Using Single-Frequency Dual-Polarization GNSS-R Based on Airborne GLORI Data to Retrieve Soil Moisture

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Abstract

In Global Navigation Satellite System - Reflectometry (GNSS - R) studies, polarization was once overlooked. However, in recent years, it has attracted growing attention. This paper focuses on exploring dual polarization for single - frequency data from the airborne GLORI experiment. Based on theoretical analysis, several retrieval algorithms for soil moisture estimation were applied. Initially, only the surface reflectivity of Left - Right (LR) and Right - Right (RR) polarizations was examined. As additional surface parameters, such as surface roughness and vegetation, were integrated into the algorithm, the retrieval accuracy, measured by RMSE, improved significantly from approximately 0.07 to 0.03. The retrieval accuracy of RR polarization is slightly better than that of LR polarization. Nevertheless, when both dual polarizations were considered, the retrieval accuracy was comparable to that of using only one polarization. When surface roughness, Leaf Area Index (LAI), and incidence angle are taken into account, the retrieval accuracy, indicated by RMSE, reaches 0.0344. This clearly demonstrates the great potential of dual polarization in soil moisture estimation. GLORI data is the first publicly available dual - polarization GNSS - R data that encompasses both coherent and non - coherent scattering. This paper further discusses the non - coherent scattering properties of LR and RR polarizations. In the context of coherent scattering, it is found that the scattering properties at LR polarization are stronger than those at RR polarization. Conversely, for non - coherent scattering, the scattering properties at LR polarization are weaker than those at RR polarization for corresponding land surface types. The analysis of dual - polarization data will contribute to future data mining for more accurate soil moisture retrieval and the design of future polarization GNSS - R payloads. The retrieval accuracy considering non - coherent scattering properties implies that both coherent and non - coherent scattering should be incorporated into future GNSS - R data sets, as they are comparable for future soil moisture retrieval algorithms.

Full Text

Abstract

In Global Navigation Satellite System Reflectometry (GNSS-R) studies, polarization was once overlooked but has recently attracted growing attention. This paper explores dual-polarization capabilities using single-frequency data from the airborne GLORI experiment. Based on theoretical analysis, we applied several soil moisture retrieval algorithms, initially examining only the surface reflectivity of Left-Right (LR) and Right-Right (RR) polarizations. As additional surface parameters such as surface roughness and vegetation were integrated, retrieval accuracy improved significantly, with RMSE decreasing from approximately 0.07 to 0.03. The RR polarization achieved slightly better accuracy than LR polarization. However, when both dual polarizations were considered together, retrieval accuracy remained comparable to single-polarization results. When surface roughness, Leaf Area Index (LAI), and incidence angle are incorporated, the RMSE reaches 0.0344, demonstrating the great potential of dual polarization for soil moisture estimation.

The GLORI dataset represents the first publicly available dual-polarization GNSS-R data encompassing both coherent and non-coherent scattering. This paper further discusses the scattering properties of LR and RR polarizations, revealing that coherent scattering is stronger at LR polarization than RR polarization, while the opposite holds for non-coherent scattering. Analysis of dual-polarization data will contribute to future data mining for more accurate soil moisture retrieval and inform the design of next-generation polarimetric GNSS-R payloads. The retrieval accuracy achieved by considering non-coherent scattering properties implies that both coherent and non-coherent components should be incorporated into future GNSS-R datasets, as they are both valuable for soil moisture retrieval algorithms.

Introduction

Over the past three decades, GNSS-R has established itself as a critical and pioneering remote sensing technique. The increasing number of in-orbit GNSS satellites has expanded the availability of incident signal sources, enhancing GNSS-R mission networks and promising significant improvements in spatial and temporal resolution.

The era of spaceborne GNSS-R missions for Earth remote sensing began with the United Kingdom Disaster Monitoring Constellation (UK-DMC), which demonstrated the potential of such missions. Surrey Satellite Technology Ltd. (SSTL), the developer of UK-DMC, later launched UK TDS-1, which while primarily designed for ocean surface measurements, also collected land surface reflected signals, showcasing capability for retrieving Earth surface geophysical parameters. In December 2012, NASA' s CYGNSS—an eight-satellite constellation with $±$38° spatial coverage—was launched to monitor pan-tropical cyclones. Subsequent research revealed that its land surface reflected signals could detect near-surface soil moisture, forest biomass, flood inundation, and soil freeze/thaw status. Later missions including WINSAT-1R, Bufeng 1-A/B, UK DoT-1, and FSSC further advanced the field. In July 2021, China’ s FengYun 3E was launched with the GNOS-R payload—marking the first globally covering GNSS-R instrument capable of ocean parameter detection and soil moisture freeze/thaw monitoring. Scheduled for 2024, the HydroGNSS mission will feature both left-hand circular polarization (LHCP) and right-hand circular polarization (RHCP) antennas, enabling dual-polarization analysis to improve soil moisture retrieval accuracy and mitigate vegetation effects.

While spaceborne missions have laid the foundation, airborne GNSS-R provides indispensable complementary capabilities. Airborne platforms enable high-resolution observations over heterogeneous terrains and controlled experiments to decouple surface effects, supporting algorithm validation and development. Recent airborne campaigns highlight unique contributions. For instance, Carreno-Luengo et al. utilized the Rongowai airborne mission to validate polarimetric GNSS-R’ s ability to detect inland waters under dense vegetation, directly informing future small satellite designs like HydroGNSS. Building on this, Zribi et al. analyzed copolarized (Γ_{RR}) and cross-polarized (Γ_{RL}) reflectivity variations over Spain’ s Urgell agricultural site using GLORI data, developing an empirical model for 100-m resolution soil moisture mapping that underscores the role of polarization in precision agriculture. Further reinforcing these findings, Jia and Savi demonstrated the sensitivity of polarimetric ratios to soil moisture and vegetation through multi-terrain airborne campaigns, establishing a foundational framework for dual-polarization retrievals that bridges theoretical models with operational applications. This developmental trajectory highlights polarization as a pivotal factor in future GNSS-R advancements.

Polarization, defining the electric field vector orientation of electromagnetic waves, endows signals with unique properties. GNSS satellites emit right-hand circularly polarized (RHCP) signals whose polarization state changes upon surface reflection, encoding information about surface characteristics like roughness, vegetation, and moisture. While early GNSS-R research focused on specular reflection using delay-Doppler maps (DDM), complex terrestrial surfaces dominated by diffuse scattering challenge this approach. Recent studies indicate that non-coherent scattering properties have gained increased interest for retrieval algorithms. In GNSS-R soil moisture remote sensing, polarization offers critical advantages: comparing reflected signal parameters under different polarizations enables more accurate soil moisture estimation and distinguishes scattering mechanisms, facilitating better understanding of processes and development of precise surface scattering models. Given the scarcity of spaceborne dual-polarization data, this paper leverages airborne GLORI data—the first providing comprehensive GNSS-R observables including reflectivity and incoherent component signal-to-noise ratio (SNR) relative to total scattering for copolarized (right-right) and cross-polarized (right-left) measurements—to demonstrate dual polarization' s potential for soil moisture retrieval. By focusing on single-frequency dual-polarization retrieval algorithms that account for non-coherent scattering properties, this work aims to establish their value for enhancing retrieval accuracy.

Theoretical Methods and Data Description

A. Dual Polarization Reflectivity

For an ideal smooth surface, reflectivity is determined by the Fresnel reflection coefficient and polarization mode. The Fresnel reflection coefficients for horizontal and vertical polarizations are as follows:

While is the incidence angle and is the complex dielectric constant, these equations demonstrate the Fresnel reflectivity for H and V polarization states, respectively. For perfectly smooth surfaces, the cross-polarization term can be disregarded. In the case of GNSS signals, the satellite transmission signal is RHCP, which can be interpreted as a linear combination of horizontal and vertical polarization components.

The equations for LR polarization reflectivity, provided below, demonstrate that it is a linear combination of the Fresnel reflectivity for vertical and horizontal polarizations.

For bare soil, the surface reflectivity (SR) can be expressed as:

where SR is the surface reflectivity, q is the incidence angle, and is the dielectric constant.

Meanwhile, Wu et al. have developed random rough surface models for GNSS-R polarization studies. They proposed the LAGRS models for land surface parameter studies, with an important component for bare soil analysis. To support future polarization GNSS-R payloads, random surface scattering models including RR polarization have been incorporated. The scattering models in LAGRS-Soil can calculate scattering properties at various polarizations, as shown in Figure 1. The figure illustrates that scattering properties vary across different polarizations. While specular reflectivity is encompassed within LAGRS-Soil' s calculation capabilities, this paper' s retrieval algorithm development will use scattering properties calculated from both the Fresnel equations and LAGRS-Soil.

For surfaces covered with vegetation, the ultimate surface reflectivity should be reduced by the vegetation layer according to:

where SR is the surface reflectivity, τ is the vegetation opacity, k is the free space wavenumber, s is the rms height, and is the incidence angle at specular directions.

B. Data Description

To the best of our knowledge, this marks the first instance where a comprehensive dataset of GNSS-R observables—including reflectivity and incoherent component SNR relative to total scattering for copolarized (right-right) and cross-polarized (right-left) measurements—has been made publicly accessible.

The GLORI campaigns were conducted in Catalonia, Spain, specifically over the Urgell region, which includes an agricultural area with two distinct components. The first segment relies on intensive irrigation, drawing water from the Pyrenees via the Urgell canal. The second segment comprises rain-fed agriculture and grassland. Land cover and in situ measurement locations are illustrated in Figure 2.

The airborne dataset was derived from raw data collected during three flights using the French research ATR-42 aircraft in July 2021 (flights 45, 46, and 47, conducted on July 22nd, 27th, and 28th, respectively) over the Urgell site.

Figure 3 shows histograms of surface reflectivity for LR and RR polarizations. Surface reflectivity at LR polarization is slightly higher than at RR polarization, with mean values of -11.98 dB and -18.83 dB, respectively. The dynamic ranges are -21.19 dB for LR and -30.13 dB for RR polarization. Histograms for RMS height, LAI, and soil moisture content are depicted in Figure 4. Given that RMS height is crucial for soil moisture correction and LAI provides vegetation parameter insights, both require correction during retrieval. Statistical details for these parameters are provided in Table 1. The mean RMS height is 0.84 cm (mode: 0.91 cm). For LAI, mean and mode values are 1.34 and 0.49, respectively. Both mean and mode soil moisture content values are 0.23 cm^3/cm^3.

The workflow for data processing and retrieval algorithms, including surface scattering, volume scattering, and dual-polarization analysis, is summarized in Figure 5.

Soil Moisture Retrieval

Since spaceborne GNSS-R payloads are typically single-polarized (using LHCP antennas to capture surface-reflected signals), LR polarization has been traditionally used to extract geophysical parameters. This section presents the retrieval algorithm for single-frequency single polarization, followed by the dual-polarization algorithm and a comparative analysis.

Artificial intelligence techniques offer new perspectives for addressing complex Earth system issues through exceptional data processing and pattern recognition capabilities. Neural networks have demonstrated remarkable success in soil moisture retrieval from remote sensing data, particularly for handling nonlinear relationships and multi-source data fusion.

In this study, Artificial Neural Networks (ANN) are employed to evaluate soil moisture retrieval algorithms. ANN development is based on the equations provided in Section II. The GLORI experiment encompasses three airborne flights (45, 46, and 47) with 564, 622, and 760 samples respectively, totaling 1,946 data points. For ANN training, 100 non-repeated samples were randomly selected as the test set, with the remaining 1,846 samples used for training.

A. Single Frequency and Single Polarization Retrieval

Equations clearly show that surface reflectivity is influenced by soil moisture, surface roughness, and vegetation optical depth—crucial parameters that must be incorporated in retrieval algorithms. Theoretical simulations for attenuation factor and surface reflectivity using the zero-order model are illustrated in Figure 6. As incidence angle increases from 0° to 30°, the vegetation attenuation factor also increases. However, when incidence angle exceeds 30°, vegetation optical depth exhibits minimal impact on the angle. Nevertheless, vegetation optical depth significantly affects attenuation factors, with attenuation decreasing as optical depth increases. The combined effects of soil moisture and vegetation optical depth are demonstrated in subfigures 6(b) and 6(c). These simulations confirm that soil moisture, vegetation optical depth, and surface roughness must all be considered in retrieval algorithm development.

Figure 7 depicts single-frequency, single-polarization soil moisture retrieval using GLORI data. The first row shows LR polarization retrieval, while the second row shows RR polarization retrieval. The first column uses only surface reflectivity, the second incorporates incidence angle, and the third and fourth columns add surface roughness (RMS height) and vegetation parameters (LAI), respectively. Input layers vary across retrieval algorithms, with detailed information provided in Table II. The table illustrates that retrieval accuracy improves significantly as input layers expand. Using only surface reflectivity yields RMSE of 0.0700 for LR (0.0681 for RR). When all parameters are employed, retrieval accuracy improves to approximately 0.03 RMSE for both polarizations.

B. Dual Polarization Retrieval

Spaceborne GNSS-R payload development increasingly requires consideration of polarization properties for surface-reflected signals. Using Fresnel equations, we can simulate reflectivity relationships for bare soil and total surface conditions. Figure 9 illustrates the relationship between LR and RR polarization surface reflectivity. For Fresnel reflectivity (smooth surfaces), LR and RR values are nearly identical. However, when vegetation is factored in, their relationship changes significantly. These theoretical simulations inform subsequent studies.

The retrieval schematic for single-frequency dual polarization is illustrated in Figure 8. Figure 10 demonstrates retrieval results for four cases utilizing both polarizations. Case 1 considers only LR and RR surface reflectivity, while Case 2 adds their ratio. The RMSE shows no improvement (0.0695 and 0.0731 respectively). Case 3 incorporates observation geometry (incidence angles), improving accuracy to RMSE of 0.0710. When surface roughness (RMS height) and vegetation parameters (LAI) are included, accuracy improves substantially to RMSE of 0.0556 and 0.0344 respectively. Detailed retrieval results are shown in Figure 11, with final accuracy metrics provided in Table II.

Discussions

While most GNSS-R soil moisture studies have focused on coherent scattering as the dominant mechanism, non-coherent scattering properties have gained increased interest. GLORI is the first publicly available airborne dual-polarization GNSS-R dataset recording both coherent and non-coherent scattering components. Corresponding analysis is presented here.

Figure 12 shows histograms of coherent scattering properties for airborne GLORI data across different land cover types (alfalfa, apple tree, maize, pear tree, wheat), with light colors indicating LR polarization and dark colors indicating RR polarization. Figure 13 presents non-coherent scattering properties for the same categories. For coherent scattering, properties at LR polarization are stronger than at RR polarization. Conversely, for non-coherent scattering, LR polarization properties are weaker than RR polarization for corresponding land surface types.

Utilizing GLORI' s non-coherent scattering properties for soil moisture retrieval yields the results presented in Table III. Each case corresponds to different training layer configurations. "NonCoh" signifies non-coherent scattering properties, with subscripts indicating polarization. represents incidence angle, LAI denotes vegetation information, and RMSE serves as the accuracy metric. Results reveal that as training layers expand from surface reflectivity alone to include surface roughness and vegetation parameters, accuracy improves from approximately 0.08 to about 0.03.

Initially, RR polarization reflected signals from Earth' s surface were considered too weak for reception. Therefore, LHCP antennas were employed to isolate direct RHCP signals from GNSS constellations and reduce multipath effects, while reflected signals were assumed to originate from specular points with scattering information ignored. However, GLORI data analysis shows that while RR polarization signals are indeed weaker than LR polarization, they are receivable and usable.

Retrieval algorithms using RR polarization and dual polarization (LR and RR) achieved accuracy comparable to single LR polarization. This finding is significant for future GNSS-R payload design, suggesting that RR polarization consideration can improve soil moisture retrieval performance. Retrieval using non-coherent scattering properties also demonstrates that non-coherent energy should not be ignored but received and utilized. The accuracy achieved by considering both coherent specular scattering and non-coherent scattering (recorded as the ratio of non-coherent to total scattering energy) was comparable to specular scattering alone. These results indicate that non-coherent scattering energy should be incorporated into GNSS-R soil moisture retrieval, and future spaceborne payloads should account for this information. With increasing availability of polarization and scattering energy information, GNSS-R payload hardware should be improved, opening new research avenues where corresponding retrieval algorithms are also suitable for deep learning approaches.

Conclusion

In recent years, GNSS-R has witnessed substantial progress with particular emphasis on polarization. Initially overlooked, polarization has emerged as a critical research area with potential to enhance remote sensing precision and accuracy. The application of dual polarization for single-frequency data, as demonstrated by airborne GLORI experiments, has opened new investigation avenues. Theoretical analyses have laid groundwork for sophisticated retrieval algorithms, leading to improved soil moisture estimation capabilities. By incorporating additional surface parameters including roughness and vegetation characteristics, researchers have observed significant accuracy improvements, as indicated by reduced RMSE values. Comparative analysis of LR and RR polarization retrieval accuracies has yielded promising results, suggesting potential for further refinement. Notably, dual-polarization exploration (LR and RR) has shown retrieval accuracies comparable to single-polarization approaches. The consideration of dual polarization in conjunction with surface roughness, LAI, and incidence angle holds significant promise for advancing GNSS-R soil moisture estimation.

Furthermore, analyses suggest that both coherent and non-coherent scattering properties should be incorporated into future GNSS-R datasets and retrieval algorithms. These advancements underscore the growing importance of polarization in GNSS-R studies and point toward a promising future trajectory for research and practical applications.

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