Vol. 24, No. 2, pp. 190-198 (2024)
Journal of Agricultural Physics
ISSN 0973-032X
http://www.agrophysics.in

Research Article

Estimating Near Surface Soil Moisture Using SAR Data and Empirical Dubois Model

SAI SRIRAM V.[1]*, JAYASREE G.[1], RAMPRAKASH T.[2] AND SRIKANTH P.[3]

[1]*Department of Soil science and Agricultural Chemistry, College of Agriculture, PJTAU, Rajendranagar, Hyderabad-500030, Telangana State*
[2]*AICRP on Weed Management, PJTAU, Rajendranagar, Hyderabad-500030, Telangana State*
[3]*Agri Informatics Division, Agricultural Sciences & Application Group, NRSC, Balanagar, Hyderabad-500042, Telangana State*

ABSTRACT

Retrieval of surface soil moisture at higher spatial resolution became effective in recent past. The current study examined the potential of C-band in EOS-04 SAR data on accuracy of prediction of soil moisture over large area in a test site i.e., college farm and student farm at College of Agriculture, PJTAU, Rajendranagar, Hyderabad. The data collected was Level 2 GRD SAR data, providing calibrated and geocoded SAR images ready for comprehensive analysis. The satellite data was acquired at two different incidence angles in order to cover the area twice with different orientation. The backscattered images were converted to sigma naught using ENVI band math Tool. In addition, ERDAS software was used to layer stack the HH (horizontal-horizontal), HV (horizontal-vertical) and VV (vertical-vertical) polarization layers. The study has demonstrated the potential of SAR data in accurately estimating soil moisture content. The results highlighted the significant impact of polarization and incidence angle on the accuracy of soil moisture estimate. Specifically, the study revealed that like-polarization (HH) is more sensitive to moisture than cross-polarization (HV). At lower incidence angles, HH polarization is more sensitive, while at higher incidence angles, VV polarization showed increased sensitivity. Furthermore, a decrease in incidence angle enhanced soil moisture estimation accuracy. Prediction of soil moisture using Dubois model further improved the accuracy.

Key words: Soil, moisture, Microwave Remote sensing, SAR, Polarization, Dubois model

Introduction

Soil moisture (SM) plays a significant role in research involving the soil-vegetation-atmosphere interfaces and environmental studies, as it regulates the flow of water and heat energy between the land and atmosphere through processes such as evaporation and plant transpiration (Yadav *et al.*, 2019). It is a critical element in soil impacting agricultural management, the surface water cycle and energy exchange in near-earth space (Xing *et al.*, 2022). Soil moisture is a crucial component in the hydrological cycle, impacting runoff, infiltration and the overall water and energy balance at the land surface (Weimann *et al.*, 1998). Accurate soil moisture information is vital for crop growth monitoring, yield estimation, drought monitoring and numerous hydrological, meteorological, agricultural and risk assessment applications (Xing *et al.*, 2019; Wang *et al.*, 2023).

Traditional soil moisture estimation methods, such as gravimetric method, neutron probe and time

*Corresponding author,
Email: saisriram.vathadi@gmail.com

domain reflectometry, provide accurate measurements at specific points but are limited by their spatial coverage (Sharma *et al*., 2018). Remote sensing technologies offer significant advantages due to their non-invasive nature and ability to cover large areas over time, making them highly valuable for comprehensive soil moisture assessment (Walker *et al*., 2004). Microwave remote sensing, is particularly effective for soil moisture detection giving all-weather, all-time coverage (Zhang *et al*., 2021). Its ability to penetrate clouds, penetrate several centimetres of soil and its sensitivity to dielectric properties make it a powerful tool for measuring soil moisture (Engman, 1990; Jackson *et al*., 1996). Synthetic Aperture Radar (SAR) is useful for estimating soil moisture because its microwave signals can penetrate clouds and are sensitive to the dielectric properties. SAR measures soil backscattering coefficients, which depend on the incident angle, polarization, dielectric constant and surface roughness. The dielectric constant and surface roughness are the main factors affecting soil backscattering coefficients (Ma *et al.*, 2021). The dielectric constant, affected by texture, temperature and moisture are important for finding soil backscattering coefficients. The principles behind soil moisture estimation using backscattering coefficients primarily focus around dielectric properties, surface roughness and the effects of polarization and incident angle. The dielectric constant, which is strongly affected by soil moisture content, plays an important role since water has a much greater dielectric constant than dry soil, making changes in soil moisture highly detectable through variations in backscattered signals (Dobson *et al*., 1985). Dielectric constant is also affected by soil texture, temperature and salinity, which are crucial for accurate modeling. Surface roughness impacts the scattering mechanism of microwave signals, with smooth surfaces reflecting signals specularly and rough surfaces causing diffuse scattering (Oh *et al*., 1992). Variations in surface roughness can either obscure or enhance the sensitivity of backscatter to soil moisture, necessitating precise calibration. Additionally, the radar's polarization and incident angle influence the interaction of microwave signals with the soil surface and subsurface, with certain combinations of these parameters enhancing the backscatter's sensitivity to soil moisture. Together, these factors form the foundation for accurate soil moisture estimation using backscattering coefficients. Various models describe the relation between backscattering factors and surface characteristics. These models include theoretical models based on physical principles. Semi-empirical models mix theoretical and empirical data and empirical models, drawn from actual data. (Bai and He, 2015). The Dubois model is a widely used empirical model (Ma *et al*., 2021) frequently used to predict soil moisture using SAR data. This model is particularly valued for its practical use and efficiency in translating SAR backscattering coefficients into soil moisture values. The importance of the Dubois model is emphasized by its extensive use in soil moisture estimation. Romshoo *et al*. (2002), demonstrated its efficiency in matching SAR readings with field-measured soil moisture. The Dubois model's benefits lay in its balance between simplicity and accuracy, making it a common option for practical soil moisture estimate despite certain inherent limits and probable inaccuracies in roughness and dielectric constant calculations (Dubois *et al*., 1995).

In summary, soil moisture is a vital component in hydrology, agriculture and meteorology, with remote sensing technologies like SAR, provides crucial data for large-scale monitoring and management applications (Thanabalan *et al*., 2022; Srivastava *et al*., 2015).

In this study, we explored soil moisture estimation using backscattering coefficients at different polarizations obtained from fine-resolution SAR data from the EOS-04 (RISAT-1A) satellite.

Materials and Methods

Study area

Soil samples were collected from several fields at the College of Agriculture, Rajendranagar, at a depth of 0 to 5 cm, scheduled to align with the satellite passes on 11 January, 2024 and 13 January, 2024. The study area is mostly flat, with the soil texture being relatively uniform across different fields. The fields are predominantly bare, except for a few where the existing crop was matured cotton and maize.

Fig. 1. Experimental plots at College and Student Farm of College of Agriculture, Rajendranagar

Soil sample collection and moisture estimation

The geographic coordinates (latitude and longitude) of each sample collection point were recorded to ensure exact location matching with satellite data. In each field the soil sample was randomly collected at three places to minimize the intra-field soil moisture variability during the analysis. Soil moisture content was determined using the gravimetric method, which includes collecting the soil samples, weighing them immediately to get the moist weight, drying them in an oven at 105°C until constant weight is reached and then reweighing to obtain the dry weight. The soil moisture content was determined using the following formula:

$$\text{Soil moisture (\%)} = ((W_1 - W_2)/W_2) \times 100 \quad (1)$$

W_1 = Weight of fresh soil with can – Weight of empty can

W_2 = Weight of Dry soil with can - Weight of empty can

Soil bulk density

Soil bulk density was measured using a core sampler to facilitate the conversion of gravimetric soil moisture to volumetric soil moisture. It was estimated by dividing the dry soil weight by the volume of the core sampler used to collect the soil.

$$\text{Bulk density} = \frac{\text{Dry weight of soil}}{\text{Volume of the core sampler}} \quad (2)$$

$$\text{Volume} = \pi r^2 h \quad (3)$$

r = Radius of the core sampler

h = height of the core sampler

Soil roughness

A roughness board was used to measure soil roughness during the satellite pass which was 0.25 cm. Roughness was measured one time as conditions were the same as no cultural practices done on the field. The soil surface was relatively smooth, which meant that its impact on backscatter values was negligible. These conditions ensured minimal variation in roughness, allowing the primary focus to remain on soil moisture content for backscatter analysis.

Satellite data

Fine-resolution satellite data from the EOS-04 satellite was obtained from ISRO's EO data hub, BHOONIDHI. The satellite uses a Synthetic Aperture Radar (SAR) sensor operating in the C-band. SAR technology employs active microwave detection, which is unaffected by weather conditions or time of day, allowing for reliable monitoring of soil moisture levels across varying field conditions. The data collected was Level 2 GRD SAR data, providing calibrated and geocoded SAR images ready for comprehensive analysis. The satellite data was acquired at two different incidence angles in order to cover the area twice with different orientation. The data was resampled to a common resolution of 4.5 m before the analysis. The details of the data are presented in Table 1.

Table 1. Particulars of satellite data used in the study

Satellite	Specifications	
	EOS-04	EOS-04
Sensor	SAR	SAR
Imaging Mode	FRS-1	FRS-1
Polarization	HH, HV, VH, VV	HH, HV, VH, VV
Date of pass	11-01-2024	13-01-2024
Pixel Spacing	4.5m	2.25m
Incidence angle	26.09°	35.93°

Data processing

The obtained satellite data were processed using ENVI software. Enhanced Lee filter with a kernel size of 5x5, was utilized to suppress the speckle noise in the data. The process was carried out independently for each polarization data. Further the backscattered images were converted to sigma naught using the following equation through ENVI band math Tool.

$$\sigma_0\,(\text{dB}) = 10\log_{10}(DN^2 - N) + 10\log_{10}(\sin i_p) - K_{dB} \quad (3)$$

where,

σ_0 (dB) is the backscattering coefficient Sigma 0 in dB

DN is the Digital Number

N is the Image Noise Bias

i_p is the per pixel incidence angle

K_{dB} is the Beta0 Calibration Constant

In addition, ERDAS software was used to layer stack the HH (horizontal-horizontal), HV (horizontal-vertical) and VV (vertical-vertical) polarization layers. This integration of many layers permitted a detailed examination of the backscatter properties. The RGB of HH, HV and VV polarizations for the dates 11-01-2024 and 13-01-2024 are shown in the Figures 2 and 3, respectively.

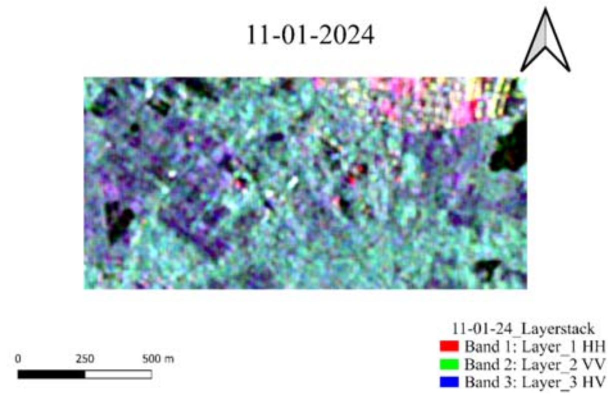


Fig. 2. Processed and layer stacked image of EOS-04 satellite acquired on 11-01-2024

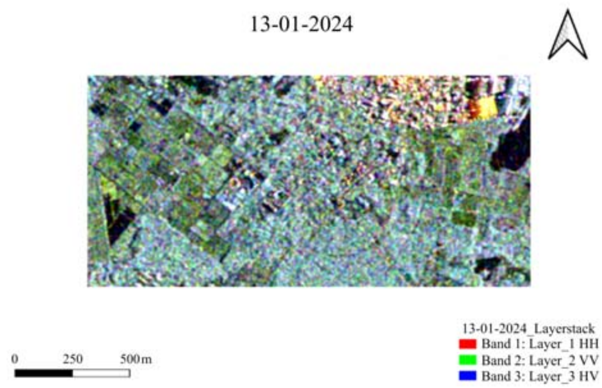


Fig. 3. Processed and layer stacked image of EOS-04 satellite acquired on 13-01-2024

Deriving backscatter values

Backscatter data for areas of interest (AOI) were extracted using ERDAS software by establishing AOIs for the precise sites of soil sample collection. The backscatter readings inside these AOIs were recorded for future investigation.

Correlation with ground truth values

The measured backscatter values from the satellite data were correlated with the ground-truth soil moisture values determined from the soil samples using regression. The coefficient of determination (R^2) was determined to examine the strength and accuracy of the connection between the satellite-derived backscatter coefficient and the ground-truth soil moisture measurements.

Soil moisture estimation using Dubois Model

Backscatter data of the C-band and incidence angle were utilized to compute the relative soil permittivity (ε) using Dubois model. Volumetric soil moisture was estimated using the ε in universal Topp's model. Initially, Dubois *et al.* (1995) created an empirical model to determine the ε using quad polarized SAR data. The backscattering coefficient (σ^0) may be determined using HH or VV polarizations.

The calculation of the dielectric constant is done using the Dubois algorithm

$$\sigma^0 = 10^{-2.75}(\cos^{1.5}\theta/\sin^5\theta)10^{0.028\varepsilon\tan\theta}(ks\sin\theta)^{1.4}\lambda^{0.7} \quad (4)$$

$$\varepsilon' = \log(\sigma^0_{HH})\,10^{2.75}(\cos\theta)^{-1.5}(\sin\theta)^5(s\sin\theta)^{-1.4}\lambda^{-0.7}/0.028\tan\theta \quad (5)$$

Where,

ε' = dielectric constant

σ^0 = the backscattering coefficient (dB)

θ = local incidence angle

k = wave number

λ =wavelength

s = surface roughness

The value of the dielectric constant obtained from equation 5 is used to estimate the value of soil moisture. The dielectric constant value is converted into soil moisture values using the TOPP algorithm (1980), namely as follows.

$$m_v = -5.3 \times 10^{-2} + 2.92 \times 10^{-2}\,\varepsilon'^2 - 5.5 \times 10^{-4}\,\varepsilon'^2 + 4.3 \times 10^{-6}\,\varepsilon'^3 \quad (6)$$

Where,

m_v = soil moisture (% by vol.)

ε' = dielectric constant

Results and Discussion

This study used both advanced satellite data processing and traditional gravimetric methods to assess soil moisture levels across two distinct days (11 January, 2024 and 13 January, 2024). The volumetric moisture content was calculated by multiplying the gravimetric moisture content with the bulk density of the soil. The data is presented in Table 2 and 3.

Fine-resolution synthetic aperture radar (SAR) data obtained from the EOS-04 satellite utilizing the BHOONIDHI portal was used to evaluate the satellite data. The Level 2 Ground Range Detected (GRD) SAR data was processed to produce Areas of Interest (AOIs) and backscatter values for the VV, HV and HH polarizations were noted.

Field-measured soil moisture was compared with backscatter data. On 11 January, 2024, the R^2 values for the VV, HH and HV polarizations were 0.7322, 0.7884and 0.1674, respectively (Fig. 4). On 13 January, 2024, the R^2 values for VV, HH and HV polarizations were 0.7408, 0.4679 and 0.2234, respectively (Fig. 5). These results showed that like-polarizations (VV and HH) show stronger sensitivity and a better correlation with soil moisture content compared to cross-polarization (HV) and among the

Table 2. Soil moisture data collected from experimental plot on 11-01-2024

Sl. No.	Latitude	Longitude	Volumetric Moisture Content (%)
1	17.3224	78.4224	28.3
2	17.3224	78.4229	6.5
3	17.3216	78.4226	13.4
4	17.3207	78.4221	4.1
5	17.3209	78.4227	22.8
6	17.3206	78.4229	2.8
7	17.3219	78.4217	10.7
8	17.3207	78.4202	19.5
9	17.3220	78.4080	4.0
10	17.3217	78.4083	3.3
11	17.3215	78.4085	2.8
12	17.3219	78.4082	3.7
13	17.3220	78.4085	2.9
14	17.3208	78.4092	7.5
15	17.3225	78.4108	12.8

Table 3. Soil moisture data collected from experimental plot on 13-01-2024

Sl. No.	Latitude	Longitude	Volumetric Moisture Content (%)
1	17.3217	78.4080	2.8
2	17.4082	78.4082	5.7
3	17.3214	78.4084	3.3
4	17.3217	78.4084	14.6
5	17.3221	78.4085	13.8
6	17.3220	78.4078	13.7
7	17.3207	78.4092	32.7
8	17.3211	78.4088	18.8
9	17.3226	78.4103	20.0
10	17.3228	78.4101	21.5
11	17.3225	78.4223	20.6
13	17.3219	78.4226	16.3
14	17.3214	78.4226	20.2
15	17.3211	78.4225	17.6
16	17.3210	78.4228	4.4
17	17.3206	78.4229	3.7
18	17.3216	78.4217	11.1
19	17.3220	78.4214	4.1
20	17.3206	78.4201	13.1

like polarizations, VV polarization showed higher correlation with volumetric soil moisture content.

The incidence angle significantly affected the relationship between backscatter data and soil moisture estimates. On 11 January, 2024, the incidence angle was 26.09 degrees, whereas on 13 January, 2024, it was 35.93 degrees. On 11 January, both HH and VV polarizations showed a strong correlation with soil moisture content. In contrast, on 13 January, VV polarization had a stronger connection with soil moisture. This suggests that at lower incidence angles, both VV and HH polarizations are sensitive to soil moisture, while at higher incidence angles, VV polarization becomes more sensitive compared to HH. Cross-polarization (HV), however, did not show a significant correlation with soil moisture at either incidence angle.

Dubois model was used to estimate dielectric constant. The estimated dielectric constant values

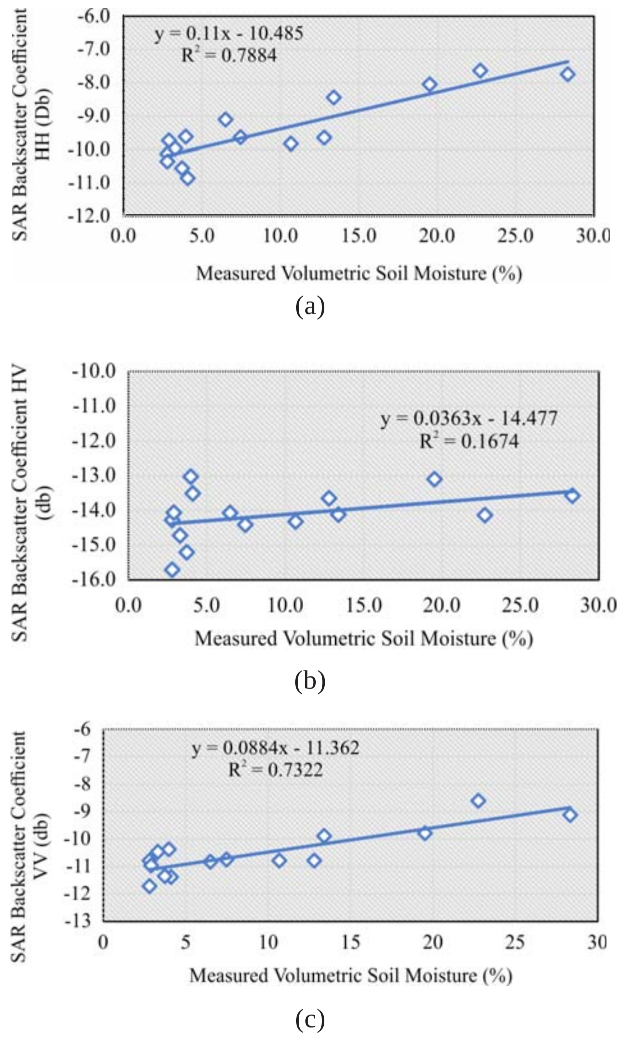
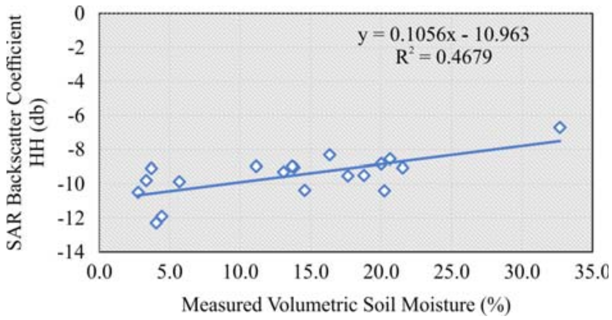


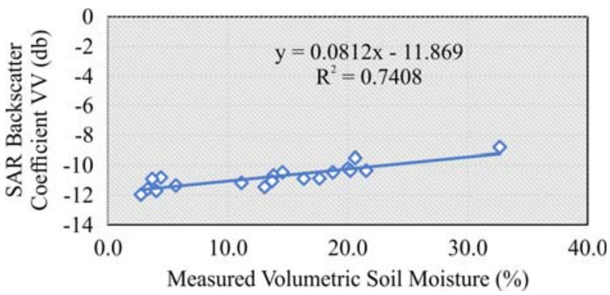
Fig. 4. the relationship between SAR backscatter coefficient and measured soil moisture for (a) HH (b) HV and (c) VV polarization on 11-01-2024

were then input into the Topp's model to calculate the soil moisture content. The estimated soil moisture values were compared with the measured soil moisture content, revealing strong correlations with R^2 values of 0.83 and 0.80 on 11-01-2024 (Figure 6a) and 13-01-2024 (Fig. 6b), respectively. Additionally, the Root Mean Square Error (RMSE) values were 6.5 on 11-01-2024 and 9.0 on 13-01-2024, further indicating the model's performance in predicting soil moisture.

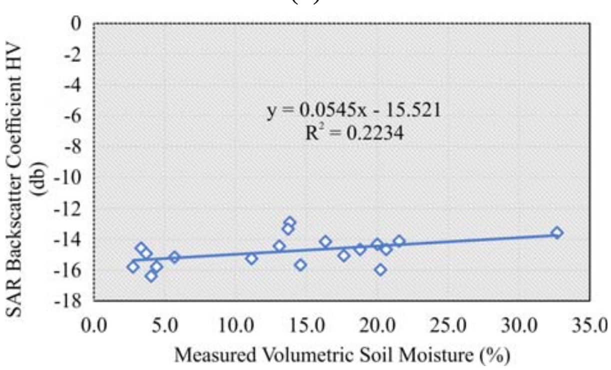
The study of soil moisture estimates using satellite data analysis and gravimetric approaches identified a number of important factors that contributed to the observed outcomes. Because they



(a)

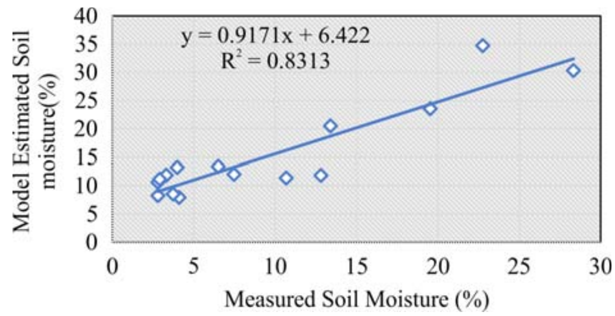


(b)

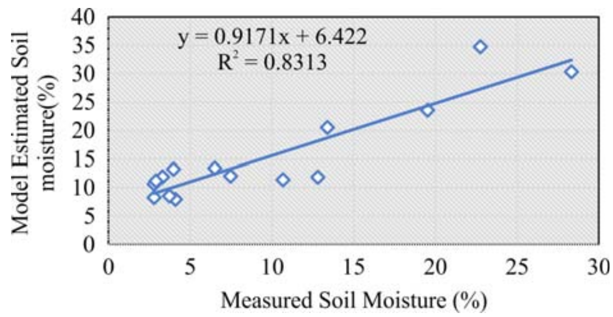


(c)

Fig. 5. The relationship between SAR backscatter coefficient and measured soil moisture for (a) HH (b) VV and(c) HV polarization on 13-01-2024



(a)



(b)

Fig. 6. The relationship between Model Estimated Soil Moisture and measured soil moisture (a) on 11-01-2024 (b) on 13-01-2024

more precisely captured surface scattering effects, like-polarizations exhibited higher sensitivity and a better correlation with soil moisture content than cross-polarizations, which were influenced by volume scattering from vegetation and other surface features. Precise measurements of soil moisture were made possible by the gravimetric approach, which acted as a trustworthy method for calibrating satellite data.

The radar incidence angle had a major effect on backscatter values greater angles decreased the sensitivity to soil moisture, while lower angles increased surface scattering. Variations in backscatter values and their relationship to soil moisture were also a result of differences in surface and ambient variables between the two dates.

The integration of the Dubois model in this work greatly improved the accuracy of soil moisture estimates using radar data. The model provided a mathematical foundation for converting radar backscatter into effective soil moisture estimations using empirical relationships and calibration data. It adjusted for different incidence angles, resulting in constant sensitivity to soil moisture across radar observations. Furthermore, the Dubois model took into consideration of surface roughness and vegetation cover, making it suitable for a wide range of environmental circumstances. Overall, adopting the Dubois model enhanced the accuracy and reliability of soil moisture evaluations, providing a solid approach for interpreting radar backscatter data in the context of changing climatic conditions. The study revealed that polarization, incident angle and environmental factors are crucial for soil moisture estimation using satellite data

Conclusions

The study has demonstrated the potential of SAR data in accurately estimating soil moisture content. It highlights the significant impacts of polarization and incidence angle on the accuracy of these estimates. Specifically, the study revealed that like-polarization (HH) is more sensitive to moisture than cross-polarization (HV). At lower incidence angles, HH polarization is more sensitive, while at higher incidence angles, VV polarization shows increased sensitivity. Furthermore, a decrease in incidence angle enhanced. soil moisture estimation accuracy.

By examining various SAR polarization modes and changing incidence angles, researchers can fine-tune remote sensing systems, enhancing their effectiveness in agricultural management and environmental monitoring.

Moreover, empirical model, such as the Dubois model used in this study, further improved estimation accuracy. These models help to refine the relationship between SAR backscatter and soil moisture, leading to more precise measurements. This fine-tuning and modeling are essential for optimizing resource allocation, irrigation scheduling and developing data-informed soil management strategies. Accurate real-time soil moisture monitoring through these enhanced methods can greatly improve agricultural productivity and water productivity through efficient irrigation scheduling, sustainability and environmental conservation efforts.

References

Bai, X. and He, B. 2015. Potential of Dubois model for soil moisture retrieval in prairie areas using SAR and optical data. *International Journal of Remote Sensing* **36**(22): 5737-5753.

Dobson, M.C., Ulaby, F.T., Hallikainen, M.T. and El-Rayes, M.A. 1985. Microwave dielectric behavior of wet soil-Part II: Dielectric mixing models. *IEEE Transactions on Geoscience and Remote Sensing* **(1)**: 35-46.

Dubois, P.C., Van Zyl, J. and Engman, T. 1995. Measuring soil moisture with imaging radars. *IEEE Transactions on Geoscience and Remote Sensing* **33**(4): 915-926.

Engman, E.T. 1990. Progress in microwave remote sensing of soil moisture. *Canadian Journal of Remote Sensing* **16**(3): 6-14.

Jackson, T.J., Schmugge, J. and Engman, E.T. 1996. Remote sensing applications to hydrology: soil moisture. *Hydrological Sciences Journal* **41**(4): 517-530.

Ma, C., Wang, S., Zhao, Z. and Ma, H. 2021. Global sensitivity analysis of a water cloud model toward soil moisture retrieval over vegetated agricultural fields. *Remote Sensing* **13**(19): 3889.

Oh, Y., Sarabandi, K. and Ulaby, F.T. 1992. An empirical model and an inversion technique for radar scattering from bare soil surfaces. *IEEE Transactions on Geoscience and Remote Sensing* **30**(2): 370-381.

Romshoo, S.A., Taikan, O. and Katumi, M. 2002. C-band radar for soil moisture estimation under agricultural conditions. *IEEE International Geoscience and Remote Sensing Symposium* **4**: 2217-2219.

Sharma, P.K., Kumar, D., Srivastava, H.S. and Patel, P. 2018. Assessment of different methods for soil moisture estimation: A review. *J. Remote Sens. GIS* **9**(1): 57-73.

Srivastava, H.S., Sharma, P.K., Kumar, D., Sivasankar, T., Mishra, R.S., Mishra, M. and Patel, P. 2015. Soil moisture variation over parts of Saharanpur and Haridwar districts (India) during November-2006 to June-2007 as observed by multi-polarized (VV/HH & VV/VH) ENVISAT-1 temporal ASAR data. *International Journal of Advanced Engineering Research and Science* **2**(1): 31-39.

Thanabalan, P., Vidhya, R. and Kankara, R.S. 2022. Soil moisture estimation using RISAT-1 and SENTINEL-1 data using modified Dubois model in comparison with averaged NDVI. *Geocarto International* **37**(25): 8624-8644.

Walker, J.P., Houser, P.R. and Willgoose, G.R. 2004. Active microwave remote sensing for soil moisture measurement: a field evaluation using ERS 2. *Hydrological Processes* **18**(11): 1975-1997.

Wang, R., Zhao, J., Yang, H. and Li, N. 2023. Inversion of soil moisture on farmland areas based on SSA-CNN using multi-source remote sensing data. *Remote Sensing* **15**(10): 2515.

Weimann, A., Von Schonermark, M., Schumann, A., Jorn, P. and Gunther, R. 1998. Soil moisture estimation with ERS-1 SAR data in the East-German loess soil area. *International Journal of Remote Sensing* **19**(2): 237-243.

Xing, M., Chen, L., Wang, J., Shang, J. and Huang, X. 2022. Soil moisture retrieval using SAR backscattering ratio method during the crop growing season. *Remote Sensing* **14**(13): 3210.

Xing, M., He, B., Ni, X., Wang, J., An, G., Shang, J. and Huang, X. 2019. Retrieving surface soil moisture over wheat and soybean fields during growing season using modified water cloud model from Radarsat-2 SAR data. *Remote Sensing* **11**(16): 1956.

Yadav, V.P., Prasad, R., Bala, R. and Kumar Vishwakarma, A. 2019. Estimation of soil moisture through water cloud model using sentinel-1A SAR data. In IGARSS 2019-2019. *IEEE International Geoscience and Remote Sensing Symposium* 6961-6964.

Zhang, L., Meng, Q., Zeng, J., Wei, X. and Shi, H. 2021. Evaluation of Gaofen-3 C-Band SAR for soil moisture retrieval using different polarimetric decomposition models. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **14**: 5707-5719.

Received: 25 July 2024; Accepted: 27 October 2024