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Internet of Things-Based Soil Nutrient Monitoring Systems for Crop Yield Prediction: A PRISMA Systematic Review of Methodologies, Machine Learning Models, and Research Gaps

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Abstract:

Global food production must rise by at least 60% by 2050, yet the inputs needed to reach that target risk accelerating the soil degradation that limits yields in the first place. The Internet of Things (IoT) and Machine Learning (ML) are increasingly used to monitor soil health and forecast crop performance in response to this pressure. Despite growing research in this area, no comprehensive synthesis has yet mapped the common methodologies in use, and it remains unclear how consistently different ML models perform once deployed across varied farming environments — a gap this review addresses. Using a PRISMA-compliant systematic review of 87 peer-reviewed studies published between 2017 and 2026, this paper examines how IoT sensor networks, wireless communication protocols, cloud architectures, and ML models are being combined to support precision agriculture. This review covers sensor deployment techniques, wireless protocols (WiFi, LoRaWAN, and NB-IoT), and ten standard ML models for multiple crop types, with the random forest regression (RFR) showing the best performance with an R2 of 0.97 across the datasets considered. The review also covers how explainable AI techniques can help farmers to comprehend and have confidence in results from model. Three common gaps are identified: a lack of interdisciplinary validation, a lack of studies from Sub-Saharan Africa, and a lack of a standardized approach to IoT sensor calibration. These findings offer a reference point for researchers, policymakers, and developers of future smart-farming systems.

Keywords: Internet of Things (IoT); soil nutrient monitoring; crop yield prediction; Machine Learning (ML); precision agriculture (PA); PRISMA; systematic review; Random Forest Regression (RFR); explainable AI; smart farming.

1. INTRODUCTION

Global food systems face a paradox: agricultural soils, already under significant strain, must yield roughly 60% more grain by 2050 to meet projected demand, yet the intensified inputs required to hit that target risk worsening the very soil degradation that caps production [1, 2]. Soil chemistry compounds this difficulty — pH can vary by whole points within a single field row, and nitrogen, phosphorus, and potassium (NPK) levels shift with microbial activity, irrigation timing, and temperature [2, 3]. These imbalances typically cut attainable yields by 20–30%, but conventional soil testing relies on laboratory analysis that takes two to three weeks to return results, by which point the fertilization window has often closed [4, 5].

The combination of IoT and ML bypasses this d elay, offering near real-time and data-driven decisions on crop monitoring and yield forecasting [54]. The IoT represents a real paradigm shift in this aspect: networks of embedded sensors can continuously monitor NPK, pH, moisture and temperature and transmit this data to cloud platforms for analysis [2, 6]. ML models trained on this real-time stream can diagnose nutrient deficiencies before the appearance of visible symptoms in the crops, providing a window of opportunity for farmers to intervene proactively [7, 8].

The outcomes are measurable – field trials carried out in India, Bangladesh and East Africa have shown reductions in water usage of about 25% and nitrogen savings of approximately 30%

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with the use of combined IoT and ML systems, without any loss in yield [9, 10].

Despite this promise, the evidence base remains fragmented. Studies differ widely in sensor technology, wireless protocol, choice of ML algorithm, crop type, geography, and evaluation method, which makes cross-study comparison difficult. The literature also skews toward well-resourced pilot deployments, which tends to mask the gap between laboratory-grade precision and real-world field reliability [5, 11]. This fragmentation motivates the systematic review presented here: a PRISMA-compliant synthesis of 87 peer-reviewed studies published between 2017 and 2026, undertaken to map the current state of evidence, surface replicable methodological patterns, and identify where future research is most needed.

Specifically, the review aims to:

1. characterize the IoT sensor technologies used for soil nutrient monitoring in precision farming;
2. evaluate the comparative performance of ML models applied to IoT-derived datasets for crop yield prediction;
3. assess how IoT data is stored, processed, and transmitted across different wireless communication protocols;
4. identify methodological gaps where existing findings have limited applicability or where further study is needed; and
5. propose actionable recommendations for designing scalable, field-deployable IoT-ML smart-farming systems.

The remainder of this paper is organized as follows. Section II presents the PRISMA methodology used in this study; Section III reviews the related literature; Section IV presents the results and discussion; Section V identifies the research gaps; and Section VI concludes the paper.

II. PRISMA METHODOLOGY

A. Review Protocol and Registration

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [12]. The review protocol was pre-registered and encompassed the following dimensions: IoT sensor systems for soil parameter monitoring, ML models for crop yield prediction, wireless communication protocols, cloud computing architectures, and explainable AI (XAI) methods in precision agriculture.

B. Eligibility Criteria

Studies were included in this review if they met all of the following criteria:

- Featured in peer-reviewed journals, conference publications, or pre-publication repositories between 2017 and 2026.
- Reported IoT or sensor based soil health/nu trients monitoring with at least one measura ble soil parameter (NPK, pH, moisture or te mperature).
- Used at least one machine learning / statisti cal
  model for crop yield assessment or soil classification.
- Reported at least one evaluation metric.
- Accessible in the English language.

Studies were excluded if they addressed only remote sensing without in situ sensors, reported no quantitative model evaluation, were opinion papers, editorials, or grey literature without peer review, or focused exclusively on livestock or non-crop applications.

C. Search Strategy

A systematic database search was conducted across five repositories — IEEE Xplore, Scopus, Web of Science, PubMed (for soil science studies), and Google Scholar — to identify relevant studies, combining controlled vocabulary and free-text search terms.

D. Study Selection and PRISMA Flow

Figure 1 presents the PRISMA flow diagram. The search yielded 3,412 records. After deduplication, 2,891 records underwent title and abstract screening, from which 312 were retrieved for full-text assessment. Following application of the eligibility criteria, 87 studies were included in the final synthesis.

Identification
Records identified via databases
n = 3,412

↓

Deduplication
Records after removal
n = 2,891
Duplicates removed: n = 521

↓

Screening
Title & abstract screened
n = 2,891
Excluded (irrelevant title/abstract): n = 2,579

↓

Eligibility
Full-text assessed
n = 312
Excluded on eligibility: n = 225
(no quant. metrics: 89; no in-situ sensor: 67;
non-English: 41; other: 28)

↓

Included
Studies in final synthesis
n = 87

Figure 1: PRISMA 2020 flow diagram illustrating study identification, screening, eligibility assessment, and final inclusion.

E. Data Extraction and Quality Assessment

Data were extracted independently by two reviewers using a standardized extraction form capturing: study location, crop type, sensor types, wireless protocol, cloud platform, ML algorithms, evaluation metrics, dataset size, and key findings. Disagreements were resolved by consensus. Study quality was assessed using a 15-item adapted checklist covering data transparency, model validation strategy, sensor calibration reporting, and geographical representativeness. Table 1 summarizes quality scores across included studies.

Table 1: Quality assessment score distribution across 87 included studies

Quality Level	Score Range	Studies (n)
High quality	12–15	24 (27.6%)
Moderate quality	8–11	41 (47.1%)
Low quality	<8	22 (25.3%)

III. LITERATURE REVIEW

A. IoT Sensor Technologies for Soil Nutrient Monitoring

1) Evolution and Definition of IoT in Agriculture

The Internet of Things (IoT) is defined as a network of physical devices containing embedded sensors, software, and communication modules that collect, send, and exchange data over the Internet autonomously [13, 14]. The first IoT applications in agriculture focused mainly on soil moisture and weather monitoring; however, continuous advances in sensor miniaturization, wireless protocols, cloud infrastructure, and edge computing have turned these systems into real-time decision-support platforms [15, 16]. This shift represents a move from calendar-based to condition-based farm management, enabling dynamic responses to spatially varied soil conditions that traditional broad-scale approaches cannot address [9].

2) Soil Sensor Types and Parameters

The reviewed studies rely on a common set of sensors to assess soil parameters. Table 2 summarizes the sensor types, monitored parameters, and frequency of deployment across the 87 included studies.

Table 2: Sensor types and deployment frequency across 87 reviewed studies

Sensor Type	Studies (n)	Parameter Monitored
Soil moisture (capacitive)	74	Volumetric water content
NPK sensor (ion-selective)	68	Nitrogen, phosphorus, potassium
Soil pH sensor	65	Acidity/alkalinity (pH)
Temperature sensor	81	Soil & ambient temperature
Humidity sensor	59	Relative humidity (%)
Rainfall sensor	43	Precipitation (mm)
Light intensity sensor	31	Solar radiation (lux)
Leaf wetness sensor	22	Surface moisture for disease risk

Soil moisture sensors are the most widely used component, present in 85% of studies, reflecting their vital importance in supporting irrigation decisions [6, 17]. NPK sensors are used in 78% of studies but show the largest variability in calibration protocols: 41% of studies report sensor drift exceeding 15% within eight weeks of field deployment in high-humidity tropical environments, a finding consistent with independent field evaluations in Tamil Nadu and Bangladesh [5, 18].

3) Wireless Communication Protocols

The literature shows that the most widely used wireless technologies in precision-agriculture IoT installations are Wi-Fi, LoRaWAN, and Narrowband-IoT (NB-IoT). Table 3 compares the technical features reported across the included studies.

Table 3: Comparison of wireless communication protocols in reviewed IoT systems.

Protocol	Range	Power	Throughput	Studies
Wi-Fi	<150 m	High	High	31
LoRaWAN	2–15 km	Low	Low	38
NB-IoT	10 km	Low	Med.	24
ZigBee	100 m	Low	Med.	9
GSM/4G	Cellular	Med.	High	19

LoRaWAN is the most popular protocol for large-scale outdoor deployments (44% of studies) due to its low power consumption, cost-effectiveness, and ability to maintain reliable communication over 2.6 km under field conditions [19, 20]. Twelve studies describe hybrid LoRaWAN/NB-IoT architectures, where sensor nodes transmit data over LoRaWAN to multi-protocol gateways that forward it via NB-IoT to cloud platforms, increasing scalability for geographically distributed farms.

4) Cloud Computing and Edge Architectures

Cloud systems form the main data aggregation, storage, and analytics backbone in 79% of the analyzed studies, with Amazon Web Services (AWS), Microsoft Azure, and the Blynk IoT platform most frequently mentioned [23, 24]. Cloud connectivity supports the training of computationally expensive ML models, long-term data archiving, and remote access to farmer-facing dashboards via mobile applications. In 23 of the studies, edge computing was used to overcome the latency and bandwidth limitations of cloud-only systems by offering local preprocessing and anomaly detection at the sensor-gateway level [24, 25]. Research on edge-cloud hybrid architectures indicates response latency reductions of 40–65% relative to pure cloud deployments - a key benefit for time-sensitive triggers such as irrigation and fertilization.

B. Machine Learning Models for Crop Yield Prediction

1) Overview of ML Approaches

Of the 87 articles reviewed, ten machine learning algorithms are sufficiently common to allow a comparative analysis. Table 4 presents their reported performance ranges across all crops and datasets.

Table 4: Performance of machine learning models for crop yield prediction across reviewed studies. R^2 = coefficient of determination; RMSE = root mean square error (kg/ha); MAE = mean absolute error (kg/ha). Ranges represent minimum–maximum across all included studies reporting each metric

Model	Type	R^2 Range	RMSE Range	MAE Range	Studies (n)
Random Forest Regression	Ensemble	0.81–0.97	142–489	98–312	71
XGBoost Regression	Boosting	0.79–0.96	155–512	110–340	58
Gradient Boosting	Boosting	0.76–0.94	178–540	121–365	49
AdaBoost Regression	Boosting	0.72–0.91	201–610	148–398	38
Decision Tree Regression	Tree	0.65–0.89	223–671	165–445	52
Support Vector Regression	Kernel	0.68–0.88	240–698	171–462	41
Ridge Regression	Regulariz.	0.61–0.86	267–742	188–491	35
Lasso Regression	Regulariz.	0.59–0.84	278–763	195–508	31
ElasticNet Regression	Regulariz.	0.57–0.83	289–781	203–519	27
K-Nearest Neighbours	Instance	0.53–0.81	312–812	221–541	34
LSTM Neural Network	Deep	0.82–0.96	138–497	95–318	29
Linear Regression	Linear	0.43–0.76	401–912	289–621	44

2) Random Forest Regression

Random Forest had the highest median R^2 (0.93) across all research analyzed, beating linear techniques by a large margin. The ensemble structure — aggregating predictions across several decision trees trained on bootstrapped subsets — has inherent robustness against overfitting on small agricultural datasets and efficiently handles the multicollinearity common among NPK, pH, moisture, and temperature variables [26, 55].

Sixteen publications specifically applied Random Forest SHAP (SHapley Additive exPlanations) value analysis, where soil moisture and nitrogen concentration were consistently identified as the two most important predictors of crop output across maize, rice, and wheat datasets [27, 28]. This result is consistent with existing agronomic theory: nitrogen gates chlorophyll assembly and carbon fixation, while soil moisture modulates nutrient uptake through the mass-flow pathway.

3) Gradient Boosting Variants (XGBoost, GBM, AdaBoost)

XGBoost had the second-highest median R^2 (0.89) and is computationally more efficient for large datasets than traditional Gradient Boosting [29, 30]. Its L1 and L2 regularization terms help reduce overfitting on datasets with fewer than 500 observations — a common limitation for field-deployed IoT devices running for less than one growing season. AdaBoost's sequential error-correction technique shows competitive performance on diverse soil datasets, though it is more sensitive to outliers [31, 32].

4) Deep Learning: LSTM Networks

Twenty-nine studies found that Long Short-Term Memory (LSTM) networks achieved competitive performance (R^2: 0.82–0.96) but remain limited to time-series applications, where the evolution of soil parameters over multiple time steps improves prediction accuracy [33, 34]. However, LSTM models require much larger training datasets (typically more than 5,000 time-step sequences) than tree-based ensemble approaches, restricting their use in studies with less than six months of sensor data. Overfitting was reported in 14 of the 29 LSTM trials where the training window was shorter than a full growing season.

5) Explainable AI Techniques

Explainability was addressed as a cross-cutting issue in 34 of the studies analyzed. LIME (Local Interpretable Model-agnostic Explanations) was used in 21 studies to explain individual forecasts, allowing farmers to verify that model recommendations are consistent with observable field conditions [27]. Thirteen studies combined satellite or drone imagery with in-situ sensor data and applied Gradient-weighted Class Activation Mapping (Grad-CAM) to visually indicate crop patches responsible for disease or stress forecasts [28]. Transparency in agricultural AI has practical importance: studies reporting XAI adoption show substantially higher farmer acceptance rates in user surveys (mean 67%) than studies without explainability features (mean 34%).

C. Soil Nutrient Dynamics and Agronomic Context

1) NPK Roles in Crop Physiology

Nitrogen, phosphorus, and potassium play distinct yet interdependent roles in crop growth. Nitrogen is central to chlorophyll synthesis, protein production, and vegetative growth; its deficiency produces characteristic interveinal chlorosis, beginning with older leaves [35, 36]. Phosphorus regulates root architectural development, ATP generation, and the hydraulic signaling pathways that control stomatal aperture under temperature stress [37, 38]. Potassium governs osmotic regulation of guard cells, and its deficiency suppresses turgor-driven stomatal opening, creating water stress even in fully irrigated soils [39].

According to Liebig's Law of the Minimum, crop growth is limited by whichever nutrient is in shortest supply relative to the crop's needs, regardless of how abundant other nutrients are [40]. This principle underscores why all three macronutrients must be monitored simultaneously and in real time - sequential or periodic laboratory analyses cannot capture the dynamic interactions that drive crop response within a single growth stage.

2) Soil Health and Microbiome Interactions

Soil health extends beyond NPK availability to include pH-dependent nutrient solubility, microbial community composition, organic matter turnover, and physical structure [41, 42]. Seven studies analyzed soil microbiome data using IoT sensors, showing that phosphorus availability estimates improved by 12–18% when mycorrhizal-activity markers were incorporated as model variables [43, 44]. These findings suggest that next-generation IoT soil-monitoring solutions will need to extend beyond electrochemical NPK detection to incorporate biological and spectroscopic characteristics.

D. Smart Agriculture and Precision Farming Frameworks

1) Precision Agriculture Definition and Components

Precision agriculture is the use of sensing, communication, computing, and data-analytics technologies to monitor and manage agricultural processes with high geographical and temporal precision [45, 46]. Its main operational goals are site-level crop management, reduction of wasted inputs, optimized resource-use efficiency, and minimized environmental externalities from fertilizer and pesticide use. The common architecture of IoT-based precision-agriculture systems, as identified across the reviewed literature, comprises four layers: (1) a perception layer of distributed soil and environmental sensors; (2) a connectivity layer of wireless nodes and gateways; (3) a processing layer of edge nodes and cloud platforms running ML inference; and (4) an application layer of farmer-facing dashboards and mobile alert systems [47, 48].

2) Automation and Actuator Integration

Thirty-one of the studies reviewed extend beyond monitoring to incorporate integrated actuator systems such as autonomous irrigation valves, variable-rate fertilizer dispensers, and drone-based spray systems controlled by ML model outputs. Studies incorporating actuators consistently show greater resource savings — mean water-consumption reductions of 31%, compared to 18% in monitoring-only systems — and mean nitrogen-application reductions of 28%, compared to 12% [49, 50]. These results suggest the value of IoT-ML integration is maximized when the feedback loop between prediction and intervention is automatic, rather than dependent on farmer action after receiving an alert.

IV. SYNTHESIS OF RESULTS AND DISCUSSION

A. Performance Synthesis

The synthesis of 87 studies in Table 4 reveals a clear performance hierarchy. Tree-based ensemble methods, particularly Random Forest and XGBoost, consistently outperform linear regression, regularized regression, and instance-based methods on IoT soil datasets. Because ensemble methods can capture complex, non-linear relationships between soil parameters and remain robust to sensor errors introduced by drift over time, they are considered superior for this application [26, 51].

Table 5 summarizes the R^2 performance range for the six most frequently reported models, drawn from the ranges reported in Table 4 across the 87 reviewed studies.

Table 5: R^2 performance range for the six most frequently reported ML models (minimum–maximum across all included studies reporting each metric; see Table 4 for full model list).

Model	R^2 Min	R^2 Max	Studies (n)
Random Forest Regression	0.81	0.97	71
XGBoost Regression	0.79	0.96	58
LSTM Neural Network	0.82	0.96	29
Decision Tree Regression	0.65	0.89	52
Support Vector Regression	0.68	0.88	41
Linear Regression	0.43	0.76	44

B. PRISMA Evidence Map

Table 5 presents a cross-tabulated evidence map of soil parameters monitored, ML models applied, and geographical distribution across the 87 reviewed studies.

Table 5: Evidence map: geographical distribution of reviewed studies by region and dominant ML approach.

Region	Studies	Dominant Model	Avg R^2
South Asia (India/BD)	31	Random Forest	0.91
East/SE Asia	19	XGBoost	0.89
Europe	12	Gradient Boost	0.87
North America	9	LSTM	0.90
Sub-Saharan Africa	7	Random Forest	0.84
Middle East	5	Decision Tree	0.79
Latin America	4	Random Forest	0.86

Sub-Saharan Africa is represented by only seven studies (8% of the corpus), despite holding approximately 60% of the world's uncultivated arable land and facing some of the most acute food security challenges. The average R^2 of 0.84

reported in African studies is also seven percentage points below the South Asian average, reflecting the difficulty of training ML models on limited, spatially sparse datasets in regions with fewer existing soil survey records.

C. Methodological Quality and Replication

A significant methodological concern across the corpus is the limited cross-domain validation of ML models. Only 14 of the 87 studies (16%) tested their trained models on independent datasets from different farms, crop types, or growing seasons. Of these 14, eleven reported R^2 degradation of 0.12–0.28 points when applied to out-of-distribution data — consistent with the broader transfer-learning literature [52, 53]. Models trained on loamy Mollisols consistently underperformed on cracking Vertisols and saline coastal soils, a finding with direct practical implications: deploying pretrained ML models without local recalibration is likely to produce unreliable recommendations for farmers in contrasting agroecological zones.

D. Sensor Calibration and Field Reliability Gap

A persistent discrepancy between laboratory sensor accuracy and field reliability emerged as the dominant theme across the reviewed studies. Ion-selective NPK sensors, which achieve ±2% accuracy under controlled conditions, exhibit drift exceeding 15% within eight weeks in high-humidity tropical deployments, owing to membrane fouling, electrode corrosion, and temperature-induced signal drift [18, 54]. Only 23% of studies reported systematic calibration protocols or drift-correction procedures, leaving the majority of reported R^2 values potentially inflated by training on miscalibrated sensor data.

V. GAPS AND FUTURE DIRECTIONS

A. Gaps Identified

Six serious gaps were observed with the PRISMA methodology:

Poor Representation of Sub-Saharan Africa: very few studies were carried out in Sub-Saharan Africa (7 of 87). Targeted IoT/ML studies are needed given the region's soil diversity, limited extension services, and acute food security challenges.

No Accepted Standard Calibration Protocols: there is no globally accepted standard for calibrating IoT sensors across the 87 reviewed studies, making cross-study comparison difficult. A universally accepted standard, similar to IUPAC or ISO protocols for laboratory soil analysis, is needed for IoT sensors.

Scalability Beyond Research Plot Scale: the majority of studies (79%) were conducted on plots smaller than two hectares. The sensor density, wireless network management, and energy requirements for larger areas (e.g. 100 hectares) remain unaddressed.

Poor Soil Biology Parameter Incorporation: very few studies (7 of 87) integrated soil biology parameters. Factors such as microbial biomass, mycorrhizal colonization, and enzyme activity play an important role in phosphorus prediction but were rarely included.

System Evaluation Over an Extended Period: most studies (71%) relied on data from a short growing season (less than six months).

Farmer Adoption and User Interface Research: very few studies (12 of 87) reported farmer feedback, often assuming a level of agronomic familiarity and digital literacy that may not reflect real-world users.

B. Future Research Directives

Based on the identified gaps, the following areas are recommended for further study:

- Development of a unified framework that supports joint machine learning model training across different farms [27].
- Design and validation of low-cost (under $50 per node), self-calibrating NPK sensor systems engineered for the high-humidity tropical conditions common in Sub-Saharan Africa and South Asia.
- Creation of a globally accessible, harmonized benchmark dataset of IoT soil-sensor readings with laboratory-verified reference values, to enable rigorous cross-study ML model comparisons.
- Closer investigation of ML studies that incorporate microbiome-activity data to improve NPK prediction accuracy, alongside greater involvement of smallholder farmers in user-interface development so the resulting systems are genuinely usable in the field.

VI. CONCLUSION

This review synthesized 87 peer-reviewed studies published between 2017 and 2026 and establishes that IoT-ML integration represents a practicable and increasingly mature approach to precision agriculture. However, the methodological literature is affected by notable weaknesses: only 16% of studies conduct cross-domain model validation, 77% omit systematic sensor-calibration reporting, and Sub-Saharan Africa — where smart farming is arguably most urgently needed — accounts for only 8% of the reviewed evidence base. Explainability techniques such as LIME and Grad-CAM demonstrably improve farmer adoption rates by nearly twofold, yet remain largely absent from deployed systems. Translating laboratory performance into farmer-accessible precision agriculture will require standardized calibration protocols, multi-season longitudinal studies, federated-learning architectures for cross-farm generalization, and participatory interface design. Addressing these gaps is essential to realizing the full potential of IoT-ML integration for global food security.

REFERENCES

[1] Z.A. Cheema and A. Khan, "Soil and cropmanage-ment for sustainable intensification," in Proc. Int. Conf. SustainableAgriculture, 2019.

[2] H. Shahab, M. Naeem, M. Iqbal, M. Aqeel, and S.S. Ullah, "IoT-driven smart agricultural technology for real-time soil and crop optimization,"Smart Agricul-tural Technology, vol. 10, p. 100847, 2025.

[3] Y. Sushma, C. J. Lakshmi, K. Rajesh, V. Hemanth, and V. Sowmyarao, "IoT based soil nutrient monitoring and analysis system," in Proc. IEEE ICICNIS, pp. 348--353,2024.

[4] R. Hartono, N. M. Yoeseph, F. A. Purnomo, M.A. Safi'ie, and S. A. T. Bawono, "Portable IoT-based soil nutrients monitoring for precision and efficient smart farming," Bulletin of Electrical Engineering and Infor-matics, vol. 13, no. 5, pp. 3326--3333, 2024.

[5] M. D. Hossain, M. A. Kashem, and S. Mustary, "IoT based smart soil fertilizer monitoring and ML based crop recommendation system," in Proc. IEEEECCE, pp. 1--6, 2023.

[6] S. R. Laha, B. K. Pattanayak, S. Pattnaik, D. Mishra, D. S. K. Nayak, and B. B. Dash, "An IoT-based soil moisture management system for precision agriculture: Real-time monitoring and automated irrigationcontrol,"inProc. IEEE ICOSEC, pp. 451--455, 2023.

[7] R. Reshma, V. Sathiyavathi, T. Sindhu, K. Selvakumar, and L. Sairamesh, "IoT based classification techniques for soil content analysis and crop yield prediction," in Proc. IEEE I-SMAC, pp. 156--160, 2020.

[8] S. Savita and V. Vimal, "Integrating IoT-based environ-mental monitoring and data analytics for crop-specific smart agriculture management: A multivariate analysis," inProc. IEEE ICTACS, pp. 368--373, 2023.

[9] B. S. Anusha, D. Prabha, A. Ghosh Bag, V.Thingu-jam, N. P. Darshan, S. Dutta, and S. Gorain, "From point sensing to intelligent systems: a comprehensive review on advanced sensor technologies for soil health monitoring,"Discover Sensors, vol. 1, no. 1, 2025.

[10] S. Kumar, K. Kaur, A. Kaur, and C. Sharma, "Revolu-tionizing crop yield prediction with machine learning," inProc. IEEE CyberCom, pp. 394--398, 2024.

[11] A. Khaliq et al., "AI-driven smart agriculture: An integrated approach for soil analysis, irrigation, and crop-fertilizer recommendations," IEEE Access, vol.13, pp. 141124--141138, 2025.

[12] M.J. Pageet al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," BMJ, vol. 372, p. n71, 2021.

[13] M. Dubey and S. Yadav, "Evolution of IoT in precision agriculture,"Smart Agricultural Technology, 2024.

[14] R.Oppong, "Integration of IoT-based sprinklers,em-bedded systems, data, and cloud computing for smart irrigation management,"World Journal of Advanced Research and Reviews, vol. 25, no. 3, pp. 126--151, 2025.

[15] A. Alijoyo et al., "Smart farming: IoT integration with AI for real-time decision making," Computers andElec-tronics in Agriculture, 2025.

[16] S. Mansoor et al., "Integration of smart sensors and IoT in precision agriculture: trends, challenges and future prospectives," Frontiers in Plant Science, vol.16, p. 1587869, 2025.

[17] J. Divya et al., "Soil moisture sensors in IoT-based precision irrigation," IEEE Sensors Journal, 2022.

[18] P. Musa, H. Sugeru, and E. P. Wibowo, "Wireless sensor networks for precision agriculture: A review ofNPKsensorimplementations,"Preprints.org, 2023.

[19] N. Noprianto et al., "Empowering IoT: leveraging data sensor communication with LoRaWAN in diverse envi-ronments," Acta Polytechnica, vol. 64, no. 6, pp. 539-- 549, 2025.

[20] W. A. Jabbar et al., "Optimising urban lighting effi-ciency with IoT and LoRaWAN integration," Discover Internet of Things, vol. 5, no. 1, 2025.

[21] S. Rajeswari, K. Suthendran, and K. Rajakumar, "A smart agricultural model by integrating IoT, mobile and cloud-based big data analytics," in Proc. IEEEI2C2, pp. 1--5, 2017.

[22] S.P. Sudha and J. B. S. Loret, "A review on machinelearning-based precision agriculture techniques for crop farming monitoring with IoT," Discover Environment, vol. 4, no. 1, 2026.

[23] H.Gonget al., "Edge computing in IoT-basedsmart agricultural systems,"Computers and Electronics in Agriculture, 2025.

[24] S. Han, H. Kim, and Y.-S. Lee, "Double random forest," Machine Learning, vol. 109, no. 8, pp. 1569--1586, 2020.

[25] H. A. Tahir, W. Alayed, and W. U. Hassan, "A feder-ated explainable AI framework for smart agriculture: Enhancing transparency, efficiency, and sustainability," IEEE Access, vol. 13, pp. 97567--97584, 2025.

[26] H.Najjaret al., "Explainability of subfield levelcrop yield prediction using remote sensing," IEEE Journal of Selected Topics in Applied Earth Observations and RemoteSensing, vol. 18, pp. 4141--4161, 2025.

[27] T. Inoue et al., "XGBoost, a machine learning method, predicts neurological recovery in patients with cervical spinal cord injury," Neurotrauma Reports, vol. 1, no. 1, pp. 8--16, 2020.

[28] B. Pan, "Application of XGBoost algorithm in hourly PM2.5 concentration prediction," IOP Conference Se-ries: Earth and Environmental Science, vol. 113, no. 1, p. 012127, 2018.

[29] S. Sun et al., "Lead-acid battery SOC predictionus-ing improved AdaBoost algorithm," Energies, vol. 15, no. 16, p. 5842, 2022.

[30] M. Mohammadagha, "Hyperparameter optimization strategies for tree-based machine learning models:A comparative study of AdaBoost, decision trees, andrandomforest,"OSF Preprints, 2025.

[31] Y. Hua et al., "Deep learning with long short-term mem-ory for time series prediction," IEEE Communications Magazine, vol. 57, no. 6, pp. 114--119, 2019.

[32] N. I. A. Kader, U. K. Yusof, M. N. A. Khalid, and N. R. N. Husain, "A review of long short-termmemoryapproach for time series analysis and forecasting," inSpringer LNCS, pp. 12--21, 2022.

[33] R.Jeevanrajet al., "The essential role of macronutri-ents and micronutrients in improving crop resilience to biotic stress," Russian Journal of Plant Physiology, vol. 72, no. 4, 2025.

[34] J.Shrestha, M. Kandel, S. Subedi, and K. K. Shah, "Role of nutrients in rice (Oryza sativa L.): A review," Agrica, vol. 9, no. 1, p. 53, 2020.

[35] K.Karmakar, S. S. Patil, and B. Kundu, "From soil to oil: The crucial roles of potassium and sulphur in enhancing oilseed crop quality," Journal of Advances in Biology and Biotechnology, vol. 27, no. 8, pp. 335--346, 2024.

[36] E. Mwende Muindi, "Understanding soil phosphorus," International Journal of Plant and Soil Science, pp. 1--18,2019.

[37] S.S. Sindhu, P. Parmar, and M. Phour, "Nutrient cy-cling: Potassium solubilization by microorganisms and improvement of crop growth," in Microorganisms in Sustainable Agriculture, Springer, pp. 175--198, 2013.

[38] M.Raminoarisonet al., "Multiple-nutrientlimitation of upland rainfed rice in ferralsols,"Journal of Plant Nutrition, vol. 43, no. 2, pp. 270--284, 2019.

[39] I. Imran and I. Ortas, "Mechanism in soil healthim-provement with soil microbial actions,"Communica-tions in Soil Science and Plant Analysis, vol. 56, no. 13, pp. 2066--2087, 2025.

[40] B.Mamathaet al., "Enhancing soil health andfer-tility management for sustainable agriculture: A re-view," Asian Journal of Soil Science and Plant Nutri-tion, vol. 10, no. 3, pp. 182--190, 2024.

[41] A.Mukherjeeet al., "Re-vitalizing of endophyticmi-crobes for soil health management and plant protection," 3 Biotech, vol. 11, no. 9, p. 399, 2021.

[42] S. Sharma et al., "Soil microbial resources: Unlocking sustainable strategies for crop productivity and soil health," Current Research in Microbial Sciences, vol. 9, no.5, p. 100468, 2025.

[43] E. M. B. M. Karunathilake et al., "The path to smart farming: Innovations and opportunities in precision agriculture," Agriculture, vol. 13, no. 8, p. 1593, 2023.

[44] S. F. A. Razak et al., "Agriculture 5.0 and explainable AI for smart agriculture: A scoping review," Emerging ScienceJournal, vol. 8, no. 2, pp. 744--760, 2024.

[45] B. Kuli et al., "Smart farming revolution: AI, IoT, and robotics in precision agriculture and

soil conservation," International Journal of Scientific Research in Science, Engineering and Technology, vol. 12, no. 2, pp. 688-- 706, 2025.

[46] P.Sahaet al., "Precision agriculture using Internetof Things and wireless sensor networks," inProc. IEEE ICDT, pp. 519--522, 2023.

[47] Y.Xing and X. Wang, "Precise application of water and fertilizer to crops: challenges and opportunities,"Frontiers in Plant Science, vol. 15, p. 1444560, 2024.

[48] G. R. Reddy, U. Kudtala, and V. S. Rao, "An IoT-driven machine learning framework for predictive crop health monitoring in precision agriculture," in Proc. IEEE ICAAIC, pp. 1806--1812, 2025.

[49] J. Karthikeyan and D. A. Murugan, "A study on en-hancing crop yield prediction with accuracy through machine and deep learning models," South Eastern Eu-ropean Journal of Public Health, pp. 1217--1227, 2024.

[50] Y. Kang et al., "Comparative assessment ofenviron-mental variables and machine learning algorithms for maize yield prediction in the US Midwest,"Environ-mental Research Letters, vol. 15, no. 6, p. 064005, 2020.

[51] J.Ansarifar, L. Wang, and S. V. Archontoulis, "An interaction regression model for predicting crop yield," Scientific Reports, vol. 11, no. 1, p. 17754, 2021.

[52] A. Xie et al., "From lab to field: Advancements and ap-plications of on-the-go soil sensors for real-time moni-toring," Eurasian Soil Science, vol. 57, no. 10, pp. 1730--1745,2024.

[53] A.B. Shaik and S. Srinivasan, "A brief survey on random forest ensembles in classification model," inSpringer LNCS, pp. 253--260, 2018.

[54] J. C. Odirichukwu, C. Ndigwe, O. A. and Njoku, "Inter-net of Things (IoT), Internet of Robotic Things (IoRT), IoT Security (IoTS) and Machine Learning Algorithms: A Review Perspective " in University of Ibadan Journal of Science and Logics in ICT Research, vol. 9, no. 1, 2023.