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Review

Advancement of Remote Sensing for Soil Measurements and Applications: A Comprehensive Review

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Abstract: Remote sensing (RS) techniques offer advantages over other methods for measuring soil properties, including large-scale coverage, a non-destructive nature, temporal monitoring, multispectral capabilities, and rapid data acquisition. This review highlights the different detection methods, types, parts, and applications of RS techniques in soil measurements, as well as the advantages and disadvantages of the measurements of soil properties. The choice of the methods depends on the specific requirements of the soil measurements task because it is important to consider the advantages and limitations of each method, as well as the specific context and objective of the soil measurements, to determine the most suitable RS technique. This paper follows a well-structured arrangement after investigating the existing literature to ensure a well-organized, coherent review and covers all the essential aspects related to studying the advancement of using RS in the measurements of soil properties. While several remote sensing methods are available, this review suggests spectral reflectance, which entails satellite remote sensing and other tools based on its global coverage, high spatial resolution, long-term monitoring capabilities, non-invasiveness, and cost effectiveness. Conclusively, RS has improved soil property measurements using various methods, but more research is needed for calibration, sensor fusion, artificial intelligence, validation, and machine learning applications to enhance accuracy and applicability.

Keywords: remote sensing (RS); soil properties and variability; multispectral analysis; satellite sensing; proximal sensing

Citation: Abdulraheem, M.I.; Zhang, W.; Li, S.; Moshayedi, A.J.; Farooque, A.A.; Hu, J. Advancement of Remote Sensing for Soil Measurements and Applications: A Comprehensive Review. *Sustainability* **2023**, *15*, 15444. https://doi.org/10.3390/su152115444

Academic Editor: Jan Hopmans

Received: 1 October 2023
Revised: 26 October 2023
Accepted: 27 October 2023
Published: 30 October 2023

1. Introduction

Soil is a diverse and intricate natural asset and the foundation for nearly all agricultural production endeavors because its physiochemical properties and nutrients play essential functions in understanding the ecosystem's dynamics [1–3]. These factors help researchers make informed decisions about various agricultural operations, allowing decision-makers to make the correct choices day-to-day [4,5]. Soil measurements that involve the systematic collection of data are essential for managing and understanding the health and quality of the soil by providing valuable information about various soil properties, such as texture, nutrient levels, structure, composition, pH, degradation, moisture, contamination, organic matter content, and soil erosion [6–8]. Accurate and timely measurements of soil properties are crucial for making informed decisions regarding land use, crop selection, and nutrient management [9]. However, soil measurements have been conducted via field surveys and laboratory analysis, which can be time consuming, labor-intensive, and expensive [10,11]. Remote sensing (RS) techniques have emerged as a promising solution to address these challenges and provide efficient and extensive soil measurement capabilities [12,13].

In the context of soil measurements, RS provides valuable information about the spatial and temporal variations in soil properties and conditions, which involves using satellite, ground-based, or airborne sensors to capture images and data related to soil properties [13–17]. These sensors can detect electromagnetic radiation reflected or emitted by the soil, which can then be analyzed to derive valuable information about its properties and interpret the information to gain insights into soil conditions, assess land degradation, manage agricultural practices, and make informed decisions for sustainable land use [18–20]. RS data come from various sources, including satellites, aerial photography, Global Position System (GPS), Light Detection and Ranging (LiDAR), ground-based sensors, radar systems, crowdsourcing, social media platforms, and historical records [5,21,22]. Each reference provides unique and valuable information that contributes to our understanding of the Earth's environment [23].

Remote sensing continues to evolve, and with technological advancements, we can expect even more data sources to emerge [24,25]. This technology has become increasingly important in modern agriculture because it provides valuable insights into crop health, yield estimation, and soil properties such as moisture content, temperature, organic matter content, and texture [26,27]. Multiple techniques have been employed to analyze soil, such as multispectral analysis, thermal infrared analysis, passive microwave remote sensing, radar remote sensing, and the fusion of multispectral and thermal infrared data [17,28,29]. While there are certain limitations to remote sensing methods for soil measurements like the challenges in capturing soil heterogeneity, soil depth, spectral and spatial resolution, limited accessibility, calibration, and validation requirements [8,20,30], their advantages, including broad coverage, non-invasiveness, non-destructive, accuracy, cost effectiveness, and repeatability, render them indispensable resources for agriculture, soil management, and environmental monitoring [21,31,32].

RS minimizes disturbance to the soil ecosystem while providing valuable insights into soil properties and associated vegetation dynamics, and by integrating with other geospatial technologies (land cover, topography, climate, and hydrology), decisions regarding land management practices and policies are adequately informed. Overall, remote sensing has revolutionized soil measurements by providing a cost-effective, efficient, and scalable approach to assess and manage soil health [33]. RS can revolutionize agriculture by providing valuable information about crop health, soil conditions, water availability, and other important factors, and it enables farmers to make informed decisions and optimize their farming practices. Monitoring large areas efficiently and detecting potential issues early on is crucial for ensuring food security, minimizing environmental impacts, and promoting sustainable agriculture [34,35]. Based on this review, we show some state-of-the-art RS techniques, data analysis, and application in agriculture, particularly in soil measurements, via a schematic framework presented in Figure 1.

From Figure 1 above, it can be deduced that RS processes extract meaningful information from remotely sensed data, which can be collected by sensor mounts which capture data in different parts that will be subject to analysis either via spectral, geospatial, or machine learning tools in each of the analysis methods. The estimation of the soil will be carried out via data analysis based on soil texture, moisture, properties, organic content, and nutrient status, where the soil measurements obtained can be presented in soil mapping or visualization or for research reports like publications or policy recommendations, as well as for decision support systems that entail agriculture planning, environmental management, and land use optimization [36].

For analyzing soil, various RS technologies can be used, such as satellite imagery, a popular method that can deliver high-resolution information on temperature, vegetation cover, and soil moisture [37]. Utilizing airborne sensors such as LiDAR or hyperspectral imaging systems is another choice that can offer even more specific data on soil characteristics [38]. The data collected are then used to generate precise soil property maps, which can guide land-use planning, agricultural practices, and environmental management [15,39]. A combination of two or more RS techniques can assess the impact of climate change on soil moisture levels or predict soil erosion risks in specific regions by incorporating various datasets into a geographic information system (GIS) to visualize and analyze complex spatial relationships, leading to more informed land management decisions [40,41].

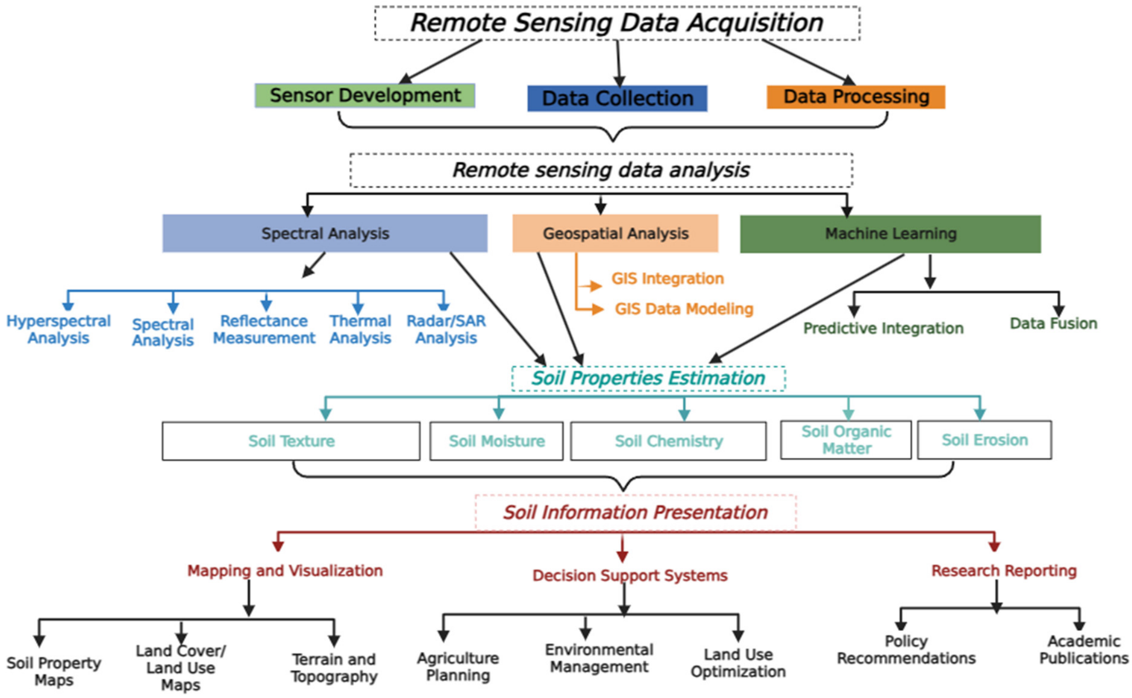

Figure 1. Schematic framework of remote sensing techniques, data analysis, and applications in soil measurements.

Via the application of electromagnetic energy, RS determines the characteristics of a target object from a distance. RS data in soil measurements have the potential to provide broad coverage of soil parameter information [30,42]. Instead of collecting data from individual soil samples, remote sensing data can be used to analyze soil properties across large areas, making them a valuable resource for agriculture, soil management, and environmental monitoring [43,44]. The data are also highly repeatable, allowing changes in soil properties to be detected over time [45,46]. For the advancement of seasonal crop development patterns, changes in soil surface moisture, texture, mineral composition, organic carbon, and other characteristics can be monitored on a regional scale from week to week [47–49]. However, further studies are required to advance remote sensing techniques for measuring soil properties, including calibration and validation, sensor fusion, machine learning, and artificial intelligence applications. Addressing these research gaps can improve the accuracy and applicability of RS-based soil property measurements.

Recent studies have indicated that the adoption of RS technologies holds promising potential to transform soil measurement practices by offering comprehensive, scalable, and cost-effective solutions [50,51]. This review paper delves into the RS technique's latest advancements and applications in soil measurements. By analyzing the capabilities and limitations of remote sensing platforms, spectral and spatial analysis methods, temporal monitoring, and integration with other datasets, this paper aims to inspire the use of remote sensing in soil measurement applications. Ultimately, these innovations can contribute to sustainable land management practices, elevate agricultural productivity, and facilitate informed decision making for environmental conservation. This review paper will explore the remote sensing methodologies employed for soil measurements, including active and passive sensing techniques. Active systems such as radar, LiDAR, and ground-penetrating radar emit signals and record the response to detect soil properties. On the other hand, passive systems rely on the measurements of reflected or emitted electromagnetic radiation from the soil surface to infer soil properties [52,53]. Furthermore, this review paper aims at the following:

- Highlighting the different detection methods, types, parts, and applications of RS techniques in soil measurements;
- Analyzing the advantages and disadvantages of the measurements of soil properties;
- Elucidating the advancements in data processing techniques and approaches used to analyze remote sensing data for soil measurement applications;
- Exploring the potential of RS for precision agriculture and site-specific soil management. Monitoring soil variability at high resolution and in real-time allows for targeted interventions, optimized resource allocation, adequate yields, enhanced environmental sustainability, and minimized inputs;
- Providing a deep understanding of the advancements in RS for soil measurement application;
- Synthesizing the latest research, methodologies, and applications to adequately update harnessing the power of RS for soil resource management, environmental monitoring, and agricultural sustainability.

A thorough investigation of relevant papers was undertaken to assess the existing literature on the advancing RS measurements of soil properties. To ensure a well-organized, coherent, and comprehensive coverage of all the essential aspects related to studying the advancement of using RS in the measurement of soil properties, this paper follows a well-structured arrangement. Section 1 covers background information on soil measurements, their importance, traditional methods, RS and its applications in various fields, and the importance of measuring soil properties for agricultural purposes; it highlights the major contributions to the review. Section 2 addresses the overview and explanation of the RS methods, types, parts, and key soil properties with various RS applications. The advances, case studies, and applications of RS for soil properties and future trends are discussed in detail. Section 5 highlights the advantages and limitations of RS methods over other measurement methods for soil properties. Substantive conclusions, recommendations, and suggestions for further studies are also provided.

2. Remote Sensing Methods for Soil Measurements

In agriculture, RS methods are increasingly used to gather data on crop health, soil moisture, erosion, and soil characteristics across large areas [54]. These techniques utilize various sensors and platforms to collect data from a distance, allowing for the large-scale, accurate, fast, and non-destructive analysis of soil characteristics [26]. The sections discuss the overview and explanation of remote sensing methods for soil analysis (spectral reflectance analysis, thermal infrared imaging, and radar remote sensing), key soil monitoring (e.g., moisture contents, organic matter, texture, fertility, and temperature) with various RS applications, as well as the RS parts used in soil monitoring. The utilization of technology in understanding the environment is truly unique and empowers us to make well-informed decisions [55–57].

2.1. Remote Sensing Methods in Soil Measurements

2.1.1. Spectral Reflectance Analysis

Spectral reflectance analysis is one of the most widely used RS techniques for soil property assessment [58]. It involves measuring the reflectance of electromagnetic radiation across different wavelengths, typically in the visible and near-infrared regions [59]. Different soil properties exhibit unique spectral signatures, allowing for their identification and quantification. The reflectance patterns observed in different wavelength ranges can provide information about various soil properties [60]. For example, the visible range

(400–700 nm) can indicate the presence of organic matter and iron oxide minerals. Near-infrared reflectance (700–1300 nm) is sensitive to soil moisture content and clay mineralogy. Shortwave infrared reflectance (1300–2500 nm) can be used to estimate soil organic carbon content and identify specific minerals like gypsum or calcite [61].

2.1.2. Thermal Infrared Imaging

Thermal infrared imaging is another remote sensing method for assessing soil properties. It involves measuring the emitted thermal radiation from the Earth's surface in the longwave infrared region (8–14 µm) [62]. Soil temperature is strongly influenced by moisture, texture, and organic matter content. By analyzing thermal infrared images, it is possible to estimate soil moisture levels and identify areas with variations in water availability [16]. Thermal infrared imaging can also detect variations in soil compaction and fertility. Compacted soils have lower porosity, reducing water infiltration rates and increasing surface temperatures [63]. By analyzing thermal patterns, it is possible to identify areas of soil compaction and assess their impact on plant growth.

2.1.3. Radar Remote Sensing

Radar remote sensing utilizes microwave signals to assess soil properties [64]. Microwaves can penetrate the soil surface, allowing for the measurement of subsurface characteristics. Radar sensors use electromagnetic waves to move down the soil, which can provide updates about moisture content and texture [65]. Radar sensors can provide information about soil moisture content, surface roughness, and texture with microwave signals interacting differently with different soil properties. By measuring the backscattered radar signal, which, when wet, has a higher dielectric constant, resulting in increased signal attenuation, it is possible to estimate soil moisture content [66]. Surface roughness can also be assessed using radar remote sensing, as rougher surfaces scatter more microwave energy. Soil texture, which refers to the relative proportions of sand, silt, and clay particles, can also be estimated using radar remote sensing. Different soil textures exhibit distinct radar backscatter responses due to variations in surface roughness and dielectric properties [67].

2.2. Remote Sensing Parts in Soil Measurements

RS techniques have significantly advanced in soil measurements using satellite, airborne, and ground-based methods for measuring soil erosion, identifying areas with high soil moisture content, and mapping soil nutrients [68]. It is also helpful in detecting soil contamination and evaluating soil fertility [69]. Figure 2 gives a thorough overview and stages of RS methods for soil analysis (spectral reflectance analysis, thermal infrared imaging, and radar remote sensing); tools for soil monitoring (e.g., LiDAR, hyperspectral, visible infrared, scanners, cameras, etc.) with various RS applications, as well as the RS parts used in soil monitoring.

RS is particularly beneficial in areas where soil samples are scarce or traditional sampling methods are impractical due to the terrain [70]. Furthermore, RS can provide data at various scales, ranging from individual fields to entire watersheds, facilitating a more extensive comprehension of soil variability. Remote sensors can offer high-resolution data across broad areas, mapping soil parameters such as organic carbon concentration and moisture content [71]. Hyperspectral RS has proven effective in accurately mapping soil properties and detecting erosion [72]. With the changes in land cover patterns, RS can identify erosion-prone areas and help implement soil conservation measures and land management strategies. However, in the case of an unmanned aerial vehicle (UAV) camera observing at nadir, the view zenith angle (VZA) was specified as 0°, as depicted in Figure 3. The VZA will move the sensor to the leading solar plane if the results are positive. Conversely, negative numbers indicate that the VZA is moving backward, with the sensor pointing away from the sun.

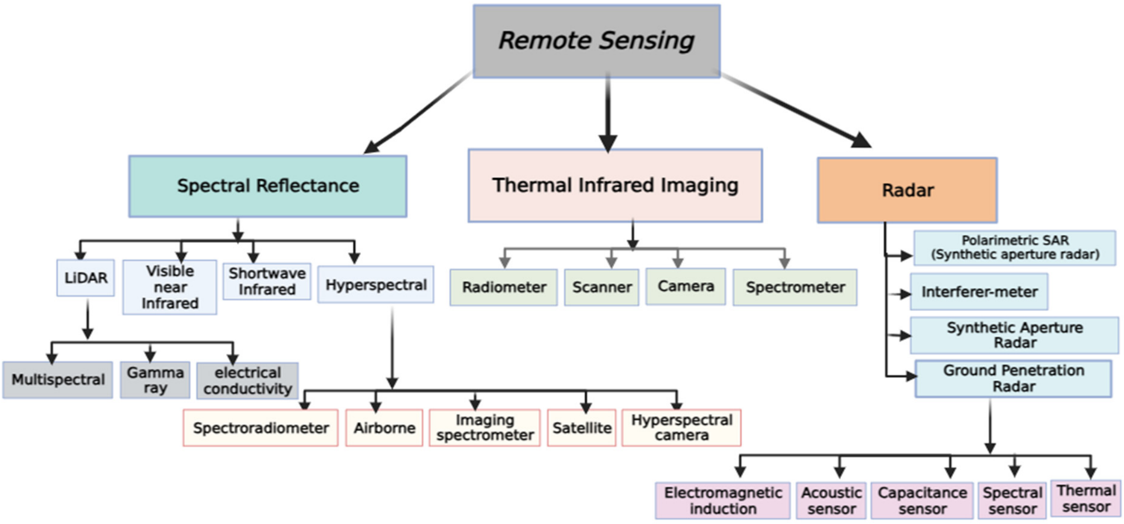

Figure 2. Remote sensing methods and types in soil measurements.

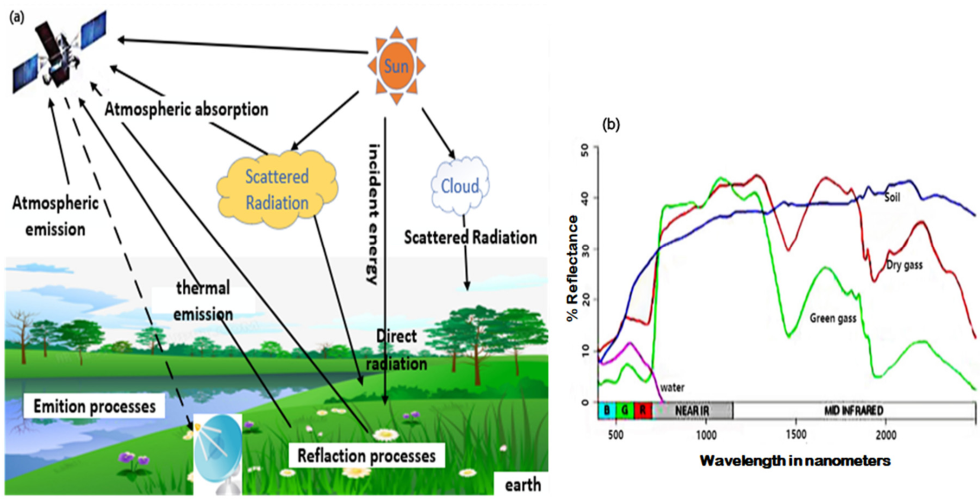

Figure 3. Basic concept of remote sensing (**a**) Multi-angle remote sensing data acquisition processes (**b**) View zenith angle (VZA) time series reflect data.

On the upper left of the diagram, color bars beneath the UAV depict the four types of remotely sensed data. The data type directs scientists to the relevant data products, indicated by the circles on the right-hand side. The data output items are grouped based on their estimated delivery time. Some crucial measures rely on picture indices and do not require multiple image calibrations. The white circles on the left side of the diagram indicate data acquired at significant field sites for this inquiry. After spectral retrieval, additional analysis can be performed. The algorithms on the lower right require geographic information system (GIS) inputs to geolocate and register the picture to ground coordinates, which explores the extent to which geographic registration is possible in real time [73]. The schematic picture in Figure 4a indicates the process by which the satellite acquires a network via the UAV, which receives signals and acquires data from the field (agricultural field—soil and air) and reflects the base station where data is processed and transferred via the internet for interpretation and analysis (relevant data extraction, data consensus), and finally transmits data to the UAV for application to soil monitoring.

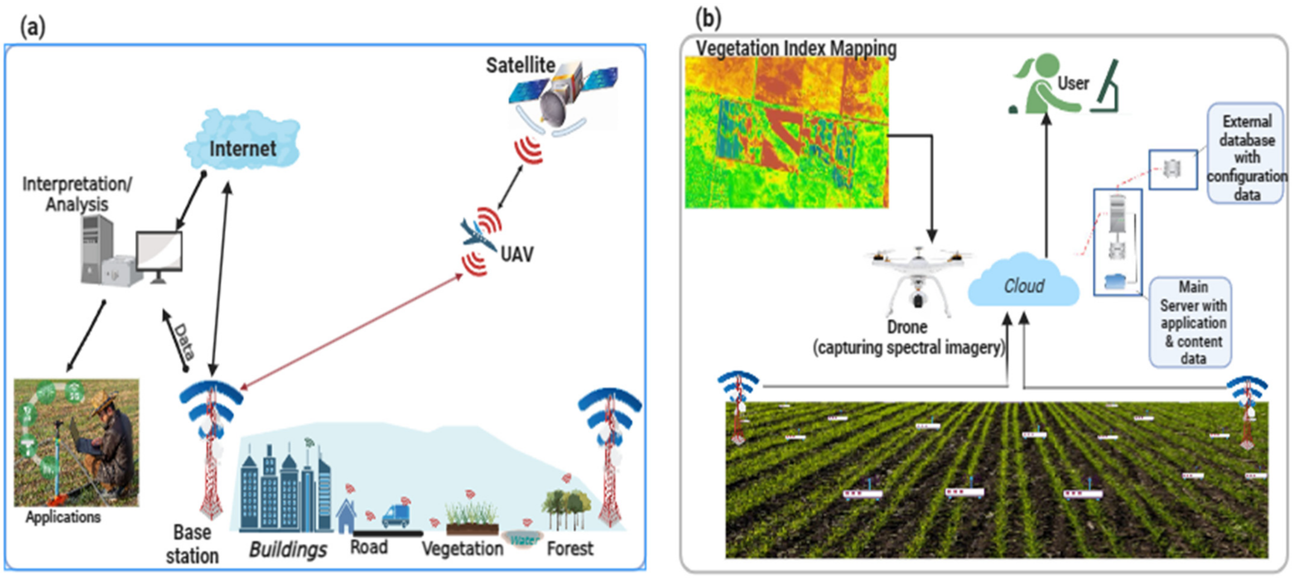

Figure 4. Applications of remote sensing: (**a**) integrated UAV concepts; (**b**) remote sensing system operation.

Figure 4b illustrates a wireless sensor network system with multiple nodes. Each node comprises a soil moisture sensor to monitor water level, a soil temperature sensor, and air temperature and humidity sensors. In conclusion, RS methods offer valuable tools for assessing and monitoring soil properties. Spectral reflectance analysis provides insights into soil characteristics based on their unique spectral signatures. Thermal infrared imaging allows for estimates of soil moisture content, compaction levels, and fertility variations. Radar remote sensing enables the assessment of soil moisture content, surface roughness, and texture. These techniques contribute to a better understanding of soil dynamics and support informed decision-making in agriculture, land management, and environmental studies.

2.3. Remote Sensing Application in Soil Measurements

RS has emerged as a powerful tool for studying various soil properties, and its applications range from estimating soil moisture content and monitoring soil erosion to mapping soil organic carbon content and assessing soil salinity levels [5]. It involves acquiring of data from a distance, typically using satellite or airborne sensors, to gather information about soil properties [74]. These data can then be analyzed to extract meaningful insights about soil properties and their applications (Table 1). The applications of RS to soil properties are diverse and encompass several important aspects of soil science. For example, near-infrared reflectance can estimate vegetation cover and biomass production, while thermal infrared measurements can measure soil moisture content. By combining data from multiple wavelengths or sensors, we can better understand soil characteristics and their interactions with the environment [75,76]. It should be noted that by providing valuable insights into these soil properties, remote sensing contributes significantly to sustainable land management practices, agricultural productivity, and environmental conservation efforts.

Table 1. Comparison of different remote sensing applications for soil measurements.

Soil Property	Remote Sensing Methods	Descriptions	References
Soil Reflectance	Optical and multispectral imaging	• Method/Advantage: Non-destructive from different wavelength or spectral bands; rapid • Aims: Assessing soil properties (soil health and fertility) over large areas • Findings: Analyzing the reflectance patterns obtained to gain insights into various aspects of soil fertility and health.	[77]
Soil Albedo	Optical and multispectral imaging	• Method/Advantage: Effective capturing of images; non-destructive and non-contact • Aim: Soil surface at different wavelengths and analyzing the reflectance values obtained. • Findings: Detect subtle differences in soil composition and land cover changes and evaluate land management practices	[78]
Spectral Signatures	Spectral analysis, hyperspectral imaging	• Method/Advantage: Efficiency, reliability, and accurately capturing images • Aim: Analyzing the reflectance pattern in spectral signatures • Finding: Identifying specific wavelengths or spectral bands that are most sensitive to soil properties and composition	[79]
Spectral Indices	Spectral analysis, multispectral imaging	• Method/Advantage: Wide coverage and accurate • Aim: To measure the intensity of electromagnetic radiation at each wavelength • Finding: Collecting data that capture reflectance or emission spectra across a wide range of wavelengths	[80]
Soil Temperature	Thermal infrared imaging, thermal sensors	• Method/Advantage: Non-invasive, non-destructive, high accuracy and resolution, real-time monitoring, passive and multispectral imaging • Amis: Monitoring temporal changes in soil temperature • Findings: Capture reflectance or emission spectra across a wide range of wavelengths	[81]
Soil Moisture	Microwave RS, Thermal sensors	• Method/Advantage: All-weather capability, penetration depth, surface roughness sensitivity, vegetation penetration • Aim: Monitoring of soil moisture content • Findings: Interact and penetrate differently with soil depending on its moisture content, texture, and structure	[52]
Soil Roughness	Microwave remote sensing, LiDAR	• Method/Advantage: High accuracy, non-invasive, cost effective, high resolution, multispectral capabilities • Aim: Determining the soil properties data and reflected signals • Finding: Soil factors like topography, surface roughness, and vegetation height are determined	[43]
Soil Electrical Conductivity (EC)	Geophysical methods (EM, GPR)	• Method/Advantage: Real-time monitoring, rapid, multi-parameter assessment, integration with other data sources • Aim: Electromagnetic infrared for sensing soil surface • Finding: Obtaining detailed soil moisture and salinity maps by scanning the soil surface with EMI sensors	[82]

Table 1. *Cont.*

Soil Property	Remote Sensing Methods	Descriptions	References
Soil Permeability	Geophysical methods (GPR)	• Method/Advantage: Non-destructive, high-resolution, cost-effective, rapid, and non-invasive approach • Aim: Using different physical principles to analyze the properties of the soil • Finding: Improved the understanding and management of soil permeability by allowing for repeated measurements without disturbing the soil	[40]
Soil Composition	Multispectral and hyperspectral imaging	• Method/Advantage: Enhanced spectral and spatial resolution, non-destructive, rapid data acquisition. • Aim: Measurement and application of RS in soil properties • Finding: Soil compositions like soil mineral composition, organic carbon content, and soil contamination are determined	[83]
Vegetation Cover	Multispectral and hyperspectral imaging	• Method/Advantage: Improved spectral and spatial resolutions, non-destructive, non-invasion, allow for temporal monitoring quantitative measurement • Aim: Analyzing the reflected or emitted radiation from vegetation • Finding: Accurate information about vegetation cover dynamic	[33]
Soil Topography	LiDAR	• Method/Advantage: High-resolution, wide coverage, rapid, high accuracy and repeatability • Aim: Studying soil erosion, landform characterization, and topographic changes with LiDAR • Finding: Estimate vegetation height, canopy structure, managing soil ecosystem, and influence organic matter accumulation	[38]
Soil Surface Characteristics	Radar imaging	• Method/Advantage: Wide area coverage, all-weather capability, high spatial resolution, and non-destructive • Aim: Soil surface characterization • Finding: For sustainable land management and environmental planning via soil surface characterization	[39]
Change Detection	Multi-temporal analysis, radar, optical imagery	• Method/Advantage: High accuracy, reliability, wide area coverage, non-invasive, flexibility, repeatability, and non-linear change detection • Aim: Estimation of soil moisture content and surface roughness • Finding: Detect the changes in underground features like bedrock or water tables	[84]
Data Fusion and Integration	Integrating multiple remote sensing data	• Method/Advantage: Improved spatial resolution, accuracy, reliability, and broad coverage • Aim: Combination of datasets from different sensors or platforms • Finding: Overcoming the limitations associated with individual sensors, such as limited spatial coverage or spectral resolution	[56]

Table 1. *Cont.*

Soil Property	Remote Sensing Methods	Descriptions	References
Soil pH	Thermal infrared imaging, thermal sensors	• Method/Advantage: Rapid, non-destructive, spatially explicit, cost-effective, and non-contact measurement • Aim: Estimation of soil pH with thermal infrared imaging • Finding: Nutrient availability and microbial activity in the soil can be detected	[15]

In Table 1, the comparison of different RS methods used in soil measurements was examined and discussed, which covers several soil properties and describes the RS methods involved in the measurements. RS has shown valuable skill in monitoring daily or temporary soil characteristics, which change with time based on factors such as time of day, weather, season, and climate. Table 1 further shows that RS applications for soil measurements significantly advanced our understanding and offer valuable insight into soil processes, properties, erosion, moisture content, fertility, and other crucial factors influencing agricultural productivity and environmental management, such as spectral reflectance analysis, thermal infrared imaging, LiDAR, and hyperspectral imaging, which are critical techniques used in this field. Each technique has its strengths and limitations, and their selection depends on the study's specific objectives and the desired level of detail required for soil analysis.

RS technology is a cost-effective and efficient tool for soil monitoring. It helps scientists and policymakers make informed decisions about agricultural practices, land use planning, and environmental conservation. Soil characteristics can be accurately detected and monitored via laboratory analysis and real-time measurements [55,56]. Due to the increasing demand for information, spectral responses can be utilized to evaluate surface and subsurface soil properties, but soil property monitoring techniques need updating [57]. Nevertheless, the benefits of remote sensing data in soil measurements far outweigh the limitations, making it an indispensable tool for soil scientists and environmental managers [45].

2.4. Remote Sensing Techniques in Soil Measurements

Remote sensing (RS) tools encompass many technologies and techniques that enable us to gather valuable data about the soil from a distance. Satellite-based tools offer global coverage and continuous monitoring capabilities (equipped with sensors that capture data in different wavelengths of the electromagnetic spectrum, including visible, infrared, and microwave) but have limitations regarding spatial resolution and cloud cover interference. In contrast, aerial-based tools provide higher spatial resolution for detailed mapping and monitoring of smaller areas but are limited by flight restrictions and higher costs (Table 2). Ground-based devices offer high-resolution data at close range and can provide detailed information about specific areas or objects of interest. Each type of remote sensing tool has its advantages and limitations, making them suitable for different applications and research needs.

Based on Table 2 above, various remote sensing tools offer distinct benefits for measuring soil, as satellite-based remote sensing can provide global coverage and long-term monitoring but may not offer a detailed spatial resolution. On the other hand, airborne remote sensing provides higher spatial resolution and more detailed information but requires specialized equipment and is more expensive. Ground-based remote sensing tools offer direct measurements at close range with high spatial resolution but have a limited coverage area. Lidar remote sensing can give detailed information about topography and vegetation structure but comes with cost considerations. Ultimately, selecting the most suitable remote sensing tool will depend on the specific study objectives, the scale of analysis, and available resources.

RS techniques such as thermal, radar, hyperspectral, and optical sensors are used for soil analysis to detect the characteristics of objects and materials from a distance during soil property measurement [21,95]. Most detection modes depend on photons tested at their related electromagnetic (EM) frequency [96] because the frequency and force of energy reflected or transmitted by the highlights in the scene being detected are usually identified and recorded by distant sensors. It should be noted that the electromagnetic radiation spectrum (EMR) comprises particles that travel in waves, and visible light is the most visible form of electromagnetic magnetic radiation.

Table 2. Comparison of different remote sensing tools in soil measurements.

Remote Sensing Tools	Advantages	Disadvantages	References
Satellite Imagery	Provides wide coverage, regular data capture, multispectral and hyperspectral capabilities for detailed analysis	Limited spatial resolution and control over data acquisition	[37,85]
Unmanned Aerial Vehicles (UAVs) and Drones	High-resolution imagery, offering flexibility in flight paths, cost effective for small-scale projects, and data acquisition timing	Limited coverage area and regulatory restrictions on flight altitude	[38,50,86,87]
LiDAR (Light Detection and Ranging)	Comprehensive data on topography, vegetation structure, canopy height high-resolution, 3D mapping capabilities and can penetrate vegetation cover	Expensive and limited penetration capabilities	[88,89]
Thermal Imaging	Non-destructive, continuous monitoring measures soil temperature and moisture, identifying water stress and irrigation needs	Requires clear sky conditions for accurate temperature and limited to surface soil temperature monitoring	[81,90]
Soil Moisture Sensors	Accurate monitoring, directly measuring soil moisture content at different depths, providing real-time data and integration for continuous monitoring	Limited coverage area and requires physical installation in the soil	[57]
Hyperspectral imaging	High spectral resolution, improved detection, classification capabilities, enhanced data analysis, non-destructive and non-contact	Limited spatial coverage, high data processing, complexity, costly, limited availability and accessibility	[33,38,79]
Ground-based remote sensing	High spatial resolution, real-time data collection, efficiency, and direct measures reflectance at different wavelengths to estimate soil composition and nutrient contents	Physical access to the soil surface can be challenging in certain terrains or land uses	[52,69]
Radar system	Versatility, all-weather capability, depth perception, high resolution, large-scale coverage, long-distance capability, and ability to combine multiple radar measurements	Limited resolution, complexity, cost, limited spectral information, and interference	[69]
Infrared (IR) sensors	Non-contact, versatile application, fast and real-time data, wide coverage and high accuracy	Limited depth perception, influenced by environmental factors, limited penetration capability, cost, and limited spectral resolution	[90,91]

Table 2. *Cont.*

Remote Sensing Tools	Advantages	Disadvantages	References
Optical sensors	High spatial resolution, multispectral capabilities, wide coverage, long-term data collection, and cost effective	Susceptibility to weather conditions, limited visibility, temporal resolution, limited data processing, and interpretation	[78,92–94]
Aerial Photography	High spatial resolution, flexibility, and rapid deployment	Limited coverage, weather dependency, and higher cost	[31]
Microwaves	Mapping vegetation, all-day operation, reliability, effectiveness, and obtaining data in adverse weather conditions	Lower spatial resolution, limited spectral information, reliance on active sensors, complex data interpretation, and limited availability of free data	[64,72]

It is worth noting that mechanical sensors measuring soil penetration resistance are often used and combined with other sensors [42,97,98]. This is demonstrated in various studies on remote sensor measurements, as shown in Table 3, whose applications range from soil compaction assessment [99] to 3D modeling of soil layers.

Table 3. Reviewed studies on remote sensors for measuring soil and related properties.

RS Method	Remote Sensor for Measuring Soil and Related Properties	Investigated Parameters	Applications	Highlights	References
Hyperspectral Imaging	Apparent Electrical Conductivity (ECa) (two sensors)	Cation exchange capacity; organic carbon; electrical conductivity; Depth to argillic horizon	The ECa of the two sensors should be compared. It is necessary to estimate a variety of soil properties.	The study improved soil properties estimation by combining ECa sensor fusion and data from various fields, with the highest R^2 predicted for the depth to the argillic horizon.	[99]
Reflectance Spectroscopy	ECa; Crop yield	pH; Calcium carbonate, elevation; stream power index; slope; organic carbon, wetness index; particle size distribution	To create a map of various soil properties and crop yield estimation, and determine variables for delineation management	The study found ECa was positively correlated with clay and negatively correlated with sand content, indicating field discrepancy. Landscape location and soil moisture were linked to management zones, and crop yields varied by management zone	[100,101]
Airborne LiDAR	ECa (two sensors	Sodium; Calcium, Potassium; Magnesium; Sulphur; Nitrogen; Phosphorus; cation exchange capacity; particle size distribution soil pH; soluble salts (implied)	Determine the relationship between ECa and several soil characteristics	ECa was predicted in six research locations using clay content, silt content, soluble salts, Na, Ca, Mg, and CEC, with strong correlations with clay content and Mg in four fields	[102]
Electrochemical Sensor	Visible-Near Infrared spectra; ECa	Organic Carbon; Electrical Conductivity; Carbon-to-Nitrogen ratio; Particle size distribution; Soil pH	Multiple soil qualities were estimated	With an R^2 of 9.3×10^{-3}, Visible/near-infrared spectra alone, ECa alone, and sensor fusion collectively produced the best soil property estimates	[85,103]
Electrochemical Sensor	Crop yield, Total carbon, Mechanical resistance; Capacitance probe; output voltage; Cone index	Bulk density, Organic matter; Clay content	Multiple soil properties were estimated and mapped. Crop yield mapping	The study estimated sand content, silt, and clay content with the highest R^2 (0.90) at 0 to 28 cm from R, and found similar patterns in bulk density, mechanical resistance, and organic matter on crop yield maps	[104]

The platform's altitude, the image's spatial resolution, and the reduced return frequency for arranged sensors are the distinguishing factors for these platforms and imaging systems [105]. Calculating different soil properties can be a valuable tool for farmers, gardeners, and others who work with soil [106]. When analyzing temporal patterns in soil and plant properties, the frequency of data collection is a crucial factor to consider. However, it is essential to note that cloud cover can affect RS images from satellites and aerial platforms, although it has a more negligible impact on ground-based remote sensing [107]. Utilizing RS is an effective method for evaluating the surface characteristics of the ground from afar. This technique assesses the chemical and physical properties of the soil matrix by measuring the upwelling electromagnetic radiation emitted or reflected from the soil [108]. With the information obtained via RS, we can distinguish differences between soil extrapolate characteristics and the soil surfaces from the radiation observed. RS technologies are widely acknowledged for providing a valuable tool for obtaining geographically and chronologically diverse information to assess soil properties accurately [109]. To account for geographically varying crop responses, information on soil variability may need to be coupled with plant information in both scenarios to improve in-season fertilization [21,31,32]. Understanding how things change over time is made more accessible by analyzing spatiotemporal changes. High-resolution tracking of spectral and spatial data changes is possible with the aid of RS. It can gain an understanding of how our environment changes because of its capacity to observe and track changes in great detail over time [110].

3. Data Sources and Platforms Used in Soil Measurements

Remote sensing data is collected from various sources, including satellite data providers, government agencies, and open-access datasets. These sources provide valuable information for various applications, such as environmental monitoring, disaster management, urban planning, and agriculture [111].

Satellite data providers are private companies that own and operate satellites equipped with sensors capable of capturing images and other data about the Earth's surface [112]. They carry sensors and cameras that capture images and data from space. These sophisticated instruments collect information at different wavelengths, allowing scientists to study various aspects of the Earth's environment [113]. Satellites provide a global perspective, covering large areas and collecting data regularly, making them invaluable for monitoring long-term trends, such as climate change [114,115]. Some well-known satellite data providers include DigitalGlobe (now part of Maxar Technologies), Airbus Defense and Space, Planet Labs, and GeoIQ [116–118]. These companies offer high-resolution imagery with varying spatial and temporal resolutions to meet user requirements [119]. They often provide commercial services to industries like defense, agriculture, energy, and infrastructure development, and they heavily rely on the commercial services provided by these companies to enhance their operations and decision-making processes.

Government agencies also contribute significantly to remote sensing data by operating satellites or partnering with satellite data providers [120,121]. RS companies provide high-quality imagery that caters to the diverse needs of users with a wide range of spatial and temporal resolutions, allowing them to meet specific requirements [27,122]. They operate satellites or collaborate with data providers to gather valuable information [120,121]. For instance, NASA (National Aeronautics and Space Administration) in the United States operates several Earth-observing satellites, including Landsat and EOSDIS (Earth Observing System Data Gateway), which have revolutionized our understanding of the Earth's dynamics and environmental changes and are regulated by the USGS (United States Geological Survey) [123,124]. In addition to its role as a satellite data provider, ESA (European Space Agency) provides free access to various datasets, including the Sentinel missions, via the ESA Data Dissemination Service (EDDS) [125–127]. GEE (Google Earth Engine) combines data from multiple sources, including Landsat, Sentinel, and other missions, allowing users to analyze and visualize remote sensing data using Google's computational infrastructure [121,128].

Satellite-Based Platform as Data Sources in Soil Measurements

Satellite-based platforms have gained popularity for soil measurements because they frequently cover large areas and revisit them [129]. These platforms use multispectral sensors that capture data across the electromagnetic spectrum, making it possible to analyze different soil properties [130]. The platform for soil measurements that operates via satellite relies on the Landsat program, a joint effort between NASA and the USGS [131]. The satellites used in this program come equipped with advanced sensors like the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) [113,132]. These sensors can effectively capture data across various spectral bands, including visible, near-infrared, shortwave, and thermal infrared [111,133]. Researchers can accurately determine essential soil properties by analyzing the reflectance values within these different bands [111,133].

The ESA's Sentinel program is a widely used satellite-based platform that features the advanced capabilities of the Sentinel-2 satellites. These satellites have a multispectral instrument (MSI) that captures data in 13 spectral bands, from visible to shortwave infrared [29,131]. The captured data can be effectively leveraged to evaluate soil properties, such as soil moisture, vegetation indices, and land cover classification [8,134]. Soil measurements can be conducted with multispectral sensors on land and in the air. In the air, hyperspectral cameras and LiDAR systems are fitted onto airborne platforms such as unmanned aerial vehicles (UAVs) and aircraft [87,135]. Hyperspectral cameras offer in-depth analysis of soil parameters [136]. LiDAR systems, on the other hand, use laser pulses to gauge the distance between the sensor and the ground, yielding valuable information on topography and soil roughness [22].

4. Advances and Case Studies of Remote Sensing Technologies Applications in Soil Measurements

Despite being a challenging task, determining soil quality is essential to environmental monitoring, particularly at the local and regional levels. Accurate soil evaluation is essential to managing soil properties effectively and ensuring sustainability, so it is exciting to see agricultural innovation in this area [137,138]. Understanding the unique characteristics of the soil allows farmers to make tactical decisions at every stage of plant development. An essential step in determining the nutrient content of the soil is soil analysis, followed by targeted treatments to ensure the best possible plant growth [139–141]. By measuring soil properties with RS, we can confidently assist farmers worldwide in achieving their objectives for sustainable agriculture [142].

The efficiency of soil measurements has dramatically increased with the introduction of real-time and near-real-time data acquisition methods. Thanks to the latest satellite imaging technology, images can be captured and processed within hours, allowing scientists to monitor soil conditions instantly [141]. It is comparable to acquiring the latest soil data on demand and accurately. Additionally, the use of machine learning algorithms has transformed soil parameter extraction. These algorithms can automatically analyze remote sensing data and provide insightful information about soil properties [133,143]. It is similar to having a knowledgeable robot that effortlessly gathers data and performs complex calculations [144].

The vegetation indices approach is another algorithm utilized for RS soil monitoring [145]. This technique scrutinizes how plants reflect and absorb light at varying wavelengths, which can provide data on the well-being and efficiency of crops and other vegetation types [146]. Researchers can pinpoint variations in soil properties that may impact plant growth and development by comparing vegetation indices for different land areas. The examination of soil features via remote sensors necessitates the utilization of algorithms to scrutinize the data obtained.

In addition to these remote sensor parts and methods, data collected from RS can be combined with ground-based measurements and laboratory analysis to enhance accuracy and reliability [147,148]. Table 4 demonstrates how other soil properties were determined using various RS types and methods. According to these investigations, RS types and methods may be used to examine various soil parameters.

From Table 4 above, we examined and analyzed various research publications on the use of RS techniques to investigate various soil properties by properly identifying the parts of the RS used for the research, the soil parameter being investigated, the research direction (objective), and the results obtained. It is noted that each of the researchers adopts the sensor parts appropriate for the set-up experiment's objective. For example, Refs. [72,101,102,143,149,150,154–157,159,161] all adopted the use of various tools in spectral reflectance due to their global coverage, high spatial resolution, long-term monitoring capabilities, non-invasiveness, cost-effectiveness, and the fact that their objectives are to assess soil fertility, moisture, nutrients, texture, and composition where spectral reflectance is found suitable.

It should also be noted that when designing an agricultural system, it is essential to incorporate sensors to monitor soil NO^{2-} levels and environmental properties such as soil temperature and moisture [162,163]. Improvements to the algorithm could be made via machine learning, allowing artificial intelligence to gather and integrate empirical data for more accurate decision-making [164,165]. Also, it should be noted that the spectral reflectance approach is a widespread algorithm employed for RS of soil properties, which entails analyzing the reflection of various light wavelengths from the soil surface, which can provide details about its composition and attributes. Researchers can compare the spectral reflectance patterns of different soils to identify dissimilarities in their properties and employ this knowledge to establish models for anticipating soil characteristics based on RS data. By recognizing comparable patterns, RS aids in defining the scope of problems discovered during field scouting [166]. It tracks pest issues, weather conditions, properties, and soil nutrient management challenges. While it took several years to develop remote sensing technology, it could promptly provide trustworthy, cost-effective products and services. Such services are now accessible to help farmers and their advisors make crop management decisions.

Table 4. Case studies of various research on remote sensing technologies in soil measurements.

Soil Features	Sensor Part	Research Directions	Results	Studies
Soil Nitrogen	Aerial hyperspectral images	To examine how the treatments and variable-rate fertilization affected winter wheat growth	In-field variable-rate fertilization was found to decrease winter wheat gaps caused by soil nitrogen content changes	[143]
Soil texture	Hyperspectral images from space-borne PROBA-CHRIS and airborne MIVIS	To assess the texture of the soil, with the performance and limitations of each system (such as the absence of the SWIR band) highlighted	The algorithm was proven to be reliable for optical atmospheric investigations and atmospheric correction	[149,150]
CO_2 leaks	Infrared Imaging Spectrometer/Airborne visible	To detect the CO_2 leaks from the soil	The use of multi-temporal hyperspectral pictures was used to detect vegetation stress signals, revealing CO_2 leaks from the soil.	[151]
Copper concentration	Hyperspectral	Estimating soil using laboratory-based hyperspectral measurements yielded encouraging results	The study reveals that utilizing second-order derivative spectra as input parameters for predicting copper concentration yields the highest estimate accuracy with a coefficient (R^2) of 0.54	[49]
Potassium Content	Hyperspectral Imaging	To better understand soil fertility, close-range hyperspectral imaging was used to quantify potassium content in cinnamon soil	The results showed that this approach works well when the potassium level is high (>100 mg/kg)	[72]

Table 4. *Cont.*

Soil Features	Sensor Part	Research Directions	Results	Studies
Soil property assessment	Electromagnetic Sensor	To identify and classify different soil types based on their spectral signatures	Spectral signatures are unique patterns of electromagnetic radiation emitted by specific materials, creating maps displaying the spatial distribution of different soil types based on sensor data acquisition periods	[33]
Monitoring soil erosion	Aerial photography and satellite imagery	To detect and quantify areas prone to erosion	Identifying areas at risk by analyzing changes in land cover, vegetation density, and topographic features, and implementing appropriate soil conservation measures	[85]
Soil Moisture	microwave radiometry and thermal infrared imaging	To determine the reflected and electromagnetic radiation from soil surface that is influenced by its moisture content	By analyzing these measurements, scientists can estimate soil moisture levels and monitor changes over time	
Organic matter content	Optical Sensor	Assessing and monitoring various soil properties, compactions, and nutrient levels	The data reveal crucial information about organic matter content, nutrient levels, pH, and compaction, which significantly impacts agricultural productivity and ecosystem functioning	[152]
Geographical monitoring, forecasting, and planning	Multispectral Remote Sensing	Identification of bucolic and farming zones using machine learning to combine low- and high-resolution multispectral images	The anticipated method outperformed previous fusion algorithms in improving images and shaping operational evaluation of bucolic and farming regions	[84]
Organic contents	Optoelectronic Sensor	To demonstrate a 1024-pixel flexible optoelectronic sensor array as active materials for an effective neuromorphic vision system	With a responsivity of 5.1×10^7 A/W and a specific detectivity of 2×10^{16} Jones, the device displays neuromorphic reinforcement learning by training the sensor array with a weak light pulse of 1 $\mu W/cm^2$	[78]
Soil properties	Optical sensors	To detect distinct light reflectance frequencies in the near-infrared, mid-infrared, and polarized light spectrum	Optoelectronic sensors distinguished between vegetation and soil plant types, making them visible in an experiment. It determines the soil moisture contents, OM, and clay	[92]
Soil properties	Mechanical Sensor	Investigating relationship between mechanical qualities and soil physicochemical parameters in croplands with four different cultivation durations	Increased bulk density and clay content increased as cultivation period increased, but SOM, Cc, and Cr progressively declined	[153]
Soil density testing	LiDAR Sensor	To calculate the volume of a hole instead of using sand or water as a replacement material	Research shows that 3D point cloud data can replace the need for drilling test holes and measuring volume in soil density testing	[154]

Table 4. *Cont.*

Soil Features	Sensor Part	Research Directions	Results	Studies
Soil surface and furrows	LiDAR	To compare and evaluate two methods for measuring and assessing the cross-sectional area and geometry of a trailing shoe sweep furrow	LiDAR data showed that irrigation increased furrow cross-sectional area in coarse sand by 11% and 34% and in loamy sand by 17% and 15%	[102]
Soil Morphology	LiDAR	Using various LiDAR systems and analyzing data to determine soil characteristics	LiDAR sensors generate light waves that bounce off objects and return to the sensor, which calculates the distance based on the time it takes for the waves to return	[155]
Soil Surface	LiDAR (Terrestial)	To distinguish between maize plants and weeds on the soil surface, a LiDAR sensor is utilized to evaluate vegetation based on distance and reflection measurements	The overall discrimination success rate using canonical discriminant analysis (CDA) was 72.2%	[156]
Topsoil properties	Airborne LiDAR	To estimate the forest topsoil properties with the LiDAR (Airborne) intensity	LiDAR-derived variables were found to be reliable predictors of four topsoil parameters with coefficients of determination (R^2) ranging from 0.46 to 0.66	[157]
Soil characteristics	Electrochemical sensor	To evaluate soil qualities and determine the nutrient content of the soil	The electrochemical sensor replaces the expensive chemical soil testing and complex soil nutrient monitoring by tracking the soil pH, salt, and micro/macro elements	[82]
Soil Quality Assessment	Electrochemical sensor	To identify cutting-edge electrochemical sensing technology for soil quality	The study proposes and develops an electrochemical sensor for soil quality detection, addressing challenges and exploring potential alternatives and potentials	[138]
Soil testing	Electrochemical sensor	An overview is presented of electrochemical sensors that use potentiometry to detect NPK levels in soil	The results show that soil testing with electrochemical sensor is very effective and accurately and quickly detected for experimentation	[158]
Soil nutrient	Electrochemical sensor	A nitrate sensor that uses electrochemical impedance spectroscopy with ion-selective electrode allows direct and continuous soil nitrate monitoring without pre-treatment	Soil nitrate can be measured dynamically with <20% error in a 7-day experiment using the sensor	[85]
Soil nutrients	Optical Sensor methods	Test optical methods for detecting soil nutrients with a portable sensor that senses nutrients in dry soil samples without extensive preparation.	The report details different testing methods for soil nutrients and can be used as a reference for future development of a portable NPK detection sensor.	[152]
Mapping soil properties	Gamma-ray sensor, Electromagnetic sensor	To minimize soil collection and monitoring duration, and expenses and anticipate an appropriate sensor for estimating soil parameters	Using multiple soil sensors is the most effective way to predict soil properties with MLR compared to using just one sensor	[159]

Table 4. *Cont.*

Soil Features	Sensor Part	Research Directions	Results	Studies
Soil properties	Gamma ray spectroscopy	Test gamma-ray spectrometer to predict soil properties in two sandy loam fields	In the energy-windows method, total nitrogen had the highest prediction accuracy (R^2 = 0.75) in the traditional field	[160]
Profile soil properties	Reflectance spectroscopy	Using multi-sensor methods to study on-site soil characteristics	The best model performance was obtained by combining preprocessing with a Gaussian smoothing filter and PLSR analysis. Furthermore, DECS outperformed VNIR spectra in estimating silt, sand, CEC, Ca, and Mg	[101]
Soil moisture monitoring	Gamma-ray spectrometer	To determine the soil moisture contents using gamma-ray emission	The preliminary data suggests that atmospheric radon concentrations affect the sensor's gamma flux. Static measurements were conducted to determine soil moisture content changes over time with precision	[161]
Surface soil moisture	Thermal Infrared	To provide an operational estimation of surface soil moisture at good spatial resolutions	The trapezoid model accurately replicated spatial and temporal patterns of observed soil moisture with a root-mean-square error of 0.06 m^3m^{-3}	[90]
Soil moisture index	Thermal Infrared Sensor	Estimate daily soil moisture with satellite data using land surface temperature changes	The new TIR technique is better at obtaining soil moisture data from satellite info in areas with clear skies and varying cloud coverage	[81]
Soil surface temperature	Thermal Infrared Sensor	To evaluate the possibility of infrared thermography (IRT) sensing in a scalable agricultural	IRT-measured SSTs and soil temperature at 10 cm depth were closely related. Biochar-amended soils showed local SST variability with lower thermal inertia	[91]

The processing of RS data has real-world applications with significant societal implications [167]. For example, using remotely sensed multispectral or radar pictures for urban surveillance, fire detection, and flood prediction has a substantial economic and environmental effect. RS has grown into a multidisciplinary science, with machine learning and signal processing algorithms now playing critical roles in efficiently processing collected data and producing accurate results [168]. Machine learning algorithms are among the other algorithms employed in the RS of soil properties [143]. These algorithms can be trained to detect remote-sensing data patterns corresponding to specific soil characteristics [169]. Predictive models can be formulated using these algorithms, which can then be applied to new datasets to estimate soil properties based on RS data. Algorithms have a crucial function in remote sensing of soil properties by enabling researchers to examine vast amounts of intricate data and identify patterns linked to specific soil characteristics [170].

5. Discussion

RS, which stands for remote sensing, refers to collecting information about an object, area, or phenomenon from a distance, typically using sensors on aircraft or satellites [74]. RS techniques have significantly advanced in measuring soil properties via satellite, airborne, and ground-based methods. These advancements have greatly enhanced our ability to understand and manage soils for various applications such as agriculture, environmental monitoring, and land resource planning. After an extensive review of the RS techniques and methods of soil properties according to their functions, applications, and parts, this review confirmed that RS allows for data collection over large and often inaccessible areas, providing a comprehensive view of soil properties across different landscapes. The advancement uses hyperspectral sensors, which can detect a wide range of wavelengths of light and provide detailed information about soil composition. However, it is noted that traditional field-based soil measurements are time-consuming and labor-intensive. Hence, RS enables rapid data collection over wide areas, reducing the time and effort required for data acquisition, increasing efficiency, achieving higher gross margins, having less environmental impact, and increasing resource use. RS always incorporates vast data from various sources, such as information and expertise about crops, soils, the environment, and economics [171–173]. The commonly used RS methods in soil property assessment are examined below, with Table 5 showing the advantages, limitations, and parameters of the RS methods.

According to the findings presented in Table 5, it can be deduced that each of the RS methods has its advantages and limitations, indicating that soil monitoring can emerge over a wide range, enabling more effective management of its critical resources. However, the choice of methods depends on the specific requirements of the soil measurement task. For example, spectral reflectance would be a suitable choice if the objective is to assess soil fertility and composition. Radar or microwave RS would be more appropriate if the focus is on monitoring soil moisture levels, especially in vegetated areas. Similarly, thermal infrared imaging is beneficial for studying temperature-related soil properties and water stress in plants. It is important to consider the advantages and limitations of each method, as well as the specific context and objective of the soil measurements, to determine the most suitable RS technique.

Table 5. Advantages, limitations, and parameters of remote sensing methods in soil measurements.

Methods	Principles	Advantages	Disadvantages	References
Spectral reflectance	Involves the measurements and analysis of the electromagnetic radiation reflected by the Earth's surface across different wavelengths.	Non-destructive nature Wide range of information about soil properties Spatially explicit nature makes it a powerful tool for understanding soil conditions over large areas. Assess multiple soil properties simultaneously	Require calibration and validation procedures and time consuming Indirect measurements of soil properties, Result validation Complexity of data interpretation Sensitive to external factors	[136,174–176]
Thermal Infrared Imaging	Tools for assessing various soil properties that can acquire insights into characteristics such as moisture content, temperature, organic matter content, texture, compaction, salinity, and erosion via evaluating the thermal patterns and attributes of soils.	Non-destructive and non-contact method Large scale resolution High spatial resolution Capture temporal variations Rapid data acquisition Potential for automation Integration with other RS techniques to obtain comprehensive data	Limited depth penetration Influence of environmental factors Complex data interpretation Expensive Limited spectral information Dependence on weather conditions Lack of standardized protocols	[29,177–179]
Radar Remote Sensing	Can be used to assess soil moisture, soil roughness, and soil composition. Also can provide valuable information about other related parameters such as soil moisture retention, soil erosion, and soil compaction.	All-weather capability Day and night operation Penetration capability Large area coverage Temporal resolution	Limited spatial resolution Complex data interpretation Limited sensitivity to soil properties Cost and accessibility Limited temporal coverage	[12,134,135]

Additionally, combining multiple methods can provide a more comprehensive understanding of soil properties and improve the accuracy of the measurements [33]. RS offers numerous advantages over other methods for measuring soil properties, including large-scale coverage, a non-destructive nature, temporal monitoring capabilities, multispectral capabilities, and rapid data acquisition. Table 6 below enumerates the advantages and limitations of RS techniques based on various parameters. However, it also has limitations related to limited vertical resolution, indirect measurements, and limited sensitivity to certain properties. When comparing different remote sensing tools based on coverage and data management, it is important to consider factors such as spatial resolution, temporal resolution, spectral coverage, and the scale of observation required. Satellite-based tools offer global coverage but with moderate to high spatial resolutions. Aircraft-based tools provide higher spatial resolutions but have limited coverage due to flight paths. Ground-based tools offer high-resolution data but are limited to specific locations. Data management requirements vary depending on the volume and complexity of the collected data.

RS also enables data collection without physically disturbing the soil, which has non-destructive characteristics that are particularly valuable in situations where preserving the integrity of the soil is important, such as in protected or fragile ecosystems [15]. Using various sensors mounted on satellites or aircraft, RS can capture information about soil properties without requiring direct contact or excavation [74]. However, RS techniques provide information about the soil's surface but cannot penetrate deeper layers [33]. The depth of information retrieval depends on the sensor type and wavelength used because some sensors can estimate soil properties at shallow depths (e.g., a few centimeters); others may only capture surface-level characteristics [180–182]. By acquiring data at regular intervals, RS allows for the identification of trends and patterns in soil properties that may not be apparent from a single snapshot [183,184]. RS relies on indirect measurements of soil properties based on spectral reflectance or emission patterns, which are influenced by various factors, including vegetation cover, atmospheric conditions, and sensor calibration. As a result, there can be uncertainties and errors in estimating soil properties. Ground validation via field sampling and laboratory analysis is often necessary to calibrate and validate remote sensing data [185,186]. RS measurements are non-destructive, in contrast to traditional soil sampling, which can alter the soil's characteristics and disturb ecosystems [187].

It is essential to consider factors such as initial investment, operational costs, accuracy, efficiency, and scalability to perform a comprehensive cost-benefit analysis of RS methods for soil measurements. For example, satellite remote sensing boasts minimal upfront expenses and reasonably priced data [188]. On the other hand, airborne sensing requires a significant initial investment due to flight operations and sensor equipment costs. In contrast, ground-based sensing requires a moderate initial investment for sensor equipment but may have higher labor costs. Satellite remote sensing boasts lower operational costs than airborne or ground-based methods, with the only ongoing expenses typically involving data processing and analysis [189]. Compared to airborne RS, which entails additional costs like flight operations and maintenance, or ground-based RS, which incurs ongoing labor costs related to fieldwork, satellite RS is a more cost-effective option. Additionally, RS using satellites is known to be reasonably accurate, while airborne RS is even more precise because it has a higher spatial resolution [190]. However, ground-based RS is the most accurate method, involving direct contact with the soil surface. Satellite RS is highly efficient for large areas, while airborne remote sensing is moderately efficient with higher spatial resolution than ground-based, which is less efficient due to limited coverage. Remote sensing via satellite is highly scalable and suitable for covering large areas, while airborne remote sensing is more effective for smaller regions. However, ground-based remote sensing has limitations as it covers a smaller area and requires more labor.

RS sensors can capture data across different wavelengths of the electromagnetic spectrum and allow for mineral composition, organic matter, and vegetation cover extract. The authors of [191] confirmed that utilizing hyperspectral imaging is one trend in soil properties RS because it involves collections of images at various wavelengths, allowing for detailed analysis of soil properties. RS data can be integrated with other geospatial data to provide more adequate details about factors influencing soil properties, which can be collected to track environmental changes such as deforestation and urbanization [192]. To monitor the health of ecosystems, RS has been used to measure changes in vegetation cover [76]. It can offer a wealth of knowledge regarding soil characteristics, but they need to be calibrated and verified using real-world data [193]. Ref. [194] affirmed that RS data are accessible remotely, making it easier for researchers, policymakers, and land managers to access and analyze the information (using UAVs) quickly and effectively gather high-resolution data on soil properties over broad areas without the need for physical presence in the field [195,196].

Table 6. Comparison of the performance methods of remote sensing on various parameters.

Advantages	Satellite	Aerial Photography	Ground-Based Sensor
Accuracy	Broad overview of large area	Aerial photography achieves sub-meter spatial resolution	provide the highest level of precision in soil monitoring
Analysis	Spatial resolution, frequency of data acquisition, and access to specialized datasets.	Higher spatial resolution	Varies depending on the type and number of sensors required
Monitoring	Well-suited for regional-scale assessments due to its broad coverage	Suitable for local-scale analysis where high-resolution data are required	Ideal for localized soil monitoring where precise measurements are needed
Accessibility	Non-destructive, highly accessible, and high temporal resolution	Non-destructive and becoming more accessible with advancements in technology	Non-destructiveness depends on the specific technique used, but itis generally highly accessible
Coverage	Global coverage and capable of collecting data over large areas	Higher spatial resolution compared to satellite but limited coverage	Detailed information about specific locations or small areas
Data Management	Generates vast amounts of data that need to be transmitted, stored, and processed efficiently	Generates large datasets but with more manageable volumes compared to satellites	produces smaller datasets that can be easily managed using standard data management practices
Disadvantages			
Resolutions	Limited spatial resolution and atmospheric interference	Effect of weather condition	Limited to localize monitoring
Sensitivity	Lack of detailed information at smaller scales	Very sensitive and expert attention	Required standard set-up
Cost	Expensive, especially if it requires frequent updates	Expensive	Expensive and capital-intensive
Availability	Required technical know-how	LiDAR or hyperspectral cameras are less accessible due to their higher cost and limited availability	Vary in terms of temporal resolution
Data transmission	Requires robust infrastructure and specialized software tools for data handling and analysis	Require network and base station for its data transmission	Errors may occur during data transmission
Functions	Highly sensitive and require thorough observation	High cost of flight paths and operational costs	Coverage is limited to the immediate vicinity of the sensor location

Advancement to Decrease Uncertainties in RS Applications for Soil Measurement

Remote sensing applications for soil measurements can be complicated due to various factors, including sensor limitations, atmospheric interference, and the intricate nature of soil properties [197,198]. Nevertheless, progress has been made in remote sensing technologies and methodologies to address these uncertainties [198]. These developments have improved soil measurements' accuracy, dependability, and efficiency through remote sensing. The emergence of high-resolution sensors has brought about a substantial breakthrough in soil measurements via remote sensing, where sensors provide an in-depth analysis of surface characteristics, thereby elevating the precision of soil measurements [199]. Their excellent spatial resolution allows them to sense even the minutest soil variations and uncover previously undetectable patterns in soil, thereby vastly improving comprehension of soil properties [200]. Also, scientists can better understand soil characteristics by merging information from various sensors and sources [95]. When combined, optical and radar sensors enhance the precision of soil moisture content and other essential factors. The amalgamation of data from numerous sensors overcomes the constraints of individual sensors, resulting in a more robust evaluation of soil conditions [200]. This breakthrough is a game-changer, supporting more informed decision-making.

Machine learning and artificial intelligence advancements have significantly improved remote sensing for soil measurements by reducing uncertainties. Machine learning algorithms can recognize patterns in remotely sensed data and accurately predict soil properties [95]. These algorithms learn from large datasets that contain ground-truth measurements, establishing relationships between remotely sensed data and specific soil parameters [199]. By leveraging machine learning techniques, researchers can improve the accuracy of soil measurements obtained via remote sensing and reduce uncertainties associated with data interpretation [197]. Implementing advanced atmospheric correction algorithms is a critical step toward reducing uncertainties in soil measurements obtained via remote sensing [198]. These algorithms are designed to eliminate atmospheric distortions that interfere with the signals received by remote sensing sensors, ultimately leading to inaccurate soil parameter estimations. With the aid of atmospheric models and ancillary data, researchers can obtain more dependable soil measurements that are less prone to error.

Finally, the future trends in RS for soil monitoring include the use of hyperspectral imaging, unmanned aerial vehicles (UAVs), machine learning and artificial intelligence (AI), the integration of multiple sensors, and real-time monitoring with decision support systems [87]. These advancements can revolutionize agriculture and environmental management by providing accurate and timely information about soil properties and conditions. By leveraging these technologies, decisions are easily made to optimize resource allocation, improve crop productivity, and promote sustainable land use practices.

6. Future Directions and Research Opportunities

The potential of RS technologies in soil measurements for various applications is vast. These technologies can aid in precision agriculture, environmental monitoring, and understanding the impact of climate change on soil health [201,202]. However, RS for soil measurements comes with several challenges that need to be addressed, including cloud cover, sensor limitations, and data processing complexities [15,203]. Despite these obstacles, we are confident that ongoing research and technological advancements can help overcome them. Soil measurements should be simple, like digging your hands into the earth [204]. Researchers have been exploring ways to gain a more comprehensive understanding of soil characteristics in recent years [6,9,153,205]. One particularly effective method combines remote sensing data with Geographic Information System (GIS) data [206]. Scientists can analyze patterns and relationships between soil properties and environmental factors by superimposing soil measurements onto spatial maps [207]. It is like piecing together a soil puzzle, where each component contributes to a bigger picture [14,208]. In addition to this, incorporating ground-based measurements is another way to enhance soil analysis [209–212]. Scientists can validate and calibrate remote sensing data by taking direct measurements at specific locations, ensuring its accuracy and speed [212], and double-checking everything to ensure the remote sensing technology is reliable [211,213,214].

In conclusion, the advancements and innovations in remote sensing technologies have significantly improved soil measurement capabilities. Integrating high-resolution imagery, enhanced spectral analysis techniques, and remote sensing with other data sources has enabled more accurate and comprehensive soil assessments [134,162,215]. As these technologies evolve, there is immense potential for further advancements in data acquisition, processing, and developing more sophisticated algorithms. However, data interpretation and validation challenges remain, necessitating ongoing research and collaboration among scientists, technologists, and policymakers. With continued efforts, the future of remote sensing technologies for soil measurements holds promising possibilities for sustainable land management and agricultural practices.

7. Conclusions

RS is an effective tool for measuring soil properties using electromagnetic and acoustic methods, which provides accurate and efficient data about the soil. This review article covers the latest advancements in remote sensing for soil measurements and their applications. It provides a comprehensive overview of this field's various techniques and technologies. The article emphasizes the significant progress made in remote sensing, which can accurately assess soil properties and monitor changes over time. Throughout the review, it is clear that satellite remote sensing is the most effective and reliable method for soil measurement applications. Compared to ground-based or airborne systems, satellite-based sensors have several advantages. They offer global coverage, which enables large-scale monitoring and analysis of soil properties across different regions and landscapes. This extensive coverage is particularly beneficial for agricultural applications, where understanding regional or global soil conditions is crucial for optimizing crop management practices. With satellite RS technology, researchers can accurately monitor soil properties over time because it has extensive coverage, which makes it even more reliable and provides a consistent tool for analyzing soil properties. It is multispectral and hyperspectral capabilities can extract valuable information about soil composition. By leveraging this powerful tool, we can better manage our land resources and gain insights into the state of the soil.

Using satellite remote sensing is a non-disruptive means of soil measurement that avoids interfering with the environment. In contrast to conventional methods that necessitate invasive sampling, this technique permits prolonged monitoring and generates valuable data for extensive analysis. While airborne and ground-based systems have unique benefits and applications, satellite remote sensing is the most efficient and practical approach to soil measurement. Its ability to cover the entire planet, provide uniform data, leverage multispectral capabilities, and do so without causing harm makes it a potent tool. The utilization of satellite remote sensing technology has the potential to enhance soil management practices and foster sustainable agriculture. Nevertheless, further investigations are required to progress soil property measurement methodologies, encompassing calibration, sensor fusion, machine learning, and AI applications. We can improve the accuracy and applicability of remote sensing-based soil property measurements by addressing these research gaps.

Author Contributions: Conceptualization: M.I.A. and J.H.; validation: M.I.A., J.H., S.L., A.J.M., A.A.F. and W.Z.; Resources: M.I.A., J.H., S.L. and W.Z.; Writing—original draft preparation, M.I.A. and J.H.; writing—review, M.I.A., J.H. and A.J.M.; Editing, M.I.A., J.H., A.J.M. and A.A.F.; supervision, M.I.A., J.H. and A.A.F.; funding acquisition: J.H. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the National Natural Science Foundation of China (No. 32071890), the National Key Technologies R&D Program of China during the 14th Five-Year Plan period (2021YFD1700904), and supported by the Henan Center for Outstanding Overseas Scientists (No. GZS2021007).

Institutional Review Board Statement: Not Available.

Informed Content Statement: Not Applicable.

Data Availability Statement: No data sharing is available.

Conflicts of Interest: The authors declare no conflict of interest.

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