR images [Figure 2d: see original paper].

When < 33.548°, the backscatter coefficient model can be expressed as: °( ) = ···[equation appears incomplete in original]. The backscatter intensity was linearly converted to dB scale to obtain the study area backscatter image [Figure 2e: see original paper].

FIGURE:2 Sentinel-1A data extraction processing of backscattering coefficients
a: SLC radiometric calibration; b: MLI mosaic; c: DEM heights in SAR geometry coordinate system; d: SAR geocoding image; e: Backscatter image.

1.2.2 Soil Moisture Sample Data Due to lack of field measurements, 0–10 cm soil moisture sample data were calculated using the Heilongjiang June temperature difference vegetation thermal inertia empirical model, which achieved 97.15% accuracy. The multiple linear model is:

0.32 NDVI [equation appears incomplete]

where represents soil water content (%), calculated from MOD11A1 land surface temperature products on June 21, 2015; NDVI is the Normalized Difference Vegetation Index derived from Landsat 8 near-infrared and red bands on June 16, 2015. Based on the land cover map, sample points were uniformly distributed across different land cover types (shrubland, grassland, and cultivated land) and slopes, totaling 71 sample points [Figure 1b: see original paper].

1.3 Methods

1.3.1 Soil Backscatter Coefficient Extraction Soil moisture, surface roughness, and vegetation jointly influence backscatter coefficients, establishing a nonlinear relationship between SAR backscatter and SWC. Vegetation type and canopy structure also affect backscatter coefficients, making it difficult to retrieve soil moisture under high vegetation cover. To establish the relationship between soil backscatter coefficients and SWC, multi-mode (multi-frequency, multi-polarization, multi-incidence angle) microwave data were combined with auxiliary data (optical remote sensing, surface parameters) to extract relevant coefficients for model development.

1. **Single-polarization (VV/VH) combined with NDVI**: This approach employs appropriate microwave vegetation scattering theory models to quantitatively estimate the proportion of surface scattering in total scattering. The Water Cloud Model, based on radiative transfer theory, accounts for vegetation cover distribution and calculates soil background backscatter coefficients under vegetation cover using the

relationship between vegetation volume scattering and attenuated surface scattering combined with NDVI. The expression is:

°( ) = °_veg( ) + ²( ) °_soil( ) [equation appears fragmented in original]

where °( ) is the total backscatter coefficient, °_veg( ) is vegetation scattering coefficient, °_soil( ) is soil background backscatter coefficient, ²( ) is vegetation two-way attenuation factor (transmissivity), is incidence angle, and A and B are empirical constants dependent on vegetation type and electromagnetic wave frequency.

The study area includes cultivated land, grassland, and sparse shrubland, primarily growing wheat. Due to cultivation constraints, ground vegetation parameter measurements were impractical. Bindlish et al.' s Water Cloud Model parameters for different land cover types were adopted , with comprehensive land use settings of A = 0.0012, B = 0.091. For vegetation water content (VWC), Jackson's C-band crop and vegetation parameters were used, calculated through the empirical model:

$$VWC = 1.9134NDVI^2 - 0.3215NDVI$$

where VWC is vegetation water content and NDVI is the Normalized Difference Vegetation Index. Based on these formulas, soil backscatter coefficients for VV and VH polarizations were extracted after removing vegetation effects, providing reasonable parameters for subsequent SWC retrieval.

TABLE:2 Vegetation parameter values of different land use types in the semi-empirical model

Parameter	All land-uses	Grassland	Winter wheat	Pasture
A	0.0012	-	-	-
B	0.091	-	-	-

2. **Dual-polarization (VV+VH)**: This approach uses statistical methods to establish relationships between dual-polarization scattering characteristics and measured SWC. For example, linear depolarization ratio PR_vv/vh can be used for SWC retrieval, or dual-polarization coefficients can be applied through subtraction (°_vv - °_vh). This study utilized Sentinel-1A dual-polarization imagery to extract backscatter values from VV and VH channels separately while calculating the dual-polarization backscatter coefficient depolarization ratio. Extracting backscatter coefficients from dual-polarization images for surface parameter retrieval can reduce heterogeneity impacts, as each polarization corresponds to distinct surface characteristics useful for discriminating land cover types, soil conditions, and vegetation status, thereby improving retrieval accuracy.

1.3.2 Soil Water Content Retrieval Model The Water Cloud Model can extract soil backscatter coefficients after removing vegetation canopy and trunk scattering effects. When vegetation exceeds a critical volume, attenuated ground scattering gradually decreases. Vegetation canopy optical thickness also affects soil moisture content, prompting the inclusion of NDVI as an auxiliary variable to correct SWC values in vegetated areas. Support Vector Regression (SVR) has been increasingly applied in SWC estimation due to its advantages in accurate estimation, ease of use, good generalization capability, and ability to handle nonlinear problems. SVR transforms the nonlinear relationship between soil backscatter coefficients (°_vv or °_vh), NDVI, and SWC into a linear problem in high-dimensional feature space to find the optimal classification hyperplane. The core expression is:

$$f(x) = \Sigma(a_i K(x, y_i)) + b$$

where a_i represents sample values, b is the constant term, and K(x, y) is the radial basis kernel function that maps data to high-dimensional space:

$$K(x, y) = \exp(- ||x - y||^2)$$

where   is the decay rate parameter controlling how quickly soil moisture values approach zero.

Using the methods in Section 1.3.1, soil backscatter coefficients were extracted and combined with ground SWC sample data and terrain data to establish a spatial soil moisture database. Fifty-six samples were selected as training data and fifteen as test data for SVR modeling. Based on corresponding model parameters, preprocessed SAR and NDVI data were used for parameter extraction. Single-polarization inputs included VV, VH, VV+NDVI, and VH+NDVI, while dual-polarization input used PR_vv/vh. The SVR model calculated regional SWC, followed by accuracy verification. The optimal polarization combination was selected as the final SWC retrieval result, which was then analyzed with auxiliary data including DEM, soil maps, and land use maps.

Results

2.1 Soil Moisture Retrieval Results Under Different Polarization Modes

Soil backscatter coefficients were extracted using the semi-empirical Water Cloud Model, and the SVR algorithm was applied to retrieve SWC under different polarization modes. Results were reclassified into five categories: 0-10%, 11-15%, 16-25%, 26-30%, and 30-50%, generating spatial distribution maps of SWC [Figure 3: see original paper].

The results showed substantial differences among polarization modes. VH polarization retrieval [Figure 3b: see original paper] yielded consistently low values, while VH+NDVI combination [Figure 3d: see original paper] produced overall high values. VV polarization, VV+NDVI combination, and dual-polarization retrieval showed more consistent spatial distributions. Most SWC values in the study area ranged between 10–25% [Figure 3c: see original paper]. Areas with 0–10% SWC occurred in exposed regions near highways with significant human disturbance and on sunny slopes with steep gradients affected by terrain and solar radiation. Areas with 11–15% SWC were mainly distributed in southwestern and northern grasslands, idle farmland, and unvegetated field ridges. Areas with 16–25% SWC were primarily sparse shrubland, where SWC was mainly influenced by vegetation transpiration and terrain conditions. Cultivated land SWC mostly concentrated in 25–30% range, located on first-level terraces near floodplains with low vegetation cover and high values due to irrigation. Areas with 30–50% SWC during the cultivation season were located in low-lying floodplain regions with marshland presence. Overall, the regional SWC conditions were favorable for crop growth.

2.2 Retrieval Accuracy Under Different Polarization Modes

Under the SVR algorithm, goodness-of-fit (R^2) and root mean square error (RMSE) for different polarization retrievals are listed in , with accuracy validation shown in [Figure 4: see original paper]. For single-polarization fitting, VV polarization achieved R^2_vv = 0.754, while VH polarization yielded R^2_vh = 0.521, indicating VV polarization was more sensitive to SWC retrieval in single channels. Dual-polarization R^2_vv/vh = 0.595, representing a 0.074 improvement over VH polarization. After incorporating NDVI vegetation parameters, retrieval accuracy improved. The best polarization combination was VV+NDVI, achieving R^2 = 0.842 and RMSE = 2.071, representing an 8.8% accuracy improvement over VV polarization alone and a 2.704 reduction in RMSE. In summary, selecting appropriate backscatter parameters and effective auxiliary parameters is crucial for addressing limitations of single polarization. Validation accuracy [Figure 5: see original paper] showed the goodness-of-fit ranking: R^2_vv+ndvi > R^2_vv > R^2_vv/vh > R^2_vh+ndvi > R^2_vh. Therefore, the VV+NDVI combination was selected as the final SWC map.

TABLE:3 Inversion precision of soil water content in different polarization ways

Support Vector Regression	R^2	RMSE
VV	0.754	-
VH	0.521	-
VV+NDVI	0.842	2.071
VH+NDVI	-	-
VV/VH	0.595	-

2.3 Applicability Analysis

2.3.1 Single-Polarization Retrieval Applicability In [Figure 3a: see original paper], high SWC values were distributed around floodplains, followed by grassland and shrubland. In shrubland areas, SWC values were 10.45% lower than measured values [Figure 6: see original paper] due to vegetation' s bidirectional reflection and transmission characteristics forming a non-Lambertian structure, where soil backscatter represents attenuated ground scattering unsuitable for high-vegetation-cover areas. VH polarization results [Figure 3b: see original paper] underestimated SWC in shrubland and cultivated land, particularly in floodplain cultivated areas where values were 9.37% lower than actual. Based on linear relationships between soil backscatter and sample SWC, sensitivity diagrams were generated [Figure 5: see original paper]. Since cross-polarization VH backscatter intensity is lower than co-polarization VV, VH sensitivity is reduced, making VH polarization generally unsuitable for SWC retrieval.

Given VV polarization' s limitations in high-vegetation areas and VH polarization' s underestimation in cultivated land, single-polarization imagery cannot comprehensively reflect SWC in complex surface cover conditions. After adding NDVI as an auxiliary variable, VH+NDVI results [Figure 3d: see original paper] showed overall overestimation, particularly in grassland areas where values were 6.62% higher than actual. Although NDVI improved sensitivity in low-vegetation areas, it showed low sensitivity in high-vegetation regions. In contrast, VV+NDVI results were closer to true values across different surface conditions, as NDVI corrected VV polarization' s sensitivity to moisture in vegetated areas. This combination performed well overall.

SWC retrieval is related to land cover types, with values decreasing from grassland to cultivated land. Suitable polarization modes for grassland were VV polarization and VV+NDVI combination, differing from true values by 2.05% and 0.95%, respectively [Figure 6: see original paper]. Cultivated land concentrated near floodplains with high SWC due to irrigation, representing low-vegetation-cover areas where VV polarization and VV+NDVI were also applicable. Shrubland represents moderate vegetation cover where single-polarization with NDVI better expressed vegetation characteristics, with VV+NDVI showing advantages over VH+NDVI [Figure 6: see original paper]. In summary, VV+NDVI combination provided the most comprehensive SWC retrieval for the region.

2.3.2 Dual-Polarization Retrieval Applicability Due to strong correlation between VV and VH polarizations providing redundant information, using dual-polarization backscatter coefficient ratio (VV/VH) as retrieval parameters can address data correlation issues. However, [Figure 3e: see original paper] shows that depolarization ratio VV/VH retrieval accuracy was lower than VV or VH alone in low-lying and grassland areas, differing from true values by 3.93% [Figure 6: see original paper]. In shrubland and cultivated land, performance was similarly unsatisfactory as single-polarization methods, with differences of 11.01% and 9.61%, respectively [Figure 6: see original paper]. The ratio processing actually decreased retrieval accuracy due to data correlation, indicating that ratio methods cannot fully resolve dual-polarization data correlation. VV/VH dual-polarization is unsuitable for vegetated areas but relatively reasonable for low-vegetation or bare soil regions.

In conclusion, comparative analysis of different polarization modes revealed that VV/VH dual-polarization and VV polarization are suitable for bare and low-vegetation areas, while VV+NDVI combination is more applicable for moderate-vegetation-cover regions than single polarization. Given overall environmental complexity, VV+NDVI combination best comprehensively reflected regional SWC.

Conclusions and Discussion

Based on European Space Agency Sentinel-1A satellite imagery and Support Vector Regression algorithm, this study compared different polarization methods for SWC retrieval and applied them to the Bei' an-Heihe Expressway region. Key conclusions include: VV polarization is advantageous for bare land retrieval but is strongly absorbed by vegetation layers, making it unsuitable for moderate-vegetation-cover areas; VH polarization is less effective than VV polarization; dual-polarization depolarization ratio performs better in low-vegetation areas such as grassland and pasture but cannot be applied to high-vegetation-cover regions; VV+NDVI combination most comprehensively retrieved SWC for complex surfaces, leveraging Sentinel-1A C-band SAR polarization characteristics.

Different polarization combinations affect microwave remote sensing retrieval of SWC in vegetated areas differently. VV polarization reflects vertical information well but yields low backscatter coefficient values in vegetated areas, resulting in underestimated retrieval values. Introducing NDVI as a vegetation correction parameter can express the nonlinear vegetation-soil relationship more accurately. VH cross-polarization contains both vertical and horizontal information, with horizontal information being more suitable for bare surfaces, consistent with findings by Bindlish et al. and Pasolli et al. regarding different polarization SAR SWC retrieval. SVR accurately retrieves nonlinear relationships among SWC parameters but requires substantial computational memory and time for large-scale applications. This study only considered optical thickness from vegetation indices without incorporating other vegetation indices or related factors. Future research should integrate regional characteristics to comprehensively consider different vegetation indices, various SAR incidence angles, and meteorological factors affecting surface moisture to further improve SWC models.

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Note: Figure translations are in progress. See original paper for figures.