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Research Article

Soil Moisture Retrieval from Sentinel-2 Data Using the Optical Trapezoidal Model (OPTRAM)

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ARTICLE INFO	ABSTRACT

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Surface soil moisture is a determining factor in developing hydrological and ecological processes, especially in the arid and semi-arid regions. Still, its accurate and extended special capacity estimation remains a challenge to the traditional ground-based techniques. In our study, we discuss prospects of the Optical Trapezoidal Model (OPTRAM) in the retrieval of soil moisture from high-resolution optical satellite data. The model exploits interactions among the vegetation indices and shortwave transformed reflectance to estimate the surface moisture without using thermal inputs. The applied over agricultural territory of semi-arid region near Beed, Maharashtra. In-situ data was collected at the same time when the satellite was over our region where we have employed gravimetric method with on ground observations in oven dry and the theta probe. To ensure cohesion between the two sets of the data, the results obtained from the gravimetric method were calibrated back to volumetric units for comparing with the results obtained from theta probe the comparison showed a good level of agreement (R^2) of 0.8873, (RMSE) of 0.033 cm^3/cm, indicating the reliability of the volumetric data obtained in the field. After this calibration, the OPTRAM retrieved soil moisture was compared to the Theta probe and used as the reference to validate latter. The comparison was strongly correlated with (R^2) 0.8253 and (RMSE) 0.0437 cm^3/ cm^3 showing that OPTRAM has been able to capture the spatial variance of surface soil moisture under different field condition. These results emphasize on the model's ability to effectively deliver reliable high-resolution estimates of soil moisture based on optical data retrieved from satellites. These results emphasize the stamina and scalability of the model for soil moisture retrieval, the present work takes up the need to assess the suitability of the Optical Trapezoidal Model (OPTRAM) for soil moisture retrieval using Sentinel-2 optical data. It is concerned with improving estimates of soil parameters in a diverse variety of land covers under a semi-arid landscape.

Keywords: soil moisture, theta probe, OPTRAM, sentinel-2

1. INTRODUCTION

Soil moisture is important in the processes of hydrology, agricultural yields, and in the state of the ecosystem. [1] Precise estimation of surface soil moisture is important for drought monitoring, irrigation planning as well as for the land surface modelling. [2], [3] the traditional in situ techniques are precise but have a limited spatial spread and, in most cases, unsuitable for large-scale applications. The consequence has seen remote sensing techniques being developed as powerful tools for estimating the soil moisture in vast areas. [4] Remote sensing platforms operating in both microwave and optical domains have been widely utilized for soil moisture retrieval. Passive and active microwave sensors, including the Soil Moisture Active Passive (SMAP) mission, the Advanced Microwave Scanning Radiometer for EOS (AMSR-E), and Sentinel-1 SAR, are sensitive to soil dielectric properties and perform well under varying weather conditions [5], [6]. However, microwave observations often suffer from coarse spatial resolution and signal degradation due to surface roughness and vegetation cover [7]. In contrast, optical sensors such as Sentinel-2 provide high spatial resolution (10–20 m) and frequent revisit times, making them particularly suitable for

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agricultural and hydrological applications at local scales [8]. The estimation of crop water stress and soil moisture using thermal and vegetation indices has evolved significantly since the foundational work by Moran et al., who established the relationship between land surface-air temperature difference (Ts–Ta) and vegetation indices like the Normalized Difference Vegetation Index (NDVI) [9] [10]. This led to the development of thermal-optical models such as the Vegetation Index–Temperature (VIT) triangle and the Thermal Optical Trapezoid Model (TOTRAM), [11] which utilize Ts–Ta and NDVI in a two-dimensional space to diagnose water stress. However, these models depend on Land Surface Temperature (LST) data, which is often compromised by atmospheric interference and limited spatial resolution [12], [13] to overcome these limitations The Optical Trapezoidal Model (OPTRAM) was developed. OPTRAM relies exclusively on optical data, eliminating the need for thermal inputs [14]. It estimates surface soil moisture using a two-dimensional feature space defined by NDVI and the Shortwave Infrared Transformed Reflectance (STR) index. STR, derived from Sentinel-2's SWIR bands, is designed to enhance sensitivity to moisture variation by minimizing the effects of vegetation cover and surface roughness. In OPTRAM, each image pixel is positioned within a trapezoidal space bounded by empirically defined wet and dry edges in the NDVI–STR domain. Soil moisture is then inferred from its location relative to these boundaries [10]. This model has demonstrated strong potential for scalable and cost-effective soil moisture retrieval using only optical imagery [15], [16] the Shortwave Infrared Transformed Reflectance (STR) as a key component of the OPTRAM model to estimate soil moisture using optical remote sensing. Rather than using raw SWIR reflectance, which can be sensitive to surface roughness and vegetation cover, STR was designed to enhance sensitivity to soil moisture changes. [17] To develop this index, the authors drew on the classical radioactive transfer theory proposed by Kubelka and Munk (1931), [18] which describes how light interacts with soil as a scattering medium. This theory helped them transform SWIR reflectance into a form that better captures moisture related variations in soil brightness, especially under partial vegetation cover. The result is a more robust index that improves the reliability of soil moisture estimation across a range of surface conditions. The outcome is a more resilient index to enhance the accuracy in determining soil moisture under diverse surface states. In this study, OPTRAM is applied to Sentinel-2 imagery acquired over agricultural fields near Beed city, Maharashtra, India a semi-arid region frequently impacted by drought. The site includes a mix of bare soil, sparse vegetation, and cultivated land, making it an ideal testbed for evaluating OPTRAM performance under diverse surface conditions. In-situ soil moisture measurements were collected through field campaigns for model validation. This research aims to assess the accuracy and operational applicability of OPTRAM in semi-arid agricultural landscapes and to contribute to the advancement of high-resolution, optical-based soil moisture monitoring techniques.

2. METHODOLOGY

2.1 STUDY AREA

The study region falls in the semiarid Marathwada region of the state Maharashtra near the Beed city, Beed district. Shown in figure 1 It is situated between longitude 75.7017°E to 18.9974°N, and longitude 75.7338°E to 19.0267°N with an area of about 11 km². While the area has a semi-arid climate, receives an average annual rainfall of approximately 505 mm, and regularly experiences frequent droughts. The crops of the area are chiefly ephemeral, seen predominantly during the Rabi season with millets, maize, pulses. The soil is mostly sandy loam, characterized by low vegetation greenness, the landscape includes a mix of sparse vegetation, urban green patches, and areas with both open and closed canopy coverage. This heterogeneity makes the region ideal for evaluating soil moisture using the Optical Trapezoidal Model (OPTRAM). The diversity in land cover from bare soil to dense vegetation provides a suitable testbed for assessing OPTRAM performance across varied surface and moisture conditions.

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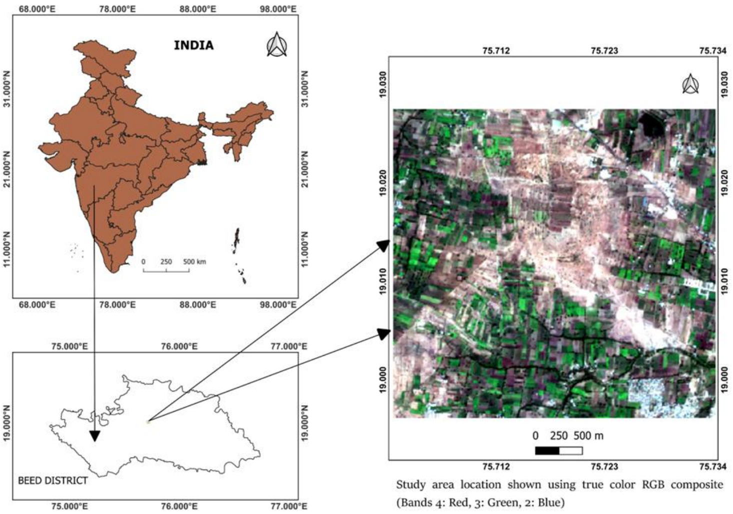

Figure 1. study area location shown using true color RGB composite bands 4,3 and 2

2.2 In-situ data

The field campaign was conducted on the same dates as the Sentinel-2 satellite overpasses to ensure consistency between satellite imagery and ground-based observations. Soil moisture was measured using two methods: in-field measurements with a Theta Probe sensor based on Time Domain Reflectometry (TDR) ML3 and laboratory analysis using the gravimetric oven-drying method. The study area, covering approximately 11 km², was divided into a 6 × 6 grid (36 cells), each measuring about 553 m × 553 m. From this grid, 35 cells were selected for sampling. Within each selected cell, multiple soil moisture readings were taken using the Theta Probe at a depth of 0–5 cm, and their average value was taken to characterize the moisture. Simultaneously, soil samples were collected from the same depth for gravimetric analysis, which involved oven-drying to determine moisture content by weight. The gravimetric results were then calibrated to volumetric soil moisture for consistency and comparison with the Theta Probe data. The geographic coordinates of all sampling locations were recorded using a mobile GPS device, ensuring accurate spatial alignment of field data with the corresponding Sentinel-2 satellite observations.

2.3 Satellite data

Sentinel-2 Level 1C data was acquired from the European Space Agency (ESA) through the Copernicus Open Access Hub. [19] The data provides high-resolution imagery, with a spatial resolution of 10 m for visible and near-infrared bands, 20 m for shortwave infrared bands, and 60 m for atmospheric correction bands. Sentinel-2 has 13 spectral bands that cover a wide range of wavelengths, allowing for detailed analysis of various surface properties, including vegetation, soil, and water. This dataset is ideal for soil moisture estimation due to its high spatial resolution and comprehensive spectral range. Sentinel-2 satellites have a revisit time of approximately 5 days, meaning they can provide frequent observations of the same location, The Sentinel-2 imagery was selected to coincide with the dates of in-situ soil moisture measurements, ensuring consistency between the satellite observations and the ground-based data The four-cloud free Sentinel-2 dataset for this study was acquired on the following dates: in December 2023 on these dates 15, 20, 25.

2.4 Pre-processing

The detailed work flow for this study is depicted in the figure 3 In this first we have done the spatial subset of study area with snap software in snap 9.0 with subset raster management using the geocoordinate's option then we have done radiometric calibration, Initially the data is in the digital number (DN) values were converted into Top-of-Atmosphere (TOA) reflectance by applying a radiometric calibration with scaling factor of 0. 0001.To obtain surface reflectance (bottom of atmosphere), atmospheric correction was done by using FLAASH module in ENVI 5.3 FLAASH relies on physics-based correction using the MODTRAN radioactive transfer modelling which contemplates for scattering and absorption effects of the atmosphere.

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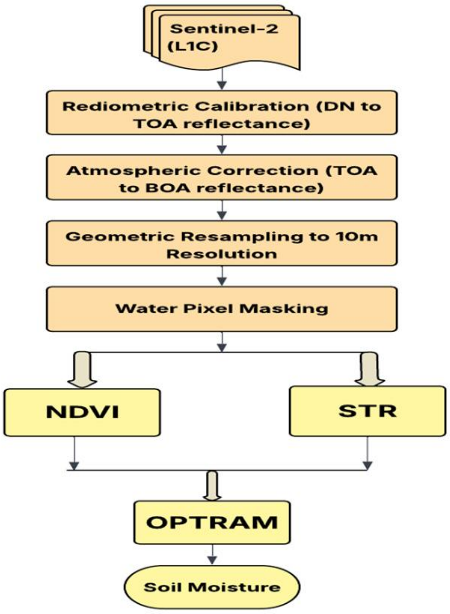

Figure 2. proposed method work flow

The custom sensor configuration was used in consideration of the Sentinel-2 specifications and a wavelength file specially-defined for the central wavelengths of the selected bands. The atmospheric model was set at Mid-latitude Summer, and the aerosol model was set as Rural, which is suitable for green spaces or non-urban areas. Visibility set to 40 km to simulate the levels of typical local atmosphere transparency and a scene centre coordinate extracted directly from the metadata of the image. The output that occurred gave surface reflectance values (BOA) bottom of atmospheric product to ensure the spatial consistency across the bands, we have done the geometric resampling the sentinel-2 data is in the form of 10 m 20 and 60 meter resolution we are using band 4 , 8 and band 12 for this study the band 8 and band 4 are 10 m resolution we have to resample the band 12 to 10 m resolution the resampling was executed in snap software by using Sen2Res plugin in SNAP 9.0 the band 12 is originally at 20 m resolution is resampled to 10 m this ensure the spatial similarity in this bands. Water bodies were outlined using the Normalized Difference Water Index (NDWI) [18] with thresholding to extract water pixels from other land-cover types. Using this a binary mask was built using mask builder and this mask was subsequently applied on the atmospherically corrected bands to mask water-affected areas to ensure the reliability of subsequent vegetation and soil moisture assessments.

2.5 OPTRAM Parameterization

The Optical Trapezoidal Model (OPTRAM) presented by sadeghi [13] is a physically-based model that estimates surface soil moisture (SSM) using shortwave infrared transformed reflectance (R_{SWIR}) and vegetation indices from optical satellite data. In this study, the Optical Trapezoidal Model (OPTRAM) was used to retrieve surface soil moisture from Sentinel-2 imagery. The model is based on the STR–NDVI feature space, where each pixel's shortwave infrared transformed reflectance (STR) and vegetation index (NDVI) define its location within a trapezoid representing dry and wet soil conditions. The core of the OPTRAM approach lies in defining a trapezoidal distribution in the STR–NDVI space the upper edge corresponds to wet soil conditions, where STR values are high. The lower edge corresponds to dry soil conditions, where STR values are low. These edges are identified empirically from the distribution of image pixels and represented as linear equations fitted to the upper and lower boundaries of the data cloud. Where STR is computed as equation (2) as a shortwave transformed reflectance and the θ is the surface soil moisture (θ_d) is the Soil moisture at dry condition (θ_w) is soil moisture at wet condition STR_d dry edge transformed reflectance STR_wwet edge transformed reflectance

Where (W) is the normalized soil moisture content expressed as equation (1)

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$$W = \frac{\theta - \theta_d}{\theta_w - \theta_d} = \frac{STR - STR_d}{STR_W - STR_d} \tag{1}$$

The shortwave Reflectance Transformation of Sentinel-2 Band 12 of (2190) nm is used to compute as following equation

$$STR = \frac{(1 - R_{SWIR})^2}{2R_{SWIR}} \tag{2}$$

where STR is the transformed SWIR reflectance for the pixel STR dry is the STR value on the dry edge (lower boundary of trapezoid) STR wet is the STR value on the wet edge (upper boundary of trapezoid) NDVI is calculated as difference vegetation index by this equation (3)

$$NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}} \tag{3}$$

The dry edge and wet edge are formed by the pixel distribution of NDVI and STR as trapezoid by estimating the intercept, slop for both dry and wet edge the equation as defined follows

$$STR_d = i_d + s_d NDVI \tag{4}$$

$$STR_w = i_w + s_w NDVI \tag{5}$$

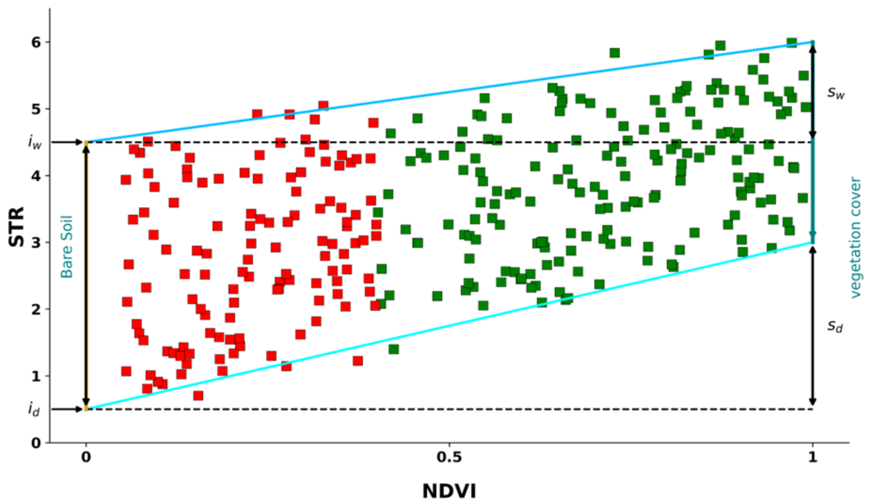

Figure 3 illustration of (OPTRAM) parameterization based on pixel distribution within the STR-NDVI based on sedghi model

i_w and s_d are the slop and intercept of the wet edge (obtained by fitting the upper limit of the NDVI–STR scatter plot) i_d and s_w are the slop and intercept of dry edge (fitted to the lower boundary) These coefficients were identified and parameterized using a Python-based approach. Specifically, we used the Linear Regression function from the sklearn linear model library to fit linear models to the upper and lower boundaries of the NDVI–STR distribution. Scatter plots were constructed using data from four Sentinel-2 images from different date's month of December to form a comprehensive multi-date feature space. This multi-date parameterization ensures that the dry and wet edges accurately represent the full range of vegetation and soil moisture conditions across the study area. The soil moisture (SM) is estimated for each pixel is function of STR and NDVI with coefficient derived from optical trapezoidal pixel distribution space The soil moisture for each pixel is computed as combination of equation (1), (4) and (5) as function of STR and NDVI as equation (6)

$$SM = \frac{i_d + s_d NDVI - STR}{i_d - i_w + (s_d - s_w) NDVI} \tag{6}$$

This method allows the model to dynamically adapt to varying vegetation cover and improves the precision of soil moisture estimation from optical data alone. This equation was implemented in the Python programming

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environment, utilizing different libraries such as NumPy for numerical operations, Rasterio for geospatial raster handling, scikit learn for linear regression modelling of the dry and wet edges, and Matplotlib for visualization of the NDVI–STR space. This implementation allowed dynamic estimation of soil moisture across varying vegetation conditions using only optical satellite data.

3. RESULT AND DISCUSSION

In this analysis workflow was executed in four main stages first we have done the pre-processing of the sentinel-2 (L1C) data which we have then calculated the NDVI and then we calculated Shortwave Infrared Transformed Reflectance from band 12 using equation (2) and the subsequent stages are as follows

3.1 NDVI-STR pixel distribution space

We have generated a scatterplot between NDVI and STR for four different dates. The resulting distribution exhibited a distinct trapezoidal shape, which aligns with the conceptual framework of the Optical Trapezoidal Model (OPTRAM). This trapezoidal geometry is critical for characterizing the spectral behaviour of soil moisture under varying vegetation conditions. The wet edge and dry edge coefficient were estimated by NDVI–STR trapezoidal feature space by fitting two linear regression lines one along the lower edge (dry edge) and another along the upper edge (wet edge). This method ensured objective, reproducible estimation of the edge lines without relying on visual interpretation. The regression yielded the following coefficients $i_{d=}0.00$, $i_w = 1.58$, $s_d = 1.71$ *and* $s_w = 1.25$ these are shown in figure in 4 the surface soil moisture was estimated by performing OPTRAM model defining the dry and wet edge lines within the NDVI–STR trapezoidal feature space. We have obtained the equations for dry edge and wet edge as follows the Dry edge equation (7) and Wet edge equation (8)

$$STR_d = 0.00 + 1.70\text{NDVI} \tag{7}$$

$$STR_w = 1.58 + 1.25\text{NDVI} \tag{8}$$

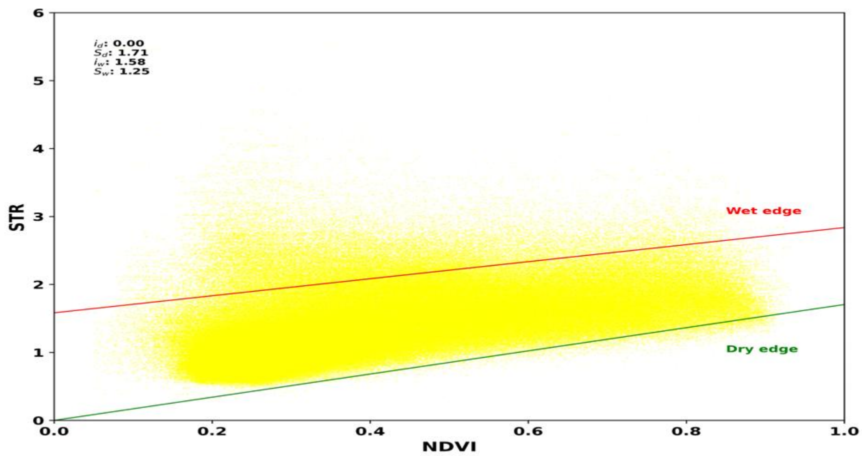

Figure 4 NDVI-STR pixel distribution pattern red line is the wet edge and the green line shown the dry edge

These equations represent the boundary reflectance conditions under the driest and wettest surface states in the image dataset. Once these boundaries were established, the soil moisture for each pixel for the 25 December 2023 was calculated using the OPTRAM formula by combining equation we have estimated soil moisture.

3.2 Validation soil moisture with in-situ data

We validated the soil moisture retrieved by the OPTRAM model using two standard methods: gravimetric and volumetric measurements with a Theta Probe. To enhance the accuracy and reliability of the soil moisture estimation, both types of measurements were analyzed and compared. Gravimetric measurements were obtained by oven-drying soil samples, while volumetric values were recorded in situ using a Theta Probe sensor. A regression analysis was conducted to evaluate the consistency and correlation between the two methods. The comparison yielded a high

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coefficient of determination (R^2) 0.8873 and a low (RMSE) 0.033 cm³/cm³, indicating strong agreement between gravimetric and Theta Probe measurements. Shown in the figure 5 these results confirm that the volumetric measurements from the Theta Probe are accurate and representative of actual field moisture conditions. Based on this validation, the Theta Probe values were selected for further analysis and used as the reference dataset for evaluating the OPTRAM-derived soil moisture estimates. This choice ensured consistency across validation points and improved the reliability of model assessment outcomes in order to assess the accuracy of the soil moisture estimates. Against available in-situ measurements of soil moisture obtained by Time Domain Reflectometry (TDR) at 35 sampling points. The outcomes as displayed in Figure 6 prove a high linear relationship between the two datasets; a coefficient of determination (R^2) at 0.8253, and (RMSE) of 0.0437 cm³/cm³. The results of the two regressions support the assertion that the OPTRAM model effectively detected spatial variations of the surface soil moisture in the field with varying conditions.

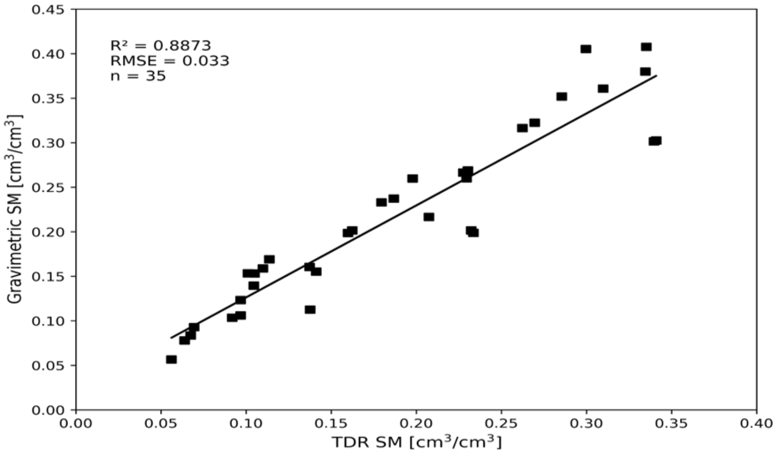

Figure 5 relationship between theta probe and gravimetric measurements

The low RMSE implies that the model was also a consistent one throughout the variety of moisture values obtained. Although with certain spread at the intermediate moisture levels, the OPTRAM estimates agreed with the TDR at close values particularly in both dry and moderately wet conditions. The good (R^2) value indicates the model's interiority, thus underlining the applicability of multi-date STR–NDVI parameterization and regression based borderline determination in field-scale soil moisture retrieval.

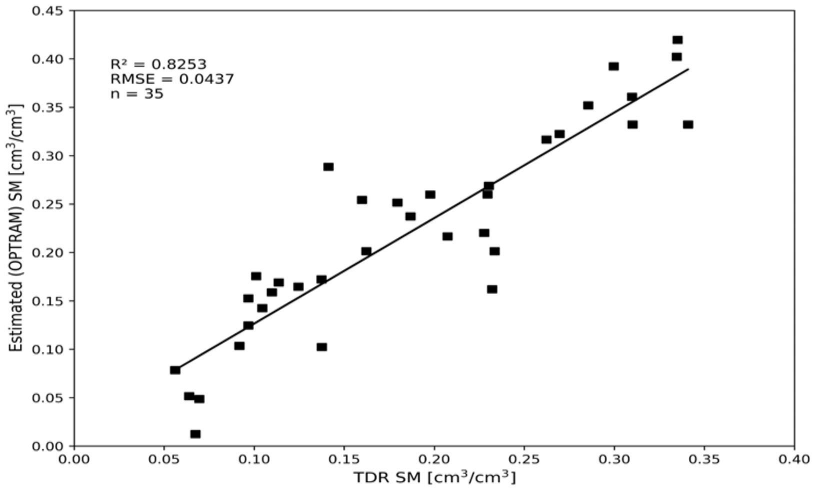

Figure 6 relationship between OPTRAM retrieved soil moisture and theta probe

3.3 OPTRAM soil moisture results

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Soil moisture was retrieved using equation (6) for each pixel that ranges from (0) dry and (1) wet, the soil moisture map shown in figure number 5 revealed clear spatial patterns. Dry areas (low SM values) were mostly found bare soil, while higher moisture values were concentrated in vegetated zones, irrigated plots, and low-lying topographic areas. The Sentinel-2 image on 25 December captured with partial vegetation cover making it well-suited for surface moisture assessment through optical Reflectance. This result confirms the capability of OPTRAM to effectively retrieve soil moisture using only optical remote sensing data, particularly when dry/wet bounds are carefully parameterized using multiple observation dates

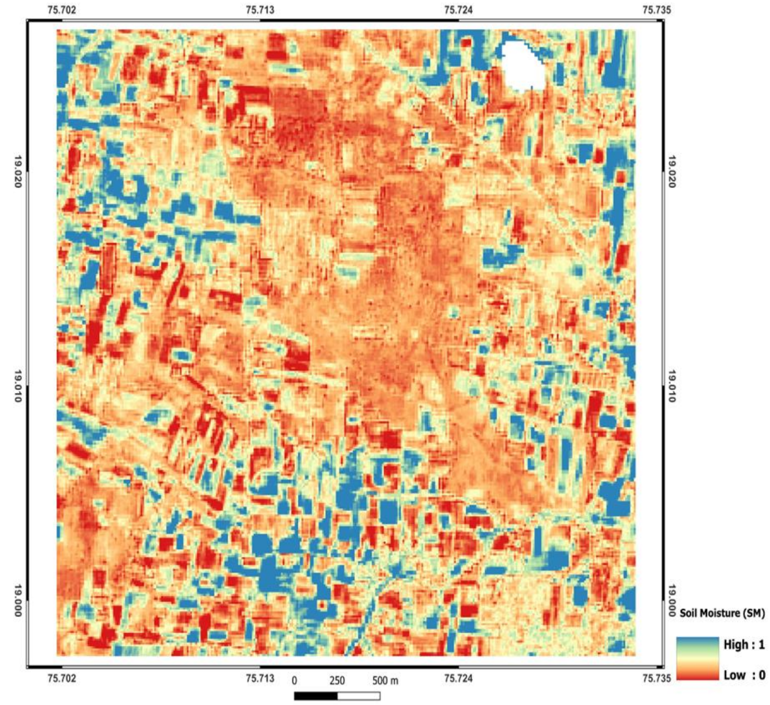

Figure 7 Soil moisture map of the study area retrieved using OPTRAM model

4. CONCLUSION

This study successfully demonstrated the application of the Optical Trapezoidal Model (OPTRAM) for retrieving surface soil moisture using high-resolution optical data from Sentinel-2 over a semi-arid agricultural region near Beed, Maharashtra. By constructing a trapezoidal feature space from NDVI and STR, and parameterizing the dry and wet edges using a multi date dataset, OPTRAM enabled accurate pixel-wise soil moisture estimation without the need for thermal inputs. Field validation using volumetric Theta Probe data and gravimetric analysis confirmed the reliability of the model outputs, with strong statistical agreement (R^2) 0.8253, (RMSE) 0.0437 cm^3/cm^3. The internal validation between gravimetric and Theta Probe readings further reinforced the credibility of the reference data used. The results highlight OPTRAM's robustness, reproducibility, and suitability for soil moisture mapping in heterogeneous, drought-prone environments. Its reliance solely on optical inputs makes it a scalable and cost-effective alternative to traditional thermal or microwave-based methods. Overall, this research supports the use of OPTRAM for operational soil moisture monitoring, and agricultural management in semi-arid landscapes, Future work can explore the integration of OPTRAM with different vegetation indices, irrigation data, or soil classification maps to further enhance moisture estimation accuracy. Expanding this approach across different agro-climatic zones will also help assess its generalizability and operational potential for broader agricultural monitoring.

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