Journal of Agrometeorology
ISSN : 0972-1665 (print), 2583-2980 (online)
Vol. No. 25 (4) : 517-524 (December - 2023)
https://doi.org/10.54386/jam.v25i4.2303
https://journal.agrimetassociation.org/index.php/jam

Research Paper

Surface soil moisture estimation in bare agricultural soil using modified Dubois model for Sentinel-1 C-band SAR data

ABISHEK MURUGESAN[1], RUCHA DAVE[1*], AMIT KUSHWAHA [1,2], DHARMENDRA KUMAR PANDEY[3] and KOUSHIK SAHA[4]

[1]*B. A. College of Agriculture, Anand Agricultural University, Anand, Gujarat, India*
[2]*Environmental Sciences and Sustainable Engineering Centre, Indian Institute of Technology Palakkad, Kerala, India*
[3]*Space Applications Centre, ISRO, Ahmedabad, Gujarat, India*
[4]*Department of Physics, Indian Institute of Technology Dharwad, Dharwad, Karnataka, India.*
**Corresponding author:rch.dave1@gmail.com*

ABSTRACT

Surface soil moisture has vital role in water energy balance, climate change and agriculture mainly for crop water requirements and irrigation scheduling. Microwave remote sensing with its unique characteristics of high penetration and sensitivity towards dielectric constant, has enabled the researchers to explore various techniques for soil moisture estimation. With the launch of Sentinel-1 (A&B) Synthetic Aperture Radar (SAR) satellites, the hindrance in accessing high spatial and temporal resolution data is eliminated. The current study focuses on surface soil moisture estimation for bare agricultural fields in the semi-arid region. Field soil moisture up to 5 cm depth using HydraGo Probe sensor and surface roughness synchronizing with satellite pass dates were collected from total 102 locations spanning four dates. Volumetric and sensor-based soil moisture are well correlated with R^2 = 0.85. The Modified Dubois Model (MDM) was applied to obtain the relative permittivity of the soil for the backscattering coefficient (σ°) for VV polarization, which is used as one of the inputs in universal Topp's model for soil moisture calculation. Model derived soil moisture is well correlated with ground-based soil moisture for the entire range of the soil moisture (0.02-0.18 m^3m^{-3}) with R^2 = 0.85 and RMSE=0.005. The entire soil moisture was categorized in three soil moisture ranges to evaluate the sensitivity. The highest correlation was observed for 0.06-0.1 m^3m^{-3} with R^2 = 0.73 and RMSE=0.003 followed by 0.015-0.6 m^3m^{-3} with R^2 = 0.81 and RMSE=0.001 and 0.11-0.18 m^3m^{-3} with R^2 = 0.48 and RMSE=0.019 which is significantly low. Performance accuracy of MDM is encouraging for bare soil moisture estimation for even the lower range of surface soil moisture.

Keywords: Modified Dubois Model, Surface Soil Moisture, Sentinel-1, Semi-empirical Model

Soil moisture being a crucial parameter controlling the water cycle and responsible for various soil -air interface processes, has gained the focus for various research area of hydrology, atmospheric science, water management, agriculture, climate change and many more where water is an important parameter (Topp *et al*., 1980; Chattopadhyay *et al.*, 2018)including aspects of climate, topography, soils, plant and microbial characteristics, disturbance, and anthropogenic impacts. Yet, at least at the global scale, models based on very different types and numbers of parameters yield similar results. Part of the reason for this is that the major NPP controls influence each other, resulting, under current conditions, in broad correlations among controls. NPP models that include richer suites of controlling parameters should be more sensitive to conditions that disrupt the broad correlations, but the current paucity of global data limits the power of complex models. Improved data sets will facilitate applications of complex models, but many of the critical data are very difficult to produce, especially for applications dealing with the past or future. It may be possible to overcome some of the challenges of data availability through increased understanding and modeling of ecological processes that adjust plant physiology and architecture in relation to resources. The CASA (Carnegie, Stanford, Ames Approach. Since the inception of soil moisture measurements, the direct method of measurement of soil moisture has been implemented (i.e., gravimetric method).

Article info - DOI: https://doi.org/10.54386/jam.v25i4.2303
Received: 5 August 2023; Accepted: 6 November 2023; Published online : 30 November, 2023

In due course of time, the importance and need of soil moisture measurement has been increased leading to the innovations in the measurement methods better than the traditional destructive, time-consuming localized measurements to measure spatially and temporally varying soil moisture.

Due to the unique capability of penetration up to some depth of the surface depending on the wavelength, microwave remote sensing especially Synthetic Aperture Radar (SAR) imaging has gained consideration among researcher working on soil moisture estimation. Especially in case of soil moisture, it is important to analyse surface roughness and dielectric properties to get accurate estimation of the moisture content. SAR data, capable of capturing this information plays a key role (Barrett *et al*., 2009; Dubois *et al.*, 1995; Mattia *et al.*, 1997; Sharma *et al*., 2019)physical, semi-empirical, or empirical, do not allow for a reliable estimate of soil surface geophysical parameters for all surface conditions. The proposed model, developed in HH, HV, and VV polarizations, uses a formulation of radar signals based on physical principles that are validated in numerous studies. Never before has a backscattering model been built and validated on such an important dataset as the one proposed in this study. It contains a wide range of incidence angles (18°-57°. Looking to the viability of the semi-empirical models over physical and empirical models where it overcomes the limitation of requirement of large number of parameters in physical model and limited application of empirical model, it has been used for various studies where both microwave and optical remote sensing data are used as model parameters (Fieuzal and Baup, 2016; Neusch and Sties, 1999).

Dubois model and Modified Dubois Model (MDM) have performed effectively for bare and sparsely vegetated land (Baghdadi *et al*., 2016)physical, semi-empirical, or empirical, do not allow for a reliable estimate of soil surface geophysical parameters for all surface conditions. The proposed model, developed in HH, HV, and VV polarizations, uses a formulation of radar signals based on physical principles that are validated in numerous studies. Never before has a backscattering model been built and validated on such an important dataset as the one proposed in this study. It contains a wide range of incidence angles (18°-57°. Previously the studies have been conducted using RISAT-1 satellite data for cropped and bare soils where the accuracy of the MDM has been proved to be better for bare and vegetation covered soil where NDVI ≤ 0.4. However, with the launch of Sentinel-1 satellite platforms (1A and 1B) by European Space Agency (ESA), operating in C-band wavelength, with 12 days receptivity with single polarization (VV or HH) and in dual polarizations (VV+VH, HH+HV), the regular and timely estimation of various crop and soil parameters have become a conceivable part.

The current study is focused on the evaluation of Modified Dubois Model for dual polarimetric Sentinal-1 SAR data using VV polarization over bare agricultural fields in the semi-arid region where, residual soil moisture in summer season also plays an important role before sowing the crop in the next growing season of monsoon.

MATERIAL AND METHODS

Study area

The study area located at central 22°30’54.39”N latitude and 72°45’40.61”E longitude is a part of rural agricultural area in the Anand District of Gujarat, India. The dominant seasonal crops are wheat and tobacco in winter (*rabi*), paddy and pearl-millet in monsoon (*kharif*) and pearl- millet in summer season. In summer season, most of the land are left fallow apart from pearl millet crop (Dave *et al*., 2019, 2023). The current study focuses on the fallow agricultural fields where no crops are grown during summer season. The fields are marked on the study area map from where the in-situ measurements for soil moisture are collected on different dates synchronous to satellite pass (Fig. 1).

Satellite data

The current study was carried out using openly accessible Sentinel-1A images. The Sentinel-1 satellite operates with two platforms 1A and 1B with temporal resolution of 12 days each (6 days for combined) with dual polarisations, Vertical (VV) and Vertical-Horizontal (HH). C-band having penetration capability up to 3-5 cm is effective in all weather conditions recording backscattering signals from the target representing various target parameters. The spatial resolution is 10 m x 10 m covering wide swath of 250 km with incidence angles ranging from 29° (near range) to 46° (far range). The local incidence angle of the current dataset is 42.11°. Ground Range Detected (GRD) and Single Look Complex (SLC) are two different product types obtained from Sentinel-1A level-1 data. Generally, standard corrections are performed on GRD products to get the square pixels. In this study, Sentinel-1A (descending pass), Interferometric Wide Swath (IW) mode GRD product is used to acquire the backscatter parameters from the fields.

Field data

In-situ soil moisture from the study fields were collected using a Stevens HydraGo Probe sensor (https://stevenswater.com/products/hydrago/) which works on the principle of ratiometric dielectric coaxial impedance providing information about soil moisture, temperature, bulk electrical conductivity and dielectric permittivity. It can measure soil moisture from the range of completely dry (*i.e.* 0% saturation) to fully saturated (*i.e.* 100% saturation). The accuracy of the device is ± 0.01 WFV (Water Fraction by Volume) for most soils and ± ≤0.03 (max) for fine textured soils. Soil moisture was measured for top 5 cm of the land surface using the calibrated HydraGo Probe on the day of Sentinel-1 pass over the study area. The gravimetric sampling was performed using the core sampler on the first day of ground data collection to calibrate the sensor probe. As a unique parameter, the surface roughness was also measured using a roughness plate. The root mean square (RMS) height was employed to define the surface roughness Fig. 2.

Field data processing

Soil moisture: A total of 102 in-situ measurements were made during the field data collection covering four dates. To obtain the moisture content in the soil, freshly weighed soil samples in the field filled in

Table 1: Sentinel-1 satellite acquisition dates and data specification over the study area.

Acquisition Dates	Incidence Angle θ (˚) (near-far)	No. of Field Samples	Soil Moisture in m^3m^{-3} (min-max)	Surface Roughness in cm (min-max)
22/Apr/2021	30.82-46.08	25	0.189-0.187	1.0-2.5
16/May /2021		28	0.033-0.075	1.1-3.56
28/May/2021		28	0.056-0.182	1.4-3.36
09/Jun/ 2021		21	0.048-0.182	1.09-3.8

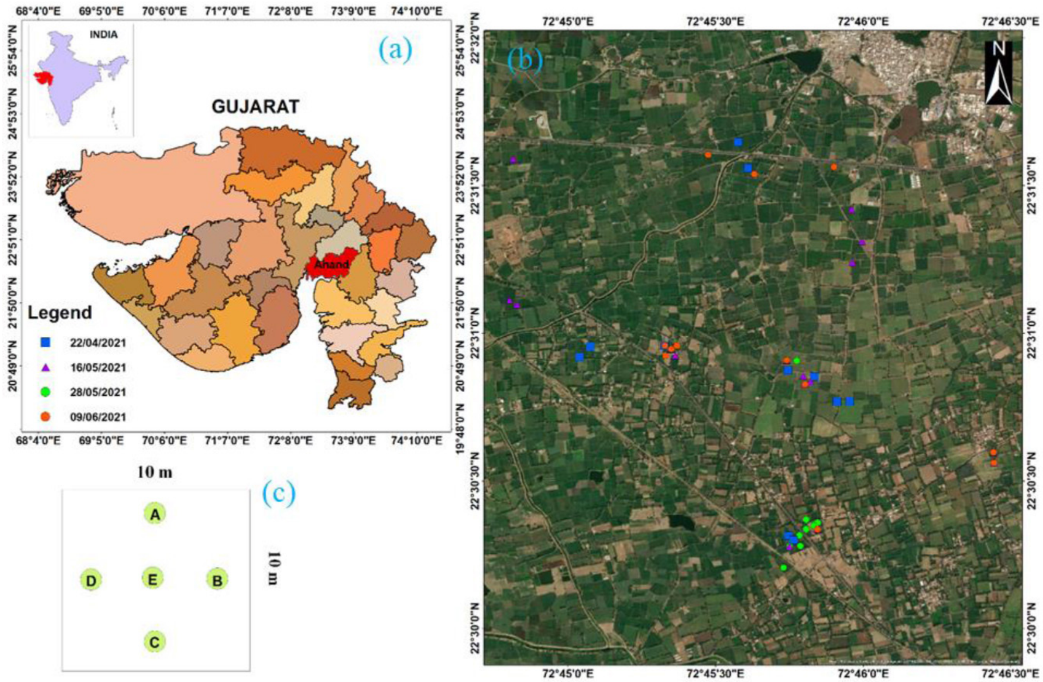

Fig. 1: (a) Location of the study area with acquisition dates synchronous to Sentinel-1 satellite pass (b) Selected fields for the in-situ measurements of soil moisture on google earth imagery (c) Sampling plan within the study fields.

the aluminium cans were taken to the laboratory for oven drying for approx. 24 hours at 105 °C temperature. Completely dried samples were weighed for dry weight. The standard formula for moisture content was applied Equation (1). The samples were collected using the core sampler with auger so that the gravimetric soil moisture can be converted to the volumetric soil moisture (m^3m^{-3}) equivalent to the unit of sensor probe. Wet weight of the soil was taken in the field and after oven drying, dry weight of the samples was observed to calculate the soil moisture content in the samples by standard formula. The gravimetric soil moisture was multiplied by the ratio of soil bulk density to water density to obtain the volumetric soil moisture (m^3m^{-3}) of each sample as per Equation (2).

For, Gravimetric soil moisture,

$$m_g = \frac{mass\ of\ water}{mass\ of\ dry\ soil} = \frac{(mass\ of\ wet\ soil) - (mass\ of\ over}{mass\ of\ oven\ dry\ soil} \quad (1)$$

For, Volumetric Soil Moisture,

$$m_v = m_g \times \frac{density\ of\ soil\ (\rho_{soil})}{density\ of\ water\ \ (\rho_{water})} \quad (2)$$

Surface roughness :The surface roughness determines the irregularities of the surface geometry which has a considerable effect on the variation in the radar return signal which is generally referred as the radar backscattering (Srivastava *et al*., 2008). For the soil surface roughness (s), Root Mean Square (RMS) Height of soil was measured using gridded roughness plate of 1 m length using standard 1 cm interval from each sampling site as shown in Fig. 2. The measurements were made parallel and perpendicular to the bare soil field furrow. The number of samplings from each location depends on the variation in the roughness as during the field survey, some fields were smooth, ploughed with moderate to high roughness. The roughness of each field location is calculated using following Equation (3).

$$\mathrm{RMS_{height}} = \mathrm{S} = \sqrt{\frac{\sum_{i=1}^{n}(Z_i - Z)^2}{n-1}} \quad (3)$$

Where, n is the number of total points on the gridded plate, Z_i is the height of the individual point, and z is the mean height in cm.

Fig. 2: (a) Soil Moisture measurement using HydraGo Probe (b) RMS height measurement using roughness plate (c) Gravimetric measurements using core sampler with auger (d) Oven drying of the samples (e) Various soil conditions during field visit.

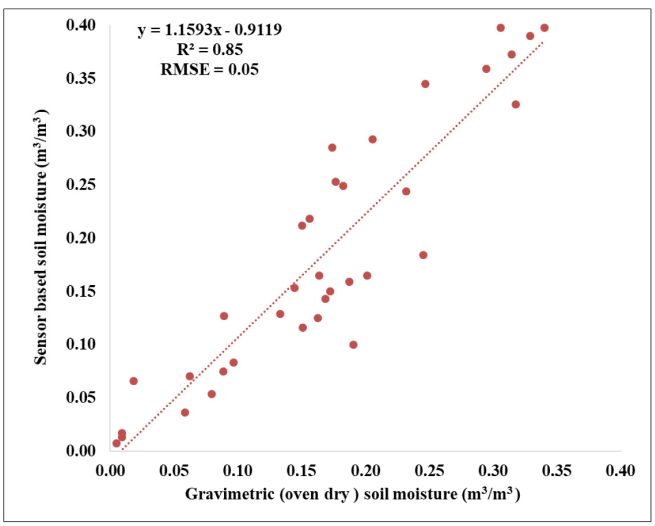

Fig. 3: Intercalibration of gravimetric and sensor-based soil moisture (m^3m^{-3})

The details of satellite acquisition dates and field measurements are given in Table 1.

Inter-calibration of gravimetric soil moisture and sensor-based soil moisture

Soil moisture sensors are calibrated with respect to field specific measurement of volumetric soil moisture (Rowlandson *et al.,* 2013)which utilize gravimetric sampling, soil moisture probes, or both, to estimate the volumetric soil water content. Soil moisture probes eliminate the need for labor-intensive gravimetric sampling. To ensure the accuracy of these probes, several studies have determined these probes need various degrees of localized calibration. This study examines six possible calibration techniques using data collected during a field campaign conducted in 2012, with soil moisture samples being collected over 55 fields in southern Manitoba, as part of the Soil Moisture Active Passive Validation Experiment 2012 (SMAPVEX12. The good correlation between gravimetric (oven dry) soil moisture and sensor-based soil moisture is observed with $R^2 = 0.84$ and RMSE =0.05 m^3m^{-3} (Fig. 3). So that, the sensor-based soil moisture was used for further processing and analysis.

Satellite data processing

Sentinel-1A C-band data processing was carried out using ESA's Sentinel Application Platform (SNAP) v6.0. Radiometric calibration, thermal noise removal, speckle filtering (using a refined Lee filter with a window size of 7 × 7), and terrain correction are carried out during the pre-processing stage of the SAR data. For correcting the terrain and computing the local incidence angle in SAR data, the Shuttle Radar Topography Mission's (SRTM) digital elevation model (DEM) data was employed with a spatial resolution of 30 m. Following pre-processing, the backscatter coefficient (σ^0) values were obtained from the VV and VH images on a linear scale and then converted in backscatter values in decibel scale () according to, $\sigma^0_{dB} = 10 * \log_{10}(\sigma^0)$.

To determine soil moisture, the Dubois model has been modified and combined with the Topp's model in the current study. The relative soil permittivity (ε) was determined using incidence angle and backscatter measurements of VV polarisation from C-band Sentinel-1A data as an input to the Dubois model. The relative permittivity obtained from the MDM is used in the Topp's

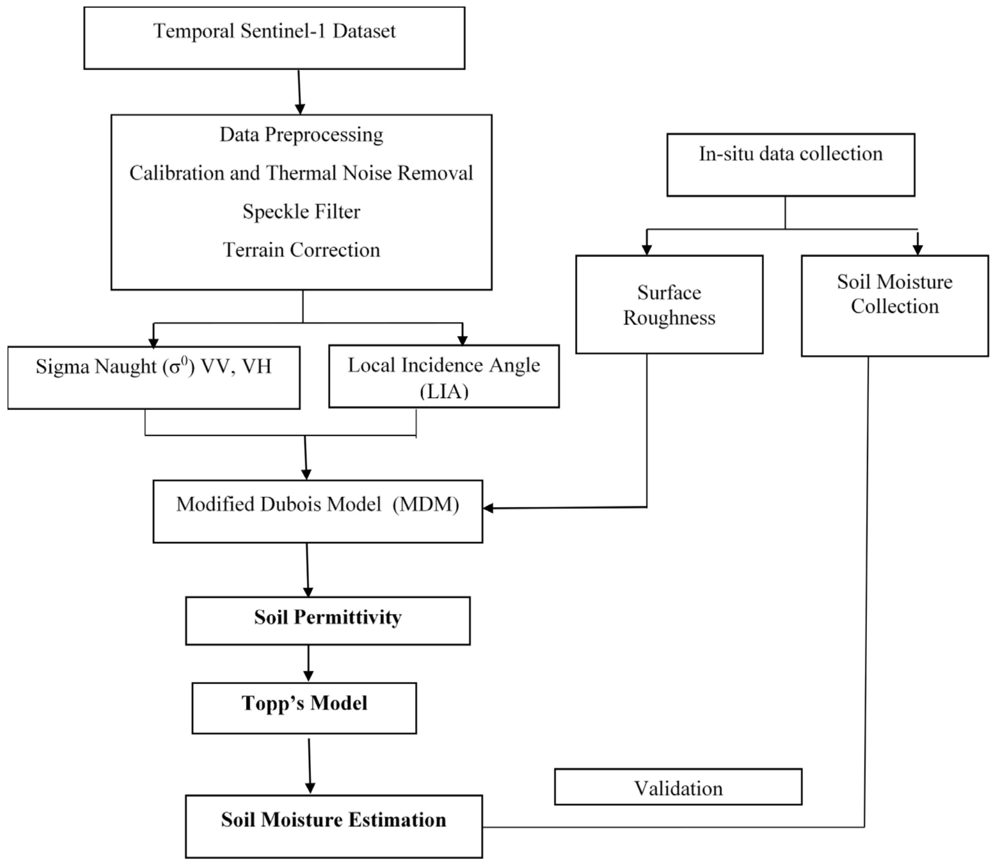

Fig. 4: Methodology flow chart for the study.

model to compute volumetric soil moisture. The entire process to retrieve the soil moisture is illustrated in the Fig. 4.

Modelling radar backscatter

The relative soil permittivity was calculated by (Dubois et al., 1995) for full polarimetric SAR data originally for multifrequency scatterometer data. The same was later evaluated for airborne images and for various dual- pol multifrequency SAR satellite data with appropriate modifications to achieve the optimum estimation of soil moisture. The efforts by various researchers have been made to modify the Dubois Model as per the availability of backscattering parameters (Sahebi and Angles, 2010)C-band SAR data in HH and HV polarization. The semi empirical approach derived by Dubois and the same modified and proposed as modified Dubois model (MDM. The present study focuses on the MDM for dual polarimetric data, where sensor parameters (θ and λ) and target parameters (ε and s) are used to build the model. The backscattering coefficients for HH and VV polarizaitons are obtained by Equations (4) and (5).

$$\sigma^0_{hh} = 10^{-2.75}\left(\frac{\cos^{1.5}\theta}{\sin^5\theta}\right) \times 10^{0.028\varepsilon\tan\theta}(k.s.\sin\theta)^{1.4}\lambda^{0.7} \qquad (4)$$

$$\sigma^0_{vv} = 10^{-2.35}\left(\frac{\cos^3\theta}{\sin^3\theta}\right) \times 10^{0.046\varepsilon\tan\theta}(k.s.\sin\theta)^{1.1}\lambda^{0.7} \qquad (5)$$

Where, θ is the incidence angle, ε is the relative soil permittivity, s is the surface roughness (cm), k = (2π/λ) is the wavenumber, and λ is the SAR wavelength. While the s and **ε** are the target parameters, which are often unknown, the s and **ε** are connected to the sensor parameters. As per above MDM equations, the sentinel-1 is having VV and VH backscattering coefficients, so equation (5) is inverted to compute the relative soil permittivity (ε) using Equation (6)

$$\varepsilon = \frac{\log(\sigma^0_{vv}) - \log(AC)}{B} \qquad (6)$$

Where, $A = 10^{-2.35}\left(\frac{cos^3\theta}{sin^3\theta}\right)$,$B = 10^{0.046\varepsilon tan\theta}$ and $C = (k.s.sin\theta)^{1.1}\lambda^{0.7}$

Using the Topp *et al.,* 1980 model (Topp's Model), the volumetric soil moisture is estimated using the soil permittivity derived from dual pol SAR data with VV polarizaiton by MDM Equation (7).

$$m_v = -5.3 \times 10^{-2} + 2.92 \times 10^{-2}\varepsilon - 5.5 \times 10^{-4}\varepsilon^2 + 4.3 \times 10^{-6}\varepsilon^3 \qquad (7)$$

RESULT AND DISCUSSION

Sentinel-1A SAR VV backscatter coefficient over bare soil is utilized in the Modified Dubois model using Topp's model to estimate the soil moisture. The accuracy of the satellite derived soil moisture is evaluated with the ground-based soil moisture. At first, the entire range spanning all four data collection dates of the in-situ soil moisture starting from 0.02 to 0.18 (m^3m^{-3}) is considered

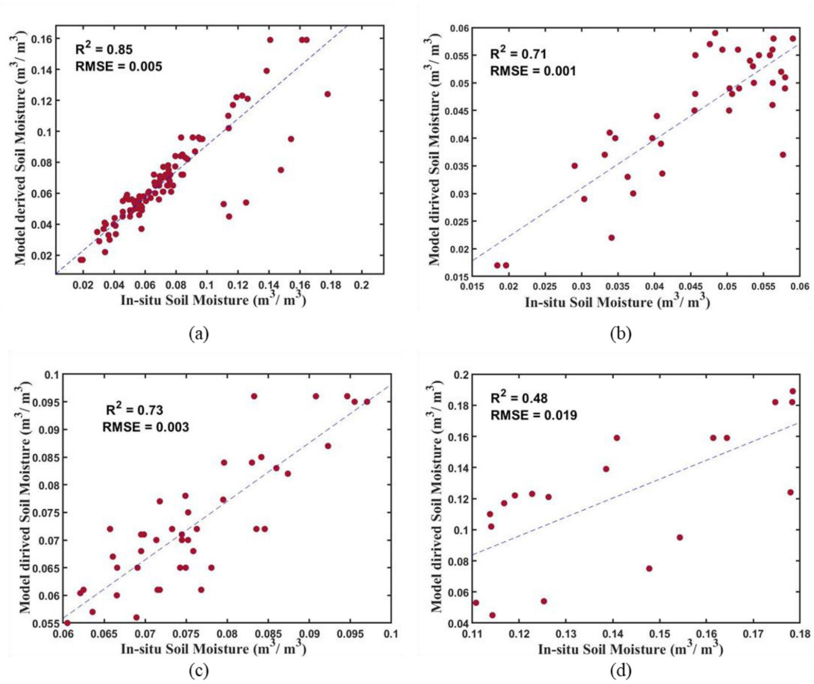

Fig. 5: In-situ soil moisture vs Model derived soil moisture (m^3m^{-3}) (a) for entire dataset (b) 0.015 to 0.06 (m^3m^{-3}) (c) 0.06 to 0.1 (m^3m^{-3}) (d) 0.10 (m^3m^{-3}) and above over bare agricultural fields.

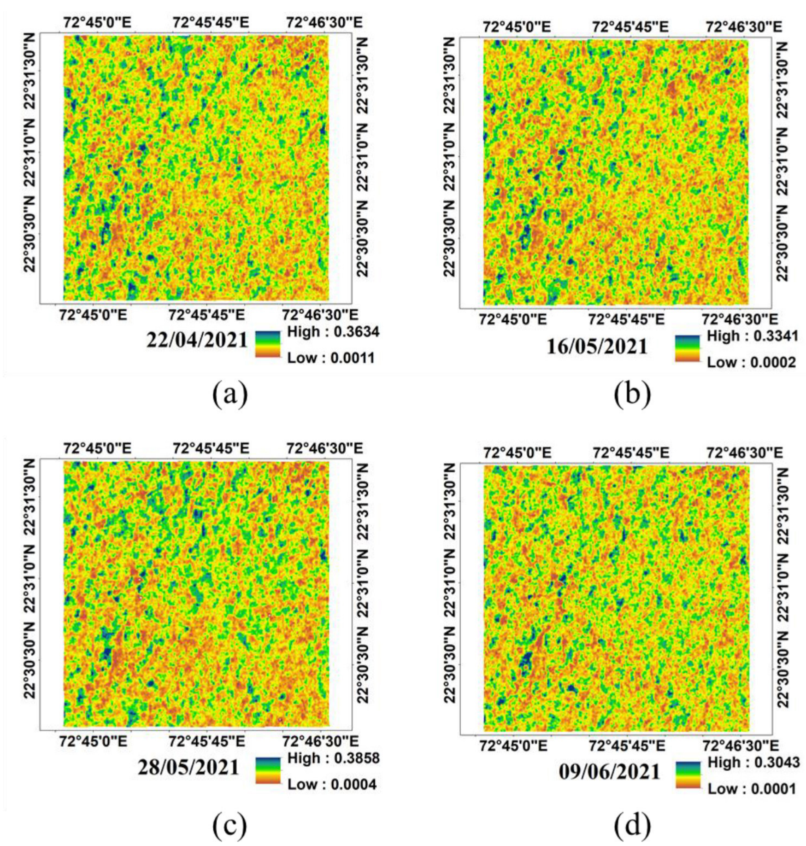

Fig. 6: Surface soil moisture estimated using Sentinel-1

for the validation. The in-situ soil moisture yields good agreement with model derived soil moisture with R^2 = 0.81 and RMSE = 0.005 (m^3m^{-3}) as shown in Fig. 5. Relationship between in-situ soil moisture and model-derived soil moisture is depicted in the scatter plot. The linear regression line is shown by the dashed line.

In-situ soil moisture ranging from 0.015 to 0.06 (m^3m^{-3}) exhibits good correlation with model derived soil moisture with R^2

= 0.71 and RMSE = 0.001(m^3m^{-3}).Soil moisture ranging from 0.06 to 0.10 (m^3m^{-3}) displays relatively better correlation with model derived soil moisture with R^2 = 0.73 and RMSE = 0.003 (m^3m^{-3}) and 0.11 to 0.18 (m^3m^{-3}) shows poor correlation with model derived soil moisture with R^2 = 0.48 and RMSE = 0.019(m^3m^{-3}) as shown in Fig. 5.

In-situ and modelled soil moister values are in good agreement up to 0.1 (m^3m^{-3}), but the same is having moderate correlation above 0.1 (m^3m^{-3}). The difference between modelled and in-situ soil moisture is moderate for lower soil moisture whereas it is larger for higher soil moisture. For the medium range of soil moisture, it gives better results. This attributes to the difference in the soil geometry (smooth or rough). Such heterogeneity in soil surface of bare land limits the potential estimation of soil moisture. The overestimation is possibly due to high backscatter value from ploughed soil with higher roughness and underestimation is probably due to low backscatter value from smooth soil surface, both were observed approximately after the soil moisture value of 0.1 (m^3m^{-3}). So that, the entire range of soil moisture is categorized. In order to evaluate the sensitivity for different soil moisture ranges, the entire dataset is categorized in three soil moisture ranges 0.015 to 0.06 (m^3m^{-3}) , 0.06 to 0.1(m^3m^{-3}) and above 0.1 (m^3m^{-3}). The surface soil moisture estimated from the Sentinel-1 data using MDM for all four dates for the study area is shown in the map. The highest and lowest estimated soil moisture values are also shown in the map (Fig. 6).

CONCLUSION

The study reveals that the MDM shows good estimate of soil moisture for bare agricultural fields for the soil moisture range of 0.02 to 0.18 (m^3m^{-3}). However, if it is categorized in different ranges, it gives inference about the sensitivity to different soil moisture values with varying correlation with observed and estimated soil moisture. Surface roughness being a significant parameter improves the soil moisture estimation if measured in bare soil as it does not get influenced by the crop geometry. Having only VV polarization in Sentinel-1, which is sensitive to the soil properties, it has been used to estimate soil moisture in MDM and Topps' model. It is manifested from this study that incidence angles ranging from 30 ° to 46 ° are suitable for the soil moisture estimation. In future, the newly launched EOS-04 (Formerly known as RISAT-1A) can be explored for the backscattering coefficients from other polarizations. A prior, timely and accurate information on available soil moisture in the bare soils can help to make planning for management of irrigation facilities to the stakeholders.

ACKNOWLEDGEMENT

The authors are highly grateful to the Director of Research, Anand Agricultural University for providing all possible support and SAC, ISRO, Ahmedabad for the collaborative project under MAHTARAM. We also sincerely acknowledge European Space Agency (ESA) for making Sentinel-1 data freely available.

Funding: The research work was funded under MAHTARAM project by SAC, ISRO, Ahmedabad.

Conflict of interest: There is no conflict of interest reported by the authors

Data availability: Data are available on request

Authors' contribution: **A. Murugesan**: Data collection and Formal analysis; **R. Dave**: Conceptualization, Methodology, Visualization, Writing-original draft, Editing; **A. Kushwaha**: Data collection and analysis; **K. Saha**: Visualization, Editing; **D. K. Pandey:** Conceptualization, Supervision

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