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Review

Soil Moisture Measuring Techniques and Factors Affecting the Moisture Dynamics: A Comprehensive Review

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Abstract: The amount of surface soil moisture (SSM) is a crucial ecohydrological natural resource that regulates important land surface processes. It affects critical land–atmospheric phenomena, including the division of energy and water (infiltration, runoff, and evaporation), that impacts the effectiveness of agricultural output (sensible and latent heat fluxes and surface air temperature). Despite its significance, there are several difficulties in making precise measurements, monitoring, and interpreting SSM at high spatial and temporal resolutions. The current study critically reviews the methods and procedures for calculating SSM and the variables influencing measurement accuracy and applicability under different fields, climates, and operational conditions. For laboratory and field measurements, this study divides SSM estimate strategies into (i) direct and (ii) indirect procedures. The accuracy and applicability of a technique depends on the environment and the resources at hand. Comparative research is geographically restricted, although precise and economical—direct measuring techniques like the gravimetric method are time-consuming and destructive. In contrast, indirect methods are more expensive and do not produce measurements at the spatial scale but produce precise data on a temporal scale. While measuring SSM across more significant regions, ground-penetrating radar and remote sensing methods are susceptible to errors caused by overlapping data and atmospheric factors. On the other hand, soft computing techniques like machine/deep learning are quite handy for estimating SSM without any technical or laborious procedures. We determine that factors, e.g., topography, soil type, vegetation, climate change, groundwater level, depth of soil, etc., primarily influence the SSM measurements. Different techniques have been put into practice for various practical situations, although comparisons between them are not available frequently in publications. Each method offers a unique set of potential advantages and disadvantages. The most accurate way of identifying the best soil moisture technique is the value selection method (VSM). The neutron probe is preferable to the FDR or TDR sensor for measuring soil moisture. Remote sensing techniques have filled the need for large-scale, highly spatiotemporal soil moisture monitoring. Through self-learning capabilities in data-scarce areas, machine/deep learning approaches facilitate soil moisture measurement and prediction.

Keywords: surface soil moisture; volumetric–tensiometric methods; moisture sensors; remote sensing methods; deep learning methods

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1. Introduction

Effective planning and management of the hydrological variables are essential, especially when the effects of climate change are worsening impact assessments and mitigation measures. Among hydrological variables, soil moisture affects many hydrological, meteorological, and vegetation growth processes. Between rainfall events, soil water storage is the primary source of water for plants, affecting the crop yields and the soil moisture levels influence the on-farm water management decisions, for instance, planting time, pesticides, herbicides, fertilizer application, and irrigation scheduling [1–3]. Surface soil moisture (SSM) is a crucial state variable of the hydrological cycle affecting the runoff, evapotranspiration, and vegetation growth [4,5]. SSM is a significant soil indicator of agricultural drought. The availability of soil moisture is a function of soil density, soil texture, soil structure, meteorological and climatic factors, soil organisms, and soil–plant–atmosphere interactions [6]. Soil water content measures the amount of water in soil pore space. Soil water content is affected by soil temperature, soil moisture, soil texture, soil organic matter, and soil organisms. The primary soil moisture sensors are the soil temperature and near-surface soil moisture.

Soil moisture is a good predictor of a future crop yield but is also a significant contributor to agricultural water security [7]. The most critical aspect of soil moisture is the depth of the soil water storage. The depth of the root zone, which is the area where plants can obtain water, is the primary factor controlling soil moisture. The adequate depth of the root zone is estimated by the amount of water applied to soil, the amount of precipitation, and the drainage of the ground. In the research studies regarding agricultural hydrologic aspects of soil moisture, the SSM (moisture depth up to 10 cm), refs. [7,8] is considered a more representative portion of the soil for these types of studies of agricultural water management.

The current trend of decreasing soil moisture is concerning. SSM is a proxy for yield-related soil moisture. Therefore, understanding the drivers and consequences of SSM is critical to predicting future yields and ultimately improving crop production and food security [9,10]. Most of the current research has examined the impacts of SSM on crop yield, except for drought. Drought is the most significant natural hazard causing yield reduction in the US agriculture sector. It is estimated that the US agriculture sector lost $50 billion worth of crops in 2015 due to drought. According to Chinese government statistics, severe drought and high temperature in the summer of 2006 caused at least 18 million residents to suffer from water shortages, while 311,300 hectares of land failed to harvest, and the economic losses were 11.74 billion yuan [11]. Drought has been shown to have negative impacts on the economy.

Despite its importance in hydrological modeling, biogeochemical, and related dynamic processes [12,13], it is difficult and expensive to measure soil moisture dynamics accurately on a regional or global scale because of high temporal and spatial soil moisture variability [14,15]. In contrast, remote sensing provides unique opportunities to continuously monitor valuable soil water measurements with high spatial and temporal resolution at a minimal cost [16–18]. By calibrating the datasets from soil moisture probes with remote sensing data, various empirical and physical models can be employed to predict the moisture content of the soil on a large spatial scale with a high temporal and spatial resolution [19–21]. However, high-level spatiotemporal in situ measurements are lacking in developing nations, and estimations of soil moisture derived from simulated and observed remote sensing methods are frequently used without adequate verification, leading to uncertain results [16].

Numerous quantitative techniques have been suggested and used to examine the dynamics and distribution of soil moisture across various scales [22]. Two techniques can determine soil moisture; (i) direct and (ii) indirect techniques. Gravimetric is the most accurate technique for measuring SSM in direct soil moisture estimation. In the indirect technique, time domain reflectometry (TDR) and frequency domain reflectometry (FDR) are the most accurate methods [23,24]. However, their spatial representation is low. The emerging technology, cosmic-ray neutron sensing (CRNS) and global positioning system (GPS), partially solve this problem. Specifically, several publications show that even under adverse conditions, the accuracy of CRNS is the same as that of the point sensors. Using SSM estimating instruments has specific advantages, such as portability, ease of installation, operation, and maintenance, relative maturity, and capability of direct measurements at various depths with high temporal resolution [25]. However, these techniques are labor intensive, expensive, and complex, and some may also be destructive (e.g., gravimetric sampling) [26].

With this in view, this paper has made efforts to critically review the suitability of soil moisture estimation techniques for small humid watersheds. Soil moisture estimation has been around for centuries, and all methods developed have had limitations. This paper will provide an overview of some soil moisture estimation techniques, their advantages and disadvantages, the current developments and future directions that the integrated approach of combining satellite and airborne data can offer, and the potential of hyperspectral data for aiding soil moisture estimation. We evaluated the suitability of the methods against the criteria, accuracy, efficiency of a resource, and areal covering. This review highlights the necessity of assessing the various techniques involved in measuring the soil moisture in mountainous regions or sloping land as the focus and review of the progress of soil moisture along with the potential optimized application of the integrated approaches in these areas.

2. Factors Influencing SSM

Spatial and temporal variation of SSM is influenced by five significant factors (Table 1); climate, topography, soil properties, vegetation, and land-use types. Climate factors, which are continuous meteorological variables, indirectly and directly affect SSM distribution. For example, incoming solar radiation and temperature causes an indirect influence through the change of contributing factors, whereas evapotranspiration (ET) and precipitation have a direct impact. Previous studies have investigated the seasonal and climatic effects on the spatiotemporal variation of soil moisture [22,27,28]. Martínez et al. [29] evaluated the impact of hydraulic properties of soil and climate type on temporal stability and found that inter-annual differences in variations of soil moisture are likely to occur in summer. Pan et al. [30] found the difference in affecting factors between rainfall and dry periods, where soil texture was most significant during dry periods, and during rainfall periods, the major elements were local vegetation and topography. Joshi and Mohanty [31] suggested that the topography and texture of soil were the two most important factors influencing the spatiotemporal variability of soil moisture at the ground and remotely sensed footprint scales. In addition, precipitation patterns dominate SSM patterns at the catchment scale (in combination with other meteorological factors). In a detailed view, influencing factors vary with the watershed's size. For example, in a small watershed, land use and topographical factors significantly affect the spatial variations in soil moisture, whereas climate primarily controls the soil moisture on a large scale [32–34]. The probable reason is that climatic conditions are comparatively consistent at a smaller level, and land use and topographical factors are highlighted, while at a larger scale, climatic factors influence the soil properties, land use, and topography [32]. Nevertheless, a detailed study of the influencing parameters is needed.

Table 1. Summary of the factors that influence the SSM.

Factors		Description	References
Climate	Incoming solar radiation	The temperature of soil and soil moisture is changed. It controls the ionic composition of soil solutions by influencing the release rates of plant litter and soil nutrients.	[35]
	Precipitation	In the case of spatial changes and uniform radiation, the heterogeneous precipitation over the landscape will cause significant changes in soil moisture.	[36]
	Evapotranspiration (ET)	Through the ET process, soil moisture is a significant source of atmospheric water vapor, including bare soil surface evaporation and plant transpiration.	[37,38]
	Temperature	Surface temperature affects the flux of longwave, sensible, and underground heat emitted. The magnitude of these fluxes controls the latent heat fluctuation.	[39]
Topography	Slope	Slopes affect processes such as seepage, underground drainage, and runoff. In steep fields, excess water can move laterally downhill in the soil and drain faster than in flat areas.	[26]
	Aspect and Gradient	The rate of ET from the surface of the soil and, consequently, SSM is affected as aspects and gradients are shown to directly regulate the received solar radiation.	[40]
	Curvature	High curvature of soil surface areas tends to cause more SSM heterogeneity than areas with low planar curvature.	[41,42]
	Relative elevation	Relative elevation (called slope position) directly influences how soil precipitation impacts SSM and indirectly influences soil surface moisture by affecting soil water redistribution.	[41,42]
Soil Properties	Texture	The texture is a significant factor that can influence the moisture permeation and water holding on the soil surface. Coarse-textured soils with the highest content of sand are more drainable than soils with finer textures (for instance, clay), resulting in lower water retention and SSM.	[43]
	Organic matter	As the particle size decreases, the decomposition of organic matter also decreases, resulting in lower water retention and an increased evaporation rate.	[44,45]
	Macro porosity	Sandy soils have few but large pores between individual particles. These macropores retain air but not water. Therefore, water is freely drained through the sandy soil compared to the clay soil.	[44,45]
Vegetation	Trees	The transpiration process requires water, which is observed through root zone moisture and affects the soil water dynamics	[46,47]
Land use types	Land use	Land mainly affects plants and related influences on infiltration rate, runoff rate, and evapotranspiration process, which show more obvious effects during the growing season.	[41,48]

3. SSM Estimation Techniques

Researchers have applied numerous techniques for estimating SSM, which can be classified into (i) classical (thermogravimetric and calcium carbide technique; ASTM D 2216 and ASTM D 944) and (ii) modern techniques e.g., tensiometer; Robinson et al. 2009, infrared moisture balance; ref. [49], which are usually employed in laboratory and field tests (Table 2). Measurement techniques can further be categorized into (i) direct (the moisture volume in the soil sample is physically measured by determining the weight of the soil (a part of the total weight of soil) by thermogravimetric), and (ii) indirect techniques (measures another variable affected by soil moisture to measure the available moisture in the soil for laboratory and field measurements) [50,51].

However, uncertainty in the measurement outputs is inherent in both classical and modern techniques [52]. In addition, methods have their pros and cons, which are summarised in Table 3.

3.1. Direct Techniues

Gravimetric or Oven Drying Technique

The gravimetric method is the classical and direct method currently used to determine SSM [53], which is the most natural and oldest technique, the standard reference [54,55]. In this method, the accurate measurement of the moisture content is ensured and is independent of the soil type and salinity. However, the destructive nature of the method does not allow a repetitive measurement [56]. In addition, the sample must be removed from the soil for laboratory work (Figure 1), limiting the continuous measurement of soil moisture records at any location [57].

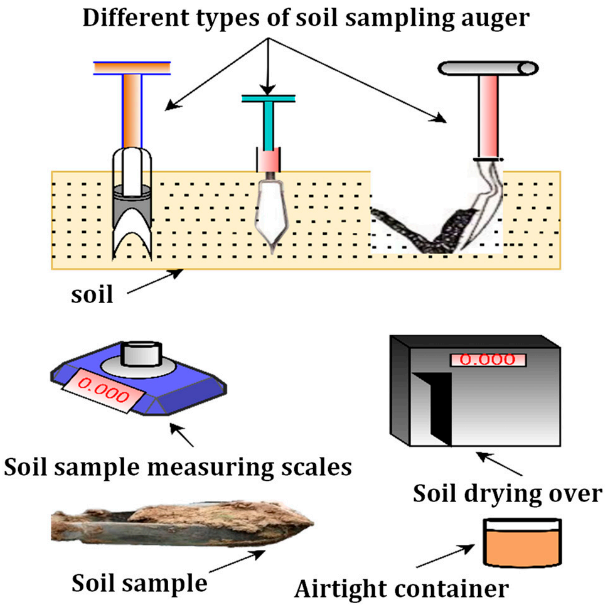

Figure 1. Schematic diagram illustrating moisture measurements using the Gravimetric method.

Table 2. Assessment of popular soil moisture measuring techniques in various classes.

Techniques	Depth	Cost-Effective	Response Time	Spatial Scale	Measured Parameter	Reference
Gravimetric method	Any depth	Cost-effective	24 h	Confined	Gravimetric moisture content	[58]
Neutron probe	<30 cm	Costly	1–2 min	Confined	Volumetric moisture content	[59]
TDR	30–60 cm	Cost-effective	~28 s	Confined	Volumetric moisture content	[60]
Capacitance and FDR	100 cm	Costly	Instant	Confined	Volumetric moisture content	[61]
Tensiometer	15–60 cm	Cost-effective	2–3 h	Confined	Soil matric potential	[62]
Gamma-ray attenuation	2.5 cm	Costly	~60 s	Confined	Volumetric soil moisture content	[62]
Capacitance sensor	20 to 50 cm	Costly	Instant	Confined	Volumetric moisture content	[63]
Gypsum block	10–30 cm	Cost-effective	2–3 h	Confined	Soil matric potential	[64]
Hygrometric	It depends on the sampling depth	Cost-effective	<3 min	Confined	water potential of soil	[64]
Ground-penetrating radar	20 cm to 500 cm	Costly	Instant	Large	Volumetric soil moisture content	[28,65]
Cosmic ray	12 to 76 cm	Costly	Instant	Large	Volumetric soil moisture content	[66]

3.2. Indirect Techniques

3.2.1. Neutron Scattering Method

The neutron dispersing technique employs a radioactive source that scatters fast neutrons (average energy 5MeV, mega electron volt) into the soil. These fast neutrons slow down with the hydrogen nuclei collision in the soil water molecule (Figure 2). Neutron dispersing is the most accurate non-destructive test with a response time of 1–2 min and is majorly beneficial in measuring a large soil volume at several depths [62]. However, significant disadvantages are there, i.e., insensitivity near the soil surface to shallow depth (≤0.3 m), the high setup cost, less portable, coarse spatial resolution, and exposure to radiation, which can cause serious health issues [59,67–69]. This moisture measurement method has been widely used in agriculture and forestry for over 50 years [70,71].

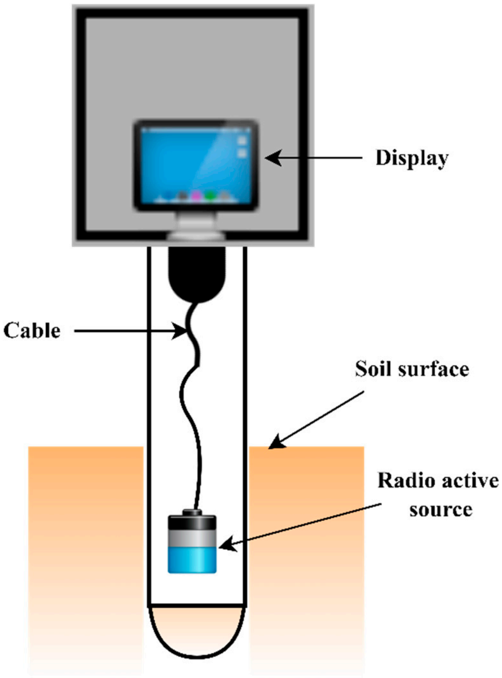

Figure 2. Schematic diagram showing moisture measurements using the Neutron scattering method.

Table 3. Summary of the advantages and limitations of various SSM estimation techniques.

Techniques	Advantage	Limitations	Reference
Gravimetric	Cost-effective, standard, and accurate for determining soil moisture.	Its implementation is labor intensive, time-consuming, destructive, and not easy to use in rocky soil. Use in heterogeneous soil profiles is complicated	[72,73]
Neutron dispersing	It is relatively easy, non-destructive, and can measure soil moisture with large volumes at different depths.	Health risks: equipment is costly and needs proper calibration when used in different soil types. The relocation of this device is complicated from one measurement location to another.	[74,75]
Gamma attenuation	Non-destructive technique, easy calibration, can provide average moisture content for profile depth, the operation is easy to automate and allows the user to map changes in soil moisture over time.	Expensive, use is problematic, health risks, in the field, has limited applicability, limited to determine the moisture content of sample having a thickness of 2.5 cm, variations in bulk density affect the measurements.	[41,64]

Table 3. *Cont.*

Techniques	Advantage	Limitations	
Resistive sensor	Cost effective, allows the soil moisture measurement at the same site over time.	Dissolution and degradation of the gypsum block. Each site and measurement range requires individual porous block and measurement interval calibration. The porous block is affected by temperature and salt. It is not suitable in fast drainage soils, like sandy soils.	[76]
FDR and Capacitance sensor	Non-destructive equipment's initial setup is relatively lower than that of TDR; after soil-specific calibration, it provides accurate measurement, and where TDR fails, it can read high salinity levels.	Requires calibration, sensors are expensive, for an extended period, their sustainability is questionable, and less accurate results due to dependency on soil and temperature	[75,76]
TDR	Non-destructive and non-labor intensive. It can provide continuous measurements and has excellent spatial and temporal resolution.	Due to complex electronics, it is expensive equipment, and applicability in highly saline soils is limited while, in clay soils, conductivity is high	[77,78]
Tensiometer	Cost effective and non-destructive, if maintained adequately, a long period of use is possible. It can provide continuous measurement without distressing the soil.	Unsuitable moisture measurement in dry soils takes time to prove the result. Due to high maintenance conditions, it is not suitable for research.	[75,76]
Hydrometric	Suited for automatic measurements and requires low maintenance with the advantage of large area coverage.	A hydrometer is impractical because it consists of an extensive, complex, expensive system.	[75,79]
Ground-penetrating radar	Non-destructive technique and can cover a large area with high resolution.	Application is problematic on steep and rocky slopes due to the bulky antenna, and trees act as a reflector in the forest, which causes erroneous data. Due to their high conductivity, many soil types are radar opaque, dissipating radar energy and limiting its use.	[76,80]
CRNS	Non-contact allows quantification of averaged soil moisture over a large area using only one probe and does not affect field agricultural activity	The health risk is costly, complex, and unable to deliver accurate deep soil water content because of the inverse relation between depth and accuracy	[81,82]
Remote sensing	Suitable for large areas and can offer fast data collection repetitively.	Costly, complex, and cannot provide accurate soil moisture measurement information like conventional techniques at the point—significant effect of soil surface conditions, low penetration depth, and low temporal resolution.	[76,83]
Machine learning/deep learning	Handle massive amounts of data, spatial and temporal estimation is easy and roust for large areas; soft-computing technique requires no instrument/equipment	Experience personnel required to develop the models, costly in the sense of computing machines used and time required, need a huge amount for data collection for global generalization	[84,85]

3.2.2. Gamma Attenuation

Another measuring technique, gamma-ray attenuation, is based on radio signals and measures soil water content with a high resolution up to a soil depth of 25 mm (Figure 3) or less in field and laboratory research. Additionally, its non-destructive nature enables repeated assessments of the physical soil parameters in the same site at various periods [86,87]. This technique is sensitive to the soil bulk density changes and SSM.

Gamma rays are riskier to operate than neutron scattering methods with higher operational costs [57].

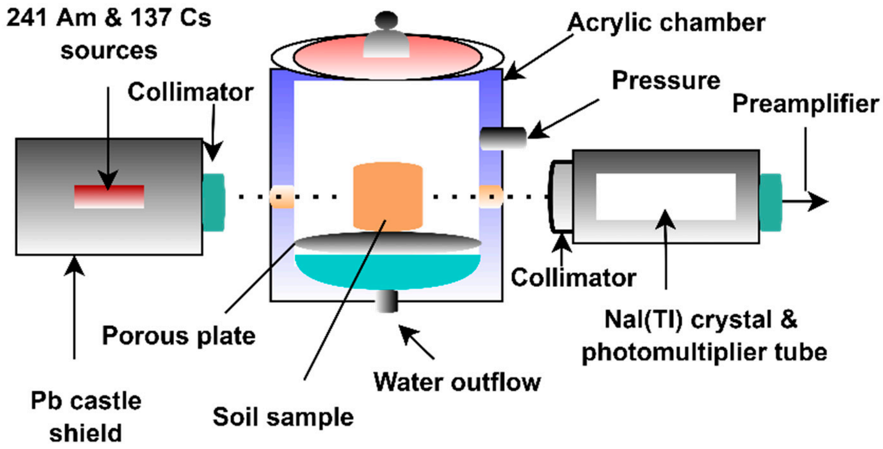

Figure 3. Schematic diagram depicting moisture measurements using the Gamma attenuation method.

3.2.3. Time Domain Reflectometry (TDR) Sensor

The TDR sensor measures the time needed for a transmitted signal to travel from one end to another [88]. TDR is advantageous for long-term in situ measurements and automation due to its high temporal resolution, quickness of achievement (about 28 s), repeatability of estimation (Figure 4), and independence from the soil texture, salt concentration, and temperature [89,90]. No soil calibration is required as the TDR method is independent of soil texture, salt content, and temperature. TDR provides non-destructive on-site monitoring without radiation-emitting sources such as gamma and neutron probes [78]. Instruments, however, have a higher initial setup cost and might lead to errors by losing reflection in extremely salty soil and increasing conductivity when soil mass is wet.

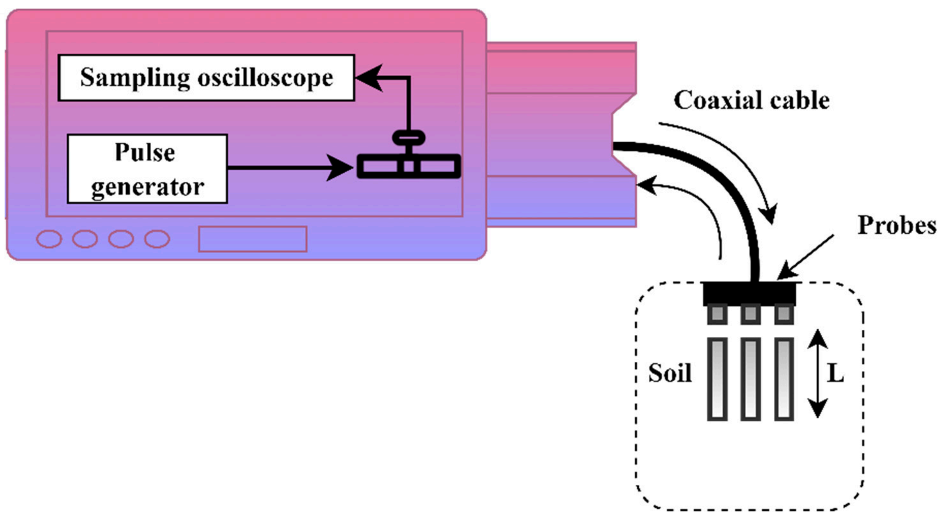

Figure 4. Schematic diagram depicting moisture measurements using the TDR method.

3.2.4. Capacitance Sensor and Frequency Domain Reflectometry (FDR)

The capacitance sensor and FDR estimate a medium's dielectric constant (Figure 5a,b) by determining the charge time taken by a capacitor in that medium [91–93]. Due to this reason, the method outcome is very soil specific and requires frequent calibration at the time of implementation. The cost for the initial setup is relatively lower than that of TDR.

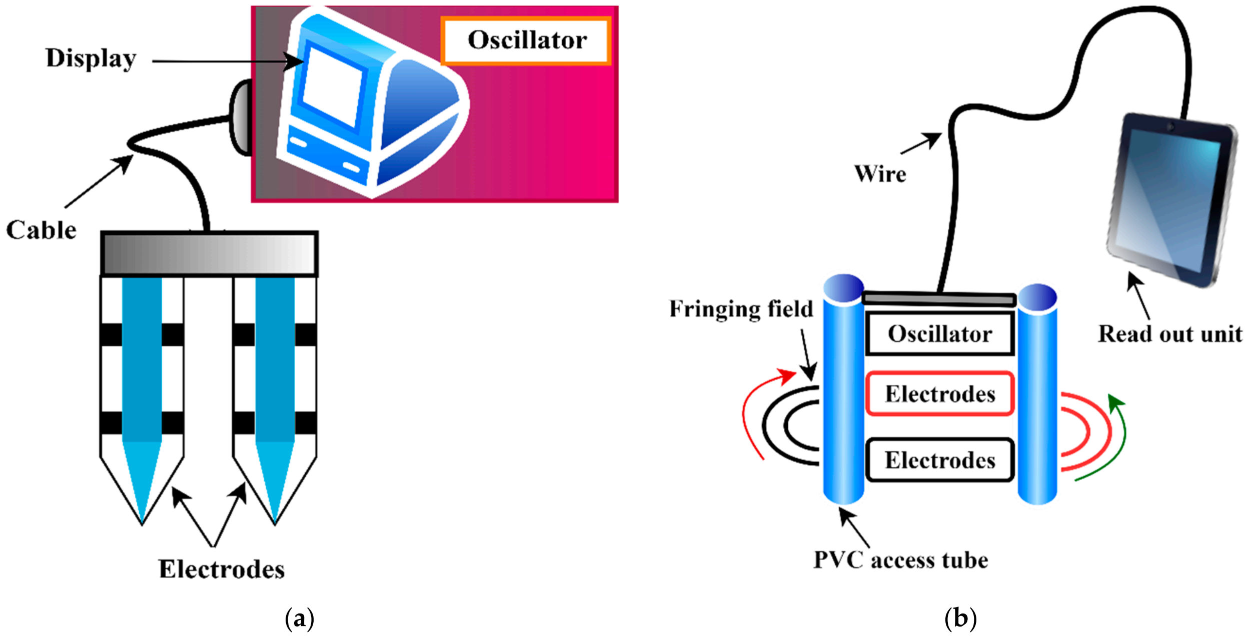

Figure 5. Schematic diagram depicting moisture measurements using two techniques (**a**) Capacitive resistor and (**b**) FDR method.

On the other hand, a frequency domain analysis has greater promise for estimating soil moisture content than time domain reflectometry methods [94]. Topp's equation (Topp, Davis, and Annan, 1980) for TDR soil moisture measurement is valid up to θ = 50%, according to the comparative study done by Rao [61] on both TDR and FDR techniques. This is because Topp's calibration equation was developed on experimental results for mineral soils with θ < 50%. The same study concluded that the FDR probe's repeatability efficiency is higher in soils when the volumetric moisture content is less than 5%, making it more sensitive in the relatively dry state of soils. However, the FDR probe has a limitation of showing erroneous results, and accuracy can be affected by the air gaps between soil, probe, and access tube [62].

3.2.5. Resistive Sensor

The resistive sensor works on the principle that an inverse relationship exists between soil moisture content and soil resistivity (e.g., increases in soil moisture content cause a decrement in soil resistivity). The soil resistivity can be quantified either way, i.e., measuring the resistivity between electrodes in soil or the material's resistivity in the equilibrium with the soil [28]. Resistive sensors are the cheapest among all the sensors, but it has less reliability and repeatability (Figure 6). This measurement technique requires individual calibration and fails to provide the results in saline soil [28].

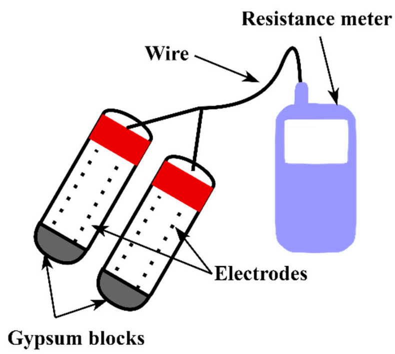

Figure 6. Schematic diagram depicting moisture measurements using the Resistive Sensor.

The commercially available sensors based on TDR, FDR, and capacitance type with their technical specifications are listed in Tables 4 and 5. From the table, the accuracy range of commercially available sensors is ±1–3% θ. The manufacturer's handbook is interesting because it omits information on the repeatability and sensitivity of these commercially accessible sensors. However, previous research has tested the performance of commercially available sensors in different soils and evaluated them as listed in Tables 6 and 7.

Table 4. Evaluation of commercially available soil moisture measurement sensors [62].

Type of Sensors	Sensors	Accuracy	Measurement Range	Repeatability	Operating Frequency	Literatures
TDR	TRIME PICO 64/32	Not reported	0–100% θ	0.20%		IMKO devices [62]
	TRIME PICO IPH/T3			0.30%		
	TRIME-IT/-EZ	±1% θ for 0–0.40 m^3/m^3; ±2% θ for 0.40–0.70 m^3/m^3	5 and 15 cm depth	Not reported	1 GHZ	
	5TM	±0.03 $m^3\ m^{-3}$	5–80 cm	Not reported	70 MHz	[95]
FDR	CS616	±2.5% θ for 0 and 0.50 $m^3\ m^{-3}$;		Not reported	70 MHZ	Campbell Scientific Schlaeger [62]
	SISOMOP Schlaeger	Relative accuracy of the permittivity of ±4%	0–1 $m^3\ m^{-3}$			
Capacitance type technique	5TE soil moisture sensor	±1 ka for (1–40 ka) and ±5 ka for (40–80 ka) 0–100%	0–100% θ	Not reported		Decagon Devices [62]
	EC 5 soil moisture sensor	±3% θ most mineral soils up to 8 dS/m ± 1–2% θ with soil-specific calibration				
	ECH2O Probes	±4% θ in medium-textured soils without calibration, and an accuracy of 1–2% θ with a soil-specific calibration	0–40% θ			
	10HS	As per standard calibration, ±0.03 m^3/m^3 in mineral soils; and ±0.02 m^3/m^3 depending upon soil-specific calibration	0% and 57% θ		70 MHZ	

θ is the volumetric water content.

Table 5. Additional soil moisture sensor comparison.

	TEROS12	TEROS11	TEROS10	EC-5	10HS
Measures	Volumetric water content, temperature, electrical conductivity	Volumetric water content, temperature,	Volumetric water content	Volumetric water content	Volumetric water content
Volume of Influence	1010 mL	1010 mL	430 mL	240 mL	1320 mL
Measurement Output	Digital SDI-12	Digital SDI-12	Analog	Analog	Analog
Field Lifespan	10+ years	10+ years	10+ years	3–5 years *	3–5 years *
Durability	Highest	Highest	Highest	Moderate	Moderate
Installation	Installation tool for high accuracy	Installation tool for high accuracy	Installation tool for high accuracy	Install by hand	Install by hand

* Choose a long-life sensor such as TEROS if field conditions are typically warm and wet.

Table 6. Soils and their physicochemical properties. Reprinted with permission from Ref. [96]. 2022, Vaz et al.

Soil	Clay	Silt	Sand	ρ_p †	ρ_b	f	SSA	LOI	CEC	EC	pH ($CaCl_2$)
		%		g cm^{-3}		cm cm^{-3}	m^2 g^{-1}	%	mmolc/100 g	dS m^{-1}	
AZ2	3	4.3	92.7	2.63	1.55	0.42	1.8	0.6	1.8	1.21	7.3
AZ6	21.5	21.4	57.1	2.59	1.4	0.55	17.5	2.1	8.2	1.32	7.6
AZ9	20.9	59.7	19.4	2.57	1.13	0.61	8.8	10	30.7	1.4	6.3
AZ11	36.7	37	26.3	2.69	1.36	0.6	30.1	3.4	14.1	0.94	7.9
AZ15	28	62.9	9.1	2.46	1.3	0.58	21.6	5.5	21.3	8.39	7.4
AZ18	68.9	17.7	13.4	2.61	1.3	0.63	50.8	6	16.3	1.65	6.5
ORG	2.6	13.7	83.7	1.83	0.38	0.79	2.1	55.1	27.3	4.8	5.9

† ρp, soil particle density; ρb, soil bulk density, f, total soil porosity ($f = 1 - \rho b/\rho p$); SSA, specific surface area; LOI, loss on ignition for organic matter content; CEC, cation exchange capacity; CE, soil electrical conductivity in the saturation extract; pH in $CaCl_2$.

Table 7. Root mean square deviation (RMSD) for measured and estimated θ of the soil is stated in Table 5. Reprinted with permission from Ref. [96]. 2022, Vaz et al.

Sensor	AZ2	AZ6	AZ9	AZ11	AZ15	AZ18	ORG	AV1 †	AV2 ‡
TDR100	0.009	0.016	0.034	0.026	0.024	0.042	0.013	0.023	0.023
Wet2	0.023	0.018	0.019	0.046	0.078	0.051	0.046	0.04	0.034
5TE	0.05	0.036	0.04	0.033	0.083	0.039	0.041	0.046	0.04
10HS	0.077	0.064	0.084	0.063	0.086	0.078	-	0.075	0.073
SM300	0.019	0.036	0.039	0.049	0.136	0.047	0.035	0.052	0.037
Theta P.	0.02	0.029	0.02	0.042	0.091	0.026	0.014	0.035	0.025
Hydra P.	0.018	0.042	0.039	0.068	0.272	0.056	0.046	0.077	0.045
CS616	0.058	0.156	0.049	0.157	0.962	0.169	0.179	0.247	0.128

† AV1: average of all soils and ‡ AV2: average of all soils but AZ15.

3.2.6. Tensiometer

A tensiometer is a primary instrument to determine the matric potential of soil (Figure 7), which is often referred to as based on principles of negative pressure (soil water tension) or soil water suction [49,97,98]. A tensiometer works only in the range of 0–1, which captures only a small portion of the entire range of available moisture. These limitations in in-depth coverage cause an inaccurate estimation of the wilting point of moisture for most crops. The technique is preferred mainly in sandy soil where moisture usually lies at a depth of fewer than 1 m but is discarded in fine-textured soil. Despite the cost-friendly and easy installation, it demands regular maintenance and is destructive in nature [98].

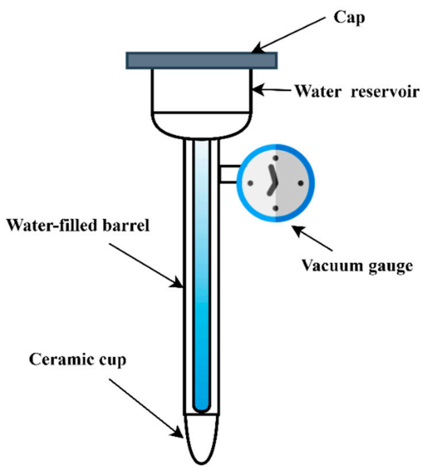

Figure 7. Schematic diagram depicting moisture measurements using the tensiometer.

3.2.7. Hygrometric Techniques

Hygrometric approaches depend on the porous medium's thermal inertia, which fluctuates according to soil surface moisture content. The essential advantage of this technique is simplicity in the apparatus and low maintenance with automated measurements and control of the irrigation system. The primary disadvantages include that hydrometer comprises a very bulky structure with a high initial setup cost causing impractical usage in some conditions [99]. In addition, deterioration effects occur on the soil components of the sensing elements and the requirement for unique calibration for each material to be tested [62].

3.2.8. Ground-Penetrating Radar (GPR)

The GPR technique can precisely map the spatial scope of near-surface objects and convert them into soil media to produce the highest resolution images of the currently available surfaces. GPR is a fine-resolution measurement technique that can monitor the variation of dielectric properties over large-scale surface and subsurface regions. This technique requires a true understanding of the methodology to gain high-quality outcomes and effective interpretations, making outcomes and their interpretations subjective (Figure 8). In addition, signal attenuation in saline soils results of GPR techniques are unreliable [28,62,65,100].

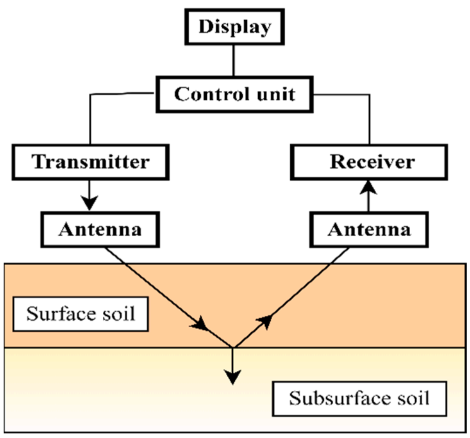

Figure 8. Schematic diagram depicting moisture measurements using the Ground-penetrating radar (GPR).

3.2.9. Cosmic-Ray Neutron Sensing (CRNS)

Measuring the average moisture content of soil over a wider area is challenging for two main reasons. First, SSM can be vastly changeable, even trim spatial levels, especially in a moderately moist environment. Second, the most common in situ soil moisture measurement methods can only provide point measurements. Keeping under consideration the resources and time, recently, the focus of research has been on broader-scale remote sensing of soil moisture [101]. However, the measurement depth for many of these approaches is still restricted to the top 5 cm of soil.

Moreover, the temporal and spatial resolutions are quite rough. One technique (Figure 9) that aims to bridge the scale gap between soil moisture in situ measurement and remote sensing is to employ a CRNS as an indicator of SSM [102]. The technique is founded on the principle of natural neutron detection on the surface. It has a maximum measuring depth of 12–76 cm and a range of around 670 m [62].

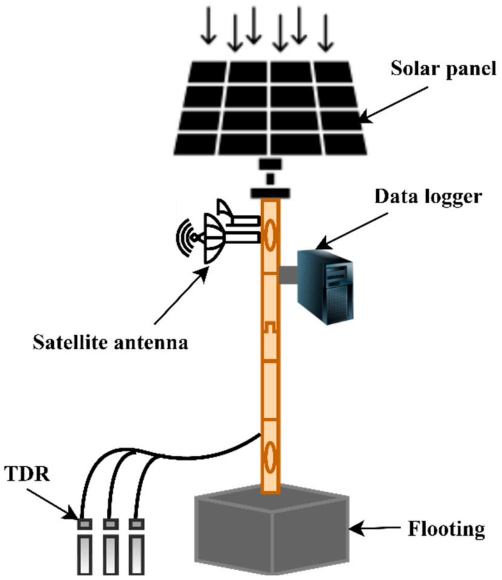

Figure 9. Schematic diagram depicting moisture measurements using Cosmic-ray neutron sensing (CRNS).

3.2.10. Remote Sensing Technique

Ground-based SSM measurement techniques are handy for direct measurements at different depths. Despite direct measurement, these point-based techniques are limited to exploring the spatio-temporal variability of SSM at a large scale by considering the predominant heterogeneity and dynamic forces distribution factors: topography, climate, soil types, vegetation coverage, and water table depth [103]. As a solution, remote sensing technology commonly provides regular updates on a global scale at a low cost [104,105]. Soil moisture can be determined from thermal and optical satellites and active, passive, and microwave sensors [54,78,104].

Remote sensing techniques for SSM include thermal infrared, visible, radar, and satellite imaging. The most common remote sensing techniques are thermal infrared, visible, and radar (Table 8). The SSM estimation accuracy using combined thermal infrared, visible, and satellite datasets is higher than that of thermal infrared; the SSM estimation accuracy could be further enhanced by adding microwave radar datasets [106].

Remote sensing techniques used to estimate the surface soil moisture include thermal infrared (TIR) and visible/infrared hyperspectral (VIR/NIR) sensors. Thermal infrared (TIR) sensors are used to measure the SSM in surface soils, which are classified as warm soils and cool soils, which are in the range of 2 °C to 50 °C and −2 °C to −50 °C, respectively.

Thermal infrared (TIR) sensors can only measure the SSM in warm soils. In contrast, visible/infrared hyperspectral (VIR/NIR) sensors measure the SSM in cool soils [107].

Table 8. Comparison of the remote sensing methods applied or available for measuring the soil moisture content. Reprinted with permission from Ref. [78]. 2022, Petropoulos et al.

Groups	Methods	Advantages	Disadvantages	Literatures
Optical	Reflectance-based methods	Availability of multiple satellites with moderate spatial resolution, promising hyperspectral sensors	Failed to correlate SM in a highly vegetated cover, poor temporal resolution with limitations at night, and clouds cover	[108–110]
	Thermal infrared-based methods	Availability of multiple satellites with moderate spatial resolution, promising relation of SSM to thermal inertia	Low temporal resolution and minimum correlation of SSM in a high vegetation cover, no measurement at cloudy conditions, and sensitivity to earth's atmosphere	[111–113]
Microwave passive	Various methods proposed	Results are mostly consistent over the bare soil surfaces; the method is feasible in clouds and daytime conditions with a higher temporal resolution	Coarse spatial resolution and vegetation cover, and surface roughness are a major influencing factor	[114,115]
Microwave active	Various methods (empirical, semiempirical, physically-based)	Fine spatial resolution can measure the SSM in clouds and daytime conditions	Low repetition of the satellite over the same place and accuracy is reliant upon the proportion of surface roughness and vegetation cover	[22,116,117]
Synergistic methods	Optical and thermal infrared	Fine spatial resolution supported by a range of satellite sensors	Empirical methods which limit the transferability and low accuracy in the cloudy state, and no nigh time measurements, low temporal resolution with lower moisture depth	[118,119]
	Active and passive microwave (MW)	Enhanced temporal resolution and measurement of SSM	Validation should be carefully handled	[120,121]
	MW and optical	Sensitivity to the vegetation and surface roughness is minimized	Scaling and validation need careful interpretation	[122]

3.2.11. Deep Learning/Machine Learning Techniques

Machine learning is a form of artificial intelligence that uses algorithms to solve problems without being explicitly programmed. This approach is often faster and more effective than traditional methods. One area where machine learning has been most useful is in the field of soil moisture measurement [123]. Machine learning has been used to develop new algorithms that can accurately predict soil moisture content, which can then be used for irrigation or other purposes [124].

Regression methods remain popular because of their simple methodology, long history of application, and successful application to a wide variety of processes by practitioners and academicians. Regression models have made it possible to predict a wide range of outcomes with high accuracy. However, for the traditional regression analysis, some statistical assumptions required to be made may lead to limited use, such as outlier data, nonlinearity, heteroscedasticity, and multicollinearity. First, regression uses multiple independent variables and cannot consider the effects of other variables. Second, if the variables are correlated, the estimated coefficients are biased in the direction of more significant coefficients ("coefficient shopping") and can produce misleading results [83].

Machine learning and deep learning techniques have been successfully applied for predicting soil moisture using remotely sensed data [125]. Different vegetation indices and spectral bands combined with weather, soil, and crop parameters could be used as input variables for estimating SSM using deep learning and machine learning approaches [126,127].

Remotely sensed data are used for predicting soil moisture at a decimeter scale. In recent years, machine learning algorithms such as artificial neural networks and convolutional neural networks have been successfully used for this purpose [128]. These algorithms have been demonstrated to perform better than traditional rule-based approaches (Figure 10) [129]. Machine learning and deep learning techniques have been successfully applied for predicting soil moisture using remotely sensed data. This technique can be used to develop high-performance soil moisture sensors for extended periods without being affected by the weather. This will help farmers save on irrigation water, which is a precious resource in arid regions [84,130–132].

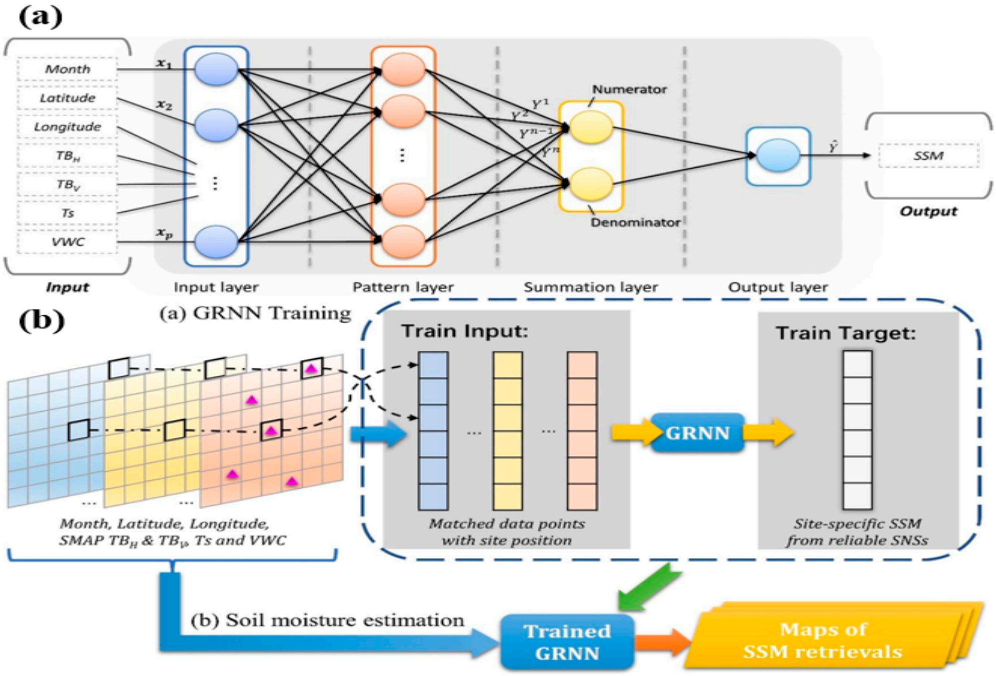

Figure 10. Schematic of the generalized regression neural network (GRNN) (**a**) SSM estimation from satellite observations using a GRNN (**b**) Reprinted with permission from Ref. [133]. 2022, Qiangqiang Yuan et al.

4. A Critical Appraisal of the Measurement Techniques

The soil's moisture content is crucial in determining the soil mass's biological, hydrological, related to agronomy, engineering, ecology, and geology features. Although earlier researchers have used various methods to determine the moisture content of soils, in in situ and laboratory-based soil moisture settings, it is still unclear whether these methods can be applied to soils with completely diverse features and what "types of moisture content" can be measured. It is, therefore, vital to critically evaluate the benefits and drawbacks of existing and innovative soil moisture measuring methods.

A critical review of the polished material available indicated that the scientists had used a variety of methods to determine the soil moisture content, including thermogravimetric and calcium carbide tests, as well as modern procedures like gamma attenuation neutron probe, dielectric techniques like FDR, electrical impedance, TDR, capacitance probe, heat pulse sensor, GPR, MEMS, tensiometer, optical and electrical resistivity methods. Dielectric procedures are among those that have been said to be highly dependable. Researchers have noted that these methods are ineffectual in various soil types, that lab and field calibrations differ from the manufacturer's requirements, and that the current calibration equations contain gaps. None offers a comprehensive method for determining the soil moisture content. For instance, the most used methods for measuring soil moisture nowadays are dielectric techniques, particularly the TDR. The authors, however, believe that the TDR sensor for measuring soil moisture is not sensitive to porosity, saturation, pore fluid, and the proportion of soil minerals available as the dielectric constant relies on the presence of minerals in the soil, which is the view of Bhat et al. [134] as well.

Comparisons of the several soil moisture measuring methods are shown in Tables 4 and 5. The criteria for quick, accurate, automated, and geographically dispersed soil moisture measurements by taking into account factors specific to the soil like salinity, ambient temperature, mineralogy, porosity, matrix structure, presence of organic matter, etc., are not being addressed by the present modern commercially accessible methodologies. Frequency dependence (TDR and FDR), time consumption (gravimetric technique, tensiometer), the need for site-specific calibration (FDR, resistive sensors), concerns with salty soils (FDR, TDR, and resistive sensors), portability issues (NMM, FDR), issues with health risks (gamma attenuation approach), and high equipment costs are the causes of this situation (viz., neutron probe, TDR, FDR). The gravimetric and tensiometric techniques require much time, and the neutron probe, TDR, and FDR require pricey equipment. The gamma attenuation approach is somewhat invasive, as it involves a lot of time and equipment for calibration.

Technical details of the capacitance type and the FDR- and TDR-type soil moisture measuring sensors are commercially available. It should be mentioned that the accuracy ranges for TDR, FDR, and capacitance sensors that are sold commercially are 1–3% θ. Another intriguing feature is that the handbook provided by the manufacturer does not list the repeatability and sensitivity of these commercially accessible sensors. The main specifications of the commonly used traditional and contemporary soil moisture methods are described in Table 2. The installation of current practices is laborious, according to the manufacturer's instructions, as probes need to be entirely in touch with the soil, and any air gaps or excessive soil compaction surrounding the probe can significantly affect the readings for soil moisture.

The neutron probe is found to have substantially higher accuracy, reproducibility, and sensitivity than the other approaches. However, the main drawbacks of neutron probes are their difficulty in data logging and installation, and their lack of security. Additionally, none of the published studies explain the "hit zone inside the soil mass" for which the moisture content measurement is being done. The effectiveness of methods often used and based on the "dielectric response" of soils with organic matter, salinity, and their general chemical, physical, and mineralogical characteristics must be extensively investigated. It is currently unclear how these approaches would apply to soils with radically different properties and what "categories of moisture content" (such as hygroscopic, gravity moisture, capillary moisture, etc.) they could measure. Investigating the applicability of various measuring techniques and the effects of these characteristics on the measurement of soil moisture is thus essential. Nanoscale soil moisture sensors must be manufactured and used to enable precise soil moisture content measurements.

5. Recommendation of Potential Soil Moisture Estimation Methods

There are numerous techniques for measuring and tracking soil water content, as was previously mentioned. Choosing a technique is sometimes tricky since each approach has benefits and drawbacks that may be significant depending on the scenario. Numerous factors should be considered when selecting a suitable approach, such as the following: application (irrigation scheduling, monitoring, research), plant kind (if present), accuracy and moisture range needed, soil parameters (texture, organic matter concentration, swelling, heterogeneity), cost (including initial costs and ongoing costs), operational skill level, and maintenance.

In the last decade, a new dimension has been added to the narrative of soil moisture monitoring: the emergence of deep soil moisture dynamics. The recent advancement of hydrologic satellites has enabled the extraction of soil moisture information at unprecedented depths into the soil profile. Soil moisture at depth is mainly controlled by the subsurface hydrologic processes, which are largely unknown and difficult to be observed. Thus, the combination of new hydro-geophysical methods with satellite observation provides an unprecedented opportunity to understand subsurface hydrology, which is likely to enhance our ability to predict water yield.

Tables 1–4 compares the approaches that are discussed so that the reader has rapid access to them. Cape [135] offered a value selection method, which Charlesworth [136] offers to determine which soil moisture measurement method is best appropriate for a given circumstance. The technique is to answer a series of questions with a yes or no response. Each question's relative significance is measured using the proper weights, and each sensor's total relative importance (T) for a given application is calculated by summing the individual scores from all questions and dividing the result by the score for the "effective range of measurement" criteria. The original approach suggested here has been modified to use this multiplication factor (0 or 1). This suggests that no sensor will be appropriate for a given application if the field measuring range does not meet the sensor's parameters. Investment, setup, operation, and maintenance expenses are added to evaluate the sensor's anticipated life cost (Cost) (L). Price divided by L yields the sensor's yearly cost (A) (A = Cost/L). The application's final sensor value (V) is calculated by dividing T by A (T/A).

The device with the most significant value V is better suited to the demands and price range. Table 3 includes an example where the neutron probe and an FDR sensor are compared. Both options involve taking a single moisture reading at ten different depths. The FDR apparatus comes with a logger and software for graphic information presentation as standard, and the neutron probe has a built-in display where, after entering the site-specific calibration, the moisture values may be viewed in addition to the count number. Both devices meet the requirements for range of measurement, accuracy, dependability, and data processing for the sample application (score = 1) [137].

On the other hand, the neutron probe does not give data logging since it cannot be left unattended in the field and requires tight routine maintenance as a radioactive instrument, and the FDR calibration is significantly reliant on soil type (score = 0). Although both tubes in the ground need sinstallation, which is equivalent in price, the total cost of the neutron probe is greater than the work involved in data gathering (requires certified personnel). Both sensors should last for 10 years. According to the value selection method, FDR is a better choice for this application. Due to the natural and artificial heterogeneity of the soil, location and instrumentation may be very important in the context of soil water measurement.

Variability in soil moisture readings can be influenced by various variables, including soil type and inherent heterogeneity, fluctuation in plant development, rainfall interception, lower application efficiency, uniformity in irrigation, etc. As a result, it is generally advised to locate the instruments in each representative zone and define the average (typical) conditions in terms of soil type, depth, plant distribution, and water sources (if irrigation). It is anticipated that research on soil water monitoring will keep creating trustworthy and affordable options as the demand to manage water more sensibly and effectively grows. To get around the fundamental drawback of needing a soil-specific calibration method, future research should concentrate on creating new methods or refining the ones already in use.

Volumetric and tensiometric in situ data are frequently required in many mass transport investigations; hence from a research standpoint, a combination instrument that offers both would be preferable. Non-contact and distant sensing methods should be improved further to assess soil moisture distribution and variation on vast scales.

6. Conclusions

The use of soil moisture monitoring is expanding, along with investments in precision irrigation infrastructure and control systems and the requirement that irrigators take greater responsibility for water consumption and nutrient loss. However, monitoring soil moisture when making irrigation selections is not simple. Irrigators should select the appropriate equipment for their irrigation system, plot of land, and land use activities. Various devices have been employed during the past few decades to estimate soil moisture. The application and resource availability determine the best method for detecting soil moisture. When selecting a technique, it is essential to consider several factors, including the need for calibration, result accuracy, repeatability, spatial resolution, usability, and cost.

The right procedures and approaches for precisely monitoring SSM are essential since soil moisture content significantly impacts plant growth. To maximize plant development, a proper irrigation schedule helps manage soil moisture, decrease loss, and maintain the ideal soil water level. Furthermore, successful and consistent deployment of precise irrigation schedules depends on objective assessments of moisture content. Each approach depends on the available resources, field circumstances, and the advantages and cons of the many accessible ways evaluated below. The direct methodology (gravimetric approach) is standardized, reliable, and cost-effective, but it takes much time and is damaging, thus no one way can be used in all circumstances.

Although expensive and lacking in measurements for the spatial scale, indirect procedures produce good results on a temporal scale. The wider measuring area is covered by remote sensing and GPR methods, although they are usually accompanied by atmospheric inaccuracies and data overlapping. The approaches for identifying the SSM in imitation and authenticity studies at local and worldwide sizes may be chosen using the current review. It will be used to generate data for judgments regarding the efficient allocation and management of soil moisture in various forms of land use, considering the several research directions of moisture content, practical application, and emerging trends as an ecosystem service. Even though the study looked at much of the literature, it was impossible to include all the research on each SSM measuring technique. This work aimed to present an overview of SSM estimating techniques. The current state of knowledge on the methods for calculating SSM and its connection to other ecosystem services will be discussed in the future.

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