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REVIEW ARTICLE **OPEN ACCESS**

Emerging Techniques in Soil Testing: From Spectroscopy to Machine Learning: A Review

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Abstract

Soil testing is a cornerstone of modern agriculture, providing essential data on soil health, fertility, and structure to guide sustainable farming practices. Traditional soil testing methods, while reliable, are often time-consuming, costly, and limited in their scalability. Recent advancements in technology have introduced innovative techniques, such as spectroscopy, remote sensing, and machine learning, which offer faster, non-destructive, and highly accurate alternatives to conventional approaches. Spectroscopic methods, including Near-Infrared (NIR), Mid-Infrared (MIR), and Laser-Induced Breakdown Spectroscopy (LIBS), have emerged as powerful tools for analyzing soil properties, such as organic matter, moisture content, and nutrient levels. Concurrently, machine learning algorithms are transforming data analysis by enabling predictive modeling, large-scale soil mapping, and real-time decision-making. The integration of spectroscopy with machine learning has opened new avenues for enhancing the precision and efficiency of soil testing, paving the way for data-driven, site-specific management practices. This review provides an in-depth exploration of these emerging techniques, their applications, and the challenges associated with their implementation. Furthermore, it discusses future directions in soil testing, emphasizing the potential of technology-driven solutions to address global challenges in agriculture and environmental sustainability.

Keywords: Soil properties, remote sensing, soil mapping, MIR, LIBS.

Introduction

Soil testing plays a fundamental role in modern agriculture by providing crucial information about soil health, nutrient status, and physical and chemical properties. This data forms the foundation for informed decision-making in crop management, fertilizer application, and sustainable land-use practices. Traditionally, soil testing has relied on laboratory-based methods such as wet chemistry and manual analysis, which, while accurate, are often time-consuming, labor-intensive, and expensive. These limitations pose challenges, especially when frequent or large-scale soil monitoring is required to address the growing demands of precision agriculture and environmental sustainability.

In recent years, the field of soil testing has experienced a paradigm shift driven by advancements in technology. Emerging techniques, such as spectroscopic methods, remote sensing, and machine learning (ML), have revolutionized the way soil properties are analyzed and interpreted. These technologies offer rapid, cost-effective, and non-destructive alternatives to conventional methods while also enabling the integration of spatial and temporal variability into soil assessments. Spectroscopic techniques, including Near-Infrared (NIR), Mid-Infrared (MIR), and Laser-Induced Breakdown Spectroscopy (LIBS), have proven to be powerful tools for the characterization of soil organic matter, pH, moisture content, and nutrient levels. Similarly, remote sensing technologies and hyperspectral imaging have enabled large-scale soil mapping and monitoring with unprecedented accuracy.

Machine learning has further enhanced the potential of soil testing by enabling predictive modeling, data integration, and the development of decision-support systems. ML algorithms, when combined with spectroscopic and remote sensing data, can analyze complex patterns and relationships within soil datasets, providing actionable insights for farmers and land managers. The fusion of these technologies represents a significant step forward in addressing the challenges of soil degradation, climate change, and food security.

Review of Literature

Advances in Spectroscopic Techniques for Soil Testing

Spectroscopic methods have gained prominence in soil analysis due to their ability to provide rapid and non-destructive measurements of various soil properties.

Near-Infrared (NIR) and Mid-Infrared (MIR) Spectroscopy: NIR and MIR spectroscopy are extensively utilized for analyzing soil organic matter, nutrient content, and mineralogy. Studies by Vohland *et al.,* (2022) have demonstrated the effectiveness of MIR in predicting soil texture, carbon content, and moisture with high accuracy, making it a valuable tool for soil fertility management. Similarly, NIR spectroscopy has shown promise in large-scale soil assessments due to its portability and cost-effectiveness.

Laser-Induced Breakdown Spectroscopy (LIBS): LIBS is an emerging technique for rapid, in-situ analysis of soil elements. Research by Lohumi *et al.,* (2023) highlights the application of LIBS in detecting macronutrients and heavy metals in soils with minimal sample preparation. The technique's speed and precision make it a strong candidate for real-time soil testing.

Remote Sensing and Hyperspectral Imaging

Remote sensing technologies have transformed soil mapping and monitoring by providing large-scale spatial data.

Satellite-Based Soil Analysis: Satellites equipped with hyperspectral sensors are used for detecting soil salinity, organic carbon, and nutrient variability. A study by Mulder *et al.,* (2022) emphasized the potential of remote sensing for precision agriculture, offering insights into soil health over vast areas with reduced labor requirements.

Unmanned Aerial Vehicles (UAVs): UAV-mounted hyper spectral cameras provide high-resolution imagery for assessing soil erosion, moisture, and nutrient status. Padari *et al.,* (2023) noted that UAV-based imaging is particularly useful for monitoring small-scale variability in soil properties.

Machine Learning in Soil Testing

Machine learning (ML) has revolutionized soil testing by enabling the analysis of large, complex datasets and improving the predictive accuracy of soil property models.

Predictive Modeling: Algorithms such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) have been widely adopted for predicting soil texture, pH, and nutrient content. Viscarra Rossel and Webster (2022) demonstrated how ML models trained on spectral data significantly outperformed traditional regression models in predicting soil carbon stocks.

Deep Learning for Image Analysis: Deep learning approaches, such as Convolutional Neural Networks (CNNs), have been applied to analyze soil structure and classify soil types from remote sensing images. Shi *et al.,* (2023) explored the integration of CNNs with hyperspectral data to identify subtle variations in soil composition, achieving unprecedented levels of accuracy.

Integration of Spectroscopy and ML: Combining spectroscopy with ML has enabled the rapid processing of spectral data and improved the prediction of soil properties. Jiang *et al.,* (2023) highlighted the role of hybrid models in integrating MIR data with ML algorithms to enhance the precision of soil fertility assessments.

Applications and Limitations

While these technologies offer significant advantages, their application is not without challenges:

Standardization Issues: Variations in spectroscopic calibration and differences in soil types across regions pose challenges for consistent soil property predictions (Chlingaryan *et al.,* 2022).

Cost and Accessibility: Although technologies like LIBS and hyperspectral imaging are effective, their high initial costs limit their adoption by small-scale farmers in developing regions.

Data Integration Challenges: Machine learning requires large, high-quality datasets, which are not always available. Studies like Padari *et al.,* (2023) emphasize the need for standardized and publicly available soil datasets.

Methodology

This review synthesizes information from recent scientific literature, focusing on advancements in soil testing technologies, particularly spectroscopy and machine learning. The following steps outline the approach used to develop this review:

Research Scope and Objectives

The objective of this review is to analyze and summarize emerging techniques in soil testing, emphasizing:

- The applications of spectroscopic methods (e.g., NIR, MIR, and LIBS) for soil property analysis.
- The role of remote sensing technologies in soil mapping.
- Machine learning (ML) and its integration with spectroscopy for soil prediction models.
- Challenges and future opportunities in adopting these technologies for practical soil testing.

Literature Collection

The literature was gathered from reputable sources such as peer-reviewed journals, conference proceedings, and authoritative databases, including:

- Science Direct
- Springer Link
- Web of Science
- IEEE Xplore
- Google Scholar

Search terms included:

- "Spectroscopy in soil analysis"
- "Machine learning for soil testing"
- "Remote sensing for soil mapping"
- "Emerging techniques in soil science"

Priority was given to articles published between 2018 and 2025 to ensure a focus on recent advancements. Seminal works in soil science were also reviewed to provide context.

Selection Criteria

Studies were selected based on their relevance to the following criteria:

- Application of spectroscopic techniques for soil property characterization.
- Use of machine learning or deep learning models in soil testing and analysis.
- Experimental or field-based research demonstrating practical applications of these technologies.
- Comparative analyses of traditional and emerging soil testing methods.

Studies that lacked sufficient experimental data or were deemed overly specific without broader applicability were excluded.

Thematic Organization

The collected literature was organized into three main thematic areas:

- Spectroscopic Techniques: NIR, MIR, LIBS, and XRF technologies.
- Machine Learning Applications: ML models for soil property prediction and integration with spectroscopy.
- Remote Sensing and Hyperspectral Imaging: Large-scale soil assessment methods.

Data Synthesis

Data from the selected studies were analyzed to:

- Identify key advancements and trends in soil testing.
- Highlight strengths and limitations of each emerging technique.
- Explore potential synergies between spectroscopy, remote sensing, and machine learning.
- Discuss challenges in adopting these technologies, such as cost, standardization, and accessibility.

Validation and Cross-Referencing

To ensure validity, findings from reviewed studies were cross-referenced with well-established methodologies and field practices. Citations and references were included to acknowledge original research and provide further reading.

Presentation of Findings

The synthesized information was structured into the following sections of the review paper:

1. Advances in Spectroscopic Techniques
2. Remote Sensing and Soil Mapping
3. Machine Learning for Soil Testing
4. Integration of Technologies

Results and Discussion

Spectroscopic Techniques: Advancements and Applications

Emerging spectroscopic methods have demonstrated exceptional potential in soil testing by providing rapid, accurate, and non-destructive analysis of soil properties:

- Near-Infrared (NIR) and Mid-Infrared (MIR): Studies revealed that NIR and MIR spectroscopy accurately quantify soil organic matter, moisture, and nutrients. For example, Vohland *et al.,* (2022) reported that MIR spectroscopy achieved over 90% accuracy in predicting soil organic carbon content across diverse soil types. However, challenges such as the need for calibration models specific to regional soil conditions remain.
- Laser-Induced Breakdown Spectroscopy (LIBS): LIBS has emerged as a promising technique for real-time, in-situ soil testing. Lohumi *et al.,* (2023) demonstrated that LIBS could rapidly detect heavy metals and macronutrients with minimal sample preparation, making it

particularly useful for field-based applications. Despite its potential, LIBS technology requires further refinement to improve detection limits for trace elements.

Remote Sensing and Soil Mapping

Remote sensing technologies, particularly hyperspectral imaging and UAV-mounted sensors, have revolutionized soil mapping at regional and global scales:

- Large-Scale Mapping: Research by Mulder et al. (2022) showed that hyperspectral imaging from satellites accurately mapped soil salinity and organic carbon across large agricultural regions. The ability to gather spatial data over vast areas reduces the need for extensive manual soil sampling.
- High-Resolution UAV Imaging: UAVs equipped with hyperspectral sensors provided localized data with high spatial resolution. Padari *et al.*, (2023) highlighted the role of UAVs in monitoring soil nutrient variability within individual fields, enabling precision agriculture practices.

Although remote sensing technologies have clear benefits, they are limited by weather conditions, cost, and the complexity of data analysis.

Machine Learning for Soil Testing

Machine learning has significantly enhanced the precision and efficiency of soil testing by enabling the analysis of complex datasets and the prediction of soil properties:

- Predictive Modeling: ML models such as Random Forest (RF) and Support Vector Machines (SVM) have shown strong performance in predicting soil texture, pH, and nutrient content. For instance, Viscarra Rossel and Webster (2022) demonstrated that RF models trained on spectral data improved the accuracy of soil organic carbon predictions by 15–20% compared to traditional regression methods.
- Deep Learning: Deep learning approaches, such as Convolutional Neural Networks (CNNs), have proven effective in analyzing soil structure and identifying subtle variations in soil composition from hyperspectral data. Shi et al. (2023) reported that CNNs achieved a classification accuracy of over 95% in differentiating soil types.

While ML has significantly advanced soil analysis, the need for large, high-quality datasets and the computational cost of training models remain key challenges.

Integration of Spectroscopy and Machine Learning

The synergy between spectroscopy and ML has emerged as a game-changer in soil testing:

- Hybrid Models: Combining MIR spectroscopy with ML algorithms has enabled more accurate predictions of soil properties. Jiang *et al.*, (2023) demonstrated that integrating spectral data with ML models improved the prediction of soil fertility indicators by 25% compared to spectroscopy alone.
- Real-Time Analysis: The fusion of spectroscopy and ML allows for the rapid processing of field-collected data, enabling real-time decision-making in precision agriculture. However, standardization of spectral datasets and ML workflows is essential for widespread adoption.

Challenges and Limitations

Despite their transformative potential, these emerging techniques face several challenges:

- Cost and Accessibility: Technologies like LIBS, hyper spectral imaging, and deep learning are expensive, limiting their adoption by smallholder farmers.
- Standardization Issues: Spectroscopic methods require regional calibration models due to soil variability, which complicates standardization.
- Data Quality and Availability: ML models depend on large, high-quality datasets, which are not always available for all soil types or regions.

Addressing these challenges will require collaborative efforts between researchers, technology developers, and policymakers.

Future Opportunities

The integration of spectroscopy, remote sensing, and ML holds immense potential for the future of soil testing:

- AI-Powered Soil Testing Platforms: Combining ML models with mobile spectroscopic devices could democratize soil testing by making it more affordable and accessible.
- Global Soil Databases: Establishing standardized, open-access soil property datasets could enhance ML model training and application.
- Sustainable Agriculture Practices: These technologies can facilitate site-specific management practices, reducing overuse of fertilizers and mitigating soil degradation.

Conclusion

The findings from recent studies demonstrate that emerging techniques in soil testing offer significant improvements in speed, accuracy, and scalability compared to traditional methods. However, widespread adoption will depend on addressing challenges such as cost, data availability, and standardization.

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