Identification of Technical Practices for Climate-Smart Agriculture (CSA) in Indonesia: A Case Study in the Sukabumi Regency, West Java

Output 2 – Identify Technologies to Support the Identification of Water Content and Soil Chemistry on Agricultural Land

Report Summarising Technology Review Findings

D2.1.1

United Nations Environment Programme (UNEP)

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Executive Summary

This review has provided a comprehensive overview of soil moisture and chemistry sensing systems, including field-implanted, remote sensing, drone-based, and combined approaches. We have identified the advantages and challenges associated with each method, along with suitable applications for different agricultural environments.

In the context of Climate-Smart Agriculture (CSA) implementation in Sukabumi region, West Java, Indonesia, the effective integration of these sensing systems could help farmers monitor soil conditions, optimize irrigation, and nutrient management, and ultimately improve crop yield and resilience to climate change.

Emerging trends in soil sensing technologies include the development of low-cost and energy-efficient sensors, improved data fusion techniques, and the integration of artificial intelligence and machine learning algorithms. These advancements hold the potential to significantly enhance the accuracy, reliability, and scalability of soil monitoring systems.

In the Sukabumi region, future research should focus on the development of tailored solutions that take into consideration local agricultural practices, crop types, and environmental conditions. Moreover, conducting field trials and validation studies in the region will be crucial for assessing the suitability and performance of different sensing technologies.

In the pursuit of implementing CSA practices in the Sukabumi region, the following recommendations are made:

- Farmers should consider adopting soil sensing technologies that are cost-effective, reliable, and suitable for their specific agricultural context. This may involve investing in a combination of sensing systems that offer complementary data on soil moisture and chemistry.
- Policymakers should prioritize the development of incentive programs and financial support mechanisms to encourage the adoption of soil sensing technologies among farmers. This could include providing subsidies, low-interest loans, or tax incentives.
- Researchers should continue to explore new sensing technologies and methodologies, particularly those that are well-suited to the unique challenges and requirements of the Sukabumi region. Additionally, collaboration between research institutions, private sector companies, and government agencies will be essential for driving innovation and promoting the widespread adoption of CSA practices.

1 Introduction

1.1 Background and Significance of Soil Moisture and Chemistry Monitoring

Soil moisture and chemistry monitoring are critical components of sustainable agricultural management, particularly in the context of climate-smart agriculture (CSA). Climate-smart agriculture aims to increase agricultural productivity, enhance adaptation to climate change, and reduce greenhouse gas emissions, ultimately contributing to food security and environmental sustainability (Lipper et al., 2014). Understanding soil moisture and chemistry dynamics is crucial for optimizing agricultural practices, such as irrigation scheduling, nutrient management, and soil conservation, which can significantly impact crop yield, water and energy use, and environmental quality.

Soil moisture is a key variable in the hydrological cycle and affects various processes, including evapotranspiration, infiltration, runoff, and percolation (Tuller & Or, 2004). Monitoring soil moisture can help farmers determine the optimal timing and amount of irrigation, reducing water wastage and associated energy consumption, while maintaining crop productivity. In addition, soil moisture monitoring can aid in the identification of waterlogging or drought conditions, allowing farmers to take timely corrective actions and minimize potential crop losses.

Various sensing techniques have been developed for measuring soil moisture content, including gravimetric, volumetric, and remote sensing methods. The gravimetric method measures the mass of water in the soil, whereas the volumetric method calculates the volume of water relative to the total soil volume. Remote sensing technologies use satellite or aircraft-based sensors to estimate soil moisture content over large areas (Njoku & Entekhabi, 1996).

Soil chemistry, on the other hand, influences nutrient availability, soil pH, and overall soil fertility, all of which are essential for crop growth and health (Sanchez, 2019). Assessing soil chemical properties can provide insights into nutrient deficiencies or imbalances, enabling targeted and efficient fertilizer application, which can lead to improved crop yield, reduced input costs, and minimized environmental impacts from nutrient leaching and runoff (J. Zhang et al., 2020). Furthermore, soil chemistry monitoring can help in the identification and management of soil-borne diseases and pests, and inform decisions related to soil amendments, crop rotation, and the selection of climate-resilient crops.

The growing interest in precision agriculture, digital farming, and the Internet of Things (IoT) has fuelled advancements in soil sensing technologies and data analytics (Kamilaris et al., 2017). A variety of soil moisture and chemistry sensors are available, ranging from low-cost, in situ sensors to advanced remote sensing platforms, such as satellites and drones, which can provide spatially and temporally resolved soil information (Mulla, 2013) . By integrating these technologies with decision support systems, farmers can make informed, data-driven decisions that align with the principles of climate-smart agriculture.

In the face of increasing climate variability and the associated risks to agricultural production, soil moisture and chemistry monitoring systems can play a pivotal role in enhancing the resilience of farming systems, while promoting sustainable resource use and environmental protection (Chlingaryan et al., 2018). Furthermore, these monitoring systems can support policies and strategies aimed at addressing global challenges, such as food security, water scarcity, and climate change mitigation.

As the global population continues to grow, agriculture must adapt to the challenges posed by climate change, resource constraints, and the need for increased productivity (Godfray et al., 2010). Soil moisture and chemistry monitoring systems, embedded within the framework of climate-smart agriculture, offer promising solutions to these challenges. However, there is still ample scope for further research and development in this area.

Emerging technologies, such as nano sensors, could enable more precise and cost-effective soil monitoring, with the potential to measure multiple parameters simultaneously. In addition, advances in data processing, machine learning, and artificial intelligence can improve the accuracy of predictive models and enhance decision-making for farmers (Wolfert et al., 2017).

Another promising avenue for future research is the integration of different soil monitoring systems and the fusion of diverse datasets, such as satellite and drone-based remote sensing data, in situ sensor networks, and crowd-sourced information. Such integrated approaches could provide more comprehensive, accurate, and timely soil information, leading to better-informed agricultural management decisions.

Moreover, research should focus on understanding the interactions between soil moisture, chemistry, and other key factors, such as soil structure, microbial communities, and plant root systems(Morris et al., 2021). This knowledge can help in developing more holistic, systems-based approaches to soil management, promoting both agricultural productivity and environmental sustainability.

Finally, efforts should be directed towards engaging farmers, policymakers, and researchers in the development, dissemination, and adoption of soil monitoring technologies and best practices. This may involve capacity-building, knowledge-sharing, and the establishment of supportive policies and incentives for the adoption of climate-smart agriculture (Läderach et al., 2020).

In conclusion, soil moisture and chemistry monitoring systems are essential tools for the implementation of climate-smart agriculture, addressing the global challenges of food security, water scarcity, and climate change mitigation. Further research and collaboration between various stakeholders are crucial for unlocking the full potential of these technologies and ensuring a sustainable and resilient future for agriculture.

1.2 Scope of Literature Review

The scope of the literature review is:

- To Identify technologies to support the identification of water content and soil chemistry on agricultural land Activity:

- To Identify existing technologies that provide data on water content and soil chemistry on agricultural land. A literature review will be carried out on existing technologies that are able to identify water content and soil chemistry on agricultural land. This review will confine itself to the following types of technologies:

    - Sensors implanted in the fields

    - Drones

- Satellite imagery
- Combination of drone and satellite imagery

- To develop a catalogue of existing technologies with relevance to the Indonesian context, guided by the four (4) key types of technologies listed above. This catalogue will be comprised of fact sheets of all the technologies reviewed which includes the following information:
  - Name, photo and title of the technology
  - Characteristics of the sensors
  - Characteristics of the transmission, Data frequency, power
  - Characteristics of the architecture of communication (how are information stored, transmitted and accessible to the users)
  - Geographic Operation-ability/ Performance standard (energy use, safety, reliability, waterproof)
  - Additional infrastructure requirement
  - Estimated cost

1.3 Overview of the Four Categories of Soil Moisture Sensing and Chemistry Sensing Systems

Soil moisture and chemistry sensing systems play a vital role in the implementation of climate-smart agriculture, enabling the monitoring and management of soil health, crop growth, and environmental sustainability. There are four main categories of soil moisture and chemistry sensing systems, each with its unique advantages, limitations, and applications: on-site implanted sensors, remote sensing satellites, drones (unmanned aerial vehicles), and combined approaches.

1.3.1 On-site Implanted Sensors

On-site implanted sensors are typically installed directly in the soil and measure moisture and chemistry parameters at specific depths and locations (Xingchao Zhang et al., 2018). These sensors offer several advantages, including continuous monitoring, real-time data, and localized information. Common types of implanted sensors include capacitive, resistive, time-domain reflectometry (TDR), frequency domain reflectometry (FDR), neutron scattering, and tensiometer sensors, each with distinct characteristics and measurement principles (Bogena et al., 2017). The architecture of these sensor systems often involves wireless communication and data transmission, allowing for the integration of soil information into decision-making processes. Despite these advantages, on-site sensors can be limited by their spatial coverage, installation and maintenance costs, and potential interference from soil properties and environmental conditions.

1.3.2 Remote Sensing Satellites

Satellite remote sensing systems use spaceborne instruments to monitor large-scale soil moisture and chemistry parameters from orbit (Mulla, 2013). These systems have the advantage of providing extensive spatial coverage, often on a global scale, and can monitor multiple soil parameters simultaneously (Entekhabi et al., 2010). Remote sensing satellites employ various techniques such as passive and active microwave, thermal infrared, and optical sensing to estimate soil properties. The spatial and temporal resolution of these systems depends on the specific satellite mission and sensor design (Petropoulos et al., 2015). Satellite-based monitoring systems are especially valuable for addressing issues related to water scarcity and climate change adaptation. However, their accuracy may be affected by atmospheric interference, vegetation cover, and soil heterogeneity, and they often require in situ calibration and validation.

1.3.3 Drones (Unmanned Aerial Vehicles)

Drones equipped with sensors for soil moisture and chemistry monitoring have emerged as a flexible and versatile alternative to satellite and on-site sensing systems (Hunt et al., 2017). These unmanned aerial vehicles (UAVs) can be deployed quickly and cover large areas with high spatial resolution, enabling precise and timely assessment of soil conditions (Mulla, 2013). Drone-based sensing systems can use various sensors, such as multispectral cameras, hyperspectral imaging, thermal infrared, and microwave sensors, to estimate soil moisture and chemistry properties (Chlingaryan et al., 2018). The system architecture and communication for drone-based monitoring typically involve the integration of flight control, sensor data acquisition, and data processing and analysis components (Hunt et al., 2017). Despite their advantages, drone-based sensing systems may be limited by their flight endurance, regulatory constraints, and the need for skilled operators and data processing expertise.

1.3.4 Combined Approaches

Combined approaches to soil moisture and chemistry monitoring involve the integration of multiple sensing systems, such as on-site sensors, satellite remote sensing, and drone-based systems. These approaches aim to leverage the complementary strengths of different sensing techniques, enhancing the accuracy and reliability of soil information. Data fusion methods and system architectures play a critical role in enabling the integration of diverse datasets and the development of comprehensive soil monitoring solutions (S. Li et al., 2018). Combined approaches have the potential to optimize data frequency and resolution, providing timely and precise soil information to support agricultural decision-making systems. However, the integration of different sensing systems can also present challenges in terms of data compatibility, communication, and the management of large, diverse datasets.

In the context of climate-smart agriculture, these four categories of soil moisture and chemistry sensing systems offer valuable tools for monitoring and managing soil health, crop growth, and environmental sustainability. Each category has its unique strengths and limitations, making them suitable for different agricultural applications and environments. For example, on-site implanted sensors may be best suited for precision agriculture and small-scale farming operations, where localized and real-time soil information is crucial. In contrast, remote sensing satellites can provide global-scale monitoring and assessment of soil moisture and chemistry patterns, supporting large-scale water and land management strategies. Drones offer the flexibility and precision needed for adaptive management of soil conditions, while combined approaches can harness the synergies between different sensing systems to deliver more comprehensive and accurate soil information.

The choice of soil moisture and chemistry sensing system depends on the specific agricultural context, the scale and complexity of the operation, and the desired outcomes and goals of the monitoring efforts. By understanding the characteristics and capabilities of each category, farmers, policymakers, and researchers can make informed decisions about the most appropriate soil monitoring solutions for their needs.

These four categories of soil moisture and chemistry sensing systems play a critical role in climate-smart agriculture by providing the necessary data to make informed decisions about crop management, irrigation, and land use. By understanding the strengths, limitations, and applications of each category, farmers, policymakers, and researchers can choose the most suitable monitoring solutions for their specific needs. Furthermore, as technology continues to advance and new sensing systems are developed, these four categories will likely evolve, offering even greater potential for improving agricultural productivity and environmental sustainability in the face of climate change.

2 On-site Implanted Sensors

2.1 Characteristics and Types of Implanted Sensors

The system architecture for field-implemented soil sensors typically consists of the following components: soil sensors, data acquisition systems, communication modules, and data processing and visualization software (L. Li et al., 2021). Each sensor type has its advantages and disadvantages in terms of cost, accuracy, and ease of installation.

2.1.1 Soil Moisture Sensors

2.1.1.1 Capacitive Sensors

Capacitive sensors measure soil moisture content by assessing the changes in the soil's dielectric constant, which is influenced by the amount of water present in the soil (Whalley et al., 2012). Capacitive sensors are based on the principle that water has a high dielectric constant, which significantly impacts the capacitance between the sensor's electrodes when the water content changes (Bogena et al., 2007).

These sensors offer several advantages, including non-invasive and non-destructive measurements, low power consumption, resistance to soil salinity, and minimal maintenance requirements (Jones et al., 2002). Additionally, capacitive sensors provide fast response times and can be cost-effective when compared to other types of soil moisture sensors (Alley et al., 2017).

However, some limitations of capacitive sensors include sensitivity to temperature fluctuations and soil type, requiring calibration for different soils and potential inaccuracies in highly heterogeneous soils (Gaskin & Miller, 1996). Furthermore, the accuracy of capacitive sensors can be affected by the presence of air gaps or stones around the sensor (Paltineanu & Starr, 1997).

2.1.1.2 Resistive Sensors

Resistive sensors measure soil moisture content by monitoring the electrical resistance of the soil, which is inversely proportional to its water content (Dalton et al., 1984). When water is present in the soil, it forms a conductive path between the electrodes, reducing the overall resistance (Hilhorst, 2000).

These sensors are relatively inexpensive and easy to implement, making them suitable for various applications (Stacheder, 2009). However, resistive sensors are sensitive to soil salinity and temperature variations, which can lead to inaccurate measurements if not accounted for (Jalota et al., 1998; Rawlins & Campbell, 2018). Additionally, the performance of resistive sensors can be influenced by soil type, texture, and compaction (Hilhorst, 2000).

To overcome these limitations, researchers have proposed combining resistive sensors with other types of soil moisture sensors or incorporating compensation techniques to improve accuracy and reliability (Seyfried & Murdock, 2004; Stacheder, 2009).

2.1.1.3 Time-Domain Reflectometry (TDR) Sensors

Time-domain reflectometry (TDR) sensors measure soil moisture content by determining the dielectric constant of the soil, which is influenced by its water content (Topp et al., 1980). TDR sensors work by sending an electromagnetic pulse along a transmission line (waveguide) that is inserted into the soil. The pulse reflects at the end of the transmission line, and the time taken for the pulse to travel along the waveguide and return is measured. The dielectric constant of the soil can be calculated from this travel time, which is then used to estimate the soil water content (Robinson et al., 2003).

TDR sensors are known for their high accuracy and precision, as well as their ability to provide reliable measurements across a wide range of soil types (Heimovaara, 1994). They are also less sensitive to temperature fluctuations and soil salinity compared to other types of soil moisture sensors (Malicki et al., 1996). However, TDR sensors are generally more expensive, require specialized equipment, and are more complex to install and operate compared to capacitive and resistive sensors (Baker & Allmaras, 1990).

2.1.1.4 Frequency Domain Reflectometry (FDR) Sensors

Frequency Domain Reflectometry (FDR) sensors measure soil moisture content by determining the dielectric constant of the soil, which is related to its water content. Similar to TDR sensors, FDR sensors use the dielectric properties of the soil to estimate its moisture content. However, FDR sensors operate by emitting a continuous electromagnetic wave rather than a pulse (Bittelli et al., 2004).

FDR sensors have some advantages over TDR sensors, including the ability to provide continuous measurements and potentially lower power consumption. These sensors also exhibit high accuracy and can be used for a wide range of soil types (Bogena et al., 2007). FDR sensors are relatively less sensitive to soil temperature and salinity compared to resistive sensors but may still be affected by these factors (Rüdiger et al., 2009).

Despite these advantages, FDR sensors are typically more expensive and complex to install and operate compared to capacitive and resistive sensors. Moreover, their performance may be affected by soil texture, organic matter content, and soil compaction (Schwank et al., 2006).

2.1.1.5 Neutron Scattering Sensors

Neutron scattering sensors, also known as neutron probes, measure soil moisture content by detecting the interaction between fast neutrons and hydrogen atoms present in soil water (Visvalingam & Tandy, 1972). The sensor emits fast neutrons that collide with the hydrogen atoms in the soil, which slows down the neutrons. The slowed-down neutrons, or thermal neutrons, are then detected by the sensor. The concentration of hydrogen atoms, and therefore the soil moisture content, can be inferred from the measured thermal neutron intensity.

COSMOS is a network of cosmic-ray soil moisture probes that measures soil moisture by detecting neutrons produced by cosmic rays. The probes are non-invasive, inexpensive, and can be deployed in remote areas. The data from COSMOS is used to improve our understanding of the water cycle and climate change (Zreda et al., 2012).

Neutron scattering sensors are known for their high accuracy and ability to provide reliable measurements at large sampling volumes (typically up to several hundred liters), making them suitable for applications in agriculture and soil science. These sensors are less sensitive to soil temperature and salinity variations compared to capacitive and resistive sensors (Evett, 2022).

However, neutron scattering sensors have some drawbacks. They require specialized equipment and licensing, as well as trained personnel for their operation, due to the use of radioactive sources Additionally, these sensors are more expensive and complex to install and operate compared to other types of soil moisture sensors (Gaskin & Miller, 1996).

2.1.1.6 Tensiometer Sensors

Tensiometers are soil moisture sensors that measure soil water potential, or matric potential, which represents the energy required to extract water from soil pores. They consist of a porous ceramic cup, a water-filled tube, and a vacuum gauge. The porous cup is in direct contact with the soil, and when the soil dries, water is pulled from the tensiometer, creating a vacuum inside the tube. The vacuum gauge measures the negative pressure, which is directly related to soil water potential (J H Dane & Hopmans, 2002).

Tensiometers are known for their simplicity, low cost, and accuracy for measuring soil water potential in the range of 0 to -85 kP. They are widely used in agricultural and soil science research for irrigation scheduling, water balance studies, and evaluating soil hydraulic properties.

However, tensiometers have some limitations. They are sensitive to temperature changes and may need frequent recalibration. Furthermore, their operating range is limited to relatively wet soil conditions since they lose functionality under high soil water tension (J H Dane & Hopmans, 2002). Additionally, tensiometers require regular maintenance to refill the water column and prevent air entry.

2.1.2 Soil Chemistry Sensors

2.1.2.1 Ion-Selective Electrodes (ISEs)

Ion-selective electrodes (ISEs) have emerged as a promising tool for soil chemistry analysis, providing direct, real-time measurements of specific ions in the soil. These sensors enable researchers and practitioners to monitor the concentration of essential nutrients, contaminants, and other relevant ions, informing agricultural decision-making and environmental assessments.

ISEs operate by selectively responding to the activity of a target ion in the presence of other ions, generating a potential that is proportional to the concentration of the target ion (Simões & Xavier, 2017). Different types of ISEs are available for detecting various ions, such as nitrate, ammonium, potassium, calcium, and heavy metals (Jun Liu et al., 2023). The development of solid-state and polymer-based ISEs has improved sensor performance in terms of selectivity, sensitivity, and stability (Radu et al., 2007).

ISEs have been widely used in soil chemistry analysis for assessing nutrient availability, soil fertility, and pollution monitoring. For example, (Y. Wang et al., 2013) used ISEs to monitor nitrate levels in agricultural soils, informing irrigation and fertilizer management practices. Likewise, (Soini et al., 2012) employed ISEs to assess heavy metal contamination in urban soils, evaluating the risk of exposure to hazardous elements.

ISEs offer several advantages as soil chemistry sensors, including simple and rapid operation, direct measurement of target ions, and the potential for in situ and real-time (Simões & Xavier, 2017). However, ISEs also face challenges, such as interference from other ions, limited long-term stability, and the need for regular calibration (Radu et al., 2007). Moreover, ISEs typically provide point measurements, limiting the spatial coverage and requiring multiple sensors or extensive sampling to obtain comprehensive soil chemistry information (Jun Liu et al., 2023).

In summary, ion-selective electrodes have demonstrated potential as soil chemistry sensors, enabling direct measurement of specific ions in agricultural and environmental contexts. Their simplicity, rapid operation, and potential for real-time monitoring make them attractive for use in the field. However, further research and development are needed to address challenges associated with interference, stability, and spatial coverage. With advancements in sensor design and materials, ion-selective electrodes may become an increasingly valuable tool for soil chemistry analysis in climate-smart agriculture and environmental monitoring.

2.1.2.2 Optical Sensors

Optical sensors have gained increasing attention as soil chemistry sensors, offering non-destructive, rapid, and precise measurements of soil constituents. By detecting changes in the absorption, reflectance, or fluorescence properties of soils, optical sensors enable the analysis of various soil properties, including nutrient concentrations, organic matter content, and contamination levels.

Optical sensors are based on the principle of light interaction with soil, which can provide information about the composition and characteristics of the soil (Chrysostome et al., 2007) . The most common optical techniques used for soil chemistry analysis include visible/near-infrared (VIS/NIR) spectroscopy, mid-infrared (MIR) spectroscopy, and laser-induced fluorescence (LIF) (McBratney et al., 2002). These techniques differ in their underlying principles, instrumentation, and the specific soil properties they can detect.

Optical sensors have been widely applied in various soil chemistry analyses. For instance, (Chang et al., 2001) utilized VIS/NIR spectroscopy to estimate soil organic matter content, while (Sithole et al., 2018) employed MIR spectroscopy to assess soil heavy metal concentrations. (Stenberg et al., 2010) used LIF to study the spatial variability of soil nitrogen content, providing valuable information for precision agriculture and nutrient management.

Optical sensors offer several advantages as soil chemistry sensors, such as non-destructive and rapid measurements, high sensitivity and precision, and the potential for real-time, in situ monitoring (McBratney et al., 2002). Moreover, optical sensors can be implemented in various platforms, including laboratory, field, and remote sensing instruments, providing flexible and comprehensive soil chemistry analysis (Chrysostome et al., 2007) .

However, optical sensors also face challenges, including the influence of soil moisture, surface roughness, and particle size on spectral measurements (Shepherd & Walsh, 2007). Additionally, the development of robust calibration models and the handling of large spectral datasets require advanced statistical and computational techniques (Stenberg et al., 2010).

In conclusion, optical sensors offer a promising solution for soil chemistry analysis, providing non-destructive, rapid, and accurate measurements of various soil constituents. While challenges remain, such as the influence of soil properties on spectral measurements and the need for advanced data processing techniques, optical sensors have the potential to revolutionize soil chemistry monitoring in agriculture and environmental assessments. Future research should focus on addressing these challenges and exploring new applications of optical sensing technologies to support climate-smart agriculture and sustainable land management.

2.1.2.3 Spectroscopy-Based Sensors

Spectroscopy-based sensors are a sub-set to the optical sensors, while not all optical sensors are spectroscopy-based. They have become increasingly popular in recent years for the analysis of soil chemistry. These sensors, which include visible and near-infrared (Vis-NIR), mid-infrared (MIR), and Raman spectroscopy, can provide rapid, non-destructive measurements of various soil constituents such as organic matter, minerals, and nutrients.

Spectroscopy-based sensors work by analysing the interaction of electromagnetic radiation with soil constituents, typically involving the absorption, reflection, or scattering of light by the sample. Vis-NIR spectroscopy measures reflectance in the visible (400-700 nm) and near-infrared (700-2500 nm) regions of the electromagnetic spectrum. MIR spectroscopy focuses on the absorption of radiation by molecular vibrations in the mid-infrared region (2500-25,000 nm), while Raman spectroscopy detects inelastic scattering of monochromatic light (usually from a laser) (Wetterlind et al., 2013).

Spectroscopy-based sensors have been extensively applied to analyse various soil properties. For instance, (Bellon-Maurel et al., 2010) used Vis-NIR spectroscopy to determine soil organic matter content, while (Cheng et al., 2021) employed MIR spectroscopy for the analysis of soil mineralogy. Raman spectroscopy has been utilized for in situ analysis of nutrient concentrations in soil samples (Waheed et al., 2018)

Spectroscopy-based sensors offer several advantages in soil chemistry analysis, including rapid, non-destructive measurements, minimal sample preparation, and the potential for in situ or remote sensing applications. However, they also face challenges, such as the need for advanced data processing and calibration techniques, sensitivity to sample heterogeneity, and potential interference from moisture and other environmental factors (Wetterlind et al., 2013).

In conclusion, spectroscopy-based sensors have shown great potential in soil chemistry analysis due to their rapid, non-destructive measurement capabilities, minimal sample preparation requirements, and potential for in situ or remote sensing applications. Vis-NIR, MIR, and Raman spectroscopy have been successfully applied to determine various soil properties, such as organic matter content, mineralogy, and nutrient concentrations. Despite challenges related to data processing, calibration, sample heterogeneity, and environmental interferences, ongoing research and development in spectroscopy-based sensors can further enhance their applicability in soil chemistry analysis and contribute to climate-smart agriculture and sustainable land management practices.

2.1.2.4 Electrochemical Sensors

Electrochemical sensors have emerged as a valuable tool for soil chemistry analysis, enabling rapid, in situ measurements of various soil constituents, such as pH, redox potential, and nutrient concentrations. These sensors work based on the electrochemical reactions occurring at the electrode-solution interface, providing quantitative information on the target analytes in the soil.

Electrochemical sensors typically include potentiometric, voltammetric, and amperometric sensors (Ali et al., 2020). Potentiometric sensors, such as ion-selective electrodes, measure the potential difference between a reference electrode and a sensing electrode. Voltammetric sensors detect current changes resulting from redox reactions of the analyte at the electrode surface. Amperometric sensors, on the other hand, measure the current generated by an electrochemical reaction between the analyte and a working electrode at a constant potential.

Electrochemical sensors have been successfully applied to various soil chemistry analyses. For instance, (Roda, 2009) employed potentiometric sensors for in situ pH monitoring in agricultural soils, while (Fiedler et al., 2007) utilized voltammetric sensors to determine redox potential in wetland soils. Amperometric sensors have been used to monitor nutrient concentrations in soil, such as nitrate and ammonium levels (E Bakker et al., 2015).

Electrochemical sensors offer several advantages for soil chemistry analysis, including real-time, in situ measurements, high sensitivity and selectivity, and low cost (Ali et al., 2020). Moreover, these sensors can be integrated into wireless sensor networks, enabling continuous monitoring and adaptive management of soil chemistry.

However, electrochemical sensors also face challenges, such as sensitivity to environmental factors (e.g., temperature, humidity), potential interferences from other ions or compounds, and the need for periodic calibration and maintenance (Ratcliffe et al., 2016).

In conclusion, electrochemical sensors represent a valuable tool for soil chemistry analysis due to their real-time, in situ measurement capabilities, high sensitivity and selectivity, and cost-effectiveness. Their potential applications include monitoring pH, redox potential, and nutrient concentrations in various agricultural and environmental settings. Despite the challenges associated with sensitivity to environmental factors, potential interferences, and calibration and maintenance requirements, the ongoing research and development of electrochemical sensors can further advance their utility in soil chemistry analysis and contribute to climate-smart agriculture and sustainable land management practices.

2.1.2.5 Microbial Fuel Cell-Based Sensors

Microbial fuel cell (MFC) sensors have emerged as a promising technology for monitoring soil chemistry. These sensors harness the ability of electrochemically active microorganisms to generate electrical signals in response to changes in the chemical environment. As a result, MFC sensors offer a unique approach to measuring various soil parameters, such as redox potential, pH, and nutrient concentrations, in real-time and without external power sources.

MFC-based sensors operate by utilizing the metabolic activity of electrochemically active bacteria to convert chemical energy present in organic matter or nutrients into electrical energy (Logan et al., 2006). This process occurs in an electrochemical cell, which consists of an anode and a cathode separated by a cation exchange membrane (Ieropoulos et al., 2016). The bacteria in the anode compartment oxidize organic matter or nutrients, generating electrons that flow through an external circuit, and ultimately reduce a terminal electron acceptor in the cathode compartment.

MFC-based sensors have demonstrated potential for monitoring various soil properties. For example, (Ng et al., 2015) developed a redox potential sensor based on an MFC, which allowed for real-time monitoring of soil redox conditions.

Additionally, (Wongrod et al., 2019) employed an MFC-based sensor to detect nitrate and ammonium ions in soil samples, offering a novel approach to nutrient monitoring.

MFC-based sensors offer several advantages for soil chemistry analysis, including real-time measurements, self-powering capabilities, and the potential for in situ monitoring (Ieropoulos et al., 2016). However, these sensors also face challenges such as sensitivity to environmental factors, potential biofouling, and limitations in detecting non-bioavailable compounds or low-concentration analytes (Ng et al., 2015).

In conclusion, MFC-based sensors offer a unique approach to soil chemistry analysis by harnessing the electrochemical activity of microorganisms to generate electrical signals in response to changes in soil properties. They have shown potential in real-time monitoring of redox potential, pH, and nutrient concentrations in soil, while being self-powered and amenable to in situ applications. Despite the challenges related to environmental sensitivity, biofouling, and limitations in detecting certain compounds or low concentrations, ongoing research and development in MFC-based sensors hold promise for enhancing their applicability in soil chemistry monitoring and contributing to climate-smart agriculture and sustainable land management practices.

2.2 System Architecture and Communication

Field-implanted sensor technologies have seen rapid advancements in recent years, offering real-time insights into soil conditions. This review examines the current state of the art in system architecture and communication for soil moisture and soil chemistry sensor technologies, using various literature sources.

2.2.1 System Architecture

A wide range of architectures has been developed for soil moisture and soil chemistry sensor systems, including centralized, decentralized, and hierarchical structures (A. Davis, 2012).

- Centralized Architecture: In centralized systems, a single data acquisition and processing unit is responsible for collecting and processing data from multiple sensor nodes. One example is the use of soil moisture sensor networks with a wireless sensor network (WSN) and a centralized data acquisition unit (Al-Fuqaha et al., 2015). However, this approach can result in communication overhead, especially in large-scale sensor networks (Al-Fuqaha et al., 2015).

- Decentralized Architecture: Decentralized architectures distribute data processing among multiple nodes in the network, reducing communication overhead and energy consumption. One example is the use of edge computing in soil sensor networks, where data is processed at the network's edge before being transmitted to the central server (Shi et al., 2016). This approach has been applied to soil moisture and soil chemistry monitoring for improved decision-making in agriculture (Georgieva et al., 2016).

- Hierarchical Architecture: Hierarchical architectures involve multiple layers of data aggregation and processing. These systems use cluster heads or gateway nodes to aggregate data from sensor nodes before transmitting to the central server (Hatanaka et al., 2015). This architecture offers energy efficiency and reduces communication overhead in large-scale sensor networks (Chakrabarty et al., 2021).

The system configuration of field implanted soil moisture and soil chemistry sensors typically consists of the following components:

- Sensing Nodes: These are the actual sensors that measure soil moisture, soil chemistry, or other relevant parameters.
- Data Transmission: The data collected by the sensing nodes are transmitted to a central control unit or a cloud-based platform via wired or wireless communication technologies.
- Data Processing and Analysis: The collected data are processed and analysed using specialized software and algorithms to provide actionable insights.
- User Interface: End-users can access the information through a user-friendly interface, such as a web application or a mobile app.

2.2.2 Communication Technologies

The communication technologies that have been employed in field implanted sensors are including:

- Wired Communication: This involves the use of cables to transmit data from sensing nodes to a central control unit. Examples include RS-485 and Ethernet.
  - Wired Connections: Wired connections, such as RS-485 and Ethernet, are also used in soil sensor networks. They offer reliable communication and high data rates but are less suitable for large-scale or remote deployments due to installation and maintenance costs.
  - Optical Communication Systems: Optical communication systems, such as fiber-optic networks, provide high data rates and immunity to electromagnetic interference. These systems have been employed in precision agriculture and soil monitoring but face challenges in terms of installation and maintenance cost.
- Wireless Communication: Wireless communication technologies offer more flexibility in sensor deployment and have been widely adopted in recent years. Wireless communication protocols such as ZigBee, LoRa, and NB-IoT are popular choices for sensor networks due to their low power consumption, long-range capabilities, and scalability.
  - ZigBee: ZigBee is a low-power, low-data-rate wireless communication protocol suitable for soil sensor networks. It has been widely used for soil moisture and soil chemistry monitoring due to its low power consumption and mesh network topology.
  - LoRa: LoRa (Long Range) is another low-power, wide-area network (LPWAN) technology suitable for agricultural and environmental monitoring. Its long-range capabilities make it an ideal choice for remote and rural areas.
  - NB-IoT: Narrowband IoT (NB-IoT) is a cellular-based communication technology offering low-power consumption and wide-area coverage. NB-IoT has been used in soil moisture and soil chemistry monitoring, allowing for reliable data transmission in agricultural applications.

- Satellite Communication: In remote areas with limited connectivity, satellite communication can be used to transmit data from sensing nodes to a central control unit or cloud-based platform.

Integration with other technologies, such as Geographic Information Systems (GIS) and remote sensing, is vital for soil sensor networks. This integration helps to improve spatial representation, data visualization, and decision-making in agriculture and environmental monitoring (Quy et al., 2022).

2.3 Data Frequency and Optimisation

Data frequency is a critical aspect of soil moisture and chemistry sensing systems, as it determines the temporal resolution and quality of the information obtained from the sensors. The optimal data frequency depends on various factors, including the specific application, environmental conditions, and sensor characteristics.

Selecting an appropriate data frequency is essential to ensure the accurate representation of soil moisture and chemistry dynamics over time. High data frequencies provide better temporal resolution and can capture rapid changes in soil conditions, such as during precipitation events or irrigation (Bogena et al., 2007). However, high data frequencies can also generate large volumes of data, potentially increasing storage, processing, and communication requirements (Vaz et al., 2013). Moreover, excessive data collection may cause power consumption issues, especially for battery-powered sensors. Thus, optimizing data frequency is crucial for balancing the trade-offs between temporal resolution, resource demands, and sensor lifetime.

2.3.1 Data Frequencies for Field-Implanted Soil Moisture Sensors

The data frequency for soil moisture sensors typically ranges from minutes to hours, depending on the specific application and environmental conditions. For example, time-domain reflectometry (TDR) sensors with a 15-minute data frequency to monitor soil moisture in an agricultural field with a 30-minute data frequency for capacitance-based sensors to assess soil moisture dynamics. In general, higher data frequencies are preferred for monitoring rapidly changing soil conditions or to inform real-time decision-making in precision agriculture applications.

2.3.2 Data Frequencies for Field-Implanted Soil Chemistry Sensors

Soil chemistry sensors, such as ion-selective electrodes, electrochemical sensors, and spectroscopy-based sensors, often have varying data frequencies depending on the target analyte and measurement technique. Ion-Selective Electrodes (ISEs) are typically used for continuous, real-time monitoring of specific ions in soil. They can provide measurements every few seconds or minutes, depending on the specific sensor and application (Eric Bakker & Telting-Diaz, 2002). Electrochemical sensors can collect data in minutes (Lin et al., 2008) and spectroscopy-based sensors, an provide rapid, non-destructive measurements of soil properties, depending on the specific sensor and application (Stenberg et al., 2010; Vasques et al., 2008).

2.3.3 Optimisation Techniques

Various techniques can be applied to optimize data frequency for field-implanted soil moisture and chemistry sensors. One approach is to use adaptive data collection algorithms, which adjust the data frequency based on observed changes in soil conditions or environmental factor. For example, a sensor could collect data more frequently during precipitation events or irrigation periods when soil moisture is expected to change rapidly. Additionally, data reduction techniques, such as data compression or aggregation, can be employed to minimize storage and communication requirements for high-frequency data.

2.4 Power Systems and Energy Management

Reliable power systems and efficient energy management strategies are crucial for the successful deployment and functioning of field-implanted soil moisture and chemistry sensors. This review discusses the various power sources, energy harvesting systems, and energy management techniques that are commonly employed in soil sensing applications.

Traditionally, field-implanted soil moisture and chemistry sensors have relied on battery power to meet their energy needs. Although batteries are relatively easy to implement and can offer long operational life, they require periodic replacement and may present environmental disposal concerns. Consequently, researchers have explored alternative power sources, such as energy harvesting systems, to enhance the sustainability and longevity of soil sensor networks.

2.4.1 Energy Harvesting Systems

Energy harvesting systems capture and convert ambient energy sources, such as solar, wind, and thermal energy, into usable electrical power. Solar energy, in particular, has shown promise as a viable power source for field-implanted sensors due to its abundance and relatively high conversion efficiency.

Solar-powered sensor nodes, for instance, can utilize photovoltaic panels to convert sunlight into electricity, which can then be stored in batteries or capacitors for use when sunlight is unavailable. However, solar-powered systems can be limited by seasonal fluctuations in sunlight availability, and their performance may be affected by shading or dirt accumulation on the panels.

2.4.2 Energy Management Techniques

Effective energy management techniques are essential for minimizing power consumption and extending the operational lifetime of field-implanted soil sensors. Various approaches have been proposed and implemented to optimize energy usage, including:

- Adaptive sampling algorithms. Adaptive sampling algorithms adjust the sensor's measurement frequency based on changes in environmental conditions or sensor input, thereby reducing power consumption without compromising data quality. For example, the sensor may take more frequent measurements during periods of rapid change (Akyildiz et al., 2002) (Anastasi et al., 2009), such as heavy rainfall or irrigation events, and less frequent measurements during stable conditions.

- Low-power sensor designs. Low-power sensor designs (Akyildiz et al., 2002) (Anastasi et al., 2009) prioritize energy efficiency by incorporating low-power electronic components, optimizing circuitry, and using energy-efficient communication protocols.

- Sleep mode and duty cycling. Sleep mode and duty cycling (Anastasi et al., 2009) involve powering down sensor components or the entire sensor node during periods of inactivity. This strategy conserves energy by reducing power consumption when measurements are not being taken or when data is not being transmitted.

- Data reduction and compression techniques. Data reduction and compression techniques (Anastasi et al., 2009) minimize the amount of data transmitted and stored, thus reducing the power consumption associated with data communication and processing. These techniques can include data aggregation, compression algorithms, and feature extraction methods that retain relevant information while reducing data volume for instance, employed a data compression technique for a wireless soil moisture sensor network, resulting in reduced data volume and decreased power consumption.

Effective power systems and energy management strategies are essential for ensuring the long-term reliability and sustainability of field-implanted soil moisture and chemistry sensors. Although battery-powered systems are still prevalent, energy harvesting systems are emerging as a promising alternative. Moreover, employing energy management techniques like adaptive sampling, low-power sensor designs, sleep mode, and data reduction can significantly enhance the energy efficiency and operational lifespan of soil sensing networks.

2.4.3 Network-Level Energy Management

In addition to energy management techniques implemented at the sensor level, network-level strategies can further optimize power consumption in soil sensor networks. These strategies aim to reduce the energy consumption of the overall network by distributing tasks and energy demands among multiple sensor nodes. Some network-level energy management approaches include:

- Energy-aware routing protocols. Energy-aware routing protocols aim to optimize the energy usage of the entire sensor network by selecting the most energy-efficient routes for data transmission (M. Liu et al., 2009). This approach can significantly reduce power consumption, particularly in large-scale sensor networks where multiple sensor nodes are deployed to cover vast areas.

- Data aggregation. Data aggregation techniques involve combining data from multiple sensor nodes to create a more concise and meaningful dataset (Yue et al., 2012). By aggregating data before transmission, energy consumption associated with data communication can be minimized, resulting in lower power requirements for the overall network.

- Load balancing. Load balancing strategies distribute tasks and energy demands among multiple sensor nodes to prevent a single node from being overburdened and to optimize energy usage across the network (Ogundile & Alfa, 2017). This approach can prolong the operational lifetime of the entire network, as energy consumption is more evenly distributed.

2.4.4 Emerging Trends and Future Research Directions

As technology continues to advance and the need for sustainable, efficient soil sensing networks grows, research in this area should focus on developing innovative power systems and energy management strategies to meet these demands. Some potential research directions include:

- Integration of multiple energy harvesting systems. By combining multiple energy harvesting systems, such as solar, wind, and thermal, sensor networks can be designed to take advantage of the unique benefits of each system and achieve a more reliable and sustainable power supply
- Energy storage improvements. Improving energy storage technologies, such as batteries and supercapacitors, will enable field-implanted sensors to store more energy and operate for extended periods without the need for frequent maintenance or battery replacement
- Machine learning and artificial intelligence for energy management. Leveraging machine learning and artificial intelligence techniques could enable more sophisticated, adaptive energy management strategies that can dynamically optimize sensor performance and power consumption based on real-time environmental conditions and sensor input.

Ultimately, the development of sustainable and efficient power systems and energy management strategies will be essential for the continued advancement and success of soil moisture and chemistry sensing networks in agriculture and environmental monitoring applications.

2.5 Cost Analysis and Application Suitability

A comprehensive cost analysis is vital for assessing the feasibility and suitability of field-implanted soil moisture and chemistry sensors in various agricultural and environmental applications. In this section, we discuss the factors influencing sensor costs, the cost components of sensor networks, and the factors to consider when evaluating the suitability of different sensor technologies for specific applications.

2.5.1 Factors Influencing Sensor Costs

Several factors can influence the overall cost of field-implanted soil moisture and chemistry sensors, including:

- Sensor technology: The choice of sensor technology (e.g., capacitive, resistive, TDR, FDR) can significantly impact the cost of a sensing system. Some technologies may be more expensive due to the complexity of the sensors or the required additional equipment.
- Sensor accuracy and precision: Generally, sensors with higher accuracy and precision tend to be more expensive. However, the additional cost may be justified in certain applications where highly accurate and precise data is crucial.
- Number of sensors and deployment scale: The cost of a soil sensor network is highly dependent on the number of sensors and the scale of deployment. Larger networks with more sensor nodes will generally require higher investment costs.
- Power systems and energy management: As discussed earlier, the choice of power system and energy management strategies can influence the cost of sensor networks. Systems relying on batteries may have lower initial costs but require periodic battery replacement, while energy harvesting systems can be more expensive initially but may result in long-term cost savings

- Maintenance and operational costs: Maintenance and operational costs, including calibration, data transmission, and data storage, can significantly impact the total cost of ownership for soil sensor networks.

2.5.2 Cost Components of Soil Sensor Networks

To better understand the costs associated with field-implanted soil moisture and chemistry sensors, it is essential to break down the cost components of sensor networks. Common cost components include:

- Sensor hardware: This includes the cost of the individual sensor units, as well as any required peripheral equipment, such as data loggers, communication devices, and mounting equipment.
- Power systems: The costs of power systems, such as batteries or energy harvesting equipment, need to be considered, including the initial investment and any ongoing replacement or maintenance costs.
- Installation and deployment: Installation and deployment costs can vary based on the size and complexity of the sensor network, as well as the labour and transportation costs required to set up the network.
- Data transmission and storage: The costs associated with transmitting and storing sensor data can vary depending on the chosen communication protocol, data frequency, and data storage method (e.g., cloud-based, or local storage).
- Maintenance and calibration: Maintenance and calibration costs, including labour, equipment, and any required consumables, should be factored into the total cost of ownership.

2.5.3 Evaluating Application Suitability

When considering the suitability of different field-implanted soil moisture and chemistry sensors for specific applications, several factors should be considered:

- Sensor accuracy and precision requirements: The required accuracy and precision of the sensing system will depend on the specific application. High-value crops or sensitive environmental monitoring applications may require more accurate and precise sensors, while other applications may tolerate lower accuracy and precision.
- Deployment scale: The size of the area to be monitored and the number of sensors needed can influence the cost-effectiveness and suitability of specific sensor technologies. Larger networks may benefit from more cost-effective sensor options or the use of data aggregation techniques to minimize costs.
- Environmental conditions: Soil moisture and chemistry sensors may have different performance characteristics under various environmental conditions, such as temperature, humidity, and soil type. Evaluating the sensors' suitability for the specific environmental conditions in the application area is crucial.
- Power availability and requirements: The availability and requirements of power sources in the deployment area can affect the suitability of specific sensor technologies. Energy harvesting systems may be more suitable in locations with

limited access to power, while battery-powered systems may be more appropriate for small-scale deployments with regular maintenance schedules.

- Data frequency and resolution: The required frequency and resolution of the collected data can influence the choice of sensor technology, as well as the associated costs for data transmission and storage. Higher data frequency and resolution may require more expensive sensor technologies or communication protocols but may provide valuable insights for specific applications.

2.5.4 Case Examples

- High-value crop monitoring: In the case of high-value crops, the investment in more accurate and precise soil moisture and chemistry sensors can lead to significant benefits, such as optimizing irrigation and fertilizer management, leading to increased crop yields and quality. In such cases, the higher costs associated with these sensors may be justified by the potential return on investment.

- Large-scale environmental monitoring: For large-scale environmental monitoring applications, deploying many low-cost sensors may be more cost-effective and suitable for providing spatially distributed data. In these cases, the use of data aggregation techniques and energy-aware routing protocols can help optimize power consumption and data transmission costs.

- Small-scale agricultural applications: In small-scale agricultural applications, the use of affordable, easy-to-install sensors can provide valuable information for optimizing water and nutrient management. In such cases, battery-powered sensors with lower data frequency and resolution may be sufficient to meet the needs of the application while minimizing costs.

A thorough cost analysis and evaluation of application suitability are critical for selecting the most appropriate field-implanted soil moisture and chemistry sensors for various agricultural and environmental monitoring applications. Balancing the trade-offs between cost, accuracy, precision, and other factors will help ensure that the selected sensor technologies provide the necessary data and insights while remaining cost-effective and suitable for the specific application.

The combination of advanced system architectures and communication technologies has led to a wide range of applications for soil moisture sensors, such as precision agriculture, drought monitoring, and flood forecasting (Vereecken et al., 2008). Future prospects include the development of low-cost, energy-efficient, and highly accurate soil moisture sensing systems, as well as the integration of machine learning algorithms to enhance decision-making processes in agriculture (Khaki & Wang, 2019) [9].

In conclusion, this review has provided an overview of the system architecture and communication technologies for field-implemented soil moisture sensors. As the need for sustainable water management and precision agriculture grows, the development and adoption of advanced soil moisture sensing systems will continue to increase. Future research should focus on enhancing sensor accuracy, reducing costs, and improving energy efficiency while incorporating machine learning techniques to facilitate better decision-making processes in agriculture. With these advancements, we can better conserve water resources and optimize agricultural productivity, ultimately benefiting farmers, ecosystems, and our global food security.

2.6 Schematics of Field Implanted Sensors Technology

Based on the literatures, information on the makers web and experiences in research and monitoring project, there are modes of field implanted sensor system as presented in Figure 2.1 to Figure 2.6:

- Soil sensor system with offline data logger
- Soil sensor system with telemetry enabled data logger
- Soil sensor system with direct connection to server without data logger
- Soil sensor system with built-in data logger and wireless direct connection to computer or gadget
- Soil sensor system which connects to server through LoRa and a gateway
- Wireless sensor network, which describe the layers of sensor, wireless connection, internet, and data processing.

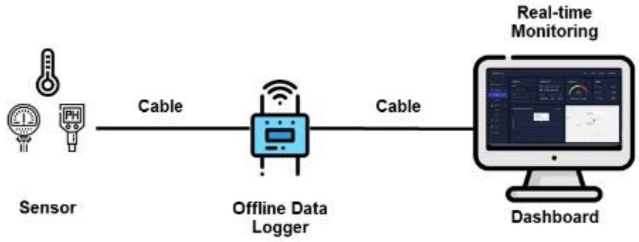

Figure 2.1 Soil sensor system with offline data logger

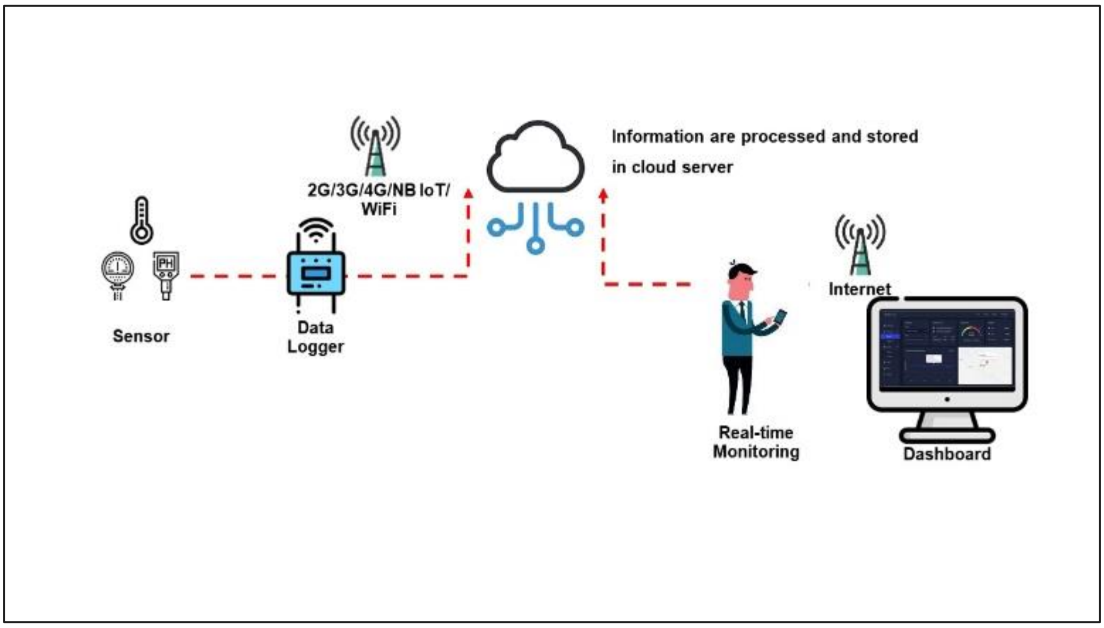

Figure 2.2 Soil sensor system with telemetry enabled data logger

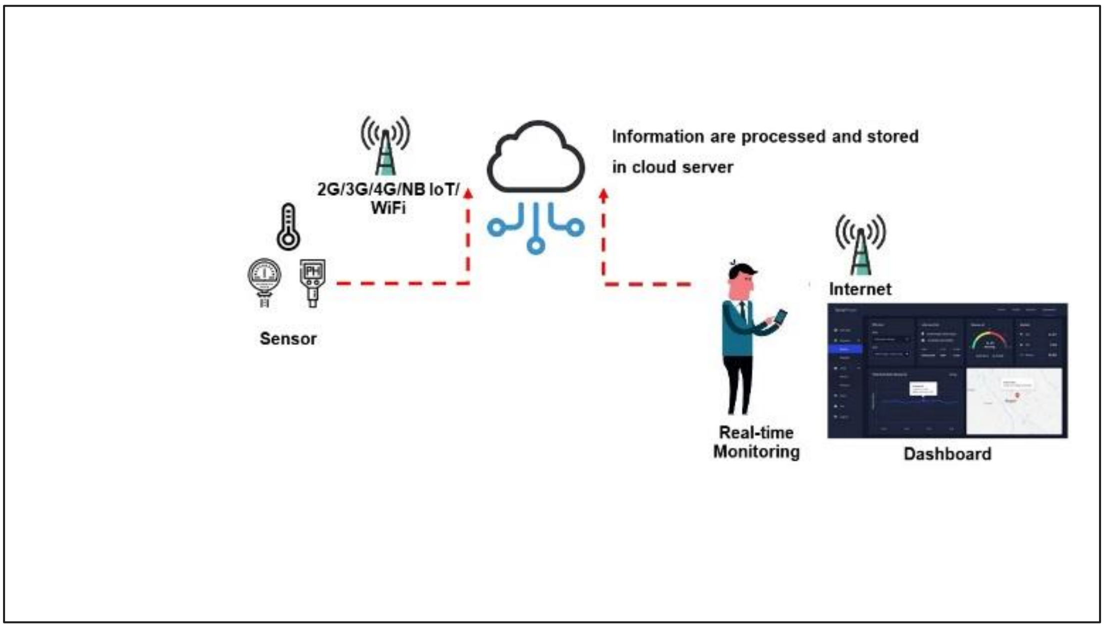

Figure 2.3 Soil sensor system with direct connection to server without data logger

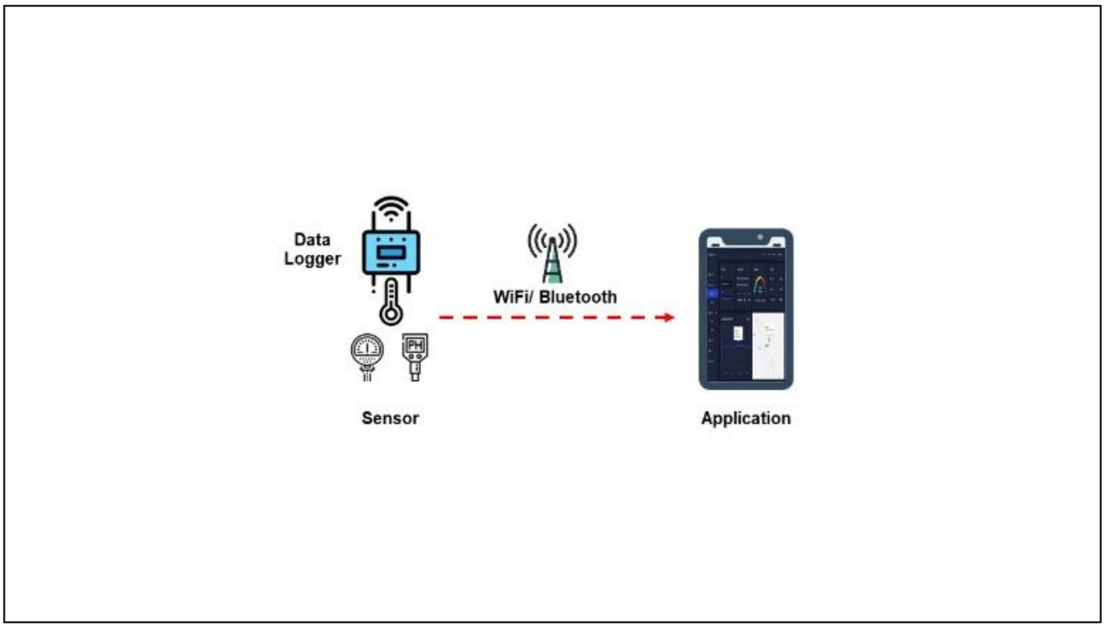

Figure 2.4 Soil sensor system with built-in data logger and wireless direct connection to computer or gadget

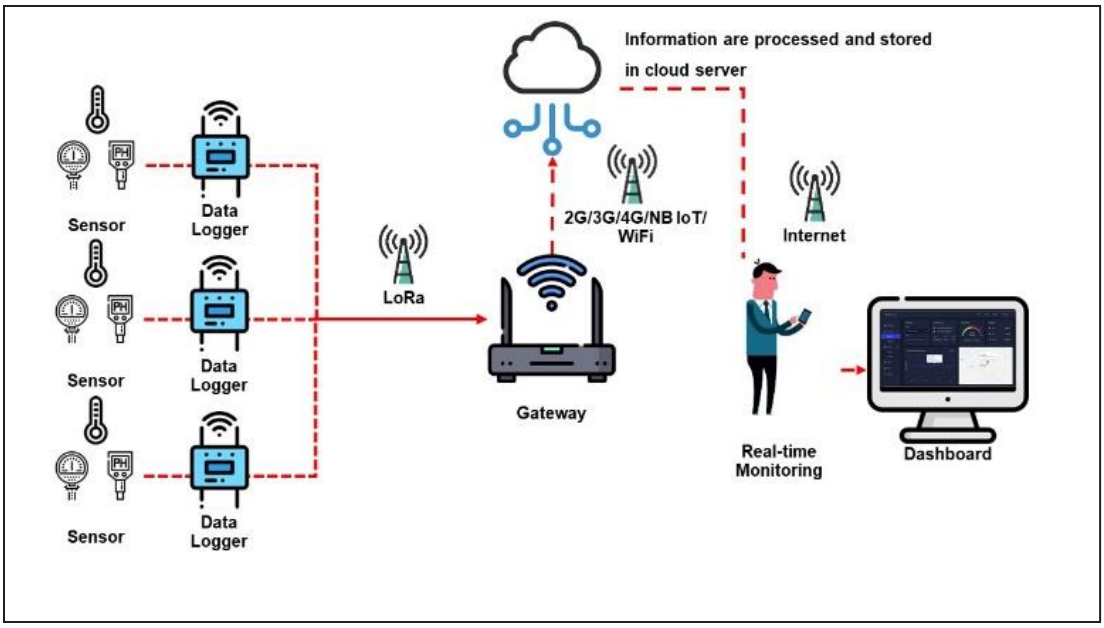

Figure 2.5 Soil sensor system which connect to server through LoRa and a gateway.

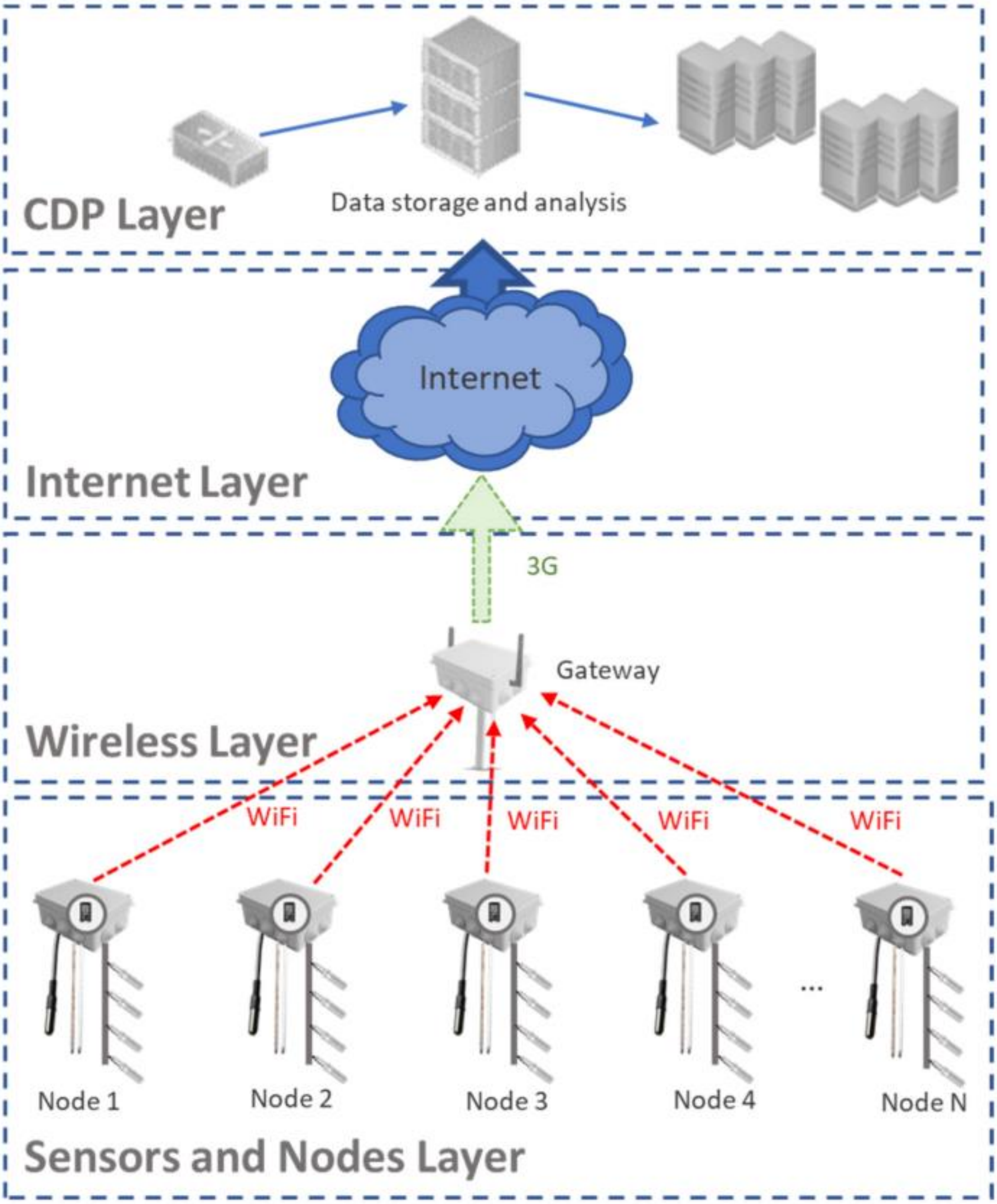

Figure 2.6 Wireless sensor network (García et al., 2021)

3 Remote Sensing Satellites

3.1 Characteristics of satellite remote sensing systems

In recent years, new satellite missions and technological advances have provided more accurate and detailed soil data, contributing significantly to our understanding of the Earth's water cycle, agricultural practices, and climate change. Satellite imagery continue to develop, we can anticipate a wealth of soil data, enabling researchers, policymakers, and agricultural managers to make better-informed decisions and improve the overall management of our planet's resources.

3.1.1 Soil Moisture Sensing from Satellites

Satellite remote sensing has become an essential tool in monitoring and understanding soil moisture (SM) at large spatial scales, providing crucial information for agricultural management, water resources, and climate research (Entekhabi et al., 2010). Various satellite missions have been designed to monitor soil moisture, utilizing different sensor technologies, resolutions, and frequencies to provide data suitable for diverse applications.

In general, there are two types of SM measurements from satellite: using passive or active microwave and using thermal and optical data.

Examples of the first approach are SMOS, SMAP, ASCAT, Sentinel-1. The advantage here is that the remote sensing signal is more directly related to SM. Also, they work regardless of cloud cover. But they usually measure only the first top centimetres and might not work well in dense vegetation cover.

Example of second approach are MODIS, Landsat, Sentinel-3. Their advantage is that they usually give SM estimate from the root-zone and work well in vegetated areas. The disadvantage is that SM must be obtained through some kind of modelling using land surface temperature and surface vegetation properties (either indices or biophysical parameters). Also, those measurements are affected by cloud cover so might not work well during cloudy periods.

One of the early and most significant satellite missions for monitoring soil moisture was the European Space Agency's Soil Moisture and Ocean Salinity (SMOS) mission (Y H Kerr et al., 2016; Yann H. Kerr et al., 2001). SMOS carries an L-band radiometer, which measures the natural microwave emissions from the Earth's surface at a wavelength of 21 cm, enabling it to retrieve soil moisture information from the top few centimetres of the soil. The L-band radiometer provides a relatively coarse spatial resolution of around 50 km, but with a high temporal resolution of three days. This high temporal resolution is beneficial for tracking soil moisture dynamics over time. The L band has an average penetration depth of about 6 cm, and penetration depth obviously increases with decreasing moisture content (Gorrab et al., 2014).

The Soil Moisture Active Passive (SMAP) mission, launched by NASA in 2015, combines both passive microwave radiometry and active radar measurements to monitor soil moisture (Entekhabi et al., 2010). The L-band radiometer on SMAP provides a spatial resolution of 40 km, while the radar system offers a higher spatial resolution of 3 km, albeit at the expense of temporal resolution. By combining these two measurements, SMAP can provide accurate soil moisture data with an intermediate spatial resolution of around 10 km, which is suitable for various applications, such as agricultural management and hydrological modelling (Entekhabi et al., 2010).

Another widely used remote sensing system for monitoring soil moisture is the Advanced Scatterometer (ASCAT), an instrument on-board the MetOp series of satellites operated by the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) (Bartalis et al., 2007). ASCAT measures the backscatter of C-band radar signals, which are sensitive to soil moisture in the top few centimeters of the soil. ASCAT provides a spatial resolution of 25 km and a temporal resolution of around one day, allowing for frequent monitoring of soil moisture dynamics. ASCAT is widely used for SM measurements but its primary role is "to measure wind speed and direction over the oceans" (https://www.eumetsat.int/ascat).

Aside from dedicated soil moisture satellite missions, several other remote sensing systems can also provide soil moisture data as a by-product of their primary objectives. For instance, the Moderate Resolution Imaging Spectroradiometer (MODIS) on-board NASA's Terra and Aqua satellites provide soil moisture data derived from land surface temperature and vegetation indices (Khellouk et al., 2021; F. Zhang et al., 2014). Similar techniques can also be used with Lalndsat(Ghasemloo et al., 2022) and Sentinel-3 (Ayari et al., 2022). Although MODIS data may not be as accurate as data from dedicated soil moisture missions, they can still provide useful information for certain applications, particularly when combined with other data sources.

Sentinel is a series of Earth observation satellites developed by the European Space Agency (ESA) as part of the European Union's Copernicus Programme. Among the various types of data collected by Sentinel satellites, soil moisture is an essential variable for applications in agriculture, water resource management, flood prediction, and climate modelling. The use of the Sentinel-1 satellite to determine soil moisture has been carried out quite extensively, such as to determine the distribution of soil moisture for the purpose of determining the workload of machinery (Imantho et al., 2022), combined with MODIS (Han et al., 2020) , or with LANDSAT 8 (Alexakis et al., 2017). An additional algorithm is needed to interpret Sentinel-1 data into soil moisture, such as using AI trained with field measurement data. Most Sentinel-1 algorithms measure the relative soil moisture (relative to the highest and lowest values observed in the full timeseries of observations) in the few top centimetres of the soil (https://land.copernicus.eu/global/products/ssm). This can be converted to volumetric soil moisture using further models.

There are several challenges associated with using satellite remote sensing for soil moisture monitoring, including the influence of vegetation, soil roughness, and topography on microwave signals (Albergel et al., 2013). Advanced algorithms and data assimilation techniques are often required to retrieve accurate soil moisture information from satellite measurements, which can be a complex and resource-intensive process. Furthermore, satellite remote sensing can only provide information on surface soil moisture, limiting its usefulness for understanding deeper soil moisture dynamics.

Despite these challenges, satellite remote sensing offers a unique opportunity to monitor soil moisture over large spatial scales and long time periods, providing critical information for various applications related to agriculture, water resources management, and climate change research. As technology and data processing algorithms continue to improve, the accuracy and usefulness of satellite-based soil moisture data are expected to increase, further enhancing our ability to manage and predict water resources and crop production in a changing world. One of the newest data processing algorithms in soil moisture estimation is SMAP-HydroBlock, which adopts the fusion method between HydroBlocks-RTM outputs (30-m resolution) and SMAP L3 brightness temperature observations (36-km resolution) using a cluster-based merging scheme. This approach has been tested throughout the United States and produces soil moisture data at a resolution of 30 m, with greater accuracy than the soil moisture data produced by SMAP (Vergopolan et al., 2021).

One promising development in satellite remote sensing for soil moisture is the emergence of CubeSats (Straub et al., 2019), small and cost-effective satellites that can be launched in groups to provide high-resolution and high-frequency data. For example, the Temporal Experiment for Storms and Tropical Systems (TEMPEST) mission aims to deploy a constellation of CubeSats to measure L-band microwave emissions, providing soil moisture data with high spatial resolution and temporal resolution (Reising et al., 2015). This new generation of satellite remote sensing systems has the potential to greatly improve our understanding of soil moisture dynamics and support climate-smart agriculture. Other future prospects are e.g., ROSE-L from ESA (https://www.eoportal.org/satellite-missions/rose-l#summary)SM).

In summary, satellite remote sensing systems play a vital role in monitoring soil moisture at large spatial scales, offering essential information for various applications related to agriculture, water resources, and climate research. Several satellite missions, such as SMOS, SMAP, and ASCAT, have been designed specifically for soil moisture monitoring, utilizing different sensor technologies to provide data with varying spatial and temporal resolutions. Although satellite-based soil moisture data may face challenges related to vegetation, soil roughness, and topography, improvements in technology and data processing algorithms continue to enhance the accuracy and usefulness of this information. Future developments, such as CubeSat constellations, promise to further advance the field of satellite remote sensing for soil moisture and support climate-smart agriculture.

3.1.2 Soil Chemistry Sensing from Satellites

Soil chemistry monitoring using satellite remote sensing is a rapidly evolving field. Several satellite systems are capable of providing valuable information on soil properties such as soil organic carbon, pH, and nutrient content. These properties are essential for understanding the fertility of the soil, its role in the carbon cycle, and its contribution to climate change. This review will provide a brief overview of the main characteristics of satellite remote sensing systems for soil chemistry monitoring.

Satellite remote sensing systems rely on the principle of detecting reflected and emitted radiation from the Earth's surface. Sensors on board satellites collect spectral data, which can be analyzed to infer the composition and properties of the soil. Different satellite systems utilize different spectral bands, spatial resolutions, and temporal resolutions depending on their specific objectives.

One of the most widely used satellites for soil chemistry monitoring is the Moderate Resolution Imaging Spectroradiometer (MODIS), a sensor on board NASA's Terra and Aqua satellites. MODIS has been employed in various studies to estimate soil organic carbon content, an essential parameter for assessing soil fertility and carbon sequestration potential (Hashimoto et al., 2011; Hengl et al., 2021; Jin & Liang, 2006; Poggio et al., 2013; Xinle Zhang et al., 2018). Multispectral satellite data can be used for prediction of soil chemical properties using multispectral satellite Images and wavelet transforms methods (Pande et al., 2022). The Visible Infrared Imaging Radiometer Suite (VIIRS) on board the Suomi National Polar-orbiting Partnership (NPP) satellite is another sensor used for similar applications (Justice et al., 2013).

Sentinel-2, part of the European Union's Copernicus Programme, offers high spatial resolution (10-20 m) and multispectral data with a wide swath, making it ideal for monitoring soil chemistry at regional to global scales (Drusch et al., 2012). Researchers have successfully used Sentinel-2 data to estimate soil properties such as pH, clay content, and nitrogen content.

Hyperspectral satellite sensors, such as the Hyperspectral Infrared Imager (HyspIRI) and the EnMAP (Environmental Mapping and Analysis Program), have the potential to provide detailed information on soil properties also PRISMA (https://www.eoportal.org/satellite-missions/prisma-hyperspectral). In the future, there will be CHIME (https://www.eoportal.org/satellite-missions/chime-copernicus). These sensors have been used to estimate soil organic carbon, clay content, and cation exchange capacity (CEC).

Despite the advances in satellite remote sensing systems for soil chemistry monitoring, there are still limitations and challenges that need to be addressed. Factors such as atmospheric interference, soil moisture content, and vegetation cover can affect the accuracy of soil property estimations. Additionally, spatial and temporal resolutions may not be suitable for all applications, especially in highly heterogeneous landscapes or for detecting rapid changes in soil chemistry.

In conclusion, satellite remote sensing systems play a crucial role in monitoring soil chemistry properties at various spatial and temporal scales. As technology continues to advance, it is anticipated that these systems will become even more accurate and cost-effective, allowing for better management of our planet's resources and the development of climate-smart agriculture.

3.2 System Architecture and Communication

- Data Acquisition: Satellite remote sensing systems rely on various sensors, including passive and active microwave radiometers (radar), optical imagers, to measure soil moisture and chemistry. These sensors can provide data at different spatial and temporal resolutions, depending on the satellite mission's specific objectives and technical capabilities.

- Data Processing: Raw satellite measurements are typically processed through a series of steps, including calibration, geolocation, atmospheric correction, and soil parameter retrieval, to generate soil moisture and chemistry products. Advanced algorithms and models, such as radiative transfer models, can be used to improve the accuracy and reliability of the retrieved soil parameters.

- Data Distribution and Access: Satellite remote sensing data are often disseminated through dedicated web portals and data centres, which provide user-friendly tools and interfaces for data search, download, visualization, and analysis. Examples of such platforms include the NASA Earthdata Search and the Copernicus Data Space Ecosystem.

- Interoperability and Standards: The use of standardized data formats and metadata, such as the NetCDF format and the Climate and Forecast (CF) metadata conventions (Eaton et al., 2009), can facilitate the exchange and integration of satellite-derived soil moisture and chemistry data with other geospatial datasets and models. This interoperability is critical for the development of effective Earth system monitoring and decision-support tools.

3.3 Data Frequency and Temporal Resolution

- Temporal Resolution: Satellite remote sensing systems can provide soil moisture and chemistry data at different temporal resolutions, depending on the sensor type, orbit characteristics, and satellite mission objectives. Temporal resolutions can range from daily observations for certain low Earth orbit (LEO) satellites to multi-day or even monthly averages for geostationary satellites platforms. Geostationary satellites have sub-hourly temporal resolution but usually quite poor (3-5 km) spatial resolutions.

- Factors Affecting Data Frequency: The frequency of soil moisture and chemistry data acquisition by satellite remote sensing systems can be influenced by various factors, including sensor revisit time, satellite swath width, and atmospheric conditions such as cloud cover (especially for optical sensors) and precipitation. These factors can affect the overall data continuity and suitability for different applications, particularly those requiring near-real-time information or high temporal resolution.

- Temporal Resolution Requirements for Specific Applications: The optimal temporal resolution for soil moisture and chemistry monitoring depends on the specific application and its requirements. For example, agricultural management practices such as irrigation scheduling and fertilizer application may require high-resolution data on the order of hours to days, while regional and global climate studies may be more focused on long-term trends and can rely on coarser temporal resolutions.

- Data Frequency Optimization: Efforts to optimize data frequency in satellite remote sensing systems include the development of multi-sensor and multi-temporal fusion techniques, which combine information from multiple satellite missions, sensors, and time periods to generate improved soil moisture and chemistry datasets with enhanced spatial and temporal resolutions. These techniques can help mitigate the limitations associated with individual satellite systems and provide more accurate and timely information for various applications.

3.4 Advantages, Limitations, and Suitable Applications

Advantages:

- Large Spatial Coverage: Satellite remote sensing systems can provide comprehensive spatial coverage of soil moisture and chemistry at regional, continental, and even global scales. This wide coverage enables the study of large-scale patterns and the monitoring of areas that may be difficult or time-consuming to access using ground-based methods (Dorigo et al., 2017).

- Consistent Data Collection: Satellites offer a consistent and continuous source of data, which can be particularly valuable for long-term monitoring of soil parameters and the evaluation of temporal trends (Albergel et al., 2013).
- Integration with Other Data Sources: Satellite-derived soil moisture and chemistry data can be easily integrated with other geospatial datasets, such as land use and vegetation maps, to support a wide range of applications, including crop yield forecasting, irrigation management, and climate change assessment.

Limitations:

- Coarse Spatial Resolution: Satellite remote sensing systems typically have relatively coarse spatial resolutions, ranging from hundreds of meters to several kilometres. This can limit their utility for applications requiring high-resolution soil moisture and chemistry information, such as precision agriculture.
- Atmospheric Effects: The accuracy of satellite-derived soil moisture and chemistry measurements can be affected by atmospheric conditions, such as cloud cover, precipitation, and water vapor, which can lead to errors and uncertainties in the retrieved data (Albergel et al., 2013).
- Signal Penetration Depth: The penetration depth of microwave and optical signals used in satellite remote sensing is generally limited to the top few centimetres of the soil surface, which may not provide a complete representation of soil moisture and chemistry throughout the entire soil profile.

Suitable Applications:

- Precision Agriculture: Remote sensing data can then be used to make decisions about how to manage the farm, such as where to apply fertilizer, water, and pesticides. Remote sensing can help farmers to improve crop yields, reduce input costs, and protect the environment.
- Large-scale Soil Moisture Monitoring: Satellite remote sensing systems are particularly well-suited for monitoring soil moisture at regional to global scales, where the need for large spatial coverage outweighs the limitations associated with spatial resolution and signal penetration depth.
- Climate Change Assessment: Satellite-derived soil moisture and chemistry data can be used to assess the impacts of climate change on soil resources and agricultural productivity, particularly in regions where ground-based monitoring networks are sparse or non-existent.
- Flood and Drought Forecasting: The integration of satellite-derived soil moisture and chemistry data with hydrological models can improve the accuracy of flood and drought forecasts, supporting water resource management and risk reduction efforts.

3.5 Schematics of Remote Sensing Technology

Example of schematics if remote sensing technology for detection of crop water needs is depicted in Figure 3.1. Three observations can synergically utilized: optical, thermal and radar (microwave), to obtain components of surface, including vegetation, soil, and water.

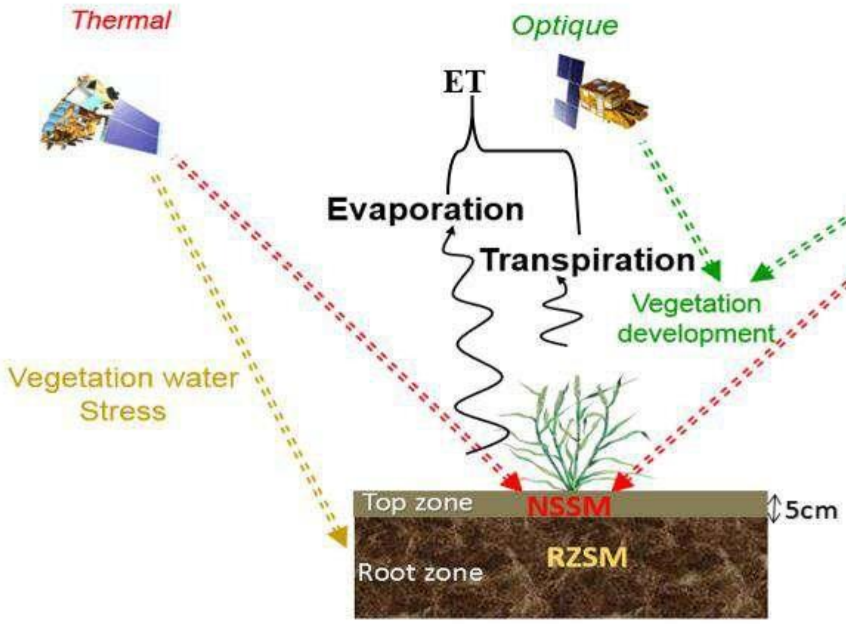

Figure 3.1 Monitoring crops water needs at high spatio-temporal resolution by synergy of optical / thermal and radar observations (Amazirh, 2019)

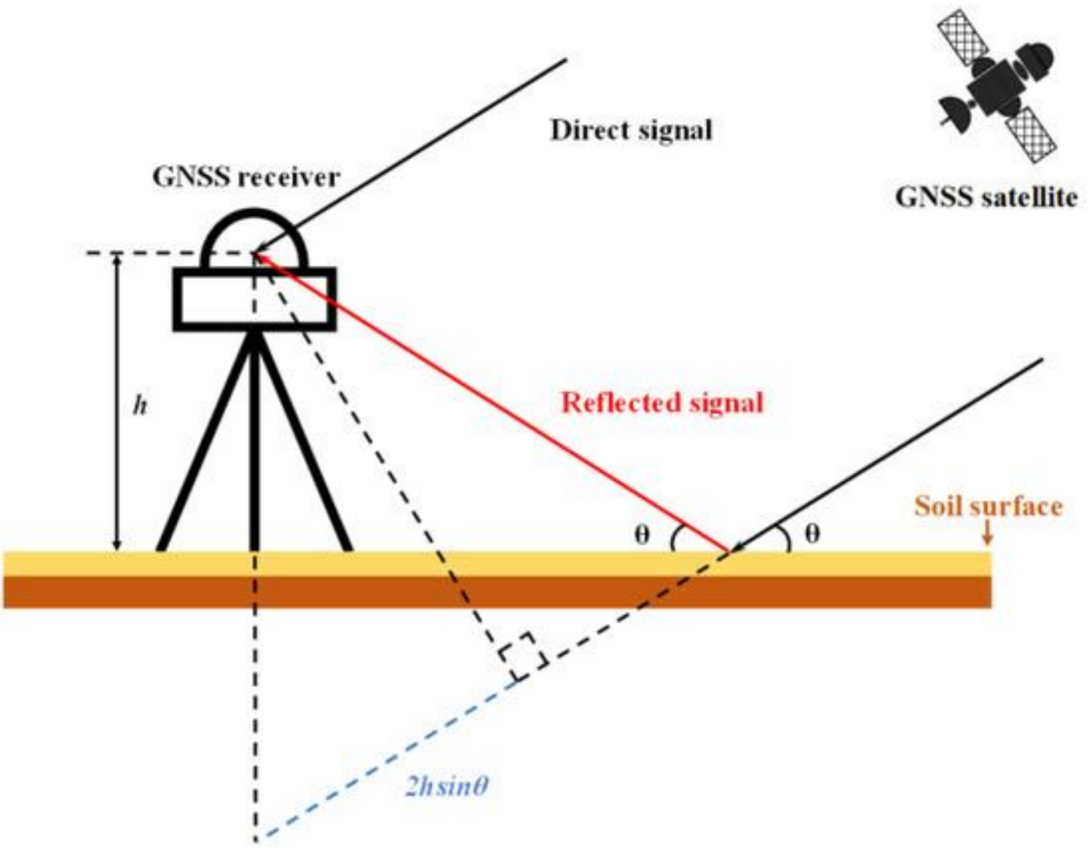

Figure 3.2 Schematic diagram of Deformation and Soil Moisture Monitoring in Loess Landslide Simultaneous Retrieved with Ground-Based GNSS (Zhou et al., 2022)

Combination of GroundBased GNSS and Satellite for monitoring soil deformation and soil moisture is shown in Figure 3.2.

4 Drones (Unmanned Aerial Vehicles)

4.1 Characteristics of Drone-Based Soil Moisture Sensing Systems

Precision agriculture's remote sensing applications have evolved from soil organic matter sensors to satellite, aerial, and mounted systems. The electromagnetic spectrum now ranges from ultraviolet to microwave, enabling advanced techniques like LiDAR, fluorescence, and thermal spectroscopy. Hyperspectral sensing enables detailed analysis of compounds, interactions, and crop properties. Numerous spectral indices cater to various applications, and improved spatial resolution allows for fine-scale evaluation. With increased temporal frequency, near real-time soil, crop, and pest management is now possible (Mulla, 2013).

With the rapid advancements in drone technology, drone-based soil chemistry sensing systems have become increasingly popular in agriculture and environmental management. The primary benefits include high-resolution and accurate data, customizable sensor payloads, real-time data collection and processing, cost-effectiveness, easy access to difficult-to-reach areas, and an integrative approach.

Remote sensing is widely used for agricultural and environmental analysis. Traditional vegetation and biodiversity monitoring relied on aerial and satellite imagery, which can be costly for high-resolution needs. UAS offer smaller, more affordable platforms for the remote sensing community. The variety of available sensors is expanding to accommodate smaller platforms with weight and dimension restrictions and to meet user and application requirements. (Colomina & Molina, 2014).

These characteristics make drone-based soil chemistry sensing systems a valuable tool for various applications, including precision agriculture, environmental assessment, and soil conservation. However, it is essential to recognize the challenges and limitations associated with these systems, such as flight endurance, payload capacity, and regulatory restrictions.

Drone technology and sensing systems continue to evolve the way of soil chemistry monitoring and management soil chemistry in agriculture and environmental research. This would ultimately lead to more sustainable agricultural practices, improved resource management, and a better understanding of the complex interactions within soil ecosystems.

4.1.1 Soil Moisture Sensing Using Drones

Drone-based soil moisture sensing systems have rapidly evolved over the past decade, proving to be an asset for precision agriculture and environmental monitoring. These systems provide a high spatial resolution and the ability to access areas that might be difficult or time-consuming for other methods of data collection (Gago et al., 2015).

One of the main characteristics of drone-based soil moisture sensing systems is the incorporation of remote sensing technology, which typically involves the use of multispectral or hyperspectral sensors. These sensors can detect variations in the reflectance and absorption of electromagnetic radiation by the soil surface, allowing for indirect estimation of soil moisture content.

Drones offer the advantage of flexible deployment, enabling data collection at a user-defined time and location. This provides researchers and farmers with the ability to closely monitor their fields and adjust their irrigation and fertilization strategies accordingly (Gago et al., 2015). The high spatial resolution of drone-based soil moisture sensing systems (von Hebel et al., 2021) allows for better identification of moisture variability within a field, which can help identify areas with differing water needs.

Moreover, drone-based soil moisture sensing systems can be integrated with other sensors to monitor various aspects of soil health, such as soil temperature, salinity, or nutrients. This multi-sensor approach can offer a more comprehensive understanding of soil conditions, which is essential for effective precision agriculture management.

However, some challenges persist for drone-based soil moisture sensing systems. One of the primary concerns is the high initial investment cost associated with the purchase of drones, sensors, and supporting software. Additionally, data processing and analysis can be time-consuming and may require specialized expertise (Adão et al., 2017; Sharma et al., 2021; Tampubolon & Reinhardt, 2015).

In summary, drone-based soil moisture sensing systems offer numerous advantages for precision agriculture and environmental monitoring. While there are some challenges related to cost and data processing, these systems hold great potential for providing timely and accurate soil moisture data to support sustainable agricultural practices.

4.1.2 Soil Chemistry Sensing Using Drones

Drones, or unmanned aerial vehicles (UAVs), have gained considerable attention in recent years as a powerful tool for soil chemistry monitoring. Their ability to collect high-resolution data in real-time makes them a promising solution for precision agriculture and environmental management.

- High-resolution and accurate data: Drone-based soil chemistry sensors can capture data at high spatial and spectral resolutions, allowing for a more detailed understanding of soil chemical properties. The data collected can be used to create detailed maps of soil nutrients, organic matter, and pH levels.

- Customizable sensor payload: Drones can be equipped with various types of sensors, such as optical multispectral or hyperspectral, or thermal imaging sensors, to analyse different soil properties simultaneously. This flexibility allows for tailored solutions that address specific needs in agriculture and environmental monitoring.

- Rapid data collection and processing: Drone-based soil chemistry sensing systems offer near real-time data collection and processing capabilities. This enables timely decision-making for agricultural management practices, such as precision fertilizer application and soil amendment strategies.

- Cost-effectiveness: Compared to satellite and manned aircraft platforms, drones are more cost-effective for soil chemistry monitoring. They require lower initial investments, and their maintenance and operational costs are significantly lower. This makes drone-based systems an attractive option for small to medium-sized farms and research institutions.

- Easy access to difficult-to-reach areas: Drones can easily access remote or challenging areas, such as wetlands, steep slopes, or regions with limited infrastructure. This enables more comprehensive soil chemistry monitoring and can provide valuable information for environmental assessments and management.
- Integrative approach: Drone-based soil chemistry sensing systems can be combined with other remote sensing techniques, such as satellite imagery or ground-based measurements, to provide a more comprehensive understanding of soil properties and improve the accuracy of data analysis.

Despite these advantages, drone-based soil chemistry sensing systems face several challenges. These include limitations in flight endurance and payload capacity, which can restrict the operational range and the number of sensors that can be carried. Additionally, regulations and airspace restrictions may limit the use of drones in some regions (Colomina & Molina, 2014).

In conclusion, drone-based soil chemistry sensing systems offer significant advantages in terms of data resolution, flexibility, and cost-effectiveness compared to traditional remote sensing platforms. As technology continues to advance, drones hold great potential for improving agricultural management practices and enhancing our understanding of soil chemical properties.

4.2 Types of Sensors for Drone-Based Soil Moisture Monitoring

As drone-based soil moisture and chemistry sensing systems have evolved, a variety of sensors have been developed to provide reliable and accurate information. In this section, we will discuss some of the most widely used sensors in drone-based soil moisture and chemistry monitoring.

- Thermal Infrared Sensors: Thermal infrared (TIR) sensors measure surface temperature, which can be used to estimate soil moisture based on the relationship between soil temperature and moisture content (N. Wang & Qu, 2009). TIR sensors have been used for soil moisture mapping at various spatial scales and are particularly useful in areas with limited ground-based measurements (Holzman & Rivas, 2016; Kustas & Hain, 2013; Rahimzadeh-Bajgiran & Berg, 2016) .
- Multispectral Sensors: Multispectral sensors measure reflectance across several spectral bands, which can be used to indirectly estimate soil moisture and various soil properties. These sensors are often used in combination with vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), to provide estimates of soil moisture and other parameters related to soil health (Alexakis et al., 2017; Bekele et al., 2023; Celik et al., 2022).
- Radar Sensors (Ground Penetrating Radar, GPR): GPR has proven to be one of the most promising methods for measuring soil moisture content due to its high resolution and non-destructive nature. Using GPR in drones will significantly reduce measurement work and will have no impact on soil and crops during the growing season. Although the GPR-based drone has not been produced yet, a prototype has been launched and works at a wide frequency, namely 250 - 2800 MHz. This GPR drone prototype can operate and provide consistent results in terms of spatial patterns and absolute soil moisture values (Wu et al., 2019).

- Hyperspectral Sensors: Hyperspectral sensors measure reflectance at a large number of contiguous spectral bands, providing detailed information on soil chemistry and properties. This information can be used to map soil properties, such as soil organic carbon, soil pH, and nutrient levels, that are crucial for climate-smart agriculture (Vohland et al., 2014). Hyperspectral sensors have also been used to assess soil moisture, although their ability to do so may be limited by their lower spatial resolution compared to multispectral sensors (Ben-Dor et al., 2009).

- LiDAR Sensors: Light Detection and Ranging (LiDAR) sensors use laser pulses to measure the distance between the sensor and the Earth's surface. These measurements can be used to create high-resolution digital elevation models (DEMs) that can help estimate soil moisture by modelling surface water flow and retention (Bretreger et al., 2021; Kemppinen et al., 2018; Southee et al., 2012). LiDAR data can also be combined with other remote sensing data to improve soil moisture estimates (Gou et al., 2019).

In conclusion, a variety of sensors can be used for drone-based soil moisture and chemistry monitoring. These sensors provide valuable information for climate-smart agriculture, enabling more efficient resource use and improved decision-making for farmers and policymakers.

4.3 System Architecture and Communication

Drone-based soil moisture and chemistry monitoring systems have rapidly advanced in recent years due to their ability to provide high-resolution spatial data in near-real-time, while minimizing the impact of their deployment on the landscape. The use of drones in agriculture enables farmers to monitor soil conditions, optimize irrigation practices, and evaluate nutrient management strategies. These systems are especially useful for precision agriculture, where site-specific management decisions are made based on the heterogeneity of soil properties within a field.

One common system architecture for drone-based soil monitoring is to equip the drone with appropriate sensors to measure soil moisture and chemistry parameters. These sensors can include multispectral, hyperspectral, or thermal cameras, as well as other specialized sensors such as LiDAR or ground-penetrating radar (GPR). The drone collects data while flying over the agricultural area and then transmits it either in real-time or after landing.

Drones often rely on wireless communication protocols to transmit data to a ground station, where it can be processed and analysed. The choice of communication protocol depends on factors such as data transmission range, data rate, power consumption, and environmental conditions. Drones utilize various communication systems like Radio Frequency (RF), Wi-Fi, cellular networks, satellite communication, and emerging Li-Fi technology for purposes such as remote control, telemetry, and data transmission. RF communication is widely used in the consumer drone industry, operating in the 2.4 GHz or 5.8 GHz frequency bands. Wi-Fi allows easy integration with smartphones and tablets, offering a limited range of a few hundred meters. Cellular networks, like 4G and 5G, enable long-range operations with higher data transmission rates. Satellite communication provides global coverage, albeit at a higher cost and latency. Li-Fi, an emerging technology using visible or infrared light, offers high-speed transmission with lower latency, showing potential for future drone communication systems.

The system architecture of drone-based soil moisture and chemistry monitoring typically comprises three main components: the drone platform, the sensing payloads, and the data processing and communication system.

- Drone platform: The drone platform includes the unmanned aerial vehicle (UAV) and its control system. UAVs can vary in size, weight, and flight endurance, with the most common types being multi-rotor, fixed-wing, and hybrid VTOL (Vertical Take-Off and Landing) platforms. The choice of drone platform is influenced by factors such as flight time, payload capacity, and cost. The control system may include manual control through a remote controller, semi-autonomous control, or fully autonomous control using pre-programmed flight plans and GPS waypoints (Colomina & Molina, 2014).

- Sensing payloads: The sensing payloads can include various types of soil moisture and chemistry sensors, as discussed earlier. Some commonly used sensors for drone-based soil monitoring include thermal infrared cameras for detecting soil temperature, visible and near-infrared cameras for vegetation indices, and multispectral cameras for assessing soil properties, such as moisture and nutrient content. Some drone systems may also include ground-penetrating radar (GPR)

- Data processing and communication system: The data processing and communication system is responsible for the acquisition, storage, processing, and transmission of the collected data. This system can involve onboard processing, data storage devices, and telemetry for real-time data transmission to a ground station or cloud-based services. The data can then be further processed and analysed using specialized software or algorithms to extract useful information for decision-making (Mulla, 2013). Data processing and analysis are crucial components of the system architecture. To maximise the usefulness of the collected data, it often needs to be processed using specialized software that can extract valuable information on soil moisture and chemistry. This software may perform tasks such as image stitching, radiometric calibration, or vegetation index calculation to generate insights that can inform agricultural decision-making.

Several challenges exist in the design and implementation of drone-based soil monitoring systems. These challenges include the integration of various sensors and systems, ensuring adequate flight endurance, and addressing data quality and accuracy issues (Rosell Polo et al., 2009). Furthermore, communication between the drone and the ground station may be affected by factors such as signal strength, line of sight, and interference from other radio frequency sources.

Despite these challenges, drone-based soil moisture and chemistry monitoring systems have shown promising results and can provide valuable information for agricultural management and research.

The integration of drones in agriculture has allowed for efficient, high-resolution, and near-real-time data collection, providing valuable insights for decision-making processes in the context of precision agriculture. As the technology advances, so too does the need for a comprehensive understanding of the strengths and limitations of various soil moisture and chemistry monitoring systems. By continuing to assess the advantages and challenges of these systems and sharing knowledge and resources, researchers, policymakers, and practitioners can better harness the full potential of drone-based technologies in agriculture.

4.4 Data Frequency and Spatial Resolution

One crucial aspect of drone-based soil moisture and chemistry monitoring is the data frequency and spatial resolution, which directly influence the accuracy and applicability of the derived information. Drones equipped with various types of sensors can provide high-resolution data with centimetre-level accuracy, depending on the sensor type and altitude. For instance, multispectral and hyperspectral cameras offer an excellent spatial resolution ranging from a few centimetres to sub-meter levels when flown at low altitudes. This enables farmers and researchers to monitor soil properties at a fine scale and identification.

Moreover, the data frequency, which refers to the interval at which measurements are taken, can be significantly higher with drones compared to satellite-based or ground-based systems. Due to their flexibility and ease of deployment, drones can be flown more frequently, allowing for rapid data acquisition and monitoring. This capability is essential in detecting changes in soil moisture and chemistry and facilitating timely decision-making in agriculture.

It is essential to note that the data frequency and spatial resolution of drone-based systems can be affected by various factors such as weather conditions, battery life, and data processing capabilities (Anderson et al., 2018). As a result, researchers and users must carefully consider these factors when designing and implementing drone-based soil monitoring systems.

In conclusion, drone-based soil moisture and chemistry sensing systems offer high data frequency and spatial resolution, making them an attractive option for precision agriculture. However, it is crucial to consider the various factors that can influence data acquisition and processing to optimize the system for specific applications.

4.5 Power Systems and Energy Management

Power systems and energy management are critical factors for the success of drone-based soil moisture and chemistry monitoring systems. The energy source for drones significantly influences their flight duration, operational range, and the weight of onboard sensors and equipment (Gupta et al., 2016). Lithium polymer (LiPo) batteries are the most commonly used power source for drones due to their high energy density, lightweight properties, and capability to deliver high discharge rates (Zarco-Tejada et al., 2012). However, the limited flight time of drones (usually 20-60 minutes) remains a challenge when covering extensive areas (Mancini et al., 2013).

Solar panels and hybrid power systems (combining solar power and fuel cells, for example) have been proposed to extend flight duration and range (Boukoberine et al., 2019; LEI et al., 2019; C. Zhang et al., 2022). Hydrogen fuel cells, in particular, have shown promise in increasing drone endurance, as they are more energy-dense and environmentally friendly than conventional batteries (“DMI Drone Flight for City Construction Demo,” 2020; “Nordic Unmanned in Hydrogen Drone Flight,” 2021; Dutczak, 2018). Furthermore, energy harvesting from the environment, such as wind, solar, and vibrations, could also contribute to enhanced power management and increase the drone's operational life (Hoseini et al., 2020; Kitchen et al., 2020; Sherman et al., 2021)

Energy management can be improved by optimizing flight paths, reducing hovering time, and using energy-efficient data collection methods (Ahmad et al., 2017; Chodnicki et al., 2022; Fevgas et al., 2022). Additionally, the integration of onboard computing capabilities can minimize data transmission requirements, thereby reducing energy consumption.

4.6 Cost Analysis and Application Suitability

In the context of drone-based soil moisture and chemistry monitoring systems, cost analysis and application suitability are crucial factors to consider. The cost of deploying and operating drones for agricultural monitoring purposes can vary significantly depending on the specific sensors, drone platform, and mission requirements. While drone technology has become more affordable over the years, it remains essential to conduct a comprehensive cost-benefit analysis to ensure a return on investment (ROI) for farmers and other stakeholders.

The initial cost of acquiring a drone and its associated sensing equipment can range from a few thousand dollars for consumer-grade systems to tens of thousands for professional-grade systems with advanced capabilities. Additionally, there are ongoing operational costs, such as maintenance, battery replacements, software licenses, and data processing fees. In some cases, using drone services provided by third-party companies may offer a cost-effective alternative to purchasing and maintaining the drone and sensor equipment directly.

In terms of application suitability, the choice of drone and sensor system should be tailored to the specific needs of the agricultural operation. Factors such as crop type, field size, topography, and local weather conditions should be taken into account when selecting the appropriate drone platform and sensor technology. Moreover, it is crucial to consider the local regulations and legal requirements for drone operation, as these may impose constraints on flight altitude, duration, and proximity to human settlements and other sensitive areas.

Ultimately, the suitability of drone-based soil moisture and chemistry monitoring systems for a particular agricultural application will depend on the balance between the costs and benefits, as well as the specific requirements of the stakeholders involved. By optimizing sensor selection, flight planning, and data processing strategies, it is possible to maximize the ROI and ensure that drone technology delivers tangible benefits in terms of improved crop management, reduced resource consumption, and enhanced environmental sustainability.

4.7 Schematics of Drone (UAV) Based Sensing Technology

Mechanism of soil moisture sensing with drone is depicted in Figure 4.1, the wave range from visible light to electromagnetic radiation are reflected by the surface. The reflection will be capture by multispectral sensor mounted on the drone. The image data then to be processed to interpret soil moisture or other soil properties. Advanced processing can be done utilizing machine learning and artificial intelligence as shown in Figure 4.2.

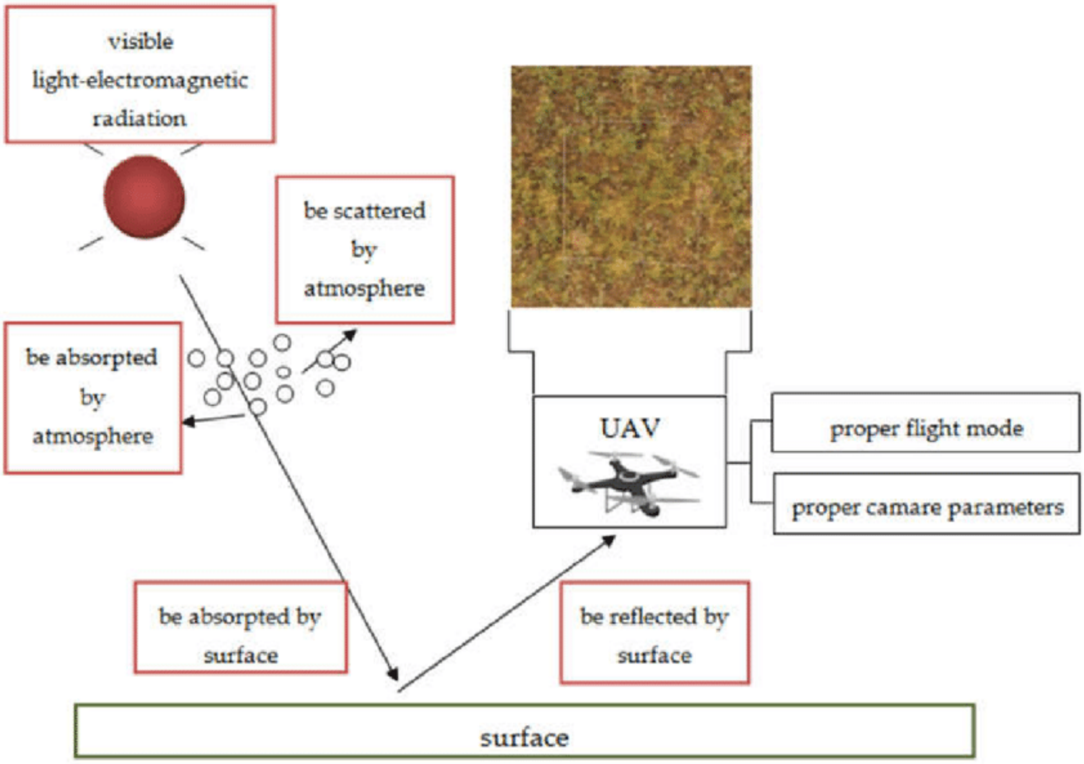

Figure 4.1 Using UAV Visible Images to Estimate the Soil Moisture (F. Lu et al., 2020)

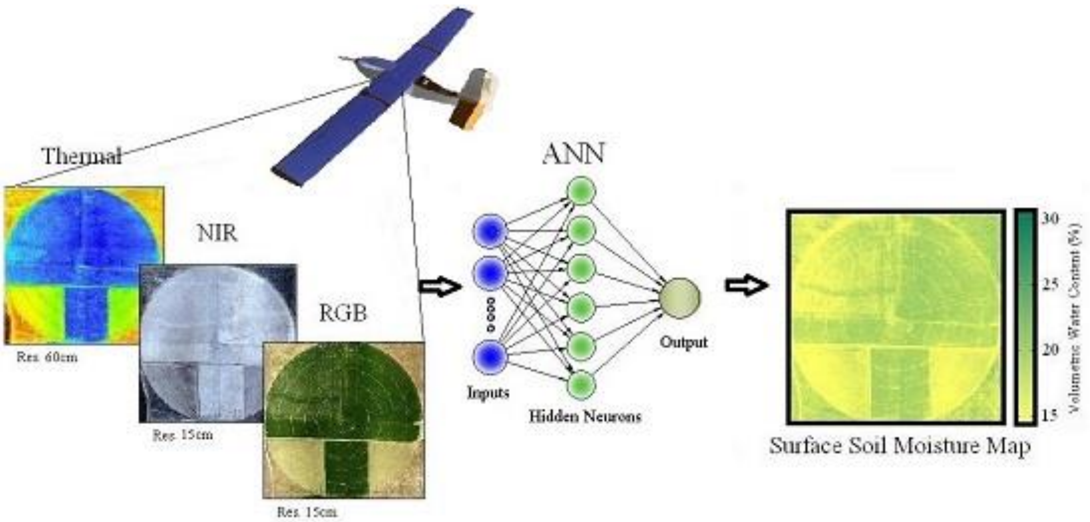

Figure 4.2 Assessment of Surface Soil Moisture Using High-Resolution Multi-Spectral Imagery and Artificial Neural Networks (Hassan-Esfahani et al., 2015)

5 Combined Approaches

Integrating multiple sensing systems, such as field-implanted sensors, remote sensing satellites, and drone-based systems, has emerged as a promising approach to overcome the limitations of individual methods and achieve a more comprehensive understanding of soil moisture and chemistry. The combined approach enables synergistic data analysis, providing valuable insights and improved accuracy for agricultural applications.

In a combined approach, field-implanted sensors serve as the foundation for continuous in situ measurements, ensuring high spatial and temporal resolution (Vereecken et al., 2008). Remote sensing satellites, on the other hand, provide large-scale, long-term monitoring of soil properties, giving valuable information on regional trends and patterns. Drone-based systems, with their high-resolution imaging capabilities and flexibility, can bridge the gap between the two, offering targeted monitoring of specific areas or time-sensitive changes.

Data fusion techniques have been developed to integrate information from different sensing systems, including statistical and machine learning-based methods (Jiangui Liu & Pattey, 2010). By combining the strengths of each method, these techniques can provide more accurate estimations of soil moisture and chemistry than individual approaches alone.

The combined approach presents several challenges, including data management and communication between different systems. Standardizing and integrating heterogeneous data sources is crucial for effective data fusion and interpretation (Piles et al., 2011). Moreover, addressing the disparities in data frequency and resolution between systems is essential for optimizing the combined approach (Crow et al., 2012).

Despite these challenges, the combined approach offers numerous benefits for climate-smart agriculture. By leveraging the strengths of each sensing system, the combined approach provides comprehensive, accurate, and actionable insights for farmers, policymakers, and researchers. This can lead to improved decision-making, enhanced agricultural productivity, and better management of natural resources.

5.1 Advantages and Challenges of Integrating Multiple Sensing Systems

Integrating multiple sensing systems, such as field-implanted sensors, remote sensing satellites, and drone-based systems, offers several advantages for monitoring soil moisture and chemistry. Many studies have highlighted the benefits of combining these sensing technologies to improve the accuracy and reliability of soil data and address some of the limitations inherent in individual sensor systems.

One of the key advantages of integrating multiple sensing systems is the ability to harness the complementary strengths of each technology. For instance, field-implanted sensors can provide high-resolution, in-situ measurements of soil moisture and chemistry, while remote sensing satellites and drone-based systems can offer broader spatial coverage and near-real-time monitoring (Montzka et al., 2017). This integration can enhance the temporal and spatial resolution of soil data, allowing for more accurate and timely assessments of soil conditions.

Furthermore, integrating multiple sensing systems can help mitigate some of the uncertainties and errors associated with individual sensors. By comparing and validating data from different sources, researchers can more effectively identify and correct for potential biases or. This can lead to more reliable soil moisture and chemistry data, ultimately informing better decision-making in agriculture and natural resource management.

Despite these advantages, there are also challenges in integrating multiple sensing systems. One significant challenge is the harmonization of data from different sources, which can involve addressing differences in spatial and temporal resolutions, data formats, and measurement units. Another challenge is the development of robust data fusion techniques and algorithms that can effectively combine and analyse data from multiple sensors.

Moreover, the cost of implementing and maintaining an integrated sensing system can be high, particularly for small-scale or resource-limited agricultural operations. However, the potential benefits of more accurate and comprehensive soil monitoring, such as improved crop management and reduced input costs, may outweigh these initial expenses in the long term.

Combining various sensing systems for monitoring soil moisture and chemistry presents numerous benefits, including enhanced accuracy, as well as better spatial and temporal resolution, while simultaneously tackling some limitations found in single sensor systems. Nonetheless, data harmonization, algorithm development, and cost-related challenges persist. Ongoing research and development efforts in this field are crucial to unlocking the full potential of integrated sensing systems for climate-smart agriculture and natural resource management.

5.2 Data Fusion Techniques and System Architectures

Data fusion techniques and system architectures have been increasingly used in soil moisture and chemistry monitoring due to their potential for providing more accurate and comprehensive information (Gasmi et al., 2022; Mahmood et al., 2012; Veum et al., 2017). Data fusion techniques involve integrating data from different sources, such as in-situ measurements, remote sensing imagery, and drone-based sensors, to improve the overall understanding of soil properties and conditions.

One of the key approaches is data fusion, which combines data from different sensing systems to improve the overall accuracy and reliability of the measurements. Data fusion techniques range from simple averaging of measurements to more sophisticated statistical or machine learning-based algorithms (Chlingaryan et al., 2018).

One popular data fusion approach is the assimilation of remote sensing data into land surface models. Such assimilation techniques can help improve the estimation of soil moisture and other related variables, such as evapotranspiration and surface runoff. For example, the assimilation of soil moisture observations derived from the Soil Moisture and Ocean Salinity (SMOS) mission into the Community Land Model (CLM) has been shown to improve the accuracy of simulated soil moisture (Rains et al., 2017).

Another common data fusion technique is the combination of different types of remote sensing data. For example, the use of optical and radar data has been shown to improve the estimation of soil moisture content (Attarzadeh & Amini, 2019; Prakash et al., 2012). Optical remote sensing can provide information on vegetation and surface characteristics, while radar data are sensitive to soil moisture variations.

In terms of system architectures, a typical approach for data fusion is the integration of different sensors on a single platform, such as a drone or a satellite. This allows the simultaneous collection of various types of data, which can then be fused to provide a more accurate representation of soil moisture and chemistry.

Another approach is to use a multi-scale hierarchical framework, where data from different sources and spatial resolutions are integrated at different levels of the analysis. This approach can help address the scale mismatch issue between various types of data and provide more accurate and representative information on soil properties.

5.3 Communication and Data Management

Communication and data management are crucial aspects of soil moisture and chemistry sensing systems. Effective communication and data management allow for accurate and timely decision-making, improving agricultural productivity and sustainability.

Recent developments in wireless communication technologies have paved the way for more efficient communication and data management in field-implanted soil sensing systems. Low-power wide-area networks (LPWAN) such as LoRaWAN and Sigfox have become popular choices due to their long-range capabilities and low energy consumption. Additionally, advancements in Internet of Things (IoT) have further facilitated the integration of soil sensors into cloud-based platforms, allowing for real-time data processing and analysis.

Satellite remote sensing systems typically rely on downlink communication for data transmission to ground stations. This data is then disseminated to end-users through various channels such as the internet, dedicated communication lines, or satellite relays.

For drone-based soil sensing systems, communication is primarily achieved through wireless technologies, such as Wi-Fi, Bluetooth, or dedicated radio frequency (RF) communication systems. Data management in these systems involves the processing and analysis of high-resolution imagery or sensor data, often requiring advanced image processing techniques, such as machine learning or artificial intelligence algorithms, to extract meaningful information.

In the context of integrating multiple sensing systems, efficient communication and data management are crucial for leveraging the strengths of each sensing modality. Several approaches have been proposed in the literature to address these challenges.

Another important aspect of communication and data management in integrated sensing systems is the use of IoT technologies to facilitate the collection, processing, and dissemination of data. The IoT-based architecture enables real-time monitoring and decision-making by providing remote access to data and facilitating seamless integration of different sensing modalities.

Interoperability and standardization are also critical aspects of communication and data management in integrated sensing systems. The development and adoption of common data formats, protocols, and metadata standards can help ensure seamless communication and data exchange between different sensing systems and end-users.

5.4 Optimization of Data Frequency and Resolution

Data frequency refers to the rate at which data is collected over time. A higher data frequency provides more detailed information about the temporal changes in soil moisture and chemistry, enabling more informed decisions for irrigation, fertilization, and other management practices. However, increasing data frequency can also lead to larger data volumes, requiring more computational power and storage capacity for processing and analysis. Additionally, high-frequency data collection may lead to increased energy consumption and shorter flight times for drones, affecting their overall operational efficiency.

The resolution of drone-based soil sensing data, on the other hand, refers to the spatial detail and accuracy of the measurements. Higher resolution data enables more precise identification of soil heterogeneities and the detection of small-scale changes in soil moisture and chemistry. High-resolution data is particularly valuable for precision agriculture applications, as it allows for the implementation of site-specific management practices that take into account variations in soil properties across a field. However, similar to data frequency, increasing data resolution can result in larger data volumes and increased computational requirements for processing and analysis.

Optimizing data frequency and resolution in drone-based soil sensing systems requires a trade-off between data quality and operational constraints such as flight time, energy consumption, and computational requirements. To achieve this balance, several approaches have been proposed in the literature. One such approach is the adaptive sampling strategy, where data is collected at different frequencies and resolutions based on the spatial and temporal variability of the target variables, which allows for the collection of high-resolution data in areas of high variability, while reducing the data frequency and resolution in more homogenous areas, thus optimizing data collection efficiency.

Another approach to optimize data frequency and resolution is the integration of drone-based sensing systems with other sources of data, such as ground-based measurements and satellite remote sensing data. This multi-source data fusion approach can improve the overall accuracy and precision of soil moisture and chemistry estimates, while also reducing the data collection requirements for the drone-based system.

Typical existing data frequency and resolution for drone-based soil sensing systems vary depending on the specific sensors used and the target variables. For instance, multispectral and hyperspectral cameras can provide spatial resolutions ranging from centimeters to meters, while data frequency can range from daily to weekly or even monthly intervals. Similarly, LiDAR-based systems can provide sub-meter resolution and data frequency of several days to weeks.

5.5 Cost-Benefit Analysis and Application Suitability

Integrating multiple sensing systems, such as field-implanted sensors, satellite remote sensing, and drones, can enhance the accuracy and resolution of soil moisture and chemistry data. However, it is vital to conduct a comprehensive cost-benefit analysis to assess the viability and appropriateness of combining these technologies in various agricultural settings.

The cost of adopting a combined approach depends on the specific technology and the application scale. Field-implanted sensors are relatively low-cost, but their installation and maintenance expenses can increase when deployed over large areas. Satellite remote sensing systems offer vast spatial coverage but may be limited by temporal resolution, cloud cover, and operational costs, although the latter is rarely concerned for satellite operational cost by user. Drone-based sensing delivers high spatial resolution but may have limited coverage and can be expensive depending on the required sensors and drone platforms.

Integrating these technologies necessitates significant investments in data processing, storage, and communication infrastructure. Data fusion techniques may be computationally intensive, requiring high-performance computing resources. Moreover, effective communication systems for transmitting, storing, and analysing large datasets are essential for the success of combined approaches.

Despite the costs, merging multiple sensing systems can provide substantial benefits. Improved data accuracy and resolution can contribute to better decision-making in agricultural practices, ultimately leading to enhanced crop yields, water use efficiency, and reduced environmental impacts. Additionally, incorporating multiple data sources can increase the resilience of monitoring systems by addressing the limitations of individual technologies.

Application suitability depends on each agricultural operation's specific needs and priorities. For example, small-scale farmers with limited resources may prioritize field-implanted sensors' affordability, while large-scale commercial operations may invest in a combined approach for optimal data accuracy and precision. Factors to consider when evaluating combined approaches' suitability include the operation scale, crop type, soil variability, available resources, and environmental considerations.

In conclusion, a cost-benefit analysis is crucial for determining the feasibility and appropriateness of combining field-implanted sensors, satellite remote sensing, and drone-based sensing systems in different agricultural contexts. Although integrating multiple sensing technologies can involve substantial costs, the benefits of enhanced data accuracy, resolution, and resilience can lead to better decision-making and more sustainable agricultural practices.

5.6 Schematics of Combined Sensing Technology

There are many combination alternatives for combined approach of soil monitoring. The flow chart of the study of soil moisture prediction from remote sensing images coupled with climate, soil texture and topography via deep learning is shown in Figure 5.1, which combine satellites data, climate data and ground data to produce soil moisture data.

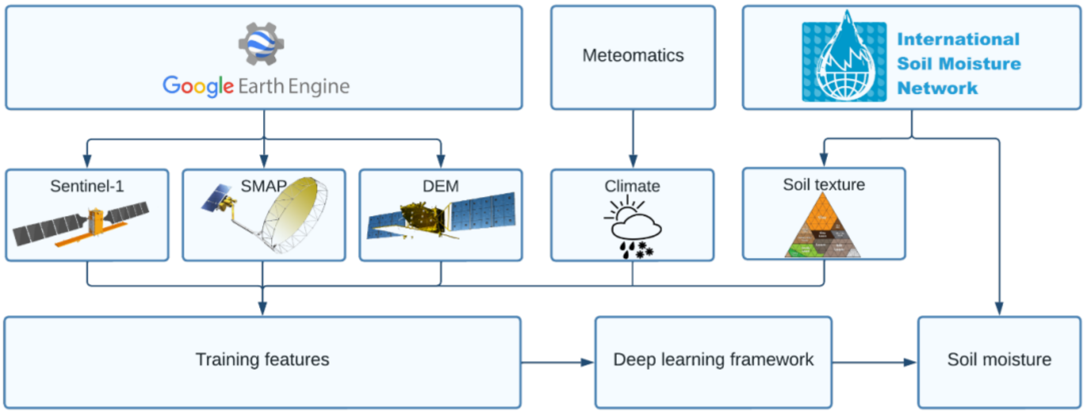

Figure 5.1 The process chart of the study of soil moisture prediction from remote sensing images coupled with climate, soil texture and topography via deep learning starting from data sources and ending with the final-user output. (Celik et al., 2022).

In Figure 5.2, the combination approach of radar Sentinel-1, optical Lansat 8 and ground measurement is presented to produce soil moisture for hydrological analysis. The combination of soil moisture monitoring by using iot and uav-sc for smart farming application is depicted in Figure 5.3.

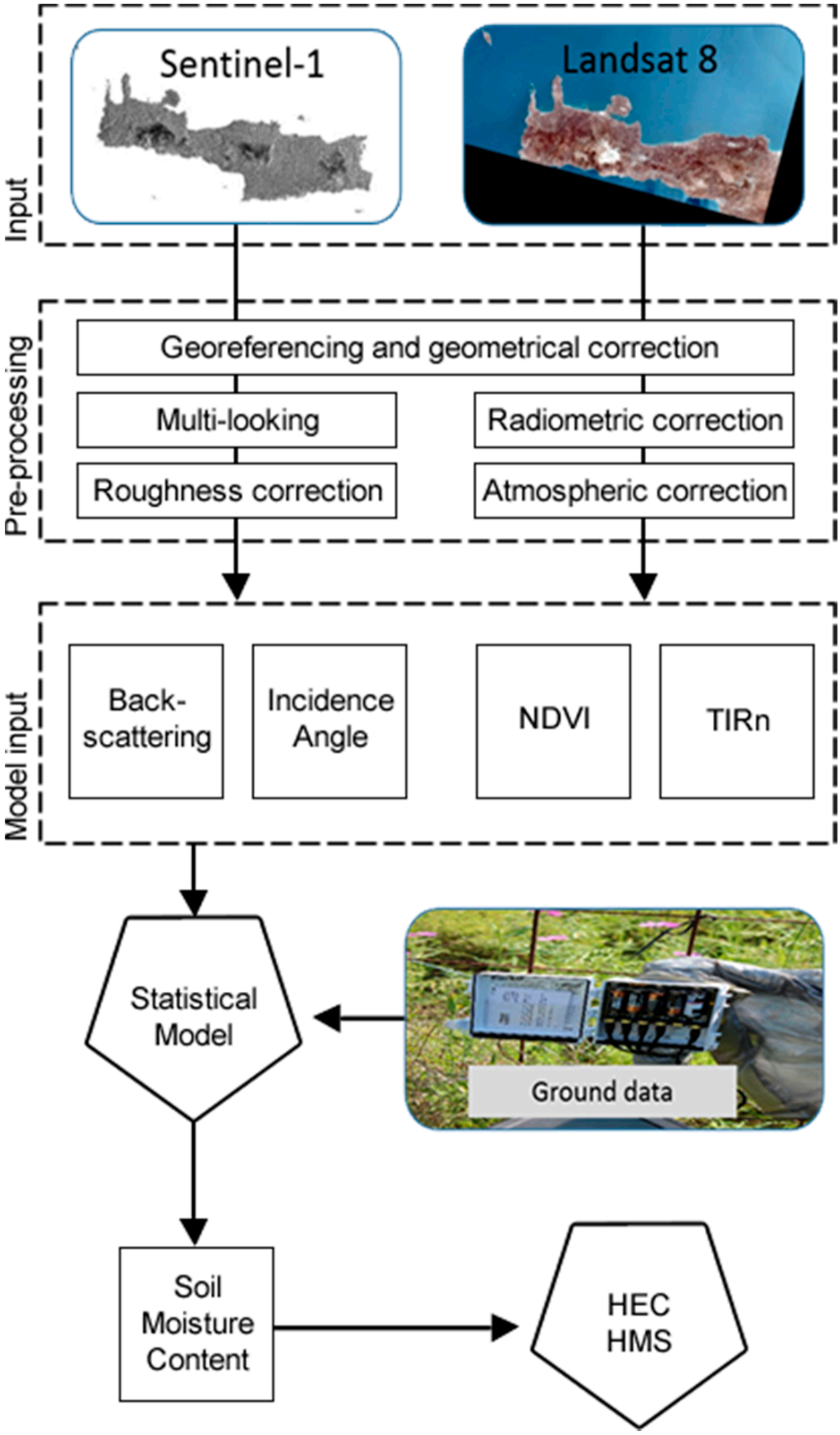

Figure 5.2 Flowchart of the overall methodology of Soil Moisture Content Estimation Based on Sentinel-1 and Auxiliary Earth Observation Products (Alexakis et al., 2017)

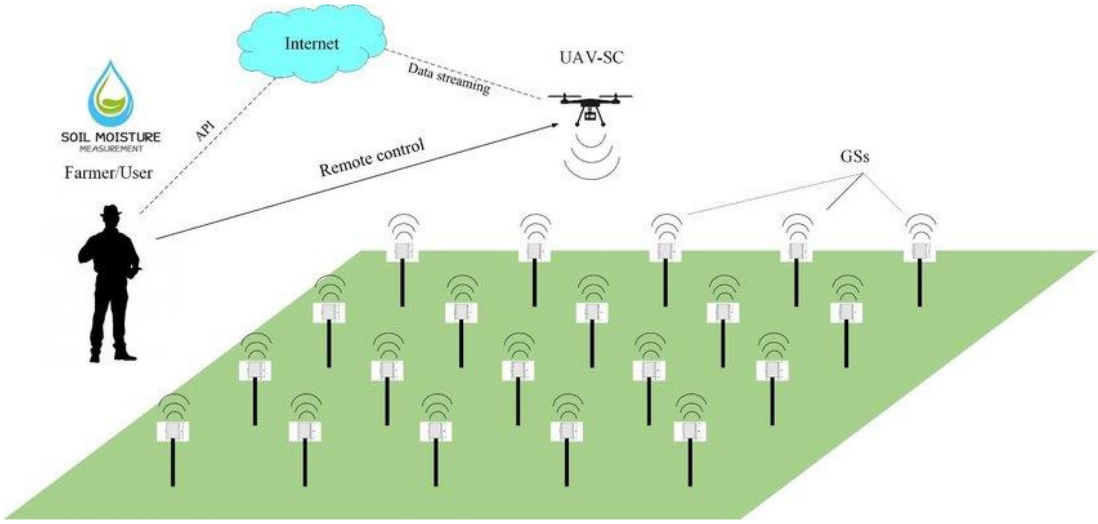

Figure 5.3 Combination of Soil Moisture Monitoring by using IoT and UAV-SC for Smart Farming Application (Duangsuwan et al., 2020)

6 Comparative Analysis

This section provides a comprehensive comparison of field-implanted sensors, satellite remote sensing, drone-based sensing, and combined sensing systems, examining their strengths, weaknesses, trade-offs, and decision-making criteria. The suitability of each system for different agricultural applications and environments, including the Sukabumi region of West Java, Indonesia, is also discussed.

6.1 Comparison of the Four Categories Across Various Parameters

- Field-Implanted Sensors:
  - Pros: Provide in-situ, real-time, and accurate measurements of soil moisture, chemistry, and other parameters; customizable for specific agricultural applications; adaptable for use with IoT-enabled devices and wireless communication networks.
  - Cons: Limited spatial coverage; expensive and labour-intensive installation and maintenance; potential for sensor degradation or malfunction over time.
- Satellite Remote Sensing:
  - Pros: Large-scale spatial coverage; continuous and long-term data acquisition; various satellite options available for monitoring soil moisture and vegetation (e.g., Landsat, Sentinel-1, Sentinel-2); data is often freely available or low-cost.
  - Cons: Lower spatial resolution compared to drone-based sensing; data quality affected by cloud cover and atmospheric conditions for passive optical sensors; less frequent data acquisition than drone-based sensing.
- Drone-based Sensing:
  - Pros: High spatial resolution; flexible and customizable data acquisition schedules; can carry various sensor payloads (e.g., multispectral, hyperspectral, thermal); provides rapid and timely data for decision-making.
  - Cons: Limited spatial coverage compared to satellite remote sensing; requires investment in drone hardware, software, and training; subject to weather and flight restrictions; data processing can be time-consuming and complex.
- Combined Sensing Systems:
  - Pros: Leverages the strengths of each individual sensing method; offers comprehensive spatial and temporal coverage; integrates various data sources for a more complete understanding of crop and soil conditions; enables advanced data analysis through data fusion techniques and machine learning algorithms.
  - Cons: Requires more extensive data processing and management; potential for data inconsistencies and uncertainties; may involve higher costs and more complex system integration.

6.2 Trade-Offs and Decision-Making Criteria

When selecting a sensing system for agricultural applications, it is essential to consider trade-offs and weigh the benefits and drawbacks of each system. Decision-making criteria should include:

- Spatial and temporal resolution: How detailed and frequent does the data need to be for specific agricultural applications?
- Cost and return on investment: What are the initial investment and maintenance cost, and does the expected increase in crop yield or reduced resource usage justify the expense?
- System complexity and ease of use: How difficult is it to implement and manage the chosen sensing system, and is the required training and support readily available?
- Data accessibility and processing: Can the collected data be easily accessed, processed, and interpreted to inform decision-making and improve crop management?

Several factors should be considered, including:

- Spatial and temporal resolution: If high spatial and temporal resolution are required, field-implanted sensors and drone-based systems are the best options.
- Data accuracy: For highly accurate data, field-implanted sensors and drone-based systems are the most suitable choices.
- Cost: Satellite remote sensing is generally the most affordable option, while drone-based systems can be more expensive.
- Ease of implementation: Satellite remote sensing offers the easiest implementation, while drone-based systems may require additional expertise.
- Data management complexity: Integrated systems typically demand the most complex data management, while field-implanted sensors are less demanding.
- Energy requirements: Field-implanted sensors usually require low to medium energy, whereas drone-based systems may have higher energy requirements.

6.3 Suitability for Different Agricultural Applications and Environments

The optimal sensing system will depend on the specific agricultural context, environmental conditions, and desired outcomes. For the Sukabumi region of West Java, Indonesia, where food production crops are a priority, a combined sensing system utilizing drone-based sensors and satellite remote sensing can provide comprehensive, high-resolution data to monitor and manage crop health, soil moisture, and nutrient status. This integrated approach offers a more complete understanding of the agricultural landscape, enabling more precise resource management and ultimately improving crop yields and sustainability.

In the Sukabumi region of West Java, Indonesia, the combined sensing system offers several advantages for various agricultural applications. By integrating multiple sensing methods, farmers can make more informed decisions about resource management, ultimately improving crop yields, efficiency, and sustainability.

- Soil moisture assessment: Field-implanted sensors offer real-time, accurate measurements of soil moisture at specific locations. By incorporating drone-based sensors and satellite remote sensing data, a more comprehensive understanding of the spatial distribution of soil moisture can be achieved. This information is valuable for optimizing irrigation strategies and scheduling, preventing water stress, and minimizing water waste.

- Nutrient management: Field-implanted sensors can be used to monitor soil chemistry parameters such as pH, electrical conductivity, and nutrient levels. Drone-based sensors, like hyperspectral cameras, can help assess nutrient deficiencies at the field scale. Combining in-situ measurements with drone and satellite data enables more targeted nutrient management, leading to improved crop health and reduced environmental impacts.

When considering the specific sensing systems for the Sukabumi region in West Java, Indonesia, it is important to keep in mind the local environmental conditions, agricultural practices, and the needs of the farmers. Given the region's tropical climate, diverse crop types, and potential for heavy rainfall and soil erosion, a well-integrated sensing system is crucial for effective agricultural management.

In order to address the diverse needs of the region's agriculture, the combined sensing system should incorporate the following components:

- Field-implanted sensors: Deploying sensors such as soil moisture probes, ion-selective electrodes, and electrochemical sensors will provide valuable information on the local soil conditions, nutrient levels, and soil moisture. This data will enable farmers to optimize irrigation and nutrient management practices for their specific crop types and environmental conditions.

- Drone-based sensors: Utilizing drones equipped with multispectral or hyperspectral cameras will enable high-resolution monitoring of crop health, pest and disease detection, and nutrient deficiencies. In addition, thermal imaging sensors can provide information on plant stress, irrigation efficiency, and canopy temperature, which can be helpful in determining optimal irrigation scheduling.

- Satellite remote sensing: Integrating data from satellite remote sensing platforms, such as Sentinel-2 or Landsat, can provide large-scale information on vegetation health and land use changes. This data can help farmers monitor the effectiveness of their agricultural management practices and identify areas that require further attention.

- Data fusion and analytics: Combining the data from field-implanted sensors, drone-based sensors, and satellite remote sensing will enable a comprehensive understanding of the agricultural landscape. Advanced data analytics, machine learning algorithms, and GIS tools can be utilized to process and analyse this data, providing valuable insights to support decision-making and optimize agricultural practices.

Given the diverse nature of the agricultural landscape in the Sukabumi region, West Java, Indonesia, there are some important considerations and trade-offs when integrating multiple sensing systems:

- Cost-benefit analysis: Implementing a comprehensive sensing system can be expensive, particularly for small-scale farmers. It is crucial to assess the potential return on investment, considering factors such as increased crop yields, reduced input costs, and improved resource efficiency. It may be necessary to explore financial incentives, subsidies, or community-based initiatives to support the adoption of these technologies by local farmers.

- Data management and communication: The integration of various sensing systems generates a large volume of data, which needs to be efficiently managed, transmitted, and analysed. Farmers must be equipped with the necessary tools and knowledge to access and interpret this data, and there may be a need for investments in communication infrastructure and training programs to support this.
- Interoperability and standardization: Ensuring that the different sensing systems are compatible and can seamlessly communicate with one another is crucial for effective data integration. Adopting standardized data formats, protocols, and interfaces will facilitate this process and enable a more streamlined approach to agricultural management.
- Environmental and social considerations: When deploying field-implanted sensors or drone-based monitoring systems, it is important to consider the potential environmental impacts, such as disruption of local ecosystems or wildlife. In addition, privacy concerns and community acceptance of drone technology should be considered to ensure the successful implementation of these sensing systems.

By carefully evaluating these factors and making informed decisions about the optimal combination of sensing systems for the Sukabumi region, it is possible to develop a tailored approach to agricultural management that addresses the specific needs and challenges of the local context.

7 Conclusions and Future Perspectives

7.1 Summary of Key Findings

This review has provided a comprehensive overview of soil moisture and chemistry sensing systems, including field-implanted, remote sensing, drone-based, and combined approaches. We have identified the advantages and challenges associated with each method, along with suitable applications for different agricultural environments.

In the context of Climate-Smart Agriculture (CSA) implementation in Sukabumi region, West Java, Indonesia, the effective integration of these sensing systems could help farmers monitor soil conditions, optimize irrigation, and nutrient management, and ultimately improve crop yield and resilience to climate change.

7.2 Emerging Trends and Future Research Directions

Emerging trends in soil sensing technologies include the development of low-cost and energy-efficient sensors, improved data fusion techniques, and the integration of artificial intelligence and machine learning algorithms. These advancements hold the potential to significantly enhance the accuracy, reliability, and scalability of soil monitoring systems.

In the Sukabumi region, future research should focus on the development of tailored solutions that take into consideration local agricultural practices, crop types, and environmental conditions. Moreover, conducting field trials and validation studies in the region will be crucial for assessing the suitability and performance of different sensing technologies.

7.3 Recommendations for Farmers, Policymakers, and Researchers

In the pursuit of implementing CSA practices in the Sukabumi region, the following recommendations are made:

- Farmers should consider adopting soil sensing technologies that are cost-effective, reliable, and suitable for their specific agricultural context. This may involve investing in a combination of sensing systems that offer complementary data on soil moisture and chemistry.

- Policymakers should prioritize the development of incentive programs and financial support mechanisms to encourage the adoption of soil sensing technologies among farmers. This could include providing subsidies, low-interest loans, or tax incentives.

- Researchers should continue to explore new sensing technologies and methodologies, particularly those that are well-suited to the unique challenges and requirements of the Sukabumi region. Additionally, collaboration between research institutions, private sector companies, and government agencies will be essential for driving innovation and promoting the widespread adoption of CSA practices.

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