SUNSHINE AGRICULTURE
e-Newsletter

ISSN (E): 2583 – 0821

Sun. Agri.:e- Newsletter, (2026) *6*(9), 111-116

Article ID: 674

Mining Data, Not Just Soil: How AI and Soil Sensors are Revolutionizing Agronomy

Abhishek Kumar[1]
Krishan Kumar Sharma[2] Hritik[3]
Anjaly Yadav[4]
Dhiraj Kumar Yadav[5]

[1]Subject Matter Specialist, Krishi Vigyan Kendra, Turki, Dr. Rajendra Prasad Central Agricultural University Pusa, Samastipur, Bihar
[2]M. Sc. Scholar
Division of Soil Science, RCSM Govt. College of Agriculture, Kolhapur Mahatma Phule Krishi Vidyapeeth Ahilyanagar, Maharashtra
[3]M. Sc. Scholar
Division of Agronomy, RCSM Govt. College of Agriculture, Kolhapur Mahatma Phule Krishi Vidyapeeth Ahilyanagar, Maharashtra
[4]Research Scholar, Department of Soil Science and Agricultural Chemistry Acharya Narendra Deva University of Agriculture and Technology Kumarganj Ayodhya, Uttar Pradesh
[5]Assistant Professor, Department of Farm Forestry, UTD, Sant Gahira Guru Vishwavidyalaya Sarguja Ambikapur, Chhattisgarh

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*Corresponding Author
Abhishek Kumar*

Available online at
www.sunshineagriculture.vitalbiotech.org

Article History
Received: 21.09.2026
Revised: 26.09.2026
Accepted: 01.10.2026

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INTRODUCTION

Soil has traditionally been studied through physical sampling, laboratory analysis, field observation and interpretation based on established agronomic principles. These methods remain fundamental to soil science because they provide reliable information about soil texture, pH, organic matter, nutrients, salinity, moisture and other important properties. However, conventional soil analysis is often periodic rather than continuous. A soil sample represents a particular location and time, while agricultural fields vary widely in space and change continuously with weather, irrigation, crop growth, microbial activity and management practices.

The emergence of soil sensors and artificial intelligence is changing this situation. Instead of viewing soil only as a material that must be sampled and analyzed, modern agronomy increasingly treats the field as a continuously changing information system. Sensors can collect information from soil at frequent intervals. At the same time, artificial intelligence can process large quantities of observations and identify relationships that may be difficult to detect through conventional analysis alone. Recent reviews describe the expanding use of soil sensors for monitoring moisture, temperature, pH, nutrients and contaminants, while artificial intelligence is increasingly being used for soil characterization, fertility management, moisture prediction, digital soil mapping and precision agriculture.

This transition can be described as a movement from soil sampling toward soil intelligence. The objective is not to replace laboratory science or agronomic knowledge. Rather, the objective is to combine field observations, laboratory measurements, sensor networks, satellite information, weather records, crop observations and machine learning into a more dynamic decision-making system.

From Soil Samples to Continuous Soil Intelligence

Conventional soil testing normally involves collecting representative samples, transporting them to a laboratory and measuring selected properties. The resulting information is valuable, but the sampling process can be expensive and time consuming when large areas need to be monitored frequently. Soil sensors introduce another dimension by allowing repeated measurements directly in the field. Moisture sensors can provide information about the water status of different soil layers. Temperature sensors can monitor thermal conditions that influence root development and microbial activity. Electrical conductivity measurements can help identify spatial variation associated with soil properties and salinity. Sensors and sensing platforms can also be developed for pH, nutrients and other soil characteristics.

Modern sensor systems can transmit observations to digital platforms through wireless communication and Internet of Things networks. Instead of receiving a single laboratory result, farmers and agronomists can potentially obtain a continuous sequence of measurements. This temporal dimension is particularly important for irrigation management because soil moisture can change considerably within a day depending on rainfall, evaporation, crop water consumption and irrigation. Advanced soil sensor reviews emphasize that sensor technologies are increasingly capable of monitoring physical and chemical characteristics in real time and that wireless sensor networks can support precision agriculture.

The Role of Artificial Intelligence

Collecting large amounts of data does not automatically create useful information. A field containing hundreds of sensors can generate thousands or millions of observations. The challenge is to interpret these observations and convert them into practical agronomic decisions. Artificial intelligence provides computational methods for this task. Machine learning algorithms can identify relationships between soil measurements, environmental conditions, crop responses and management practices. Common approaches include random forests, support vector machines, artificial neural networks and other ensemble or deep learning methods.

For example, an agricultural system may collect soil moisture, temperature, electrical conductivity, weather and crop growth information. A machine learning model can use historical observations to identify conditions associated with crop water stress. The system can then estimate future soil moisture or identify areas where irrigation may be required. AI is also useful because relationships in agricultural systems are rarely simple. Crop performance is influenced simultaneously by soil, weather, genotype, water availability, nutrients and management. Artificial intelligence can process multiple variables simultaneously and detect nonlinear relationships within complex datasets. Recent research in soil science identifies applications involving digital soil mapping, soil fertility management, moisture prediction, contamination monitoring and soil carbon assessment.

Soil Sensors and Precision Irrigation

Water management is one of the most immediate applications of soil sensing. Traditional irrigation schedules often rely on fixed intervals or general recommendations. Such approaches may not adequately reflect actual soil moisture conditions. Sensor-based irrigation provides an opportunity to measure soil moisture directly. If sensors are installed at different depths, the system can monitor the movement and availability of water within the root zone. Artificial intelligence can then combine soil moisture measurements with weather forecasts, crop growth stage and historical irrigation information.

The resulting system can support decisions about when irrigation should occur and how much water may be required. This is particularly important in regions where groundwater depletion and water scarcity are major concerns. Recent research has also emphasized the integration of Internet of

Things sensors, remote sensing and artificial intelligence for soil moisture prediction. However, researchers have identified challenges related to sensor calibration, differences among soil types, spatial and temporal resolution, data heterogeneity and model transferability between locations. Therefore, AI-based irrigation should not be viewed as a simple automated replacement for agronomic judgment. The quality of the recommendation depends strongly on the quality of sensor observations, calibration and local validation.

Artificial Intelligence for Nutrient Management

Nutrient management is another important area in which data-driven agronomy can contribute to resource efficiency. Traditional soil testing provides information about nutrient concentrations, but field-scale variability means that nutrient requirements may differ substantially from one part of a field to another. Combining soil sampling with proximal sensors, remote sensing, crop observations and machine learning can help generate spatial estimates of soil fertility indicators. Machine learning and remote sensing research has demonstrated the potential to estimate chemical, physical and biological soil indicators using multidimensional datasets.

This creates the possibility of site specific nutrient management. Instead of applying the same fertilizer rate across an entire field, agronomists can divide the field into management zones according to measured and predicted characteristics. Such systems may contribute to improved nutrient use efficiency. They can also reduce unnecessary fertilizer application where soil nutrient availability is already adequate. Nevertheless, AI-generated nutrient recommendations should be calibrated using laboratory measurements and crop response data because predicted soil properties are estimates rather than direct chemical measurements.

Important Applications of AI and Soil Sensors in Agronomy

Agronomic application	Major data sources	Role of AI	Potential management outcome
Irrigation management	Soil moisture, temperature, rainfall, weather data, crop stage	Predict soil moisture and crop water demand	More precise irrigation scheduling
Nutrient management	Soil tests, electrical conductivity, remote sensing, crop growth data	Predict nutrient variability and management zones	Site specific fertilizer application
Soil health assessment	Organic matter, pH, moisture, biological indicators, sensor observations	Identify patterns and estimate soil health indicators	Targeted soil improvement practices
Salinity monitoring	Electrical conductivity, soil moisture, remote sensing	Map spatial and temporal salinity variation	Improved irrigation and reclamation decisions
Soil carbon assessment	Soil measurements, spectroscopy, remote sensing, environmental data	Estimate and map soil carbon	Carbon monitoring and conservation planning
Yield prediction	Soil, weather, crop growth and management data	Identify relationships between environmental conditions and yield	Improved production planning
Soil compaction detection	Soil physical measurements, proximal sensing, machinery data	Identify compacted zones	Targeted traffic and tillage management
Decision support	Multiple sensor, weather and crop datasets	Combine observations and generate predictions	More timely agronomic decisions

Mining Data from the Soil

The phrase data mining is particularly relevant to modern agronomy because soil systems contain patterns that are difficult to identify through isolated measurements. Consider a field where soil moisture is recorded every hour for several months. At the same time, weather information, crop growth, fertilizer applications and yield elements are collected. Individually, each dataset provides limited information. When combined, however, they can reveal relationships between rainfall, soil water availability, crop development and yield.

Machine learning can search for such relationships. The process can involve data cleaning, feature selection, model development, validation and prediction. Historical observations can be divided into training and testing datasets so that the model can be evaluated using observations that were not used during model development. This approach changes the role of soil information. Instead of asking only, "What is the nutrient concentration in this sample?" agronomists can ask broader questions such as, "How does nutrient availability change across the field?" or "How does soil moisture interact with weather and crop development?" This is one of the major conceptual changes introduced by digital agronomy.

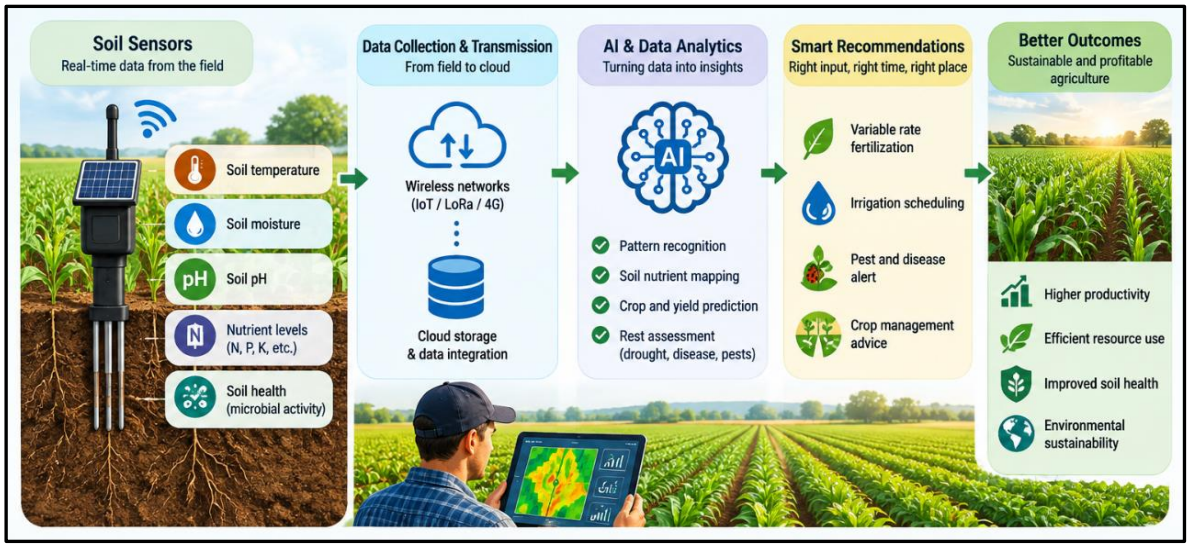


Figure: Integration of soil sensors and artificial intelligence (AI) enables real-time data collection advanced analysis and smart decision-making for improved crop productivity efficient resource use and sustainable soil health.

Integration with Remote Sensing

Ground-based sensors provide detailed information at particular locations, while satellites and unmanned aerial vehicles can provide spatial information across much larger areas. Combining these data sources can therefore improve agricultural monitoring. Remote sensing can provide information about vegetation condition, surface characteristics and spatial variation. Soil observations can provide direct or indirect information about soil properties. Machine learning can integrate these different sources.

Research on machine learning and remote sensing has demonstrated the use of soil quality indicators, environmental data, remote sensing observations and crop management information within predictive frameworks. This integration can support digital soil mapping and the creation of spatially explicit management zones. For example, a field may contain areas with different moisture holding capacities or nutrient availability. A combination of field sensors and remote sensing can help identify these zones more efficiently than uniform field sampling alone.

Soil Health Monitoring

Soil health is multidimensional and cannot be represented by a single measurement. It includes chemical, physical and biological characteristics as well as the capacity of soil to perform important ecosystem functions. Artificial intelligence can assist by integrating multiple soil health indicators. Recent research highlights applications of AI in soil fertility, soil moisture, soil carbon, contamination monitoring and digital soil mapping.

A future soil health monitoring system could combine information about organic matter, soil moisture, temperature, pH, nutrient status, microbial indicators and crop performance. Repeated measurements would allow agronomists to identify trends rather than relying only on individual sampling events. This could be especially useful for evaluating long-term practices such as conservation agriculture, residue management, cover cropping, organic amendments and reduced tillage.

The Importance of Data Quality

Artificial intelligence is only as reliable as the data used to develop and operate it. Poor sensor calibration, missing observations, inconsistent sampling depths, inaccurate laboratory measurements and environmental noise can produce unreliable predictions. One important challenge is that soil conditions vary enormously between regions. A model developed using data from one soil type or climatic environment may not perform equally well in another region. Recent reviews have highlighted data scarcity, uncertainty, regional bias, lack of standardization and limited model transferability as important challenges for AI applications in soil science. Therefore, field validation remains essential. AI should be treated as a decision support technology rather than an unquestionable authority.

From Black Box Models to Explainable Agronomy

Another challenge is explainability. Some advanced machine learning models can produce highly accurate predictions while providing limited information about why a particular prediction was generated. For agronomy, explanation matters because farmers and scientists need to understand whether a recommendation is consistent with known soil and crop processes. An unexplained prediction can be difficult to trust, particularly when it affects fertilizer application, irrigation or other economically important decisions. Explainable artificial intelligence can help identify which variables contributed most strongly to a prediction. This can connect computational models with agronomic reasoning. The future of AI in agriculture therefore depends not only on improving predictive accuracy but also on improving transparency, uncertainty estimation and communication.

Economic and Practical Considerations

High technology agriculture should not automatically mean high-cost agriculture. For widespread adoption, sensing systems need to be affordable, durable, energy efficient and easy to maintain. Low-cost sensors and wireless communication technologies are expanding opportunities for small and medium-scale farms. However, sensor purchase is only one component of the total cost. Installation, calibration, maintenance, connectivity, data storage and technical support also require consideration. The most practical systems may therefore combine a limited number of high-quality sensors with strategic soil sampling and remote sensing rather than attempting to install sensors everywhere. This hybrid approach can provide a balance between measurement density and cost.

Future Perspectives

- The next stage of digital agronomy is likely to involve greater integration among sensors, artificial intelligence, remote sensing, robotics and farm management platforms. Soil sensors will increasingly function as components of interconnected agricultural systems rather than isolated instruments.

- Future systems may use edge computing to process data close to the sensor, reducing dependence on continuous internet connectivity. Artificial intelligence may also become increasingly capable of combining sensor measurements with satellite observations, weather forecasts and crop images.
- Digital soil models may eventually provide continuously updated representations of soil conditions. Such systems could help farmers and agronomists monitor changes in soil moisture, nutrient availability, compaction, salinity and soil carbon over time.
- Recent literature emphasizes that the development of intelligent soil management will require better integration of heterogeneous datasets, standardized measurements, explainable models and stronger validation across different environments.

CONCLUSION

The future of agronomy is increasingly moving from occasional measurement toward continuous observation and intelligent interpretation. Soil sensors provide frequent information about changing field conditions, while artificial intelligence provides the analytical capability needed to transform large datasets into useful agronomic knowledge. The most important transformation is therefore not simply the installation of sensors or the adoption of artificial intelligence. It is the integration of soil science, sensor technology, remote sensing, data analytics and agronomic expertise into a unified decision-making framework. Mining data from soil can help reveal spatial variability, temporal changes and complex relationships among soil, water, climate and crops. When properly calibrated and validated, these technologies can support more precise irrigation, nutrient management, soil health assessment and resource conservation. The objective should not be to replace the agronomist with an algorithm. The objective should be to give agronomists better information, faster observations and stronger analytical tools. In this sense, the future of agriculture may depend not only on what farmers put into the soil, but also on how effectively they can understand and use the enormous amount of information emerging from it.

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