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# Systematic Review of Remote Sensing Prediction Models and Tools for Estimating Surface Soil Moisture Content of an Area

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**ABSTRACT:** Soil Moisture is a critical parameter for water resource management, agriculture, and disaster prediction. Different methods are used to estimate Soil Moisture. Hence, the objective of this paper was to systematically review remote sensing (RS) prediction models and tools for estimating surface soil moisture (SM) content of an area using different scholar ‘s methodologies, and their performance. Survey of previous studies have highlighted some general areas and explored RS methods for soil moisture estimation, focusing on both active and passive sensors. Studies have also discussed the principles, strengths, and limitations of different techniques. However, there are some key areas that were less covered and need attention. As a result, this systematic review paper presents a wide range of comparative assessments of RS SM estimation models and tools by assessing their technique and methods, their performance Evaluation level (Coefficient of Determination R), the environment where the model could suitably perform better and the essential parameters considered for improving the known Machine Learning models for SM prediction further attention as discussed under this paper.

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Soil Moisture (SM) is one of the important factors among others that play part in fields such as agriculture, environmental science, and hydrology. In agriculture for instance, SM has been a vital and essential parameter for monitoring farming activities, predicting natural disasters, and managing water supply for irrigation(Chadha *et al*., 2018; Muñoz-Carpena *et al.*, 2007; Panuska *et al*., 2015) SM also has a great relationship with crop emergence and growth, crop yields and productivity (Chadha *et al*., 2018). Precise and real-time information on SM content is essential for various applications, including drought monitoring, flood prediction, crop management, and climate modeling. Remote Sensing (RS) technology has revolutionized the way we gather data on SM, offering cost-effective, spatially comprehensive, and temporally frequent measurements(Klemas *et al*., 2014). This capability has spurred the development of numerous RS SM estimation models and tools. The accurate estimation of SM through RS is of paramount importance, given its wide-ranging implications for water resource management and ecosystem health. Various algorithms and sensors have been developed to estimate SM from satellite, airborne, and ground-based platforms. These models and tools vary in

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terms of their data sources, temporal and spatial resolutions, and the methods they employ to derive SM information. Researchers and decision-makers must assess the performance and reliability of these models and tools to select the most suitable approach for their specific needs. Most of the scholars who have presented their review works related to Machine learning RS tools for moisture predictions have not comprehended much of the factors that contributed to either low or high correlation factor (R) which is the major factor for the performance evaluation of various models developed, studies in Vestberg, (2018) and Klemas *et al* (2014) highlighted the machine learning algorithms used by scholars to estimate moisture but does not assess the genuine reason for the performance improvement or variation of the correlation factor. The works have also less comprehended the environment where the model could be suitably used. It is important to choose an appropriate RS approach for specific applications. There are different RS approaches for SM estimation. Some of the notable RS approaches include: Microwave: Passive Microwave Radiometry Utilizes natural microwave emissions from the Earth's surface and Active Microwave Sensing (RADAR) which measures backscattered signals from radar pulses (Klemas *et al.*, 2014; Lakhankar *et al*., 2009; Ray *et al*., 2017; Schmugge, 1985; Wigneron *et al.*, 1998)

Infrared Thermometry is the method that measures temperature variations on the soil surface, which are related to SM. The method was suggested and used in various studies for RS SM prediction (Zeng *et al*., 2016; Seo *et al*., 2021). Visible and Near-Infrared (VNIR) Spectroscopy methods utilize reflectance properties in the visible and near-infrared spectra to infer SM. Zeng *et al* (2016) studied soil salinity, whereby near infrared to short-wave infrared reflectance spectra were measured in a controlled laboratory environment for samples representing a wide range of salinity levels. The method was also used to study surface moisture prediction based on geometrical attributes of an inverted Gaussian (IG) function fitted to hyperspectral reflectance. Hence, the objective of this paper was to systematically review remote sensing (RS) prediction models and tools for estimating surface soil moisture (SM) content of an area using different scholar 's methodologies, and their performance also to provide an in-depth analysis of their strengths, weaknesses, and applicability across different geographic regions and land cover types.

## MATERIALS AND METHODS

*Search Strategy:* Online Search databases tools which included Scopus, Google Scholar, and Web Science were used in this review to acquire scholar's publications. In recognition of the rapid advancement of technology, only studies conducted between 2021 and 2023 were considered. Search filters were established to screen for English-language study abstracts. Titles and abstracts were explored using "RS, tools for SM measurement". Terms that intersected with SM, RS tools, machine learning algorithms for SM, and unknown aerial vehicles UAV models for SM prediction were used to search filter criteria.

*Selection criteria:* The inclusion and exclusion criteria for this review are as follows: A study was involved it was in line with the following criteria;

i. Assessed RS SM measurement and prediction tools - models, computer software, and mobile apps used to measure or predict SM.
ii. Do an original research paper with quantitative SM assessment contents?

A study was excluded if:

i. If the article lacks quality materials regarding SM Measurement/prediction though it present RS methodology.
ii. If the article lacks or does not comprise RS tools
iii. If the article is completely not retrieved.
iv. If the article is published before the year 2021
v. Duplication

Initially, 41 articles were selected based on inclusion criteria, when all that exclusion criteria were applied a total of 21 articles were sampled. Further removal of the duplicate articles was done and 11 actual studies were selected for this review.

*Authors' Contribution to this Study:* One author (PY) performed the initial literature search; subsequently, titles and abstracts were carefully screened by two authors (MN, GK), adhering to the established inclusion/exclusion criteria. Following this screening phase, full-text copies of selected studies were obtained; comprehensive reviews including data extraction were done by three authors (PY, MN, GK).Any uncertainties arising during the screening and selection processes underwent resolution through consensus discussions involving all three aforementioned authors (PY, MN, GK). Data extraction encompassed retrieval of crucial information from each paper such as author's name, publication year, country, study design, sample size, target population, topic category (Soil moisture, remote sensing, and Remote Sensing models for Soil moisture prediction), and description about Usability, security, reliability and accessibility, primary outcomes, and limitations listed by respective studies.

## RESULTS AND DISCUSSION

Various studies have demonstrated the accurate estimation methods of SM. This study has comprehensively reviewed the RS techniques of various scholars. The reviewed literature suggests that regular methods include but are not limited to the use of machine learning methods and enhanced or combination of various machine learning algorithms are more frequently used (Vestberg, 2018; Araya *et al*., 2020; Jia *et al*., 2020a; Jo *et al*., 2020; Rani *et al*., 2022; Zhang *et al*., 2019a, 2019b)

The study examines forty-one (41) articles of which final screening involves eleven (9) research papers, revealing that 88.9% of these studies have presented machine learning predictions models developed by using either known machine learning algorithms or enhanced machine learning algorithms (Vestberg, 2018; Klemas *et al*., 2014). However, 11.1% of the reviewed papers presented the novel deep learning (DL) as the RS technique for SM prediction.

*Factors considered in our comparative Assessment:* The performance of the RS model developed in terms of correlation was a crucial factor in determining how well the presented machine learning models or techniques would perform better. For Machine Learning models developed the performance of models is measured in terms of mean absolute error (MAE) as in equation 1, mean bias error (MBE) as shown in equation 2, and the coefficient of determination ($R^2$) (as shown in equation 3) (Araya *et al*., 2020) and they are determined as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(|x_i - \widetilde{x_i}|) \qquad (1)$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(\widetilde{x_i} - x_i) \qquad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_i - \widetilde{x_i})^2}{\sum_{i=1}^{N}(x_i - \widetilde{x_t})^2} \qquad (3)$$

where the $N$ is the number of observations; x is the measured value; $\hat{y}$ is the predicted value; and $\bar{y}$ is the mean of measured values (Araya *et al*., 2020).

Author in Shi *et al* (2018) has used the ensemble Kalman filter (EnKF) approach a Machine learning (ML) surrogate model. It is a hybrid model which comprise with remote sensing-derived SM (SM) observations and RS leaf area index (LAI). The performance of the model was done and it yielded $R^2$ > 0.72. The model has proven to be more effective in "Vegetated areas" compared to "Extreme arid deserts"

The study has also reviewed an approach presented by the author in Mehri *et al* (2023), where the prediction of maize crop coefficient from UAV multisensory RS using machine learning methods is done. The model which also predicts SM is developed in combination with Six ML algorithms (linear regression-LR, polynomial regression-PR, exponential regression-ER, random forest regression-RFR, support vector regression-SVR, and deep neural network-DNN). The performance of the model is done by comparing the correlation regression for each of the aforementioned algorithms and in turn for $R^2$ = 0.85, RMSE = 0.0089 m3/m3).

A low-cost approach for SM prediction using multi-sensor data and a machine learning algorithm was also developed and is presented by Nguyen *et al* (2022). The method used to develop this model is Machine Learning integrated with multi-sensor data fusion (Sentinel-1(S1) C-band dual polarimetry synthetic aperture radar (SAR), Sentinel-2 (S2) multispectral data, and ALOS Global Digital Surface Model (ALOS DSM).

The model is evaluated using machine learning techniques and it yielded highest performance of ($R^2$ = 0. 891; RMSE = 0.875%) compared to random forest regression (RFR) machine learning algorithm. The model is also effective under Vegetated areas" compared to "Extreme arid deserts"

This study has also observed that the author in Meenakshi and Naresh (2023) has described a Machine learning-based classifying polluted soil health and productivity analysis in the Tamil Nadu delta area in the water management system. A model was deduced using the Decision tree and Naive Bayes methods. The model is evaluated and its Correlation regression o R= 0.86 proves that the model is effective.

Another machine learning approach is described by the author in Rodriguez-Alvarez *et al* (2023) depicting the Modeling and theoretical analysis of the Global Navigation Satellite System-Reflectometry (GNSS-R) SM retrieval framework, based on the random forest and support vector machine learning approach as illustrated in Fig 1.

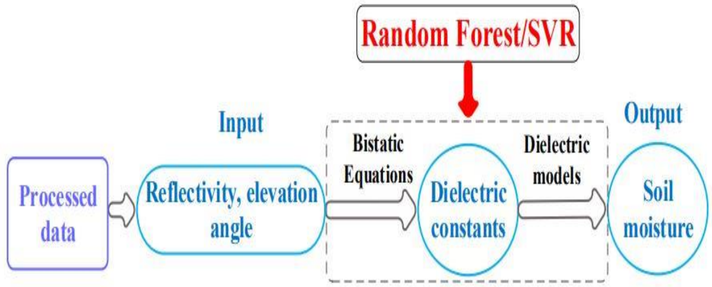


**Fig 1:** Machine Learning Flowchart GNSS-R SM Retrieval Model (Jia, Y; Jin, S; Savi, P; Yan, Q; Li, W. (2020a))

**Table 1.** Comparison of RS Models extracted from records considered under this study

| S/N | References | Approach Method/Tool used | Year | Performance Evaluation level (Coefficient of Determination R) | Resolution | Moisture detection Parameters | Applicable Environment |
|---|---|---|---|---|---|---|---|
| 1 | (He et al., 2022) | Ensemble Kalman filter (EnKF) approach, Machine learning (ML) surrogate model | 2022 | R2 > 0.72 | 10 m spatial resolution | Land surface temperature | Vegetated areas |
| 2 | (Shao et al., 2023) | Model developed in combination of Six ML algorithms (linear regression-LR, polynomial regression-PR, exponential regression-ER, random forest regression-RFR, support vector regression-SVR, and deep neural network-DNN) | 2023 | R2 = 0.85, RMSE = 0.0089 m3/m3) For SM prediction | 10 m spatial resolution | Vegetation fraction, VIs, texture, and thermal information | Vegetated areas |
| 3 | (Nguyen et al., 2022) | ML Model + multi-sensor data fusion (Sentinel-1(S1) C-band dual polarimetry synthetic aperture radar (SAR), Sentinel-2 (S2) multispectral data, and ALOS Global Digital Surface Model (ALOS DSM) | 2022 | The designed model yielded highest performance of ($R^2$ = 0. 891; RMSE = 0.875%) 'compared to random forest regression (RFR) | 10 m spatial resolution | Red-Edge Chlorophyll Index | Vegetated areas |

This model is like other popular known machine learning (ML) methods which are flexible and are able to handle nonlinear problems. The author under this study has suggested the future work has to be done for a larger area with sufficient ground-based reference SMC to generalize the findings.

A Deep Learning-Based Framework for SM Content Retrieval of Bare Soil from Satellite Data is developed using deep learning (DL) + Gaussian process regression (GPR). The model is much effective if could be used to predict the moisture in bare Soil (Dabboor *et al.*, 2023). Another study explored under this review is a novel deep learning architecture comprising with a set of U-Net semantic segmentation model with a sequence-to-sequence ConvLSTM layers in order to capture pixel-wise satellite image content spatial correlation property of SMC. It is a SM prediction model based on Satellite Data Using a Novel Deep Learning algorithm (Habiboullah and Louly, 2022).

Table 1 has summarized sample studies, the way performance evaluation of models and tools developed by different scholars. The information includes the remote sensing and machine learning approaches or method or tool used Performance. The performance valuation level reached (Coefficient of Determination R) after applying specific ML algorithm is also presented. The table also has revealed the resolution of the data, finally, applicable environment of the model is also revealed.

*Technological trend for Soil Moisture studies:* Revealing technological trend is important for the future development of tool or model for Soil Moisture studies. Technological change is the result of improvement of the already existing technologies and the invention of new ones is for improving the existing products in the market while also creating new ones. It can also be possible to increase the efficiency of a product and increase in output.

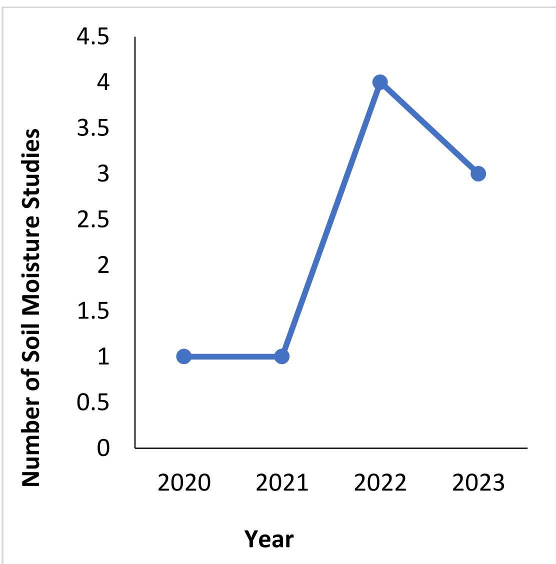


**Fig 2:** Trend of Remote Sensing Soil Moisture Studies carried out in four consecutive years

This study has analyzed the trend of previous consecutive four years from 2020 to 2023 on the number of studies in soil moisture prediction area as presented in Fig 2. The Results shows there is increase number of studies year to year, with its climax in year 2022 where 44.4% of all screened studies, conducted soil moisture survey. This results shows soil Moisture prediction studies are the future promising area and has a great role in sustainable agriculture, water resource management, climate and other related fields.

The choice of suitable ML technique typically depends on several factors, including; data size, quality as well as the diversity of the data to be analyzed.

Under this review we have highlighted different types of machine learning techniques and the frequency of their uses. Fig 3 illustrate this argument and the results shows most scholars used the hybrid ML techniques in their Analysis. The Author in (Senthil Kumar et al., 2023) outline the effectiveness of using hybrid algorithm for results comparable or comparative ways.

RS models for moisture prediction are no doubt important to be assessed as long as you are to design or improve the method or tools for moisture prediction. RS together with machine learning technologies has brought significant revolution and has optimistic impact to Agriculture and industries in general. The evidence to this are the studies conducted by (Bjarnason, 2016; Chadha *et al*., 2018; Habiboullah and Louly, 2022; Klemas *et al*., 2014; Lakhankar *et al*., 2009; Nguyen *et al*., 2022; Rani *et al*., 2022; Ray *et al*., 2017). There are number of studies conducted in various agricultural sectors from soil exploration, plant growth monitoring and agricultural product harvesting (Brendel, 2021; Chadha *et al*., 2018; Irmak *et al*., 2019; Rodriguez-Alvarez *et al*., 2023; Shao *et al*., 2023).

Under this review, the authors have in depth examined some of the recent RS technologies, methodologies and tools used for SM measurement and prediction (Dabboor *et al*., 2023; Habiboullah and Louly, 2022; Rodriguez-Alvarez *et al*., 2023). Comparative assessment for each selected technology was done. The aim is to assist different scholars who wish to progress on searching for improved solution to choose appropriate RS approach for specific applications.

Preliminary results have highlighted majority of the scholars have used machine learning and deep learning methodologies for SM prediction(Araya *et al*.,2020; Jia *et al*., 2020a, 2020b; Lei *et al*., 2020; Meenakshi and Naresh, 2023; Rani *et al*., 2022). Performance in terms of accuracy, usability environment, costs and accessibility were the major factors considered for comparative assessment of RS methodologies and tools for the moisture determination. After reviewing different studies, the results, has shown performance in term of coefficient of Determination (R) as significant factor for the assessment. Many of the studies (7 out of 9) 78% uses coefficient of determination to check how far the predicted value is closer to the observed value.

Furthermore, the usability environment is another factor which was taken for our comparative assessment, although few studies addressed the issue (5 out of 11 (45%)). The results have highlighted that the designed RS tools and methods for moisture prediction can be used and chosen best for various environment such as "Vegetated areas", "Extreme arid deserts", polluted soil and bare soil.

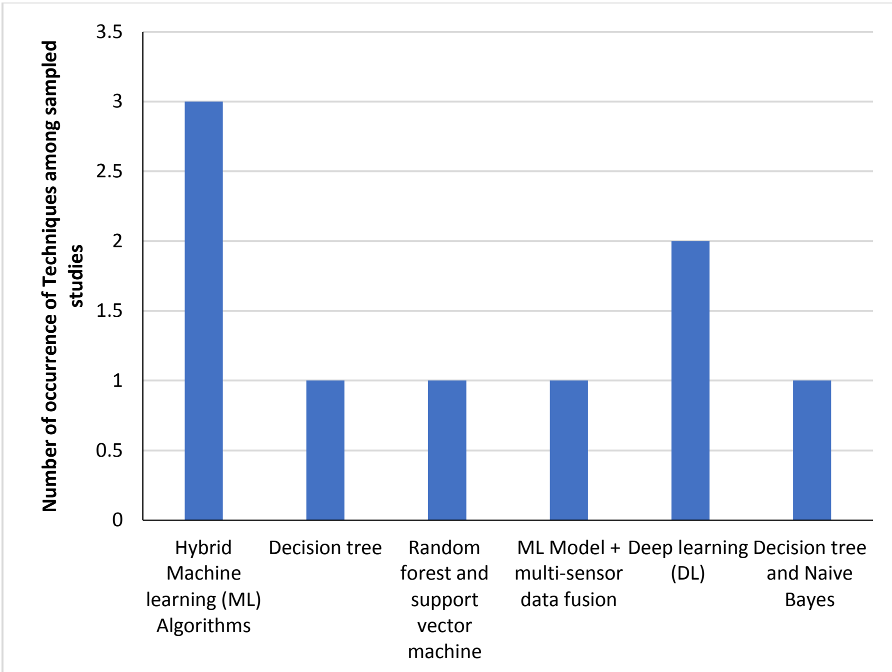


**Fig 3**. Various Moisture Computation Techniques

Spatial resolution is the least parameter for used for comparing the RS tools and methods for moisture prediction, only one out of eleven (9%) of the studies has highlighted the necessity of considering spatial resolution. This comprehensive systematic literature review, has done intensively comparative assessment of RSM for SM prediction. Different methodologies, approaches and evolving technological advancements that are proposed by various scholars are presented and highlighted, the study has assessed and compared one method to another by looking either of the aforementioned parameters as shown in table 1.

*Conclusion:* This systematic review has highlighted various remote sensing (RS) prediction models and tools used for estimating surface soil moisture (SM) content. For each tool, the methods suggested, the performance reached and the applicable environment were clearly exposed, which was the major contribution of this study. The repercussion of the study to academic scholars is to give knowledge prior comprehensive RS design under different grounds. Future works could focus on continued development and implementation of RS tools for surface soil moisture estimation for supporting agriculturalists, water resource management practitioners, and environmental monitoring scholars.

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