



IoT- and Machine Learning-Based Smart Agriculture Monitoring: A Review of Technologies, Sensing, and Decision Support

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Abstract. Agricultural practice in India has evolved from knowledge-intensive traditional systems to technology-supported approaches that combine sensing, communication, cloud services, and data-driven analytics. This review examines how Internet of Things (IoT) infrastructure and Machine Learning (ML) can be combined for smart agriculture monitoring and decision support. The discussion covers historical agricultural practices, IoT architecture, field sensing, soil and environmental monitoring, irrigation support, crop-condition assessment, and ML techniques reported for agricultural prediction. The reviewed approaches use variables such as soil moisture, soil temperature, pH, humidity, rainfall, nutrient status, weather observations, and remotely sensed information. ML methods reported in the literature include decision trees, support vector methods, random forest, Cubist, K-means, regression models, gradient-boosted trees, extreme learning machines, and convolutional neural networks. The review also reorganizes the technology stack into a practical monitoring cycle in which sensors acquire observations, a gateway transfers the data, analytics interpret the measurements, and recommendations are returned to the farming process. The synthesis indicates that IoT provides the observation and communication layer, while ML can convert heterogeneous measurements into predictions or recommendations. The paper identifies opportunities for integrated, affordable, and continuous monitoring while also highlighting constraints related to connectivity, cost, data quality, interoperability, and adoption.

Keywords: Smart agriculture, Internet of Things, Machine Learning, smart sensing, precision farming, soil monitoring, irrigation, CNN.

I. Introduction

Agriculture in the Indian subcontinent has a long history of crop cultivation, animal domestication, water management, storage, and adaptation to local environmental conditions. Evidence discussed in the source study places early agricultural activity in the Neolithic period, with cultivation and domestication practices developing over successive generations. In South India, rice, sugarcane, millets, cereals, pulses, cotton, coconut, areca, plantain, and other crops formed part of diverse agricultural systems. Practices such as weeding, irrigation, manuring, crop protection, and water storage supported sustained cultivation. The Kallanai dam on the Kaveri is presented in the source material as an early example of durable water-regulation infrastructure. During the Chola period, irrigation administration and tank-and-channel networks further demonstrate the importance of organized water distribution [1], [2].

Contemporary agriculture faces a different set of pressures. Urbanisation can reduce cultivated land, agricultural labour availability can decline as people move towards cities, and food production must respond to changing environmental and economic conditions. These pressures have encouraged the adoption of technologies that can reduce manual monitoring and support timely farm decisions. IoT enables field devices and agricultural equipment to exchange observations, whereas ML provides methods for learning relationships within collected data and producing predictions or recommendations [3].

Smart agriculture therefore represents an extension of traditional farm knowledge through connected sensing and computational decision support. Sensors can capture soil moisture, temperature, humidity, water level, nutrient status, and other variables. Gateways and communication networks transfer measurements to local or cloud-based processing systems, where analytical models can be applied. The resulting information can then support irrigation, crop monitoring, disease assessment, and other farm-management activities.

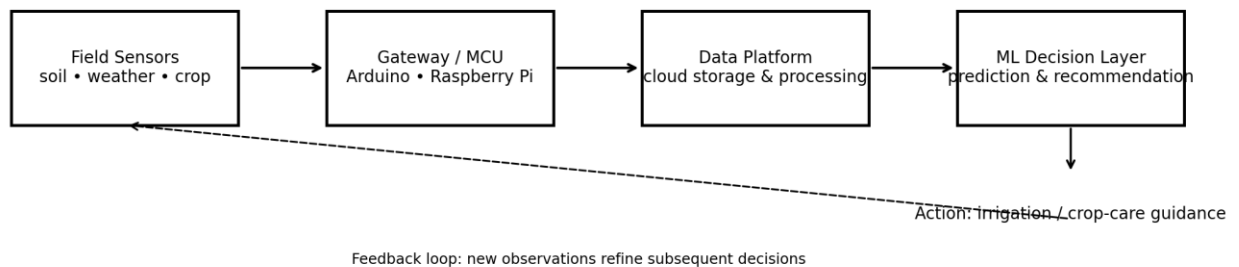


Fig. 1. Redesigned IoT-ML smart agriculture monitoring cycle.

II. Review Methodology

The work is structured as a technology-focused review of smart farming. The source material reports that research from publishers and scientific outlets such as Springer, Elsevier, Wiley, and MDPI was considered, together with books, book chapters, conference proceedings, articles, and research reports. Particular attention was given to recent literature and to smart-agriculture practices reported in different geographical settings, including African agriculture. The review was organized around three technology layers: IoT connectivity and infrastructure, smart sensing, and ML-based analysis and decision support [29]–[35]. For the methodological synthesis, studies were grouped according to the agricultural variable or task addressed and the computational approach employed. Examples include soil-moisture estimation, soil organic carbon and total nitrogen prediction, nutrient-solution monitoring, irrigation recommendation, environmental monitoring, crop-condition assessment, and disease-related monitoring. The comparison emphasizes the input attributes and analytical methods rather than treating all models as directly comparable, because the reviewed studies use different datasets, sensing configurations, validation procedures, and objectives.

III. Smart Farming Architecture

A practical smart-farming architecture can be viewed as a continuous four-stage process. First, field sensors acquire measurements from soil, crops, water systems, and the surrounding atmosphere. Second, a microcontroller or gateway collects and forwards those observations through technologies such as Wi-Fi, ZigBee, cellular networks, or other suitable links. Third, a data platform stores and prepares the measurements for analysis. Fourth, analytical and ML models transform the observations into predictions, classifications, or recommendations. The recommendation can be used to guide irrigation, crop care, disease surveillance, or other farm actions. New observations then enter the system again, forming a feedback cycle.



The source material identifies platforms and components such as Arduino, Raspberry Pi, microcontrollers, GPS, cellular communication, ZigBee, Wi-Fi, and cloud services as examples of infrastructure used in smart farming. Their exact configuration depends on the field setting, communication requirements, sensing range, and cost constraints. The key architectural principle is the separation of data acquisition, communication, analytics, and action so that each layer can be adapted to the application.

IV. IoT and Machine Learning Approaches in Smart Farming

Several reviewed studies demonstrate how IoT observations can be coupled with ML models. A wrapper-based feature-selection approach combined with the PART classifier was reported for crop-production support, achieving an accuracy of 92.51% in the cited work. The source notes that the approach was primarily based on time-series information and was not designed for future prediction [4].

Other work combined pH, soil-moisture, salinity, and electromagnetic sensing with a Multi-Layer Perceptron for agricultural-land assessment. In another low-cost IoT design, temperature, rainfall, and humidity measurements were transmitted to a cloud environment and used with Logistic Regression, Support Vector Machines, Multiple Linear Regression, and K-means clustering for crop and environmental assessment [5], [6]. Raspberry Pi, NodeMCU/ESP8266, and cloud platforms such as ThingSpeak are examples of implementation components reported in the source material.

Irrigation-oriented systems have also used decision trees, regression techniques, support-vector methods, K-means clustering, gradient-boosted regression trees, and related hybrid strategies. These approaches use variables such as soil moisture, soil temperature, humidity, weather conditions, solar radiation, and rainfall to estimate water requirements or provide irrigation guidance. Reported studies include SVR combined with K-means clustering for soil-moisture-related tasks and GBRT-based approaches for irrigation recommendation [16], [21].

Remote and non-contact sensing has also been incorporated into smart agriculture. Thermal imaging, satellite observations, hyperspectral imagery, and VIS-NIR spectroscopy have been used to estimate crop, soil, or irrigation-related properties. The reviewed literature includes Random Forest, Cubist, LS-SVM, SVR, XGBoost, KNN, ELM, and CNN/deep-learning approaches for such tasks [18]–[26].

Table 1. Reorganized comparison of reviewed smart-farming approaches

No.	Agricultural task	Main attributes	Analytical approach
1	Soil organic carbon and total nitrogen estimation	SOC, TN	Ensemble learning
2	Nutrient-solution composition monitoring	pH, temperature, flow rate	ELM / DBN-ELM
3	IoT-enabled irrigation management	Soil moisture, temperature, climate	SVR + K-means
4	Surface soil-moisture prediction	Surface moisture	ELM regression
5	Soil-moisture downscaling	Soil moisture	Random Forest, Cubist
6	Atmospheric and soil-condition detection	Humidity, temperature, moisture, rainfall	MLR + K-means
7	Soil-property estimation from VIS-NIR	TN, SOC, moisture	LS-SVM, Cubist
8	Irrigation recommendation	Temperature, solar radiation, humidity	GBRT, regression trees, boosted trees
9	IoT-based smart agriculture monitoring	Moisture, temperature, humidity	Decision tree
10	Spatial SOC prediction	Temperature, annual rainfall	Cubist, XGBoost, RF, SVM, KNN
11	Hyperspectral soil-moisture estimation	Soil moisture	SVR
12	Environmental data collection	Moisture, temperature, humidity, wind, sunlight	SVMr
13	Soil-attribute prediction	Soil characteristics	Deep learning, CNN
14	Weather-based crop recommendation	Water-related weather variable, temperature	ELM, SVM, ANN
15	Affordable IoT smart farming	Soil, temperature, moisture	Linear regression, SVM

V. IoT Infrastructure for Agricultural Monitoring

IoT contributes the communication and observation backbone of smart agriculture. Connected devices can link field equipment, sensor nodes, gateways, cloud services, and user interfaces so that agricultural conditions can be observed without requiring continuous physical inspection. The source review describes applications extending from smart homes and transportation to smart agriculture, with agriculture-specific uses including irrigation management, crop monitoring, livestock tracking, and supply-chain support [29], [33], [34].

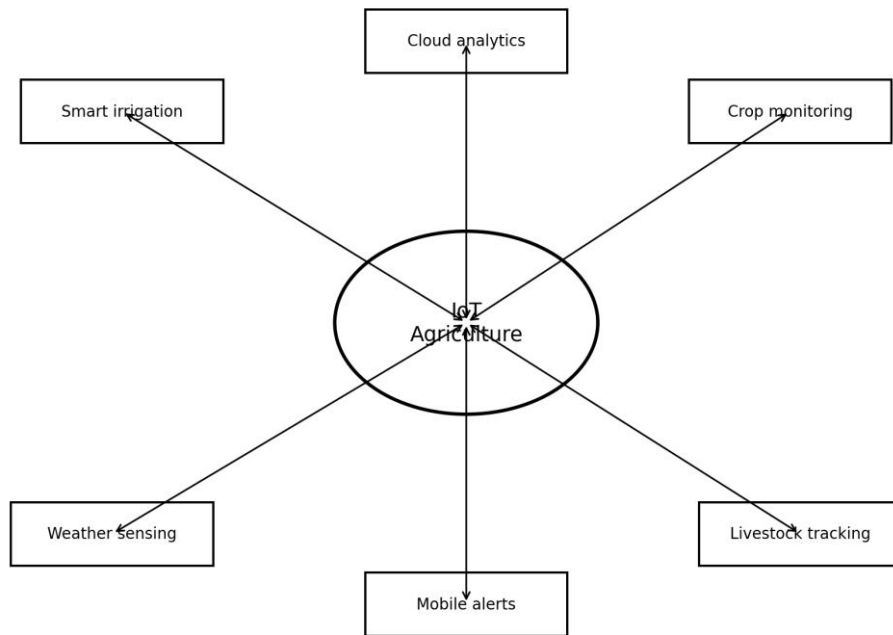


Fig. 2. Redesigned view of the IoT ecosystem surrounding agricultural operations.

Wireless sensor networks are particularly useful when observations must be collected at multiple locations within a field. Sensor nodes can capture local conditions and forward measurements to a gateway. The gateway can then transfer the information to cloud or server infrastructure for storage and analysis. The combination of sensing, communication, and analytics enables remote monitoring and can shorten the interval between observation and farm action.

The reviewed literature also reports IoT-supported disease monitoring in which satellite imagery and field sensors are used to detect crop problems and communicate analytical results through a web server. Such systems illustrate how sensing does not need to be limited to a single sensor type: ground observations can be combined with remote observations to provide a broader representation of field conditions [30].

VI. Smart Sensing for Agriculture

Sensing is the first operational layer of a smart-farming system because ML predictions are dependent on the quality and relevance of the observations supplied to the model. The reviewed systems employ sensors for soil moisture, soil temperature, air temperature, humidity, pH, nutrient status, water level, and related variables. Soil sensors can support the assessment of moisture and fertility, while climate sensors provide information about environmental conditions. These measurements can subsequently be used for irrigation control, crop monitoring, yield support, and livestock applications [32].

A sensing system should therefore be designed around the agricultural question being addressed. For irrigation, soil moisture and weather variables are central. For soil-health assessment, pH, nutrient indicators, moisture, and related soil properties become important. For disease monitoring, environmental measurements can be combined with images or other observations. The source material also identifies communication mechanisms and intelligent-sensor applications that connect sensing with automated or semi-automated agricultural services [35].

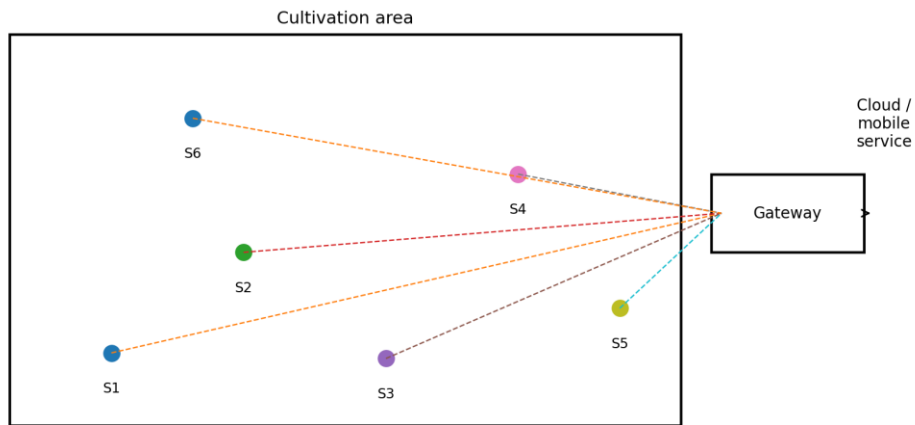


Fig. 3. Redesigned wireless sensor-network arrangement for a cultivated field.

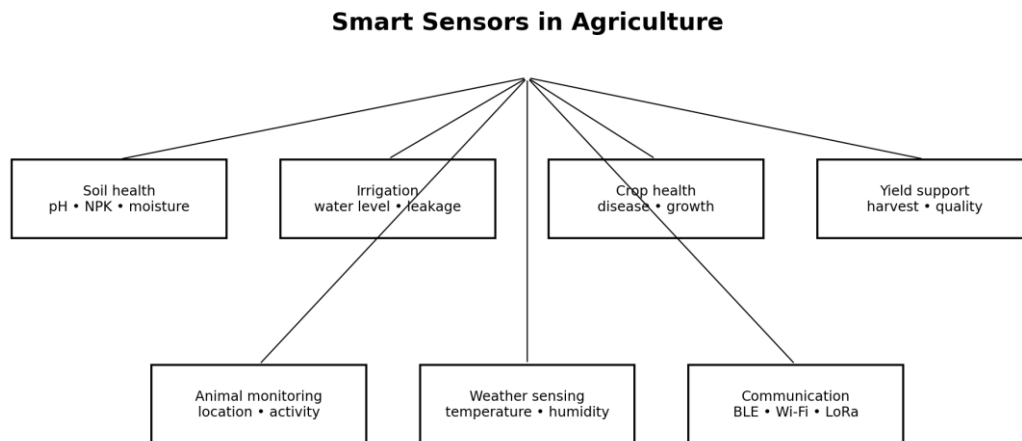


Fig. 4. Redesigned classification of major smart-sensor applications in agriculture.

VII. Distribution of Reported Iot Applications

The source review reports a survey of 67 studies covering agricultural IoT applications during the period discussed in the original paper. The reported distribution included 16% precision agriculture, 16% irrigation monitoring, 13% soil monitoring, 12% temperature monitoring, 11% animal monitoring, 11% humidity monitoring, 5% air and disease monitoring, and 7% water monitoring; the source further notes that fertilisation monitoring accounted for 4% of the studies. These percentages are reproduced here as a synthesis of the source review rather than as a new bibliometric analysis.

Reported distribution of IoT applications in smart agriculture

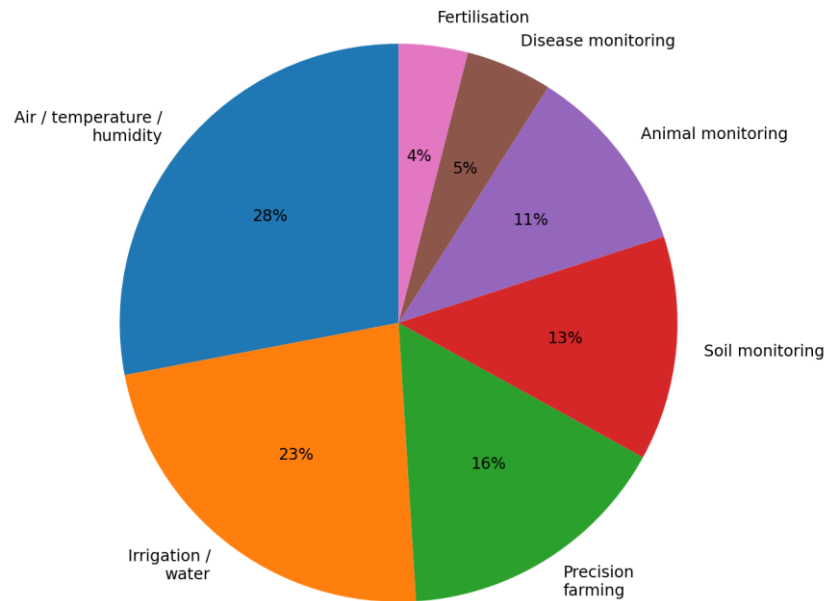


Fig. 5. Redrawn representation of the application distribution reported in the reviewed survey [31], [34].

VIII. Machine Learning for Agricultural Decision Support

ML extends IoT monitoring by learning patterns from historical observations. In the reviewed literature, classification methods are used when the output is a category, while regression methods estimate continuous agricultural quantities such as soil moisture or environmental variables. Clustering can be used to organize observations into groups, and ensemble methods combine multiple learners to improve predictive performance. Deep-learning approaches, including CNNs, are particularly relevant when the input contains images or complex high-dimensional patterns [14]–[28].

The suitability of a model depends on the task and data structure. For example, SVR and regression-oriented models are frequently associated with soil-moisture estimation, while Random Forest, Cubist, XGBoost, and other ensemble methods appear in soil-property prediction. CNN and deep-learning methods are useful when image or spectroscopic representations are involved. The reviewed studies demonstrate that there is no single algorithm that is appropriate for every smart-farming problem; model selection must consider the measurement type, prediction target, computational resources, and operational setting.

**Swoc Analysis of Iot-Enabled Smart Agriculture**

Strengths Continuous field observation; reduced dependence on manual inspection; data-supported irrigation and crop management; integration of sensors, communication, cloud services and ML.	Weaknesses Dependence on connectivity and power; sensor maintenance and calibration; deployment cost; data-quality and interoperability challenges; need for technical skills.
Opportunities Precision agriculture; remote advisory services; integration of weather and satellite information; affordable sensor platforms; scalable analytics and automation.	Challenges / Threats Changing environmental conditions; cyber-security and privacy risks; equipment failure; variable network availability; adoption barriers and operational costs.

IX. Conclusion

Food production is influenced by population growth, environmental change, groundwater availability, labour constraints, land-use change, and crop losses associated with pests and diseases. Against this background, smart agriculture provides a technology pathway for more continuous observation and more informed farm management. The reviewed literature shows that IoT can connect field sensors and agricultural devices, while ML can transform the resulting observations into predictions, classifications, or recommendations.

The review also indicates that smart agriculture is not a single technology but an integrated stack involving sensing, communication, data storage, analytics, and action. Soil moisture, temperature, humidity, pH, nutrient indicators, weather observations, imagery, and spectral measurements can each contribute to specific agricultural tasks. Future systems can benefit from interoperable sensing platforms, reliable communication, affordable deployment, better-quality datasets, explainable analytics, and stronger integration between recommendations and practical farm operations. Continued research is therefore required to make connected agricultural monitoring more accessible and useful across diverse farming environments.

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