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Multiple linear regression model-based soil moisture mapping using sentinel 1A synthetic aperture radar data

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Abstract
The present study was conducted in Perambalur district, Tamil Nadu from September 2018 to January 2019 and soil moisture mapping was accomplished using Sentinel-1A Synthetic Aperture Radar (SAR) data. Ground truth measurements were carried out to estimate the soil moisture employing a gravimetric method concurrently with satellite passes. Standard SAR data processing techniques were applied to derive backscattering coefficients (σ0) for both VV and VH polarizations. These coefficients were then used, along with local incidence angle, to empirically estimate soil moisture. The results revealed that low backscattering coefficients in September 2018 and January 2019 indicating drier conditions, whereas higher values were observed during the northeast monsoon season in October, November, and December 2018, indicating increased soil moisture content. Multiple linear regression analysis was performed to establish relationships between soil moisture, backscattering coefficients, and local incidence angle for both VV and VH polarizations. In September 2018, VV-derived soil moisture ranged from 2.27% to 7.14%, while VH-derived moisture was higher at 26.74%. October 2018 exhibited a wider range of soil moisture, with VV-derived values ranging from 4.85% to 29.17%, and VH-derived values ranging from 5.22% to 26.73%. Multiple linear Regression is highly related with observed and predicted soil moisture on both VV and VH polarization. This study demonstrates that SAR data, particularly VV polarization, can be effectively utilized to map and monitor soil moisture with a high degree of reliability. These findings have significant implications for assessing agricultural drought and monitoring soil moisture conditions in near real-time.

Keywords: Soil moisture, SAR data, multiple linear regression, polarized data

1. Introduction
Soil, the product of the weathering of rocks and minerals, serves as a crucial medium for plant growth and a habitat for various terrestrial organisms, making it an essential component of our ecosystem. The presence of soil moisture at varying levels significantly influences crop growth and ultimately determines crop yield, as water is a critical component for crops during various growth stages. Soil can be categorized based on its moisture content, ranging from saturated soil (Baghdadi *et al*., 2004; Rombach *et al*., 1997) [3, 24] with a moisture content of about -0.001 bars or less, which requires minimal energy for plant uptake, to field capacity, where moisture is available between -0.05 and -0.33 bars. At the other extreme is the wilting point, when the plant requires substantial energy (around 15 bar pressure) to extract water. Therefore, understanding soil moisture content in a cropping system or region is essential for planning agricultural activities and implementing efficient water and nutrient management strategies (Kanga *et al*., 2017; Rather *et al*., 2018) [14, 21].
Conventionally, soil moisture is been estimated through labor-intensive gravimetric methods or by using portable equipments and sensors such as Tensiometers, Gypsum blocks, Time Domain Reflectometers, and Neutron Probe moisture meters. However, these measurements are often point-based and time-consuming, lacking spatial information. With the advancement of Remote Sensing and Geographic Information System (GIS) techniques, the spatial and temporal estimation of soil moisture has become more feasible, with numerous studies exploring these possibilities in recent decades. Near-surface soil moisture cannot be directly measured using radar remote sensing; instead, it is estimated based on the dependency of backscatter intensity on the dielectric constant of the observed medium, a principle well-documented in various studies (Bell *et al*., 1980; Schmugge *et al*., 1996; Engman *et al*., 1991; Topp *et al*., 1980) [6, 25, 10, 29].

Researchers such as Peng *et al*. (2015) [18] and Petropoulos *et al*. (2015) [19] have demonstrated the potential of utilizing microwave, optical, and thermal sensor data for soil moisture retrieval. Microwave remote sensing sensors have particularly stood out for their advanced and reliable soil moisture product retrieval capabilities. Several microwave satellites, including the Advanced Microwave Scanning Radiometer (AMSR-E), the Advanced Scatterometer (A-SCAT), Soil Moisture and Ocean Salinity (SMOS), and the Soil Moisture Active Passive (SMAP), are operational and provide data for soil moisture retrieval at various spatial and temporal resolutions. The accuracy of these soil moisture products is typically validated through direct comparisons with in-situ soil moisture measurements or data from different satellites (Albergel *et al*., 2012; Dorigo *et al*., 2015 and Peng *et al*., 2015) [1, 8, 18].

Furthermore, the availability of data from Synthetic Aperture Radar (SAR) satellites such as RADARSAT-2, RISAT-1, TerraSAR-X, and Sentinel-1A has expanded the possibilities of enhancing soil moisture retrieval techniques (Ulaby *et al*., 1986) [30]. The backscattering coefficient ($\sigma 0$) obtained from microwave sensors is directly linked to the dielectric properties of the surface soil, which predominantly depend on moisture content. As a result, numerous empirical and semi-empirical models have been developed and employed to extract soil moisture information from radar backscattering coefficients. SAR satellites, operating in C-band or X-band, are particularly valuable for monitoring surface features (Oh *et al*., 2002; Oh *et al*., 2004; Dubois *et al*., 1995; Fung *et al*., 1992; Attema *et al*., 1978) [17, 15, 9, 11, 2], including moisture and vegetation. Notable models like the polarimetric scattering model by Oh *et al*. (1992) [16] and the Dubois model utilized by Bai *et al*. (2015) [4] have contributed to the accurate retrieval of soil moisture from SAR data, which can be acquired in single, dual, or multi-polarization modes with varying incident angles.

With this background knowledge an attempt was made to retrieve surface soil moisture form Sentinel-1A SAR data and generate soil moisture map of Perambalur District of Tamil Nadu during the period 2018 to 2019.

2. Previous work

Soil moisture, a pivotal variable in agriculture, weather prediction, and hydrological modeling, exerts a significant influence on agricultural activities and weather patterns. Accurate monitoring of surface soil moisture, especially within the 0 to 5cm depth range, is essential for optimizing crop production and assessing drought conditions (Verhoest *et al*., 2008) [31]. This comprehensive review explores a range of methods for measuring and estimating soil moisture, with a particular focus on their applicability to the study in Perambalur district, Tamil Nadu, utilizing Sentinel-1A Synthetic Aperture Radar (SAR) data.

2.1 Ground-Based Methods

The review begins by examining conventional ground-based observations such as the gravimetric method and tensiometers, which offer precise but often labor-intensive measurements. The gravimetric method, involving soil sample collection and weighing, serves as a valuable reference for validating other estimation techniques (Robock *et al*., 2000) [23]. Tensiometers, measuring capillary tension in soil water, provide insights into available soil moisture levels but may not fully indicate plant growth limitations (Wang and Schmugge, 1980) [6].

2.2 Time Domain Reflectometry

Time Domain Reflectometry (TDR) probes, efficient tools for measuring soil moisture at various depths, are discussed for their rapid and accurate readings but can present challenges related to probe insertion and soil disturbance (Bramer *et al*., 2018; Ren *et al*., 1999) [7, 22].

2.3 Advanced Remote Sensing Techniques

Soil moisture sensors measure how wet the soil is. For example, sensor called TDR, uses electricity to check the soil. Remote sensing is a great way to figure out how much water is in the soil over big areas. It can also help scientists understand how the land and the air work together, which is useful for predicting weather and climate. Different tools like satellites, airplanes, and ground devices are used for remote sensing. These tools can show details very well, and they can see deep into the ground, which makes it easy to use them for studying water in the soil.

2.4 Microwave Remote Sensing

Microwave remote sensing, particularly using radar waves, is emphasized as a powerful tool for soil moisture estimation. The ability of radar waves to penetrate subsurface soil layers makes them suitable for this purpose. However, their accuracy can be affected by factors such as soil roughness, vegetation, and crop height (Pierdicca *et al*., 2010) [20].

2.5 Integration of Remote Sensing Data

The review further highlights the integration of remote sensing data from various sources, both passive and active, to enhance soil moisture estimation. The Soil Moisture Active Passive (SMAP) satellite, combining passive and active microwave sensors, represents a compromise between spatial scale and accuracy (Thoma *et al*., 2008) [28].

2.6 SAR-Based Models

The focus then narrows down to Synthetic Aperture Radar (SAR)-based models for soil moisture estimation. These models offer spatially explicit and timely information over large areas. Several models, including the PolSAR model, Water Cloud Model, Ratio Vegetation Method, and Dubois Model, are discussed for their capabilities in accurately estimating soil moisture (Ballester Berman *et al*., 2013; Bai *et al*., 2015; Joseph *et al*., 2010) [5, 4, 13]. Soil texture analysis's crucial role in influencing remote sensing data and the importance of validation in assessing the accuracy of soil moisture estimation models are also emphasized. Establishing relationships between soil moisture and meteorological variables further enhances the precision of these models (Gorrab *et al*., 2015) [12].

3. Materials and methods

3.1 Study area

The study focused on mapping soil moisture using Synthetic Aperture Radar (SAR) satellite data, particularly Sentinel-1A, within the Perambalur district (Figure 1a) of Tamil Nadu. Perambalur district is situated in a semi-arid agro-climatic region of Tamil Nadu, spanning from 78°38'6.396" to 79°9'48.884" East longitude and 11°31'24.953" to 11°3'18.871" North latitude. The district experiences an average annual rainfall of 908 mm, with 52 percent of this

precipitation occurring during the South West monsoon, 34 percent during the North East monsoon, and the remainder distributed across the winter and summer seasons. Temperature ranges from a maximum of 40 °C to a minimum of 22 °C during different seasons. The soils in the Perambalur district vary in texture, primarily encompassing red and black soils and texture ranging from clay to sandy loam. These soils are typically deep to very deep and possess a high water-holding capacity, making them suitable for rainfed crop cultivation. In the North East zone of the district, soils are predominantly red sandy loam, clayey loam, and saline soils, while the North West zone, including Veppanthattai, Peramalur, and Alathur blocks, features non-calcareous red and black cotton soils, along with clay soils.

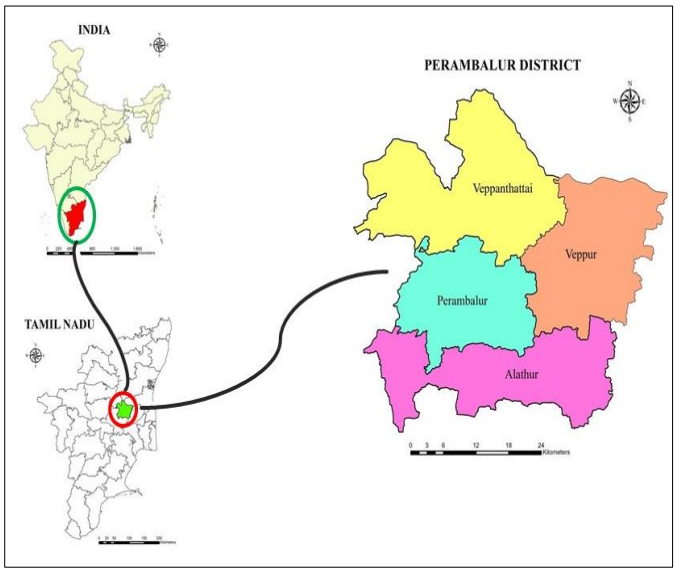

Fig 1a: Study Area Map

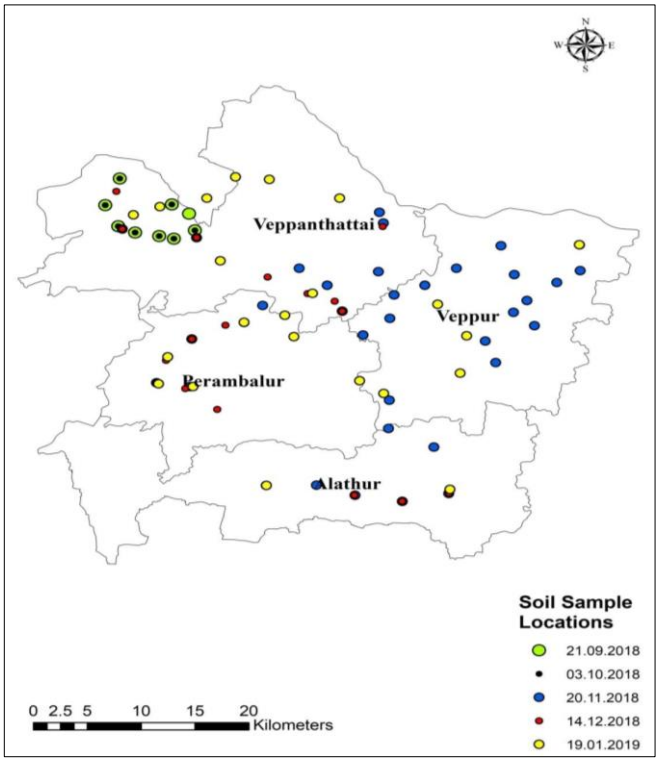

Fig 1b: Ground truth collection at various location of various date

3.2 Satellite data

Synthetic Aperture Radar (SAR) data is a versatile tool with the capability to operate in all weather conditions, including cloud penetration, and can provide imagery during rainy seasons, day, and night. In this study, we specifically utilized data from the Sentinel-1A mission, which offers four distinct resolutions of C-band image modes. Satellite data collected on the following respective dates 21 Sep, 03 Oct, 20 Nov, 14 Dec 2018 and 19 Jan 2019. For our research, we focused on the Interferometric Wide Swath (IW) mode, characterized by a 250 km swath width, exceptionally short revisit times, and rapid product delivery. This mode is particularly valuable for land imagery services. Sentinel-1A satellite data included both VV (vertical-vertical) and VH (vertical-horizontal) polarization.

To validate and complement our SAR data, ground truth data collection was carried out during the study period. This involved estimating in-situ soil moisture levels and recording essential terrain parameters. Ground truth data collection occurred at periodic intervals, aligning with the pass dates of the Sentinel-1A satellite, totaling five observations. The initial soil moisture measurements were determined using the gravimetric method. On the 21 Sep, 03 Oct, 20 Nov, 14 Dec 2018 and 19 Jan 2019 these respective dates collected ground truth. A visual representation of the ground truth points recorded during the survey can be found in Figure 1b.

3.3 Methodology

This study focused on processing Sentinel-1A Synthetic Aperture Radar (SAR) data and conducting various mapping activities, employing a suite of software tools for efficient data handling and analysis. The software tools used in this research included SNAP tool 6.0 for SAR data processing, ArcGIS 10.6 and QGIS 2.18 for GIS analysis and mapping, R-Studio 3.5 for statistical analysis, and Microsoft Excel 2007 & 2010 for mathematical analysis.

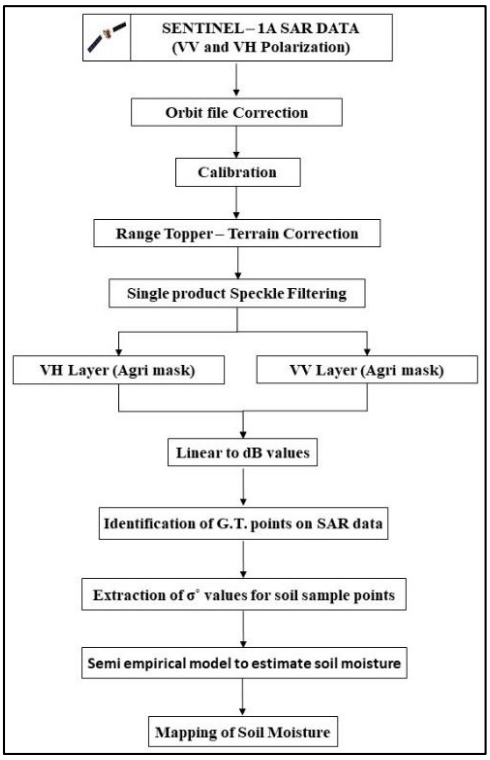

Fig 2: Flow chart Depicting Soil Moisture Mapping Methodology

3.3.1 Pre-processing

The pre-processing phase involved the extraction of a subset of the Perambalur district in Tamil Nadu from the Sentinel-1A IW GRDH dataset. This step aimed to reduce orbital errors, radiometric distortion, geometric distortion, and speckle noise, ensuring the accuracy of subsequent analyses.

Orbital correction was carried out using precise orbit files provided by the Copernicus Precise Orbit Determination (CPOD) services. These files were downloaded directly to the SNAP toolbox, and the correction process involved considerations of radar wavelength, satellite position, slant range, and satellite relative velocity.

Radiometric correction addressed issues related to backscattering trends in wide swath SAR images, which can cause variations in brightness across the image. An equation was employed to calculate the sigma naught value, resulting in more accurate representation of surface backscattering.

Geometric correction accounted for SAR geometry effects such as foreshortening, shadows, and layover, which can distort data. This correction utilized Digital Elevation Models (DEM) to convert image coordinates into three-dimensional geographic coordinates.

Local Incidence Angle Maps were generated to improve radiometric accuracy by considering local terrain variations. This approach reduced radiometric impact and enhanced data quality.

3.3.2 Post-processing

Post-processing steps included speckle filtering, which exploited the temporal correction of speckle noise between images to reduce noise. The Refined Lee filter was used for this purpose. Intensity values were converted to decibels (dB) to ensure a more even distribution of backscattering information.

Empirical models were developed to establish relationships between soil moisture, local incidence angle, and backscattering coefficients. Multiple Linear Regression (MLR) was employed, with soil moisture as the dependent variable and backscattering coefficients and local incidence angles as independent variables.

$$\sigma^0 = a.m_s + b \text{ ……equation} \quad (1)$$

$$m_s = \sigma^0_{TR,}\theta_i \text{……equation} \quad (2)$$

$$m_s = a + b.\sigma^0_{TR,} + c.\theta_i \text{……equation} \quad (3)$$

4. Results

The research results presented in Tables 2, 3, 4, 5, and 6 provide valuable insights into the relationship between ground truth soil moisture and radar backscattering coefficients ($\sigma 0$) obtained from different polarizations (VV and VH) for various observation dates. These observations were conducted in different locations within the study area, shedding light on the dynamics of soil moisture and its correlation with radar data.

Table 2: Gravimetric soil moisture (%) and Radar backscattering coefficient (σ^0) obtained during 21 September 2018

S. No	Village Name	21.09.2018		
		Soil Moisture (%)	σ^0 (VV) dB	σ^0 (VH) dB
1.	Udumbiam	7.14	-11.87	-21.84
2.	Poolambadi	3.00	-12.13	-20.26
3.	Arumbavur	6.02	-10.69	-17.68
4.	Arumbavur	2.27	-13.72	-21.44
5.	Thaluthalai	6.67	-11.31	-18.11
6.	Vengalam (west)	6.02	-11.33	-16.04
7.	Vengalam (east)	6.32	-12.58	-18.57
8.	Venganur	5.56	-11.39	-16.26
9.	Venganur	6.93	-10.74	-17.13

On September 21, 2018 (Table 2), nine locations were sampled, with soil moisture levels ranging from 2.27% to 7.14%, and corresponding $\sigma 0$ values for VV polarization ranging from -13.72 dB to -10.69 dB, and for VH polarization ranging from -21.84 dB to -16.04 dB. Notably, two villages, Arumbavur and Poolambadi, recorded exceptionally low moisture levels at 2.27% and 3%, respectively.

Table 3: Gravimetric soil moisture (%) and Radar backscattering coefficient ($\sigma 0$) obtained during 03 October 2018

S. No	Village Name	03.10.2018		
		Soil Moisture (%)	σ^0 (VV) dB	σ^0 (VH) dB
1.	Udumbiam	11.81	-9.05	-19.61
2	Poolambadi	7.53	-8.77	-17.92
3.	Arumbavur	29.17	-8.35	-14.24
4.	Arumbavur	10.47	-10.70	-18.70
5.	Thaluthalai	5.92	-9.16	-17.84
6.	Vengalam (west)	12.16	-9.92	-15.53
7.	Vengalam (east)	5.21	-12.52	-17.67
8.	Venganur	4.85	-10.07	-15.90

Observations on October 3, 2018 (Table 3) included eight locations, with soil moisture varying from 4.85% to 29.17%. Corresponding $\sigma 0$ values for VV polarization ranged from -12.25 dB to -8.35 dB, and for VH polarization, from -19.61 dB to -14.24 dB. It's worth mentioning that the dB values were relatively higher compared to the previous observation date.

Table 4: Gravimetric soil moisture (%) and Radar backscattering coefficient (σ0) obtained during 20 November 2018

S. No	Village Name	20.11.2018		
		Soil Moisture (%)	σ^0 (VV) dB	σ^0 (VH) dB
1.	Agaram	11.67	-8.03	-13.37
2.	Ladapuram (east)	10.77	-8.30	-15.80
3.	Kalarampatti (R.f)	15.35	-11.30	-16.39
4.	Agaramsigoor	7.57	-5.55	-12.71
5.	Vayalapadi	9.02	-7.33	-14.49
6.	Olaippady (west)	9.81	-7.87	-14.15
7.	Olaippady (west)	11.33	-8.52	-14.25
8.	Puduvettagudi	7.98	-6.75	-12.82
9.	Paravai (west)	8.49	-7.75	-13.65
10.	Paravai (east)	10.53	-7.61	-14.41
11.	V.kalathur	10.14	-8.51	-14.03
12.	Nannai (east)	12.44	-10.85	-15.05
13.	Vadakalur	10.71	-8.49	-14.27
14.	Perumathur (north)	11.16	-9.08	-14.08
15.	Ponnagaram	10.93	-7.68	-13.77
16.	Keelapuliyur north	14.00	-7.79	-14.28
17.	Keelapuliyur	9.46	-8.37	-14.28
18.	Keelapuliyur (south)	10.50	-9.95	-15.49
19.	Alathurgate	13.64	-10.11	-15.46
20.	Karai (east)	10.61	-8.58	-15.19
21.	Aiyinapuram	10.55	-9.29	-17.09
22.	Thevaiyur (south)	10.71	-9.60	-14.01
23.	Kolathur (east)	12.04	-8.76	-15.58
24.	Gudalur	10.12	-7.79	-13.90
25.	Adhanur (south)	12.58	-8.35	-14.36
26.	Kurumbapalayam	11.15	-7.81	-15.03
27.	Perali (south)	13.13	-9.37	-15.87
28.	Veppanthattai (north)	11.63	-8.08	-13.86
29.	Vengalam (east)	11.07	-8.62	-13.82
30.	Arumbavur	11.44	-8.28	-15.63
31.	Vallapuram	11.54	-8.94	-13.83
32.	Mettupalayam (south)	9.34	-7.46	-14.78
33.	Nerukupai	12.65	-9.03	-15.52
34.	Esanai	11.69	-7.72	-14.30
35.	Esanai	11.75	-9.71	-15.95
36.	Melapuliyur (east)	12.15	-11.09	-13.78

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Subsequent observations on November 20, 2018 (Table 4) involved 36 locations, showcasing soil moisture levels between 7.57% and 15.35%. The σ0 values for VV polarization spanned from -11.30 dB to -5.55 dB, while for VH polarization, they ranged from -17.09 dB to -12.71 dB. The majority of points exhibited σ0 values between -7 and -9 for VV polarization and between -13 and -15 for VH polarization.

Table 5: Gravimetric soil moisture (%) and Radar backscattering coefficient (σ0) obtained during 14 December 2018

S. No	Village Name	14.12.2018		
		Soil Moisture (%)	σ^0 (VV) dB	σ^0 (VH) dB
1.	Ladapuram (east)	13.70	-10.08	-14.91
2.	Kalarampatti (R. F)	14.83	-10.61	-15.38
3.	Thambiranpatti	11.06	-9.34	-15.72
4.	Alathurgate	16.16	-11.12	-15.99
5.	Aiyinapuram	12.22	-9.71	-15.79
6.	Kolathur (east)	14.81	-11.89	-15.30
7.	Gudalur	9.83	-7.75	-15.22
8.	Veppanthattai (north)	11.56	-9.36	-15.46
9.	Vengalam (east)	14.19	-10.02	-15.99
10.	Arumbavur	9.37	-8.40	-14.61
11.	Vallapuram	11.69	-9.00	-15.68
12.	Poolambadi	12.71	-8.97	-16.53
13.	Brahmadesam	11.57	-8.65	-14.54
14.	Anukkur	13.01	-8.93	-15.41
15.	Anukkur	9.74	-7.87	-14.53
16.	Esanai	11.13	-10.27	-15.53
17.	Esanai	12.99	-12.34	-18.22
18.	Melapuliyur (east)	12.94	-11.43	-16.88
19.	Ladapuram (east)	13.05	-10.74	-16.25

The dataset for December 14, 2018 (Table 5) included 19 locations, featuring soil moisture percentages from 9.37% in Arumbavur to 16.16% at Alathurgate. The $\sigma 0$ values for VV polarization varied between -12.34 dB and -7.75 dB, while for VH polarization, they ranged from -16.88 dB to -14.53 dB.

Table 6: Gravimetric soil moisture (%) and Radar backscattering coefficient ($\sigma 0$) obtained during 19 January 2019

S. No	Village Name	19.01.2019		
		Soil Moisture (%)	σ^0 (VV) dB	σ^0 (VH) dB
1.	Alathurgate	3.97	-10.75	-16.97
2.	Noothappur (south)	4.03	-10.77	-17.03
3.	Noothappur (south)	6.37	-5.07	-15.68
4.	Venganur	5.65	-9.84	-16.51
5.	Venganur	4.78	-11.78	-18.18
6.	Veppanthattai (north)	6.98	-12.21	-17.22
7.	Esanai	5.76	-10.25	-17.02
8.	Melapuliyr west	4.14	-11.38	-16.11
9.	Ladapuram (east)	3.69	-11.34	-17.56
10.	Gudalur	3.87	-11.00	-15.67
11.	Earikari	3.96	-11.09	-17.03
12.	Anukkur	5.44	-9.35	-15.56
13	Brahmadesam	3.84	-11.97	-16.25
14.	Perali (north)	4.55	-10.87	-16.37
15.	Kavulpalayam	4.10	-11.82	-17.07
16.	Kunnam	4.87	-11.56	-17.54
17.	Elumur (east)	4.44	-10.08	-16.70
18.	Murukkankudi	6.59	-10.62	-16.08
19.	Agaramsigoor	6.41	-7.73	-13.91
20.	Pimbalur	3.86	-9.79	-15.53

The final set of observations, conducted on January 19, 2019 (Table 6), encompassed 20 locations, revealing relatively lower soil moisture levels, ranging from 3.69% to 6.98%. The $\sigma 0$ values for VV polarization were distributed between -12.21 dB and -5.07 dB, while for VH polarization, they ranged from -18.18 dB to -13.91 dB. Notably, $\sigma 0$ values were generally higher for VV polarization during this period.

The method of soil moisture retrieval employed in this study utilized Sentinel-1A Synthetic Aperture Radar (SAR) data, specifically the backscattering coefficient ($\sigma 0$) along with the local incidence angle. The relationship between soil moisture and radar parameters was established through empirical models, allowing for the estimation of soil moisture content by inverting the model using linear regression analysis (Equation 1).

$\sigma 0 = . ms + b$ ……Equation 1

Where 'a' and 'b' are coefficients, and 'ms' refers to the surface soil moisture. The empirical model adopted in this study was based on the influence of soil moisture and local incidence angle on backscattering coefficients, as developed (Equations 2 and 3).

$ms = \sigma TR, 0\ \theta i$……Equation (2)

$ms = a + b.\ \sigma TR, 0 + c.\ \theta i$……Equation (3)

Here, $\sigma TR0$ represents the backscattering coefficient (Transmitted: Received),
θi is the local incidence angle.
'ms' is considered the dependent variable,
while $\sigma TR0$ and $c.\ \theta i$ are independent variables.

The multiple linear equations generated using this process for various dates and two polarizations are presented in Table 7. These equations provide a means to estimate soil moisture based on radar parameters.

Table 7: Multiple Linear equation obtained for different dates

S. No	Date	VV Polarization	VH Polarization
1.	21-09-2018	y = 35.7234 + 1.2283 * X1 - 0.3759 * X2	y= 20.9251+0.3110* X1 - 0.2291 X2
2.	31-10-2018	y = -211.033 + 1.6864 * X1 + 5.6713 * X2	y= -200.261+1.2299* X1 + 5.5238 X2
3.	20-11-2018	y = -7.2600 - 0.8771 * X1 + 0.2655 * X2	y= -12.1077-0.8642* X1 + 0.3028 X2
4.	14-12-2018	y = -19.1106 - 0.9340 * X1 + 0.5426 * X2	y= -38.1568-0.8642* X1 + 0.8980 X2
5.	19-01-2019	y = 1.3351 + 0.3916 * X1 + 0.1861 * X2	y= 2.1363+0.5067* X1 + 0.2699 X2

5. Discussion

The relationship between radar backscattering coefficient ($\sigma 0$) and soil moisture is a fundamental aspect of remote sensing applications for monitoring and understanding soil moisture dynamics. This study investigated this relationship by analyzing *in-situ* soil moisture data and radar backscattering coefficients obtained from SAR data, focusing on both VV and VH polarizations.

5.1 Dielectric Properties and Soil Moisture

The relationship between $\sigma 0$ and soil moisture is rooted in the dielectric properties of materials. Dielectric constant, a critical component of these properties, plays a pivotal role in the interaction between electromagnetic waves and interacting object viz., soil. In dry conditions, most earth objects exhibit dielectric constants in the range of 3 to 8, whereas water has a remarkably higher dielectric constant of 80. This vast contrast in dielectric constants between dry soil and water forms the basis for the potential estimation of soil moisture through radar backscattering.

5.2 Temporal Variability in Radar Backscattering Coefficients

Analysis of radar backscattering coefficients from SAR data revealed interesting temporal patterns. Specifically, during September 2018 and January 2019 (Table 2 to 7), when the study area received minimal rainfall, the soils were predominantly dry. Consequently, low $\sigma 0$ values were recorded, in agreement with the well-established association between $\sigma 0$ and volumetric soil moisture. However, a notable deviation was observed in the case of VV polarization, where $\sigma 0$ values remained relatively high. This discrepancy may be attributed to site-specific effects, a phenomenon previously documented in remote sensing studies (Singh *et al*., 2007) [33]. These site-specific factors can introduce variability in the relationship between soil moisture and $\sigma 0$, complicating the interpretation of radar data.

5.3 Seasonal Influence on Soil Moisture

Further investigation of radar data revealed that soil moisture and $\sigma 0$ values exhibited a strong seasonal pattern. Specifically, during the northeast monsoon season spanning October, November, and December 2018, soil moisture levels (Figure 3) were elevated. This increase in soil moisture was mirrored by higher $\sigma 0$ values, aligning with the findings of previous studies that emphasized the connection between radar backscattering and soil moisture. These results underscore the sensitivity of radar signals to changes in soil moisture content and surface roughness.

5.4 Empirical Model for Soil Moisture Retrieval

To quantitatively assess the relationship between *in-situ* soil moisture and radar backscattering coefficients, an empirical model proposed was employed. This model incorporates both $\sigma 0$ and the local incidence angle (θi) to estimate soil moisture. Multiple linear regression analysis was carried out to develop this relationship, resulting in a set of equations that describe the interdependence of these variables. This study highlights the strong connection between radar backscattering coefficients and soil moisture content. By leveraging an empirical model and SAR data, the study successfully retrieved soil moisture values across different time periods. The results (Figure 3) indicate the potential of satellite-based sensors to provide near-real-time assessments of soil moisture levels, which are crucial for monitoring agricultural drought and other environmental applications. However, it is essential to consider site-specific effects and polarization selection when interpreting radar data for soil moisture estimation.

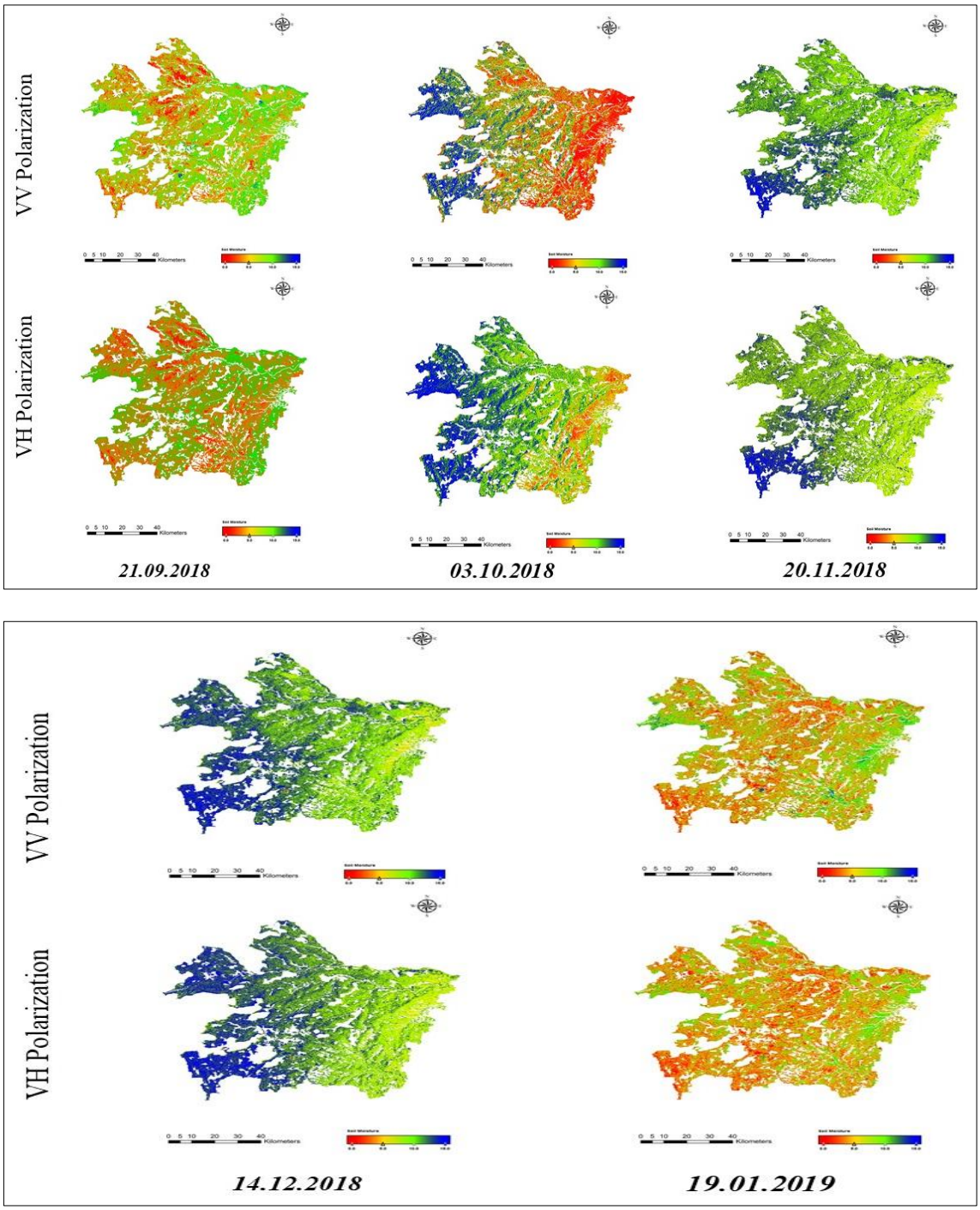

Fig 3: Soil moisture map

6. Conclusion

By utilizing SAR (Synthetic Aperture Radar) data, it is evident that soil moisture can be reliably retrieved through analysis. This is primarily due to the strong and well-established relationship between SAR signal backscatter (expressed in decibels, dB) and soil moisture content.

Thus, the surface soil moisture data derived from satellite sensors would help to determine the soil moisture status in near real time and assess the possibility of occurrence of agricultural drought in the region. In future there is a need to develop common methodology and moisture retrieval algorithm to deal with varying satellite products.

7. Data Share Statement

The manuscript, code book, and analytic code contain data that will be made available upon reasonable request. The data is stored in a public, open-access repository. Open Access Copernicus provided the relevant data, which can be obtained from the Sentinel 1A hub, Survey of India, NASA power hub and The Department of Remote Sensing and GIS, Directorate of Natural Resource Management, Tamil Nadu Agricultural University.

8. Ethical standards and consent to participate

Since the data used in this study is publicly available and does not contain personal information such as individual names or household addresses, ethics approval was not necessary.

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