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Advances in Soil Analysis Techniques for Sustainable and Precision Agriculture: A Review

Diksha S. Patil1[1] and Vaishali S. Patil[2]
Research Student, Department of Computer Science[1]
Assistant Professor, Department of Electronics[2]
Willingdon College, Sangli, Maharashtra, India[1,2]

Abstract: *Soil analysis is key for farming yield, ecological sustainability, and global food security. From the ancient times, civilizations have known soil fertility's impact, leading to the modification of agronomic practices. Organized soil science occurred in the nineteenth century, followed by laboratory chemical and physical testing methods in the twentieth century. While conventional techniques like chemical analyses and hydrometer-based texture analysis are reliable, they are often time-consuming, destructive, and costly, limiting their scalability for extensive agricultural fields. The advent of precision agriculture has transformed soil analysis, integrating technologies such as remote sensing, GIS, computer vision, and image processing. These improvements simplify fast, non-destructive, site-specific estimation of soil properties, assisting efficient decision-making for irrigation, fertilization, and crop management. Particularly, Field-Programmable Gate Array (FPGA)-based systems have kept interest due to their capability for real-time, high-speed, and energy-efficient soil analysis in the field.*

The advancement of soil analysis methods is summarized in this article, which compared conventional approaches with contemporary technologies. It highlights the importance of image processing and FPGA based technologies for efficient and cost-effective soil testing. These advanced technologies enhance sustainable soil management, soil health monitoring, and play a crucial role in sustainable agriculture and food security.

Keywords: Field-Programmable Gate Array (FPGA), Soil analysis precision agriculture remote sensing, Geographic information systems (GIS), Computer vision, Image processing.

I. INTRODUCTION

All over history, soil has been a fundamental component of civilizations, particularly those that depend on agronomy. Fertile soil is critical for grain production, as ancient cultures such as the Egyptians and a historical region of West Asia understood. In order to control soil water content and assure steady agricultural production, the Mesopotamians created irrigation systems [1]. As early as the fifth century BCE, agronomy in ancient China was codified into a highly developed discipline that included crop rotation plans, ploughing methods, and soil types. Techniques like soil mounding and thorough composting were developed to maintain soil fertility and give soil health top priority [2,3]. The 19th era saw the development of soil science, which classified soils based on their formation processes as dynamic, living systems influenced by parent material, climate, creatures, relief, and time in his book Russian Chernozem, where he categorized soils according to their development processes [4]. As such, further research into techniques of conservation and soil fertility became possible. The development of chemicals in the early decades of the twentieth century saw the introduction of systematic soil analysis, the concept of fertilizer, and nutrient management. Indeed, agriculture was transformed in the process since it became possible for farmers to enrich their soil with nutrients such as potassium, phosphorus, and nitrogen [5].

Expansion of Precision Agriculture and Sustainable Soil Management ensures that agricultural production continues into the future. While the emphasis has shifted in the last few decades to sustainable soil management and the

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sustainability of soil, methods such as organic agriculture and no-tillage agriculture have become popular means of maintaining good soil quality. Precision agriculture has brought about changes to soil analysis in the late twentieth and early twenty-first century. With the aid of technologies such as satellite imagery, aerial imagery via drones, and geographic information systems, farmers are able to observe the condition of the soil over a large tract of land, allowing for site-specific application of irrigation and fertilizers. Moreover, through computer vision, scientists are able to obtain precise information on the soil's composition and structure, including its moisture content and texture [6].

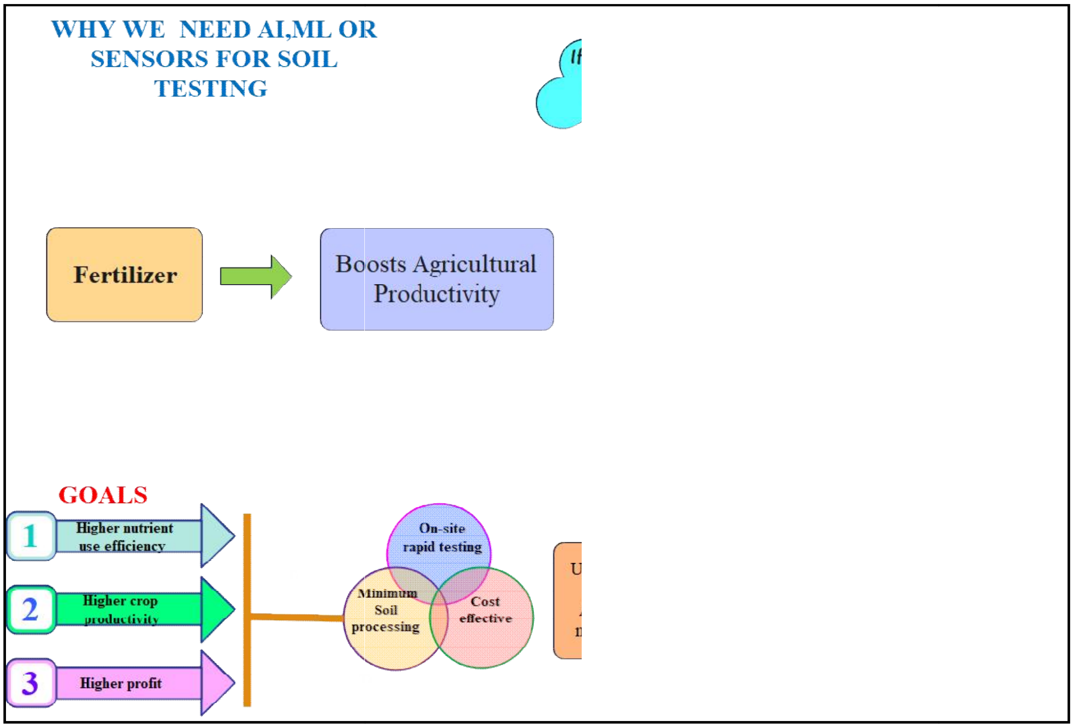

Fig. 1. Illustration of soil analysis using advanced techniques.

Figure 1. shows that why the advanced techniques are used for soil analysis. Conventional soil analysis techniques such as the Walkley-Black method and hydrometer technique are accurate; however, they are very time-consuming and destructive in nature. This means that for conducting soil analysis, the samples need to be collected and transported to the laboratory, thus making it difficult to scale up the process. The technological developments have enabled us to use more efficient and non-destructive methods such as FPGA based image processing techniques for soil analysis [7-9].

II. LITERATURE REVIEW

Soil science has come a long way since its beginning days, starting from primitive agricultural practices, all the way through the modern day technology-driven procedures that we use today. It has become very important to maintain healthy soil as food demand continues to grow. This journey from primitive agriculture methods to modern advanced techniques illustrates how far the development in soil science has come. It has become very important to maintain healthy soil as food demand continues to grow. Through technologies like FPGA-based image processing, we have been able to contribute towards solving this problem through providing accurate insight into soil conditions. Using these innovative technologies, we can assure soil fertility, develop sustainable agricultural techniques, and increase food security throughout the world [10]. There are many limitations associated with traditional soil analysis methodologies that make them both costly and inefficient. It becomes imperative to analyze soil in order to optimize crop growth and improve soil fertility in agriculture. Thus, we have designed and developed some advanced technologies using image processing through FPGAs.

Soil has always been an important resource in agricultural societies, with the ancient civilizations of Egypt, Mesopotamia, and China having devised sophisticated techniques of maintaining soil fertility, irrigation, crop rotation, and composting. The formal emergence of soil science in the nineteenth century was marked by soil classification and the study of soil fertility, while soil testing using chemical methods followed in the early twentieth century [11,12].

However, in the last few decades, emphasis has been placed on soil management and precision farming to cater to rising global food requirements. Advanced technologies like remote sensing, GIS, drones, and computer vision have facilitated widespread soil monitoring, offering live data about various soil characteristics, such as moisture, texture, and organic matter content. But conventional techniques of soil testing, which include Walkley–Black and hydrometer analyses, are manual, destructive, slow, and spatially limited in their coverage, rendering them ineffective for widespread application [13-15].

Advanced soil analysis techniques overcome these limitations by offering non-destructive, rapid, and cost-effective assessment of soil properties. Image processing and hyperspectral analysis have demonstrated improved accuracy in estimating soil characteristics compared to conventional methods. Soil Organic Matter (SOM), a key indicator of soil fertility, carbon sequestration, and environmental sustainability, has traditionally been measured using chemical and thermal methods, but modern image-based and FPGA-assisted approaches provide objective, real-time SOM estimation with higher efficiency [16].

Soil moisture, another critical factor influencing plant growth, nutrient uptake, and productivity, has been conventionally measured using gravimetric and sensor-based techniques. While accurate, these methods are often laborious or limited in scalability. FPGA-based image processing systems have emerged as promising tools for real-time soil moisture estimation, supporting precision irrigation and automated agricultural management. Additionally, monitoring soil electrical conductivity (EC) and pH is essential for assessing soil salinity, nutrient availability, and crop health, enabling effective soil and fertilizer management practices. Soil parameters such as electrical conductivity (EC), pH, texture, organic matter, and moisture content play a vital role in soil quality assessment, crop productivity, and sustainable agricultural management. Traditionally, these parameters are measured using laboratory-based and field-based methods, which, although accurate, are often time-consuming, labour-intensive, and costly. Traditional soil EC measurement techniques include the soil solution extraction method, soil probe method, and electromagnetic induction (EMI) method, each providing useful information about soil salinity and nutrient status but being sensitive to factors such as soil moisture and temperature. Similarly, soil pH is conventionally measured using pH meters, soil test kits, and laboratory analysis methods, which require careful calibration, sample preparation, and controlled conditions to achieve reliable results [17–20].

Soil texture, another critical soil property influencing water retention, aeration, nutrient availability, and root growth, is traditionally determined using methods such as the hydrometer method, pipette method, sieve analysis, and field texturing techniques. While these methods are widely accepted, they require extensive sample preparation and are not suitable for rapid, large-scale soil assessment. To overcome these limitations, advanced techniques using image processing, machine learning, FPGA-based systems, and sensor fusion approaches have gained significant attention. FPGA-based systems offer advantages such as high-speed processing, low power consumption, and real-time performance, making them suitable for soil parameter estimation in field conditions. Several studies demonstrated accurate real-time measurement of soil pH and EC using FPGA-based image processing and electronic measurement units integrated with ADCs and cameras [21-23].

Recent research highlights the use of digital image processing and computer vision techniques for analyzing soil properties by extracting color, texture, and spectral features from soil images. Techniques such as RGB and HSV color space analysis, principal component analysis (PCA), and machine learning models including ANN, KNN, and regression methods have shown strong correlations with soil pH, EC, organic matter, moisture content, and texture. These approaches provide non-destructive, low-cost, and portable alternatives to laboratory testing.

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Advanced soil texture measurement techniques using FPGA-based image processing, X-ray computed tomography (CT), and laser profilometry enable accurate estimation of particle size distribution and surface roughness in both laboratory and field environments. Additionally, remote sensing, hyperspectral imaging, and proximal soil sensors have proven effective for large-scale soil monitoring and spatial variability analysis [24-30].

Innovative systems integrating IoT, wireless sensor networks, microcontrollers, NFC-based color sensors, and smartphone cameras have further enhanced real-time soil analysis capabilities. These systems allow continuous monitoring, cloud-based data analysis, and decision support for precision agriculture applications. However, challenges such as ambient lighting variations, sensor calibration, and soil moisture effects still influence measurement accuracy, emphasizing the need for controlled illumination and sensor fusion techniques [31-40].

In conclusion, while conventional soil analysis methods remain reliable, modern image processing, FPGA-based systems, machine learning, and remote sensing technologies offer promising solutions for rapid, accurate, cost-effective, and real-time soil assessment. These advanced techniques have the potential to revolutionize soil quality monitoring and support informed decision-making in precision agriculture, environmental management, and sustainable farming practices [41-50].

III. TECHNOLOGY OVERVIEW

With the evolution of agricultural technologies, soil analyses have evolved from laboratory tests to rapid, non-invasive, and on-site methods. New methodologies include remote sensing, GIS, image processing, and machine learning, which allow the specific determination of soil characteristics like moisture content, texture, salinity, and organic matter. Computer vision algorithms detect colors, textures, and spectra of soils using images, and machine learning models analyze the intricate correlation between the extracted information and soil variables[51-60].

Field-Programmable Gate Arrays (FPGAs) are critical components of soil analysis in real time because of their parallel computing ability, low latency, and energy efficiency. FPGA-based solutions enable fast image processing, sensor data acquisition, and edge analytics, thereby making them ideal for precision agriculture applications. In addition, Internet of Things (IoT)-based frameworks allow the continual monitoring of soil conditions and cloud computing capabilities.

A comparative summary of traditional soil analysis techniques and advanced technology-driven approaches is presented in Table below, highlighting improvements in speed, scalability, accuracy, and field applicability. A comparative summary of traditional soil analysis techniques and advanced technology-driven approaches is presented in Table below, highlighting improvements in speed, scalability, accuracy, and field applicability.

TABLE I

Soil Parameter	Traditional Methods	Advanced / FPGA-based Methods	References
Soil Organic Matter (SOM)	Walkley–Black chemical titration, thermal methods; labour-intensive, destructive, slow	FPGA-based hyperspectral imaging, image processing, ANN/KNN models; non-destructive, real-time, portable	11–16, 26–27, 34
Soil Moisture	Gravimetric, tensiometer, neutron probe; accurate but time-consuming, limited spatial coverage	FPGA-based sensors, image processing, IoT-enabled sensing; real-time, high-throughput, scalable	17–24
Soil Texture	Hydrometer, pipette, sieve analysis; requires extensive sample prep, not suitable for large-scale	FPGA-based imaging, X-ray CT, laser profilometry, computer vision; rapid, accurate, field-deployable	21, 31–34
pH	pH meter, soil test kits, laboratory titration; requires careful calibration and controlled	FPGA-based image processing, sensor fusion, portable devices; real-time estimation, low-cost	28–30

	conditions		
Electrical Conductivity (EC)	Soil solution extraction, soil probes, EMI; sensitive to moisture, temperature, limited scalability	FPGA-based real-time measurement, IoT-integrated sensors; continuous monitoring, automated analysis	28–30
Spatial & Large-scale Monitoring	Manual sampling, lab analysis; low temporal resolution	Remote sensing, hyperspectral imaging, IoT, GIS, drone-based monitoring; high spatial & temporal resolution	36–42

IV. CONCLUSION

This paper has provided an exhaustive discussion on how soil analysis methods have evolved over time from laboratory-based techniques to more innovative methodologies powered by cutting-edge technology. Traditional methods of assessing soil characteristics like the content of organic matter, moisture, pH, electrical conductivity, and texture were previously regarded as very reliable; however, such tests were limited due to the time, money, and effort required as well as the difficulty scaling such practices. Advances in technology in areas like image processing, machine learning, remote sensing, and FPGA technologies have made huge progress in revolutionizing soil analysis by allowing quick and precise measurements of soil composition without destructive testing. Literature reveals that FPGA-based analysis techniques are characterized by such advantages as speed, energy-efficiency, and fast computation, thereby rendering these technologies highly suitable for soil testing purposes.

Moreover, the incorporation of imaging systems and intelligent algorithms together with Internet of Things technology has improved the potential of soil analysis technologies to provide precision irrigation and fertilization. In conclusion, it can be stated that existing literature suggests that advances in soil analysis technologies can prove valuable for agricultural practices in the future.

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