Pertanika J. Trop. Agric. Sci. 49 (S3): 1 - 30 (2026)

PERTANIKA JOURNALS

TROPICAL AGRICULTURAL SCIENCE

Journal homepage: http://www.pertanika.upm.edu.my/

Review Article

Review of the IoT-Enabled Sensor System for Nutrient Management in Crop Production: Sensor Technologies and Future Trends

Md. Asib Biswas[1,2], Md. Kamal Uddin[1]*, Susilawati Kasim[1], Mohd Firdaus Mohd Anuar[1], S.M.M. Shahriar Tonmoy[1,2], Ahmad Suhaizi Mat Su[3], Fakrulradzi Idris[4], and A K M Zakir Hossain[5]

[1]*Department of Land Management, Faculty of Agriculture, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia*
[2]*Fram Management Division, Bangladesh Rice Research Institute, 1701 Gazipur, Bangladesh*
[3]*Department of Agriculture Technology, Faculty of Agriculture, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia*
[4]*Centre for Telecommunication Research and Innovation, Fakulti Teknologi dan Kejuruteraan Elektronik dan Komputer, Universiti Teknikal Malaysia Melaka, Durian Tunggal, 76100 Melaka, Malaysia*
[5]*Department of Crop Botany, Faculty of Agriculture, Bangladesh Agricultural University, 2202 Mymensingh, Bangladesh*

ABSTRACT

Optimising nutrient management is critical for sustainable and cost-effective crop production. This review investigates how Internet of Things (IoT) sensor technologies help farmers monitor nitrogen (N), phosphorus (P), and potassium (K) to support precision farming. Although IoT-based nutrient sensing devices have developed rapidly, most existing reviews focus on a single sensing technology or general precision agriculture applications. Few integrate sensor technologies, calibration approaches, field validation, and future trends in real-time NPK management. This review addresses that gap by examining IoT-enabled NPK sensor systems for precision fertiliser management. Current research explores NPK sensors using electrochemical and optical technologies, alongside pH, moisture, and temperature sensors, microcontrollers, communication modules, and cloud-based platforms. When properly calibrated, IoT-based NPK systems can provide reliable real-time nutrient monitoring and improve nutrient use efficiency (NUE) through sustainable practices, potentially increasing crop yields while reducing environmental impact.

ARTICLE INFO

Article history:
Received: 03 July 2026
Accepted: 27 August 2026
Published: 20 November 2026

DOI: https://doi.org/10.47836/pjtas.49.S3.01

E-mail addresses:
asibbau71@gmail.com (Md. Asib Biswas)
mkuddin@upm.edu.my (Md. Kamal Uddin)
susilawati@upm.edu.my (Susilawati Kasim)
m.firdaus@upm.edu.my (Mohd Firdaus Mohd Anuar)
smstonmoy47@gmail.com (S.M.M. Shahriar Tonmoy)
asuhaizi@upm.edu.my (Ahmad Suhaizi Mat Su)
fakrulradzi@utem.edu.my (Fakrulradzi Idris)
zakir@bau.edu.bd (A K M Zakir Hossain)
* Corresponding author

© Universiti Putra Malaysia Press

The review evaluates calibration methods, their advantages and disadvantages, and their effects on field testing and sensor performance over time. It also considers agricultural applications across major crop types and identifies challenges involving farm operations, reliable data, rural internet access, and electronic waste. This assessment highlights the potential of IoT-integrated NPK sensing for precision fertiliser management and real-time nutrient monitoring, while emphasising the need for better calibration, reliability, and field validation. Integrating advanced sensing technologies with precision farming tools and artificial intelligence could support more efficient nutrient management and sustainable crop production.

Keywords: Internet of Things (IoT), NPK sensor, precision agriculture, sensor calibration, nutrient management, real-time nutrient monitoring

INTRODUCTION

Researchers need to develop efficient, sustainable methods for growing crops to solve the dual problem of rising population numbers and environmental limitations that block global food security. The world needs to enhance its agricultural productivity because the global population will reach 9.7 billion by 2050 (Food and Agriculture Organization [FAO], 2017). The main challenge which researchers face in this field involves handling three vital macronutrients, which include nitrogen, phosphorus, and potassium, because these elements enable plants to grow, develop, and produce their maximum yields (Sardans & Peñuelas, 2021). Fertilisation methods used in traditional farming systems lead to problems because they result in excessive nutrient application, creating unsustainable soil conditions, environmental harm, and increased operational expenses (Chojnacka & Moustakas, 2024).

Farmers who apply fertiliser s without proper timing or application methods harm soil health and create nutrient runoff problems, which decrease their farming profits (Pandian et al., 2024). To solve these problems, researchers require the urgent development of nutrient management solutions that use site-specific data to optimise input methods based on actual soil and crop conditions (Vullaganti et al., 2025). Precision fertilisation, supported by advances in sensing technologies, enables farmers to boost nutrient use efficiency, reduce environmental hazards, and achieve better financial outcomes (Getahun et al., 2024).

Smart farming, which uses IoT, remote sensing, AI and big data analytics, has brought about fundamental changes to traditional agricultural methods. IoT-enabled sensor systems provide continuous monitoring of essential parameters, including NPK levels and soil pH, temperature, and moisture (Anwar et al., 2023; Hashim et al., 2024). The system uses soil sensor networks that connect to low-power microcontrollers and wireless communication protocols, such as LoRaWAN, to provide operators with real-time data via cloud-based dashboards. Farmers can use the integrated system to obtain fertilisation

recommendations that adapt to changing field conditions (Idris et al., 2024). IoT-based fertigation systems reduce human intervention and minimise human error compared to conventional manual fertigation (Idris et al., 2024). IoT-based farming helps reduce time and energy for farmers while minimising resource waste, potentially increasing crop productivity . The potential application of IoT in smart irrigation systems will help conserve water, reduce water usage by 70%, further improve crop production, and create a huge opportunity for water resources conservation and food security (Morchid et al., 2026). Most current IoT-based nutrient management systems are still at the prototype or experimental stage. They often lack proper agricultural experimental design standards and validation through plant-based testing. The majority of existing research focuses only on nutrient monitoring, not on complete nutrient management or optimisation of fertiliser practices (Fauziah et al., 2024). The recent improvements in IoT-based fertigation technology, which is a combination of NPK sensors and microcontrollers, have demonstrated that their integration has triggered a notable increase in the efficiency of nutrient delivery, bringing about the consumption of fertiliser being reduced by as much as 30%, leading to the same or higher yield (Inayah et al., 2026).

Although there has been some progress, current research and review articles mainly cover basic sensor technologies or nutrient-monitoring applications and do not address the integration of sensor technologies, calibration techniques, Internet of Things (IoT) architecture, field validation, communication technologies, and practical fertiliser management strategies within a comprehensive system. Furthermore, many IoT-based nutrient management systems are still in the prototype/experimental stage and have not been standardised in agricultural experimental designs, widely tested in the field, or evaluated in depth using plants (Fauziah et al., 2024). Other obstacles, such as sensor calibration, data reliability, internet connectivity in remote areas, energy use, and e-waste management, further slow the widespread use of these technologies. This review overcomes these drawbacks by thoroughly analysing the IoT-based NPK sensor systems for precision nutrient management. The review critically discusses existing NPK sensing techniques, calibration methods, IoT architectures, communication protocols, cloud-based platforms, and their use in various crop cultivation systems. In addition, it explores the issues of implementation in the field and summarises the latest advances in AI nutrient management and opportunities for future development with the combination of AI, blockchain technology and autonomous agricultural systems.

The novelty of this review is the interdisciplinary perspective which combines elements of agronomy, sensor engineering, as well as IoT technologies and data science to enable a system-level evaluation of IoT-enabled nutrient management. This review not only compares sensor performance and calibration procedures but also brings together the application of sensors in precision agriculture, the practical problems associated with

their use, and future technological developments, unlike previous reviews that mainly focused on individual sensing technologies or on precision agriculture in general. Hence, the purpose of this review is to provide a comprehensive overview of IoT-based nutrient sensor systems and their contributions to increasing and optimising nutrient utilisation efficiency, sustainable crop production, and global food security.

METHODOLOGY

This review is supported by a structured approach to select the literature to assess the use of IoT-based sensor systems in nutrient management for crop production. Scientific literature relevant to the research was selected using search engines such as Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink, Wiley Online Library, and Google Scholar (the primary search engine), with a focus on publications primarily from 2017 to 2026. The keywords for identifying the relevant publications were sensor-enabled IoT, NPK sensors, soil nutrient sensing, precision agriculture, sensor calibration, smart farming, nutrient management or combinations of multiple keywords.

The selected literature was analysed and synthesised by theme, including sensor technologies, sensing principles, calibration/validation, IoT architecture, communication technologies, agricultural applications, challenges, future trends, and others. The identified technologies were assessed against one another to identify their strengths, shortcomings, and research gaps, and to highlight opportunities to enhance nutrient management for sustainable crop production via IoT.

COMPONENTS OF IOT-BASED NUTRIENT MONITORING SYSTEMS WITH FUNCTIONS

IoT systems with integrated sensors, microcontrollers and communication modules and cloud-based dashboards enable agriculture to practice real-time site-specific nutrient management.

Nutrient Sensors

Nutrient sensors are an important part of soil analysis and IoT technologies, in particular, those that utilise ion-selective electrodes (ISE) and either optical- or electrochemical-based methods (Figure 1). These sensors analyse soil and report in real time, at an on-site, granular level, on the critical nutrient ions: nitrate (NO_3^-), phosphate (PO_4^{3-}) and potassium (K^+).

Probes constructed from advanced stainless steel, such as those manufactured by Renke Electronics (2024), offer versatility in soil conditions. These sensors and methods have been shown to be suitable for laboratory comparisons, with a low error rate of 8.47% (Musa et

al., 2023). However, the soil conditions consistent with the use of these probes, such as moisture, pH and temperature, should be taken into account to improve the calibration of these sensors (NiuBoL, 2024).

The promising performance of digital technologies and smart fertigation systems (sensors, GPS, GIS, automation, etc.) has yet to be validated for real-world, long-term use for sustainability. Therefore, while the overgeneralised claims pertaining to the soil sensors may indicate reliability, this must be supported with soil-specific calibration for the soil at the impacted sensors.

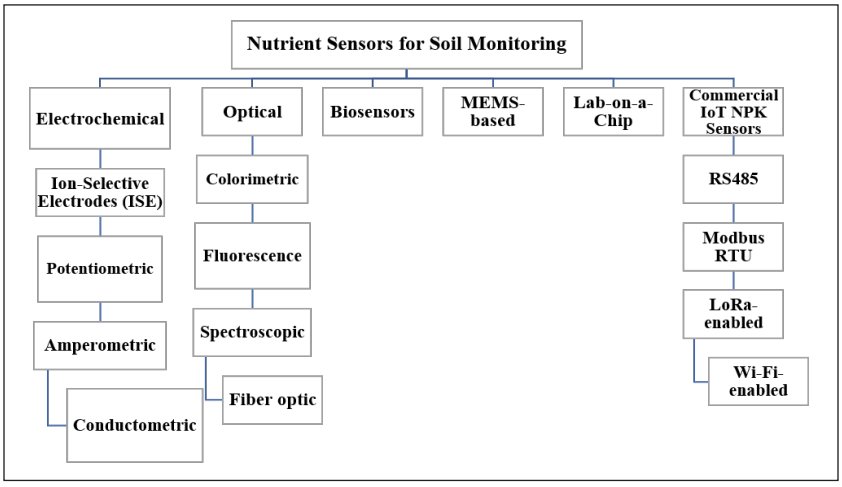


Figure 1. Different types of nutrient sensors used for soil nutrient monitoring

Microcontrollers and Embedded Systems

Microcontrollers such as ESP32, Arduino Uno, and Raspberry Pi (Table 1) function as devices which process data and transmit information (Figure 2). The ESP32 device enables wireless connections with cloud services because it consumes minimal power and includes Wi-Fi and Bluetooth capabilities, which maintain stable analogue-to-digital conversion results (Sudarmaji et al., 2024). The Arduino boards serve as common tools for sensor calibration and prototyping needs, but users must obtain additional modules to achieve connectivity and storage capabilities. The Raspberry Pi system provides advanced computational capabilities that support complex applications involving image-based nutrient-deficiency detection and artificial intelligence analysis (Billa et al., 2023). These controllers establish essential connections between sensor networks and cloud dashboards that operate in real time, enabling decision-making for digital farming operations (Figure 3 and Table 1).

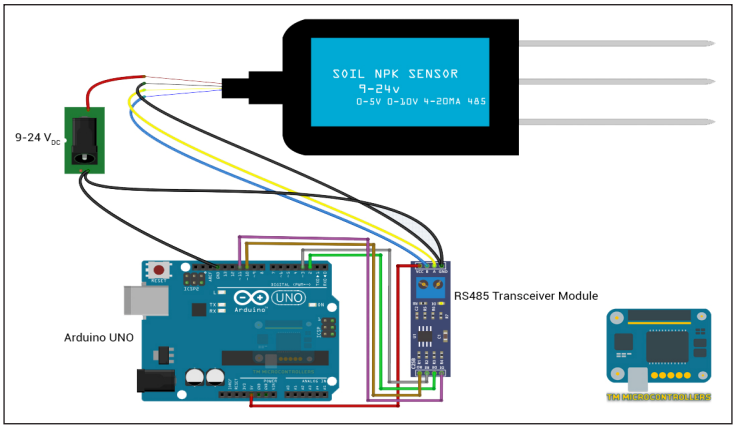


Figure 2. An NPK sensor with Arduino (Teach Me Micro, 2023)

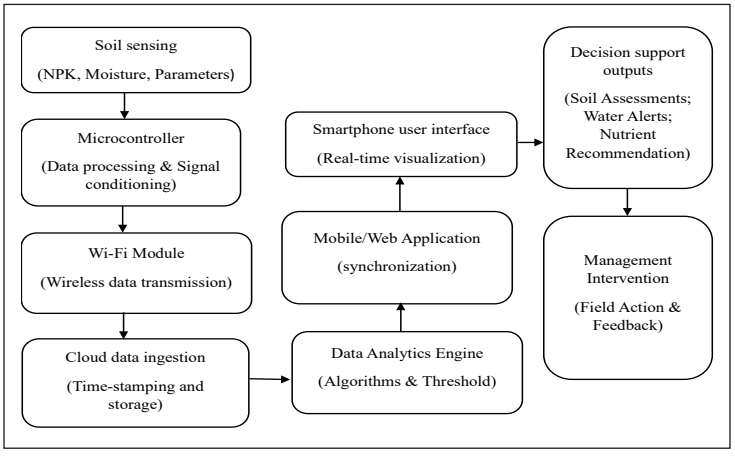


Figure 3. Architecture of IoT-based plant nutrient control system (Anjaneyulu et al., 2024)

Table 1
Information on some controllers utilised by researchers in IoT-based agricultural management

Controllers Name	Function	Authors
NodeMCU ESP8266	Internet access to transmit to ThingSpeak; data is saved in the micro-SD memory and processed.	Karinia et al., 2021; Nofriandi et al., 2023
Thingspeak	Functioned as an IoT cloud platform for receiving, storing, and remotely visualising real-time sensor data on a smartphone	Karinia et al., 2021; Nofriandi et al., 2023;
Arduino-based IoT device	Collects sensor data, processes it, and sends it to the cloud for real-time remote monitoring and control.	Rivas-Sánchez et al., 2019
Raspberry Pi	Used for complex farm IoT systems, enabling fast data processing, device integration, and live monitoring, ideal for large-scale agriculture.	Billa et al., 2023

Table 1 (*continued*)

Controllers Name	Function	Authors
ESP32 microcontroller	A low-cost, low-power device with built-in Wi-Fi and Bluetooth, commonly used in IoT systems to collect data from sensors, process it locally, and transmit it wirelessly to cloud platforms (like ThingSpeak) or mobile devices for real-time monitoring and control.	Idris et al., 2024
LoRaWAN	Facilitates long-distance, low-power wireless communication between IoT devices and gateways, ideal for remote and energy-efficient data transmission.	Arshad et al., 2022

Communications Technologies

Various technologies can be leveraged to achieve wireless data transmission: Wi-Fi in the short range (Table 3), LoRaWAN, Zigbee, and NB-IoT in the long range with low power consumption, etc., of which LoRaWAN in particular is very popular in rural areas of agriculture because it is highly scalable, has a long range (>10 km), and has low power consumption (Augustin et al., 2016). This technology allows several sensors to send data to a central server and is known to perform well in low-signal environments. Studies analysing these technologies in a comparative fashion often refer to their bandwidth, power consumption, and cost as a trade-off of the networks (Kochhar et al., 2019) (Table 2).

Table 2
Performance metrics of WSN (Wireless Sensor Network) communication technologies

Communication Module with Range	Frequency with Data rate	Nodes	Cost & Power	Communication System
Wi-Fi (20-100 m)	2.4 GHz 2-54 Gbps	32 nodes per network	High & High	Access point to the device
Bluetooth (1-100 m)	2.4-2.485 GHz 1-3 Mbps	8 active nodes per piconet	Low & Moderate	Master slave & peer-to-peer
Zigbee (10-20 m)	2.4 GHz 20-250 Kbps	65,000 nodes per network	Low & Low	Peer-to-peer
GPRS (In range of mobile network area)	900-1800 MHz 56-114 Kbps	1000 nodes per network	High & High	Base station to device
LoRa (>10 km)	169 MHz, 868 MHz, 433 MHz 0.3-50 Kbps	10,000 nodes per gateway	Moderate & Low	Peer-to-peer
XStream (5-16 km)	2.4 GHz 10-20 Kbps	7 channels, 65000/channels	Low & Low	Peer-to-peer

Source: Jawad et al. (2017)

Cloud Platforms and Dashboards

Sensors and their associated data can be managed, visualised, and stored on centralised platforms, including ThingsBoard, Thingspeak, Firebase, and AWS IoT. These dashboards provide actionable insights via real-time graphs, alerts, and predictive analytics by processing sensor data (Okhovat & Bauer, 2021). With the help of cloud-based thresholds, farmers and agronomists can optimise the scheduling and amount of fertiliser applications, thereby improving fertiliser NUE and reducing environmental impact (Bhatt et al., 2024). More sophisticated dashboards integrate AI algorithms and historical data processing, enabling the creation of adaptive Decision Support Systems (DSS) that respond to changes in the field.

Sensor Calibration and Nutrient Detection Activities

In the context of continuous nutrient tracking and precision nutrient management for IoT-based NPK sensors, calibration is critical to ensuring their accuracy, reliability, and stability over time. Environmental changes and electronic drift could cause sensor performance to decline over time, which would also affect the accuracy of the measurements they can make (Musanase et al., 2023; NiuBoL, 2025). Traditionally, calibration starts by developing a baseline configuration to stabilise sensor outputs and reduce background noise. The sensor is then put into soil samples or standard nutrient solutions with known concentrations, and an electrical response (voltage, EC, current, or optical absorbance) is measured. The calibration curve is then formed by applying the appropriate regression equation to the sensor response to convert raw sensor data into quantitative nutrient measurements (Ma et al., 2020).

The overall calibration process is common to most NPK sensing systems, but the exact calibration process will vary depending on the sensing technology used. Generally, calibration is the process of comparing sensor measurements with a laboratory analysis or a certified standard solution. Sensor probes should be cleaned before calibration, and electrochemical sensors should be stabilised in standard solutions before use. Base data are then collected under controlled conditions, and systematic differences between the sensor reading and the reference data are eliminated by means of offset corrections or regression analysis-based calibration equations. This is a standardised approach to reduce systematic error and enhance measurement consistency prior to field deployment (Musanase et al., 2023; NiuBoL, 2025).

Calibration Approaches Based on Sensing Technology

The following section summarises the calibration approaches available for the sensing technology. The requirements for calibration vary widely and depend on the measurement

principles of the different sensing technologies. Ion-selective electrode (ISE) sensors measure the activity of nutrient ions directly using the Nernst equation and typically require two-point calibration with standard solutions of known ion concentrations to determine the electrode slope and intercept (Li et al., 2019). To reduce the variation between electrodes and ensure the uniformity of the measurements, advanced ISE systems use baseline correction and two-point normalisation **(**Kim et al., 2013). ISE sensors offer moderate analytical precision and direct measurement of nutrients, but the sensor membranes age, temperatures fluctuate, and ionic interferences require periodic recalibration.

In contrast, some commercially available low-cost RS485 soil nutrient sensors (NPK) measure the electrical conductivity of the soil (EC) indirectly rather than the levels of N, P, and K ions directly (Musanase et al., 2023). In the calibration phase, the EC values obtained from the sensors are first correlated with the EC concentration in the lab, and empirical regression models are then developed to obtain the NPK concentration. This method significantly lowers sensor price and is suitable for field deployment in a short time; however, prediction accuracy is highly dependent on the soil textures, moisture levels, fertiliser compositions, and the calibration data set. Thus, most of the time, EC-based sensors need to be calibrated at the point of use in practical applications.

Optical and colourimetric sensors use a different calibration approach, based on the Beer - Lambert law: changes in light absorbance are used to determine nutrient concentration. Calibration is performed by selecting the wavelengths at which each nutrient exhibits the highest absorbance and by creating calibration curves using nutrient solutions. The absorbance values are then used to fit linear regression models to convert them to nutrient concentrations (Kumbhare & Kumbhar, 2023). Optical sensors typically offer greater analytical sensitivity in the laboratory but generally require additional sample manipulation and are less well suited for continuous in situ monitoring of nutrients.

Environmental factors and soil properties such as moisture content, temperature, pH, soil texture, salinity, organic matter, and ionic interference significantly affect sensor accuracy. These should therefore be taken into account when calibrating to help to ensure more reliable measurements in the field. Of these, soil moisture has one of the most important effects, as it directly affects ionic mobility and electrical conductivity. Calibration is recommended under standard soil moisture conditions in several studies to enhance repeatability and minimise variation in soil moisture measurements (Estrada et al., 2025; Fathima et al., 2026). Similarly, calibration models should be developed independently for each soil texture, as the contents of clay, organic matter, and cation exchange capacity affect the sensor's response. The calibrated models for sandy soils might then not be directly applicable to clay or loam soils without large prediction errors (Fathima et al., 2026). The incorporation of environmental sensors and compensation algorithms to minimise the influence of environmental conditions is also proposed (Postolache et al., 2022).

Furthermore, sensors should be recalibrated every 6-12 months due to sensor drift, membrane degradation, and exposure to environmental factors for extended periods of time (NiuBoL, 2025). Depending on the characteristics of the sensor's response, the relationship between the sensor's output and the nutrient concentration can be modelled using an appropriate regression model. If the sensor output is approximately proportional to the nutrient concentration, a linear regression can model the relationship between them (Jaja et al., 2026).

A linear calibration model is often used when the sensor response is proportional to the nutrient concentration, as in Equation 1:

$$Y = AX + B \quad [1]$$

where X is the raw sensor reading, Y is the nutrient concentration of the solution, A is the calibration slope, and B is the offset. If the sensor response is nonlinear, a second-order polynomial regression model can be used to improve the calibration relationship. A general nonlinear calibration relationship is given as in Equation 2:

$$C = a + bV + cV^2 \quad [2]$$

where C is the nutrient concentration measured in mg kg^{-1}, V is the sensor voltage or absorbance response, and a, b and c are regression coefficients derived from curve fitting.

The simplicity and high coefficient of determination under controlled laboratory conditions make linear regression a commonly used method (Fathima et al., 2026; Li et al., 2019). Soil is a heterogeneous medium, and a number of non-linear relationships are common due to variations in moisture, salinity, and texture. Therefore, second- or third-order polynomial regression models tend to yield more accurate calibrations for complex soils, especially for potassium estimation (Estrada et al., 2025).

Polynomial regression can be used to enhance the calibration model when the sensor's output is nonlinear (Jaja et al., 2026). This model can be written as in Equation 3:

$$Ci = \beta_0 + \beta_1 Vi + \beta_2 Vi^2 + \varepsilon i \quad [3]$$

where Ci is the concentration of the nutrient measured (mg kg^{-1}), Vi is the sensor signal for the nutrient, β0 is the intercept, β1 and β2 are regression coefficients, and εi is random error.

Once the regression coefficients are obtained using least-squares fitting, the resulting model can be used in the future to estimate nutrient concentrations in real time based on sensor measurements. The statistical measure of the coefficient of determination (R2) is usually used to assess calibration performance, as in Equation 4:

$$R^2 = 1 - [\Sigma (C_i - \hat{C}_i)^2 / \Sigma (C_i - \bar{C})^2] \quad [4]$$

This is done using the measured nutrient concentrations C_i, the predicted nutrient concentration with the calibration model $\hat{C}_i$, and the mean measured concentration $\bar{C}$. Numbers closer to 1 indicate greater agreement between predicted and measured values. Other indicators of performance that are often used to measure the accuracy of predictions and the robustness of the model include root mean square error (RMSE) and mean absolute error (MAE).

Calibration is crucial to these validation methods, as accurate interpretation of sensor readings and precision fertiliser management decisions rely on a reliable calibration. It has been shown that low-cost sensors that have been calibrated to detect soil nutrient availability can be used to detect spatial and temporal changes with good accuracy when compared with laboratory analysis. For instance, a 5-pin RS485 sensor was used to successfully measure soil nutrient variability and yielded nutrient measurements consistent with laboratory methods, thus serving as a reliable tool for making fertiliser management decisions (Musanase et al., 2023). Likewise, models generated by correlating electrochemical and optical sensor responses with laboratory-derived nutrient data have estimated the availability of soil nutrients (N, P, K) in real time with high predictive accuracy (Sulaeman et al., 2024).

Appropriate agronomic nutrient thresholds are also needed for the interpretation of calibrated sensor measurements. They are the lowest nutrient concentration needed to prevent nutrient deficiencies and to promote maximum crop growth. No recommendations were made for this nutrient in rice production because the concentrations found in most soils are generally above the lowest levels generally correlated with nutrient deficiency (about 30 and 110 mg kg^{-1} for nitrogen and available potassium, respectively). The range of leaf nutrient concentrations of ~2.5% N and ~0.10% P are also critical for healthy plant development. The desirable nutrient levels in Malaysian rice soils are total N 0.22%, available P 31 mg kg^{-1}, and exchangeable K 0.29 cmolc kg^{-1} (Panhwar et al., 2023). Using calibrated sensor output with these agronomic thresholds can develop decision-support algorithms that provide site-specific fertiliser recommendations.

Overall, calibration is one of the most important factors affecting the performance of NPK sensors used in IoT. However, there is no consistent calibration protocol because calibration varies with the sensing technology used, soil characteristics, and environmental conditions. ISE sensors have high analytical accuracy and are used less frequently, whereas EC-based sensors are more costly and are better suited to large-scale applications but rely heavily on site-specific calibration models. Optical sensors offer high laboratory precision but are less useful for continuous field monitoring. Adaptive calibration techniques with environmental compensation algorithms and machine learning methods should therefore

be explored in the future to achieve higher sensor accuracy over the long term, decrease calibration frequency, and make the use of nutrient-sensing systems in IoT more feasible in precision agriculture.

APPLICATIONS IN PRECISION AGRICULTURE

By enabling site-specific, real-time, and data-driven nutrient management techniques, the integration of IoT-based nutrient monitoring systems is transforming precision agriculture. Across the diverse cropping systems, these technologies provide better decision-making and improve fertiliser use efficiency.

Site-Specific Nutrient Management (SSNM)

Site-Specific Nutrient Management (SSNM) greatly improves nutrient supply efficiency by reducing the variations in nutrients, which are both spatially and temporally distributed. The IoT soil sensors, which come with GPS and data analytics integration, identify the real-time NPK levels in very small zones, thus allowing the delivery of nutrients according to need. These data are used to create SSNM maps and field-specific fertiliser plans that lead to higher nitrogen uptake and assimilation (Dobermann et al., 2002). According to Buresh et al. (2010), real-time sensing is a powerful way of recovering nutrients. NPK sensors in Figure 4 can determine the nutrient concentrations by three methods: electrochemical, conductivity, or optical. The electrochemical method identifies NO_3^-, PO_4^{3-}, and K^+ ions using selective ion electrodes and simultaneously establishes a relationship between ion concentration and electrical potential (Table 3). EC (Highly Conductive Soil) is connected to nutrient content through conductivity techniques (Renke Electronics, 2024; NiuBoL, 2024), and optical methods work by measuring reflectance in the visible and NIR spectral regions (Adhikary et al., 2024).

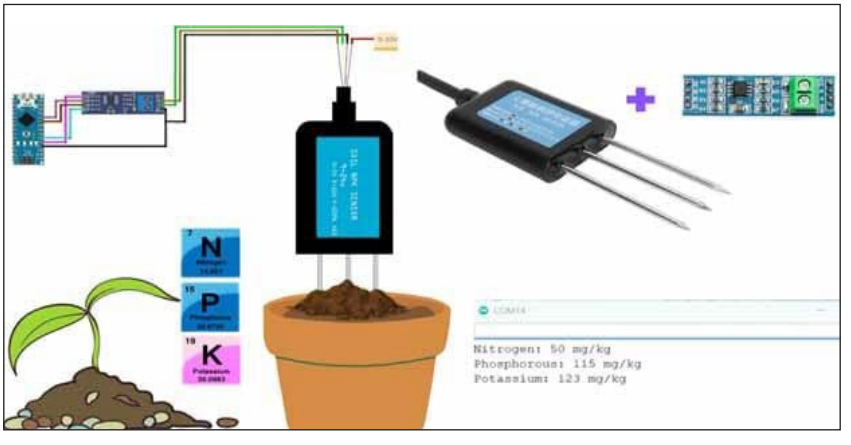


Figure 4. A pictorial view of an IoT-Enabled soil NPK sensor system (Saleem et al., 2024)

Table 3
Technical specifications of an IoT-enabled 8-in-1 soil nutrient sensor system

Parameter	Range/Description	Accuracy %
Communication Module	RS485	-
IoT Module	ESP8266 WiFi-enabled circuit	-
Cloud Integration	Jiousu IoT Cloud Server (CSV export, real-time monitoring, analysis, and visualisation)	-
Supply Voltage	DC 5 - 24V	-
Power Consumption	15 mA @ 12 V DC	-
Baud Rate	9600 bps	-
Temperature Range	−40 °C to 85 °C	±1.0 °C
Soil Moisture Range	0% to 100% (Relative Humidity)	±5%
Electrical Conductivity	0 to 10,000 µS/cm	±5%
Nutrient Range (NPK)	Nitrogen (N): 0 - 200 mg kg^{-1} Phosphorus (P): 0 - 200 mg kg^{-1} Potassium (K): 0 - 200 mg kg^{-1}	±10%
pH Range	0 to 14	±10% (precision)
Salt (Salinity) Range	0 to 10,000 µS/cm	±5%
Response time (NPK; EC)	<1s	

Source: Shahab et al. (2025)

There are also hybrid sensors that measure humidity, pH, and temperature along with nutrients for better accuracy (Musa et al., 2023). The sensor's output data are corrected using algorithmic or machine-learning models to determine nutrient levels, their distribution, and sufficiency (Chen et al., 2025). The real-time data from the IoT sensors are sent to the cloud, where they help in the decision-making process for the site-specific fertiliser application. This approach not only improves nutrient use efficiency but also reduces losses and maintains yield (Adhikary et al., 2024; Chen et al., 2025).

Real-Time Fertiliser Scheduling

Real-time sensors integrated into IoT systems have made it possible to monitor nutrient demands dynamically and optimally apply fertiliser s accordingly for the entire crop cycle. For example, nitrogen supply can be adjusted based on the crop's developmental stage and data from chlorophyll or soil nitrate sensors. This method eliminates the problem of fertilising too much and guarantees proper and on-time nutrient delivery to the plants, particularly in the case of the most demanding ones like rice and maize. IoT platforms enable remote fertigation monitoring and management, along with control of settings; if any parameters exceed thresholds, alerts are triggered (Idris et al., 2024). The use of IoT technology for nutrient tracking mitigates the possibility of nutrient imbalances and ensures the production of healthy crops. NPK sensors, which can be conductivity, optical, or ion-selective (Table 4), implement the detection of nutrients (Renke Electronics, 2024).

Accuracy has been improved by using hybrid sensors that account for both pH and moisture data (Musa et al., 2023). The raw data collected are calibrated and corrected based on environmental conditions such as temperature and salinity (NiuBoL, 2024). Such monitoring, when maintained continuously, can show when there is a nutrient shortage and suggest fertilisers of a particular type and at the right amount on the spot instantly (Adhikary et al., 2024), thus making it easier for them to be retained in the soil and at the same time preventing losses caused by leaching or volatilisation (Musa et al., 2023).

Table 4
Some nutrient measuring technologies in IoT-based nutrient management system

Technologies	Advantages	Disadvantages	Representative Authors
Ion-Selective Electrodes (ISEs)	Direct ion measurement (NO_3^-, NH_4^+, K^+); Real-time output, Low power, easy IoT integration, Inexpensive; Response time: seconds to minutes; Moderate robustness	Signal drift requires frequent calibration• Temperature and interfering ion sensitivity; membrane fouling; limited selectivity for some nutrients	Morawska et al., 2024
Optical Spectroscopy (UV-Vis, MIR, NIR, Fluorescence)	Non-destructive; multi-nutrient detection; fast & high throughput; moderate to high cost; Response time: seconds to minutes; moderate robustness	Affected by soil moisture & texture; requires calibration models and indirect nutrient estimation	Qi et al., 2024
Electrochemical Impedance Sensors	Low cost; sensitive to ion variations; Moderate robustness; Typical accuracy moderate-high; Suitable for in situ	Influenced by soil salinity & moisture; requires site-specific calibration	Manjushree et al., 2024
Chlorophyll Meters (SPAD)	Fast, non-destructive; good for N assessment; robustness is high under consistent crop growth	Indirectly affected by leaf thickness and stress; cannot measure P, K	Ali & Saleem, 2024
Soil EC, pH, and Moisture Sensors	Low cost; essential for nutrient availability; Typical accuracy high; Robustness high	Indirectly affected by soil salinity; cannot directly measure NPK	Idris et al., 2024
Biosensors (Enzyme/ Microbial Sensors)	High specificity for nitrate/ phosphate; lower drift for ISE	Limited robustness in field soil; higher cost and stability issues; Short biological lifespan	Sonowal et al., 2025
Nano-Sensors (CNT, Graphene, Metal Oxide)	Ultra-high sensitivity; fast response time; can be made flexible; Moderate robustness	Expensive fabrication; Field durability is still limited; commercialisation still limited	Yadav et al., 2023
IoT-Linked Fertigation Sensors (EC/pH/ Flow)	Automated nutrient delivery; real-time control; Typical accuracy is high with high robustness	High installation and maintenance costs; Requires periodic calibration	Sood et al., 2025

Integration with Variable Rate Technology (VRT)

Using Variable Rate Technology (VRT) in combination with AI is an emerging trend in precision agriculture that is undeniably beneficial, particularly in applications where fertiliser is used. VRT is the combination of crop seed, agrochemicals, and soil characteristic maps (Rokhafrouz et al., 2021). VRT uses sensor-based (real-time feedback) and map-based (prescription maps) methods. VRT is enhanced with IoT-generated nutrient maps, particularly for automating site-specific fertiliser applications. VRT technology can optimise fertiliser rates and adjust them to improve crop yield and nutrient use efficiency (NUE) in wheat and maize (Khosla et al., 2008). Using VRT, a range of fertiliser (12.59-50.41 kg/ha) was successfully adjusted based on driven shaft speed and sensor height (40-100 cm) at varying stages of rice growth. NDVI improved, and sensor-based VRT was able to reduce the use of nitrogen (Mirzakhaninafchi et al., 2022).

The NPK sensors that measure soil nitrate, phosphate, and potassium (Eldeeb et al., 2023) using ion-selective and electrochemical methods are part of this system (Table 5). These measurements, taken in conjunction with geo-referenced GPS, form the basis of the nutrient maps. Variable-rate applicators, in conjunction with GPS, adjust to changes in the device and improve efficiency in the use of one or more fertilisers (Musa et al., 2023). The use of integrated, data-driven systems supports adaptive and sustainable nutrient management.

Case Examples in Major Crops: Rice

IoT enables real-time nutrient monitoring, which has altered the best methods of precision agriculture, especially rice farming. When these systems are paired with soil and water sensors, they help provide accurate split nitrogen (N) applications, which reduces nitrogen losses and improves nitrogen left in grain yields. NDVI readings (Table 6) for rice indicate this, shifting from 0.49 to 0.69 as nitrogen levels increase from 75 to 225 kg/ha. This demonstrates enhanced crop vigour through sensor-based variable-rate technology (Mirzakhaninafchi et al., 2022). The system demonstrated its efficacy with sensor heights (40 - 100 cm) and rice growth stages, helping achieve 45% savings in fertiliser input. The combination of monitoring parameters (soil temperature, moisture, EC, pH, and nutrients) has shown positive effects on crop growth. In Pakistan, an IoT-based rice system enabled real-time management of crop parameters, improving productivity (Shahab et al., 2025). Controlled fertigation management improved water-use efficiency by 64%, increased crop yield by 35%, reduced weed growth, and reduced nutrient leaching. Drip fertigation helps to increase nutrient use efficiency by up to 29% and enhances water use efficiency by 70% (Singh & Singh, 2026).

Table 5
Some related research work on nutrient sensor detection system

Authors	Echnology Involved	Purpose of the Study	Major Findings	Research Gap
Bristow et al., 2022	Ion-selective electrode (nitrate ISE) linked with LoRaWAN IoT node	To develop and validate a soil nitrate sensor node for real-time field monitoring and cloud reporting	Validated real-time nitrate monitoring with LoRaWAN; effective for fertiliser decision support	Long-term field trials and multi-ion (full NPK) integration are not shown
Eldeeb et al., 2023	Potentiometric ISE (TDDA nitrate)/electrochemical array	Fabricate a selective nitrate ISE for in-situ soil measurement	Demonstrated the high nitrate selectivity and in-soil applicability	Sensor drift and long-term stability in diverse soils need more assessment
Catini et al., 2022	Lab-on-a-chip (microfluid) colorimetric platform (automated reagent mixing)	Build an automated LOC platform for continuous colorimetric nutrient assays (nitrite/nitrate)	Demonstrated automated, continuous colorimetric assays with low reagent use; suitable for in-field deployment	Robustness and reagent cartridge lifetime for long deployments require improvement
Clinton-Bailey et al., 2017	Microfluidic LOC for in-situ phosphate (improved "phosphate blue" assay)	In situ measurement of soluble reactive P with a microfluidic analyser	Lab-grade phosphate assay miniaturised for field use; good sensitivity and autonomy	Integration into multi-analyte (NPK) platforms and ruggedisation for soils remains needed
Baumbauer et al., 2022	Printed potentiometric nitrate sensors (inkjet-printed ISEs)	Produce low-cost, printable nitrate sensors for soil monitoring	Printed sensors showed practical sensitivity and could be mass-fabricated affordably	Field lifetime, reference electrode stability, and multi-ion capability need work
Lal et al., 2023	Electrochemical & optical sensors for nitrate	Review field-deployable nitrate sensing technologies and suitability for agricultural monitoring	Electrochemical and optical methods are promising for field nitrate sensing; they highlighted trade-offs between cost, accuracy, and field robustness	General need for standard field validation protocols and multi-parameter integration
Hossain, 2024	Electrochemical sensors (nanoparticles, graphene) for nutrients	Survey recent electrochemical developments for nutrient (NPK) detection across water/ soil samples	Advances in nano-materials (CuNPs, graphene) improved sensitivity and selectivity	Few studies demonstrate long-term, in-soil operation across varying matrices (soil, salinity, moisture)
Xu et al., 2024	Graphene ISFET / transconductance-based nitrate sensor	Develop an ultra-sensitive graphene ISFET for nitrate detection	Achieved ultra-low detection limits and fast response for aqueous nitrate	Translation from aqueous proof-of-concept to heterogeneous soil measurement and fouling mitigation is needed

Table 6
Accuracy percentage of different agricultural sensor technologies for soil and crop monitoring

Description	Parameter	Accuracy (%)	References
DHT11 + NodeMCU ESP8266 + an on/off switch + a reset button	Soil temperature and Humidity	99.93% and 99.95%	Nofriandi et al., 2023
SHT11 + NodeMCU ESP8266 + Arduino Uno + an on/off switch + a reset button + SD card	Soil moisture	99.95%	Karinia et al., 2021
NDVI sensor	Crop canopy reflectance	0.83% to 4.92% system error in fertiliser application	Mirzakhaninafchi et al., 2022
NPK sensor	Nitrogen, Phosphorus, Potassium	Error rate: 8.47% compared to laboratory control sensors Accuracy approx.: 91.53%	Musa et al., 2023

IoT systems for maize help address fluctuations from pests such as the Fall Armyworm and irregular rainfall (Aruna Balla et al., 2019). In Nigeria, IoT-supported climate monitoring has shown promise for year-round maize production (Nwankwo et al., 2019).

The introduction of IoT into wheat cultivation has enabled top-dressing N based on canopy reflectance readings and real-time soil nitrate rates, thereby improving N recovery efficiency through optical sensing (Raun et al., 2002). The sprinkler system based on IoT enhanced efficiency in saving water (55%), and it saved 25% of fertiliser by optimising irrigation and fertilisation timings, respectively, according to the stage of wheat growth and soil moisture levels. The system implementation resulted in better and more accurate wheat production (Kumar & Choudhury, 2022). Through this approach, wheat crops can achieve higher quality, such as higher protein content, which is a market necessity (Singh et al., 2025).

Using IoT fertigation systems in horticulture, nutrient runoff decreased by 30%, and the eggplant harvesting process was accelerated with minimal fertiliser (Idris et al., 2024). The use of NPK sensors in hydroponics has proven to be effective as IoT systems have provided remarkable improvements in growth and metrics in red spinach and pak choi, as well as significant increases in plant height, biomass and leaf area (Sania et al., 2025).

BENEFITS OF IOT-BASED NUTRIENT MANAGEMENT

Improved Nutrient Use Efficiency (NUE)

IoT devices provide site-specific fertiliser application, supplying nutrients just where and when needed by enabling real-time, high-resolution monitoring of soil NPK levels and supplementary factors, such as moisture and pH. This significantly increases nutrient uptake by crops and minimises waste, effectively improving NUE. IoT-driven decision support

platforms empower farmers to make these precision interventions reliably (Shahab et al., 2025). The system, in short, helps determine the minimum required fertiliser application, thereby reducing excessive and unnecessary fertiliser use, promoting cost savings, and minimising environmental damage (Anjaneyulu et al., 2024). According to the research findings, when put together, the total application of fertilisers was reduced by 45% compared to a conventional blanket area, which was a manifestation that the system was cost-effective and environmentally safe (Mirzakhanafchi et al., 2022). The use of IoT to encourage smart farming contributed to the reduction of the environmental impact by avoiding the excessive use of fertiliser, as well as encouraging sustainable farming (Sahab et al., 2025).

Yield Optimisation and Input Cost Reduction

Using IoT-informed nutrient management can improve crop yields by 15% to 30% and reduce fertiliser use by 10% to 40%, thereby significantly reducing costs (Mirzakhaninafchi et al., 2022). When combined with decision-support systems and variable-rate technology, a 45% reduction in fertiliser use compared to traditional methods was achieved. Real-time monitoring of soil health is made possible by low-cost multi-sensor nodes that track pH, EC, moisture, temperature, and NPK. Machine learning and IoT analytics help to determine the optimal nutrient requirements and the best planting dates for the crops, based on historical soil conditions and weather data (Shahab et al., 2025). Such systems can further reduce fertiliser use by 20% to 40% and water use by 50% (Shahab et al., 2025; Thelkar et al., 2025), while promoting environmental sustainability and reducing runoff.

Environmental Impact Mitigation

Paying attention to how the use of resources is managed through IoT in the context of environmental performance in the reviews of sustainable agriculture is critical. IoT systems provide real-time information on soil nutrient availability, enabling precise fertiliser application to avoid nutrient leaching (Anjaneyulu et al., 2024). In this way, the health of the soil is achieved, and pollution of water systems due to fertilisers, which are often responsible for eutrophication, is limited. Farmers who use only the required amount of NPK are said to help the environment while sustaining the health of the crops (Shahab et al., 2025).

Improved Soil Health and Long-Term Sustainability

Farmers can tailor their fertiliser application to real soil conditions with NPK sensors instead of applying fertilisers based on guesswork. This approach can increase crop production, reduce environmental impacts, and conserve resources. With constant monitoring of the

sensors, farmers will be able to make adjustments to their soil management practices, along with the nutrient compounds, pH level and organic content of their soil. With continuous monitoring, farmers can also intervene before these issues become problematic, along with erosion, salinity, and contamination (Zeptogreens, 2025). Well-distributed and balanced nutrient management will promote soil fertility, sustain agriculture to meet increasing food needs, and protect the environment (Adak, 2025).

Scalability and Adaptability Across Different Farming Systems

Nutrient management sensors can be used on large commercial farms as well as smallholder farms. They can be used on any type of farm because of their sturdy, all-weather construction. Integrated with advanced algorithms and machine learning, these sensors respond to various environmental factors, including weather, soil type, and crop growth. With their innovative sensing technology, farmers receive accurate data on their soil and crops in real-time, which assists them in making better management decisions (Adhikary et al., 2024).

Water-Nutrient Balance

When NPK sensors are combined with the soil moisture monitors, the farmers can examine the interaction of water and nutrients in their fields to a much better degree. Both nutrients and water should be properly managed in order to increase the crop yield and, at the same time, save on resources.

Enhanced Decision-Making for Farmers and Agronomists

The advanced NPK sensors can provide real-time farm soil nutrient data, allowing farmers to apply the right quantities of fertiliser s at the right time. By increasing agricultural production, minimising the impacts on the environment, and reducing the process of overfertilisation, it ensures environmental and economic sustainability (Zeptogreens, 2025). The information provided by sensors helps farmers make informed decisions in crop planning and fertilisation, enabling them to achieve long-term productivity and sustainable agriculture.

CHALLENGES AND LIMITATIONS

Nutrient management systems based on IoT have a number of limitations to their use, particularly when using them in fields:

Sensor Calibration and Soil Heterogeneity

In agriculture, IoT-based NPK sensors are used; however, IoT requires some technical knowledge to ensure accurate data and operations (Van Deursen & Mossberger, 2018). Farmers must receive training to learn how to operate and maintain these devices. Unlike cheaper sensors that have no calibration, more expensive systems have to be recalibrated consistently to provide accurate measurements in different environments (Miller et al., 2025). There are many types of soil, each with varying levels of pH, salinity, and organic matter. All of these factors complicate nutrient sensing, necessitating customisation to a particular field. Without proper recalibration, sensors may report false data, which can lead to harmful nutrient applications. As a result, many farmers lack the expertise needed to use technology more effectively (Musa et al., 2023).

Data Reliability and Sensor Drift

Several researchers have mentioned possible challenges with the storage, processing, and analysis of the vast quantities of data collected by sensors in IoT-based farming (Dash et al., 2019). The misuse of farmers' data would become a breach of farm privacy, so it would be important to implement data protection and security. Pierce & Nowak (1999) describe cases of data drift with cheap sensors, as environmental changes require frequent recalibration. Limited large-scale real-world testing makes it difficult to assess the effectiveness and functionality of these sensors (Fauziah et al., 2024). The flexibility and productivity of wireless sensor networks are backed by strong data protection and solid analytical governance to enhance the trust of farmers (Musa et al., 2023).

Connectivity in Rural Settings

Challenges exist around IoT Reliability, especially for remote internet connections. Weak and intermittent connectivity are particularly problematic for real-time data transfer and monitoring (Tyagi & Sreenath, 2021). Poor infrastructure limited wireless communication (cellular, Wi-Fi, or LoRaWAN), and inadequate precision farming decision-making are all interrelated problems (Wolfert et al., 2017). Furthermore, it can be difficult to gauge practical feasibility because large-scale field trials are still limited (Fauziah et al., 2024). That said, data on nutrients can be captured in real time and uploaded to scalable cloud solutions for remote access and monitoring, such as Google Firebase (Anjaneyulu et al., 2024).

Cost and Accessibility for Smallholder Farmers

Farming technology faces several hurdles, especially in developing nations, due to high setup costs and ongoing system maintenance for things like sensors, gateways, and cloud

technology (Banerjee, 2019). Financial system burdens, coupled with insufficient digital skills, hinder IoT integration. In an effort to address these burdens, farmers can receive alerts and other feedback through mobile apps, such as those designed with the Nodular API, increasing accessibility (Anjaneyulu et al., 2024). In addition, cloud services, predictive analytics, and artificial intelligence enhance user experience and contribute to overall scale (Sahab et al., 2025).

E-Waste

One of the products of agricultural technologies is electronic trash (e-waste), e.g., NPK sensors. When hazardous materials leak into soil and water, they can contaminate the environment and pose health risks because these materials have limited lifespans and high rates of degradation (Adhikary et al., 2024; The Engineer, 2025).

FUTURE PROSPECTS AND INNOVATIONS

Integration with "Artificial Intelligence"/ "Machine Learning" for Predictive Analytics

Artificial Intelligence (AI) and Machine Learning (ML) algorithms now function as essential components of predictive nutrient management models in IoT systems. The models use sensors to analyse current environmental conditions to predict soil nutrient changes, provide fertiliser application recommendations, and help identify nutrient deficiencies at an early stage (Eze et al., 2025). Site-specific nutrient management, crop productivity, efficient use of resources, and reduced environmental impacts are achieved with supervised machine learning based on soil moisture, pH, and nutrient data to accurately predict fertiliser application needs (Narayanan et al., 2026).

Blockchain for Traceable and Transparent Fertiliser Management

Blockchain technology enables transparent nutrient input tracking while ensuring complete accountability through its secure documentation process, which verifies all fertiliser supply and application operations (Banerjee, 2019; Pang et al., 2024). The combination of blockchain technology with IoT systems enables users to monitor fertiliser information in real time, including tracking the specific type and amount of fertiliser and the application time, while establishing an unchangeable record that enables both traceability and sustainability compliance verification.

Remote Sensing and Drone Integration

The combination of drone imaging technology and satellite remote sensing systems together with IoT-based in-situ sensor networks enables farmers to monitor their crops from multiple distances. The combination of high-resolution NDVI (Normalized Difference Vegetation Index)

and chlorophyll content measurements from aerial platforms with ground-level NPK data enables researchers to identify spatial nutrient deficiencies with higher accuracy (Vashishth et al., 2024). The system enables farmers to apply fertiliser s only to specific areas, which leads to reduced fertiliser application and improved nitrogen use efficiency. Low-altitude UAS provide a new and flexible, low-cost and high-resolution platform for precision agriculture; however, they need to be standardised and processed further to ensure precise use (Zhang & Kovacs, 2012).

Autonomous Nutrient Management Systems

Next-generation agricultural systems are moving toward autonomy by merging IoT infrastructure with robotics, AI/ML, and real-time decision engines. The autonomous fertiliser sprayers and drone-based nutrient applicators use sensor data to perform targeted fertilisation without any need for human operators. The systems use closed-loop feedback mechanisms to achieve three benefits, which include better application efficiency, decreased need for workers, and minimised environmental hazards.

Next-Generation Sensors: Bio-Sensors and Nano-Sensors

Scientists have developed highly sensitive biosensors which use nitrate reductase enzymes to measure nutrient content in soil and plant samples. The sensors deliver immediate nutrient feedback when they connect to IoT platforms, which enables users to take quick action. Nano-sensors that use graphene and carbon nanotube materials demonstrate excellent sensitivity because they can detect very small amounts of essential ions, while their components can be made into small and flexible sensor systems (Yadav et al., 2023). The technologies provide excellent potential for developing affordable portable devices that can frequently monitor nutrient levels. Future researchers can use this type of sensor and also multi-nutrient sensing.

Biodegradable and Ultra-Low-Power Sensor System

The necessity of analytics ecosystems to incorporate environmentally responsible approaches is further necessitated by the expanding scope of IoT in agriculture. Degradable sensors, made of fully biodegradable materials, as opposed to traditional electronics, support the reduction of e-waste and offer an eco-friendly alternative (Matiieshyn, 2025). Ultra-low-power sensor nodes, allowing intermittent data collection and transmission, will provide increased longevity of the devices while preserving data fidelity. These developments reflect the heightened interest in cost-effective device longevity and energy- and environmentally sustainable designs in agricultural monitoring systems (Zahedi et al., 2024).

Cybersecurity and Data Privacy

As NPK sensor systems become more integrated through wireless networks and cloud-based systems, cybersecurity and privacy will be major concerns. Going forward, the need of the hour is to focus on developing secure communication protocols, data encryption techniques, authentication, and intrusion detection systems to ensure that sensor networks are not subjected to cyber-attacks and unauthorised access. The safety, confidentiality, and availability of sensor data are crucial for accurate decision-making in precision agriculture. Further, adequate cloud storage solutions and privacy-enhancing data-sharing mechanisms need to be developed to boost farmer trust and facilitate the adoption of smart farming solutions.

Large-Scale Field Implementation

Very little literature has examined the IoT-enabled NPK sensor in real farming environments, as most studies have been conducted in lab settings or under small-scale experimental conditions. Future work needs to focus on large-scale, long-term field testing in various soil types, climates, cropping systems, and management strategies to more accurately test the performance of sensors in real-world agricultural applications. In addition, detailed economic evaluation (including cost-effectiveness, maintenance, scalability and farmer adoption) must be done to determine the commercial viability of such technologies. These studies will enable the adoption of NPK sensor-based IoT systems from the research lab to commercial precision fertiliser management.

CONCLUSION

IoT-based nutrient management systems represent an innovation in smart farming, enabling real-time monitoring and data-driven decision-making that strengthen NUE, crop productivity, and environmental sustainability. The incorporation of NPK sensor-based monitoring successfully identified changes in soil nutrients in real-time, allowing for accurate and timely fertiliser administration. By reducing losses and matching crop nutrient needs, this strategy greatly increased fertiliser usage efficiency. As a result, rice yield and the yield performance of other crops increased under sensor-data-driven optimised fertiliser schemes. Current research has yet to carry out large-scale, long-term field validations for sensor accuracy, system reliability, and economic feasibility in diverse agricultural conditions, particularly for smallholder farming systems. The broader adoption is still being hindered by challenges with sensor calibration, rural connectivity, and affordability. Collaboration between agronomists, engineers, data scientists, and policymakers is necessary to achieve a scalable impact. Future research should prioritise the development of reliable, low-cost, and intelligent IoT-based NPK sensing systems

integrated with artificial intelligence and decision-support tools for climate-resilient and sustainable crop production.

ACKNOWLEDGEMENT

The author gratefully acknowledges the valuable contributions of all co-authors and the continuous support provided by Universiti Putra Malaysia (UPM), Malaysia, and the PARTNER (Program on Agricultural and Rural Transformation for Nutrition, Entrepreneurship and Resilience in Bangladesh) Project (grant number: PARTNER/APCU-BARC-02/HRD/2024/586), Ministry of Agriculture, Bangladesh. The author is also thankful to the Bangladesh Agricultural Research Council (BARC) and the Bangladesh Rice Research Institute (BRRI).

REFERENCES

Adak, S. (2025). Smart agriculture with NPK sensors: A sustainable approach to soil health and fertiliser optimisation in guava farming. *Journal of Scientific Research and Reports, 31*(7), 45-52. https://doi.org/10.9734/jsrr/2025/v31i73227

Adhikary, R., Sudham, V., & Sualsingh, S. (2024). Real-time soil nutrient monitoring using NPK sensors: Enhancing precision agriculture. In *2024 2nd International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES)* (pp. 1-4). IEEE. https://doi.org/10.1109/SCOPES64467.2024.10991026

Anjaneyulu, M., Gaud, P. D., Keerthika, S., Merugu, R., Almusawi, M., Asha, V., Thethi, H. P., & Praveen. (2024). Sustainable practices for plant nutrient control using IoT. *E3S Web of Conferences, 507*, Article 01039. https://doi.org/10.1051/e3sconf/202450701039

Anwar, W., Quader, T., Zakaria, M., & Motaharul Islam, M. (2023). IoT-based decision making of irrigation and fertiliser management for marginal farmers in Bangladesh. In M. S. Hossain, S. P. Majumder, N. Siddique, M. S. Hossain (Eds.), *The fourth Industrial Revolution and Beyond* (Vol. 980, pp. 673-682). Springer Singapore. https://doi.org/10.1007/978-981-19-8032-9_48

Arshad, J., Aziz, M., Al-Huqail, A. A., Zaman, M. H. u., Husnain, M., Rehman, A. U., & Shafiq, M. (2022). Implementation of a LoRaWAN-based smart agriculture decision support system for optimum crop yield. *Sustainability, 14*(2), Article 827. https://doi.org/10.3390/su14020827

Augustin, A., Yi, J., Clausen, T., & Townsley, W. M. (2016). A study of LoRa: Long range and low power networks for the Internet of Things. *Sensors, 16*(9), Article 1466. https://doi.org/10.3390/s16091466

Balla, A., Bhaskar, M., Bagade, P., & Rawal, N. (2019). Yield losses in maize (*Zea mays*) due to fall armyworm infestation and potential IoT-based interventions for its control. *Journal of Entomology and Zoology Studies, 7*(5), 920-927. https://www.entomoljournal.com/archives/2019/vol7issue5/PartO/7-4-22-657.pdf

Banerjee, A. (2019). Blockchain with IoT: Applications and use cases for a new paradigm of supply chain driving efficiency and cost. In *Advances in Computers* (Vol. 115, pp. 259-292). Elsevier. https://doi.org/10.1016/bs.adcom.2019.07.007

Baumbauer, C. L., Goodrich, P. J., Payne, M. E., Anthony, T., Beckstoffer, C., Toor, A., Silver, W., & Arias, A. C. (2022). Printed potentiometric nitrate sensors for use in soil. *Sensors, 22*(11), Article 4095. https://doi.org/10.3390/s22114095

Bhatt, K., Agrawal, C., & Bisen, A. M. (2024). A review on emerging applications of IoT and sensor technology for Industry 4.0. *Wireless Personal Communications, 134*, 2371-2389. https://doi.org/10.1007/s11277-024-11054-x

Billa, P., Venkatesh, K., Sai, J. V., Lohith, K., & Kumar, A. S. (2023). Effective monitoring and protecting system for agriculture farming using IoT and Raspberry Pi. *Materials Today: Proceedings*, *80*(Part 3), 2917-2920. https://doi.org/10.1016/j.matpr.2021.07.065

Bristow, N., Rengaraj, S., Chadwick, D. R., Kettle, J., & Jones, D. L. (2022). Development of a LoRaWAN IoT node with ion-selective electrode soil nitrate sensors for precision agriculture. *Sensors, 22*(23), Article 9100. https://doi.org/10.3390/s22239100

Catini, A., Capuano, R., Tancredi, G., Dionisi, G., Di Giuseppe, D., Filippi, J., Martinelli, E., & Di Natale, C. (2022). A lab-on-a-chip-based automatic platform for continuous nitrites sensing in aquaculture. *Sensors, 22*(2), Article 444. https://doi.org/10.3390/s22020444

Chen, X., Zhang, H., & Wong, C. U. I. (2025). Dynamic monitoring and precision fertilisation decision system for agricultural soil nutrients using UAV remote sensing and GIS. *Agriculture, 15*(15), Article 1627. https://doi.org/10.3390/agriculture15151627

Clinton-Bailey, G. S., Grand, M. M., Beaton, A. D., Nightingale, A. M., Owsianka, D. R., Slavik, G. J., Connely, D. P., Cardwell, C. L., & Mowlem, M. C. (2017). A lab-on-chip analyzer for *in situ* measurement of soluble reactive phosphate: Improved phosphate blue assay and application to fluvial monitoring. *Environmental Science & Technology, 51*(17), 9989-9995. https://doi.org/10.1021/acs.est.7b01581

Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: Management, analysis and future prospects. *Journal of Big Data, 6*, Article 54. https://doi.org/10.1186/s40537-019-0217-0

Dobermann, A., Witt, C., Dawe, D., Abdulrachman, S., Gines, H. C., Nagarajan, R., Satawathananont, S., Son, T. T., Tan, P. S., Wang, G.H., Chien, N. V., Thoa, V. T. K., Phung, C. V., Stalin, P., Muthukrishnan, P., Ravi, V., Babu, M., Chatuporn, S., Sookthongsa, Sun, Q., Fu, R., Simbahan, G. C., & Adviento, M. A. A. (2002). Site-specific nutrient management for intensive rice cropping systems in Asia. *Field Crops Research, 74*(1), 37-66. https://doi.org/10.1016/S0378-4290(01)00197-6

Eldeeb, M. A., Dhamu, V. N., Paul, A., Muthukumar, S., & Prasad, S. (2023). Electrochemical soil nitrate sensor for in situ real-time monitoring. *Micromachines, 14*(7), Article 1314. https://doi.org/10.3390/mi14071314

Estrada, O., Ramos, G., Lizarazo, M., & Jimenez, D. (2025). Digital transformation accelerator. Technical report of the probe: Low-cost portable soil fertility sensors: Myth or reality?. *14*. https://hdl.handle.net/10568/180684

Eze, V. H. U., Eze, E. C., Alaneme, G. U., Bubu, P. E., Nnadi, E. O. E., & Okon, M. B. (2025). Integrating IoT sensors and machine learning for sustainable precision agroecology: Enhancing crop resilience and resource efficiency through data-driven strategies, challenges, and future prospects. *Discover Agriculture, 3*, Article 83. https://doi.org/10.1007/s44279-025-00247-y

Fathima, N., Kumar, S. B. V., & Bagali, M. U. (2026). An embedded IoT-based system for real-time NPK soil quality monitoring in precision agriculture. *Engineering, Technology & Applied Science Research, 16*(2), 33211-33217. https://doi.org/10.48084/etasr.17091

Fauziah, N. O., Fitriatin, B. N., Fakhrurroja, H., & Simarmata, T. (2024). Enhancing soil nutritional status in smart farming: The role of IoT-based management for meeting plant requirements. *International Journal of Agronomy, 2024*(1), Article 8874325. https://doi.org/10.1155/2024/8874325

Food and Agriculture Organization of the United Nations (FAO). (2017). *The future of food and agriculture: Trends and challenges.* https://openknowledge.fao.org/server/api/core/bitstreams/2e90c833-8e84-46f2-a675-ea2d7afa4e24/content

Getahun, S., Kefale, H., & Gelaye, Y. (2024). Application of precision agriculture technologies for sustainable crop production and environmental sustainability: A systematic review. *The Scientific World Journal, 2024*(1), Article 2126734. https://doi.org/10.1155/2024/2126734

Hashim, N., Ali, M. M., Mahadi, M. R., Abdullah, A. F., Wayayok, A., Kassim, M. S. M., & Jamaluddin, A. (2024). Smart farming for sustainable rice production: An insight into application, challenge, and future prospect. *Rice Science, 31*(1), 47-61. https://doi.org/10.1016/j.rsci.2023.08.004

Idris, F., Latiff, A. A., Buntat, M. A., Lecthmanan, Y., & Berahim, Z. (2024). IoT-based fertigation system for agriculture. *Bulletin of Electrical Engineering and Informatics, 13*(3), 1574-1581. https://doi.org/10.11591/eei.v13i3.6829

Inayah, I., Agustirandi, B., Budiman, M., Djamal, M., & Faizal, A. (2026). IoT-based fertigation management for enhancing Cilembu sweet potato productivity: An experimental study. *Smart Agricultural Technology, 13*, Article 101780. https://doi.org/10.1016/j.atech.2026.101780

Jaja, M. E., Nkemeni, V., Tsafack, P., Brosselard, P., Nicole, G., & Patrick, J. (2026). Optical sensor characterization for rapid detection of nitrogen, phosphorus, and potassium concentrations in soil. *Discover Sensors, 2*, Article 17. https://doi.org/10.1007/s44397-026-00048-y

Jawad, H. M., Nordin, R., Gharghan, S. K., Jawad, A. M., & Ismail, M. (2017). Energy-efficient wireless sensor networks for precision agriculture: A review. *Sensors, 17*(8), Article 1781. https://doi.org/10.3390/s17081781

Karinia, Y., Violita, V., Tarigan, H., Sudiar, N. Y., & Yulkifli, Y. (2021). Soil moisture measurement tools using SHT11 sensors based on the Internet of Things. INVOTEK: *Jurnal Inovasi Vokasional dan Teknologi, 21*(3), 165-174. https://doi.org/10.24036/invotek.v21i3.928

Khosla, R., Inman, D., Westfall, D. G., Reich, R. M., Frasier, M., Mzuku, M., Koch, B., & Hornung, A. (2008). A synthesis of multidisciplinary research in precision agriculture: Site-specific management zones in the semi-arid western Great Plains of the USA. *Precision Agriculture, 9*(1), 85-100. https://doi.org/10.1007/s11119-008-9057-1

Kim, H. J., Sudduth, K. A., Hummel, J. W., & Drummond, S. T. (2013). Validation testing of a soil macronutrient sensing system. *Transactions of the ASABE, 56*(1), 23-31. https://doi.org/10.13031/2013.42582

Kochhar, A., & Kumar, N. (2019). Wireless sensor networks for greenhouses: An end-to-end review. *Computers and Electronics in Agriculture, 163*, Article 104877. https://doi.org/10.1016/j.compag.2019.104877

Kumbhare, N., & Kumbhar, S. R. (2023). Detection of macronutrients (NPK) using LED-based spectroscopy method. *International Journal of Engineering Development and Research, 11*(1), 34-39. https://rjwave.org/ijedr/papers/IJEDR2301006.pdf

Lal, K., Jaywant, S. A., & Arif, K. M. (2023). Electrochemical and optical sensors for real-time detection of nitrate in water. *Sensors, 23*(16), Article 7099. https://doi.org/10.3390/s23167099

Li, Y., Yang, Q., Chen, M., Wang, M., & Zhang, M. (2019). An ISE-based on-site soil nitrate nitrogen detection system. *Sensors, 19*(21), Article 4669. https://doi.org/10.3390/s19214669

Ma, L., Duan, T., & Hu, J. (2020). Application of a universal soil extractant for determining the available NPK: A case study of crop planting zones in central China. *Science of the Total Environment, 704*, Article 135253. https://doi.org/10.1016/j.scitotenv.2019.135253

Manjushree, S. G., Ashoka, S., & Adarakatti, P. S. (2024). A brief review on basic principles of electrochemistry and electrochemical sensing devices. In *Real-Time Applications of Advanced Electrochemical Sensing Devices* (pp. 1-20). https://doi.org/10.1088/978-0-7503-5377-9ch1

Matiieshyn, P. (2025, July 16). *Ultra-low power system design: Overcoming key engineering challenges. Power Electronics News*. https://www.powerelectronicsnews.com/ultra-low-power-system-design-overcoming-key-engineering-challenges/

Miller, T., Mikiciuk, G., Durlik, I., Mikiciuk, M., Łobodzińska, A., & Śnieg, M. (2025). The IoT and AI in agriculture: The time is now—A systematic review of smart sensing technologies. *Sensors, 25*(12), Article 3583. https://doi.org/10.3390/s25123583

Mirzakhaninafchi, H., Singh, M., Dixit, A. K., Prakash, A., Sharda, S., Kaur, J., & Nafchi, A. M. (2022). Performance assessment of a sensor-based variable-rate real-time fertiliser applicator for rice crop. *Sustainability, 14*(18), Article 11209. https://doi.org/10.3390/su141811209

Morawska, K., & Wardak, C. (2024). Application of ionic liquids in ion-selective electrodes and reference electrodes: A review. *ChemPhysChem, 25*(7), Article e202300818. https://doi.org/10.1002/cphc.202300818

Morchid, A., Alblushi, I. G. M., Khalid, H. M., Alami, R. E., Sitaraman, S. R., & Muyeen, S. M. (2026). High-technology agriculture system to enhance food security: A concept of smart irrigation system using the Internet of Things and cloud computing. *Journal of the Saudi Society of Agricultural Sciences, 25*, Article 42. https://doi.org/10.1007/s44447-025-00096-7

Musa, P., Sugeru, H., & Wibowo, E. P. (2024). Wireless sensor networks for precision agriculture: A review of NPK sensor implementations. *Sensors, 24*(1), Article 51. https://doi.org/10.3390/s24010051

Musanase, C., Vodacek, A., Hanyurwimfura, D., & Uwitonze, A. (2023). Calibration of five-pin soil sensor for soil monitoring of greenhouses in Rwanda. In *Proceedings of the 13th International Workshop on Computer Science and Engineering (WCSE 2023),* 263-268. https://doi.org/10.18178/wcse.2023.06.039

Narayanan, R., Kabaleeswaran, K. K., Raghunathan, B., Selvaraj, D., & Guruprakash, K. S. (2026). Optimizing fertiliser use for enhanced crop yield through machine learning algorithms. *AIP Conference Proceedings, 3345*(1), Article 020188. https://doi.org/10.1063/5.0298092

NiuBoL. (2023, September 6). *Soil NPK sensors: Working principle and parameters*. https://www.niubol.com/Product-knowledge/Soil-NPK-Sensors-Principle.html

NiuBoL. (2025, September 11). *Calibrating soil sensors for long-term accuracy.* https://www.niubol.com/Product-knowledge/Calibrating-Soil-Sensors-for-Long-Term-Accuracy.html

Nwankwo, W., Olayinka, A. S., & Umezuruike, C. (2019). Boosting self-sufficiency in maize crop production in Osisioma Ngwa Local Government with internet of things (IoT)-climate messaging: A model. *African Journal of Agricultural Research, 14*(7), 406-418. https://doi.org/10.5897/AJAR2018.13753

Okhovat, E., & Bauer, M. A. (2021). Monitoring the smart city sensor data using Thingsboard and Node-Red. In *2021 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/IOP/SCI)* (pp. 425-432). IEEE. https://doi.org/10.1109/SWC50871.2021.00064

Pandian, K., Mustaffa, M. R. A. F., Mahalingam, G., Paramasivam, A., Prince, A. J., Gajendiren, M., Mohammad, A. R. R., & Varanasi, S. T. (2024). Synergistic conservation approaches for nurturing soil, food security and human health towards sustainable development goals. *Journal of Hazardous Materials Advances, 16*, Article 100479. https://doi.org/10.1016/j.hazadv.2024.100479

Pang, S., Teng, S. W., Murshed, M., Van Bui, C., Karmakar, P., Li, Y., & Lin, H. (2024). A survey on evaluation of blockchain-based agricultural traceability. *Computers and Electronics in Agriculture, 227*(Part 2), Article 109548. https://doi.org/10.1016/j.compag.2024.109548

Panhwar, Q. A., Shamshuddin, J., Naher, U. A., Razi, I. M., Yusoff, M. A., Ali, A., & Depar, N. (2023). Enhancing rice production on acid sulfate soil using bio-fertilizer in combination with ground magnesium limestone or biochar. *Malaysian Journal of Soil Science, 27*, 70-79.

Pierce, F. J., & Nowak, P. (1999). Aspects of precision agriculture. *Advances in Agronomy, 67*, 1-85. https://doi.org/10.1016/S0065-2113(08)60513-1

Postolache, S., Sebastião, P., Viegas, V., Postolache, O., & Cercas, F. (2022). IoT-based systems for soil nutrients assessment in horticulture. *Sensors, 23*(1), Article 403. https://doi.org/10.3390/s23010403

Qi, X., Lian, Y., Xie, L., Wang, Y., & Lu, Z. (2024). Water quality detection based on UV-Vis and NIR spectroscopy: A review. *Applied Spectroscopy Reviews, 59*(8), 1036-1060. https://doi.org/10.1080/05704928.2023.2294458

Raun, W. R., Solie, J. B., Johnson, G. V., Stone, M. L., Mullen, R. W., Freeman, K. W., Thomason, W. E., & Lukina, E. V. (2002). Improving nitrogen use efficiency in cereal grain production with optical sensing and variable-rate application. *Agronomy Journal, 9*4(4), 815-820. https://doi.org/10.2134/agronj2002.8150

Renke Electronics. (2024). *Soil NPK sensor: Principle and applications in agriculture*. https://www.renkeer.com/product/soil-npk-sensor/

Rivas-Sánchez, Y. A., Moreno-Pérez, M. F., & Roldán-Cañas, J. (2019). Environment control with low-cost microcontrollers and microprocessors: Application for green walls. *Sustainability, 11*(3), Article 782. https://doi.org/10.3390/su11030782

Rokhafrouz, M., Latifi, H., Abkar, A. A., Wojciechowski, T., Czechlowski, M., Naieni, A. S., Maghsoudi, Y., & Niedbała, G. (2021). Simplified and hybrid remote sensing-based delineation of management zones for nitrogen variable-rate application in wheat. *Agriculture, 11*(11), Article 1104. https://doi.org/10.3390/agriculture11111104

Saleem, M. F., Raza, A., Sabir, R. M., Safdar, M., Faheem, M., Al Ansari, M. S., & Hussain, S. (2024). Applications of sensors in precision agriculture for a sustainable future. In *Agriculture and aquaculture applications of biosensors and bioelectronics* (pp. 109-137). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-2069-3.ch0066

Sania, H., Fevria, R., Vauzia., & Razak, A. (2025). Effect of sensor and based NPK on the growth of Pakcoy (*Brassica rapa* L.) cultivation hydroponic. *Jurnal Biologi Tropis, 25*(1), 807-813. https://doi.org/10.29303/jbt.v25i1.8514

Sardans, J., & Peñuelas, J. (2021). Potassium control of plant functions: Ecological and agricultural implications. *Plants, 10*(2), Article 419. https://doi.org/10.3390/plants10020419

Shahab, H., Naeem, M., Iqbal, M., Aqeel, M., & Ullah, S. S. (2025). IoT-driven smart agricultural technology for real-time soil and crop optimisation. *Smart Agricultural Technology, 10*, Article 100847. https://doi.org/10.1016/j.atech.2025.100847

Singh, M., & Singh, K. (2026). Enhancing crop productivity and soil health through precision fertigation: Advancements, challenges and future prospects. *Applied Water Science, 16*, Article 130. https://doi.org/10.1007/s13201-026-02767-4

Singh, N. K., Singh, V., Harishankar, Panotra, N., Painkra, V. K., Sulochna, Manhas, S., Singh, S., Rajesh, G. M., & Singh, H. S. (2025). Next-generation nutrient management strategies for wheat: Enhancing productivity and soil quality. *Journal of Experimental Agriculture International, 47*(5), 525-541. https://doi.org/10.9734/jeai/2025/v47i53441

Sonowal, K., Borthakur, P. P., & Pathak, K. (2025). Advances in enzyme-based biosensors: emerging trends and applications. *Engineering Proceedings*, *106*(1), Article 5. https://doi.org/10.3390/engproc2025106005

Sood, T., Kapoor, S., Kaur, J., Hussain, N., & Sood, S. (2025). Fertigation: A paradigm shift in nutrient delivery for sustainable agriculture. *Agricultural nutrient pollution and climate change: Challenges and opportunities* (pp. 135-164). Springer. https://doi.org/10.1007/978-3-031-80912-5_5

Sudarmaji, A., Gunawan, B., Nugraha, F., Arini, N., & Mulyani, S. (2024). Smart soil moisture control based on IoT ESP-32 for horticulture cultivation in coastal area. *BIO Web of Conferences, 96*, Article 04001. https://doi.org/10.1051/bioconf/20249604001

Sulaeman, Y., Sutanto, E., Kasno, A., Sunandar, N., & Purwaningrahayu, R. D. (2024). Developing and testing a portable soil nutrient detector in irrigated and rainfed paddy soils from Java, Indonesia. *Computers, 13*(8), Article 209. https://doi.org/10.3390/computers13080209

Teach Me Micro. (2023, May 29). *Using an NPK sensor with Arduino*. https://www.teachmemicro.com/using-an-npk-sensor-with-arduino/

The Engineer. (2025, April 1). *Biodegradable sensors could boost crops and reduce e-waste*. https://www.theengineer.co.uk/content/news/biodegradable-sensors-could-boost-crops-and-reduce-e-waste

Thelkar, A. R., Jerusha, D., Babu, S. B. T., Ali, S., & Mahender, K. (2025). IoT-based monitoring systems for optimized crop yield management. *International Journal of Environmental Sciences*, *11*(4), 254-261. https://theaspd.com/index.php/ijes/article/view/2026

Tyagi, A. K., & Sreenath, N. (2021). Cyber physical systems: Analyses, challenges and possible solutions. *Internet of Things and Cyber-Physical Systems, 1*, 22-33. https://doi.org/10.1016/j.iotcps.2021.12.002

van Deursen, A. J. A. M., & Mossberger, K. (2018). Any thing for anyone? A new digital divide in internet-of-things skills. *Policy & Internet, 10*(2), 122-140. https://doi.org/10.1002/poi3.171

Vashishth, T. K., Sharma, V., Sharma, K. K., Chaudhary, S., Kumar, B., & Panwar, R. (2024). Integration of unmanned aerial vehicles (UAVs) and IoT for crop monitoring and spraying. In *Internet of Things applications and technology* (pp. 95-117). Auerbach Publications. https://doi.org/10.1201/9781003458401-7

Vullaganti, N., Ram, B. G., & Sun, X. (2025). Precision agriculture technologies for soil site-specific nutrient management: A comprehensive review. *Artificial Intelligence in Agriculture, 15*(2), 147-161. https://doi.org/10.1016/j.aiia.2025.02.001

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming: A review. *Agricultural Systems, 153*, 69-80. https://doi.org/10.1016/j.agsy.2017.01.023

Xu, Y., Zhou, P., Simon, T., & Cui, T. (2024). Ultra-sensitive nitrate-ion detection via transconductance-enhanced graphene ion-sensitive field-effect transistors. *Microsystems & Nanoengineering, 10*, Article 137. https://doi.org/10.1038/s41378-024-00768-4

Yadav, N., Garg, V. K., Chhillar, A. K., & Rana, J. S. (2023). Recent advances in nanotechnology for the improvement of conventional agricultural systems: A review. *Plant Nano Biology, 4*, Article 100032. https://doi.org/10.1016/j.plana.2023.100032

Zahedi, A., Liyanapathirana, R., & Thiyagarajan, K. (2024). Biodegradable and renewable antennas for green IoT sensors: A review. *IEEE Access, 12*, 189749-189775. https://doi.org/10.1109/ACCESS.2024.3515274

Zeptogreens. (2024, December 24). I*nnovative approaches to soil health monitoring with NPK sensors*. LinkedIn. https://www.linkedin.com/pulse/innovative-approaches-soil-health-monitoring-npk-3dnrc/

Zhang, C., & Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: A review. *Precision Agriculture, 13*(6), 693-712. https://doi.org/10.1007/s11119-012-9274-5