A Novel Soil Moisture Retrieval Algorithm for FY-3E GNOS-R Leveraging Multi-Angle Observations

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Abstract

Objective: Develop effective FY-3E GNOS-R algorithm for global soil moisture retrieval.Methods:1.Incorporate first-order vegetation model, consider density, and volume scattering.2.Use multi-angle GNOS-R observations, combine with SMAP data for optimization.3.Tailor algorithm for diverse surface conditions; parameterize surface roughness based on angle.Results: Achieve enhanced retrieval accuracy, RMSE: 0.0235, 0.0264, 0.0191 (g/cm3) for bare, low vegetation, and dense vegetation areas.Limitations: Limited to one month of data; further testing required for broader applicability.Conclusions: GNOS-R proves a robust tool, surpassing previous techniques for global soil moisture estimation.

Full Text

Preamble

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Abstract

Objective: Develop an effective FY-3E GNOS-R algorithm for global soil moisture retrieval.

Methods: (1) Incorporate a first-order vegetation model, considering density and volume scattering. (2) Utilize multi-angle GNOS-R observations combined with SMAP data for optimization. (3) Tailor the algorithm for diverse surface conditions and parameterize surface roughness based on incidence angle.

Results: Achieved enhanced retrieval accuracy with RMSE values of 0.0235, 0.0264, and 0.0191 g/cm^3 for bare, low vegetation, and dense vegetation areas, respectively.

Limitations: Current analysis is limited to one month of data; further testing is required for broader applicability.

Conclusions: GNOS-R proves to be a robust tool that surpasses previous techniques for global soil moisture estimation.

Keywords: GNSS-Reflectometry; GNOS-R; soil moisture; SMAP

Introduction

Surface soil moisture (SM) is pivotal in controlling the exchange of water and energy between land surfaces and the atmosphere, making it crucial for hydrological modeling, agricultural management, and numerical weather forecasting. Over the past three decades, Global Navigation Satellite System-Reflectometry (GNSS-R) has emerged as a promising remote sensing technique, garnering increasing interest from the scientific community [1-2]. While its initial applications predominantly focused on ocean surface studies, its scope has expanded to land surface analyses [3]. However, the development of land surface applications remains challenging due to the complexity of land surface geophysical parameters. These applications include soil moisture estimation, vegetation biomass measurement, flood inundation mapping, and soil freeze/thaw detection [4-7]. Among these, soil moisture monitoring via GNSS-R is currently a rapidly expanding field, given that the L-band has been identified as an optimal frequency for soil moisture monitoring.

Following the implementation of soil moisture monitoring using ground-based GPS receivers, several space-borne GNSS-R missions have been launched in the last two decades, each contributing to the advancement of this field. For instance, the UK DMC, which commenced in 2003, demonstrated the potential of GNSS-R for soil moisture detection [8]. The TechDemoSat-1 (TDS-1) satellite, launched in 2014, provided valuable insights into soil moisture monitoring despite ceasing operations in 2019 [9]. NASA's Cyclone Global Navigation Satellite System (CYGNSS), launched in 2016 and initially intended for oceanic hurricane studies, has also facilitated efficient soil moisture retrieval research [10]. Subsequent missions such as WINSAT-1R, UK-Dot-1, and China's first GNSS-R satellite mission, BuFeng-1 A/B, launched in 2017, 2019, and 2019, respectively, further expanded GNSS-R payloads [11]. Future missions include ESA's HydroGNSS, scheduled for launch in 2024, targeting four hydrological essential climate variables (ECVs), one of which is soil moisture [12].

The FengYun-3E (FY-3E), the fifth satellite in China's polar-orbiting meteorological satellite series, embodies a new generation of GNSS-R sensor: the GNSS Occultation Sounder II (GNOS-II) [13]. The GNOS-II consists of both the GNSS-Radio occultation payload and the GNSS-Reflectometry payload, the latter referred to as GNOS-R. One of the critical attributes of GNOS-R is its global coverage. [Figure 1: see original paper] provides an overview of the evolution of space-borne GNSS-R missions and payloads. Notably, the upcoming ESA HydroGNSS, together with existing missions like SMOS and SMAP, will provide continuity between current and future L-band missions [14,15].

Distinct from traditional radar or radiometer technologies, GNSS-R operates as a bistatic or multi-static radar and offers unique features arising from its changing measurement geometry. With GNSS-R, the locations of specular points and incidence angles along the satellite track vary with the movement of GNSS transmitters and GNSS-R receivers. This variability results in changing footprint areas, making it impossible to precisely repeat the same measurement conditions from orbit to orbit. Most current works have not taken detailed incidence angle information into consideration [16-21].

While Al Khaldi et al. [22] proposed a method to correct the impact of incidence angle on GNSS-R surface effective reflectivity by normalizing the reflectivity of different signal incidence angles to the nadir direction, as shown in [Figure 3: see original paper]a, this approach loses valuable information contained in the observation geometry. In this study, we propose an improved soil moisture retrieval method using GNOS-R data that leverages observation geometry information. Unique to this approach is the use of specular incidence angle data to correct the effects of surface roughness and vegetation—two critical factors influencing final soil moisture accuracy. By utilizing observation geometry information, we note that surface roughness varies for different specular incidence angles, which allows us to derive distinct roughness coefficients based on the observation geometry. Unlike previous studies that used normalized angle information, our method applies zero-order and first-order scattering models to correct vegetation effects according to observation geometry, thereby retaining valuable information that would be lost through normalization methods.

The remainder of this paper is organized as follows: Section 2 presents the datasets and methodology, Section 3 provides results and analysis, Section 4 offers discussion, and Section 5 concludes with potential future work for GNOS-R.

2.1 FY-3E GNOS-R Dataset

Delay-Doppler Mapping (DDM) is the fundamental observation of GNSS-R. Compared to the conventional uniform DDM from TDS-1 and CYGNSS Level 1 products, the DDM generated by the GNOS-R receiver is non-uniform, enabling denser sampling near the specular point. An onboard DDM is presented in [Figure 2: see original paper]. During our analysis, we assume that the DDM is dominated by coherent scattering. To calculate surface reflectivity (SR), we use the following equation, which is commonly employed for TDS-1 or CYGNSS but slightly modified to suit GNOS-R SR [23]:

$$SR = \frac{P_{peak} - N}{EIRP \cdot G \cdot \frac{\lambda^2}{(4\pi)^2} \cdot \frac{1}{R_{sp}^2 R_{tp}^2} \cdot BRCS\text{-}Factor}$$

where SR is the surface reflectivity, R_{sp} and R_{tp} are the distances from the specular point to the receiver and transmitter, respectively, P_{peak} is the peak DDM power, N refers to noise, and $BRCS\text{-}Factor$ is the Bistatic Radar Cross Section Factor [23]. $EIRP$ represents the GNSS Effective Isotropic Radiated Power and pattern, while G is the receiver antenna gain.

Unlike the pan-tropical coverage of CYGNSS, FY-3E GNOS-R has the unique capability of near-global coverage (within the latitude range of $±$85°). It should be mentioned that latitudes higher than 85° have negligible soil moisture content; therefore, "global" here refers to coverage of soil moisture on Earth. Daily observations cover 24% of land surfaces. The specular reflection points of FY-3E GNOS-R on a single day (August 10, 2021) are shown in [Figure 3: see original paper], where the colorbar indicates the SR values. GNOS-R achieves global coverage approximately every 15 days. Here, we employ the first month after GNOS-R launch for our soil moisture retrieval algorithm development.

2.2 Ancillary Data from SMAP

The Soil Moisture Active Passive (SMAP) satellite, designed by NASA, was launched on January 31, 2015. Operating in the L-band, the satellite has an average revisit period of 2-3 days. SMAP's unique advantage is its capability to combine L-band radar and microwave radiometry, enabling simultaneous acquisition of high-resolution radar data and high-precision microwave radiometry [23].

Based on the EASE-grid 2.0, NASA has released three soil moisture products with varying spatial resolutions: (1) a high-precision soil moisture product with 36 km resolution using only SMAP polarization brightness temperature; (2) a low-precision soil water product with 3 km resolution using only SMAP radar backscatter coefficient; and (3) an intermediate-precision soil moisture product with 9 km resolution incorporating both active and passive observations. NASA provides soil moisture products for SMAP's ascending orbit (6 PM local solar time) and descending orbit (6 AM local solar time) freely through the National

Snow and Ice Data Center (NSIDC). However, the radar component failed in July 2015, and since then all measurements have originated solely from the radiometer.

In this study, we utilized the most recent version of the SMAP soil moisture product, known as Level-3 (L3). The most noteworthy change in this version is the replacement of the single-channel algorithm (SCA-V) with the dual-channel algorithm (DCA) as the baseline algorithm. Additionally, the maximum bulk density value has been revised from 1 to 2.65. For our final retrieval, we combined ascending and descending orbit data from each day. We also incorporated ancillary soil characteristic data including bulk density, clay fraction, and roughness coefficient. To account for vegetation effects, we included vegetation water content (VWC) and opacity (τ). Both VWC and τ were estimated for the retrieval because we aimed to evaluate their impact on final retrieval accuracy.

2.3 Land Cover and Land Type Classification

During our analysis, we employed the MODIS Land Cover Type Product (MCD12Q1), which has a 500 m spatial resolution and annual temporal coverage from 2001 to 2020. We used data from 2020, assuming land cover and land type information remained consistent with our study period. Maps following the International Geosphere-Biosphere Programme (IGBP), University of Maryland (UMD), and Leaf Area Index (LAI) classification schemes are provided. The 18 IGBP classification legends and class descriptions can be found in the reference [24], with global land cover information shown in [Figure 4: see original paper].

For the final soil moisture retrieval, we reclassified the IGBP legends into three types: barren, low-vegetation, and forest. Consequently, we utilized three distinct retrieval algorithms tailored to these land cover categories, with detailed information presented in .

3. Methodology

This section presents a comprehensive overview of the theoretical underpinnings and methodology employed in our GNOS-R soil moisture estimation process, including simulations that illustrate the formulas and demonstrate the principles behind our analysis and algorithms.

3.1 Bare Soil Formula and Simulations

Under bare soil conditions, surface roughness significantly influences final soil reflectivity. The surface reflectivity (SR) of bare soil can be modeled using Equation (3) [25]:

$$SR_{bare} = \frac{\cos\theta}{\cos\theta + ks} \cdot |\mathcal{R}|^2 \cdot \exp(-2ks\cos\theta)$$

where SR_{bare} is a function of incidence angle θ, k is the signal wavenumber, and s is the surface root-mean-squared height representing surface roughness conditions. $\mathcal{R}$ is the Fresnel reflection coefficient. For the LR polarization of GNOS-R, $\mathcal{R}$ can be modeled as a linear combination of reflectivity at horizontal and vertical polarizations using Equations (4-6) [3,25]:

$$\mathcal{R}_{LR} = \frac{1}{2}(\mathcal{R}_{vv} + \mathcal{R}_{hh})$$

$$\mathcal{R}_{vv} = \frac{\cos\theta - \sqrt{\varepsilon_r - \sin^2\theta}}{\cos\theta + \sqrt{\varepsilon_r - \sin^2\theta}}$$

$$\mathcal{R}_{hh} = \frac{\sqrt{\varepsilon_r - \sin^2\theta} - \varepsilon_r\cos\theta}{\sqrt{\varepsilon_r - \sin^2\theta} + \varepsilon_r\cos\theta}$$

where ε_r is the dielectric constant, and $\mathcal{R}_{vv}$ and $\mathcal{R}_{hh}$ are the Fresnel reflectivity at vertical and horizontal polarizations, respectively.

[Figure 6: see original paper] illustrates the relationship between bare soil surface reflectivity and specular incidence angles, with volumetric soil moisture content in subfigures (a), (b), and (c) set to 0.1, 0.3, and 0.5, respectively. As soil moisture content increases, bare soil surface reflectivity calculated using Equations (3)-(6) also increases. Different colored lines represent various surface roughness conditions, indicated by the root-mean-squared height (s). As incidence angle increases, surface reflectivity for bare soil shows a decreasing trend for larger angles, typically between 60° and 80°. During these ranges, different roughness conditions have minimal effects on surface reflectivity. However, as surface roughness increases ($s = 1.0, s = 1.5, s = 2.0$), surface reflectivity increases with incidence angles ($0° \leq \theta \leq 45°$). This trend becomes more pronounced for larger root-mean-squared heights. Therefore, the final surface reflectivity of bare soil is influenced by both specular incidence angles and surface roughness, with the degree of influence varying depending on specific conditions.

SMAP roughness coefficients cannot be used directly for GNSS-R retrieval because GNSS-R operates as a bistatic forward-scattering radar system, whereas SMAP's radiometer works in passive emission mode with completely different microwave physical mechanisms. Therefore, we propose two formulas (Case 1 in Equation 7 and Case 2 in Equation 8) to correct surface roughness information obtained from GNOS-R observations. The distinction between these equations lies in the representation of cosine, with the former involving squaring and the latter not.

Case 1:

$$SR_{rough} = \exp(-C_1 \cdot \cos^2\theta)$$

Case 2:

$$SR_{rough} = \exp(-C_2 \cdot \cos\theta)$$

Using these formulas, we obtain regression coefficients C_1 and C_2, from which the corresponding GNOS-R surface roughness coefficients can be calculated.

3.2 Vegetation Formula and Simulations

In vegetated regions, signal attenuation impacts soil moisture retrieval accuracy. We incorporated both zero-order and first-order vegetation scattering models to account for these effects. [Figure 7: see original paper] presents a schematic of GNSS-R reflection from a three-layer model (air, vegetation, and soil). Figure 7a illustrates the zero-order model, while Figure 7b depicts the first-order model including volume scattering. The soil layer is shown with a curved interface to represent surface roughness.

Under zero-order conditions, GNSS signals attenuate through the vegetation layer in both incident and reflection directions, as shown in Figure 7a. The zero-order model formula is [25]:

$$SR_{veg0} = \gamma^2 \cdot SR_{bare}$$

where transmissivity γ accounts for signal attenuation by the vegetation layer and can be expressed through an empirical term for vegetation opacity τ and incidence angle θ:

$$\gamma = \exp\left(-\frac{\tau}{2}\csc\theta\right)$$

[Figure 8: see original paper] demonstrates that as incidence angle (θ) increases, transmissivity (γ) also increases, while decreasing as vegetation opacity (τ) increases. The trend of γ versus θ remains nearly constant for incidence angles between 30° and 80°, but becomes more pronounced for angles below 30°.

The main difference between Figures 8b and 8c lies in soil moisture content (0.3 and 0.5 volumetric content, respectively). Both figures show that surface reflectivity calculated using the zero-order model (Equations 11 and 12) follows similar trends with respect to incidence angles but with different amplitudes. Higher soil moisture contents yield higher surface reflectivities under corresponding conditions. For fixed soil moisture content, higher vegetation opacity τ results in lower surface reflectivity due to increased attenuation. Conversely, when both soil moisture content and τ are fixed, surface reflectivity increases as incidence angle increases (between 0° and 45°), but the trend reverses for angles below 45°.

The first-order model, depicted in Figure 7b, accounts for vegetation volume scattering, which is not considered in the zero-order model. The formulas for the first-order model are [26]:

$$SR_{total} = \gamma^2 \cdot SR_{bare} + SR_{vol}$$

$$\gamma = \exp(-B \cdot \tau \csc \theta)$$

$$SR_{vol} = A \cdot \tau \cdot \sin \theta$$

where SR_{vol} represents the volume scattering term, B is related to the two-way propagation path, and A is related to vegetation density. It should be noted that while τ is obtained from SMAP products, we believe this parameter cannot be directly utilized in GNOS-R soil moisture retrieval because the microwave physical mechanisms differ. Therefore, coefficients A and B are employed for correction.

[Figure 9: see original paper] shows vegetation volume scattering (SR_{vol}) increasing with specular incidence angles, particularly evident for angles below 30°, after which it becomes constant and nearly independent of incidence angle. For fixed τ, SR_{vol} also increases with τ. Surface reflectivity for both soil moisture contents is highly related to vegetation opacity (τ) and specular incidence angle. Specifically, surface reflectivity increases with incidence angle when below 40° but decreases for angles above 50°.

As illustrated in Figures 8 and 9, simulations of surface reflectivity for both zero-order and first-order models exhibit strong dependence on incidence angles, making careful consideration of these angles essential for soil moisture retrieval. Because the first-order model accounts for volume scattering effects that cannot be ignored at L-band frequencies, we utilize its formulas (Equations 13-15) for subsequent soil moisture retrieval.

3.3 Soil Moisture Retrieval Algorithms

Based on different land cover types, we adopted distinct soil moisture retrieval methods, with the workflow shown in [Figure 10: see original paper]. From GNOS-R data, we use Equations (1) and (6) to calculate surface reflectivity. Ancillary data include SMAP products and IGBP classification data, which we use to classify land cover into three categories: barren soil, low vegetation, and high forest.

For barren soil, we apply Equations (7)-(10) to obtain surface roughness correction coefficients specific to GNOS-R, enabling removal of roughness effects. The resulting pure Fresnel reflectivity is then used to retrieve soil moisture content via a database built from the dielectric constant model. For vegetated surfaces, we employ the first-order model (Equations 13-15) combined with SMAP vegetation parameters (VWC and τ) to derive regression coefficients that quantify vegetation attenuation and volume scattering. After removing these effects and accounting for surface roughness (Equations 7-10), we retrieve soil moisture content using the same method as for barren soil.

4.1 Performance of SM Retrieval for Barren Land Type

Most current GNSS-R soil moisture inversion research directly uses SMAP roughness coefficients for correction. However, SMAP's roughness coefficient represents surface roughness observed in back-scattering direction, while GNSS-R has forward-scattering characteristics, meaning their observation mechanisms differ significantly. Therefore, we re-evaluated and estimated SMAP roughness coefficients using Equations (7) and (8) to correct GNOS-R surface roughness information. The calculated coefficients C_1 and C_2 range between -10 and 0. For Case 1, the GNOS-R roughness coefficient ranges from 0 to 6, while for Case 2 it ranges from 0 to 15. The coefficient for Case 1 appears lower than Case 2 because the roughness coefficient formulations in Equations (7) and (8) differ in their treatment of θ—Case 1 employs $\cos^2\theta$ while Case 2 uses $\cos\theta$.

We divided incidence angles θ into 10° intervals, with results shown in [Figure 11: see original paper]. The roughness coefficients for GNOS-R vary with observation geometry, specifically the specular incidence angle, because surface roughness conditions differ at different observation angles. In other words, the same target can exhibit different roughness characteristics depending on observation geometry. summarizes GNOS-R roughness coefficients for different observation geometries. For Case 1, as incidence angle increases, the minimum GNOS-R surface roughness coefficient changes from 1.4 to 3, while the maximum ranges from 4 to 5.5. For Case 2, the minimum increases from 1.5 to 4, while the maximum changes from 11 to 14.1. Roughness coefficients vary significantly every 10°.

After correcting GNOS-R surface soil roughness across different specular incidence angle ranges, we retrieved soil moisture content, with results presented in [Figure 14: see original paper]. The left column shows Case 1 and the right column shows Case 2, with rows representing different incidence angle ranges separated by 10° intervals. Retrieval accuracy for both cases is summarized in , with detailed RMSE values for each 10° interval. The final combined RMSE values are 0.0235 and 0.0224 for Cases 1 and 2, respectively.

4.2 Soil Moisture Retrieval in Low Vegetation Coverage Areas

The basic formula for vegetated soil moisture is presented in Equations (13)-(15). This section evaluates different SMAP vegetation parameters (VWC and τ) for final retrieval accuracy. In Equation (14), parameter B is related to the two-way propagation path. Previous studies used a constant ($B = 0.091$) derived from backscattering cases for CYGNSS soil moisture estimation. However, we recalculate B parameters (B_1 and B_2) for each GNOS-R grid based on specular incidence angle information because backscattering values cannot be directly applied to GNSS-R due to fundamentally different scattering mechanisms.

Two cases are evaluated for 2γ:

Case 1: $\gamma = \exp(-B_1 \cdot \mathrm{VWC} \cdot \csc\theta)$
Case 2: $\gamma = \exp(-B_2 \cdot \tau \cdot \csc\theta)$

In Equation (15), parameter A is related to vegetation density. When multiplied by vegetation parameters (VWC or τ from SMAP), it becomes the vegetation volume scattering term. Previous work used a fixed constant ($A = 0.0012$), but we recalculate this parameter for each GNOS-R grid for the same reasons as parameter B:

Case 1: $SR_{vol} = A_1 \cdot \mathrm{VWC} \cdot \sin\theta$
Case 2: $SR_{vol} = A_2 \cdot \tau \cdot \sin\theta$

For parameter C, two cases are also employed to correct surface roughness effects, as SMAP surface roughness coefficients cannot be directly used for the same reasons mentioned for parameters A and B:

Case 1: $SR_{rough} = \exp(-C_1 \cdot h \cdot \cos\theta)$
Case 2: $SR_{rough} = \exp(-C_2 \cdot h \cdot \cos\theta)$

Summarizing, the total surface reflectivity considering both surface roughness and vegetation effects can be expressed through four cases:

Case 1: $SR_{total} = \exp(-C_1 h \cos\theta) \cdot \gamma^2 \cdot SR_{bare} + A_1 \cdot \mathrm{VWC} \cdot \sin\theta$
Case 2: $SR_{total} = \exp(-C_2 h \cos\theta) \cdot \gamma^2 \cdot SR_{bare} + A_2 \cdot \tau \cdot \sin\theta$
Case 3: $SR_{total} = \exp(-C_3 h \cos^2\theta) \cdot \gamma^2 \cdot SR_{bare} + A_3 \cdot \mathrm{VWC} \cdot \sin\theta$
Case 4: $SR_{total} = \exp(-C_4 h \cos^2\theta) \cdot \gamma^2 \cdot SR_{bare} + A_4 \cdot \tau \cdot \sin\theta$

[Figure 12: see original paper] shows the distribution of coefficient A for the four cases. For Cases 1 and 3, the vegetation input parameter from SMAP is VWC, while for Cases 2 and 4 it is τ. Roughness correction uses h for Cases 1 and 2, and $h\cos\theta$ for Cases 3 and 4. The vegetation density correction parameter A ranges from -0.1 to 0.12 for Case 1, -0.8 to 1.88 for Case 2, -0.2 to 0.12 for Case 3, and -0.9 to 0.82 for Case 4, with dynamic ranges of 0.22, 2.68, 0.14, and 1.72, respectively.

The two-way propagation path correction parameter B is shown in [Figure 13: see original paper]. For Case 1, B ranges from 0 to 1, while for Case 2 it ranges from 0 to 7. The significant difference arises from using different vegetation parameters (VWC versus τ). Although color distributions appear similar, the values differ substantially.

The surface roughness correction parameter C is shown in [Figure 14: see original paper], with value ranges of -15 to 20, -13 to 60, -30 to 65, and -30 to 63 for the four cases, respectively. Dividing incidence angles into 10° intervals significantly improves retrieval accuracy. presents RMSE values for low vegetation coverage areas. Without considering incidence angle, RMSE values are 0.0973 and 0.0558 for Cases 1 and 2, respectively. However, with 10° angle division, accuracy improves significantly, with RMSE ranging from 0.025 to 0.047 and decreasing as incidence angle increases. After combining all incidence angles, final RMSE values are 0.0235 and 0.0224 for Cases 1 and 2, respectively.

4.3 Soil Moisture Retrieval for High Forest Coverage Areas

For high forest coverage areas, we apply the same method described in Section 3.2, using coefficient A to adjust forest density information through Equations (22)-(25). The distribution of coefficient A for the four cases is shown in [Figure 15: see original paper], with ranges of -0.08 to 0.18 for Case 1, -1.0 to 2.0 for Case 2, -0.2 to 0.20 for Case 3, and -0.5 to 1.0 for Case 4. These values are similar to those for low-vegetation conditions with minor differences.

The two-way propagation path correction parameter B is shown in [Figure 16: see original paper], ranging from 0 to 0.18 for Case 1 and 0 to 0.9 for Case 2—significantly different from low vegetation conditions. This demonstrates that coefficient B depends heavily on land surface type, requiring appropriate correction information for each category.

The roughness correction coefficients C for the four cases are shown in [Figure 17: see original paper], ranging from -25 to 35 for Case 1, -33 to 60 for Case 2, -30 to 135 for Case 3, and -20 to 93 for Case 4. Incorporating incidence angles divided into 10° intervals significantly improves retrieval accuracy, with detailed results in . Final RMSE values for the four cases are 0.0195, 0.0191, 0.0215, and 0.0222, respectively.

5. Discussion

The algorithm presented here heavily relies on observation geometry, specifically the specular incidence angle. Incorporating this information significantly improved retrieval accuracy across all land surface types: bare soil, low vegetation, and forest coverage areas. [Figure 18: see original paper] and summarize the distribution of specular incidence angles, with most data (24.66%) falling between 21° and 30°, followed by 26.87% between 31° and 40°. The 11°-20° range accounts for 17.97%, nearly identical to the 41°-50° range (19.67%). Only 8.43% of observations fall within 0°-10°, and 2.40% exceed 50°.

6. Conclusion

This paper presents a soil moisture retrieval algorithm for FY-3E GNOS-R based on the first-order model commonly used for radiometers, adapted for GNOS-R with corrections for surface roughness, two-way propagation attenuation, and vegetation density. Vegetation effects on surface reflectivity are fully considered through evaluation of vegetation water content and opacity, while surface roughness impacts are also assessed. The soil moisture model incorporates vegetation volume scattering through reformulated first-order modeling, with surface roughness effects amended by new coefficients. Global land cover types are divided into barren, low vegetation, and high forest categories, requiring three distinct retrieval algorithms. Comparison of FY-3E GNOS-R soil moisture with reference SMAP data shows good consistency. Unlike normalized angle information inversion, the most significant improvement of our algorithm is enhanced accuracy through explicit use of angle information. Under different angles, soil moisture retrieval accuracy is effectively corrected according to GNSS-R's unique roughness characteristics. The optimal RMSE is 0.0235 g/cm^3 for barren conditions. For low vegetation and high forest, we corrected vegetation density and two-way propagation path effects through corresponding coefficients, achieving RMSE values of 0.0264 and 0.0191, respectively. This work evaluates FY-3E GNOS-R as a complementary tool for global soil moisture estimation. Although limited to one month of test data, results fully demonstrate this new GNSS-R data's capability to achieve accurate soil moisture retrieval. Most importantly, this method provides complete correction parameters for roughness coefficients, vegetation density, and two-way propagation path specifically oriented to GNOS-R.

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Figure Legends

Requirement: Place all figure captions and legends on this page, arranged in order of appearance in the main text.

Fig. 1 The development of space-borne GNSS-R missions or payloads.

Fig. 2 FY3E GNOS-R Non-Uniform DDM measurement.

Fig. 3 Specular reflection points of FY-3E GNOS-R on August 10, 2021, while the colorbar on the right-hand side indicates the SR of GNOS-R.

Fig. 4 Global land cover and land use map.

Fig. 6 Relationship between bare soil surface reflectivity and specular incidence angle. The lines with different colors represent different surface roughness conditions, as indicated in the legend. The surface root-mean-squared height is denoted by "s". The volumetric soil moisture content in subfigures (a), (b), and (c) are 0.1, 0.3, and 0.5, respectively. The clay fraction for both conditions is 50%.

Fig. 7 Illustration of zero-order model (a) and first-order model (b).

Fig. 8 Scattering features of zero-order model: transmissivity (a) and surface reflectivity versus the specular incidence angles (b,c); while the soil clay fraction and s for both figure b and c are 0.5 and 0.1, respectively, and the soil moisture content for figure b is 0.3, while the one for figure c is 0.5.

Fig. 9 Scattering features of first-order model. The vegetation volume scattering reflectivity as shown in Equation 6 is shown in figure a, while the total surface reflectivity are presented in figure b and c and the clay fraction and s are 0.5 and 0.1 for, respectively, while the soil moisture content for figure b is 0.3, and the one for figure c is 0.5.

Fig. 10 Flowchart for FY-3E GNOS-R soil moisture retrieval.

Fig. 11 Comparisons between SMAP roughness coefficients and the ones of GNOS-R for different incidence angles θ.

Fig. 12 Values of vegetation density correction parameter A for four cases.

Fig. 13 Values of two-way propagation path correction parameter B for four cases.

Fig. 14 Values of surface roughness correction parameter C for four cases.

Fig. 15 Forest density correction coefficient (A).

Fig. 16 Two-way propagation path correction parameter B.

Fig. 17 Roughness correction coefficients C for four cases.

Fig. 18 Histogram of incidence angles.

Tables

Table 1 MCD12Q1 International Geosphere-Biosphere Program (IGBP) legend and re-classified land cover types.

Table 2 GNOS-R surface roughness coefficients for different observation geometry of two cases.

Table 3 Soil moisture retrieval accuracy of RMSE.

Table 4 RMSE for low vegetation coverage areas.

Table 5 RMSE for high forest.

Table 6 Percentages of incidence angles.

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