water

MDPI

Review

Approaches for Assessment of Soil Moisture with Conventional Methods, Remote Sensing, UAV, and Machine Learning Methods—A Review

Songthet Chinnunnem Haokip [1], Yogesh A. Rajwade [2], K. V. Ramana Rao [2], Satya Prakash Kumar [2], Andyco B. Marak [1] and Ankur Srivastava [3,*]

[1] The Graduate School, IARI, ICAR-Central Institute of Agricultural Engineering, Bhopal 462038, India; haokip7696@gmail.com (S.C.H.); andycomarak11@gmail.com (A.B.M.)
[2] ICAR-Central Institute of Agricultural Engineering, Bhopal 462038, India; yogesh.rajwade@icar.org.in (Y.A.R.); kvramanarao1970@gmail.com (K.V.R.R.); satyaprakasmar27@gmail.com (S.P.K.)
[3] School of Life Sciences, Faculty of Science, University of Technology Sydney (UTS), Ultimo, NSW 2007, Australia
* Correspondence: ankur.srivastava@uts.edu.au

Abstract

Soil moisture or moisture content is a fundamental constituent of the hydrological system of the Earth and its ecological systems, playing a pivotal role in the productivity of agricultural produce, climate modeling, and water resource management. This review comprehensively examines conventional and advanced approaches for estimation or measuring of soil moisture, including in situ methods, remote sensing technologies, UAV-based monitoring, and machine learning-driven models. Emphasis is primarily on the evolution of soil moisture measurement from destructive gravimetric techniques to non-invasive, high-resolution sensing systems. The paper emphasizes how machine learning modules like Random Forest models, support vector machines, and AI-based neural networks are becoming more and more popular for modeling intricate soil moisture dynamics with data from several sources. A bibliometric analysis further underscores the research trends and identifies key contributors, regions, and technologies in this domain. The findings advocate for the integration of physics-based understanding, sensor technologies, and data-driven approaches to enhance prediction accuracy, spatiotemporal coverage, and decision-making capabilities.

Keywords: in situ measurement; bibliometric analysis; machine learning; precision agriculture; random forest; remote sensing; soil moisture; UAV monitoring

check for updates

Academic Editor: Keith Smettem

Received: 4 July 2025
Revised: 7 August 2025
Accepted: 8 August 2025
Published: 12 August 2025

Citation: Haokip, S.C.; Rajwade, Y.A.; Rao, K.V.R.; Kumar, S.P.; Marak, A.B.; Srivastava, A. Approaches for Assessment of Soil Moisture with Conventional Methods, Remote Sensing, UAV, and Machine Learning Methods—A Review. *Water* **2025**, *17*, 2388. https://doi.org/10.3390/w17162388

1. Introduction

1.1. Overview of SMC (Soil Moisture Content)

The temporary storage of water in the soil's accessible pores is known as soil moisture and plays a key role in land–surface–atmosphere feedbacks [1,2]. In addition to supporting numerous research areas, namely, flood risk analysis and climate predictions, soil moisture is necessary for managing agricultural water supplies. Effective management of water not only helps in conserving the valuable resource (i.e., water) but also boosts crop profitability and helps prevent soil salinization. Additionally, regulators can utilize soil water content (SWC) data to verify pumping records, promoting accountability among water users, and enhancing the equilibrium between agricultural and environmental water needs [3].

In agriculture, increasing crop growth and yield depends critically on the availability of water or moisture in the soil. Crop development is largely impacted by the levels of soil moisture, as it aids in nutrient absorption, supports microbial activity, and helps regulate soil temperature [4]. In agricultural practices, a clearer understanding of soil moisture content (SMC) distribution plays a pivotal role in improving crop production and minimizing the risk of water stress in crops [5]. Determining soil moisture content or moisture content of soil (SMC) offers significant potential to enhance the efficiency of agricultural water use while safeguarding both the environment and water resources. Real-time monitoring of water status in agriculture can lead to increased productivity and improved water use efficiency. Although the carbon-cycle mechanism affects crop water stress and soil respiration, surface water content patterns can help predict the lowest and highest temperatures at the regional level [6].

Climate change has increased the challenges by raising temperatures and causing droughts, which lower vegetation growth and increase plant mortality. This highlights the necessity for effective soil moisture monitoring since it impacts soil moisture levels and increases the risk and vulnerability of these ecosystems [7].

Soil moisture estimation can be conducted at various spatial (local and global) scales. In regard to the local scale, measurement is usually carried out in the field by either a direct method or indirect method depending upon the measurement methods. Conventionally, the level of SMC in a soil sample is measured mainly by the direct method or gravimetric method. The soil sample is properly dried in a hot-air oven and the decrease in the weight before drying and after drying of the soil sample provides insight into the moisture content. The standard drying temperature of 105 °C in a hot-air oven is used for determining soil moisture content by the gravimetric method, where the loss in weight due to drying is expressed as a ratio of water mass to dry soil mass (g/g). In contrast, volumetric moisture content refers to the volume of water per unit volume of soil (cm^3/cm^3). These values are related through the soil bulk density (g/cm^3), allowing conversion between gravimetric and volumetric moisture contents. This method is destructive, laborious, time-consuming, and measures soil moisture only at discrete locations. However, indirect methods that integrate automated sensors, such as theta probes, are designed to estimate soil moisture in real time and on an even broader scale. Theta probes are soil moisture sensors that directly measure volumetric water content (θ, in cm^3/cm^3) by detecting changes in the soil's dielectric constant. These probes are calibrated prior to use, either using soil-specific calibration curves or factory settings, to ensure accurate moisture readings under field conditions. Such indirect methods can estimate the moisture of a soil column at different depths at various locations.

Synoptic coverage of the Earth's surface at different temporal and spatial scales is provided by satellite photographs (e.g., Sentinel-1, Sentinel-2, and Radarsat-2). According to [8–10] and others, microwaves and observational satellite images within the optical band have been found to be effective in assessing surface soil moisture on both global and regional scales. In 2009, the European Space Agency (ESA) launched the Soil Moisture and Ocean Salinity (SMOS) mission under the ESO-EO project. Later, as part of the Earth System Science Pathfinder (ESSP) mission, the National Aeronautics and Space Administration (NASA) deployed the Soil Moisture Active Passive (SMAP) in 2015. With a spatial resolution ranging from 1 to 50 km, these satellite missions deliver moisture products on a daily to eight-day revisit period. Particularly in areas with complicated topography and inaccessible places, the soil moisture data obtained from these satellite missions are lacking [11].

Due to its capacity to penetrate through the soil's uppermost layer and its sensitivity to the dielectric characteristics of the material, microwave remote sensing has been widely used in the field of soil moisture [12,13]. A permittivity gradient is visible in microwave signals, with water having a value of around 80 and dry soil having a value of about 2 [14,15]. For measuring soil moisture from microwave imagery, several backscattering models have been developed, including theoretical, empirical, and semi-empirical approaches [16–24]. Usually, these models need quad-polarized microwave pictures (VV, VH, HH, and HV), although, in some places, these images are rarely accessible. Machine learning algorithms, which use backscatter values from various polarizations along with other auxiliary data like topography and vegetation indices as input features have been developed to get around and address this restriction. Once trained, these models can forecast soil moisture using the given input variables, but they first need in situ soil moisture data for training and validation. Apart from direct soil-moisture sensing methods, modeling approaches also play a crucial role in estimating antecedent soil moisture (ASM) for applications in areas lacking in situ observations [25].

In the recent past, machine learning algorithms and deep learning technology have played a monumental role in the analysis of SM. The coming of these advanced technologies has enabled the identification of intricate patterns and relationships within data, helping to uncover correlations and causations between moisture content and other predictive factors that may not necessarily provide immediate evidence through traditional statistical approaches. These emerging technologies have been incorporated in various areas, including spatial and temporal SM monitoring, for downscaling and upscaling of SM data, modeling non-linear interactions between SM and environmental factors, producing global and regional high-resolution spatially continuous SM datasets, and supporting dataset testing and dataset validation, among other applications [26,27].

The application of models like machine learning is rapidly increasing across various applications due to their high computational efficacy. The increasing number of articles on soil moisture estimation that use machine learning approaches is another indication of this trend. Between 2000 and 2025, a total of 7035 publications were released, which is similar to the use of machine learning in agriculture, including 570 reviews articles, which were recorded in PubMed. Notably, from 2000 to 2022 (up to 24 March 2025), 199 publications were recorded in the PubMed database that focus solely on machine learning for soil moisture, including three reviews. A significant portion of these studies has utilized in situ soil moisture data and satellite imagery to train and validate machine learning models. It would be valuable to explore the advantages and disadvantages of various methods and sensors commonly employed for in situ or ground truth measurements, as well as to discuss approaches related to remote sensing-based machine learning techniques for soil moisture estimation.

VOSviewer version 1.6.20 (Visualization of Similarities Viewer) was employed, a software tool designed for creating and visualizing bibliometric networks that is widely used to map co-occurrence relationships among keywords, authors, and publications. This tool provides interactive visualizations that reveal clusters, link strengths, and thematic structures within large datasets.

In VOSviewer, the following three primary types of visualizations are used to explore bibliometric networks: network visualization, overlay visualization, and density visualization. The network visualization represents items (such as keywords, authors, or articles) as nodes, with lines indicating the strength of relationships like co-occurrence or co-citation. Items that are closely related are grouped into clusters, each assigned a distinct color, which helps to visually identify thematic areas within the dataset.

The overlay visualization builds on the network map by adding an additional variable, such as the average publication year or citation impact, and uses a color gradient (typically from blue to yellow) to indicate the value of that attribute. This allows researchers to easily spot emerging topics or high-impact research areas.

Lastly, the density visualization emphasizes areas of the map where items are densely packed using a heatmap effect, where regions with a high concentration of items appear in warm colors (yellow or red), while sparse areas appear in cooler tones (green or blue). This visualization is particularly useful for identifying research hotspots and thematic concentrations within the field.

In VOSviewer, a cluster is a group of closely related items (such as keywords, authors, or publications) that share strong interconnections, representing a specific research theme or topic. A link refers to a direct relationship between two items—for example, co-authorship, co-citation, or keyword co-occurrence—while the link strength indicates how strong that relationship is (e.g., how many times two authors have collaborated or two keywords have appeared together). The total link strength of an item is the sum of its link strengths with all other items, reflecting its overall connectivity and influence within the network. Clusters are visually distinguished by color, and items with stronger links are placed closer together in the visualization.

Below Figures 1–3 illustrate the bibliometric analysis of machine learning research in agriculture (2020–2025) using PubMed data. It includes (1) a network visualization showing 24 items across seven clusters with strong interconnections, (2) an overlay map highlighting emerging topics, and (3) a density view reflecting research concentration areas.

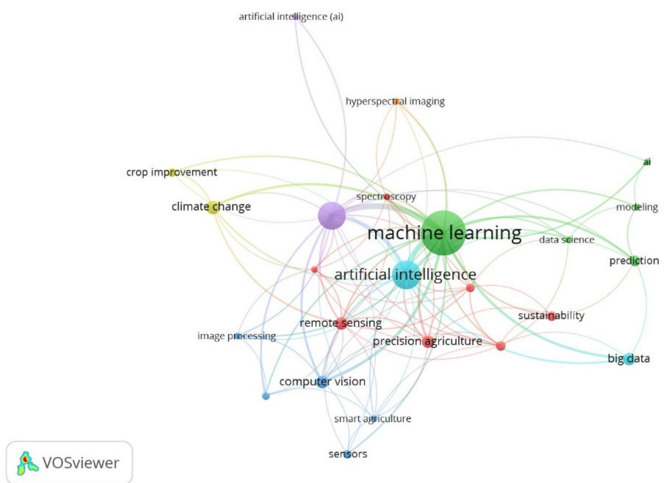


Figure 1. Total number of articles available on machine learning for agriculture in between the years 2020 and 2025 (till 24 March 2025) and available in PubMed. Network visualization: items: 24; clusters: 7; links: 101; total link strength: 365.

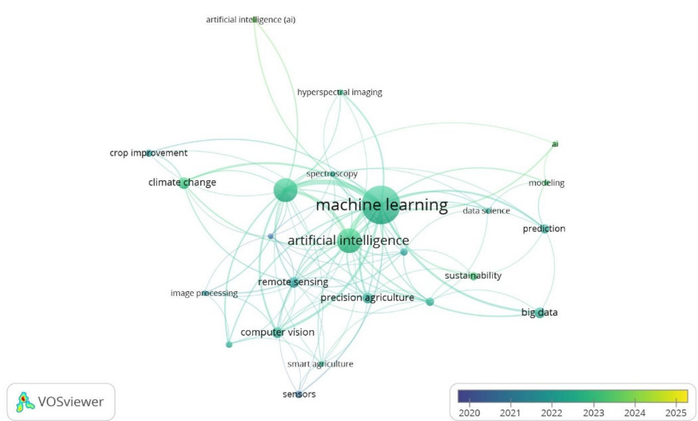


Figure 2. Total number of articles available on machine learning for agriculture in between the years 2020 and 2025 (till 24 May 2025) and available in PubMed. Overlay visualization: items: 8; clusters: 3; links: 14; total link strength: 40. The color bar shows the average publication year.

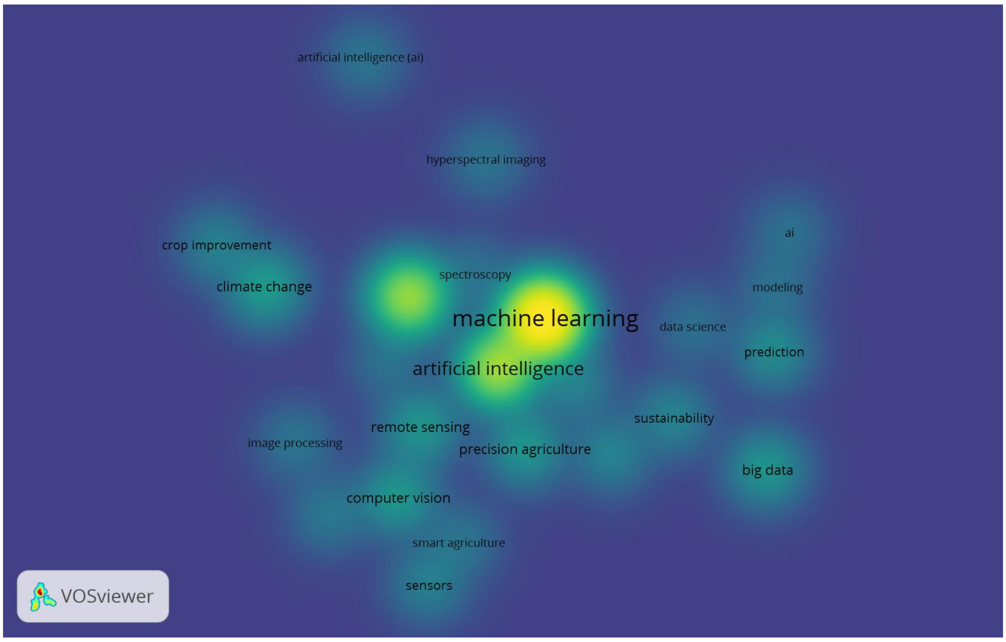


Figure 3. Total number of articles available on machine learning for agriculture in between the years 2020 and 2025 (till 24 May 2025) and available in PubMed. Density visualization. (Note: The colors indicate item density—the warmer color (yellow) shows areas with a high concentration of items, while the cooler color (green) represents lower density. The round areas correspond to clusters of related items, and their size reflects the number of items and strength of their connections.)

1.2. Importance of Soil Moisture Measurement

A crucial factor in environmental and agricultural settings is soil moisture. It describes the quantitative amount of water that is present in the soil and influences several other processes that are critical to climate modeling, growth of plants, and management of water resources. In agriculture, understanding soil moisture levels is key to optimizing irrigation practices, enhancing crop yield, and minimizing water stress. Soil moisture also impacts nutrient uptake, microbial activity, and the regulation of soil temperature, which are all essential for plant health.

The total availability of moisture in the soil has a significant impact on how much energy is exchanged between the Earth's surface and atmosphere. It has a major impact on soil fertility, plant health and growth, and the likelihood of soil erosion. It also represents the water availability of the soil [28,29]. Monitoring soil moisture helps in early detection of droughts and can assist in disaster risk management. Additionally, soil moisture influences carbon sequestration, contributing to the global carbon cycle and climate change processes. One of the most important factors in agriculture for maximizing crop growth and yield is the total amount of plant-available water stored in the soil. While volumetric water content provides useful information, it is not sufficient on its own. The plant-available water within the effective root zone determines how much water is accessible to crops. Therefore, accurate soil moisture assessment requires both the depth of measurement and a clear definition of plant-available water.

The development of crops is influenced by the level of soil moisture, which promotes nutrient absorption, supports microbial activity, and helps regulate soil temperature. Table 1 presents a concise overview of key studies, highlighting the authors, methodologies employed, and principal findings across various approaches to soil moisture estimation.

Table 1. Summary of different methods, technology used, key findings, and accuracy by various authors.

Reference	Technology Used	Calibration Method	Soil Depth	Key Findings	Model/Accuracy
[30]	Soil reflectance in VIS NIR, portable sensors equipped with DGPS	Gravimetric method	15 cm	Accurate SM prediction using reflectance	R^2 = 0.95
[31]	Veris-3100 + geostatistical modeling	Laboratory	30 cm	Demonstrated utility of proximal sensing for SM in water-stressed conditions	Gaussian smoothing
[32]	TDR 300 probe	Comparison with SM probes	20 cm	Strong SM–EC correlation within 5 m computation rings	R^2 = 0.79
[33]	Hyperspectral imagery	Gravimetric method	30 cm	NIR bands correlated well with SM	PLSR: MAPE less than 11%
[34]	FieldSpec ASD + TRIME-PICO/TDR-100	Calibration via probe comparison	3.7 & 5 cm	Consistent SM image in clay; variable in sand (surface more accurate)	SM range image accuracy of 5% (surface), 17% (deeper)
[35]	VIS-NIR spectrometer	Not specified	Not specified	General model not reported	
[36]	Optic fibers + Decagon FDR sensor	Not specified	6 cm	Cost-effective for continuous SM in a 0 to 35% range	-
[37]	Cubert sensor with TDR probes	Sensor comparison	2.5–20 cm	Highlights error propagation from inhomogeneous SM	ET model: R^2 = 73.1%
[38]	ASD AgriSpec spectrometer	Lab	-	Good results when using mix soil texture	SMLR (R^2) = 0.937
[39]	Gaia Sorter Hyperspectral System	Standard oven-dried at 105 °C	0 to 10 cm	Selected wavelengths (695–796 nm) using CARS-SPA provided optimal band filtering	Multiple linear regression: R^2 = 0.83
[40]	Cubert UHD 285 Snapshot Hyperspectral Camera	Various in situ TDR sensors	2 to 20 cm	GPR-ML significantly enhanced prediction of SM versus PCA, DT, RF, and Bayesian models	GPR-ML: R^2 = 0.97
[41]	Dual UAVs using bistatic radar for soil analysis	TDR-150 Sensor	Surface layer	Analyzed soil reflection using Brewster angle for groundwater and heterogeneity mapping	Not applicable
[42]	UAV along RGB, NIR, and thermal cameras	Field truth data	Topsoil	UAV imagery yielded more actionable moisture insights than traditional remote sensing	Relevance vector machine: RMSE value 3.04%
[43]	DJI Matrice along with a hyperspectral camera	Oven-dried at 105 °C	0 to 10 cm	Feature optimization and XGBoost resulted in highly accurate moisture estimation	FOD-XGBoost model: R^2 = 0.885
[44]	DJI Phantom	TZS-ECW-G Probe	10 cm	Aimed to increase UAV adoption for SM monitoring in dry regions	MLR: R^2 = 0.86 for stable moisture; R^2 = 0.77 for higher readings
[45]	Fixed-Wing AggieAir UAV (RGB, NIR, and thermal)	TDR sensors	15, 45, and 76 cm	Gaussian process model outperformed ANN and SVM for deep-layer soil prediction	GP at 76 cm: R^2 value 0.8
[46]	DJI Matrice with hyperspectral imagery	Gravimetric method	0 to 10 cm	Random Forest outperformed ELM in predictive accuracy	PIR model (RF-based): R^2 = 0.907
[47]	DJI S900 along High-res RGB, RedEdge multispectral, and TIR cameras	Gravimetric method	10 and 20 cm	RFR was highly accurate across growth cycles irrespective of sensor types	RFR outperformed KNN (R^2 = 0.78)
[48]	Multispectral sensor MicaSense RedEdge-MX	Field Scout TDR-350	10 and 20 cm	Multispectral and multivariate models proved more effective, especially in deeper zones	RER > PLSR/KNN/BPNN: R^2 value 0.8

Table 1. *Cont.*

Reference	Technology Used	Calibration Method	Soil Depth	Key Findings	Model/Accuracy
[49]	Multispectral with thermal Camera	SMC probes	Topsoil	PCA helped dimensionality reduction; canny edge detection enhanced thermal image clarity	RBFNN/PCA-RBFNN: $R^2 \approx 0.93$
[50]	UAV + PulsOn440 radar	Hygrometer	Topsoil	CNNR integrating vegetation indices (NDVI, MSAVI, and DVI) exceeded SVR and GRNN in performance	CNNR: $R^2 = 0.92$
[51]	Nano-Hyperspec + SoilNet (55 nodes)	Theta probe	5 cm	Canopy complexity was a limiting factor; VHGPR model performed well in water-limited zones	VHGPR: $R^2 = 0.8$
[52]	UAV + thermal camera	Profile probe	0 to 100 cm	Water stress impacted root mass and sugar content; thermal imagery identified this accurately	ANOVA: $R^2 = 0.28$ (roots), $R^2 = 0.94$ (sugar)
[53]	Landsat-8, Radarsat-2, ASTER DEM V002, DJI	Gravimetric method	5 cm	Developed a regression model using Landsat-8 height index with band B5 in karst terrain	Partial least squares regression (PLSR): $R^2 = 0.36$
[54]	UAV mounted with thermal and multispectral sensors	Smc probe	15 and 40 cm	A new water dynamics model linking soil and plant water status was introduced for hazelnut orchards	Kalman filter for continuous tracking
[55]	Sentinel-2B multispectral data	METER EC-5 sensors	5–10 cm	Traditional tillage influenced SM readings more than land cover, with terrain properties aiding better SM prediction	XGBoost with terrain data: R^2 value 0.8
[56]	Sentinel-1A satellite	DM8 Tensiometer + Penetrometer	15 & 25 cm	Soil moisture and workability distributions were mapped, but higher sample diversity is required for soil type variability	Multi-polynomial regression: 83.6% (train), 81.2% (test) accuracy
[57]	SMAP L3 with L-band radar & MODIS	Three ground station networks	5 cm	Incorporating surface temperature, evaporation efficiency, and topographic data enhanced model outputs	SVR and FNN performed best with Z-score and tanh normalization
[58]	Sentinel-2 remote sensing	TDR multisensory probes	15, 30, etc.	Two-way ANOVA showed improved yield and biomass with irrigation & fertigation strategies	Yield increased by +116.10%, biomass +119.71%, drainage losses decreased by 41.0%
[59]	Sentinel-2 imagery	Hydra probes	5 and 10 cm	NDVI space enhanced the OPTRAM model, improving SM mapping at field scale	OPTRAM with improved parameter fitting: R^2 between 0.60 and 0.66
[60]	Sentinel-2 with NDVI analysis	EC-5 capacitive sensor (METER)	15, 35 and 50 cm	Combining NDVI with soil variables improved irrigation management in maize crop; real-time analysis reduced SM variance	Variance dropped from 85% to <25% across crop stages
[61]	Digital impedance analyzer with modified commercial sensor	Lab-based LCR meter	Not Applicable	Introduced a low-cost FEM-based capacitive sensor system, not previously investigated in SM detection	Finite element modeling (FEM) used for sensor simulation
[62]	Wireless underground sensor	Not applicable	Not Applicable	Wireless link between buried sensors demonstrated a communication range of up to 3 m	Not applicable

Table 1. *Cont.*

Reference	Technology Used	Calibration Method	Soil Depth	Key Findings	Model/Accuracy
[63]	Capacitive sensors insulated with varnish	Gravimetric method	Not specified	Cu and AGS materials were most responsive to SM changes; insulation improvements are necessary to ensure long-term use	Regression R^2: 0.958 (Cu), 0.953 (AGS)
[64]	SM sensor integrated with WSN and IoT	Not specified	Not specified	Real-time monitoring system that tracks SM, humidity, and air temperature, with image processing via ThingSpeak	Utilized ANN and image analysis
[65]	Weather station with soil moisture sensor (W-SSS) using SHT-10	Not mentioned	10 & 28 cm	Created a budget-friendly W-SSS using accurate sensors and wireless/cloud infrastructure for environmental monitoring	Not available
[66]	Capacitive sensors in IoT	Capacitive hygrometer	Not stated	Sensors interface with microcontrollers and transmit data through LoRaWAN communication	Regression modeling applied
[67]	IoT sensors for paddy environments	Laboratory testing	Not reported	Designed a cost-efficient and easy-to-use system combining various sensors and communication methods	Not available

2. Different Approaches for Soil Moisture Measurement

2.1. In Situ Method for Soil Moisture Analysis

There are two categories for the in situ approach of measuring soil—the direct approach and the indirect method. The direct method, which uses thermogravimetric measurement to compare the weight or volume before and after drying, includes the conventional oven drying method, as well as weight-based and volume-based methods. Other than this, every automated methodology now in use is classified as an indirect method. By making holes in the Earth, the direct approach—also referred to as the destructive method—estimates the moisture content of soil. This disturbs the root zone of the soil and may eventually affect infiltration and drainage properties. Stated differently, the indirect technique measures soil moisture by establishing a correlation between the physical and chemical qualities of soil and its moisture content [68].

Several methods, like in situ or ground truth measurements, physically based models, and remote sensing, are also a way of estimating SMC (presented in Table 2 below) [69]. However, it is still difficult to measure SMC accurately due to the regional heterogeneity in soil quality, terrain, vegetation cover, and climate, which makes large-scale assessments tough. Single-point measurements at predetermined sites are used in traditional SMC estimating methods. The gravimetric method, while highly accurate, is destructive, time-consuming, and costly. Indirect techniques for estimating SMC include gamma-ray scanners [70]; neutron probes [1]; frequency-domain reflectometry, or FDR [71]; and time-domain reflectometry (TDR).

Table 2. Conventional methods and their characteristics.

Method	Accuracy	Major Advantages	Major Disadvantages	Cost	Soil Suitability	References
Gravimetric	High	- Easy setup and high accuracy - Direct method - Used in calibration of indirect methods	- Time-consuming - Labor-intensive - Destructive	Low	All	[72,73]

Table 2. *Cont.*

Method	Accuracy	Major Advantages	Major Disadvantages	Cost	Soil Suitability	References
TDR	High	- Highly responsive - Less destructive - Automation possible	- Expensive - Calibration required	Medium	All except saline soil	[74,75]
FDR	High	- Highly responsive - Less destructive - Automation possible	- Less performance in saline and conductive heavy clay soils	Medium	All except clayey and silty soils	[28]
Gamma ray	High	- Non-destructive - Real-time monitoring - Deep penetration	- Limited spatial resolution - Can determine smc having a thickness of up to 2.5 cm only	Costly	All	[28,76]
Tensiometer	High	- Cost-effective and non-destructive - Continuous reading without disturbing the soil	- Not suitable for dry soil - Constant monitoring required	Cost-Effective	Not favorable for dry condition	[77,78]
Capacitance sensor	High but depends on several factors	- Non-destructive - Accurate measurement - High levels of salinity can be read	- Proper calibration required - High sensor cost - Accuracy is dependent of soil type and temperature	Costly	All	[77]

2.1.1. Gravimetric Method

A conventional and generally used method for calculating surface soil moisture (SSM), the gravimetric method is frequently used as the standard for precision. It offers reliable moisture measurements that are unaffected by variations in soil texture or salinity. Despite its precision, the method is inherently destructive, as it involves removing soil samples for oven drying in a laboratory setting. This characteristic makes it unsuitable for repeated measurements at the same location and limits its ability to provide continuous moisture data over time [79]. Figure 4 below presents the process of the gravimetric method.

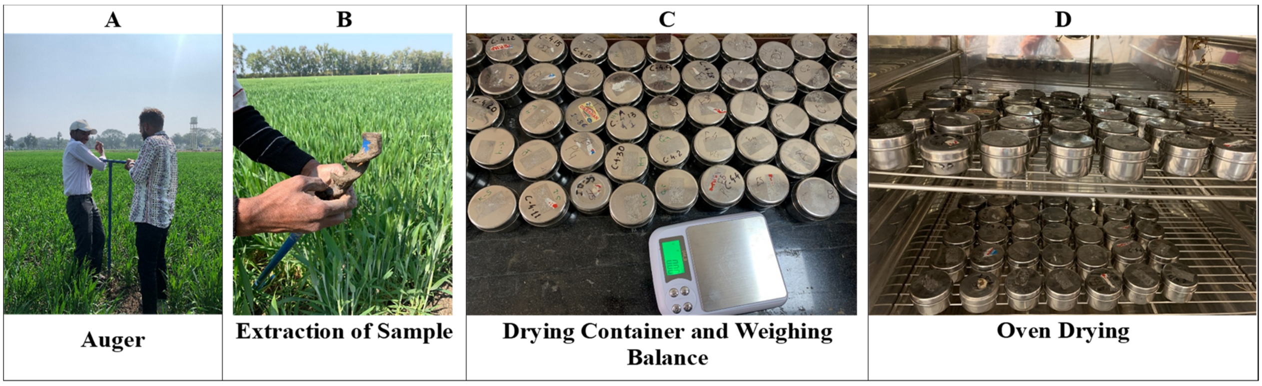


Figure 4. Process of gravimetric method (in situ method) for volumetric water content measurement. (**A**): Collection of samples in the field using auger; (**B**) Extraction of sample at multiple depths; (**C**) Weighing of the samples before and after drying; (**D**) Drying of samples in hot air oven at 105 °C for 24 h.

2.1.2. Time-Domain Reflectometry (TDR)

By timing the passage of an electromagnetic pulse through a waveguide embedded in the soil, these sensors are able to estimate the smc of the soil (Figure 5). The dielectric properties of the soil, which change with the moisture content, have an impact on this transit time. Because of its high temporal resolution, quick data capture (around 28 s), and reliable observations, TDR is especially helpful for long-term, in situ monitoring [76]. A major property of TDR is that it does not require soil-specific calibration, as it remains largely unaffected by soil texture, salinity, and temperature. Additionally, it offers a non-destructive, radiation-free method for continuous soil moisture assessment. However, the system involves a relatively high initial cost and may encounter accuracy issues in highly saline soils or very wet conditions due to signal loss or increased [80].

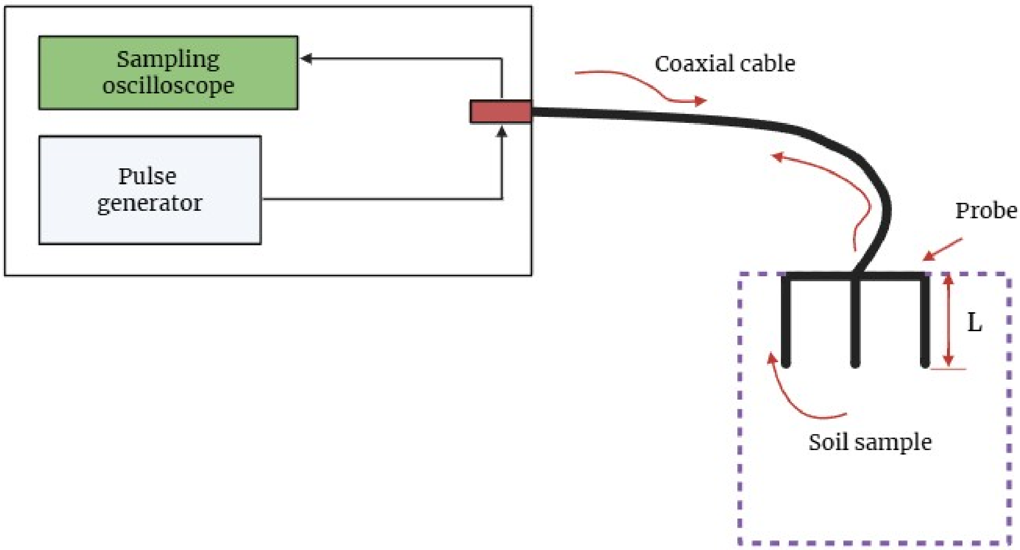


Figure 5. Schematic diagram of moisture measurement with time-domain reflectometry (TDR).

2.1.3. Capacitance and Frequency-Domain Reflectometry (FDR) Sensors

By examining how long it takes a capacitor buried in the soil media to be charged, it calculates the dielectric constant of a medium (Figure 6a,b) [81]. Because this process is heavily influenced by the specific soil properties, it often necessitates repeated calibration during deployment. Although the initial setup cost of these systems is relatively low, frequency-domain techniques are generally considered more promising than time-domain reflectometry (TDR) methods for assessment of soil moisture content. In a comparative analysis, it was found that Topp's equation (developed by Topp, Davis, and Annan in 1980) remains valid for TDR-based soil moisture measurements up to a volumetric water content of 50%. This limitation is due to the fact that the equation was derived from experiments on mineral soils with moisture levels below 50%.

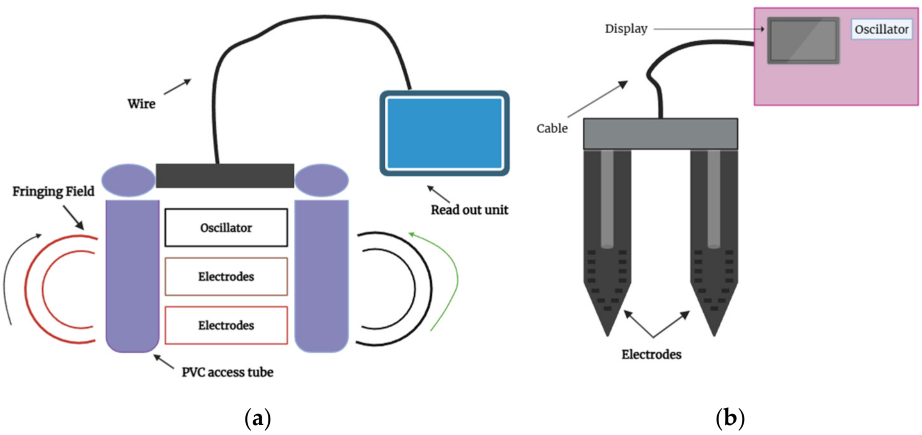


Figure 6. Illustration comparing two moisture measurement techniques: (**a**) frequency-domain reflectometry (FDR) and (**b**) capacitive sensing.

2.1.4. Gamma Ray

Both laboratory and field studies can benefit from the use of gamma-ray attenuation, which is one method that uses radioactive signals to accurately measure smc, usually up to a depth of about 25 mm or less (Figure 7). Its non-invasiveness, which permits repeated measurements of soil physical characteristics at the same site over time without altering the soil structure, is one of its main advantages. According to [82], this approach has especially higher sensitivity to changes in soil bulk density and surface soil moisture variations.

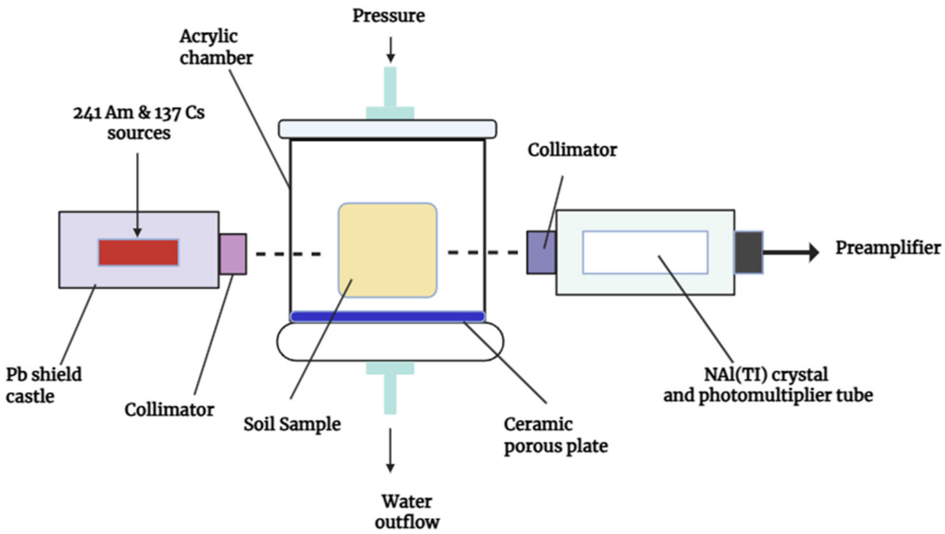


Figure 7. Detailed diagram of moisture measurement using the gamma-attenuation technique.

However, compared to neutron-scattering methods, gamma-ray techniques involve greater safety concerns and come with higher operational expenses due to the use of radioactive materials.

2.1.5. Tensiometer

Tensiometer—a fundamental device used to measure the matric potential in the soil (Figure 8), which reflects the soil water tension or suction based on the principle of negative pressure. This instrument functions effectively only within a limited range of 0 to -1 bar, which represents a narrow segment of the total soil moisture availability. Due to this restricted measurement range, it is not suitable for accurately determining the wilting point for most crops. Tensiometers are most effective in sandy soils, where moisture is typically found at shallow depths (less than 1 m), but they are generally unsuitable for fine-textured soils. Although tensiometers, compared to other techniques, have relatively low-cost and are simple to install, they require constant maintenance and are considered invasive to the soil environment [68].

2.2. Remote Sensing Approaches

Ground-truth-based soil moisture measurement approaches are useful for obtaining direct readings at various soil depths. Despite providing useful data, point-based approaches are limited in their capacity to capture the large-scale spatiotemporal variability of soil surface moisture (SSM). This limitation arises because of the influence of key components, such as topography, climatic conditions, composition of soil dynamics, vegetative cover, and water table depth, which contribute to significant heterogeneity and variable distribution patterns.

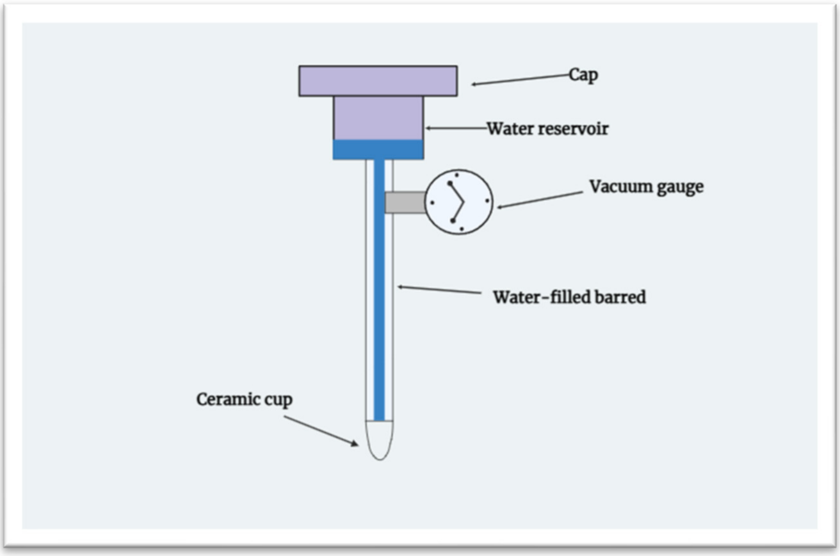


Figure 8. Detailed diagram of measurement using a tensiometer to measure the matric potential in the soil.

To address this challenge, remote sensing technology offers a cost-effective solution by providing frequent, global-scale updates. Moisture content can be assessed using thermal and optical satellites, along with a range of sensors, including active, passive, and microwave technologies [9,76,83,84]. One effective approach for tracking the temporal and geographical variations in moisture content (SMC) at different scales is the remote sensing approach. Images from the optical, thermal, and microwave portions of the electromagnetic spectrum can be obtained by remote sensing. Surface reflectance, or reflected radiation from the Earth's surface, is used by optical remote sensing to calculate the smc of the soil on the surface. This method offers moisture data of soil with better spatial resolution [85]. Soil spectral reflectance is affected by intrinsic factors as texture, organic matter, and mineral composition, all of which are influenced by soil moisture [86,87]. The changes in soil spectral signature caused by varying moisture levels can be analyzed by observing bare soil under various moisture conditions, where the variation is attributed solely to moisture content [88–90]. Recent laboratory findings have demonstrated the impact of SMC on soil reflectance behavior, emphasizing the significance of remote sensing in estimating SMC [91,92]. Apart from direct retrieval techniques, hydrological modeling approaches that utilize remote sensing data offer an alternative pathway for indirect soil moisture estimation. For instance, ref. [93] proposed the AD2 (approximate distributed approach), which enhances the calibration of lumped hydrological models by integrating spatially distributed physical information such as land use and topography derived from remote sensing. Although primarily designed for hydrological simulations, such approaches contribute to soil moisture estimation by providing improved spatial representation of surface and sub-surface hydrological processes.

Figure 9 depicts the study of spectral signature and reflectance analysis of a field using remote-sensing imagery data. The figure illustrates a bare agricultural field (A) divided into various grids for systematic sampling (B). Point data are collected at the center of each grid cell as sampling points. These discrete point measurements are then spatially interpolated using interpolation methods like inverse distance weighting (IDW) and Kriging in a GIS environment. The resulting map provides a continuous representation of spectral reflectance across the entire field (C). The color gradient illustrates the spatial variability in reflectance values, highlighting differences across the field surface.

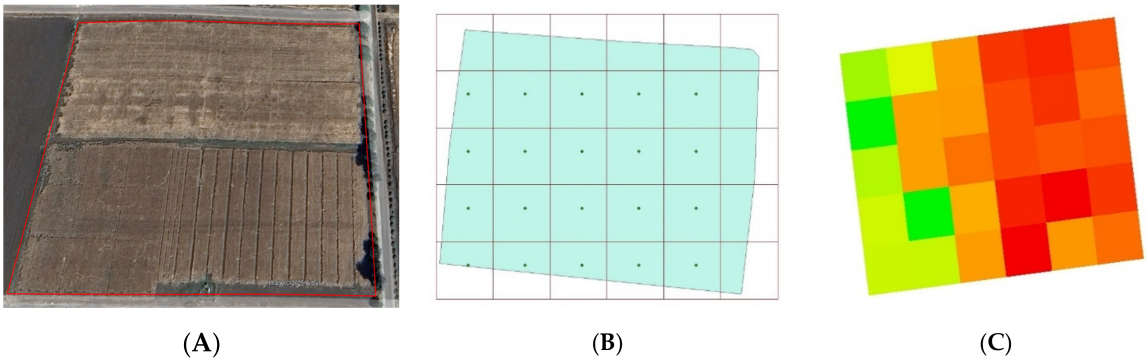


Figure 9. Study of spectral signature and reflectance analysis using remote sensing images. (**A**) Location of a study area (bare soil); (**B**) Division of study area into various grids for sampling of point data; (**C**) Output map with representation of spectral reflectance across the entire field.

However, because of its very limited geographical and temporal resolution, satellite-based remote-sensing data application has limits. Despite these obstacles, significant strides have been achieved in recovering SMC through the analysis of its correlations with land-surface data collected from satellites. The basis for determining SMC using optical and thermal remote sensing data is the relationship between SMC and vegetation indices (VI) or surface spectral data. SMC is frequently estimated using the soil line equation, which combines vegetation cover and soil reflectance. Because spectral reflectance of soil in these bands typically declines with an increase in SMC, thermal infrared wavelengths are especially helpful in this situation.

Critical information about a range of agricultural and environmental aspects, such as growth status of a crop, SMC, evapotranspiration, temperature of land surface, and even pest infestations, can be assessed from remote sensing data with high geographical and temporal resolution. Because of these developments, remote sensing is now a highly effective tool for controlling and monitoring soil moisture. The vegetative index and analysis of a single spectral signature are the two commonly utilized methods in optical remote sensing of smc [94]. By using the contrast between the spectral reflectance in the water-absorption and non-absorption bands, single spectral analysis develops the link between soil moisture and reflectance from the surface [95]. An overview of remote sensing methods, including their methods, benefits, and drawbacks, is given in Table 3 below for estimating soil moisture.

Table 3. Overview of remote sensing techniques for soil moisture estimation with advantages, limitations, and references.

Category	Technique	Pros	Cons	Reference
Optical Method	Reflectance-usage methods	Moderate spatial resolution; potential with upcoming hyperspectral missions.	Limited performance over dense vegetation; low temporal resolution; sensitive to cloud cover.	[85]
Thermal Infrared	Thermal infrared-usage methods	Moderate resolution; strong correlation between soil moisture and thermal inertia.	Low revisit rates; atmospheric influence; limited in vegetated and cloudy conditions.	[96]
Microwave Passive	Various methods	Reliable over bare soils; effective under cloudy skies with higher temporal frequency.	Coarse resolution; affected by vegetation and surface roughness.	[97]
Microwave Active	Empirical, semi-empirical, and physical methods	High spatial resolution; capable in cloudy and daytime conditions.	Limited revisit frequency; prominently sensitive to surface roughness and vegetative cover.	[98]

Table 3. *Cont.*

Category	Technique	Pros	Cons	Reference
Synergistic Methods	Optical and thermal infrared	Enhanced moisture content retrieval using multiple sensor data.	Empirical limitations; poor performance under clouds; restricted sensing depth.	[99]
	Active and passive microwave	Improved temporal resolution and soil moisture detection.	Requires careful scaling and validation.	[100]
Optical and Thermal	Thermal sensor, vegetation index and spectral reflectance	Strong correlation between soil moisture and land-surface temperature (LST) indicates that LST can serve as an effective tool for early monitoring of vegetation status.	Coarse spatial resolution may miss small-scale variations.	[101]

2.3. UAV for Moisture Content Estimation

Establishing models that link soil moisture (SM) to quantifiable remote sensing predictors or indicators like temperature of soil surface and vegetative indices is essential given the features of SM detection using UAV-based remote sensing [46]. The usefulness of spatial variability analysis through different vegetation indices has been demonstrated by a number of studies that have mostly concentrated on the direct assessment of soil moisture using multispectral images [6,88]. Significant promise exists for developing a dependable and reasonably priced technique for spatially mapping important soil characteristics, including bulk density, hydraulic properties, soil moisture, soil texture, and organic matter, using UAV-based multispectral imaging. Unlike satellite-based data, UAV data provide much higher spatial resolution, increasing the potential of better and precise predictions of soil moisture content and better navigation over temporal resolution. In comparison to traditional in situ methods of measurements, UAVs can cover larger areas in relatively lesser time while also providing detailed assessments of spatial variability within fields.

In the agriculture industry, unmanned aerial vehicles (UAVs) have become a more affordable option than traditional remote sensing platforms [102–105]. While satellite-based remote sensing offers broad spatial coverage and generally reliable precision for estimation of moisture content of soil (SMC) on a larger scale, it is less suitable for capturing small-scale or frequent changes in agricultural environments [106,107]. In contrast, UAV-based remote sensing is particularly advantageous for estimating SMC at the field level due to its affordability, high-frequency deployment capability, and ultra-high spatial resolution often achieving imagery with pixel sizes as small as 1–2 cm [107]. Employing UAVs mounted with thermal infrared, RGB, and multispectral camera (Figure 10) has provided considerable promise for precise and frequent SMC monitoring in agricultural contexts, supporting a wide range of practical applications [47,108–110]. Figure 10 shows the multispectral sensor mounted in a UAV and the calibration process using a calibration board.

Figure 10. UAV-mounted with multispectral camera, sensor components, and calibration process. (In pic.: Multispectral camera model is MicaSense-RedEdge P and drone is Agribot by IOTech).

Unmanned aerial vehicles (UAVs) provide a highly effective solution for monitoring soil moisture, offering advantages, such as precise measurement, rapid data collection, scalability, and cost efficiency. With benefits including accurate measurement, quick data collection, scalability, and cost effectiveness, unmanned aerial vehicles (UAVs) provide a very effective way to monitor soil moisture. Equipped with a range of sensors—including optical, thermal infrared, and LiDAR—UAVs serve as versatile platforms for remote sensing. These systems can capture imagery at exceptionally high spatial resolutions, often down to centimeter or sub-centimeter scales, providing much detailed spatial analysis and accurate mapping of distribution of soil moisture in agricultural environments [94]. In our analysis, we discovered the most highly used sensors on UAVs for soil moisture (SM) monitoring, as follows:

- RGB cameras: These types of sensors are mostly used for mapping vegetation and take pictures in the visible light spectrum. They are popular because they are inexpensive and simple to use, and they generate high-resolution color images with red, green, and blue bands [111].
- Multispectral and hyperspectral cameras: In order to calculate vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI), these sensors gather data over a variety of spectral bands. These indices are instrumental in evaluating vegetation health, physical soil attributes, and soil moisture levels. The data from these cameras often require radiometric and atmospheric corrections to ensure accuracy [43].
- Thermal cameras: These sensors detect infrared radiation to create temperature maps and identify thermal patterns. They are particularly valuable in estimating evapotranspiration and detecting variations in temperature in land surface, closely linked to soil moisture content [112]. In agriculture, thermal imaging is extensively applied for assessing crop water stress and improving irrigation efficiency [113].
- Shortwave near-infrared (SWIR) cameras: these instruments generate reflectance indices in the SWIR range that closely relate to the water content in plant tissues, enabling indirect assessment of soil moisture levels through vegetation analysis.
- LiDAR: This remote sensing technique is widely utilized for constructing high-resolution 3D terrain models and is essential for applications such as flood detection, snow depth measurement, and erosion analysis. Despite its effectiveness, LiDAR is relatively costly and often requires additional processing steps, including ground filtering, to ensure data accuracy [114]. Table 4 presents different sensors and their influence due to weather conditions and their calibration process.

Table 4. Weather-induced effects on UAV RGB, NIR, thermal, and LiDAR sensors—data quality challenges and mitigation approaches.

Sensor Type	Influence of Weather Conditions	Impact on Data Quality	Calibration	Reference
RGB Camera	Cloud cover, variable sunlight (solar angle), shadows, and haze reduce contrast and affect surface reflectance measurements.	Reflectance inconsistency, shadow artifacts, over/under-exposed regions.	Radiometric calibration using reflectance panels	[115]
NIR Sensor	Atmospheric moisture and haze scatter NIR wavelengths, altering vegetation reflectance; sun angle changes spectral response.	Errors in vegetation indices (e.g., NDVI), spatial inconsistency in reflectance values.	Calibration with multi-level reflectance targets	[116]

Table 4. *Cont.*

Sensor Type	Influence of Weather Conditions	Impact on Data Quality	Calibration	Reference
Thermal Camera	Ambient temperature fluctuations, wind cooling of surfaces, humidity, and solar heating drift thermal readings during flights.	Inaccurate surface temperature maps; thermal drift; variability in emissivity assumptions.	Blackbody calibration targets	[117]
LiDAR Sensor	Fog, rain, dust, and humidity scatter and attenuate laser pulses, reducing return strength.	Reduced point density, increased noise, poorer vegetation penetration, and degraded elevation accuracy.	Boresight and range calibration	[118]

The figure below (Figure 11) provides an overview of the key functions and operational limitations of onboard sensors incorporated in remote sensing applications. A tabular summary of UAV-based soil moisture estimation studies, including authors, methods, and key findings (2019–2022), is presented in Table 4 below. Table 5 provides a summary of UAV based moisture estimation methods and key findings.

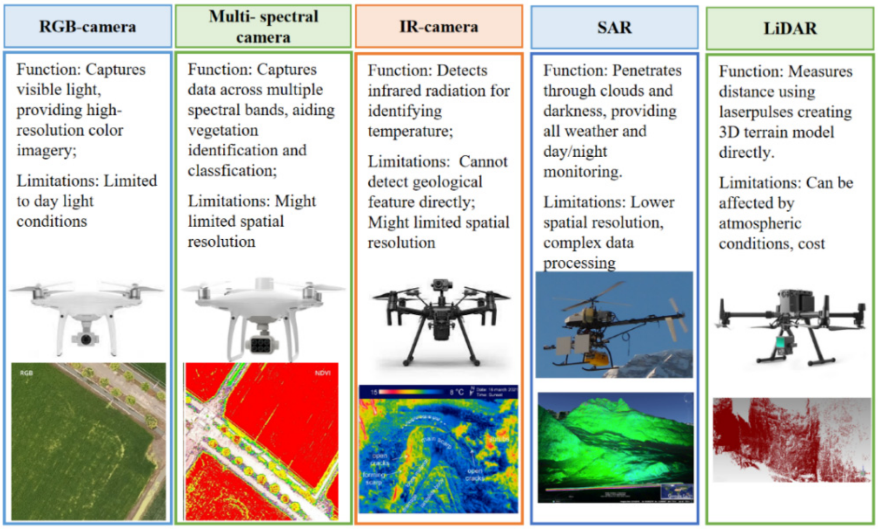


Figure 11. Overview of the key functions and operational limitations of onboard sensors used in remote sensing applications [119].

Table 5. Summary of UAV-based moisture content estimation studies, methods, and key findings.

Reference	Year	Methods Used	Key Findings
[120]	2021	UAV multispectral imaging; machine learning (Random Forest); multiple linear regression	Built models between vegetation indices and SMC at different crop stages; high accuracy and model stability.
[47]	2023	UAV RGB, NIR, and thermal infrared sensors; NDVI analysis; patch trait quantification	Evaluated Green NDVI (GNDVI) and vegetation patch impacts on soil moisture; showed trait influence on SMC monitoring accuracy.
[44]	2020	UAV visible-band imagery; brightness analysis; correlation with ground SMC; statistical modeling	Image brightness strongly correlated with SMC; combining brightness with vegetation cover improved estimation accuracy.

Table 5. *Cont.*

Reference	Year	Methods Used	Key Findings
[111]	2022	UAV-mounted RGB and thermal sensors; texture and temperature analysis; regression modeling	Discovered relationships between soil texture, surface temperature, and SMC in arid regions; useful for localized water management strategies.
[69,121]	2017, 2025	UAV with hyperspectral bands	Helps in ground moisture content mapping, ultimately for risk management during extreme events

In addition to the above summary of UAV applications and machine learning method for soil moisture estimation, the following table (Table 6) highlights recent studies (2023–2025) with a focus on UAV-based data acquisition and model performance.

Table 6. Summary of UAV and machine learning techniques for moisture content estimation.

Reference	Moisture Content Data	Remote Sensing Inputs	Satellite/ Platform	Machine Learning Models	Best-Performing Model	Performance Metrics	Study Area
[122]	TDR	NDVI, radar backscatter (VV, VH), incidence angle, DEM	Sentinel-1 & Sentinel-2	ANN, GRNN, SVR, RF, RNN, AutoML Boosting, EL, BDT	ANN	RMSE = 0.04 m^3/m^3; R^2 = 0.80	India
[10]	TDR	NDVI and NTR reflectance	UAV	Various ML models	Not specified	RMSE = 0.04 cm^3/cm^3; Nash–Sutcliffe efficiency > 0.90	USA
[123]	TDR	Radar backscatter (VV, VH)	Sentinel-1	ANN, RF, SBC, WM, etc.	SBC	R^2 = 0.64; bias = −0.01 m^3/m^3	India
[124]	TDR	NDWI, radar backscatter (VV, VH)	Sentinel-1, Landsat-7 & -8	ANN, LRM	ANN	RMSE = 0.04 cm^3/cm^3; R^2 = 0.73	Ethiopia
[125]	TDR	Optical reflectance	Landsat-8	ANN, RF, SVM, Elastic Net (EN)	RF	NS = 0.73	Iran
[126]	Oven-dry method	Spectral reflectance	UAV	ANN, RF, SVM, Relevance Vector Regression (RVR), Boosted RT (BRT)	BRT	R^2 = 0.91; RMSE = 1.48%; RPD = 3.396%	China
[127]	TDR	Radar backscatter (VV, VH), incidence angle	Sentinel-1	Random Forest (RF)	RF	R^2 = 0.86; RMSE = 3%	New Zealand

2.4. Approach Using Machine Learning

In recent years, machine learning techniques for estimating soil moisture have drawn a lot of attention, mainly due to their potential to improve accuracy and efficiency over conventional methods. Beyond agricultural monitoring, remote sensing and machine learning techniques are increasingly applied in fields such as energy infrastructure [128]. To create predictive models, these methods usually integrate a variety of different data sources, such as in situ observations, meteorological data, and remote sensing. For example, deep learning methods, random forests, and support vector machines (SVMs) have been incorporated to understand the non-linear interactions between soil moisture and its influencing elements.

Furthermore, integrating sensor data and machine learning has enabled real-time moisture content monitoring, which is essential for the field of precision agriculture and management of water resource [1]. These advancements enhance the growing importance of machine learning in environmental monitoring and agricultural practices, paving the way for future sustainable water management strategies. Table 7 below presents a comparison of soil moisture assessment methods, their accuracy, cost, and climatic applicability.

Table 7. Comparison of soil moisture assessment methods by accuracy, cost, and climatic applicability.

Method	Accuracy	Cost	Spatial Resolution	Temporal Resolution	Applicability
In Situ	High accuracy	High	Very fine	Continuous or scheduled (depends on instrumentation)	Highly reliable in all climatic conditions
Satellite Remote Sensing	Moderate to low (depends on resolution)	Low to moderate	Coarse to moderate	Revisit cycle	Effective for large-scale monitoring
UAV-Based Sensing	High accuracy	Moderate to high (equipment + field operation costs)	Very high (cm-level spatial resolution)	Flexible (on-demand flights, weather dependent)	Highly effective for field-to-farm scale; weather constraints (rain, wind); requires site-specific calibration procedures.
Machine Learning Models	Variable	Moderate (computational resources, data availability)	Dependent on input data resolution	Can generate high-frequency estimates (model-based)	Scalable to different climates

Machine learning, a subset of artificial intelligence, allow systems to analyze data and solve complex problems without the need for explicitly defined rules. Compared to conventional methods, it often delivers faster and more efficient solutions. One prominent application of machine learning is in moisture content estimation in soil, where it has been used to create predictive models that support agricultural practices such as irrigation management [129,130].

Among machine learning techniques, regression analysis continues to be widely utilized due to its simplicity, long-standing history, and proven effectiveness across many disciplines. These models can predict diverse outcomes with considerable precision. However, conventional regression approaches depend on specific statistical assumptions, which can restrict their applicability. Challenges such as the presence of outliers, non-linear relationships, heteroscedasticity, and multicollinearity can compromise the validity of the results. Additionally, standard regression approaches typically incorporate multiple independent variables but may overlook interactions or latent effects. When the correlations among the variables are high, it can lead to distortion of coefficient, leading to biased interpretations and potentially misleading conclusions—a phenomenon sometimes referred to as "coefficient inflation" [131]. The below table (Table 8) provided presents a compilation of recent studies focusing on the incorporation of remote sensing technologies and machine learning models for moisture content estimation.

Table 8. Summary of data used and the ML model/algorithm used and their findings.

Year	Input/Data Used	Model/Algorithm	Key Findings/Outcomes	Reference
2017	Oklahoma Mesonet data (65 stations)	ROI, IDW, Co-Kriging	ROI was more precise than traditional interpolation methods like IDW	[132]
2020	Landsat-8 thermal and optical data	Random Forest (RF)	RF achieved highest prediction accuracy in restoration areas of semi-arid Iran	[125]

Table 8. *Cont.*

Year	Input/Data Used	Model/Algorithm	Key Findings/Outcomes	Reference
2020	Soil/environmental variables	RF, SVM, MARS, CART	Growing preference for RF due to better performance and interpretability	[111]
2021	Coarse-resolution satellite SM products	Random Forest (RF)	Increased SM map resolution to 30 m, enhancing utility for fine-scale applications	[133]
2022	Review of ML in SM studies	ANN, SVM, CART, RF	Concluded RF and CART as more interpretable than SVM/ANN	[134]
2023	Satellite-derived surface variables (0–5 cm)	Random Forest (RF)	Provided daily SM estimates at 1 km spatial resolution incorporating machine learning	[26]
2023	Mixed remote sensing inputs	Ensemble: KNR + RF + XGBoost	Ensemble model outperformed others in SM estimation accuracy	[26,40]
2024	Remote sensing hydroclimatic data	Multiscale Extrapolative Learning Algorithm (MELA)	Predicted SM at multiple depths monthly in semi-arid regions	[135]
2024	Watershed data (climate, land use)	SWAT	Simulates the effect of land management on water, nutrients, and sediments	[136]
2024	Land surface, atmospheric data	CLM (Community Land Model)	Integrates biogeophysical processes to simulate SM accurately	[137]
2024	Regional-scale climate and topography	VIC (Variable Infiltration Capacity)	Balances water and energy fluxes; captures spatial SM variation	[138]
2024	Soil hydraulic and solute transport parameters	Hydrus-1D	Simulates vertical water and solute flow in variably saturated media	[139]
2025	C-band SAR data, Sentinel-2A, Landsat-8	ANN, MLR, backscattering coefficients ($\sigma°$: VV and VH)	ANN models performs better than MLR models with high R^2 and low RMSE	[140]

3. Bibliometric Analysis of In Situ or Ground Truth Soil Moisture Applications and Machine Learning Techniques

Using VOSviewer (Visualization of Similarities), a popular tool for building and visualizing bibliometric networks, a thorough bibliometric analysis was conducted in order to methodically identify the current research trends and applications related to in situ moisture content measurement and machine learning approaches. VOSviewer is an open-source tool commonly employed for large-scale bibliometric studies and the visualization of relationships between scientific entities, such as keywords, authors, and publications [123].

3.1. Data Collection and Methodology

This analysis was focused on author-supplied keywords from over one thousand research articles indexed in the PubMed database, covering the period of 10 years from January 2015 to May 2025. In addition to restricting the results to include only English-language publications, we employed a sophisticated Boolean search method within the PubMed platform, which can be assessed to guarantee a comprehensive dataset at the following: (https://pubmed.ncbi.nlm.nih.gov/, accessed on 1 June 2025).

The search queries combined the phrase “soil moisture” with specific methods or sensor types. The primary focus was on commonly used in situ soil moisture measurement techniques, including the following:

- ➢ Gravimetric method;
- ➢ Tensiometer;
- ➢ Time-domain reflectometry (TDR);
- ➢ Frequency-domain reflectometry (FDR);
- ➢ Gamma-ray probe.

The metadata extracted from PubMed was imported into VOSviewer for further processing. Specifically, we employed co-keyword burst analysis to explore the frequency and strength of associations among keywords, alongside their clustering tendencies over time.

3.2. Network Construction and Cluster Analysis

Like mentioned in the introduction section, in VOSviewer, bibliometric maps are composed of items (e.g., keywords or terms) and links that indicate relationships or co-occurrence between items. A link is established when two keywords occur together in a single publication. The link strength measures this connection, with higher values indicating more frequent co-occurrence. The total link strength reflects the aggregate number of co-occurrences between a given item and all other items in the dataset.

Clusters are groups of closely related items and are visually represented by distinct colors in the generated map. These clusters are created using the VOS clustering algorithm, a widely recognized method for network-based data classification and bibliometric mapping [141,142]. Figures 12–16 below provide a visual representation of the overall maps.

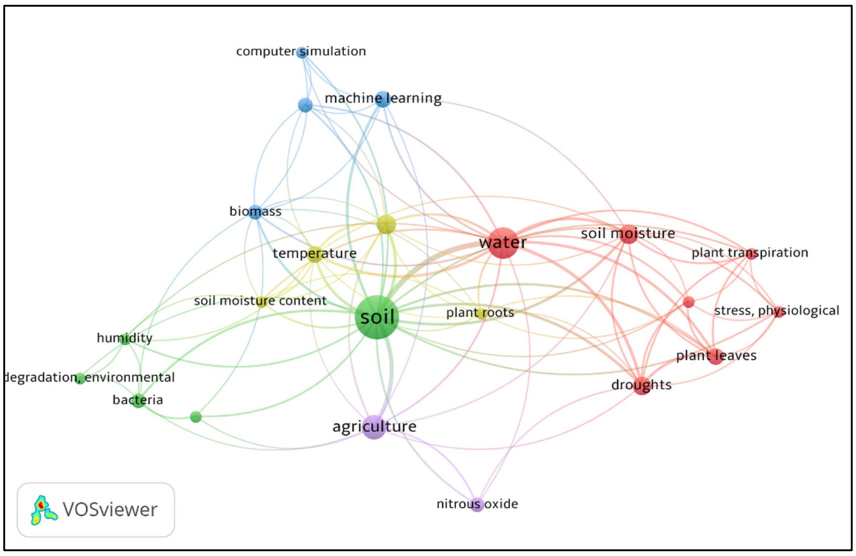


Figure 12. Gravimetric method for soil moisture estimation (items: 22; clusters: 5; links: 94; total link strength: 183).

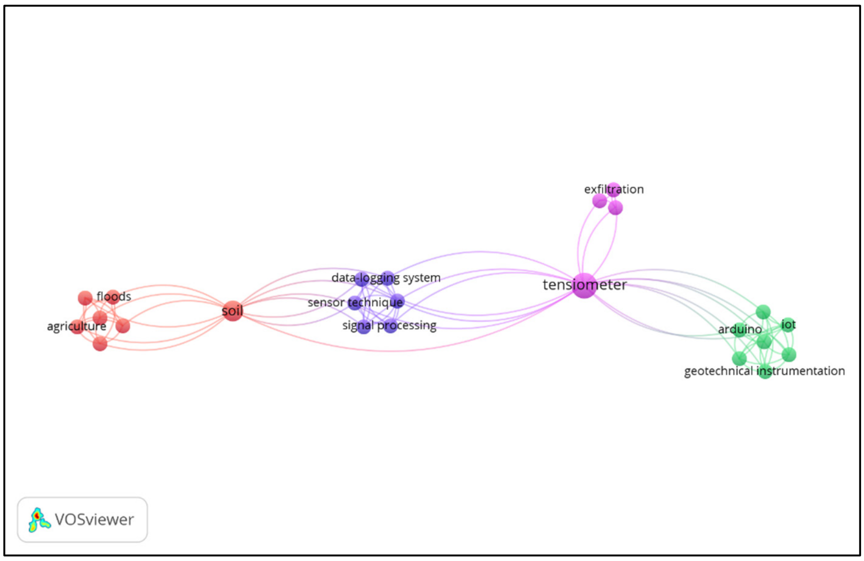


Figure 13. Tensiometer method for soil moisture estimation (items: 24; clusters: 4; links: 83).

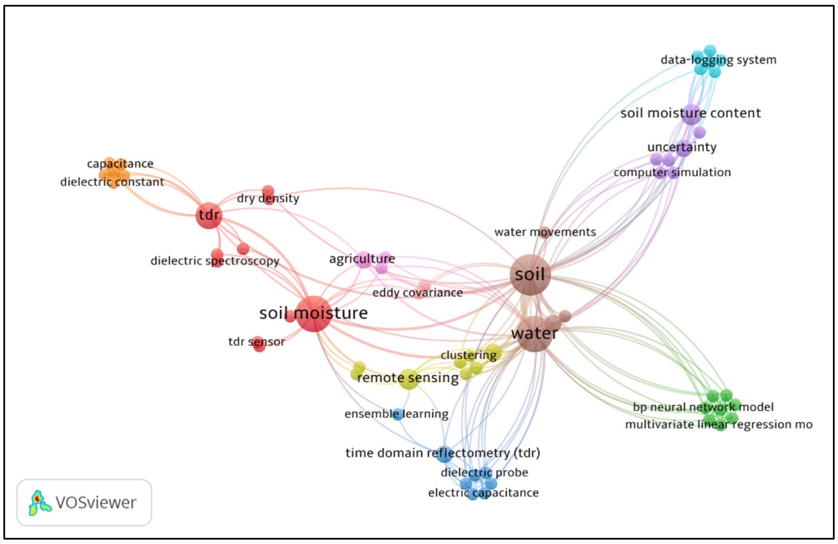


Figure 14. TDR method for soil moisture estimation (items: 63; clusters: 10; links: 243; total link strength: 268).

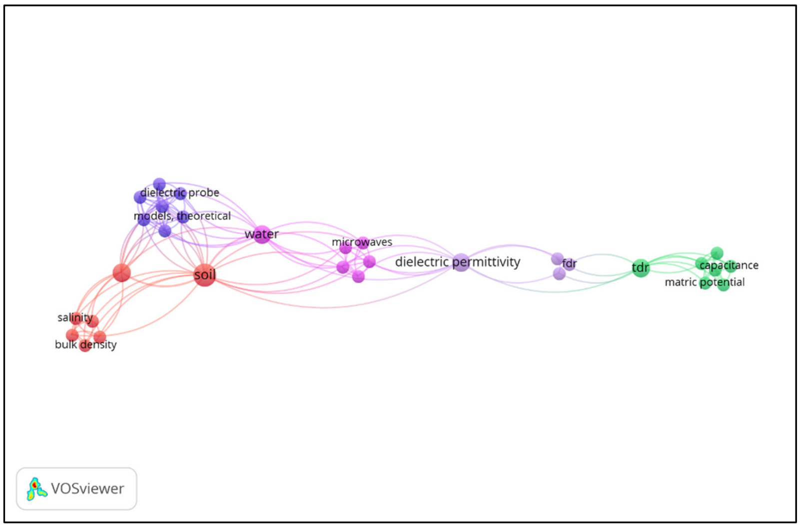


Figure 15. FDR method for soil moisture estimation (items: 11; clusters: 5; links: 123; total link strengths: 125).

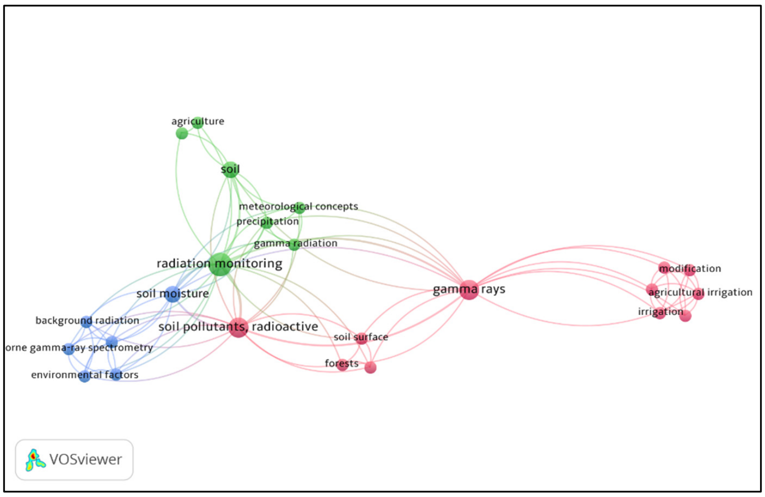


Figure 16. Gamma-ray method for soil moisture estimation (items: 24; clusters: 4; links: 91; total link strength: 98).

3.3. Comparative Analysis of In Situ Methods

We analyzed each method individually to assess its relative prominence in the literature. For each method or sensor type, we recorded the size of the clusters, number of links, and total link strength. These parameters provide insight into the scientific attention and research connectivity associated with each technique.

The results, as displayed in Figures 12–16 and Table 9, reveal the following:

- The time-domain reflectometry (TDR) was associated with the highest number of clusters (10), indicating a wide range of application contexts and diverse keyword associations;
- As the most extensively linked and cited tool for in situ moisture content in soil monitoring, time-domain reflectometry (TDR) showed the most links (243) and the highest total link strength (268). Interestingly, TDR was commonly associated with phrases like vegetation, drought, electrical conductivity, and validation;
- With a total link strength of 183, the neutron probe came in second in terms of connectivity, demonstrating its adaptability despite some drawbacks and significance in soil moisture research;
- In contrast, the use of tensiometer method showed the lowest number of links (83) and the least total link strength (85), suggesting limited usage in contemporary field applications, possibly due to its narrow measurement range, high maintenance needs, and ineffectiveness in dry or deep soils.

Table 9. Bibliometric comparison of leading soil moisture measurement techniques.

Methods	Items	Clusters	Links	Total Links	Keywords
Gravimetric method	22	5	94	183	Soil moisture
Tensiometer	24	4	83	85	Moisture content
Time-domain reflectometry (TDR)	63	10	243	268	Soil moisture, TDR
Frequency-domain reflectometry (FDR)	11	5	123	125	Soil moisture, FDR
Gamma-ray probe	24	4	91	98	Gamma-ray attenuation

Across all in situ techniques analyzed, commonly associated application-related terms included field calibration, drought monitoring, and electrical conductivity. These terms emphasize key themes in current soil moisture research, particularly in relation to climate variability, irrigation optimization, and sensor performance validation.

The analysis revealed a wide range of key areas where in situ sensors for soil moisture analysis are prominently utilized. These included the following:

➢ Remote sensing;
➢ Irrigation management;
➢ Control systems;
➢ Hydrological modeling;
➢ Precision agriculture;
➢ Geospatial sensor networks;
➢ Data simulation techniques;
➢ Flood risk monitoring;
➢ Landscape irrigation.

Since in situ sensor data are heavily integrated with satellite or aerial observations for extensive monitoring of the environment and modeling efforts, remote sensing evolved as the most commonly associated application among them. The fact that terminology from agriculture, hydrology, and sensor networks frequently occur together further emphasizes how multidisciplinary soil moisture research is and how important it is to managing water resources and the environment.

3.4. Analysis of Machine Learning Techniques Applied to Soil Moisture Prediction

The analysis was expanded in the study's second half to correlate the relationship between machine learning methods and soil moisture research. A refined search was executed using the query "soil moisture" OR "machine learning" within the PubMed advanced search interface. This broader query aimed to capture a wider spectrum of research integrating data-driven approaches with soil moisture estimation and modeling.

The resulting bibliographic dataset was again processed using VOSviewer to conduct a co-keyword burst analysis. This analysis enabled the identification of machine learning algorithms that have gained significant traction in soil moisture studies, particularly those involving in situ measurements.

The results, visualized in the figures below, indicate that the commonly applied machine learning method in this domain are as follows:

- ➢ Random Forest (RF);
- ➢ Artificial neural networks (ANNs);
- ➢ Support vector machines (SVMs).

These three algorithms consistently demonstrated strong co-occurrence with soil moisture-related keywords, underscoring their widespread adoption for tasks such as soil moisture prediction, data imputation, spatial interpolation, and integration with remote sensing data.

Figure 17 presents a visual map of key research themes related to machine learning applications in soil moisture estimation, based on 200 PubMed articles published between 2015 and 2025. The size of each circle reflects how often a keyword appears, with "machine learning", "soil", and "remote sensing" being the most frequent and central terms. Keywords are grouped into clusters using different colors, indicating thematic areas, such as drought monitoring, crop prediction, environmental monitoring, sensor technology, and specific machine learning techniques, like random forest, SVM, and XGBoost. The connections among keywords (lines) show how closely related the topics are, helping to reveal trends, research focus areas, and interdisciplinary links in the field.

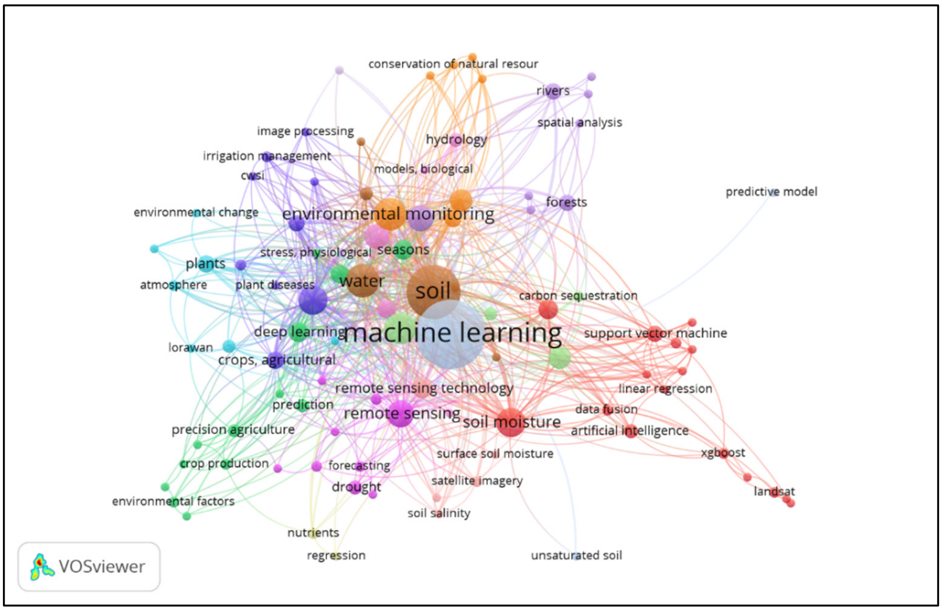


Figure 17. Integration of machine learning methods for estimation of soil moisture. PubMed database: 200 articles published during the years 2015–2025 were considered.

3.4.1. Random Forest Model for Soil Moisture Analysis

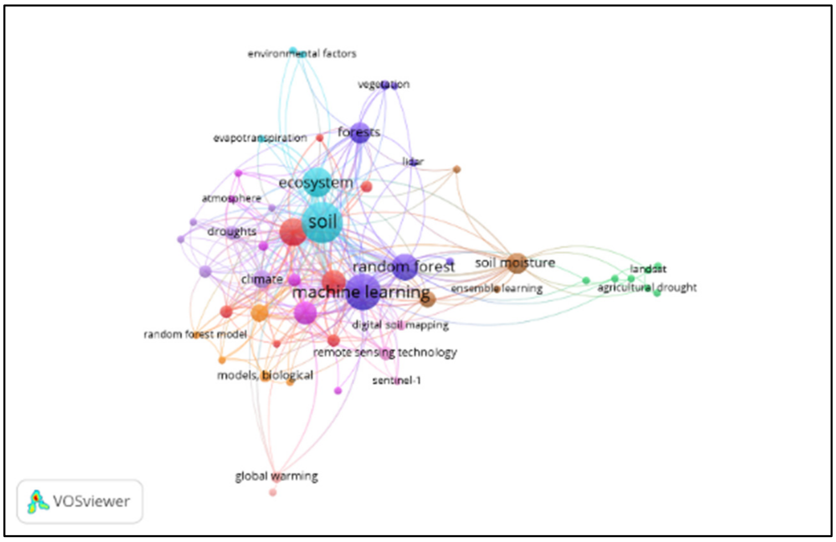
A popular machine learning approach for forecasting and analyzing the dynamic of soil moisture is the Random Forest (RF) model, which can handle complicated interactions, high-dimensional datasets, and non-linear correlations. RF is an ensemble learning method that builds many decision trees during training, each based on random subsets of features and distinct bootstrap samples of the data. For regression tasks like estimating soil moisture, the final result is produced by combining the predictions from each individual tree, usually through averaging.

In each tree, a random subset of features is considered at every split, which increases model diversity and reduces correlation among trees. According to the original formulation, the default hyperparameters for regression typically involve generating 200 decision trees, with p/3 features (where *p* is the total number of input features) evaluated at each split. However, more recent studies emphasize the importance of hyperparameter optimization, as default settings may not yield optimal performance across different datasets or application domains [10].

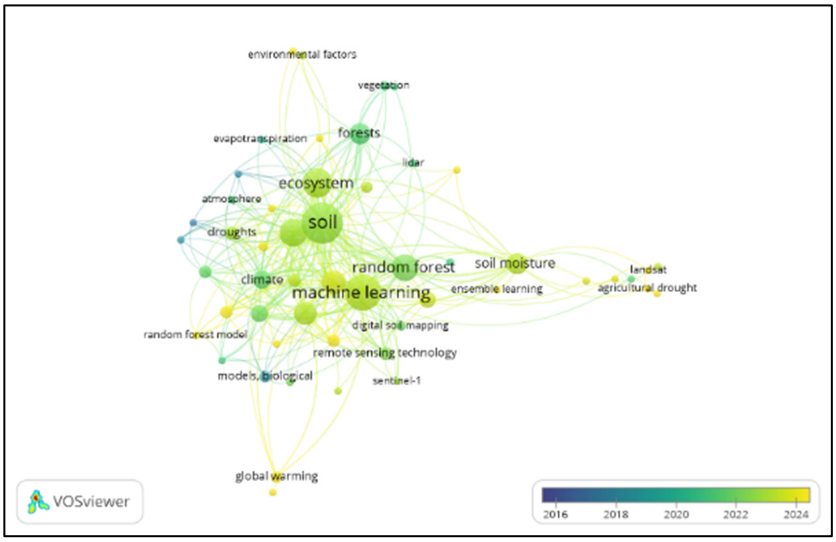
In soil moisture analysis, RF models are often trained using a variety of input variables, including meteorological data (e.g., precipitation and temperature), remote sensing indices (e.g., NDVI and land-surface temperature), topographic features, soil texture, and vegetation parameters. This flexibility enables RF to integrate heterogeneous data sources, improving prediction accuracy across spatial and temporal scales.

Overall, the RF model serves as a powerful tool in modern soil moisture research, supporting applications in irrigation scheduling, drought monitoring, precision agriculture, and hydrological modeling. Figure 18a,b illustrates the distribution and relationships of randomly applied methods for soil moisture estimation across 149 studies from 2015 to 2025.

This VOSviewer visualization illustrates the evolution of research themes over time based on keyword co-occurrence in scientific publications. Larger nodes such as “machine learning”, “soil”, and “random forest” indicate topics with a high number of publications. The color gradient, ranging from blue (earlier years like 2015) to yellow (recent years like 2025), shows how the research focus has shifted. Earlier studies emphasized topics like “droughts” and “evapotranspiration” (blue–green), while recent publications increasingly explore areas like “soil moisture”, “ensemble learning”, and “agricultural drought” (yellow). The dense network of connections suggests interdisciplinary integration, particularly in environmental monitoring using machine learning. Overall, the map highlights growing interest in applying advanced computational methods to soil- and climate-related challenges. Overall, research is progressing more toward using modern tools like machine learning to study soil and climate issues.



(**a**)



(**b**)

Figure 18. (**a**,**b**) Random method used for soil moisture estimation between 2015 and 2025 considering the available 149 articles during this period (items: 52; clusters: 10; links: 257; total link strength: 513).

3.4.2. Artificial Neural Networks (ANNs)

Artificial neurons are the building blocks of neural networks, often known as artificial neural networks (ANNs). A feed-forward neural network is frequently utilized for regression tasks such as determining soil moisture. A neural network is structured with the following three main layers: the input layer, hidden layers, and the output layer (Figure 19).

The input layer, hidden layers, and output layer are the three primary layers that make up a neural network. The dataset's features are transferred to the input layer and then to the hidden layers. Several neurons in these hidden layers use weights to process the incoming data. Additionally, each neuron has a bias term that aids in more efficient output adjustment. The final prediction or response is produced in the output layer. After each layer, an activation function is applied to determine whether a neuron should pass its output forward. This function introduces non-linearity, allowing the network to learn and solve complicated problems that simple linear models cannot handle. Figure 20a,b show the use of artificial-neural-network (ANN) methods for soil moisture estimation based on 106 research articles from 2015 to 2025.

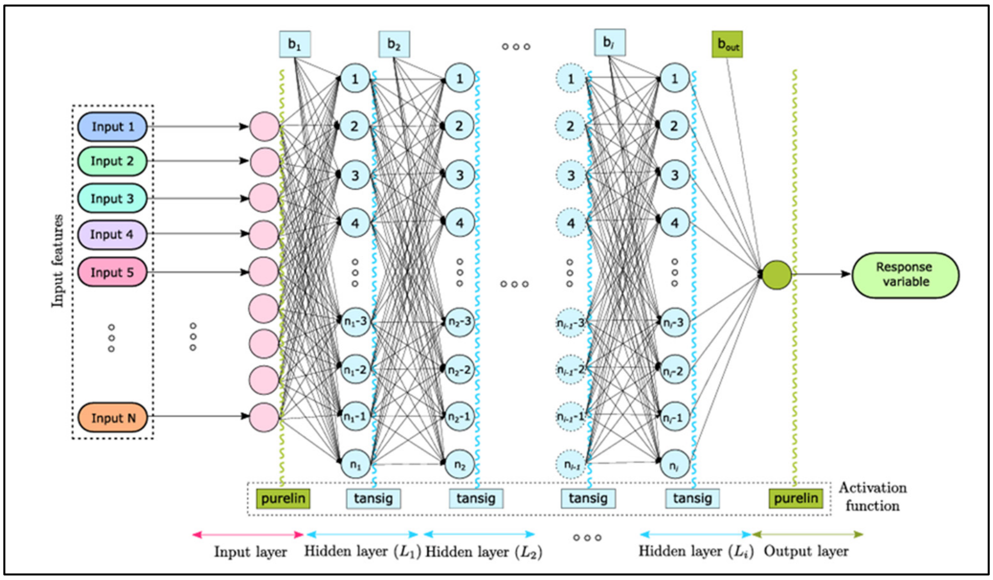
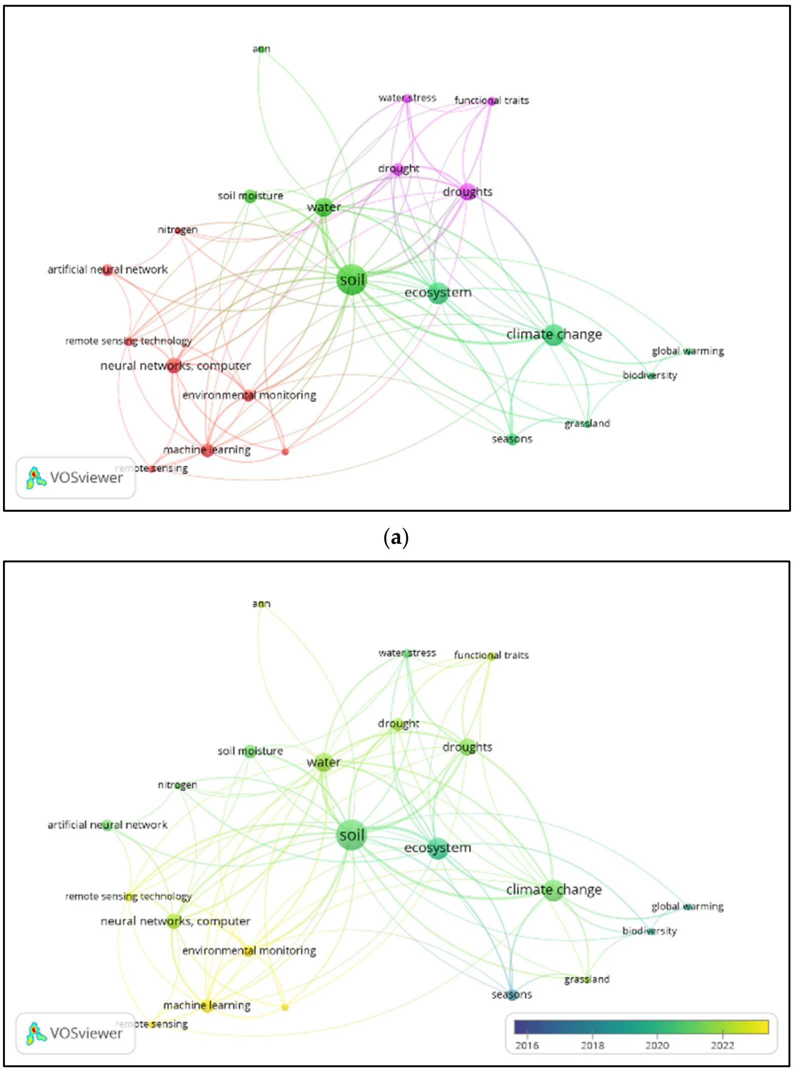


Figure 19. Working architect of the ANN model [124].



(**a**)

(**b**)

Figure 20. (**a**,**b**) ANN method used for soil moisture estimation between 2015 and 2025 considering the available 106 articles during this period (items: 22; clusters: 4; links: 96; total link strength: 249).

Typically, linear functions (such as purelin) are applied in the input layer and output layer of the network, while hidden layers use non-linear functions like the hyperbolic tangent sigmoid (tansig) to better capture complex patterns. In a feed-forward neural network, each neuron is connected only to neurons in the next layer, ensuring that the flow of information moves in one direction without forming any loops. To train this type of network effectively, the backpropagation algorithm is commonly used. This method involves repeating calculations to adjust the weights and biases, aiming to minimize the error between the model-predicted value and actual value [142].

3.4.3. Support Vector Machine

Strong supervised learning models for both classification and regression applications are support vector machines (SVMs), which are frequently employed in soil moisture analysis. In this regard, SVMs aid in the prediction of soil moisture levels by utilizing input parameters, including rainfall, temperature, vegetation indices, and satellite data.

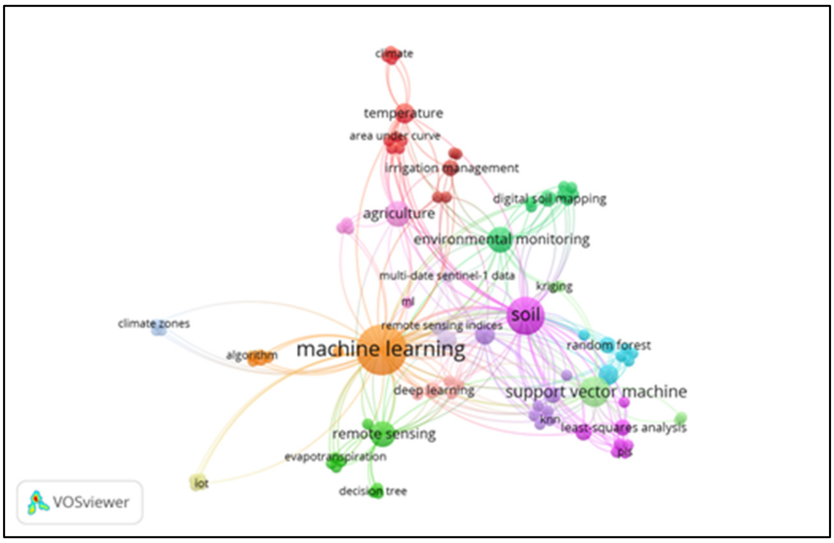
They function by determining the appropriate border or hyperplane to maximize the distance (margin) among various data classes while effectively separating them. The performance of generalization is enhanced by this margin maximization. SVMs can handle intricate, non-linear interactions by converting the input information into higher-dimensional spaces through the use of kernel functions. This enables the model to identify boundaries more successfully. Due to their strong generalization ability and resistance to overfitting, SVMs are highly accurate and reliable in a wide range of applications, particularly while using high-dimensional or limited datasets [143].

The figure (Figure 21a,b) below represents a bibliometric network analysis of the relationship between different research terms in machine learning and related fields. The nodes represent keywords, and the size of each node indicates the frequency of publications with that term. The colors of the edges show the publication years, with yellow indicating earlier years and green indicating more recent publications. It highlights the increasing focus on topics like "machine learning", "soil", and "remote sensing" in research in recent years. This visualization can help track the evolution of research trends over time, emphasizing the rise of machine learning techniques in agriculture and environmental monitoring.

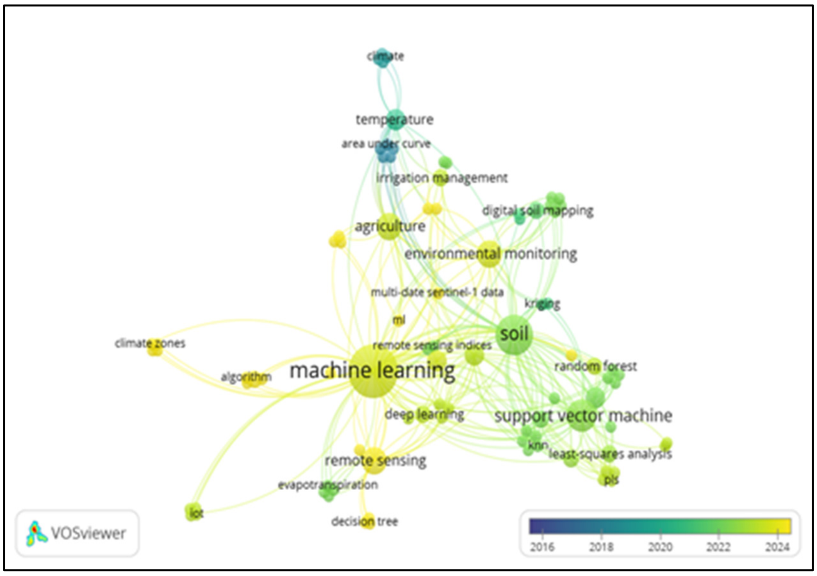
Table 10 below provides a bibliometric comparison of major machine learning methods used in soil moisture estimation. Random Forest appears as the most widely applied technique with 52 items and the highest total link strength (513), indicating strong research connectivity. Support vector machine shows the largest number of items (89) and clusters (14), reflecting broad application but relatively lower link strength (400). ANN, while having fewer items (22), demonstrates focused research with four clusters and moderate link strength (249), suggesting a more specialized but connected usage.

Table 10. Bibliometric comparison of leading machine learning methods for soil moisture measurement techniques.

Methods	Items	Cluster	Links	Total Links Strength
Random Forest (RF)	52	10	257	513
Artificial Neural Networks (ANNs)	22	4	96	249
Support Vector Machine	89	14	355	400



(**a**)



(**b**)

Figure 21. (**a**,**b**) SVM method used for soil moisture estimation between 2015 and 2025 considering the available 37 articles during this period (items: 89; clusters: 14; links: 355; total link strength: 400).

Machine learning models like regression methods are commonly employed to forecast soil moisture levels. According to a bibliometric study, Random Forest, neural networks, and support vector machines are leading as the most frequently applied algorithms in this field (Table 8). The performance of these models is highly influenced by the quality and relevance of the input features used. These features must effectively represent the target variable, e.g., moisture content in our case. It is crucial to select input variables that accurately reflect the physical processes associated with soil moisture. However, including too many features, even relevant ones, can lead to decreased model performance due to overfitting or redundancy. Therefore, choosing suitable and informative features is often more vital than the selection of the machine learning algorithm itself.

Among the algorithms, Random Forest has emerged as the most widely used for estimating soil moisture. It accounts for 149 publications, spread across 10 clusters, with 257 interconnections and a total link strength of 513. China leads in terms of research output in this area, particularly in integrating remote sensing inputs with machine learning for moisture content prediction.

4. Limitations & Conclusions

4.1. Limitations

Despite the growing capabilities of soil-moisture estimation techniques, several limitations persist across both traditional and modern approaches. Despite their accuracy, in situ techniques are frequently labor-intensive, spatially constrained, and unsuitable for extensive monitoring. Although they provide more spatial coverage, remote sensing technologies have drawbacks include cloud interference, poor resolution, and decreased accuracy in difficult terrain or dense vegetation. UAV-based methods provide high-resolution data but are constrained by flight duration, weather conditions, and regulatory restrictions. Machine learning models, although powerful, are mostly dependent on the quality and representativeness of input features and training data. Overfitting, lack of generalizability, and the "black-box" nature of some algorithms can reduce their transparency and reliability. Furthermore, limited access to high-quality, long-term datasets and the lack of standardized protocols for model validation continue to hinder reproducibility and scalability. Addressing these limitations is essential for improving the operational deployment and scientific rigor of soil moisture monitoring systems.

4.2. Conclusions

Accurate and timely soil moisture estimation is fundamental to advancing sustainable agriculture, efficient water resource management, and climate resilience. This review has synthesized the progression of soil moisture measurement techniques—from traditional gravimetric and sensor-based in situ methods to cutting-edge remote sensing, UAV platforms, and machine learning-driven models. While each approach offers unique benefits, their limitations underscore the need for integrated systems that combine spatial scale, temporal frequency, and contextual accuracy.

Machine learning techniques or algorithms particularly Random Forest, artificial neural networks, and support vector machines have stepped-up as powerful tools for capturing the non-linear and heterogeneous nature of soil moisture dynamics. However, their effectiveness is contingent on the quality and relevance of input features, underscoring that robust feature selection often outweighs algorithm choice in model performance. The bibliometric analysis further reveals a rapidly growing body of research, with China and institutions like the Chinese Academy of Sciences leading in scholarly output.

Despite these advancements, challenges such as data inconsistency, sensor limitations, model generalizability, and the absence of standardized protocols remain. The path forward lies in fostering interdisciplinary collaboration and embracing hybrid frameworks that fuse physical models, sensor networks, and artificial intelligence. Such approaches will enable the development of next-generation soil-moisture monitoring systems—scalable, adaptive, and capable of informing critical decisions in agriculture, disaster mitigation, and environmental stewardship.

Author Contributions: Conceptualization, S.C.H.; methodology, Y.A.R., K.V.R.R., S.P.K., A.B.M., and A.S.; software S.C.H. and Y.A.R.; resources, Y.A.R., K.V.R.R., S.P.K., A.B.M., and A.S.; data curation, S.C.H. and Y.A.R.; writing—original draft preparation, S.C.H.; writing—review and editing, Y.A.R., K.V.R.R., S.P.K., A.B.M., and A.S.; visualization, S.C.H.; supervision, Y.A.R., K.V.R.R., and S.P.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Zhao, T.; Shi, J.; Lv, L.; Xu, H.; Chen, D.; Cui, Q.; Jackson, T.J.; Yan, G.; Jia, L.; Chen, L.; et al. Soil moisture experiment in the Luan River supporting new satellite mission opportunities. *Remote Sens. Environ.* **2020**, *240*, 111680. [CrossRef]
2. Sabater, J.M.; Jarlan, L.; Calvet, J.-C.; Bouyssel, F.; De Rosnay, P. From near-surface to root-zone soil moisture using different assimilation techniques. *J. Hydrometeorol.* **2007**, *8*, 194–206. [CrossRef]
3. Guan, Y.; Grote, K. Assessing the Potential of UAV-Based Multispectral and Thermal Data to Estimate Soil Water Content Using Geophysical Methods. *Remote Sens.* **2024**, *16*, 61. [CrossRef]
4. Li, S.; Pezeshki, S.R.; Goodwin, S. Effects of soil moisture regimes on photosynthesis and growth in cattail (*Typha latifolia*). *Acta Oecologica* **2004**, *25*, 17–22. [CrossRef]
5. Sánchez, N.; González-Zamora, Á.; Piles, M.; Martínez-Fernández, J. A new Soil Moisture Agricultural Drought Index (SMADI) integrating MODIS and SMOS products: A case of study over the Iberian Peninsula. *Remote Sens.* **2016**, *8*, 287. [CrossRef]
6. Hassan-Esfahani, L.; Torres-Rua, A.; Jensen, A.; McKee, M. Assessment of surface soil moisture using high-resolution multi-spectral imagery and artificial neural networks. *Remote Sens.* **2015**, *7*, 2627–2646. [CrossRef]
7. Brandt, M.; Hiernaux, P.; Rasmussen, K.; Mbow, C.; Kergoat, L.; Tagesson, T.; Ibrahim, Y.Z.; Wélé, A.; Tucker, C.J.; Fensholt, R. Assessing woody vegetation trends in Sahelian drylands using MODIS based seasonal metrics. *Remote Sens. Environ.* **2016**, *183*, 215–225. [CrossRef]
8. Njoku, E.G.; Entekhabi, D. Passive microwave remote sensing of soil moisture. *J. Hydrol.* **1996**, *184*, 101–129. [CrossRef]
9. Mohanty, B.P.; Cosh, M.H.; Lakshmi, V.; Montzka, C. Soil Moisture Remote Sensing: State-of-the-Science. *Vadose Zone J.* **2017**, *16*, 1–9. [CrossRef]
10. Babaeian, E.; Sadeghi, M.; Jones, S.B.; Montzka, C.; Vereecken, H.; Tuller, M. Ground, Proximal, and Satellite Remote Sensing of Soil Moisture. In *Reviews of Geophysics*; Blackwell Publishing Ltd.: Oxford, UK, 2019; Volume 57, pp. 530–616.
11. Baldwin, D.; Manfreda, S.; Lin, H.; Smithwick, E.A. Estimating root zone soil moisture across the Eastern United States with passive microwave satellite data and a simple hydrologic model. *Remote Sens.* **2019**, *11*, 2013. [CrossRef]
12. Ahlmer, A.-K.; Cavalli, M.; Hansson, K.; Koutsouris, A.J.; Crema, S.; Kalantari, Z. Soil moisture remote-sensing applications for identification of flood-prone areas along transport infrastructure. *Environ. Earth Sci.* **2018**, *77*, 533. [CrossRef]
13. Li, Y.; Yan, S.; Chen, N.; Gong, J. Performance evaluation of a neural network model and two empirical models for estimating soil moisture based on sentinel-1 sar data. *Prog. Electromagn. Res. C* **2020**, *105*, 85–99. [CrossRef]
14. Altese, E.; Bolognani, O.; Mancini, M.; Troch, P.A. Retrieving soil moisture over bare soil from ERS 1 synthetic aperture radar data: Sensitivity analysis based on a theoretical surface scattering model and field data. *Water Resour. Res.* **1996**, *32*, 653–661. [CrossRef]
15. Barrett, B.W.; Dwyer, E.; Whelan, P. Soil moisture retrieval from active spaceborne microwave observations: An evaluation of current techniques. *Remote Sens.* **2009**, *1*, 210–242. [CrossRef]
16. Oh, Y.; Sarabandi, K.; Ulaby, F.T. An Empirical Model and an Inversion Technique for Radar Scattering from Bare Soil Surfaces. *IEEE Trans. Geosci. Remote Sens.* **1992**, *30*, 370–381. [CrossRef]
17. Oh, Y.; Sarabandi, K.; Ulaby, F.T. Semi-empirical model of the ensemble-averaged differential Mueller matrix for microwave backscattering from bare soil surfaces. *IEEE Trans. Geosci. Remote Sens.* **2002**, *40*, 1348–1355. [CrossRef]
18. Oh, Y. Quantitative retrieval of soil moisture content and surface roughness from multipolarized radar observations of bare soil surfaces. *IEEE Trans. Geosci. Remote Sens.* **2004**, *42*, 596–601. [CrossRef]
19. Dubois, P.C.; Engman, T. Measuring Soil Moisture with Imaging Radars. *IEEE Trans. Geosci. Remote Sens.* **1995**, *33*, 915–926. [CrossRef]
20. Fung, A.K.; Li, Z.; Chen, K.S. Backscattering from a Randomly Rough Dielectric Surface. *IEEE Trans. Geosci. Remote Sens.* **1992**, *30*, 356–369. [CrossRef]
21. Sahebi, M.R.; Angles, J. An inversion method based on multi-angular approaches for estimating bare soil surface parameters from RADARSAT-1. *Hydrol. Earth Syst. Sci.* **2010**, *14*, 2355–2366. [CrossRef]
22. Kweon, S.K.; Oh, Y. A modified water-cloud model with leaf angle parameters for microwave backscattering from agricultural fields. *IEEE Trans. Geosci. Remote Sens.* **2015**, *53*, 2802–2809. [CrossRef]
23. Svoray, T.; Shoshany, M. SAR-based estimation of areal aboveground biomass (AAB) of herbaceous vegetation in the semi-arid zone: A modification of the water-cloud model. *Int. J. Remote Sens.* **2002**, *23*, 4089–4100. [CrossRef]
24. Yadav, V.P.; Prasad, R.; Bala, R.; Vishwakarma, A.K. An improved inversion algorithm for spatio-temporal retrieval of soil moisture through modified water cloud model using C- band Sentinel-1A SAR data. *Comput. Electron. Agric.* **2020**, *173*, 105447. [CrossRef]
25. Lazzari, M.; Piccarreta, M.; Ray, R.L.; Manfreda, S. Modeling Antecedent Soil Moisture to Constrain Rainfall Thresholds for Shallow Landslides Occurrence. In *Landslides—Investigation and Monitoring [Internet]*; 2020; Available online: https://www.intechopen.com/chapters/72592 (accessed on 29 July 2025).
26. Han, Q.; Zeng, Y.; Zhang, L.; Wang, C.; Prikaziuk, E.; Niu, Z.; Su, B. Global long term daily 1 km surface soil moisture dataset with physics informed machine learning. *Sci. Data* **2023**, *10*, 101. [CrossRef]

27. Sungmin, O.; Orth, R. Global soil moisture data derived through machine learning trained with in-situ measurements. *Sci. Data* **2021**, *8*, 170. [CrossRef] [PubMed]
28. Dobriyal, P.; Qureshi, A.; Badola, R.; Hussain, S.A. A review of the methods available for estimating soil moisture and its implications for water resource management. *J. Hydrol.* **2012**, *458–459*, 110–117. [CrossRef]
29. Yuan, H.; Liang, S.; Gao, Y.; Gao, Y.; Lian, X. Experimental study on estimating bare soil moisture content based on UAV multi-source remote sensing. *Geocarto Int.* **2025**, *40*, 2448985. [CrossRef]
30. Kodaira, M.; Shibusawa, S. Using a mobile real-time soil visible-near infrared sensor for high resolution soil property mapping. *Geoderma* **2013**, *199*, 64–79. [CrossRef]
31. Landrum, C.; Castrignanò, A.; Mueller, T.; Zourarakis, D.; Zhu, J.; De Benedetto, D. An approach for delineating homogeneous within-field zones using proximal sensing and multivariate geostatistics. *Agric. Water Manag.* **2015**, *147*, 144–153. Available online: https://www.sciencedirect.com/science/article/pii/S0378377414002121 (accessed on 9 May 2025). [CrossRef]
32. Balla, I.; Milics, G.; Deákvári, J.; Fenyvesi, L.; Smuk, N. Connection Between Soil Moisture Content and Electrical Conductivity in a Precision Farming Field. 2013. Available online: http://www.epa.hu/03100/03114/00015/pdf/EPA03114_acta_agronomica_ovariensis_2013_2_021-032.pdf (accessed on 9 May 2025).
33. Lim, H.H.; Lee, S.R.; Cheon, E.; Nam, Y. Soil Water Content Regression Analysis of Measurement Data from Hyperspectral Camera in Weathered Granite Soils. In *E3S Web of Conferences*; EDP Science: Les Ulis, France, 2023.
34. Bablet, A.; Viallefont-Robinet, F.; Jacquemoud, S.; Fabre, S.; Briottet, X. High-resolution mapping of in-depth soil moisture content through a laboratory experiment coupling a spectroradiometer and two hyperspectral cameras. *Remote Sens. Environ.* **2020**, *236*, 111533. [CrossRef]
35. Liu, J.; Zhang, D.; Yang, L.; Ma, Y.; Cui, T.; He, X.; Du, Z. Developing a generalized vis-NIR prediction model of soil moisture content using external parameter orthogonalization to reduce the effect of soil type. *Geoderma* **2022**, *419*, 115877. [CrossRef]
36. Leone, M.; Consales, M.; Passeggio, G.; Buontempo, S.; Zaraket, H.; Youssef, A.; Persiano, G.; Cutolo, A.; Cusano, A. Fiber optic soil water content sensor for precision farming. *Opt. Laser Technol.* **2022**, *149*, 107816. [CrossRef]
37. Keller, S.; Riese, F.M.; Stötzer, J.; Maier, P.M.; Hinz, S. Developing a Machine Learning Framework for Estimating Soil Moisture with Vnir Hyperspectral Data. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* **2018**, *IV-1*, 101–108. [CrossRef]
38. Xu, C.; Zeng, W.; Huang, J.; Wu, J.; Van Leeuwen, W.J.D. Prediction of soil moisture content and soil salt concentration from hyperspectral laboratory and field data. *Remote Sens.* **2016**, *8*, 42. [CrossRef]
39. Wu, T.; Yu, J.; Lu, J.; Zou, X.; Zhang, W. Research on inversion model of cultivated soil moisture content based on hyperspectral imaging analysis. *Agriculture* **2020**, *10*, 292. [CrossRef]
40. Tang, B.; Xie, W.; Meng, Q.; Moorhead, R.J.; Feng, G. Soil Moisture Estimation Using Hyperspectral Imagery Based on Metric Learning. In Proceedings of the 21st IEEE International Conference on Machine Learning and Applications, ICMLA 2022, The Bahamas, Caribbean, 12–14 December 2022; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2022; pp. 1392–1396.
41. Linets, G.; Bazhenov, A.; Malygin, S.; Grivennaya, N.; Chernysheva, T.; Melnikov, S. Algorithm for the Joint Flight of Two Uncrewed Aerial Vehicles Constituting a Bistatic Radar System for the Soil Remote Sensing. *Pertanika J. Sci. Technol.* **2023**, *31*, 2031–2045. [CrossRef]
42. Hassan-Esfahani, L.; Torres-Rua, A.; Ticlavilca, A.M.; Jensen, A.; McKee, M. Topsoil moisture estimation for precision agriculture using unmmaned aerial vehicle multispectral imagery. In Proceedings of the IEEE Geoscience and Remote Sensing Symposium (IGARSS), Quebec, QC, Canada, 13–18 July 2014; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2014; pp. 3263–3266.
43. Ge, X.; Ding, J.; Jin, X.; Wang, J.; Chen, X.; Li, X.; Liu, J.; Xie, B. Estimating agricultural soil moisture content through UAV-based hyperspectral images in the Arid region. *Remote Sens.* **2021**, *13*, 1562. [CrossRef]
44. Lu, F.; Sun, Y.; Hou, F. Using UAV visible images to estimate the soil moisture of steppe. *Water* **2020**, *12*, 2334. [CrossRef]
45. Aboutalebi, M.; Allen, N.; Torres-Rua, A.F.; McKee, M.; Coopmans, C. Estimation of soil moisture at different soil levels using machine learning techniques and unmanned aerial vehicle (UAV) multispectral imagery. In *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping IV, Proceeding of the SPIE Defense + Commercial Sensing, Baltimore, MD, USA, 2019*; SPIE-International Society for Optical Engineering: Bellingham, WA, USA, 2019; p. 26.
46. Ge, X.; Wang, J.; Ding, J.; Cao, X.; Zhang, Z.; Liu, J.; Li, X. Combining UAV-based hyperspectral imagery and machine learning algorithms for soil moisture content monitoring. *PeerJ* **2019**, *7*, e6926. [CrossRef]
47. Zhang, J.; Liu, T.; Wang, J.; Li, H.; Wang, Z.; Zhang, F.; Yuan, H. A simple but effective evaluation criterion for parameters optimization of EPO and its application to moisture insensitive prediction of soil organic matter. *Chemom. Intell. Lab. Syst.* **2023**, *236*, 104794. [CrossRef]
48. Cheng, M.; Jiao, X.; Liu, Y.; Shao, M.; Yu, X.; Bai, Y.; Wang, Z.; Wang, S.; Tuohuti, N.; Liu, S.; et al. Estimation of soil moisture content under high maize canopy coverage from UAV multimodal data and machine learning. *Agric. Water Manag.* **2022**, *264*, 107530. [CrossRef]

49. Li, W.; Liu, C.; Yang, Y.; Awais, M.; Ying, P.; Ru, W.; Cheema, M.J.M. A UAV-aided prediction system of soil moisture content relying on thermal infrared remote sensing. *Int. J. Environ. Sci. Technol.* **2022**, *19*, 9587–9600. [CrossRef]
50. Guo, J.; Bai, Q.; Guo, W.; Bu, Z.; Zhang, W. Soil moisture content estimation in winter wheat planting area for multi-source sensing data using CNNR. *Comput. Electron. Agric.* **2022**, *193*, 106670. [CrossRef]
51. Döpper, V.; Rocha, A.D.; Berger, K.; Gränzig, T.; Verrelst, J.; Kleinschmit, B.; Förster, M. Estimating soil moisture content under grassland with hyperspectral data using radiative transfer modelling and machine learning. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *110*, 102817. [CrossRef]
52. Quebrajo, L.; Perez-Ruiz, M.; Pérez-Urrestarazu, L.; Martínez, G.; Egea, G. Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet. *Biosyst. Eng.* **2018**, *165*, 77–87. [CrossRef]
53. Luo, W.; Xu, X.; Liu, W.; Liu, M.; Li, Z.; Peng, T.; Xu, C.; Zhang, Y.; Zhang, R. UAV based soil moisture remote sensing in a karst mountainous catchment. *CATENA* **2019**, *174*, 478–489. [CrossRef]
54. Bono Rossello, N.; Fabrizio Carpio, R.; Gasparri, A.; Garone, E. A novel Observer-based Architecture for Water Management in Large-Scale (Hazelnut) Orchards. In Proceedings of the IFAC-PapersOnLine, Sydney, Australia, 4–6 December 2019; Elsevier B.V.: Amsterdam, The Netherlands, 2019; pp. 62–69.
55. Abebrese, D.K.; Biney, J.K.M.; Kara, R.S.; Báťková, K.; Houška, J.; Matula, S.; Badreldin, N.; Truneh, L.A.; Shawula, T.A. Estimating the spatial distribution of soil volumetric water content in an agricultural field employing remote sensing and other auxiliary data under different tillage management practices. *Soil Use Manag.* **2024**, *40*, e12981. [CrossRef]
56. Imantho, H.; Seminar, K.B.; Hermawan, W.; Saptomo, S.K. A Spatial Distribution Empirical Model of Surface Soil Water Content and Soil Workability on an Unplanted Sugarcane Farm Area Using Sentinel-1A Data towards Precision Agriculture Applications. *Information* **2022**, *13*, 493. [CrossRef]
57. Sun, H.; Cui, Y. Evaluating downscaling factors of microwave satellite soil moisture based on machine learning method. *Remote Sens.* **2021**, *13*, 133. [CrossRef]
58. Filintas, A. Soil Moisture Depletion Modelling Using a TDR Multi-Sensor System, GIS, Soil Analyzes, Precision Agriculture and Remote Sensing on Maize for Improved Irrigation-Fertilization Decisions. *Eng. Proc.* **2021**, *9*, 36.
59. Ma, C.; Johansen, K.; McCabe, M.F. Combining Sentinel-2 data with an optical-trapezoid approach to infer within-field soil moisture variability and monitor agricultural production stages. *Agric. Water Manag.* **2022**, *274*, 107942. [CrossRef]
60. Fontanet, M.; Scudiero, E.; Skaggs, T.H.; Fernàndez-Garcia, D.; Ferrer, F.; Rodrigo, G.; Bellvert, J. Dynamic Management Zones for Irrigation Scheduling. *Agric. Water Manag.* **2020**, *238*, 106207. [CrossRef]
61. Placidi, P.; Vergini, C.V.D.; Papini, N.; Cecconi, M.; Mezzanotte, P.; Scorzoni, A. Low-Cost and Low-Frequency Impedance Meter for Soil Water Content Measurement in the Precision Agriculture Scenario. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 1–13. [CrossRef]
62. Chinh Pham, X.; Thao Nguyen, T.P.; Le, M.T. Pathloss Modelling and Evaluation for A Wireless Underground Soil Moisture Sensor Network. In *Lecture Notes in Networks and Systems*; Springer Science and Business Media Deutschland GmbH: Berlin/Heidelberg, Germany, 2023; pp. 335–345.
63. Syrový, T.; Vik, R.; Pretl, S.; Syrová, L.; Čengery, J.; Hamáček, A.; Kubáč, L.; Menšík, L. Fully printed disposable IoT soil moisture sensors for precision agriculture. *Chemosensors* **2020**, *8*, 125. [CrossRef]
64. Yang, J.; Sharma, A.; Kumar, R. IoT-based framework for smart agriculture. *Int. J. Agric. Environ. Inf. Syst.* **2021**, *12*, 1–14. [CrossRef]
65. El-Magrous, A.A.; Sternhagen, J.D.; Hatfield, G.; Qiao, Q. Internet of things based weather-soil sensor station for precision agriculture. In Proceedings of the IEEE International Conference on Electro Information Technology, Brookings, SD, USA, 20–22 May 2019; IEEE Computer Society: Los Alamitos, CA, USA, 2019; pp. 092–097.
66. Coelho, A.D.; Dias, B.G.; De Oliveira Assis, W.; De Almeida Martins, F.; Pires, R.C. Monitoring of soil moisture and atmospheric sensors with internet of things (IoT) applied in precision agriculture. In Proceedings of the 2020 14th Technologies Applied to Electronics Teaching Conference, TAEE 2020, Porto, Portugal, 8–10 July 2020; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2020.
67. Thirisha, R.; Sugumar, D.; Sugitha, K.; Asha Sherin, J.; Dharshini, V.; Jose, A.V.; Tryphena, T.P. Precision Agriculture: IoT Based System for Real-Time Monitoring of Paddy Growth. In Proceedings of the 2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology, ICSEIET 2023, Ghaziabad, India, 14–15 September 2023; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2023; pp. 247–251.
68. Singh, D.N.; Kuriyan, S.J. Estimation of unsaturated hydraulic conductivity using soil suction measurements obtained by an insertion tensiometer. *Can. Geotech. J.* **2003**, *40*, 476–483. [CrossRef]
69. Qi, H.J.; Jin, X.; Zhao, L.; Dedo, I.M.; Li, S.W. Predicting sandy soil moisture content with hyperspectral imaging. *Int. J. Agric. Biol. Eng.* **2017**, *10*, 175–183. [CrossRef]
70. Chen, Y.; Li, M.; Si, B.; Hu, Y. Measuring Soil Water Content Using the Cosmic-ray Neutron Probe: A Review. *J. Irrig. Drain.* **2021**, *40*, 26–36.

71. Ren, D.; Chen, F.; Pu, H.Y.; Zhang, Y.; Li, Y.P. Advances in Soil Moisture Monitoring Using Cosmic Ray Neutron Probe Method. *J. Ecol. Rural. Environ.* **2019**, *35*, 545–553.
72. Reynolds, S.G. The gravimetric method of soil moisture determination Part I A study of equipment, and methodological problems. *J. Hydrol.* **1970**, *11*, 258–273. [CrossRef]
73. Francesca, V.; Osvaldo, F.; Stefano, P.; Paola, R.P. Soil Moisture Measurements: Comparison of Instrumentation Performances. *J. Irrig. Drain. Eng.* **2010**, *136*, 81–89. [CrossRef]
74. Ojo, E.R.; Bullock, P.R.; L'Heureux, J.; Powers, J.; McNairn, H.; Pacheco, A. Calibration and Evaluation of a Frequency Domain Reflectometry Sensor for Real-Time Soil Moisture Monitoring. *Vadose Zone J.* **2015**, *14*, 1–12. [CrossRef]
75. Veldkamp, E.; O'Brien, J.J. Calibration of a Frequency Domain Reflectometry Sensor for Humid Tropical Soils of Volcanic Origin. *Soil Sci. Soc. Am. J.* **2000**, *64*, 1549–1553. [CrossRef]
76. Petropoulos, G.P.; Griffiths, H.M.; Dorigo, W.; Xaver, A.; Gruber, A. Surface Soil Moisture Estimation: Significance, Controls, and Conventional Measurement Techniques. In *Remote Sensing of Energy Fluxes and Soil Moisture Content*; CRC Press: Boca Raton, FL, USA, 2013; pp. 29–48.
77. Tarantino, A.; Ridley, A.M.; Toll, D.G. Field measurement of suction, water content, and water permeability. *Geotech. Geol. Eng.* **2008**, *26*, 751–782. [CrossRef]
78. Jones, S.B.; Wraith, J.M.; Or, D. Time domain reflectometry measurement principles and applications. *Hydrol. Process* **2002**, *16*, 141–153. [CrossRef]
79. Verstraeten, W.W.; Veroustraete, F.; Feyen, J. Assessment of evapotranspiration and soil moisture content across different scales of observation. *Sensors* **2008**, *8*, 70–117. [CrossRef] [PubMed]
80. Hu, S.; Wu, H.; Liang, X.; Xiao, C.; Zhao, Q.; Cao, Y.; Han, X. A preliminary study on the eco-environmental geological issue of in-situ oil shale mining by a physical model. *Chemosphere* **2022**, *287*, 131987. [CrossRef]
81. Minet, J.; Lambot, S.; Delaide, G.; Huisman, J.A.; Vereecken, H.; Vanclooster, M. A Generalized Frequency Domain Reflectometry Modeling Technique for Soil Electrical Properties Determination. *Vadose Zone J.* **2010**, *9*, 1063–1072. [CrossRef]
82. Pandey, J.; Chamoli, V.; Prakash, R. A review: Soil moisture estimation using different techniques. In *Advances in Intelligent Systems and Computing*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 105–111.
83. Wagner, W.; Blöschl, G.; Pampaloni, P.; Calvet, J.-C.; Bizzarri, B.; Wigneron, J.-P.; Kerr, Y. Operational readiness of microwave remote sensing of soil moisture for hydrologic applications. *Hydrol. Res.* **2007**, *38*, 1–20. [CrossRef]
84. Dutta, R. Remote Sensing of Energy Fluxes and Soil Moisture Content. *J. Spat. Sci.* **2015**, *60*, 196–197. [CrossRef]
85. Anne, N.J.P.; Abd-Elrahman, A.H.; Lewis, D.B.; Hewitt, N.A. Modeling soil parameters using hyperspectral image reflectance insubtropical coastal wetlands. *Int. J. Appl. Earth Obs. Geoinf.* **2014**, *33*, 47–56.
86. Wang, L.; Qu, J.J.; Hao, X.; Zhu, Q. Sensitivity studies of the moisture effects on MODIS SWIR reflectance and vegetation water indices. *Int. J. Remote Sens.* **2008**, *29*, 7065–7075. [CrossRef]
87. Casamitjana, M.; Torres-Madroñero, M.C.; Bernal-Riobo, J.; Varga, D. Soil moisture analysis by means of multispectral images according to land use and spatial resolution on andosols in the colombian andes. *Appl. Sci.* **2020**, *10*, 5540. [CrossRef]
88. Demattê, J.A.M.; Sousa, A.A.; Alves, M.C.; Nanni, M.R.; Fiorio, P.R.; Campos, R.C. Determining soil water status and other soil characteristics by spectral proximal sensing. *Geoderma* **2006**, *135*, 179–195. [CrossRef]
89. Lesaignoux, A.; Fabre, S.; Briottet, X. Influence of soil moisture content on spectral reflectance of bare soils in the 0.4–14 μm domain. *Int. J. Remote Sens.* **2013**, *34*, 2268–2285. [CrossRef]
90. Sadeghi, M.; Jones, S.B.; Philpot, W.D. A linear physically-based model for remote sensing of soil moisture using short wave infrared bands. *Remote Sens. Environ.* **2015**, *164*, 66–76. [CrossRef]
91. Ångström, A. The Albedo of Various Surfaces of Ground. *Geogr. Ann.* **1925**, *7*, 323–342.
92. Fabre, S.; Briottet, X.; Lesaignoux, A. Estimation of soil moisture content from the spectral reflectance of bare soils in the 0.4–2.5 μm domain. *Sensors* **2015**, *15*, 3262–3281. [CrossRef]
93. Manfreda, S.; Mita, L.; Dal Sasso, S.F.; Samela, C.; Mancusi, L. Exploiting the use of physical information for the calibration of a lumped hydrological model. *Hydrol. Process* **2018**, *32*, 1420–1433. [CrossRef]
94. Zhang, D.; Zhou, G. Estimation of soil moisture from optical and thermal remote sensing: A review. *Sensors* **2016**, *16*, 1308. [CrossRef]
95. Bowers, S.A.; Smith, S.J. Spectrophotometric Determination of Soil Water Content. *Soil Sci. Soc. Am. J.* **1972**, *36*, 978–980. [CrossRef]
96. Lei, S.G.; Bian, Z.F.; Daniels, J.L.; Liu, D.L. Improved spatial resolution in soil moisture retrieval at arid mining area using apparent thermal inertia. *Trans. Nonferrous Met. Soc. China* **2014**, *24*, 1866–1873. [CrossRef]
97. Kong, X.; Dorling, S.R. Near-surface soil moisture retrieval from ASAR Wide Swath imagery using a Principal Component Analysis. *Int. J. Remote Sens.* **2008**, *29*, 2925–2942. [CrossRef]
98. Vereecken, H.; Huisman, J.A.; Pachepsky, Y.; Montzka, C.; Van Der Kruk, J.; Bogena, H.; Weihermuller, L.; Herbst, M.; Martinez, G.; VanderBorght, J.; et al. On the spatio-temporal dynamics of soil moisture at the field scale. *J. Hydrol.* **2014**, *516*, 76–96. [CrossRef]

99. Holzman, M.E.; Rivas, R.; Piccolo, M.C. Estimating soil moisture and the relationship with crop yield using surface temperature and vegetation index. *Int. J. Appl. Earth Obs. Geoinf.* **2014**, *28*, 181–192. [CrossRef]
100. Liu, Y.Y.; Dorigo, W.A.; Parinussa, R.M.; de Jeu, R.A.M.; Wagner, W.; McCabe, M.F.; Evans, J.P.; van Dijk, A.I.J.M. Trend-preserving blending of passive and active microwave soil moisture retrievals. *Remote Sens. Environ.* **2012**, *123*, 280–297. [CrossRef]
101. Holzman, M.; Srivastava, A.; Rivas, R.; Huete, A. Evaluating the Relationship Between Vegetation Status and Soil Moisture in Semi-Arid Woodlands, Central Australia, Using Daily Thermal, Vegetation Index, and Reflectance Data. *Remote Sens.* **2025**, *17*, 635. [CrossRef]
102. Zhuang, X.; Shi, R.; Liu, C. Data fusion of satellite remotely sensed images and its application in agriculture. In *PIAGENG 2010: Photonics and Imaging for Agricultural Engineering*; SPIE: Bellingham, WA, USA, 2011; p. 77520T.
103. Watts, A.C.; Ambrosia, V.G.; Hinkley, E.A. Unmanned aircraft systems in remote sensing and scientific research: Classification and considerations of use. *Remote Sens.* **2012**, *4*, 1671–1692. [CrossRef]
104. Mulla, D.J. Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosyst. Eng.* **2013**, *114*, 358–371. [CrossRef]
105. Khose, S.B.; Mailapalli, D.R.; Biswal, S.; Chatterjee, C. UAV-based multispectral image analytics for generating crop coefficient maps for rice. *Arab. J. Geosci.* **2022**, *15*, 1681. [CrossRef]
106. Wang, S.; Ibrom, A.; Bauer-Gottwein, P.; Garcia, M. Incorporating diffuse radiation into a light use efficiency and evapotranspiration model: An 11-year study in a high latitude deciduous forest. *Agric. For. Meteorol.* **2018**, *248*, 479–493. [CrossRef]
107. Yu, N.; Li, L.; Schmitz, N.; Tian, L.F.; Greenberg, J.A.; Diers, B.W. Development of methods to improve soybean yield estimation and predict plant maturity with an unmanned aerial vehicle based platform. *Remote Sens. Environ.* **2016**, *187*, 91–101. [CrossRef]
108. Li, W.; Li, M.; Awais, M.; Ji, L.; Li, H.; Song, R.; Cheema, M.J.M.; Agarwal, R. Research on Assimilation of Unmanned Aerial Vehicle Remote Sensing Data and AquaCrop Model. *Sensors* **2024**, *24*, 3255. [CrossRef]
109. Yu, F.; Zhang, Q.; Xiao, J.; Ma, Y.; Wang, M.; Luan, R.; Liu, X.; Ping, Y.; Nie, Y.; Tao, Z.; et al. Progress in the Application of CNN-Based Image Classification and Recognition in Whole Crop Growth Cycles. *Remote. Sens.* **2023**, *15*, 2988. [CrossRef]
110. Wigmore, O.; Molotch, N.P. Weekly high-resolution multi-spectral and thermal uncrewed-aerial-system mapping of an alpine catchment during summer snowmelt, Niwot Ridge, Colorado. *Earth Syst. Sci. Data* **2023**, *15*, 1733–1747. [CrossRef]
111. Paridad, P.; Sasso, S.D.; Pizarro, A.; Mita, L.; Fiorentino, M.; Margiotta, M.; Faridani, F.; Farid, A.; Manfreda, S. Estimation of soil moisture from UAS platforms using RGB and thermal imaging sensors in arid and semi-arid regions. *Acta Horticulturae. Int. Soc. Hortic. Sci.* **2022**, 339–348. [CrossRef]
112. Hsu, W.L.; Chang, K.T. Cross-estimation of soil moisture using thermal infrared images with different resolutions. *Sensors Mater.* **2019**, *31*, 387–398. [CrossRef]
113. Bellvert, J.; Zarco-Tejada, P.J.; Marsal, J.; Girona, J.; González-Dugo, V.; Fereres, E. Vineyard irrigation scheduling based on airborne thermal imagery and water potential thresholds. *Aust. J. Grape Wine Res.* **2016**, *22*, 307–315. [CrossRef]
114. Acharya, B.S.; Bhandari, M.; Bandini, F.; Pizarro, A.; Perks, M.; Joshi, D.R.; Wang, S.; Dogwiler, T.; Ray, R.L.; Kharel, G.; et al. Unmanned Aerial Vehicles in Hydrology and Water Management: Applications, Challenges, and Perspectives. *Water Resour. Res.* **2021**, *57*, e2021WR029925. [CrossRef]
115. Beyer, M.; Iraheta, A.; Gerchow, M.; Kuehnhammer, K.; Callau-Beyer, A.C.; Koeniger, P.; Dubbert, D.; Dubbert, M.; Sánchez-Murillo, R.; Birkel, C. UAV-Based Land Surface Temperatures and Vegetation Indices Explain and Predict Spatial Patterns of Soil Water Isotopes in a Tropical Dry Forest. *Water Resour. Res.* **2025**, *61*, e2024WR037294. [CrossRef]
116. Ma, L.; Liu, Y.; Yu, X.; Zhan, C.; Zhang, B.; Lu, L.; Liu, Z.; Li, B.; Sun, G.; Wang, Q. The Utility of Gordon's Standard NIR Empirical Atmospheric Correction Algorithm for Unmanned Aerial Vehicle Imagery. *J. Indian Soc. Remote Sens.* **2021**, *49*, 2891–2901. Available online: https://link.springer.com/article/10.1007/s12524-021-01434-2 (accessed on 29 July 2025). [CrossRef]
117. Gerchow, M.; Kühnhammer, K.; Iraheta, A.; Marshall, J.D.; Beyer, M. Enhanced flight planning and calibration for UAV based thermal imaging: Implications for canopy temperature and transpiration analysis. *For. Glob. Change* **2025**, *8*, 1457762. Available online: https://www.frontiersin.org/journals/forests-and-global-change/articles/10.3389/ffgc.2025.1457762/full (accessed on 29 July 2025). [CrossRef]
118. Dreissig, M.; Scheuble, D.; Piewak, F.; Boedecker, J. Survey on LiDAR Perception in Adverse Weather Conditions. In Proceedings of the IEEE Intelligent Vehicles Symposium, Anchorage, AK, USA, 4–7 June 2023.
119. Sun, J.; Yuan, G.; Song, L.; Zhang, H. Unmanned Aerial Vehicles (UAVs) in Landslide Investigation and Monitoring: A Review. *Drones* **2024**, *8*, 30. [CrossRef]
120. Zhang, F.; Wu, S.; Liu, J.; Wang, C.; Guo, Z.; Xu, A.; Pan, K.; Pan, X. Predicting soil moisture content over partially vegetation covered surfaces from hyperspectral data with deep learning. *Soil Sci. Soc. Am. J.* **2021**, *85*, 989–1001. [CrossRef]
121. Yang MDer Hsu, Y.C.; Tseng, W.C.; Tseng, H.H.; Lai, M.H. Precision assessment of rice grain moisture content using UAV multispectral imagery and machine learning. *Comput. Electron. Agric.* **2025**, *230*, 109813. [CrossRef]

122. Singh, A.; Gaurav, K.; Sonkar, G.K.; Lee, C.C. Strategies to Measure Soil Moisture Using Traditional Methods, Automated Sensors, Remote Sensing, and Machine Learning Techniques: Review, Bibliometric Analysis, Applications, Research Findings, and Future Directions. *IEEE Access* **2023**, *11*, 13605–13635. [CrossRef]
123. Chaudhary, S.K.; Srivastava, P.K.; Gupta, D.K.; Kumar, P.; Prasad, R.; Pandey, D.K.; Das, A.K.; Gupta, M. Machine learning algorithms for soil moisture estimation using Sentinel-1: Model development and implementation. *Adv. Space Res.* **2022**, *69*, 1799–1812. [CrossRef]
124. Ayehu, G.; Tadesse, T.; Gessesse, B.; Yigrem, Y.; Mmelesse, A. Combined use of sentinel-1 sar and landsat sensors products for residual soil moisture retrieval over agricultural fields in the upper blue nile basin, ethiopia. *Sensors* **2020**, *20*, 3282. [CrossRef]
125. Adab, H.; Morbidelli, R.; Saltalippi, C.; Moradian, M.; Ghalhari, G.A.F. Machine learning to estimate surface soil moisture from remote sensing data. *Water* **2020**, *12*, 1–28. [CrossRef]
126. Araya, S.N.; Fryjoff-Hung, A.; Anderson, A.; Viers, J.H.; Ghezzehei, T.A. Advances in soil moisture retrieval from multispectral remote sensing using unoccupied aircraft systems and machine learning techniques. *Hydrol. Earth Syst. Sci.* **2021**, *25*, 2739–2758. [CrossRef]
127. Hajdu, I.; Yule, I.; Dehghan-Shoar, M.H. Modelling of near-surface soil moisture using machine learning and multi-temporal sentinel 1 images in New Zealand. In Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS), Valencia, Spain, 22–27 July 2018; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2018; pp. 1422–1425.
128. Afanaseva, O.V.; Tulyakov, T.F. Comparative Analysis of Image Segmentation Methods in Power Line Monitoring Systems. *Int. J. Eng. Trans. A Basics* **2026**, *39*, 1–11.
129. Sarwar, A.; Peters, R.T.; Mohamed, A.Z. Linear mixed modeling and artificial neural network techniques for predicting wind drift and evaporation losses under moving sprinkler irrigation systems. *Irrig. Sci.* **2020**, *38*, 177–188. [CrossRef]
130. Ahmad, S.; Kalra, A.; Stephen, H. Estimating soil moisture using remote sensing data: A machine learning approach. *Adv. Water Resour.* **2010**, *33*, 69–80. [CrossRef]
131. Rasheed, M.W.; Tang, J.; Sarwar, A.; Shah, S.; Saddique, N.; Khan, M.U.; Khan, M.I.; Nawaz, S.; Shamshiri, R.R.; Aziz, M.; et al. Soil Moisture Measuring Techniques and Factors Affecting the Moisture Dynamics: A Comprehensive Review. *Sustainability* **2022**, *14*, 11538. [CrossRef]
132. Yuan, S.; Quiring, S.M. Comparison of three methods of interpolating soil moisture in Oklahoma. *Int. J. Clim.* **2017**, *37*, 987–997. [CrossRef]
133. Vergopolan, N.; Chaney, N.W.; Pan, M.; Sheffield, J.; Beck, H.E.; Ferguson, C.R.; Torres-Rojas, L.; Sadri, S.; Wood, E.F. SMAP-HydroBlocks, a 30-m satellite-based soil moisture dataset for the conterminous US. *Sci. Data* **2021**, *8*, 264. [CrossRef]
134. Rani, A.; Kumar, N.; Kumar, J.; Sinha, N.K. Machine learning for soil moisture assessment. In *Deep Learning for Sustainable Agriculture*; Elsevier: Amsterdam, The Netherlands, 2022; pp. 143–168.
135. Duarte, E.; Hernandez, A. A Review on Soil Moisture Dynamics Monitoring in Semi-Arid Ecosystems: Methods, Techniques, and Tools Applied at Different Scales. *Appl. Sci.* **2024**, *14*, 7677. [CrossRef]
136. Arnold, J.G.; Srinivasan, R.; Muttiah, R.S.; Williams, J.R. Large area hydrologic modeling and assessment part I: Model development. *J. Am. Water Resour. Assoc.* **1998**, *34*, 73–89. [CrossRef]
137. Lawrence, D.M.; Fisher, R.A.; Koven, C.D.; Oleson, K.W.; Swenson, S.C.; Bonan, G.; Collier, N.; Ghimire, B.; van Kampenhout, L.; Kennedy, D.; et al. The Community Land Model Version 5: Description of New Features, Benchmarking, and Impact of Forcing Uncertainty. *J. Adv. Model. Earth Syst.* **2019**, *11*, 4245–4287. [CrossRef]
138. Hamman, J.J.; Nijssen, B.; Bohn, T.J.; Gergel, D.R.; Mao, Y. The Variable Infiltration Capacity model version 5 (VIC-5): Infrastructure improvements for new applications and reproducibility. *Geosci. Model Dev.* **2018**, *11*, 3481–3496. [CrossRef]
139. Šimůnek, J.; Brunetti, G.; Jacques, D.; van Genuchten, M.T.; Šejna, M. Developments and applications of the HYDRUS computer software packages since 2016. *Vadose Zone J.* **2024**, *23*, e20310. [CrossRef]
140. Adamala, S.; Velmurugan, A.; Swarnam, T.P.; Palakuru, M.; Subramani, T.; Jaisankar, I.; Nanda, B.K.; Kumari, N.; Srivastava, A. Soil moisture mapping in Indian tropical islands with C-band SAR and artificial neural network models. *Environ. Monit. Assess.* **2025**, *197*, 758. [CrossRef]
141. Rejeb, A.; Abdollahi, A.; Rejeb, K.; Treiblmaier, H. Drones in agriculture: A review and bibliometric analysis. In *Computers and Electronics in Agriculture*; Elsevier B.V.: Amsterdam, The Netherlands, 2022; Volume 198.
142. Singh, A.; Gaurav, K. PIML-SM: Physics-Informed Machine Learning to Estimate Surface Soil Moisture From Multisensor Satellite Images by Leveraging Swarm Intelligence. *IEEE Trans. Geosci. Remote Sens.* **2024**, *62*, 1–13. [CrossRef]
143. Huang, Y. Improved SVM-Based Soil-Moisture-Content Prediction Model for Tea Plantation. *Plants* **2023**, *12*, 2309. [CrossRef] [PubMed]