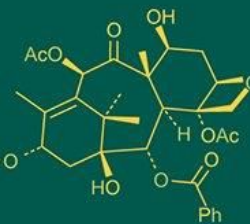


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Ganesh MC
 Young Professional, Soil
 Testing Lab, Technology
 Evaluation Center, Coffee
 Board, Gonikoppal,
 Karnataka, India

SA Nadaf
 Scientist CRSS, Coffee Board,
 Chettalli, Karnataka, India

Digital soil mapping: Revolutionizing precision agriculture

Ganesh MC and SA Nadaf

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Abstract

Digital Soil Mapping (DSM) is a transformative technology that is reshaping the field of precision agriculture by providing high-resolution, data-driven insights into soil properties. Unlike traditional soil mapping techniques, which are often time-consuming, expensive, and limited in spatial coverage, DSM integrates advanced technologies such as remote sensing, geographic information systems (GIS), machine learning, and cloud computing to generate dynamic, accurate, and real-time soil maps. These maps enable farmers to optimize resource use, improve crop productivity, and reduce environmental impact by tailoring inputs such as water, fertilizers, and pesticides to the specific needs of different soil zones. DSM is particularly valuable in addressing global agricultural challenges such as soil degradation, climate change, and the increasing demand for food. However, challenges related to data quality, technical complexity, and accessibility remain barriers to widespread adoption, especially for smallholder farmers in developing countries. This review article explores the fundamentals of DSM, its core technologies, and applications in precision agriculture. Additionally, it discusses global case studies, current limitations, and emerging trends, emphasizing DSM's potential in revolutionizing sustainable agriculture and ensuring food security for the future.

Keywords: Digital soil mapping, precision agriculture, remote sensing, soil variability, machine learning

1. Introduction

1.1 Soil: The Foundation of Agriculture

Soil is often referred to as the "foundation of agriculture" due to its crucial role in supporting plant growth and enabling food production [3, 4]. It provides essential nutrients, water, and a stable medium for plant roots to grow, while also influencing plant health, crop yield, and overall agricultural productivity [1, 2]. Soil properties such as texture, pH, organic matter content, and nutrient availability directly affect the fertility and health of crops [19, 24]. For instance, the balance of nutrients like nitrogen, phosphorus, and potassium determines the ability of soil to support healthy plant growth, while moisture retention capacity influences irrigation practices [18, 20].

The quality of soil is highly variable, with differences in properties depending on factors such as parent material, topography, climate, and biological activity [5, 6]. These variations create challenges for farmers, as the soil's ability to sustain crops can vary significantly even within the same field [9, 12]. Understanding soil's complex nature and mapping its characteristics is essential for optimizing agricultural practices and ensuring sustainable crop production [8, 13].

While soil has been studied and managed for centuries, the need for more detailed and timely soil data has grown as agricultural demands increase [7, 11]. Accurate, high-resolution soil data can make the difference between successful crop cultivation and inefficient or unsustainable farming practices [10, 15].

1.2 Traditional Soil Mapping and Its Limitations

Historically, soil surveys and mapping relied on labour-intensive methods that included field sampling, manual soil analysis in laboratories, and the creation of static soil maps [14, 16]. These traditional soil surveys were often conducted on a limited geographical scale, with results that were typically slow to update [22, 25]. The methods involved in traditional soil

Corresponding Author:
Ganesh MC
 Young Professional, Soil
 Testing Lab, Technology
 Evaluation Center, Coffee
 Board, Gonikoppal,
 Karnataka, India

mapping are time-consuming, expensive, and prone to human error, which makes them less efficient for large-scale, real-time soil monitoring [17, 19].

In traditional soil surveys, a relatively small number of soil samples are taken from various locations within a region, and laboratory analysis is used to determine various soil properties [23, 28]. This process often results in soil maps that are based on point data, which may not fully capture the spatial variability of soil properties across a broader landscape [21, 26]. Additionally, the data gathered through traditional surveys often becomes outdated, especially in regions where land use and climatic conditions are changing rapidly [24, 29].

The limitations of traditional soil mapping methods have driven the search for more efficient, scalable, and dynamic approaches to soil assessment—leading to the rise of Digital Soil Mapping (DSM) [3, 4]. Unlike traditional methods, DSM provides continuous, real-time, and high-resolution data, making it more adaptable to the needs of modern agriculture [27, 30].

1.3 The Need for Digital Soil Mapping

The global agricultural industry faces numerous challenges that demand more accurate, timely, and detailed soil data [1, 3]. These challenges include

- **Increasing Global Food Demand:** With the world's population expected to reach 9.7 billion by 2050, food demand is projected to increase significantly. [32,35] To meet this demand, agricultural productivity must be improved, which requires a better understanding of soil health and how it varies across large areas [31, 33].
- **Declining Arable Land:** The amount of available arable land is decreasing due to urbanization, industrialization, and environmental degradation [34, 39]. As a result, there is greater pressure on the remaining farmland to produce higher yields while minimizing the environmental impact [40, 42].
- **Soil Degradation:** Soil erosion, salinization, and nutrient depletion are major problems that threaten agricultural sustainability [36, 38]. Soil degradation affects both the quantity and quality of crops, and if left unmanaged, it can lead to reduced land productivity, desertification, and food insecurity [37, 38].
- **Climate Change:** Changes in climate patterns, including increased temperature, altered precipitation patterns, and more frequent extreme weather events, are affecting soil properties and agricultural productivity [42, 45]. For instance, droughts can lead to decreased soil moisture levels, while heavy rainfall can cause soil erosion [41, 44]. There is a need for data-driven tools to help farmers adapt to these shifting conditions [43, 48].

Traditional soil mapping methods are unable to address these complex challenges efficiently. Digital Soil Mapping (DSM) has emerged as a promising solution, offering the ability to generate high-resolution, dynamic soil maps that can be used to optimize agricultural practices and ensure more sustainable land management [46, 49].

DSM uses a combination of remote sensing, geostatistics, and machine learning to generate predictive models of soil properties [47, 50]. These maps can be updated frequently, offering real-time insights that allow farmers to make data-driven decisions, such as adjusting irrigation schedules, applying fertilizers more efficiently, and selecting crops that

are best suited to the soil conditions of a particular field [46, 51].

1.4 Precision Agriculture: The Link Between DSM and Efficiency

Precision agriculture (PA) is a farming approach that uses data-driven technology to optimize crop production and resource use [48, 51]. The key idea behind PA is to make farming practices more efficient by considering the spatial variability within fields, rather than applying the same practices across an entire area [47, 54]. DSM is at the heart of precision agriculture because it provides the detailed, site-specific soil data needed to implement these practices effectively [1, 13].

- **Resource Optimization:** DSM allows farmers to apply fertilizers, pesticides, and water more efficiently by tailoring these inputs to the specific needs of each soil zone [48, 58]. For example, areas of the field with rich, fertile soil may require fewer nutrients, while areas with poor soil may need more intensive treatment [38, 54]. By applying inputs precisely where and when they are needed, farmers can reduce costs, improve efficiency, and minimize the environmental impact of excessive input use [48, 51].
- **Improved Crop Yields:** With DSM, farmers gain insights into soil properties that affect crop growth, such as soil moisture, nutrient content, and texture [44, 54]. This knowledge enables farmers to make informed decisions about which crops to plant, when to plant them, and how to manage them throughout the growing season [43, 50]. Ultimately, this leads to improved crop yields and higher profitability [38, 51].
- **Sustainability:** DSM is crucial for sustainable farming practices, as it helps reduce input waste and ensures that farming practices are adapted to the local environmental conditions [4, 18]. By managing soil health more effectively and minimizing the overuse of fertilizers and water, DSM helps mitigate the negative impacts of farming on the environment, such as nutrient runoff, soil erosion, and water depletion [9, 12].

1.5 Scope and Objectives of the Review

This review aims to provide a comprehensive overview of Digital Soil Mapping (DSM) and its role in transforming modern agriculture [4, 56]. The primary objectives of this review are:

- **Defining Digital Soil Mapping:** A detailed explanation of DSM, its key components, and how it works to create accurate, high-resolution soil maps [48, 51].
- **Examining DSM Technologies:** An exploration of the core technologies behind DSM, such as remote sensing, GIS, machine learning, and cloud computing [48, 57].
- **Applications of DSM in Agriculture:** A discussion of the various ways DSM is applied in precision agriculture, including its role in nutrient management, irrigation, crop modeling, and erosion risk assessment [18, 35].
- **Global Case Studies:** An examination of DSM implementation in different regions of the world, showcasing successful use cases in both developed and developing countries [4, 9].
- **Challenges and Limitations:** An analysis of the obstacles to DSM adoption, including data quality,

technical complexity, infrastructure limitations, and farmer engagement [34, 53].

- **Future Directions:** A look at emerging trends in DSM, including hyperlocal soil mapping, crowdsourced data collection, real-time soil monitoring, and the integration of DSM with carbon markets [28, 31].

Through this review, we aim to highlight the potential of DSM in improving agricultural productivity, ensuring environmental sustainability, and contributing to the global effort to feed a growing population [48, 51]. Furthermore, we will address the challenges that must be overcome to make DSM accessible and beneficial for all farmers, particularly those in developing regions [13, 19].

2. Fundamentals of Digital Soil Mapping

Digital Soil Mapping (DSM) is a cutting-edge technology that has transformed the way soil properties are assessed, mapped, and managed in modern agriculture. DSM integrates geospatial technologies, remote sensing, machine learning, and statistical modeling to create high-resolution, dynamic, and predictive soil maps [47, 51]. These maps provide actionable insights into soil characteristics, enabling precision agriculture practices that optimize inputs, improve crop yields, and promote sustainable land management [13, 19]. This section delves into the core concepts of DSM, its evolution from traditional soil surveys, and the fundamental components that make DSM a powerful tool for modern farming [13, 19].

2.1 What is Digital Soil Mapping (DSM)?

Digital Soil Mapping refers to the process of using geospatial data, advanced statistical models, and remote sensing technologies to predict and map the distribution of soil properties across a given area [13, 19]. Unlike traditional soil surveys that rely on point-based sampling and labor-intensive laboratory analysis, DSM generates continuous, high-resolution maps that represent soil variability over large regions [48, 51].

According to McBratney *et al.* (2003), DSM is "the creation and population of a geographically referenced soil database using field and laboratory observation methods coupled with spatial and non-spatial soil inference systems." Essentially, DSM uses predictive modeling to estimate soil properties in areas where direct measurements are not available, filling gaps in soil data and offering a more comprehensive and scalable approach to soil mapping [13, 19].

DSM relies on spatial data (e.g., topography, climate, vegetation) and non-spatial data (e.g., field measurements, remote sensing imagery) to model soil properties [18, 20]. The goal of DSM is to create soil maps that are not only accurate but also dynamic and continuously updated, reflecting changes in soil conditions and agricultural practices over time [48, 51].

2.2 Evolution from Traditional Soil Surveys

Traditional soil mapping methods involved physically collecting soil samples from various locations, followed by laboratory analysis to determine the properties of the soil at each sample point [18, 50]. These surveys, while effective at providing valuable information about soil properties, were time-consuming, costly, and often limited in scale [18, 20]. The resulting maps were typically static and could become outdated quickly, as they did not account for the dynamic

nature of soil properties or changes in land use and climate [48, 51].

The limitations of traditional methods led to the development of Digital Soil Mapping, which offers several advantages:

- **Speed:** DSM allows for the rapid collection and processing of data over large areas, reducing the time required to generate soil maps [18, 20].
- **Resolution:** Unlike traditional surveys, which provide data at discrete points, DSM creates continuous maps that represent soil variability across entire landscapes, capturing finer variations in soil properties [38, 40].
- **Updatability:** DSM maps can be updated frequently, providing real-time insights into changing soil conditions due to factors such as seasonal variations, land management practices, and weather patterns [13, 19].
- **Cost Efficiency:** By using remote sensing and other data sources, DSM significantly reduces the need for costly field sampling and laboratory analysis, making it more cost-effective, especially at large scales [3, 9].

The transition from traditional soil surveys to DSM marks a shift from static, localized data to dynamic, global-scale soil mapping, enabling more effective and informed decision-making in agriculture [23, 49].

2.3 Key Components of DSM

Several key components work together in the process of Digital Soil Mapping to generate high-resolution, reliable soil property maps [18, 20]. These components include soil observations, environmental covariates, statistical models, validation, and the creation of soil maps themselves [18, 40]. Each element plays an essential role in ensuring the accuracy, relevance, and utility of DSM outputs [48, 51].

a) Soil Observations

Soil observations serve as the foundation of DSM, providing the primary data used to predict and map soil properties [18, 20]. These observations are typically gathered through direct soil sampling or in-field sensors and may include properties such as pH, texture (sand, silt, clay), organic matter content, moisture levels, and nutrient concentrations [48, 50].

- **Field Sampling:** Soil samples are taken from different points across the field or region, typically using grid-based sampling or random sampling methods [18, 27]. The collected samples are analyzed in laboratories to measure specific soil properties [18, 29].
- **In-Field Sensors:** Modern sensors, such as electrical conductivity (EC) sensors and visible-near-infrared (Vis-NIR) spectrometers, allow for the real-time measurement of soil properties directly in the field [18, 24]. These sensors enable high-resolution data collection without the need for laboratory analysis [18, 20].

b) Environmental Covariates

Environmental covariates are factors that influence soil properties and are used to explain spatial variations in soil characteristics [18, 23]. These covariates may include

- **Topographic Data:** Terrain features such as elevation, slope, and aspect impact soil moisture retention, erosion susceptibility, and plant growth [18, 40]. Digital Elevation Models (DEMs) are often used to capture topographic information [48, 51].

- **Climatic Data:** Climate factors, such as temperature, rainfall, and solar radiation, influence soil moisture levels, temperature, and biological activity [38, 50]. These variables play a crucial role in determining soil fertility and plant growth conditions [3, 9].
- **Vegetation and Land Use:** Data derived from vegetation indices (e.g., NDVI) provide indirect information about soil health and fertility, as healthy plants are often a reflection of favorable soil conditions [38, 40]. Land use patterns also influence soil properties by affecting organic matter content, compaction, and nutrient availability [3, 9].
- **Geological and Hydrological Data:** The composition of soil parent material, as well as nearby water bodies, impacts the soil's texture, structure, and moisture-holding capacity [48, 51].

These covariates are essential for predicting soil properties in regions where direct observations are sparse, and they help to explain the spatial distribution of soil conditions across large areas [18, 20].

c) Statistical and Machine Learning Models

The heart of DSM lies in the statistical models and machine learning techniques used to analyze soil data and make predictions about soil properties in unobserved areas [48, 50]. Some of the most common modeling approaches include

- **Geostatistical Methods:** Techniques like Kriging are used to interpolate soil observations and predict values for unmeasured areas [38, 51]. These methods rely on the assumption that soil properties exhibit spatial autocorrelation (i.e., soil properties are similar in neighboring areas) [18, 20].
- **Regression Models:** Traditional regression models, such as Multiple Linear Regression (MLR) and Partial Least Squares Regression (PLSR), are used to correlate soil properties with environmental covariates, allowing predictions of soil characteristics across larger areas [8, 30].
- **Machine Learning:** More recent advancements in DSM leverage machine learning algorithms like Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting to improve prediction accuracy [48, 51]. These methods handle complex, non-linear relationships between soil properties and environmental factors [3, 5].
- **Deep Learning:** In some cases, deep learning models, such as Convolutional Neural Networks (CNNs), are used to process large datasets, such as satellite imagery, to identify patterns and make predictions about soil properties [28, 51].

These modeling techniques allow for the creation of highly accurate, predictive soil maps that capture the variability in soil conditions across vast landscapes [43, 51].

d) Model Validation and Accuracy Assessment

To ensure the reliability and accuracy of DSM predictions, models must be validated using independent datasets or field observations [48, 55]. Validation is typically performed through:

- **Cross-Validation:** A process where the model's performance is evaluated by partitioning the available data into training and testing subsets [48, 57].

- **Bootstrapping:** A statistical method used to estimate the accuracy of a model by repeatedly sampling from the original data and assessing performance on these resampled datasets [48, 50].
- **Uncertainty Quantification:** DSM models often incorporate uncertainty quantification to estimate the confidence level of predictions [28, 51]. Models such as Regression Kriging and Ensemble Modeling combine multiple algorithms to provide a more reliable estimate of soil property predictions and their associated uncertainty [48, 51].

This validation process is crucial for ensuring the accuracy and applicability of DSM maps in real-world agricultural settings [8, 31].

e) Soil Maps and Visualization

The end product of DSM is the soil map, which visually represents the predicted soil properties across the study area [44, 51]. These maps can be continuous surfaces (e.g., contour maps) that show spatial variability or categorical maps that classify regions into distinct soil types or fertility zones [48, 55]. Soil maps are often visualized using GIS platforms, allowing farmers and land managers to interact with the data and make decisions based on the soil conditions specific to their land [5, 7].

2.4 The DSM Workflow

The typical workflow for DSM involves several stages, each of which contributes to the creation of accurate, actionable soil maps [48, 57]. These stages are:

1. **Data Collection:** Soil samples, remote sensing images, and environmental data are gathered from the field, satellites, and other sources [8, 23].
2. **Data Processing and Analysis:** Raw data is cleaned, pre-processed, and integrated into a cohesive dataset. This may involve normalizing data, dealing with missing values, and transforming raw data into usable formats [18, 23].
3. **Modeling and Prediction:** Statistical or machine learning models are used to correlate soil observations with environmental covariates and make predictions for areas with sparse data [8, 23].
4. **Validation:** The model's predictions are tested against independent datasets to assess the accuracy and reliability of the results [18, 23].
5. **Map Creation:** The final soil maps are generated, providing farmers with detailed information on soil properties across their land [16, 29].
6. **Decision Support:** The maps are integrated into farm management systems, allowing farmers to make informed decisions about irrigation, fertilization, crop selection, and soil conservation [38, 39].

3. Technologies Powering Digital Soil Mapping (DSM)

Digital Soil Mapping (DSM) leverages a combination of cutting-edge technologies to deliver high-resolution, real-time soil data that enhances precision agriculture [38, 39]. These technologies—ranging from remote sensing and soil sensors to machine learning and cloud computing—play a crucial role in making DSM a dynamic and scalable solution for managing soil resources more efficiently [8, 23]. This section explores the key technologies that power DSM and how they contribute to the creation of accurate, actionable soil maps [28, 31].

3.1 Remote Sensing

Remote sensing refers to the acquisition of soil and environmental data from a distance, typically using satellites, aircraft, drones, or other aerial platforms [28, 37]. This technology allows for the large-scale, non-invasive monitoring of soil conditions, enabling farmers and land managers to gain insights into soil variability without having to conduct exhaustive field surveys [28, 30].

- **Satellite Platforms:** Satellites such as Landsat, Sentinel-2, and MODIS provide essential data for DSM by capturing imagery across multiple spectral bands [28, 35]. These platforms use electromagnetic radiation in various wavelengths (e.g., visible, infrared, thermal) to gather information about the soil surface [38, 51]. Satellite-based data is valuable for detecting soil moisture, organic content, and soil texture, as well as for monitoring changes in soil health over time [28, 33].
- **Spectral Indices:** Remote sensing data can be analyzed using spectral indices, which are mathematical formulas that help interpret soil properties [28, 36]. Some of the most commonly used indices in DSM include
 - **Normalized Difference Vegetation Index (NDVI):** Often used to assess vegetation health, NDVI also provides indirect information about soil fertility and moisture since healthy vegetation depends on good soil quality [28, 33].
 - **Soil-Adjusted Vegetation Index (SAVI):** This index is designed to minimize the effect of soil background when measuring vegetation cover, providing more accurate insights into soil moisture and fertility in areas with sparse vegetation [48, 51].
 - **Brightness and Texture Indices:** These indices help detect soil organic matter and moisture by analyzing the reflectance properties of soil surfaces [28, 36].
- **Thermal Sensors:** Satellite platforms equipped with thermal sensors can measure soil surface temperatures, which are critical for assessing soil moisture and heat stress [28, 31]. Soil temperature influences microbial activity, nutrient availability, and overall soil health, making it a key parameter for understanding soil dynamics [44, 51].

Remote sensing enables the creation of comprehensive, continuous soil maps over large areas, helping farmers make informed decisions about land use, crop selection, and resource allocation [19, 29].

3.2 Proximal Soil Sensing

Proximal soil sensing involves using sensors placed directly in or on the soil to measure soil properties [44, 53]. This technology provides high-resolution, localized data, making it a valuable complement to remote sensing [2, 5].

- **On-site Sensors:** Various soil sensors can be used to measure specific soil characteristics [5, 9]. Some of the most common sensors include:
 - **Electrical Conductivity (EC) Sensors:** These sensors measure the ability of soil to conduct electrical current, which is influenced by soil salinity, moisture content, and texture [38, 51]. EC data can be used to map soil fertility and moisture distribution [44, 55].
 - **Visible-Near-Infrared (Vis-NIR) Spectrometers:** These spectrometers measure the absorption and

reflectance of light in the visible and near-infrared wavelengths, providing insights into soil organic matter, texture, and mineral content [54, 58].

- **Gamma Radiometry:** This method uses gamma radiation to measure soil density and composition, helping to map soil texture and structure [44, 51].
- **Mobile Platforms:** Proximal sensors are often mounted on mobile platforms such as tractors, drones, or handheld devices, making it easy to collect data across fields [2, 4]. Drones and autonomous vehicles can rapidly cover large areas, allowing for high-resolution soil data collection without disrupting farming activities [12, 14].

Proximal sensing is highly effective in providing real-time, field-specific data, which is essential for making timely decisions about soil management, irrigation, and fertilization [2, 4].

3.3 Geographic Information Systems (GIS)

Geographic Information Systems (GIS) are integral to DSM as they provide the platform for storing, analyzing, and visualizing spatial data [22, 24]. GIS allows for the integration of diverse data sources, including soil observations, environmental covariates, and remote sensing data, to create comprehensive soil maps [12, 41].

- **Data Layering:** GIS enables the layering of multiple types of data (e.g., topography, vegetation, climate, soil properties) to understand their spatial relationships [2, 4]. This multi-layered approach is crucial for assessing how different factors interact and influence soil conditions [16, 29].
- **Interpolation Techniques:** GIS supports advanced geostatistical methods such as Kriging (a form of spatial interpolation) and Inverse Distance Weighting (IDW) to predict soil properties in areas where direct measurements are unavailable [21, 24]. These techniques help create continuous soil maps by estimating values for unsampled areas based on nearby data points [42, 44].
- **Map Generation:** GIS provides tools for creating detailed, interactive soil maps that can be used for decision-making [32, 34]. These maps can be visualized as continuous surfaces (e.g., contour maps) or as categorical maps (e.g., soil type classifications) to inform site-specific management practices [32, 34].
- **Zonal Analysis:** GIS allows for the segmentation of large regions into smaller zones with similar soil properties [32, 34]. This approach helps in creating farm management zones for more targeted interventions such as fertilization, irrigation, and crop selection [42, 44].

GIS plays a critical role in synthesizing large datasets and transforming them into actionable insights that farmers can use to manage their land more efficiently [2, 4].

3.4 Machine Learning and Statistical Methods

Machine learning (ML) and statistical methods are the backbone of modern DSM [21, 34]. These techniques allow for the analysis of large datasets and the creation of predictive models that can map soil properties across large areas with high accuracy [42, 44].

- **Traditional Models:** Earlier DSM models primarily relied on geostatistical techniques, such as Multiple Linear Regression (MLR) and Principal Component Regression (PCR), to establish correlations between soil

observations and environmental covariates [7, 9]. While these models can be effective, they may struggle to capture complex, non-linear relationships between variables [6, 8].

- **Machine Learning Algorithms:** Recent advancements in DSM have been driven by machine learning algorithms that can process large datasets and uncover complex patterns in soil data [4, 9]. Some common ML techniques used in DSM include:
 - **Random Forest (RF):** An ensemble learning method that combines multiple decision trees to predict soil properties [32, 35]. RF is effective in handling large, noisy datasets and provides insights into the relative importance of various soil covariates [4, 7].
 - **Support Vector Machines (SVM):** A supervised learning algorithm used for classification and regression tasks [42, 44]. SVM is particularly effective when dealing with high-dimensional datasets and complex relationships between variables [32, 34].
 - **Gradient Boosting:** A boosting algorithm that builds an additive model by combining weak prediction models [42, 44]. It is effective in improving the accuracy of soil property predictions by reducing bias and variance [42, 44].
- **Deep Learning:** In some cases, Convolutional Neural Networks (CNNs) and other deep learning models are used, particularly in the analysis of remote sensing imagery [2, 4]. Deep learning algorithms excel at extracting features from large, high-dimensional datasets and can generate highly accurate soil maps based on satellite or drone imagery [52, 54].
- **Uncertainty Quantification:** DSM models often incorporate uncertainty quantification techniques to assess the reliability of predictions [38, 51]. By using **Ensemble Modeling**, multiple algorithms are combined to reduce prediction error and provide confidence intervals for model outputs [22, 34].

3.5 Cloud Computing and IoT

Cloud computing and the Internet of Things (IoT) are transforming the way soil data is collected, processed, and shared in real-time [22, 44]. These technologies enable farmers and agricultural professionals to access up-to-date soil information from anywhere, facilitating more responsive and efficient decision-making [52, 54].

- **Cloud Computing:** Platforms such as **Amazon Web Services (AWS)**, **Google Earth Engine**, and **Microsoft Azure** provide the computational power and storage capacity needed to process large volumes of soil data [52, 4]. Cloud-based systems allow for the integration of remote sensing data, soil observations, and machine learning models, enabling the creation of real-time, dynamic soil maps [38, 51]. Cloud computing also supports collaborative data sharing, making it easier for stakeholders to access and contribute to soil data repositories [52, 54].
- **IoT-based Soil Sensors:** IoT-enabled sensors embedded in the soil or deployed across fields collect real-time data on soil moisture, temperature, pH, and nutrient levels [38, 57]. These sensors transmit data to cloud platforms for analysis, providing farmers with up-to-date information about soil conditions [48, 52]. IoT-

based sensors can help monitor soil health continuously, allowing for timely interventions in farming practices, such as adjusting irrigation schedules or applying fertilizers [28, 51].

4. Applications in Precision Agriculture

Digital Soil Mapping (DSM) has emerged as a game-changing tool in precision agriculture, offering the ability to map soil properties with unprecedented accuracy and detail [12, 14]. By providing high-resolution, real-time data on soil characteristics, DSM enables farmers to make more informed decisions, optimize resource use, and increase productivity [32, 34]. Precision agriculture is all about making farming more efficient by adjusting practices to match the specific needs of different parts of a field [32, 44]. This section explores the various applications of DSM in precision agriculture, focusing on how it helps improve efficiency, reduce waste, and contribute to sustainable farming practices [12, 34].

4.1 Variable Rate Technology (VRT)

Variable Rate Technology (VRT) is one of the most significant applications of DSM in precision agriculture [4, 7]. VRT enables farmers to apply agricultural inputs—such as fertilizers, pesticides, and water—at varying rates depending on the specific needs of each part of a field [7, 4]. DSM provides the detailed soil data needed to implement VRT effectively by identifying areas of the field with different soil properties (e.g., texture, moisture content, nutrient levels) [32, 34].

- **Tailored Input Application:** DSM-generated soil maps allow for the creation of prescription maps, which guide the VRT systems to apply inputs only where they are needed [42, 54]. For example, areas with nutrient-rich soil require less fertilizer, while areas with poor soil may require additional nutrients [4, 7]. This targeted application ensures that resources are used efficiently, reducing costs and minimizing environmental impact [7, 45].
- **Improved Efficiency and Cost Reduction:** By optimizing the use of fertilizers, water, and pesticides, VRT helps to lower input costs and reduce excess application, which is a major environmental concern [34, 56]. Additionally, VRT ensures that the right amount of input is applied at the right time and place, reducing the risk of over-fertilization, water runoff, and pest resistance [23, 34].
- **Increased Yield and Soil Health:** Tailored input applications lead to healthier crops and higher yields, as they receive the precise nutrients and care they need based on the soil conditions in each part of the field [45, 48]. This approach ensures that each zone of the field is treated in a way that maximizes its potential, while maintaining soil health and minimizing degradation [32, 34].

4.2 Precision Irrigation

Irrigation is one of the most water-intensive activities in agriculture, and inefficient irrigation practices can lead to significant water wastage, increased costs, and lower crop yields [32, 36]. DSM plays a pivotal role in optimizing irrigation by providing detailed, real-time data on soil moisture and water-holding capacity [36, 39].

- **Soil Moisture Mapping:** DSM-generated soil maps that include soil moisture content and water retention capacity allow farmers to identify areas of the field that require more or less water [34, 39]. Soil moisture levels vary across fields due to differences in soil texture, organic matter content, and topography [6, 9]. DSM provides the data necessary to understand these variations and optimize irrigation accordingly [45, 49].
- **Water Use Efficiency:** By integrating DSM with weather data and evapotranspiration models, farmers can adjust irrigation schedules and methods to ensure that water is used efficiently [32, 34]. For instance, areas with high moisture retention may not need frequent watering, while drier zones may require more irrigation [1, 2]. This results in reduced water usage, lower costs, and minimal waste [16, 29].
- **Improved Crop Health:** Precision irrigation ensures that crops receive the right amount of water at the right time, which promotes healthy growth [32, 34]. Under- or over-irrigation can lead to problems such as water stress, root rot, or nutrient leaching [45, 49]. DSM helps mitigate these risks by providing precise, site-specific recommendations for irrigation [32, 34].

4.3 Soil Fertility and Nutrient Management

Soil fertility is a key factor in determining agricultural productivity. However, soil fertility varies significantly across a field due to differences in soil properties such as pH, organic carbon content, and nutrient availability [36, 39]. DSM provides high-resolution soil maps that help farmers assess fertility levels and make informed decisions about nutrient management [16, 29].

- **Mapping Soil Nutrients:** DSM allows for the mapping of soil nutrients (e.g., nitrogen, phosphorus, potassium) and other properties like organic carbon and pH, which influence soil fertility [52, 54]. By understanding soil nutrient levels, farmers can create precise fertilization plans tailored to the needs of each zone within the field [32, 36].
- **Site-Specific Fertilization:** With DSM-generated soil maps, farmers can apply fertilizers at varying rates based on the soil's nutrient content [52, 54]. This site-specific approach ensures that fertilizers are applied only where they are needed, reducing fertilizer costs, preventing nutrient runoff, and promoting healthy soil [32, 34].
- **Sustainable Fertilizer Use:** Over-fertilization not only increases costs but also leads to environmental problems such as nutrient leaching into water bodies, contributing to pollution and eutrophication [32, 34]. By using DSM for nutrient management, farmers can minimize these risks and improve soil health in the long term [42, 44].

4.4 Erosion and Land Degradation Risk Assessment

Soil erosion and land degradation are significant concerns in agriculture, especially in areas with steep terrain, excessive rainfall, or unsustainable land management practices [4, 5]. DSM can help identify areas at risk of erosion and land degradation, enabling farmers to implement preventative measures [52, 54].

- **Erosion Risk Mapping:** By combining DSM with topographic data (e.g., slope, elevation) and climatic data (e.g., rainfall), it is possible to create maps that

predict areas of a field prone to erosion [12, 23]. Soil erosion can lead to the loss of topsoil, which reduces soil fertility and increases the need for external inputs like fertilizers and water [42, 44].

- **Land Degradation Indicators:** DSM can also be used to assess other forms of land degradation, such as salinization, compaction, and nutrient depletion [16, 29]. By identifying areas suffering from degradation, farmers can take corrective actions such as applying organic amendments, adjusting farming practices, or implementing soil conservation techniques (e.g., contour plowing, terracing) [36, 55].
- **Sustainable Land Management:** By using DSM for erosion and land degradation risk assessment, farmers can adopt more sustainable practices that protect their soil resources [6, 9]. This is particularly important for long-term land productivity and the prevention of further degradation [26, 49].

4.5 Land Suitability and Crop Modeling

Selecting the right crop for a given piece of land is critical for maximizing productivity and ensuring that farming practices are sustainable [26, 29]. DSM helps assess land suitability by mapping soil properties and comparing them with the requirements of different crops [16, 29].

- **Matching Soil Properties to Crop Needs:** DSM enables the mapping of soil properties such as texture, nutrient levels, and moisture retention [16, 29]. By comparing this data with the specific requirements of different crops, farmers can determine which crops are best suited for each zone within a field, leading to higher yields and better resource use [4, 6].
- **Supporting Crop Diversification:** Crop diversification, which involves planting different crops to reduce risk and enhance soil health, can be optimized with DSM [16, 29]. By understanding the soil requirements of different crops, farmers can select the right mix of crops for their land, improving biodiversity and resilience to pests, diseases, and climate change [34, 46].
- **Climate Adaptation:** As climate change impacts agriculture, DSM helps farmers adapt by selecting crops that are resilient to changing environmental conditions. By analyzing soil properties in conjunction with climate data, farmers can make informed decisions about which crops to plant and when to plant them.

5. Global Case Studies and Implementations

Digital Soil Mapping (DSM) has been implemented across various regions of the world, showcasing its potential to revolutionize agriculture by providing detailed and actionable soil data for improving farming practices [16, 29]. These global case studies highlight the diverse applications and benefits of DSM, illustrating its impact on productivity, sustainability, and environmental management [16, 49]. This section presents several key global implementations of DSM, from both developed and developing countries, that provide valuable insights into how DSM can be integrated into agricultural practices [16, 19].

5.1 USA: Soil Survey Geographic Database (SSURGO)

In the United States, the Soil Survey Geographic Database (SSURGO) is a highly successful and widely used DSM

initiative developed by the Natural Resources Conservation Service (NRCS) of the U.S. Department of Agriculture. SSURGO provides detailed, high-resolution soil data to farmers, researchers, and land managers [6, 24].

- **High-Resolution Soil Maps:** SSURGO offers soil maps that cover the entire country, with data on soil properties such as texture, pH, organic matter content, and nutrient levels [3, 6]. These maps are publicly available and are widely used by agricultural professionals for land management and decision-making [26, 29].
- **Accessibility:** By making these maps freely available, SSURGO helps farmers access valuable information about their soil, allowing for better decision-making regarding fertilization, irrigation, and crop selection [16, 29].
- **Applications:** SSURGO has been used for various applications, including precision agriculture, environmental protection, and land use planning [36, 49]. It has helped farmers optimize input usage, reduce costs, and minimize environmental impact, contributing to more sustainable farming practices [16, 25].

5.2 EU: LUCAS Soil & e-SOTER

In the European Union, two key projects—LUCAS Soil and e-SOTER—have been pivotal in advancing DSM for sustainable land management, policy-making, and farming [15, 57]. These projects are funded and coordinated by the European Commission.

- **LUCAS Soil Project:** The LUCAS (Land Use/Cover Area Frame Statistical Survey) project is a pan-European initiative designed to collect and analyze soil data across the EU. LUCAS provides high-resolution soil maps that cover critical soil properties such as pH, organic carbon, and nutrient content [49, 49]. These maps help farmers and policymakers make informed decisions regarding land use and agricultural practices [46, 49].
- **e-SOTER:** The European Soil Data and Information System (e-SOTER) integrates data from various sources, including field surveys, satellite imagery, and environmental covariates, to provide harmonized soil information across Europe [6, 29]. This database supports sustainable farming practices and policy decisions at the EU level [6, 9].
- **Policy and Research Applications:** LUCAS and e-SOTER provide valuable data for the development of EU-wide agricultural policies and environmental regulations [16, 29]. These projects help farmers adjust their practices to optimize yields while minimizing environmental degradation, particularly in areas with poor soil quality or risk of erosion [46, 49].

5.3 Australia: Soil and Landscape Grid of Australia

The Soil and Landscape Grid of Australia is a national DSM infrastructure project that provides high-resolution soil data for the entire country [46, 49]. The project integrates machine learning, soil sensors, and remote sensing to deliver comprehensive soil maps [16, 29].

- **National Coverage:** The Soil and Landscape Grid provides high-resolution soil property maps across Australia, including data on soil texture, pH, moisture, and organic carbon content [36, 39]. These maps are generated using both field-based data and remote

sensing information, ensuring comprehensive coverage of Australia's diverse agricultural landscapes [46, 49].

- **Machine Learning and Sensors:** The project uses machine learning algorithms to process data from a wide array of sources, including soil sensors and satellite imagery [26, 28]. These algorithms predict soil properties across areas where field data is sparse, allowing for highly accurate soil maps that can be updated regularly [16, 49].
- **Impact on Agriculture:** The Soil and Landscape Grid has been instrumental in improving soil management in Australia, particularly in regions with high variability in soil properties [16, 29]. By providing farmers with accurate, up-to-date soil data, the project has helped optimize land management, improve productivity, and support sustainable farming practices [46, 49].

5.4 Brazil: EMBRAPA Soil Digital Program

In Brazil, the EMBRAPA (Brazilian Agricultural Research Corporation) Soil Digital Program is a key initiative that combines DSM with land use planning to promote sustainable farming practices, especially in the Amazon region [16, 39].

- **Sustainable Land Use:** The EMBRAPA Soil Digital Program focuses on integrating soil data with land use planning to ensure that farming practices in Brazil's diverse ecosystems are sustainable [46, 49]. The program emphasizes the need to balance agricultural expansion with environmental conservation, particularly in sensitive areas like the Amazon rainforest [16, 29].
- **Integration with Land Use Planning:** DSM in Brazil is used to assess soil fertility, moisture, and other properties, helping farmers make informed decisions about where to plant specific crops and how to manage soil resources sustainably [16, 19]. The integration of DSM with land use data allows policymakers and farmers to identify the most suitable areas for farming and those that should be preserved for environmental reasons [26, 29].
- **Impact on Sustainability:** The EMBRAPA Soil Digital Program has played a significant role in promoting sustainable agriculture in Brazil, helping to reduce deforestation and land degradation [32, 34]. By providing accurate, high-resolution soil data, the program enables farmers to adopt practices that improve productivity while minimizing environmental impact [56, 59].

5.5 Africa: AfSIS (Africa Soil Information Service)

The Africa Soil Information Service (AfSIS) is a groundbreaking initiative that uses crowdsourced soil data and machine learning to create soil maps across the African continent [42, 54]. AfSIS aims to address the lack of soil data in many African countries, helping farmers optimize soil management and improve food security [32, 34].

- **Crowdsourced Data Collection:** AfSIS uses mobile apps to collect soil samples from farmers and local communities across Africa [23, 45]. This crowdsourcing approach allows for the collection of large volumes of soil data at a fraction of the cost of traditional soil surveys [35, 45].
- **Machine Learning for Mapping:** AfSIS uses machine learning algorithms to process the crowdsourced soil data, creating high-resolution soil maps that predict soil

properties across vast areas of the continent [23, 45]. These maps are valuable for improving soil fertility, managing irrigation, and selecting appropriate crops for different regions [34, 39].

- **Impact on Food Security:** AfSIS has had a significant impact on improving soil management in Africa, particularly in regions where soil data is sparse [46, 47]. By providing farmers with accurate and up-to-date information, the initiative has helped increase crop yields and promote more sustainable farming practices, contributing to food security across the continent [45, 49].

5.6 India: Bhuvan Soil Mapping & Soil Health Card Scheme

In India, the Bhuvan Soil Mapping initiative, developed by the Indian Space Research Organisation (ISRO), and the Soil Health Card Scheme, launched by the Ministry of Agriculture, are important government-led efforts to integrate DSM into national agricultural practices [56, 59].

- **Bhuvan Soil Mapping:** Bhuvan is a digital platform developed by ISRO that provides soil maps for various regions of India [12, 45]. The platform integrates satellite imagery, GIS, and field data to create comprehensive soil maps that are accessible to farmers and researchers across the country [23, 24].
- **Soil Health Card Scheme:** Launched by the Indian government, the Soil Health Card Scheme provides farmers with personalized soil health reports [23, 45]. These reports include recommendations on the appropriate use of fertilizers, soil amendments, and other inputs based on soil samples collected from their fields [34, 45].
- **Government Integration:** Both the Bhuvan Soil Mapping platform and the Soil Health Card Scheme are integrated into the government's agricultural advisory services, helping farmers access soil data and recommendations directly [45, 56]. These initiatives aim to promote better soil management and sustainable farming practices in India's diverse agricultural landscapes [2, 4].

6. Limitations and Challenges

While Digital Soil Mapping (DSM) offers numerous advantages in optimizing agricultural practices, improving productivity, and ensuring sustainability, its widespread adoption faces several challenges. [32,34] These challenges are mainly related to technical, economic, and socio-political factors, which must be addressed to fully realize the potential of DSM [3, 7]. In this section, we explore the limitations of DSM and the obstacles hindering its broad implementation across diverse agricultural landscapes [12, 34].

6.1 Data Scarcity and Quality Issues

One of the major barriers to the effective implementation of DSM is the scarcity and inconsistency of high-quality soil data [32, 54]. Soil data, which serves as the foundation of DSM, is often limited in many regions, especially in developing countries [32, 44]. The lack of comprehensive and up-to-date soil data hampers the accuracy and reliability of DSM models [16, 29].

- **Inconsistent Legacy Data:** Many regions, particularly in the Global South, suffer from outdated or incomplete soil datasets, which were often gathered through traditional methods [32, 34]. These datasets are

insufficient for building accurate and predictive models in DSM, as they may not capture the full range of soil variability or may be based on different standards [4, 7].

- **Limited Real-Time Data:** While DSM relies on continuous data to update soil maps dynamically, real-time data collection remains a challenge in many areas [7, 9]. The need for frequent soil sampling, which is both labor-intensive and costly, further complicates the process of collecting timely data [3, 6].
- **Access to Satellite Imagery:** While satellite imagery plays a critical role in DSM, some regions may face limited access to high-resolution satellite data due to costs, data restrictions, or geographical constraints (such as frequent cloud cover) [42, 54]. This limits the ability to obtain reliable and accurate soil data, especially in developing countries [32, 36].

6.2 Technical Complexity

The technical complexity of DSM is a significant barrier to its widespread adoption [6, 9]. The integration of multiple technologies such as remote sensing, machine learning, GIS, and geostatistics requires specialized knowledge and expertise [42, 54].

- **Geostatistical and Machine Learning Expertise:** The successful implementation of DSM requires an in-depth understanding of geostatistics, spatial analysis, and machine learning algorithms [32, 44]. These technical skills are not widely available among farmers or agricultural extension workers, especially in rural areas where DSM has the potential to make the most significant impact [16, 29].
- **Data Integration:** DSM involves integrating data from diverse sources, such as soil sensors, satellite imagery, and environmental covariates [32, 34]. The challenge of combining these various data types into a coherent system that produces reliable soil maps can be complex and requires expertise in data processing and analysis [3, 7].
- **Model Calibration and Validation:** Machine learning models used in DSM must be carefully calibrated and validated using field data to ensure accurate predictions [32, 34]. However, the lack of high-quality validation data, particularly in remote regions, makes it difficult to assess the reliability of DSM predictions [12, 14].

6.3 Infrastructure and Cost

DSM relies on advanced infrastructure, including sensors, satellites, cloud computing platforms, and high-performance computing systems [32, 54]. The high costs associated with acquiring, operating, and maintaining this infrastructure pose a significant challenge, especially for smallholder farmers in developing countries [16, 29].

- **High Initial Investment:** The initial costs of DSM tools—such as soil sensors, remote sensing data, and GIS software—can be prohibitively expensive for many farmers [32, 34]. Additionally, the costs associated with data storage, cloud services, and the need for reliable internet connectivity add to the financial burden [16, 29].
- **Lack of Local Infrastructure:** In many regions, particularly in rural and remote areas, the necessary infrastructure for implementing DSM may be lacking [22, 34]. These areas may suffer from poor internet connectivity, limited access to electricity, or a lack of

technical support services, all of which hinder the adoption of DSM technologies ^[32, 34].

- **Ongoing Maintenance Costs:** Beyond the initial investment, there are ongoing maintenance costs associated with DSM systems, such as sensor calibration, data processing, and software updates ^[16, 29]. These costs may not be sustainable for small-scale farmers, especially those with limited financial resources ^[42, 44].

6.4 Uncertainty and Model Transferability

Despite the advancements in DSM technology, the uncertainty associated with predictions and the limited transferability of models across regions remain significant challenges ^[1, 3].

- **Model Accuracy and Uncertainty:** DSM models rely on predictions to estimate soil properties in areas where direct measurements are unavailable ^[32, 54]. However, these models are subject to uncertainties due to variations in soil types, climate conditions, and land management practices ^[4, 7]. This uncertainty can affect the accuracy of soil maps and limit their reliability for decision-making ^[4, 9].
- **Limited Transferability Across Regions:** DSM models developed for one region may not be directly applicable to another due to differences in soil properties, climate, and land use ^[7, 9]. For example, a model developed for temperate climates may not perform well in tropical regions with different soil types and rainfall patterns ^[32, 34]. This lack of transferability can limit the applicability of DSM in diverse agricultural systems and landscapes ^[16, 29].
- **Calibration and Adaptation:** To ensure accurate predictions, DSM models often require extensive calibration and adaptation to local conditions ^[42, 54]. This process can be time-consuming and costly, especially in regions with limited soil data and technical expertise ^[42, 44].

6.5 Farmer Engagement and Usability

One of the biggest challenges in the widespread adoption of DSM is ensuring that the technology is user-friendly and accessible to farmers, particularly smallholder farmers who may have limited access to technology and technical expertise ^[32, 34].

- **Complexity of Soil Data:** Soil data produced by DSM systems can be complex and difficult for farmers to interpret ^[6, 9]. Many farmers lack the necessary training to understand and apply detailed soil maps and recommendations ^[46, 49]. This lack of understanding can hinder the adoption of DSM technologies, as farmers may be reluctant to rely on data they cannot interpret ^[26, 29].
- **User-Friendly Tools and Interfaces:** To maximize the impact of DSM, it is essential to develop simplified, user-friendly platforms that present soil data in an intuitive and accessible manner ^[6, 9]. These tools should provide actionable insights that are easy for farmers to understand and implement in their day-to-day farming practices ^[16, 19].
- **Training and Support:** Adequate training and support services are critical to helping farmers adopt DSM technologies ^[46, 49]. This includes not only technical training in the use of tools and equipment but also

providing extension services that help farmers interpret soil data and make informed decisions based on DSM outputs ^[36, 39].

- **Cultural and Linguistic Barriers:** In many regions, language and cultural differences can make it challenging to design DSM tools that are universally accessible ^[16, 19]. Ensuring that DSM platforms are available in local languages and tailored to local agricultural practices is essential for promoting adoption ^[26, 29].

7. Emerging Trends and Future Directions

The field of Digital Soil Mapping (DSM) is rapidly evolving with continuous advancements in technology, data availability, and applications in agriculture ^[36, 39]. These emerging trends promise to further enhance the accuracy, accessibility, and impact of DSM, enabling farmers and land managers to adopt even more precise and sustainable practices ^[46, 49]. This section explores some of the key emerging trends in DSM, highlighting the innovations and future directions that are likely to shape the future of soil management in agriculture ^[6, 39].

7.1 Hyperlocal DSM

Hyperlocal DSM refers to soil mapping at the farm or field level with exceptional detail ^[16, 49]. This trend focuses on generating highly localized soil data, providing farmers with precise insights into the soil conditions of each part of their fields ^[6, 39].

- **Farm-Level Mapping:** With advancements in drone technology and soil sensors, DSM is moving from regional to hyperlocal applications. Drones equipped with high-resolution cameras and sensors can rapidly collect data on soil properties such as moisture, texture, and temperature ^[16, 29]. This allows for the generation of soil maps at a much finer spatial resolution, enabling farmers to monitor and manage soil health at the individual field level ^[6, 19].
- **AI-Driven Insights:** The integration of Artificial Intelligence (AI) and machine learning with hyperlocal DSM allows for the processing of vast amounts of data collected from drones and in-field sensors ^[26, 29]. These AI algorithms can identify soil variability patterns and provide tailored recommendations for managing each zone within a field, making farming practices even more precise and responsive ^[46, 49].
- **Real-Time Monitoring:** Real-time soil data collection through sensors and drones allows for continuous monitoring of soil conditions, providing farmers with up-to-date information on soil moisture, nutrient levels, and other critical parameters ^[36, 49]. This dynamic approach to soil mapping enables farmers to make immediate decisions and adjust practices as needed throughout the growing season ^[16, 19].

Hyperlocal DSM promises to significantly enhance precision agriculture by providing farmers with more detailed and actionable soil information, ultimately leading to more efficient use of resources and improved crop productivity ^[6, 9].

7.2 Participatory and Crowdsourced Soil Mapping

Participatory and crowdsourced soil mapping has gained momentum as a cost-effective and inclusive approach to

generating soil data [46, 49]. This trend leverages local knowledge and community participation to gather large amounts of soil information, often at a lower cost than traditional soil surveys [36, 39].

- **Mobile Apps for Data Collection:** Mobile platforms such as the SoilCollect app and OpenTEAM are enabling farmers, local organizations, and even citizen scientists to contribute soil data [46, 49]. These apps allow individuals to collect soil samples and upload them for analysis, making soil data collection more accessible and widespread [16, 29].
- **Community Engagement:** By involving local communities in the soil data collection process, participatory mapping fosters greater ownership of soil management practices and increases the likelihood that farmers will adopt sustainable practices [56, 57]. This approach is especially valuable in regions with limited access to professional soil surveys and where traditional data collection methods are too costly or logistically challenging [46, 49].
- **Large-Scale Data Generation:** Crowdsourcing can generate soil data on a much larger scale, allowing for the creation of extensive soil maps that cover vast agricultural regions [36, 49]. This is particularly useful in areas where government-funded soil mapping programs may be limited or unavailable, providing farmers with critical data for improving soil health and productivity [36, 39].

7.3 Real-Time Soil Mapping

Real-time soil mapping refers to the continuous and dynamic collection of soil data, which is integrated into decision-making processes without delay [26, 49]. This innovation is made possible by advances in sensor technology, cloud computing, and the Internet of Things (IoT), enabling real-time updates to soil maps [26, 29].

- **Real-Time Data Collection:** IoT-based soil sensors placed in fields can measure soil parameters such as moisture, pH, temperature, and electrical conductivity in real time [16, 29]. This data is transmitted directly to cloud platforms, where it is processed and analyzed to provide immediate insights into soil conditions [6, 9].
- **Dynamic Soil Maps:** Unlike traditional static soil maps, real-time soil mapping allows for the continuous updating of soil maps as new data is collected [44, 47]. This enables farmers to adjust their practices on the fly, such as altering irrigation schedules, applying fertilizers, or addressing nutrient deficiencies based on the most current soil data available [34, 37].
- **Automation and Smart Systems:** Real-time soil mapping can be integrated with automated farming systems, such as precision irrigation or autonomous tractors [44, 47]. These systems can adjust operations automatically based on soil conditions, improving efficiency and reducing resource wastage [44, 47].

7.4 Blockchain for Data Integrity

As DSM technology becomes more widespread, ensuring the integrity, security, and transparency of soil data is increasingly important [54, 57]. Blockchain technology is emerging as a potential solution to address these concerns by providing a secure, decentralized platform for storing and sharing soil data [14, 17].

- **Data Authentication:** Blockchain can be used to create an immutable record of soil data, ensuring that the information remains secure and cannot be tampered with [44, 47]. Each data point, whether it's soil moisture, pH, or nutrient levels, is timestamped and stored on a distributed ledger, providing a transparent history of the data [44, 47].
- **Supply Chain Transparency:** In agriculture, blockchain can track the entire journey of soil data from the field to the marketplace, enabling consumers to trace the sustainability and environmental impact of farming practices [14, 17]. This transparency can help build trust between farmers, consumers, and regulators, and incentivize sustainable farming practices [43, 57].
- **Smart Contracts:** Blockchain enables the use of smart contracts, which can automate transactions based on predefined conditions [24, 47]. For example, farmers who adopt sustainable soil management practices could receive financial rewards or subsidies automatically once their soil data is verified on the blockchain [24, 37].

7.5 Integration with Carbon Markets

Soil carbon sequestration is one of the most promising strategies for mitigating climate change, as healthy soils can store large amounts of carbon [4, 7]. DSM is increasingly being integrated with carbon markets to track soil carbon levels and support the creation of carbon credits [14, 17].

- **Soil Carbon Mapping:** DSM technologies, such as remote sensing and soil sensors, can be used to measure and map soil carbon content across agricultural lands [4, 8]. These soil carbon maps are essential for quantifying the amount of carbon stored in soil and determining the effectiveness of various land management practices in enhancing soil carbon sequestration [44, 47].
- **Monitoring, Reporting, and Verification (MRV):** DSM can be a critical tool in the MRV process for carbon credits [14, 17]. By providing accurate, real-time data on soil carbon stocks, DSM allows for more transparent and verifiable reporting of carbon credits, which are essential for participating in carbon trading programs [4, 7].
- **Incentives for Sustainable Practices:** Integration with carbon markets provides farmers with financial incentives to adopt practices that improve soil health and increase carbon sequestration, such as reduced tillage, agroforestry, and cover cropping [14, 27]. By participating in carbon markets, farmers can generate additional income while contributing to global efforts to combat climate change [34, 37].

8. Policy and Institutional Framework

The successful adoption and integration of Digital Soil Mapping (DSM) into agricultural practices require robust policies, institutional support, and collaborative efforts from various stakeholders [24, 37]. Governments, international organizations, the private sector, and research institutions all play crucial roles in creating an environment that encourages the development and widespread use of DSM technology [44, 57]. This section explores the importance of government support, the role of international bodies, public-private partnerships, and national policy recommendations that can help accelerate the adoption of DSM for sustainable agricultural development [4, 37].

8.1 Importance of Government Support in Funding DSM Projects

Governments play a critical role in the development and promotion of Digital Soil Mapping [4, 17]. Financial support and the creation of enabling policies are essential to overcoming the challenges of high upfront costs, limited access to technology, and data scarcity [4, 37]. Government involvement can help ensure that DSM is accessible to farmers, researchers, and policymakers, particularly in developing regions [4, 7].

- **Government Funding and Research Grants:** Public funding is essential for developing DSM infrastructure, such as soil sensors, satellite platforms, and cloud-based data storage systems [43, 44]. Governments can provide research grants to universities, agricultural institutions, and private companies working on advancing DSM technology [4, 7]. This funding can help lower the costs of developing and deploying DSM systems and ensure they are widely available [13, 14].
- **Subsidies and Incentives for Farmers:** To encourage the adoption of DSM, governments can provide financial incentives such as subsidies or tax breaks for farmers who invest in DSM tools, sensors, or technology [33, 34]. These incentives can make DSM more affordable for smallholder farmers, particularly in developing countries where access to advanced technology is often limited [3, 4].
- **Infrastructure Development:** Governments can invest in the necessary infrastructure to support the widespread use of DSM, including expanding internet access, improving power supply in rural areas, and developing soil data repositories [53, 54]. These investments are essential for ensuring that farmers have access to reliable soil data and the tools needed to use that data effectively [43, 44].

8.2 Role of International Bodies (FAO, ISRIC, CGIAR)

International organizations have a pivotal role in promoting the use of DSM globally, particularly in addressing the challenges of soil degradation, food security, and sustainable land management [53, 45]. These organizations help coordinate efforts, provide technical expertise, and facilitate collaboration between governments, the private sector, and research institutions [3, 4].

- **FAO (Food and Agriculture Organization):** The FAO plays a key role in advocating for the adoption of DSM as part of sustainable agricultural practices [53, 54]. Through initiatives like the Global Soil Partnership (GSP), the FAO promotes soil health and provides guidelines for the use of DSM in land management and farming [43, 44]. The FAO also supports the development of soil-related policies and contributes to the creation of global soil monitoring systems [23, 44].
- **ISRIC (International Soil Reference and Information Centre):** ISRIC is a global leader in soil information, providing the World Soil Information Service (WoSIS) and developing tools for soil data integration and sharing [3, 4]. ISRIC's efforts in global soil mapping help promote the use of DSM for sustainable land management [43, 44]. Their expertise in geospatial technologies, soil modeling, and data analysis is crucial for the development of high-resolution soil maps that can be used worldwide [33, 14].

- **CGIAR (Consultative Group for International Agricultural Research):** CGIAR is a global research organization that focuses on improving food security and sustainable agriculture [3, 41]. Through its soil and water programs, CGIAR helps integrate DSM into agriculture by providing research, training, and policy support [43, 44]. Their work on soil health, climate-smart agriculture, and sustainable land management is essential for advancing the use of DSM in developing countries [36, 47].

8.3 Promoting Public-Private Partnerships (PPPs)

Public-Private Partnerships (PPPs) are essential for the development, deployment, and scaling of DSM technologies [13, 14]. These partnerships bring together government agencies, private companies, research institutions, and non-governmental organizations to address the challenges of soil data collection, technology development, and implementation [23, 24].

- **Technology Development:** PPPs can help drive innovation in DSM technology by encouraging private companies to invest in research and development of new soil sensors, satellite platforms, and machine learning algorithms [32, 44]. Collaborations between public institutions and private companies can accelerate the commercialization of DSM technologies and make them more accessible to farmers worldwide [53, 54].
- **Cost Reduction:** Private companies can provide the technical infrastructure needed to support DSM, including cloud computing, sensor networks, and data storage [3, 4]. By collaborating with governments, these companies can offer affordable, scalable solutions that reduce the overall cost of DSM adoption [32, 34]. PPPs can also help subsidize the costs of DSM tools for smallholder farmers, enabling them to access the benefits of the technology [43, 44].
- **Data Sharing and Accessibility:** PPPs can also facilitate the creation of soil data repositories and data-sharing platforms that make soil data accessible to a wider audience [34, 56]. By partnering with governments and international organizations, private companies can contribute to the development of standardized soil data formats and systems that ensure interoperability across different regions and technologies [3, 4].

PPPs are essential for overcoming financial, technical, and logistical barriers to DSM adoption [13, 19]. By leveraging the strengths of both public and private sectors, these partnerships can help accelerate the widespread implementation of DSM and support sustainable agricultural practices [34, 56].

8.4 Recommendations for National Soil Mapping Policies

For DSM to reach its full potential, governments must develop comprehensive soil mapping policies that support the integration of DSM into agricultural and land management practices [13, 19]. These policies should focus on the following areas:

- **National Soil Data Repositories:** Governments should establish centralized databases to store soil data collected through DSM systems [34, 56]. These repositories should be accessible to farmers, researchers, and policymakers, ensuring that soil data can be used for decision-making and long-term

planning^[3, 4]. Data sharing platforms should adhere to open data standards, allowing stakeholders to access and use the data efficiently^[43, 44].

- **Soil Health Standards and Certification:** National policies should define soil health standards and establish certification processes for sustainable soil management practices^[45, 47]. This can help incentivize farmers to adopt DSM and other sustainable practices by providing them with clear guidelines and rewards for soil health improvement^[42, 44].
- **Legal Frameworks for Data Sharing:** Clear legal frameworks must be developed to govern the collection, storage, and sharing of soil data^[52, 56]. These frameworks should ensure that soil data is used ethically, that farmers' rights to their data are protected, and that the data can be shared across organizations and regions to support broader soil health goals^[53, 54].
- **Incentives for Adoption:** Governments should introduce financial incentives such as subsidies, tax credits, and grants to encourage the adoption of DSM technologies, particularly among smallholder farmers and rural communities^[52, 55]. These incentives can help offset the high initial costs of DSM tools and infrastructure, making the technology more accessible^[50, 51].
- **Training and Extension Services:** To ensure that farmers are able to effectively use DSM tools, governments should invest in training and extension services that provide hands-on support for adopting DSM in the field^[56]. These services should focus on improving farmers' technical knowledge, interpreting soil data, and implementing site-specific soil management practices^[57].

9. Conclusion

Digital Soil Mapping (DSM) has the potential to revolutionize agriculture by providing detailed, real-time insights into soil properties that can significantly improve soil management, optimize resource use, and boost productivity. As this review has highlighted, DSM offers numerous advantages over traditional soil mapping methods, including higher resolution, real-time updates, cost efficiency, and the ability to incorporate vast datasets from remote sensing, soil sensors, and machine learning models. These advantages make DSM an essential tool for precision agriculture, enabling farmers to make informed decisions and apply site-specific management practices that enhance crop yields while minimizing environmental impact.

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