Pertanika J. Sci. & Technol. 34 (5): 2835 - 2885 (2026)

PERTANIKA JOURNALS

SCIENCE & TECHNOLOGY

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

Review Article

Wireless Sensor Network and Leveraging IoT on Agro Farming: A Review

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ABSTRACT

Precision agriculture is an integrated, sensor-fusion-based framework for agricultural management and monitoring, adaptable to both small-scale consumer plots and large-scale commercial farming operations. This paradigm addresses the multi-faceted limitations of traditional, labour-intensive farming practices by replacing them with continuous monitoring, closed-loop sensor networks, and advanced computing systems. Specifically, Wireless Sensor Networks (WSNs) have emerged as a prominent mechanism for real-time environmental measurement and data acquisition, enabling timely interventions. This review examines the adaptation of various wireless radio technologies and protocols designed to bridge the gap between qualitative human observation and quantitative plant metrics. Furthermore, multi-sensor applications and comparative analyses are discussed to highlight expanded sensing capabilities and their integration with actuation components. Recent advancements have further enhanced these platforms by incorporating cloud-edge computing within the Internet of Things (IoT) domain. The primary objective of this paper is to analyse WSN architectures, topology models, wireless connectivity choices, and real-world implementations, and to evaluate the potential of IoT to create borderless farm management systems. Finally, the integration of artificial intelligence (AI) into WSN-IoT automation is explored, offering scalable solutions to combat the complex challenges facing global food crop production and the global hunger index.

Keywords: Data-driven agriculture, edge computing, Internet-of-Things, precision farming, remote sensing, smart agriculture, wireless sensor network, ZigBee

ARTICLE INFO

Article history:
Received: 01 May 2026
Accepted: 22 September 2026
Published: 30 October 2026

DOI: https://doi.org/10.47836/pjst.34.5.13

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INTRODUCTION

Accelerated human population growth is driving rapid increases in global food demand despite diminishing resource availability. This pressure was further

e-ISSN: 2231-8526

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intensified by the COVID-19 pandemic, which disrupted not only global healthcare infrastructure and medical supply chains, but also critical agricultural networks. A 2020 survey reported pandemic-induced food insecurity, with approximately half of the countries surveyed experiencing partial or full-service interruptions in food-producing sectors. The COVID-19 pandemic disrupted all four pillars of food security: availability, access, utilisation, and stability through labour shortages, supply chain breakdowns, and export restrictions that threatened global food supplies (Ben Hassen & El Bilali, 2024; Kakaei et al., 2022; Laborde et al., 2020). After that, the situation has been worsened by countries involved in long-period war zones, for instance, the Russia-Ukraine war, as both countries are major global producers and exporters of food crops and fertilisers, compounding pandemic-era disruptions with new supply shocks (Ben Hassen & El Bilali, 2022; Kakaei et al., 2022).

Besides the previously mentioned factors, Earth's global warming is well known as a major threat to farming activities worldwide. It has significantly affected crop yields when normal climates and essential resources were disrupted. In addressing the existing global warming issue, studies have also reported that the widespread use of pesticides has led to pest resistance, damage to soil biodiversity, and increased environmental pollution. Moreover, the non-natural fertiliser substances in the farming process is likely to contribute to disastrous chemical pollution of soil, aquatic and air quality (Kumar & Ilango, 2018; Saccone & Vallino, 2025).

Food and Hunger

By observing figures closer to the current perspective, the Global Hunger Index (GHI), an annual peer-reviewed study that measures hunger levels on a scale, has reported that nearly 690 million people worldwide are underfed or starving. While 144 million children are suffering from undernutrition problems, 5.3 million of them passed away before reaching 5 years old in 2018 (von Grebmer et al., 2020). South Asia recorded the second-highest GHI score globally at 26.0, closely following Sub-Saharan Africa's score of 27.8. On the GHI severity scale in Figure 1, these scores fall within the 20.0-34.9 range, indicating a "serious" hunger situation. Additionally, the State of Food Security and Nutrition in the World 2021 report highlighted that the COVID-19 pandemic severely disrupted food supply chains and heightened economic uncertainty, exacerbating global malnutrition. However, this upward trend began years before the pandemic and has now impacted an additional 40 million people globally (von Grebmer et al., 2021)

Meanwhile, the impact of the pandemic has likely escalated food insecurity in Malaysia. Data from the Global Hunger Index (GHI) reveals that Malaysia ranked 59th (out of 107 countries) in 2020 and 58th (out of 116 countries) in 2021. With a consistent score of 12.8, the nation remains categorised at a 'moderate' severity level (von Grebmer

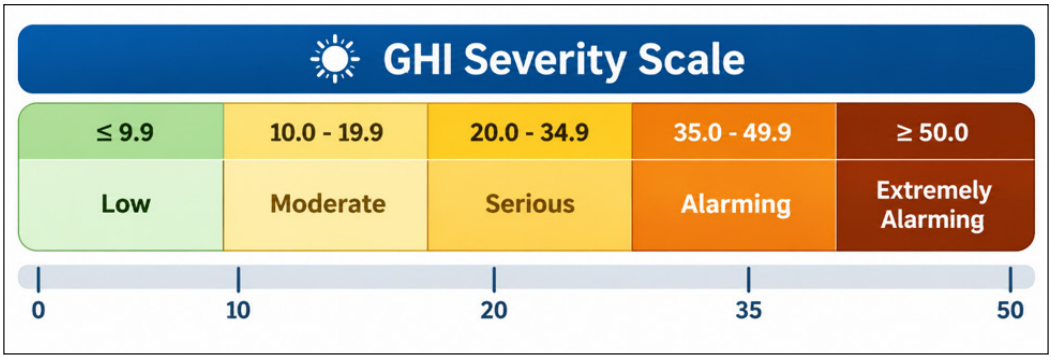
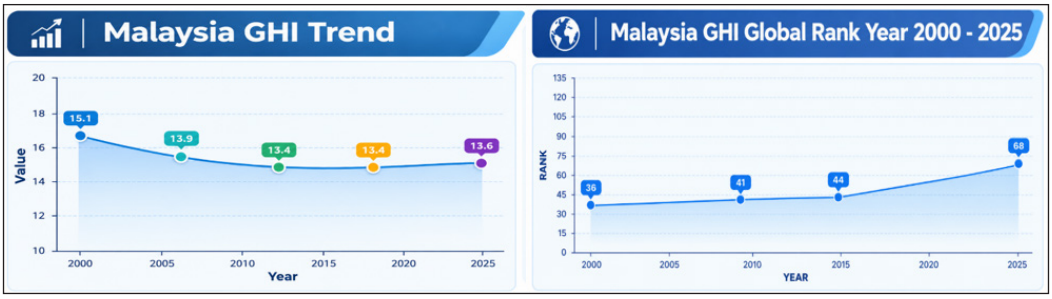


Figure 1. Global hunger index severity scale



(a) (b)

Figure 2(a) and (b). Malaysia's global trend among 136 countries in 2000, 2008, 2016, and 2025

et al., 2020; von Grebmer et al., 2021). As illustrated in Figure 2(a), the trends for GHI parameters show a steady line for undernourished in the Malaysian population, but the total GHI scores have increased by 3.22% from 2012 to 2021. Figure 2(b) indicates that our country's hunger level has increased relative to 2000, ranking 68th globally compared to 36th in 2000. Consequently, Malaysian food security frameworks and supply networks must respond proactively to any disruptions within agricultural supply chains. A pertinent example is the 2023 global rice shortage, which severely affected national food security, market pricing, and overall costs. This crisis was precipitated by geopolitical issues, severe climate change, crop diseases, and natural disasters (Shan, 2023). Additionally, these situations reduce the yields of staple food crops due to conventional plantation practices in Malaysia's farming sector.

Agro Farming, Precision Agriculture and Smart Farming

Unfortunately, there remains a lack of clear strategies for managing these complex farming issues at scale. Considering these emerging global challenges, researchers must develop advanced methodologies to increase the volume and quality of food production without

harming ecosystems. This can be achieved through precision agriculture solutions that leverage wireless platforms, such as Wireless Sensor Networks (WSN) and Internet of Things (IoT) technologies (Mendez et al., 2011; Shafi et al., 2019; Shamshiri et al., 2020).

In general, agriculture, precision farming and smart farming are related but not identical concepts. In the literature, agriculture is the science, practice, or discipline of cultivating plants and producing food, and some papers phrase it more broadly as the practice of growing plants or plant growth. Precision farming, also called precision agriculture in most papers, is a farm management approach that measures field, crop, or livestock conditions and uses spatial, temporal, or site-specific data to apply inputs more precisely for higher productivity, profitability, resource efficiency, and lower environmental impact. Smart farming is usually defined as a more digitally connected form of farming that uses IoT, sensors, software, cloud systems, AI, and real-time data to monitor, automate, analyse, and optimise farm operations and decisions (Abioye et al., 2021; Mowla et al., 2023).

This paper provides an overview of device-aided farming technologies and evaluates their potential to enhance crop yields, in alignment with the global 'Zero Hunger' strategy (SDG 2). Specifically, it highlights the significance of automated farming through WSN architectures that leverage IoT and Edge Computing, while offering a comprehensive review of the wireless communication protocols and sensors utilised in the precision agriculture domain. Finally, the subsequent section outlines the systematic review methodology employed for literature selection.

REVIEW METHODOLOGY

To ensure a comprehensive and refined synthesis of the existing literature on Wireless Sensor Networks (WSN) and the Internet of Things (IoT) in the smart agriculture landscape, this review was conducted following a structured literature mapping framework based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) reporting logic, adapted for a critical narrative-synthesis review rather than a full systematic meta-analysis. The process flow of this review is illustrated in Figure 3.

Electronic databases, including Scopus, Web of Science, and IEEE Xplore, were queried for publications up to early 2026. The search strings combined specific keywords relevant to the study's scope, including:

"Wireless Sensor Network" OR "WSN"

AND ("Internet of Things" OR "IoT" OR "Cloud Computing" OR "Edge Computing")

AND ("Precision Agriculture" OR "Smart Farming" OR "Agro Farming"). Articles were screened based on peer-reviewed journal or high-impact conference status, studies presenting valid hardware architectures or computational frameworks for agricultural

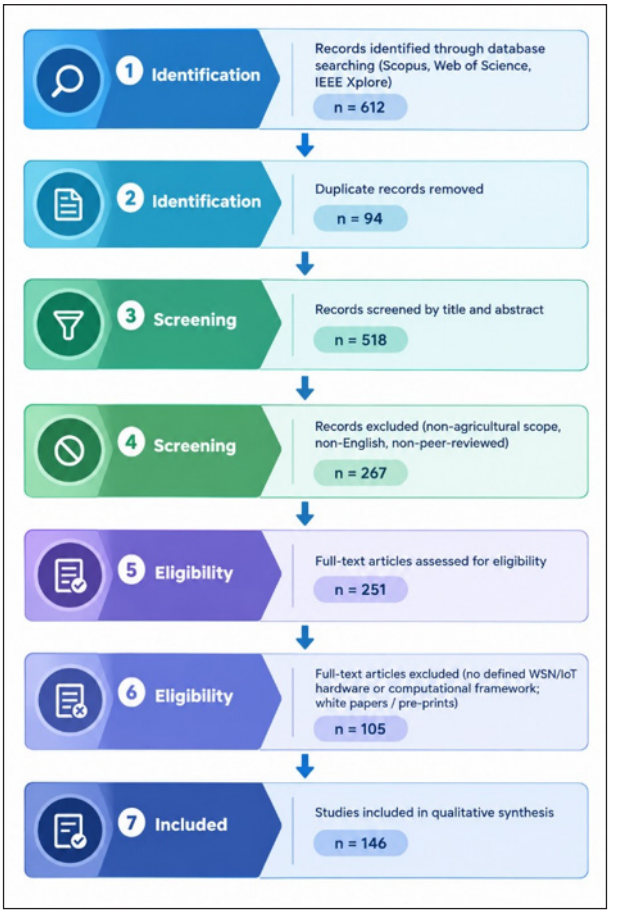


Figure 3. PRISMA-style study identification and selection flow diagram

commissioning, and all papers were required to be written in English. Most of the selected papers were published between 2019 and 2020, allowing the review to capture possible effects on food crop farming during the pandemic period, while fundamental and theoretical subjects were drawn from a wider range of publication years. Exclusion criteria eliminated non-peer-reviewed sources, white papers, pre-prints, and studies lacking a clearly defined agricultural application.

Study selection followed four stages: identification, screening, eligibility, and inclusion. An initial search across the three databases yielded 612 records. After removing 94 duplicate records, 518 titles and abstracts were screened against the scope defined above, of which 267 were excluded for falling outside the agricultural domain, being non-English, or not peer reviewed. The remaining 251 full-text articles were assessed for eligibility; 105 were further excluded for lacking a defined hardware architecture or computational framework, or for being white papers or preprints. This process yielded a final set of 146 studies retained

for qualitative synthesis, along with a smaller set of foundational and theoretical references used to frame core WSN/IoT/AI concepts.

WIRELESS SENSOR NETWORK (WSN)

Wireless Connectivity and Data Delivery in the Precision Agriculture Domain

Wireless connectivity has become a core component of modern precision agriculture, enabling real-time monitoring of soil moisture, temperature, crop health, and environmental conditions across geographically dispersed farm fields (Jawad et al., 2017; Mowla et al., 2023; Thakur et al., 2019). The transition from wired to wireless data transmission in agricultural settings has been driven by the need to reduce labour costs, simplify deployment across vast rural landscapes, and scale sensor networks to cover larger farm areas (Alahmad et al., 2023; Tang et al., 2024). Various wireless data technologies and cellular mobile networks, as shown in Table 1, will then be incorporated depending on range, frequency, bandwidth, speed, power consumption, portability, and internet capability of the platform (Buchli et al., 2012; Khanh et al., 2022; Meraj et al., 2015; Zulkifli & Noor, 2017). A diverse ecosystem of communication protocols, including LoRaWAN, Wi-Fi, ZigBee, NB-IoT, Sigfox, LTE, and emerging 5G technologies, now underpins the Internet of Farming (IoF), each offering distinct trade-offs in range, data rate, power consumption, and cost (Avşar & Mowla, 2022; Damsgaard et al., 2022; Singh & Sobti, 2021). The data transportation platform with internet connectivity is also defined as IoT-ready devices, which are the most precious assets in the food production domain, from raw farm substances to their final ready-to-consume stage. Therefore, the importance of this review is to emphasise the potential of wireless sensor networks and the Internet of Things (IoT) as targeted approaches for the supervision of the food and agricultural industries. ZigBee and LoRaWAN excel in private, low-power farm topologies; cellular LPWAN solutions such as NB-IoT and LTE-M eliminate the need for local gateway backhaul links by connecting agricultural

Table 1
Wireless cellular network generation comparison

Generation	Year	Technology	Frequency	Speed	Network	Features
1G	1981	AMPS	30Khz	2.4Kb/s	PSTN	voice only, analogue
2G	1999	GSM	900-1.8Ghz	64Kb/s	PSTN	voice, data, web
3G	2002	WCDMA	1.2-2Ghz	2Mb/s	Packet Network	voice, data, web, media, streaming
4G	2010	LTE	2-8Ghz	100Mb/s	Internet	voice, data, web, HD media, streaming
5G	2015	MIMO	3-30Ghz	>1Gb/s	Internet	voice, data, web, HD media, streaming, low power, higher speed

sensors directly to cellular towers (Baronti et al., 2007; Ertürk et al., 2019; Waseem et al., 2025). Hence, they are superior for highly distributed open-field setups despite cellular subscription fees.

The deployment of precision agriculture (PA) architecture has been reported to increase crop yields tremendously while conserving natural resources, reducing land exploration, deforestation, and pollutants (van der Goot et al., 2016). The definition of precision agriculture, or precision farming, is an integrated information and automation methodology aided by artificial intelligence and management systems. PA is used to monitor and manage crops efficiently by optimising planting input information, such as water quality, soil conditions, fertiliser, and climate, by analysing the outcomes of the process (Kloas et al., 2015; Yanes et al., 2020). Nowadays, the precision farming concept is still presumed to be a complex practice or costly, even though it has been implemented over the last few decades with several benefits (Glenn et al., 1998). PA monitoring of diversity can be extended in many ways, for example, by utilising geolocation data from the NAVSTAR Global Positioning System (GPS). It used to be supplementary and beneficial information for improving crop health or growing schemes by providing geographical data, soil mapping, weather forecasts, and information on natural disasters and other threats (Baseca et al., 2019; Buchli et al., 2012; Glenn et al., 1998).

For instance, Cambra et al. (2015) proposed a sprayer map using GPS geolocation data and drone video. The purpose of integrating GPS data into their system was to precisely spray the fluid solution onto the correct area while optimising herbicide and fertiliser usage (Cambra et al., 2015). While Glenn et al. (1998) reported in their studies there was an unknown variation that affected soybean and corn crop yields from a central Missouri farm in the United States from 1992 to 1994 (Glenn et al., 1998). After the investigation, the study successfully identified these factors by linking the GPS receiver to the Geographic Information System (GIS) on the yield maps to show the fractions of phosphorus, potassium, and pH in the soil test data (Glenn et al., 1998). These two data types precisely locate the soil organic profiles and the related treatments used to neutralise unbalanced fertilising, as shown in Figure 4. There are numerous manual methods for cultivating healthy crop practices. However, they require labour-intensive efforts, which is likely a burdensome factor in modern farming. Therefore, to make the agricultural domain smarter in processing, a rigorous method, such as a Wireless Sensor Network (WSN), is preferable. The following section discusses the WSN variants which can be used in the agricultural domain.

WSN Architecture

In the context of precision farming, an emerging solution known as Wireless Sensor Networks (WSN) has been deployed extensively in the agricultural sector (Kandris et al., 2020; Lata et al., 2019; Miskam et al., 2009). WSN is defined as a low-cost, low-powered,

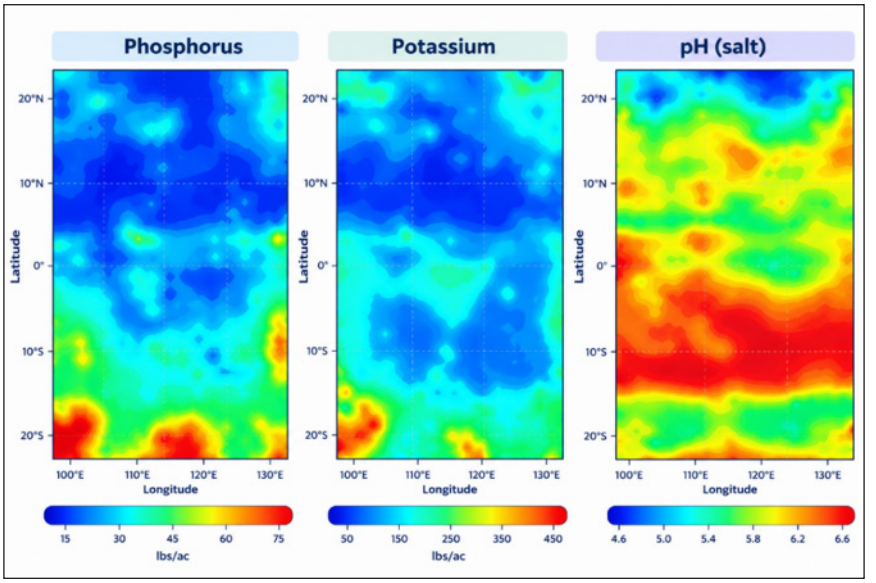


Figure 4. Fraction of soil test information map at Missouri farms reported by Glenn Davis
Source: Adapted from (Davis et al., 1998)

portable, or tiny sensing device technology, incorporating a proprietary radio protocol and communication standards, to perform self-networking via a Personal Area Network (PAN) with selectable topology patterns and a self-routing mechanism (Lata & Verma, 2022; Wang et al., 2006). WSNs generally comply with the IEEE 802.15.4 ZigBee standard, widely used for wireless data acquisition and self-monitoring in multi-sector applications since its inception (Baronti et al., 2007; Buratti et al., 2009). In the agricultural domain, it has been well-suited due to the offering of power-efficient, self-distributed networking, as well as solar-to-battery-operated capability (Iqbal Khan et al., 2022; Jawad et al., 2017). In the WSN ecosystem, groups of spatially dispersed sensor nodes can establish ad hoc, autonomous interconnectivity with one another using wireless radio frequency (RF) on a designated frequency band (Iqbal Khan et al., 2022; Kandris et al., 2020; Mowla et al., 2023). A sensor node, also known as a mote, is an integrated embedded system module consisting of a microprocessor, writable EEPROM data memory, an RF transceiver, and interface peripherals such as an analogue-to-digital converter (ADC). As illustrated in Figure 5(b), the node also incorporates one or more sensors alongside a portable DC power source (Miskam et al., 2009; Nasirudin et al., 2011).

Figure 6 summarises the WSN deployment to provide agricultural benefits. Basically, WSN nodes use on-board sensors to measure fluctuations in parameter conditions in the localised environment (Buratti et al., 2009; Prodanović et al., 2020). A dedicated transducer measures the target parameter, and the measurement signals are converted into relative electrical magnitudes before being sampled by an Analog-to-Digital Converter (ADC) and

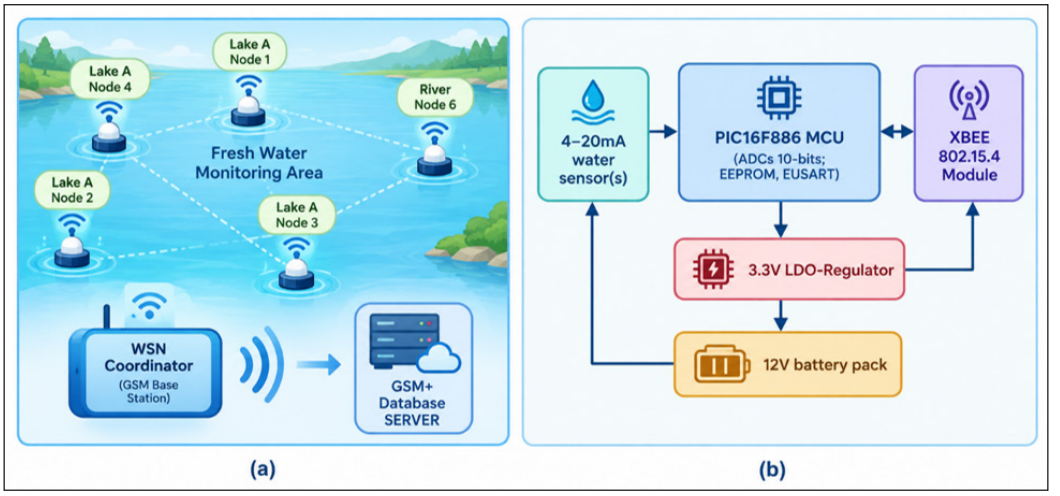


Figure 5. (a) WSN point-to-point and multi-point network topology with a GSM base station for lake water monitoring. (b) Wireless ZigBee sensor node architecture used in the (a) setup
Source Adapted from (Nasirudin et al., 2011)



Figure 6. Key features of WSN implementation in the agricultural domain

finally processed by the microprocessor. WSN networks can also optionally be equipped with a positioning sensor or a mobilisation unit, such as the Automatic Packet Reporting System (APRS) or the Global Positioning System (GPS) (Buchli et al., 2012). Additionally, the system can be integrated with a Global System for Mobile Communication (GSM) cellular module for extended-distance, point-to-point, and cross-border data uplinks and downlinks, as shown in Figure 5(a) (Wang et al., 2010; Zamora-Izquierdo et al., 2019).

Typically, WSN frameworks utilise multi-hop routing, allowing data to 'hop' between nodes, sharing an identical cluster or group ID as it propagates toward a designated drop-

off point, commonly referred to as the “Base Station”. This network topology and the seamless interconnectivity between mote devices enable the WSN to harvest low-data-rate, real-time environmental data across expansive agricultural areas, funnelling it directly to coordinators and gateway points (Jawad et al., 2017; Zamora-Izquierdo et al., 2019). Then, the local host server or computing devices at the base station will record and process the data packet accordingly. As illustrated in Figure 5(a), the Base Station can serve as a data logging point, perform supervisory control over the WSN motes concurrently, and transmit related information to the person in charge or to external networks. Furthermore, the WSN database server can sort crop information more precisely, including mote battery health, PAN IDs, on-board sensor types, raw data, and timestamps. Initially, before the emergence of IoT infrastructure, decision algorithms, such as fuzzy logic, were processed on the WSN's local server (Kishore et al., 2013; Navulur et al., 2017; Verma et al., 2013).

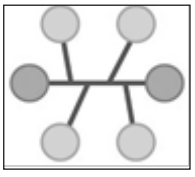
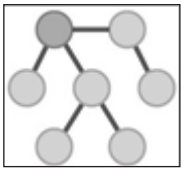
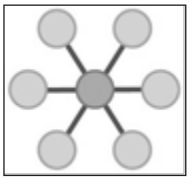
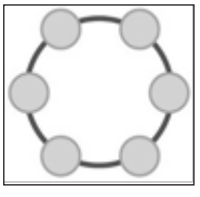
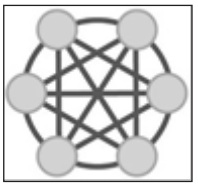
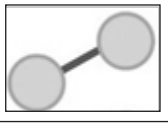
The management program on the server will analyse the incoming data, then execute the regulation command codes back into the network topology to the target node or send a notification alarm to the farmer via General Packet Radio Service (GPRS) ASCII text messages on the GSM network (Ghribi & Logrippo, 2000; Nasirudin et al., 2011). Thus, has brought limitations and less flexibility for heavier real-time processing or cross-border farm management due to GSM network limitations and fees. On the other hand, WSN characteristics have proven most beneficial for modern agricultural practices. In summary, WSN is highly scalable to accommodate small or huge network memberships with autonomous topology formation based on the node’s operability mode, energy saving or extended coverage (Ojha et al., 2015).

ZigBee is well-known as the finest WSN ‘asset’, a low-power, low-cost wireless networking standard built on top of the IEEE 802.15.4 physical (PHY) and medium access control (MAC) layers (Haque et al., 2022). Typically, a node requires very low power, typically 1 mW or less, enabling the battery to last for years. The standard provides a range of up to 150 meters outdoors using direct-sequence spread spectrum (DSSS). At the core hardware level, such as 0.18 μm CMOS transceivers, they consume approximately 14.7 mA in receive mode and 15.7 mA in transmit mode (Hullamani & T. N., 2021; Kluge et al., 2006). A ZigBee network can scale from a single mote device up to approximately 64,000 nodes (Ashok Somani, 2012). The ZigBee Alliance defines the upper network and application layers, whereas IEEE 802.15.4 specifies the lower hardware and radio transmission requirements (Paul & Singh, 2015). Furthermore, ZigBee networks possess self-healing and ad hoc capabilities, enabling them to establish robust connections even in highly complex routing configurations, such as distributed mesh topologies (Poole, 2004; The ZigBee Alliance, 2015). Additionally, WSN protocols and compliant devices are safeguarded by robust digital encryption standards, typically utilising at least 128-bit AES (Advanced Encryption Standard) security to ensure data integrity (Jawad et al., 2017). In such a report, ZigBee achieves low latency in direct, single-hop deployments

suitable for real-time field monitoring. A 12-hectare plantation deployment recorded a latency of 20-25 milliseconds (ms) with a 95% data transmission success rate (Gitakarma et al., 2025). Consequently, the system exhibits robust immunity against malicious attacks, thereby safeguarding sensitive data from specific agricultural zones and strategic food crops (Gitakarma et al., 2025; Hullamani & T. N., 2021; Mowla et al., 2023).

Furthermore, six types of network topologies are commonly implemented within WSN and IoT infrastructures, as outlined in Table 2 (Kishore et al., 2013; Verma et al., 2013).

Table 2
Summary of Wireless Sensor Network common topology patterns

Topology Name	Pattern	Description	Limitation
Bus		Single path & linear connectivity to nodes. Easy routing Moderate scalability	Performance drops with the number of nodes
Tree		Tree-Bus element networks. Parent-child hierarchy & best organised. Highest scalability, distance & flexibility	Lost 'child' nodes links risk if base/ server fails
Star		Centralised data sinking point. Single path routing. LAN computer network style	Lost all links risk if base/ server fails. Short distance
Ring		Two-way routing circular path. No server needed; data passes through all nodes. WAN computer network style	Broken link risk if one node fails. Slower than Star
Mesh		Highest data traffic. Multiple paths & simultaneous transmission. Robust against broken links	High complexity algorithm. Redundant connection. Costly
Point-to-Point		Conventional, simple topology & no server. Single channel routing path, long range, high speed, large data target	Low scalability to expand. Lost link risk if one node fails

The star topology features a single central sink node, which establishes a direct connection to the base station (Khan et al., 2022; Kishore et al., 2013). The primary strategy behind this formation is to minimise data forwarding delays, thereby reducing routing latency to the server (Baronti et al., 2007). In contrast, multi-sink or distributed configurations, such as a bus topology, can handle heavier data traffic, cover larger agricultural areas, and accommodate energy conservation strategies (Morais et al., 2008; Shafique et al., 2020). A hierarchical formation, such as a tree topology, can assign priorities to nodes based on their role or location in the network. Therefore, the system can efficiently administer the WSN network (Carlos-Mancilla et al., 2016; Osseiran et al., 2020). The fundamental design of a sensor node can be represented by the block diagram shown in Figure 7(a). An embedded logical processor, such as a microcontroller unit (MCU), will become the 'brain' part of each node.

Break it down to basics: commonly, a node is designed to perform on-board processing and computing, such as the conversion of analogue signals (voltage, resistance, and capacitance) into digital binary or hexadecimal (Miskam et al., 2009; Nasirudin et al., 2011). For instance, the Analogue-to-Digital Converter (ADC) module on the PIC16F886 microcontroller converts the analogue DC voltage signals from sensors into digital values. These input signals typically range from 0–5 Vdc or 0–3.3 Vdc. To consider a scenario where a sensor operates within an output voltage range of 0–3.3 V, Full $_{Scale\ Voltage\ Range}$ = 3.3. Then, given the ADC's largest scale on the MCU = 10 bits = (2^{10}) = 1024 -1 = 1023. Finally, 3.3/1023 = 0.0032 volts per 1 LSB. During reading, the measured sensor output voltage is 2.4 V; therefore, the conversion is (2.4 ÷ 0.0032 = 750), resulting in a digital decimal value of 750. This value is written to the MCU memory as 750 (dec), 1011101110

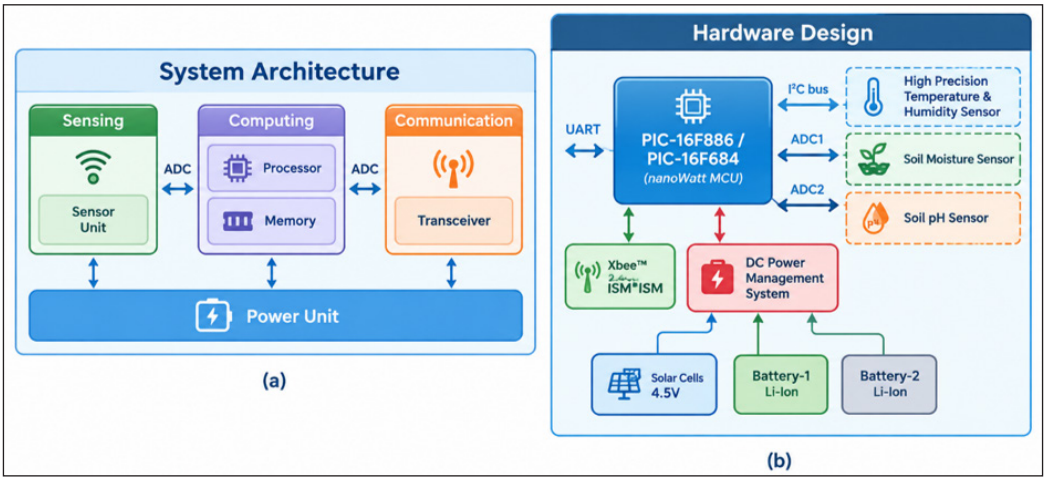


Figure 7. A typical sensor node architecture: (a) a sensor node specifically designed for paddy crop monitoring; (b) Hardware Design
Source Adapted from (Nasirudin et al., 2011)

(bin), or 0x2EE (hex). Figure 7(b) illustrates a sensor node driven by an 8-bit PIC16F684 microcontroller, featuring two ADC channels for analogue sensors (WQ101 and WL400) and one digital channel for the SHT75 temperature and humidity sensor. The proposed system utilises a bi-directional (full-duplex) UART serial interface on an XBee 2.4 GHz wireless transceiver to establish a tree-topology network configuration via Digi firmware (Miskam et al., 2009; Nasirudin et al., 2011).

Table 3 presents various wireless radio-frequency platforms and protocols, along with relevant parameters applicable to WSNs (Baronti et al., 2007; Effah et al., 2023; Wang et al., 2006). In a typical deployment, several device technologies support large-scale networks with high node counts. For instance, Sigfox can accommodate up to 1,000,000 devices per base station, while ZigBee supports up to 64,000 nodes per coordinator, and LoRaWAN

Table 3
Wireless radio technology general specification and comparable features

Wireless Technology	Standards	Frequency (MHz)	Data Rate	Physical Range (m) Typical	Topology/ Network	Key Features
ZigBee	IEEE 802.15.4	868/ 2400	250	100	Mesh/ LPAN	Low power, self-healing mesh, no direct internet IP
LoRaWAN	IEEE 802.15.4g	433/868/ 915	50	10000	Mesh/ LPWAN	ultra-low power, long range, high latency
MiWi	IEEE 802.15.4	2400	250	100	Mesh/ WPAN	low power, Microchip™ proprietary
6LoWPAN	IPv6 802.15.4	2400	250	100	Mesh/ WPAN	very low power, direct internet IP,
Bluetooth	IEEE 802.15.1	2400	1000	10	Point-to-point/ WPAN	very low power, limited range
SigFox	N/A (proprietary)	868/928	600	10000	Star/ LPWAN	ultra-low power, low cost & bandwidth, extreme range
WiFi	IEEE 802.11a, b,g,n	2400	150000	100	Point-to-point/ WLAN	very high power, large data, shorter range, less standalone
GPRS-GSM	N/A (cellular)	900 - 1800	190	35000	Point-to-point/ WAN	global roaming, SIM card to stand alone, power drain, paid data

Table 3 (*continued*)

Wireless Technology	Standards	Frequency (MHz)	Data Rate	Physical Range (m) Typical	Topology/ Network	Key Features
NB-IoT	N/A (cellular)	600 - 2200	160	5000	Star/ LPWAN	ultra-low power, extreme range, high latency, less portable
LTE-M	N/A (cellular)	700 - 2600	1000	10000	Star/ LPWAN	Ultra-low power, high mobility, low latency, power drain
4G-LTE	N/A (cellular)	600 - 3800	100000	8000	Star/ WWAN	High-speed data, low latency, high cost, power drain
5G	N/A (cellular)	600 - 4700	1000000	5000	Star-Mesh/ WWAN	ultra high-speed data, low latency, slice network, highest cost, infra complexity

handles roughly 10,000 nodes per gateway (Ashok Somani, 2012; Chi et al., 2014; Iqbal Khan et al., 2022). Conversely, traditional technologies such as classic Bluetooth, Wi-Fi, and GSM-GPS support significantly lower node capacities, accommodating only 8, 32, and 1,000 devices, respectively. Furthermore, analysis of manufacturer specifications indicates that in transmission mode, ZigBee draws the lowest power, at 36.9 mW, compared to 100 mW for LoRaWAN and 122 mW for Sigfox (Alqurashi et al., 2023; Ertürk et al., 2019; Jawad et al., 2017). Jawad et al. (2017) suggested XBee wireless transceiver modules, ZigBee protocol-compliant devices, have strong potential for deployment in farming zones due to their low duty cycle, low latency, long coverage, supported topologies, and low peak power consumption (Alqurashi et al., 2023; Lavric et al., 2019). While Zulkifli and Noor (2017) incorporate the Active Radio Frequency Identification (RFID into the WSN framework driven by ZigBee 2.4GHz hardware (Zulkifli & Noor, 2017).

In contrast to the ZigBee protocol, Wi-Fi technology is less feasible for field-deployed sensor nodes due to constraints regarding power consumption, network topology, and unoptimized data payloads (Ikpehai et al., 2019). While Sigfox, ZigBee, and LoRaWAN each trade off scalability, throughput, range, and deployment control differently. Sigfox for ultra-light wide-area sensing, ZigBee for local mesh networks, and LoRaWAN for flexible private or public LPWAN deployments (Mekki et al., 2019; Orlovs et al., 2025; Saqlain et al., 2025). In conclusion, WSN platforms have proven to be both resilient and reliable for deployment in open-field farming (Carlos-Mancilla et al., 2016; Gitakarma et al., 2025).

Agricultural Sensor Solution

Sensor technologies offer countless opportunities to optimise precision agriculture, transforming raw environmental data into actionable insights for sustainable crop management, as mentioned earlier. Table 4 outlines a selection of sensors utilised in precision agriculture, along with their respective capabilities (Ji et al., 2019; Shin et al., 2025). Several of the listed sensors are dedicated to the intensive measurement of soil quality parameters, while others capture ambient air quality metrics. Additionally, specialised sensors are included to evaluate crop leaf health. Typically, these sensors can be interfaced directly with the General-Purpose Input/Output (GPIO) pins of WSN nodes via standard analogue and digital communication protocols, including ADC, I2C, SPI, and UART (Chapungo & Postolache, 2021; Nasirudin et al., 2011).

Table 4
Multi-sensor types with key information and comparison implemented in the precision agriculture domain

Sensor Model	Functionality	Key Benefits	Limitations
A. Soil Moisture, Electrical Conductivity (EC) & Temperature Sensors			
ECHO 10HS	Soil moisture VWC (volumetric water content)	Analogue voltage output, large measurement volume, characterising a wider area	Does not measure Temp, sensitive to high-salinity soils, older legacy model
ECHO EA10	Soil moisture for low EC soils.	Analogue voltage output, low cost, good for standard – medium texture soils.	Very sensitive to changes in soil temperature & EC
ECHO EC5	Soil moisture (VWC).	Compact size great for small pots, greenhouse bags, or laboratory columns, low cost.	Smaller volume measurement; may miss dry/wet spots in soil, lower accuracy in high EC
5TE Sensor	Soil moisture, EC, temperature	All-in-one measurement, excellent for tracking fertiliser run-off & salinity alongside moisture.	Program design requires careful installation to avoid air gaps, which will heavily skew readings
Hydra probe 2	Soil moisture, EC, dielectric, temperature	Industrial-grade accuracy and durability, soil-specific calibration less dependent	High cost, bulky size, will disturb soil compound
MP406	Soil moisture, temperature	High-accuracy ADR (Amplitude Domain Reflectometry) technology, stable	Expensive, requires proprietary loggers, requires attentive calibration for peak accuracy
Pogo II	Soil moisture & temperature	Excellent portability, Wi-Fi/Bluetooth enabled, smartphone apps ready for rapid field surveys	Expensive, measures top surface layer only or dug hole

Table 4 (*continued*)

Sensor Model	Functionality	Key Benefits	Limitations
B. Heavy Metal, Gases, and Soil Quality Sensors			
GreenTag (RFID)	Soil moisture, temperature & heavy metals	Wireless, battery-free (passive RFID); sensors can be completely buried without cable	Short-range reads (requires reader to be very close); heavy metal detection via RFID is still experimental
MIKROE-1630	Gases (air quality)	Low-cost, easy plug-and-play integration with RPi/ Arduino hardware	Low precision, cross-sensitive to multiple gases (detects general mix, not specific isolated gases)
PXRF with VNIR	Soil properties, heavy metal	True laboratory-grade elemental analysis in the field & highly precise.	Extremely expensive; X-ray tools require radiation safety training & licensing to operate
NixPro Sensor	Soil colour analysis (Munsell)	Affordable soil colour standardisation; eliminates human visual inconsistency	Soil must be dried and ground for accuracy; does not measure nutrients
Portable Electrochemical System (PES)	On-site heavy metal	High sensitivity to specific metals, more affordable than portable XRF scanners.	Requires field sample preparation before testing (e.g., mixing soil with liquid buffers)
Arduino/ RPi-based Potentiostat	Heavy metal & integration	Electrochemistry basis, open-source, highly customizable, very low-cost to build	Not industrial grade, requires strong coding and electronics knowledge to build & calibrate
HMstat	Heavy metal (ADC/DAC)	Heavy metal analysis in a portable form factor	Research-grade/custom-built, lacks support of mainstream, commercial sensors
MG811	Carbon Dioxide (CO2) Sensor	Low to high concentrations of CO2, reliable measurement, low cost	Requires continuous heating element (draws high power/battery drain), needs frequent calibration
C. Leaf, Plant, and Photosynthesis Sensors			
BetaTherm 100K6A1B	Temperature	Incredibly low-cost, tiny, & fast response to temperature changes	Highly fragile, requires a custom voltage-divider circuit, and coding equation conversion from Ohms to Celsius.
ΔLA-C	Leaf-to-air temperature	Highly specialised & precise for thin-needle plants, e.g., Conifers	Extremely delicate setup, not useful for broad-leaf crops
LW100	Plant moisture	Durable, easy to mount in agricultural canopies	Requires calibration, angle adjustments on specific crop leaf

Table 4 (*continued*)

Sensor Model	Functionality	Key Benefits	Limitations
LT-2 M, LT-1P	Leaf temperature	Sub-miniature design, non-destructive, continuous monitoring of a single leaf	Physically clamping potentially can alter the leaf's natural microclimate
CI-340 System	Comprehensive photosynthesis/gas exchange	Portable, all-in-one field laboratory for plant physiology, highly comprehensive data	Expensive, requires regular calibration of gas chambers, steep learning curve
RTH-11, RTH-48	Leaf temperature & humidity/wetness	Great for general automated greenhouse climate control	General-purpose accuracy
FI-LP, MP, SP	Fruit growth sensors (Dendrometers).	Allows continuous, non-destructive monitoring of fruit swelling/shrinking (water stress)	Specific models for specific fruit sizes; mounting is prone to scarring the fruit
D. Light Sensors			
BH1750FVI	Light intensity (Lux)	Very low-cost, I2C digital output, stable reading	Saturates easily in direct, bright sunlight, measures human visible spectrum (Lux)
HOBO S-LIA-M003	Photosynthetic Light (PAR) Photosynthetically Active Radiation	High accuracy, measures exact wavelengths of light that plants use for photosynthesis	Proprietary systems (HOBO), costly

One of the sensing examples is yield sensors, which are typically integrated into harvesting machinery to automatically log production data. For instance, grain systems utilise mass flow sensors to record grain inflow alongside the vehicle's real-time geographic position (Kumhálová & Matějková, 2017; Liu & Li, 2017). Yield monitoring facilitates long-term strategic decision-making in precision agriculture. At the conclusion of the growing season, this method is used to map the spatial distribution of crop yields (Leng & Huang, 2017; Mekonnen et al., 2020). Subsequently, Geographic Information System (GIS) software, such as ArcInfo, MapInfo, and ESRI platforms, is employed to analyse the collected spatial data (Vuran et al., 2018).

Electrical conductivity (EC) sensors are employed to visualise crop yield and field topography. Electrical conductivity is a measurement of the ability of soil to conduct current. The EC method is used to measure phosphorus and cation concentrations in water, as well as the depths of the drainage system and the roots (Navulur et al., 2017). The EC maps are used to divide the area into zones. Variable irrigation rates, variable seeding rates, and drainage management can all be incorporated into the zoning. The apparent Electrical

Conductivity (ECa) and Visible Near Infrared Reflectance (VNIR) can be used to map EC using Electromagnetic Induction (EMI) methods (VNIR) (Hassan Hayatu et al., 2020). Commercial tools, such as the Veris 3100 and EC400 sensors and GPS systems, are readily available (Navulur et al., 2017; Vuran et al., 2018).

Nitrogen, potassium, and phosphorus are macronutrients critical to crop growth in soil. Fertiliser applications can be evaluated by analysing these nutrients and their potential effects. Reflectance spectroscopy is used to measure the macro-nutrients' reflection and absorption properties using optical detection (Dong et al., 2013; Research & Markets, 2020). Nitrate and sulphate concentrations in natural water sources can be detected using planar electromagnetic sensors (Aleksandrova, 2018). The impedance of the sensor array is correlated with nitrate and sulphate concentrations, enabling measurement of their levels. Micronutrients in the soil can be studied using electrochemical, VIS-NIRS, and ATR techniques (Luce et al., 2017). Because these methods use a membrane that reacts to only one ion, they can detect only one ion among soil macronutrients (Hassan Hayatu et al., 2020). It is necessary to build a detector array for soil macronutrient sensing to achieve simultaneous detection of multiple ions (Ji et al., 2019).

Contemporary Wireless IoT Solutions

A contemporary discussion of wireless communication has included NB-IoT, LTE-M, 5G, and private 5G networks because they address different IoT requirements rather than replacing one another with a single universal option (Osseiran et al., 2020; Vaezi et al., 2022). Across the literature, the main selection axes are coverage, power, device density, latency, mobility, and deployment control (Moges et al., 2023). Technology roles: NB-IoT is a 3GPP LPWA cellular technology introduced in LTE Release 13, purposely for IoT connectivity. It was designed for wide-area IoT connectivity with low device complexity, long battery life, massive device support, and extended coverage, while reusing much of LTE to speed deployment and product development (Akpakwu et al., 2018; Xu et al., 2018). It is commonly positioned for applications such as asset tracking, smart buildings, smart cities, and environmental monitoring (Akpakwu et al., 2018; Waseem et al., 2025). LTE-M is another 3GPP cellular IoT option that, unlike NB-IoT, is used when applications need more bandwidth and higher data rates while still fitting the mobile IoT category (Routray & Mohanty, 2024).

Recent reviews treat LTE-M, NB-IoT, EC-GSM-IoT, and NR-RedCap as the major standardised CIoT family, reflecting a portfolio approach rather than a winner-take-all architecture (Moges et al., 2023). 5G is framed as the broader wireless platform that targets massive connectivity, low latency, reliability, and higher spectral efficiency beyond what earlier generations were optimised to provide (Shafique et al., 2020; Sufyan et al., 2023). The literature consistently describes 5G as supporting three broad service classes,

including eMBB and mMTC, and as an enabler for demanding IoT domains such as industrial automation, smart cities, and remote surgery (Osseiran et al., 2020; Vaezi et al., 2022). Table 5 shows a brief comparison of contemporary IoT wireless technology and deployment contexts (Routray & Mohanty, 2024; Sufyan et al., 2023; Vaezi et al., 2022; Wen et al., 2022). NB-IoT remains important in the 5G-era IoT, but its mechanisms still need improvement to ensure seamless coexistence with 5G NR (New Radio standard) (Gbadamosi et al., 2020). Security and energy efficiency are recurring cross-technology constraints across 5G IoT communication systems (Khanh et al., 2022).

Table 5
Comparison of contemporary IoT wireless technology and deployments

Technology	Ideal Event	Core Strength	Main Limitation
NB-IoT	Static, low-data sensors	Low power & deep coverage	Limited data rate, evolving 5G coexistence challenges
LTE-M	Higher-rate mobile IoT	More bandwidth than NB-IoT	Higher resource & power use than narrowband LPWA
Public 5G	Mixed consumer and IoT workloads	Low latency, scale, and QoS ambitions	Capacity & resource pressure in dense advanced use cases
Private 5G	Enterprise and industrial sites	Dedicated control, customised security, local optimisation	Deployment, slicing, TSN & interference design complexity

Leveraging the Internet of Things

With respect to the economic aspect, the smart agriculture market revenue was projected to reach USD 6.5 billion by Q4 of 2021, indicating a greater impact of COVID-19 than in 2020, when it was USD 5.6 billion (Research & Markets, 2020). The increasing demand for food crop products, however, has not been matched by farmers' capabilities and facilities to fulfil the requirements of the digital market. Therefore, enhancements are required in terms of portability and ease of use to deploy the IoT infrastructure into the farmer's daily practices. Fundamentally, smart IoT crop farm management can also be summarised as shown in Figure 8, coexisting with a conventional WSN architecture, but with the difference of internet-cloud-based or edge-computing interoperability. Initially, some smart farming architectures relied solely on IEEE 802.11 network protocol devices to acquire sensor data and to actuate sprinklers for irrigation using a fuzzy logic control algorithm (Ramli et al., 2020). For instance, Akhtar et al. (2021) proposed a model incorporating Edge Computing in IoT and farm-field distributed wireless sensors for soil heavy-metal detection, assessment, and monitoring. Translating raw sensor data into implementable insights for farmers using artificial intelligence and big data analytics models. Another smart solution, called the Internet of Underground Things, is to bury sensors underground to penetrate the soil layer and maintain network communication on the ground (Dong et al., 2013; Vuran et al., 2018).

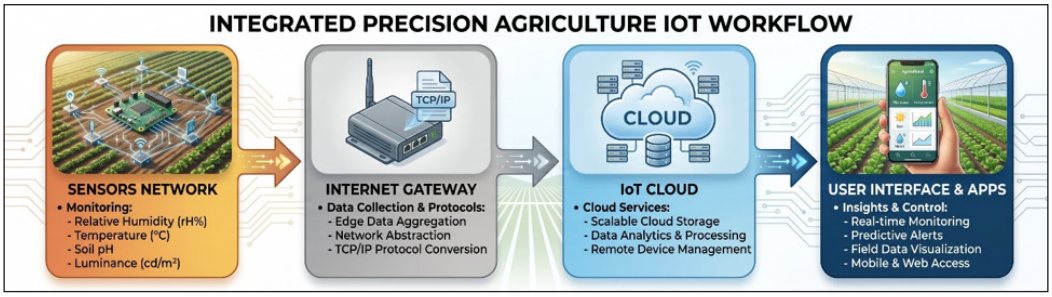


Figure 8. The Internet-of-Things (IoT) block system overview for smart farming and agriculture applications

To date, the deployment of WSNs with Internet of Things (IoT) frameworks has transformed the agricultural sector into a smarter, more intelligent production process, even in remote areas with reduced human intervention (Aleksandrova, 2018; Zamin et al., 2019). The integration of IoT with other electronic platforms has become an emerging approach due to its flexibility in enabling real-time monitoring, smart decision-making, and automation via remote devices from remote locations (Farooq et al., 2019; Ramli et al., 2020). By observing the architecture stacks, the Wireless Sensor Network (WSN) is homogeneously integrated with the IoT framework, which is the keystone for deriving a fully automated process known as the smart farming model (Gitakarma et al., 2025; Zulkifli & Noor, 2017). This model will provide a comprehensive ecosystem for WSN devices operating 24 hours a day, 7 days a week, on cloud-IoT-based Artificial Intelligence (AI), thereby autonomously administering crop fields or potting areas from anywhere across the globe. The sensor node is designed to periodically stream the recorded plant information and related data to the device coordinator (sink point) of each cluster, thereby bridging them to the terminal endpoint, which is known as the base station. The base station telemetry is either integrated with an on-site internet data server or uplinked to a remote server via a TCP/IP gateway to complete the IoT system routing. The system will then actively uplink and downlink streaming to IoT cloud computing for global remote access, automation processes, and supervision (Shafi et al., 2019). With larger integrated datasets coming through IoT platforms in agriculture, AI algorithms will perform optimal optimisation for farmers to smartly manage their crops using more sophisticated techniques compared to conventional methods (Gluhak et al., 2011).

The integration of machine learning significantly enhances agricultural productivity, as intelligent algorithms process and analyse massive streams of incoming data for both model training and real-time inference. Consequently, these systems enable autonomous management of various aspects of crop production, including disease detection, optimal harvest scheduling, automated planting, precision weeding, and environmental forecasting (Mekonnen et al., 2020). Notably, WSN and IoT technologies operate synergistically; sensor networks deployed across the field aggregate and bridge real-time data to an internet

gateway, allowing cloud-based algorithms to execute responsive IoT commands and AI-driven tasks.

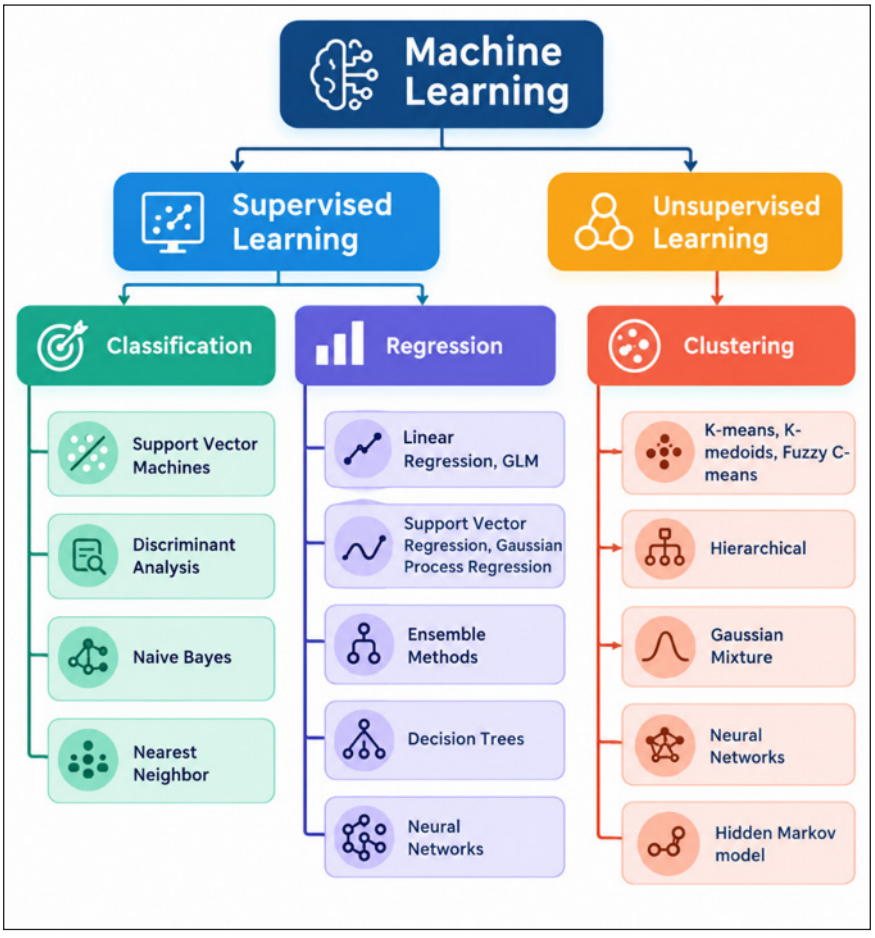


Figure 9. Machine learning classification and elements overview
Source: Adapted from (Shiksha, 2023)

Figure 9 shows the outline of the artificial intelligence method driven by machine learning (ML), which is divided into supervised and unsupervised learning (Mekonnen et al., 2020). Predictive elements of an unsupervised model, such as K-means, use clustering on a spread data set to identify distinct features or attributes in the farming field or crops. For instance, Hassan Ibrahim Hayatu et al. (2020) used the K-means clustering algorithm to study soil fertility across different regions in Nigeria. Therefore, such results will assist farmers in determining suitable crops to be planted in the targeted area with different soil nutrient attributes (Hassan Hayatu et al., 2020). Another IoT approach by Mekonnen et al. (2020) integrated WSN and ML into the system to monitor the smart farm prototype, as

illustrated in Figure 11 (Mekonnen et al., 2020). Figure 10 shows the clustering technique and prediction for the data set belonging to the domain (Hassan Hayatu et al., 2020; Sharma, 2024). Table 6 shows the number of Machine Learning (ML) algorithms in smart agriculture practice (Mekonnen et al., 2020).

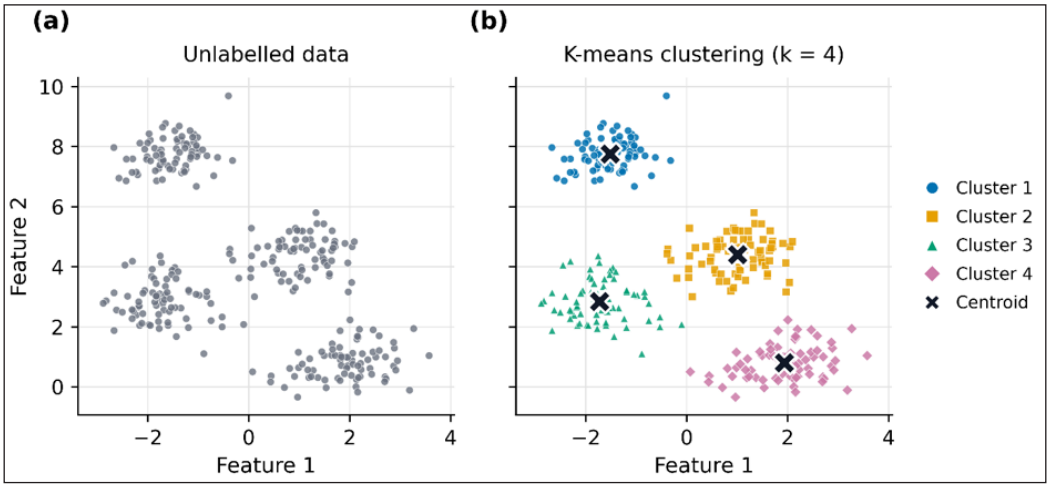


Figure 10. (a) Visualising the dataset. (a) K-means estimator methods calculate the number of clusters and the centroid to determine the soil fertility region (Shiksha, 2023)

Most of the electronic platforms are based on WSN ZigBee protocols, connected to various sensors, and supported by IoT frameworks. Finally, agricultural WSN-IoT is best organised as a layered cyber-physical stack linking field sensing, wireless communication, edge or cloud computation, and application intelligence, with consensus that WSNs remain the core data-acquisition layer and IoT extends them to remote control, analytics, and automation (Effah et al., 2023; Friha et al., 2021; Montalvo et al., 2025). Table 8 compares application architectures in agricultural WSN-IoT systems.

Table 6
Summary of Machine Learning method in Smart Agriculture implementation

Algorithms	Approach	Application	Data Acquisition
Extreme Learning Machine and Kernel-based ELM	Compares the approach with back-propagation (BP), SVM and Elman through simulations	To predict temperature and humidity in a greenhouse environment	ZigBee WSN-based
Fuzzy Logic	Fuzzy rules are used to predict the climate using temperature and humidity; the predicted climate and soil pH from the sensor are concurrently used to predict the crop to be grown	To predict the type of crop to be grown using sensor data from soil pH, temperature, and humidity. Critical information about the field is sent to farmers' mobiles using GSM	GSM and GPS WSN-based

Table 6 (*continued*)

Algorithms	Approach	Application	Data Acquisition
ARIMA	A WSN-based system called "Agri-prediction" was used to collect air temperature, soil temperature, air humidity, soil humidity and luminosity. ARIMA model was implemented to predict sensor data. ARIMA model was compared with ANN and RF, where the former model outperformed the others by producing the lowest MAE	To anticipate crop dysfunction proactively, farmers are then notified with possible remedies through smartphones. The model was tested in greenhouse Arugula cultivation, with gains associated with leaf development and weight	LoRa WSN-based
Data mining techniques, linear regression, and Apriori algorithm	Association rules are applied for data mining to find relationships among temperature, humidity, soil moisture, and yields of lemon and vegetables. Implemented linear regression to model the relationship between inputs	To analyse the sensor data for predicting suitable temperature, humidity, and soil moisture of crops in the future	WSN-based
Naive Bayes Kernel Algorithm	Real-time sensor data have been used to understand and quantify hidden correlations; pest/disease, humidity, temperature, pressure, pH value, nitrogen, soil moisture, and soil temperature are used	In forecasting and detecting pest/disease accurately using historical and real-time sensor data to monitor crop quality	ZigBee WSN-based
Bayesian Statistics	Sensor and weather data used to forecast changes and overall crop quality, image processing for weed extraction	A cloud-based decision support system uses the best algorithm to optimise events based on sensor data, scheduling irrigation based on moisture content sensors and weather forecast	WIFI and MQTT sensor-based with Raspberry Pi and Arduino MCU
Neural networks & Multi-Layer Perceptron (MLP)	MLP& neural network models are used to train on input sensor data to decide land cultivation in terms of four decision classes	For the assessment of agricultural land suitability	WSN-based

Smart Farming as Modern-Day Agriculture

Smart devices have infiltrated all aspects of our daily lives, including healthcare and wellness, smart homes, automobiles and logistics, intelligent cities and industries, thanks to the Internet of Things (IoT). Farming has undergone a series of technological transformations in the last few decades, becoming increasingly industrialised and

technologically oriented. Modern farmers can better manage their livestock and crops by using a variety of agricultural smart devices, making their operations more predictable and productive (Aleksandrova, 2018). As a result, there has been an increase in the use of intelligent agriculture technologies around the globe. It's worth noting that IoT's agricultural market share is expected to reach $5.6 billion, according to Research and Markets (2020).

Now it is possible to implement advanced tools and a variety of methodologies with reasonable costs for agricultural IoT devices, as predicted by BI Intelligence since 2020. The AgriTech system, for example, is an integrated application technology developed to benefit farming processes (Ilie, 2018). The terms “intelligent farming” and “smart agriculture” also generally refer to IoT-based solutions for autonomous data collection, such as wireless sensor network nodes and self-constructed topologies. Farmers can be informed by the system application, make decisions, and develop various parameters for their fieldwork, such as livestock production and the collection of environmental and machine metrics. By utilising smart agricultural sensors to monitor crop status, farmers can determine exactly how much pesticide and fertiliser to use to optimise productivity. The same can be said for the idea of practising intelligent agriculture. Figure 11 represents a model of smart agriculture incorporating WSN-IoT and Cloud or Edge Computing concepts for agriculture-centric applications, equipped with WSN infrastructure in the farm field. Figure 12 represents an emerging farming model by integrating the orbital

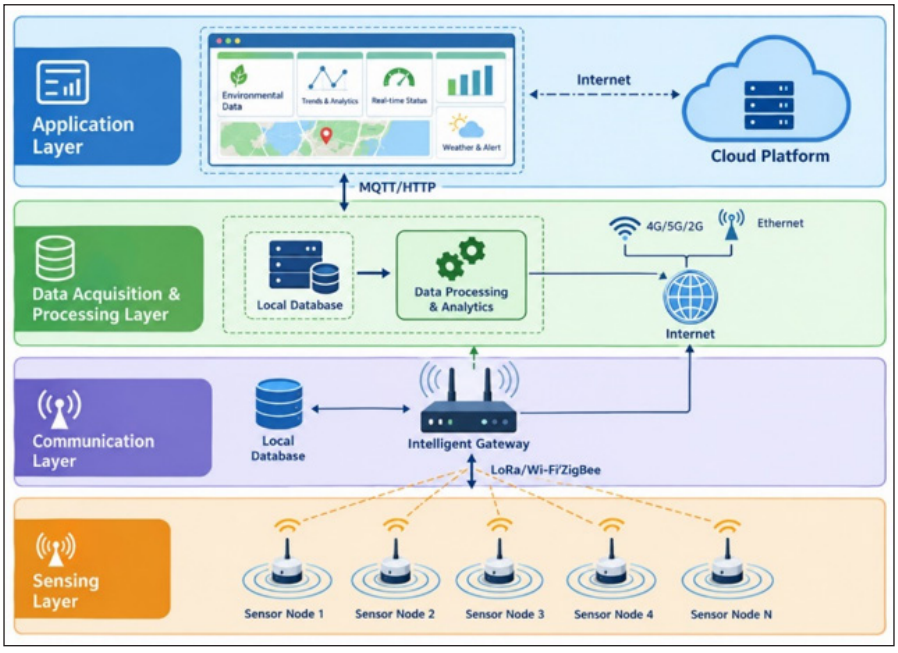


Figure 11. WSN-IoT and Cloud Edge Computing concept for the agriculture domain application

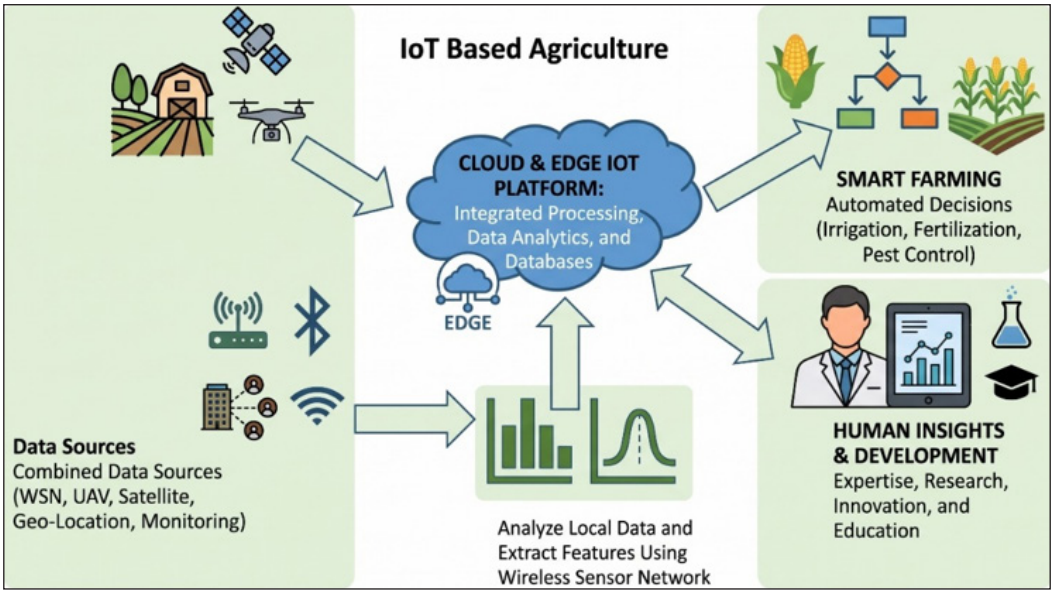


Figure 12. WSN-IoT and Cloud Edge Computing concept for the agriculture domain application

satellite uplink-downlink communication trajectory from sky to the ground for precision spatial data management (Mekonnen et al., 2020). In this model, various ground sensors are distributed over a larger area, with data storage, real-time processing, analysis, and automation handled by cloud computing. This allows farmers to make the most informed decisions possible.

Advanced sensors and intelligent cameras will precisely assist farmers in monitoring crop growth, periodic fertilisation, and setting threshold alarms until the ideal harvesting date. As developed by Deepfield Labs (Kushwaha et al., 2016), the Bonirob can analyse soil pH and phosphorus levels in real time by liquidising a soil sample. It is expected to automate the growth and harvest of entire hectares of barley. Another method, called SIM farming, involves farmers receiving a warning on their computers when an area has been disturbed. Additionally, tool developers such as Aerobotics have already commercialised software that analyses infrared drone imagery to detect areas of unhealthy vegetation (Human, 2018). Their software can identify unhealthy vegetation using images captured by a drone. The system is also capable of distinguishing between crop varieties and unwanted weeds on the farm, and it is continuously improved by the machine learning (ML) algorithm. Another approach is utilising Micro Aerial Vehicles (MAVs) and piloted light aircraft fitted with multispectral cameras for data-acquisition missions. They were flying over large farm areas in various locations nationwide (Gago et al., 2020). For smart-assist crop monitoring, Planet Labs provides CubeSat satellites that capture weekly photographs of entire farms from space (Kimm et al., 2020).

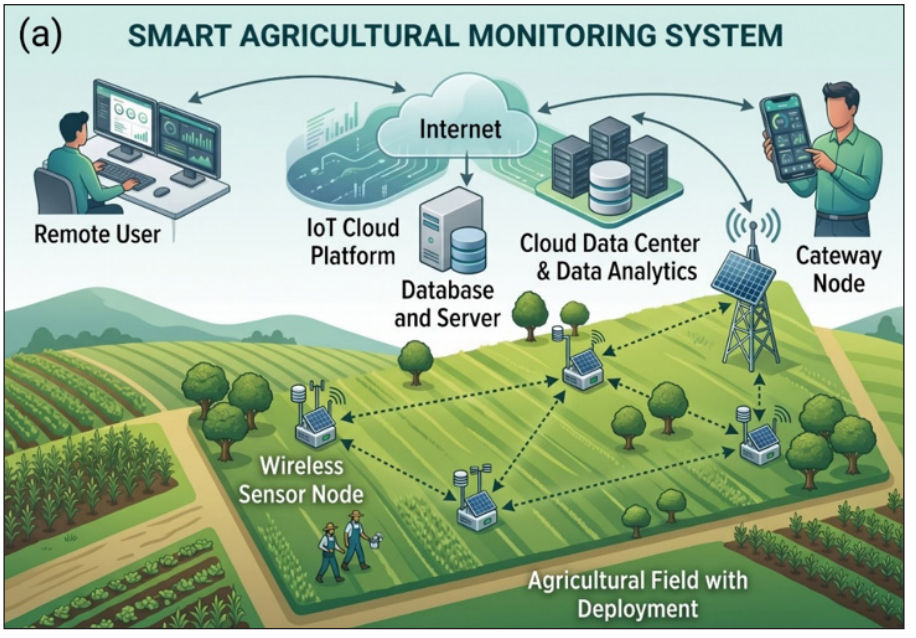
Challenges in IoT-Farming

The Internet of Things (IoT) enables living and non-living objects to have unique identifiers and to autonomously transmit data over the internet without human-to-computer interaction (Gluhak et al., 2011). According to a 2015 report by Juniper Research, more than 13.4 billion devices were connected to the Internet of Things (IoT) globally. The study projected substantial growth over the following years, forecasting that the ecosystem would expand to 38.5 billion connected devices by 2020 (Sto ces et al., 2016). Currently, the Internet of Things (IoT) is rapidly expanding into nearly every sector of modern society (Vermesan & Friess, 2013). Its primary domains encompass smart healthcare, smart cities, industrial automation, autonomous vehicles, smart homes, and precision agriculture (Suresh et al., 2014). To realise a fully interconnected IoT ecosystem, widespread internet connectivity across both residential and commercial sectors is imperative. This infrastructural demand has risen steadily, mirroring the growth in global internet penetration, which reached 73.8% in 2026, up from 42.8% in 2016 (Statista Research Department, 2026).

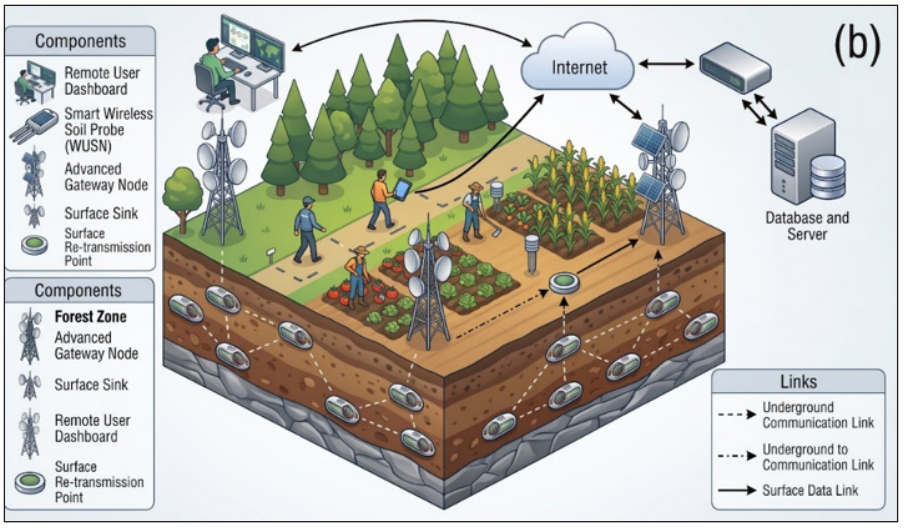
While Internet of Things (IoT) devices have significantly increased the demand for internet services, infrastructure growth could be restricted. This is largely because Internet Service Providers (ISPs) in major countries worldwide are still mostly in an exploratory phase regarding large-scale deployment (Jazayeri et al., 2015). IoT has been actively incorporated into the European Digital Agenda since 2016 (Osseiran et al., 2020). It is a key pillar of Horizon 2020, the European framework for research and innovation, and was backed by targeted European Commission funding windows between 2016 and 2017 (Cambra et al., 2015). Additionally, the European Commission established the Alliance for Internet of Things Innovation (AIOTI) in March 2015. This alliance was designed to facilitate deep cooperation on IoT standardisation and market development, connecting the EU Commission directly with key tech sectors and stakeholders (Kloas et al., 2015; Sto ces et al., 2016).

Currently, platform and communication protocol fragmentation represents a critical challenge, directly contributing to interoperability issues across diverse Internet of Things (IoT) devices and their respective ecosystems (Burhan et al., 2018; Gyory & Chuah, 2017). In precision agriculture, this challenge is intensified by a market dominated by proprietary systems, which severely hinders seamless data exchange and connectivity across different farming equipment (Ahmad, 2014).

Despite these interoperability barriers, comprehensive agricultural telemetry inherently depends on diverse of sensing topologies. As highlighted by Ojha et al. (2015), effective crop monitoring requires integrating two distinct networking layers into the IoT framework: terrestrial and underground WSNs. The structural and topological differences between these two deployment models are illustrated in Figure 13, showing (a) a conventional Terrestrial Wireless Sensor Network (TWSN) and (b) a Wireless Underground Sensor Network (WUSN).



(a)



(b)

Figure 13. (a) Terrestrial Wireless Sensor Networks (TWSNs) model. (b) Wireless Underground Sensor Networks (WUSNs) model (Ojha et al., 2015)

Conventional Terrestrial Wireless Sensor Networks (TWSNs) rely on over-the-air transmission to monitor ambient and canopy conditions. In contrast Wireless Underground Sensor Networks (WUSNs) deploy sensing nodes underneath the soil surface to assess

plants root-zone variables. In a typical WUSN topology, buried nodes transmit telemetry to an above-ground farm gateway via underground-to-aboveground links, after which the data is forwarded to remote servers via internet-enabled gateways. Nevertheless, subterranean communication encounters substantial radio frequency attenuation, where signal degradation within the dielectric soil medium, significantly decreases effective distance relative to the atmosphere-space terrestrial links (Ojha et al., 2015).

Role of Edge Computing and Smart Sensing

WSN (Wireless Sensor Networks), IoT (Internet of Things), Edge Computing, and Cloud Computing are not competing concepts; they represent different layers of a modern, distributed data ecosystem. WSN and IoT are the data generators (the eyes and ears), while Edge and Cloud computing are the data processors (the brain and muscle) (Zamora-Izquierdo et al., 2019). Returning to the agricultural context, Edge computing offers a promising solution for smart agriculture, enhancing real-time analysis and decision-making, and reducing network bandwidth constraints compared to native cloud processing (Gong et al., 2025; Santhosh et al., 2025). Cloud-Edge-Device collaborative computing in agriculture enables distributed intelligence, real-time processing, and adaptive decision-making to improve food security and resource management (Gong et al., 2025). For example, by implementing smart sensing and edge computing, the system will improve soil assessment and heavy metal monitoring in real time, thereby significantly benefiting a country's food farming industry on a large scale (Akhtar et al., 2021; Nguyen et al., 2024). Although numerous smart sensing systems are being developed, their implementation in developing countries remains challenging due to a lack of high-speed internet infrastructure. One viable solution to this problem could be edge computing, in which essential data is offloaded from the cloud to the cloud's edge, and this is where the smart sensing with edge computing paradigm comes in (Lytos et al., 2020). In Table 7, a comparison of features of Edge and Cloud computing in the WSN-IoT domain is presented.

Table 7
A Direct Comparison of Edge and Cloud computing in WSN-IoT application

Feature	Edge Computing	Cloud Computing
Location	Physically close to the WSN/IoT devices	Remote, centralized data centres
Latency	Extremely low (milliseconds), near real-time	Higher (hundreds of milliseconds), dependent on web server speed
Bandwidth	Conserves bandwidth by filtering data locally	High bandwidth consumption to transfer raw data
Processing Power	Limited - optimized for filtering, alerts, basic AI	Massive - optimized for Big Data, ML training, deep storage

Table 7 (*continued*)

Feature	Edge Computing	Cloud Computing
Offline Operation	Can function autonomously without internet connection	Completely internet access dependence
Data Privacy	Data can be anonymized locally, reduce transit exposure to data	Data must travel over the web, but benefits by top-tier security

APPLICATION DOMAINS IN SMART AGRICULTURE

Recent progress in precision agriculture highlights a paradigm shift toward context-aware intelligence and complex algorithmic optimisation across edge-cloud boundaries. To provide clearer comparison across use cases, this section reorganises agricultural WSN-IoT deployments into five structured application domains – Crop Health & Microclimate Monitoring, Precision Irrigation Management, Controlled-Environment Agriculture (Greenhouses & Aquaponics), Remote Sensing & Aerial/Terrestrial Robotics, and Livestock Telemetry & Animal Welfare. Each domain follows a standardised comparative template: (i) Common Architectural Topology, (ii) Core Sensing and Communication Technologies, (iii) Domain-Specific Bottlenecks and Failures, and (iv) Key Architectural Lessons Learned. A master comparative evaluation (Table 8) closes the section with a direct side-by-side assessment across all five domains.

Table 8
Master comparative evaluation across the five smart-agriculture application domains

Domain	Common Topology	Core Technologies	Main Bottleneck	Design Takeaway
Crop Health & Microclimate	Star/tree (terrestrial) + underground relay hop (WUSN)	NPK/EC/pH probes, ZigBee/LoRa, ML fertilizer classifiers	Underground signal attenuation, short WUSN range	Fuse terrestrial + underground data streams
Precision Irrigation	Star, sensor-to-controller closed loop	Soil moisture/flow sensors, IoT weather station, deep-learning ETo	Site-specific model validity, limited field validation	Couple real-time feedback with predictive ETo modelling
Controlled-Environment (Greenhouse/ Aquaponics)	Enclosed star, node-to-local-gateway	Moisture/pH/DO sensors, solar nodes, mobile app bridge	Multi-subsystem coupling complexity	Trade RF/power constraints for tighter closed-loop control
Remote Sensing & Robotics	Ground WSN + independent aerial/ satellite tier	NDVI/multispectral imaging, CubeSat, cloud fusion	Ground-truth/ imagery misalignment, flight cost & weather	Fuse imagery with ground sensors, not as a substitute
Livestock Telemetry & Welfare	Mobile node to fixed gateway (opportunistic)	RFID/BLE tags, accelerometers, ZigBee/NB-IoT backhaul	Intermittent connectivity, battery drain, tag damage	Prioritize delay-tolerant links and rugged hardware

(i) Common Architectural Topology

Star or tree-based terrestrial motes report to a field gateway that uplinks to the cloud; WUSN deployments add an underground-to-surface relay hop, with a surface gateway bridging the buried nodes to the internet.

(ii) Core Sensing and Communication Technologies

Soil NPK/EC/pH probes and ambient temperature/humidity sensors are interfaced over ADC/I2C, most paired with ZigBee or LoRa radios; NPK recommendation layers add a Gaussian Naïve Bayes or comparable ML classifier at the gateway or cloud tier.

(iii) Domain-Specific Bottlenecks and Failures

Nodes in WUSNs experience severe radio attenuation underground, leading to shorter transmission distances (typically under 10 m) and higher power consumption; wired underground alternatives avoid attenuation but are impractical due to the risk of damage from planting activity (Ojha et al., 2015).

(iv) Key Architectural Lessons Learned

Terrestrial and underground sensing are complementary rather than substitutable – surface nodes capture canopy/microclimate conditions while underground nodes capture root-zone nutrient status; recommendation accuracy depends more on fusing both data streams than on either sensing layer alone.

Precision Irrigation Management

Irrigation schedules have advanced beyond static thresholds through intelligent optimisation of Reference Evapotranspiration (ETo); these frameworks process localised microclimate sensor arrays using deep learning models to predict moisture loss, enabling precision-driven drip irrigation control (Bashir et al., 2023). Automated data-driven approaches such as HRLDAS and AquaCrop claim to effectively save 10-40% of water without affecting crop yield (Zhao et al., 2023). A descriptive monitoring is presented for mustard leaf cultivation, utilising an IoT cloud-based weather station associated with a WSN device to sense soil moisture and automatically control a water-drip mechanism in a greenhouse (Abioye et al., 2021). In Figure 14, system is driven by a Raspberry Pi 3 as the main controller, a VH400 moisture sensor, and a YF-S201 flow meter, with the data modelled in MATLAB for predictive and dynamic validation of the relationship between irrigation water volume, ETo loss, and soil moisture level (Abioye et al., 2021).

(i) Common Architectural Topology

Star topology linking soil-moisture and flow sensors to a Raspberry Pi/microcontroller hub, which fetches weather-station ETo data from the cloud and actuates a solenoid valve or DC pump.

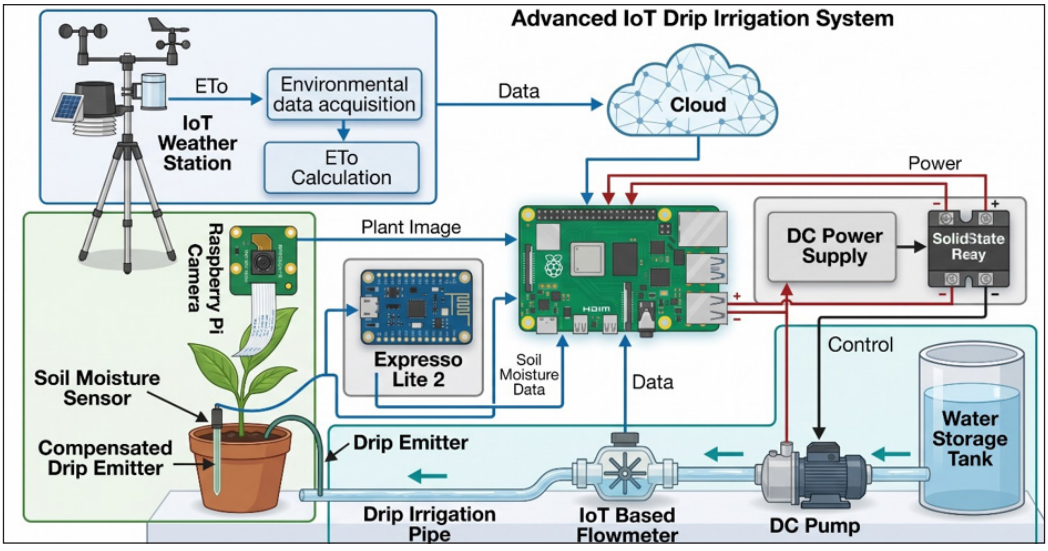


Figure 14. Automatic water drip irrigation and monitoring system architecture for mustard leaf cultivation in a greenhouse
Source: Adapted from (Abioye et al., 2021)

(ii) Core Sensing and Communication Technologies

Soil moisture probes (e.g., VH400), flow meters, IoT-based weather stations, and deep-learning ETo prediction models feeding a closed control loop.

(iii) Domain-Specific Bottlenecks and Failures

Model validity is highly site-specific: studies calibrated in one greenhouse profile (e.g., centrally peaked vs centrally depressed) do not generalise across profile types without recalibration, and several reported systems were not validated against actual field-based crop yield outcomes.

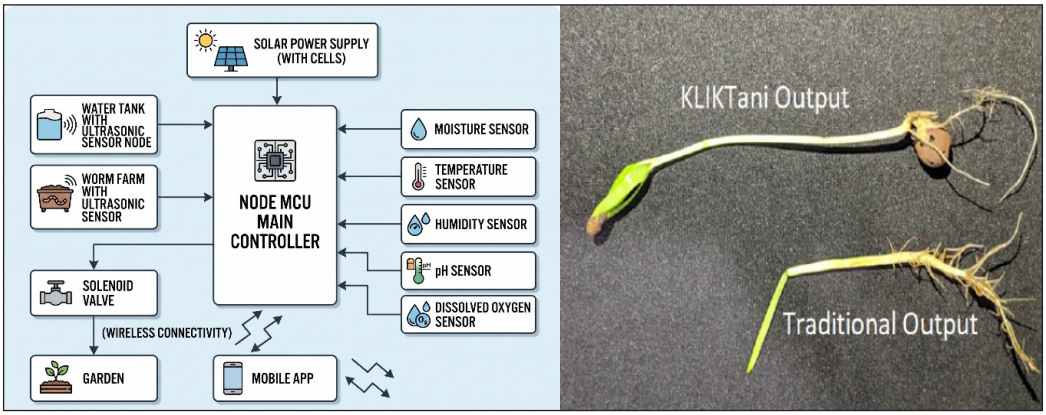
(iv) Key Architectural Lessons Learned

Coupling real-time soil moisture feedback with predictive ETo modelling, rather than static timers, is what delivers the reported water savings; the actuation layer (valve/pump control) is comparatively simple once the sensing and prediction layers are reliable.

Controlled-Environment Agriculture (Greenhouses & Aquaponics)

Other implementations set temperature and luminosity profiles inside greenhouses using WSN multi-sensor nodes and mathematical models; the central finding is that the original Equal Step (ES) technique is not suitable for centrally peaked or centrally depressed

greenhouse profiles, while Equal Segment Area (ESA) remains applicable across profile types (Lata & Verma, 2022; Lata et al., 2019), although this line of work did not validate the model against actual crop growth.



(a) (b)

Figure 15. (a) KLIKTani system architecture diagram. (b) The Kangkung vegetable size and growth rates after 7 days planted by IoT KLIKTani (Zamin et al., 2019)

In Malaysia, Zamin et al. (2019) developed the KLIKTani model, using smart IoT with red and tiger worm vermiculture to facilitate edible farming and Kangkung vegetable fertilisation; after 7–14 days, the experiment showed better outcomes in Kangkung size and growth rate compared to conventional planting as shown in Figure 15 (Zamin et al., 2019). Werner Kloas et al. (2015) applied a related concept in the ASTAF-PRO aquaponics system for tomato and fish co-cultivation in a greenhouse (Kloas et al., 2015), where fish-breeding water waste feeds the hydroponic planting system and water/air-quality sensors (pH, temperature, nitrate-to-ammonia concentration) manage the coupled system's stability (König et al., 2018; Yanes et al., 2020).

(i) Common Architectural Topology

Enclosed-environment star topology; sensor nodes report to a local Node MCU or gateway, which drives actuators (solenoid valves, worm-farm/nutrient dosing units) and is optionally bridged to a mobile app.

(ii) Core Sensing and Communication Technologies

Moisture, temperature, humidity, pH, and dissolved-oxygen sensors (for aquaponics variants) are typically on solar-powered nodes with short-range wireless connectivity to a local controller.

(iii) Domain-Specific Bottlenecks and Failures

System complexity increases sharply when coupling two subsystems (e.g., fish tank and hydroponic bed in aquaponics); several greenhouse-profiling studies also lacked field validation with actual food crops, limiting confidence in generalising lab results to production settings.

(iv) Key Architectural Lessons Learned

Controlled-environment deployments trade the harsher RF and power constraints of open fields for tighter, more complex closed-loop control and multi-subsystem coordination; smaller-scale local experiments (e.g., KLIKTani) demonstrate measurable growth benefits but require field-scale validation before broader claims can be made.

Remote Sensing & Aerial/Terrestrial Robotics

Uferah Shafi et al. (2019) proposed a precision agriculture approach that combines ground-deployed WSN-IoT devices with multispectral imaging from an aerial vehicle (drone) for crop abnormality monitoring (Figure 16). The farming area was deployed with a star-distributed wireless sensor topology to measure soil, ambient air temperature, and humidity

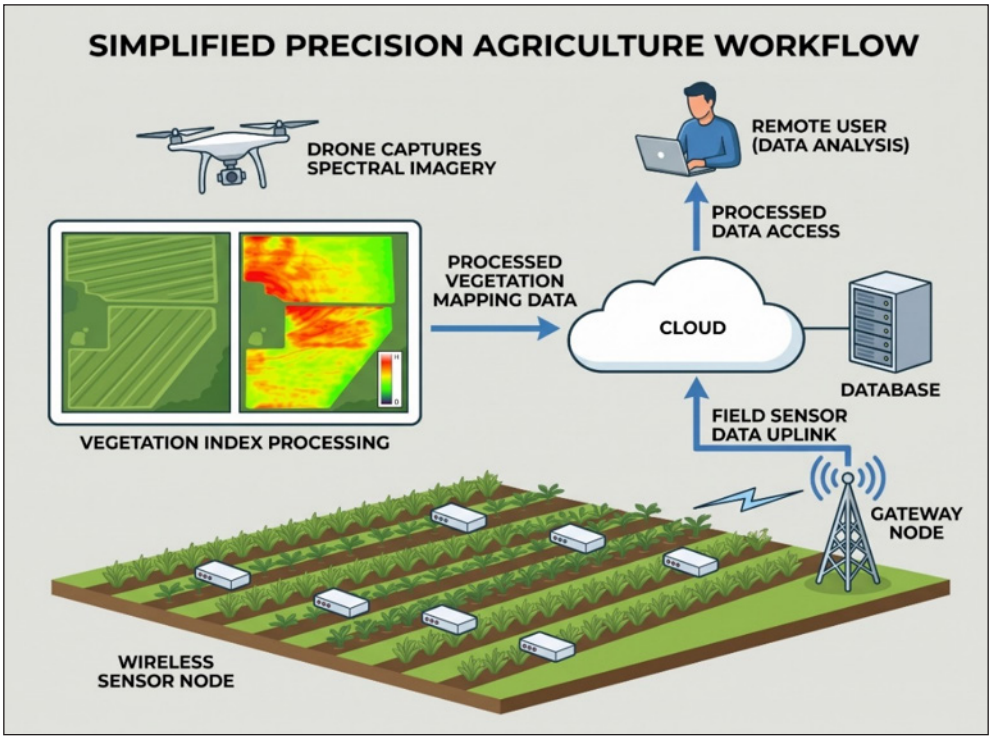


Figure 16. The NDVI and IoT-Based Precision Agriculture was published by Uferah Shafi et al., 2019

(Shafi et al., 2019), while the drone captured multi-spectral images to determine chlorophyll levels using NDVI (Normalised Difference Vegetation Index) computation. All monitoring data were uploaded to a cloud server, and crop health status was classified following NDVI mapping (Shafi et al., 2019). The IoT cloud system manages the collected data, and users access information through a web portal or mobile application that alerts farmers to crop health status via graphical data and scale maps, particularly useful for differentiating grain health and ripeness across large wheat or paddy fields.

(i) Common Architectural Topology

Ground star-topology WSN combined with an independent aerial (drone/UAV) or satellite imaging tier; both streams converge at a cloud server for fused analysis.

(ii) Core Sensing and Communication Technologies

Ground-temperature/humidity sensors, multispectral/NDVI-capable drone cameras, and CubeSat satellite imagery (e.g., Planet Labs) for wide-area coverage, integrated via cloud-based classification pipelines.

(iii) Domain-Specific Bottlenecks and Failures

Requires tight integration between ground-sensor calibration and imaging-derived indices; misalignment between sensor ground truth and spectral imagery reduces classification reliability, and aerial/satellite passes are constrained by flight costs, weather, or revisit frequency.

(iv) Key Architectural Lessons Learned

Large-area crop-health classification is most effective when NDVI/multispectral imagery is fused with, not substituted for, ground WSN data; imagery gives spatial coverage while ground sensors provide the calibration anchor.

Livestock Telemetry & Animal Welfare

Beyond crop and soil monitoring, WSN and IoT technologies have also been applied to flora-and-fauna and livestock-farming contexts, extending real-time monitoring to animal health, location, and welfare. Kandris et al. (2020) classify livestock-farming WSN applications alongside greenhouse and crop-monitoring deployments, noting that livestock telemetry typically combines RF-based identification (RFID/BLE ear tags) with photographic or camera-based sensing for behaviour and health observation, mirroring the crop/environmental sensing stack illustrated in Figure 17 but applied to animals rather than plants (Kandris et al., 2020). As shown in the taxonomy in Figure 18, livestock is categorized as a distinct sensing target alongside soil, crops, environmental and machinery categories, with ear-tag and health-monitoring devices leverage the same short-range and

cellular connectivity layers (Bluetooth, ZigBee, NB-IoT/4G-5G) deployed elsewhere across agricultural WSN-IoT architectures.

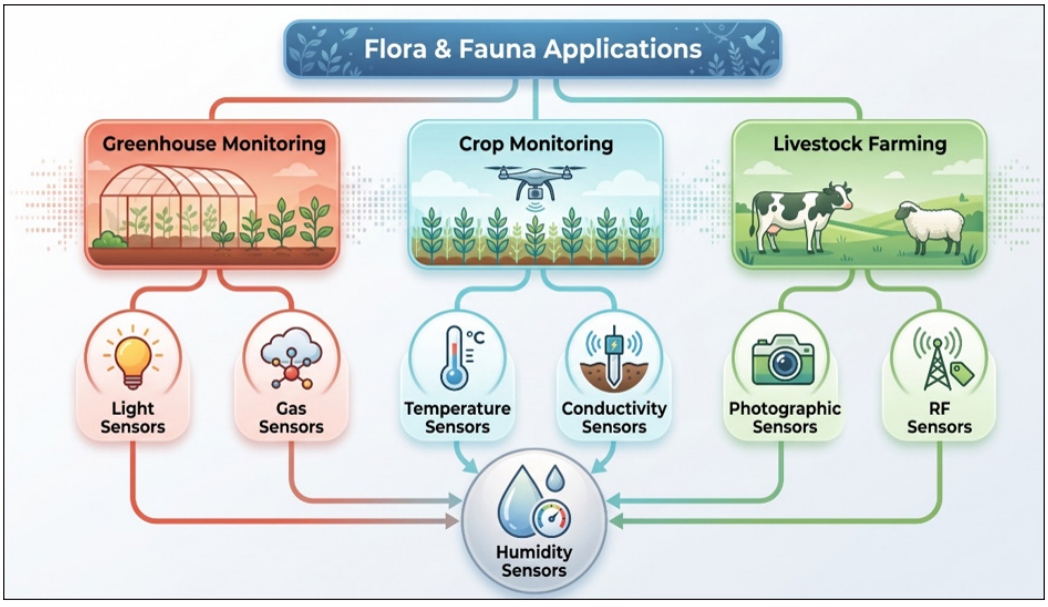


Figure 17. Flora and fauna application monitoring

(i) Common Architectural Topology

Mobile-node topology: wearable ear-tag or collar-mounted sensors move with the animal and connect opportunistically to fixed gateways distributed across pasture or barn areas, rather than the fixed-node star/tree topologies typical of crop monitoring.

(ii) Core Sensing and Communication Technologies

RFID/BLE ear tags, accelerometer-based activity and health monitors, and photographic/RF sensors for behaviour tracking, typically backhauled via short-range mesh (ZigBee/Bluetooth) to a farm gateway, with NB-IoT or cellular links used for wide-ranging or free-grazing herds.

(iii) Domain-Specific Bottlenecks and Failures

Mobility of the sensing node itself is the central challenge; unlike fixed crop sensors, animal-worn devices experience variable and intermittent connectivity, higher battery drain from continuous motion sensing, and physical risk of tag damage or loss, none of which arise in static field deployments.

(iv) Key Architectural Lessons Learned

Livestock telemetry architectures need to prioritise opportunistic, delay-tolerant connectivity and ruggedised, low-maintenance hardware over the raw throughput or dense node-count optimisations that dominate crop-sensing network design; welfare and productivity outcomes depend as much on tag durability and battery life as on sensing accuracy.

Table 9
Comparison of application examples in agricultural WSN-IoT systems

Application Domain	Sensing Parameter	Communication & Computing	Main Contribution	Key Limitation
Open-field WSN	Soil and ambient sensors	Terrestrial or underground WSN	Large-area monitoring and automation	Underground attenuation, higher energy
Greenhouse irrigation	Moisture, flow, weather inputs	IoT cloud, predictive model	Irrigation volume estimation, save water	Controlled setting limits generalisation
Aquaponics / hybrid farming	Water quality and air sensors	IoT monitoring, controllers	Resource reuse and coupled management	System complexity across subsystems
Remote sensing agriculture	Soil nodes + multispectral imaging	Cloud analytics	Large-area crop health classification	Requires sensor-imaging integration
Context-aware agronomy	Soil fertility, salinity, temperature	IoT, ML models	Actionable fertilizer or ET recommendations	Data quality & context mapping complexity
Livestock telemetry	Ear-tag/collar motion, RFID/ BLE	Mobile-node WSN, NB-IoT/ cellular backhaul	Health/welfare and productivity monitoring	Mobility-driven connectivity & battery limits

Table 9 additionally summarises representative application examples at the level of individual studies, complementing the domain-level synthesis in Table 8. On the architectural network layer, managing large data flows from multivariant sensors across all five domains requires high-efficiency communication paradigms. Researchers have successfully implemented novel caching frameworks for information-centric IoT, utilising deep reinforcement learning via Proximal Policy Optimisation (PPO) to minimise backhaul congestion and optimise data placement at edge nodes (Asmat et al., 2024). The foundational reliability of data collection also relies on accurate node-location metrics within distributed layouts; this is directly addressed by robust localisation algorithms like PSLDV-Hop, which fuses Particle Swarm Optimisation (PSO) with targeted refinement processes to compute accurate WSN node coordinates over complex, irregular field topologies (Hadir

et al., 2021; Kaur et al., 2025; Rehman et al., 2025). Together, these advances increase data-matrix integrity, node localisation accuracy, power longevity, and real-time precision for the autonomous management of widespread vegetable and fruit crops at the farm scale.

As claimed by Kloas et al. (2015), about 70% of water resources have been consumed and wasted across various agricultural mass-production processes (Kloas et al., 2015), reinforcing the relevance of the aquaponics and precision-irrigation approaches discussed above. To achieve integrated decision-making across domains, Carlos-Mancilla et al. (2019) suggested a Smart Decision System (SDS) to manage large IoT data flows – from acquisition to actuation (watering, fertilising, crop condition, and others) – keeping the farmer informed (Baseca et al., 2019; Carlos-Mancilla et al., 2016). In crop-essential monitoring such as irrigation and fertilisation, wireless sensors provide advantages in cost-effectiveness, commissioning time, flexibility, and safety over wired alternatives. Dionisis Kandris et al. (2020) conducted a survey on the evolving use of WSN across healthcare, environmental, defence, and agricultural applications (Kandris et al., 2020), underscoring that the architectural lessons summarised in Table 9 are broadly consistent with WSN deployment patterns observed outside agriculture as well. Figure 18 delineates primary taxonomy of smart agriculture distributions.



Sub-Category	Measurement / Monitor Examples
Soil	• Moisture sensor, NPK
Crop/Plant	• Plant health, Chlorophyll sensor • Drone imagery
Environmental	• Temperature, Humidity
Livestock	• Ear tag, Health monitor
Machinery	• Tractor telematics • Fuel consumption

Environment Type	Characteristics / Examples
In-Situ Terrestrial	• Ground-based sensors • Local fields
Aerial	• Drones, High-altitude imagery
Spaceborne	• Satellites • Regional / Global coverage
Controlled Environment	• Greenhouses, Vertical farms • Indoor facilities

Connection Type	Network / Technology Examples
Short-Range	• Bluetooth, Zigbee, Wi-Fi
Long-Range LPWAN	• LoRaWAN, Sigfox
Cellular	• 4G / 5G, NB-IoT
Satellite	• Remote field connectivity



Layer	Functions / Examples
Cloud Layer	• Data Center • Big Data analytics (Centralized)
Fog/Gateway Layer	• Field Server • Local processing (Intermediate)
Edge Layer	• On-device processing • Sensor nodes (Decentralized)

Objective	Key Applications
Yield Forecasting	• Prediction and supply chain management
Precision Irrigation	• Optimized water usage
Pest & Disease Management	• Early detection and control
Livestock Health Monitoring	• Welfare and productivity
Resource Optimization	• Fertilizer, fuel, labor efficiency

Level	Operation & Human Involvement
Manual	• Human-in-the-loop (Manual data logging and control)
Semi-Autonomous	• Assisted systems (e.g., tractor autopilot with supervision)
Fully Autonomous	• Unmanned operation (Independent rovers, automatic drone swarms)
Swarm Automation	• Coordinated robotics (Multiple agents working together)

Figure 18. Architectural Taxonomy on Smart Agriculture deployment

SYNTHESIS, CRITICAL REFLECTION, AND FUTURE RESEARCH DIRECTIONS

Global disruptions over the past decade were intensified by pandemic-induced economic shifts and severe supply chain vulnerabilities, such as in the 2023 global rice shortage. Therefore, this situation has elevated food security to an urgent national priority. For nations navigating moderate-scale food-security challenges, traditional farming methods are no longer sufficient to buffer against the impacts of unpredictable climate change, geopolitical friction, and resource scarcity. This review has comprehensively evaluated the transformative role of Precision Agriculture (PA), demonstrating how integrating Wireless Sensor Networks (WSNs) and Internet of Things (IoT) architectures can shift modern farming from a reactive practice to a proactive, data-driven science. This concluding section consolidates the evaluation into five parts: a synthesis of major findings; the core technological trade-offs identified across the review; the critical research gaps and evaluation-methodology weaknesses that remain; emerging trends likely to shape the next generation of systems; and a brief note on the scholarly-presentation audit performed on this manuscript.

Synthesis of Major Findings

Through a systematic examination of current device-aided technologies, this paper consolidates findings across four layers of the agricultural cyber-physical stack:

- Hardware and Data Acquisition: at the foundational level, low-power microcontrollers (such as the PIC16F886 and PIC16F684) act as the backbone of field-deployed motes, conditioning and converting real-time analogue sensor data via internal ADCs and routing digitised payloads over standard interfaces (I2C, SPI, UART).
- Protocol Scalability and Efficiency: wireless communication technologies present clear power/capacity trade-offs. Legacy protocols such as Wi-Fi and classic Bluetooth are constrained by heavy power draw and limited node capacity; ZigBee stands out for energy-efficient, high-density localised areas (36.9 mW transmission power, self-healing mesh), while Sigfox and LoRaWAN offer massive scalability (up to 1,000,000 and 10,000 nodes per base station, respectively) suited to expansive agricultural zones.
- Network Topologies: star topologies minimise routing delay to a central server, while multi-sink, tree, or mesh configurations provide the structural resilience needed to gather data across vast open fields without draining node batteries.
- Application-Layer Convergence: across all five application domains reviewed (Table 9), data collection consistently functions as the entry point rather than the end goal – the review's central finding is that the operational value of WSN-IoT systems is realised only once sensing is coupled with spatial visualisation and cognitive computation.

Advanced NPK mapping, for example, shows that IoT telemetry aligns closely with laboratory chemical analysis, with a Gaussian Naïve Bayes classifier achieving 94% test accuracy for fertiliser recommendation, enabling systems to autonomously dictate agricultural scheduling and actuation.

Core Technological Trade-offs

Across the domains reviewed, three structural trade-offs recur and should guide technology selection in future deployments:

- Communication range vs. bandwidth/power: LPWAN options (Sigfox, LoRaWAN, NB-IoT) trade throughput and latency for range and battery life, while ZigBee and Wi-Fi trade range for higher data rates and lower per-hop latency – no single protocol dominates across all agricultural scenarios (Table 2, Table 5).
- Edge-compute autonomy vs. energy/storage cost: pushing inference to the edge reduces bandwidth pressure and enables offline operation (Table 7) but constrains the model complexity that can run on-node and adds hardware/energy cost that must be justified by the value of faster, local decisions.
- Low-cost sensor accessibility vs. long-term calibration stability: affordable sensors (e.g., low-cost EC or gas sensors, Table 4) widen access to smallholder and developing-region deployments but frequently trade away long-term calibration stability and cross-sensitivity resistance found in industrial-grade instruments, creating a recurring accuracy/affordability tension not yet resolved in the literature.

Critical Research Gaps and Evaluation Methodologies

Despite the undeniable potential of WSN, IoT, and AI synergy, several persistent bottlenecks limit widespread, reliable open-field deployment:

- Subterranean signal attenuation in WUSNs, which continues to restrict underground node range to under 10 metres and elevates power draw beyond what is acceptable for long-term unattended deployment (Section: Crop Health & Microclimate Monitoring).
- Cybersecurity and data privacy: agricultural WSN-IoT systems inherit the same attack surface as other IoT deployments – unauthenticated sensor-to-gateway links, weak key management on constrained motes, and cloud-side data exposure – yet security is addressed unevenly across the reviewed literature, with encryption (e.g., 128-bit AES on ZigBee) often treated as a protocol default rather than a deployment-level design decision. Edge-local anonymisation (Table 7) offers a partial mitigation but is not yet standard practice.
- Cross-platform interoperability and standardisation: proprietary systems dominate the market, fragmenting protocols and data formats across vendors and severely hindering

data exchange between different farming equipment – this remains the single most cited structural barrier to scaling smart-farming pilots into production systems.

- Data management and long-term evaluation benchmarks: most studies reviewed report short-duration trials (weeks to a single season) rather than multi-season field validation, and no standardised benchmark protocol exists for comparing yield, water-saving, or accuracy claims across studies – a gap that future work should address through standardised, multi-season evaluation methodologies with openly reported datasets.

Emerging Trends and Strategic Future Directions

Building on the gaps identified above, several transformative paradigms are positioned to shape the next generation of agricultural WSN-IoT systems:

- TinyML on low-power microcontrollers: running compact ML inference directly on field motes (rather than solely at the edge gateway or cloud) could reduce the communication overhead identified in Section B while enabling faster, autonomous, on-node decisions for tasks such as pest/disease pattern recognition.
- Federated Learning for privacy-preserving farm analytics: training shared ML models across multiple farms without centralising raw sensor data would directly address the data-privacy gap noted in Section C, while still allowing smallholders to benefit from aggregated model improvements.
- Agricultural Digital Twins: virtual, continuously updated replicas of physical fields or greenhouses – fed by the WSN-IoT sensing layers reviewed throughout this paper – could support the multi-season, standardised evaluation methodologies called for in Section C by allowing scenario testing before physical intervention.
- Satellite-Direct LPWAN connectivity: extending NB-IoT/LoRaWAN-class links directly to low-earth-orbit satellite backhaul would remove the cellular/local-gateway dependency that currently limits deployment in remote or developing-region farmland lacking terrestrial infrastructure.
- Biodegradable, in-soil sensors: emerging low-cost, environmentally degradable sensor platforms could relax the trade-off between sensor accessibility and long-term ecological impact identified in Section B, particularly for WUSN-style underground deployments that are otherwise difficult to retrieve at the end of life.

CONCLUSION

Global disruptions over the past decade, intensified by pandemic-induced economic shifts and severe supply chain vulnerabilities such as the 2023 global rice shortage, have elevated food security to a critical national priority. For nations navigating moderate-scale food

security challenges, traditional farming methods are no longer sufficient to buffer against unpredictable climate changes, geopolitical friction, and resource scarcity. This review has comprehensively evaluated the transformative role of Precision Agriculture (PA), demonstrating how integrating Wireless Sensor Networks (WSNs) and Internet of Things (IoT) architectures can shift modern farming from a reactive practice to a proactive, data-driven science.

Key Technical Synthesis

Through a systematic examination of current device-aided technologies, this paper highlighted the core hardware and architectural frameworks required to achieve large-scale smart farming:

- Hardware and Data Acquisition: At the foundational level, low-power microcontrollers (such as the PIC16F886 and PIC16F684) act as the backbone of field-deployed motes. These devices effectively condition and convert real-time analogue sensor data via internal Analogue-to-Digital Converters (ADCs) and route the digitised payloads using standard interfaces (I2C, SPI, UART).
- Protocol Scalability and Efficiency: Wireless communication technologies present clear trade-offs in power and capacity. While legacy protocols like Wi-Fi and classic Bluetooth are constrained by high power consumption and limited node capacity, specialised protocols offer robust alternatives. ZigBee stands out as an exceptionally energy-efficient option for high-density, localised areas due to its low transmission power (36.9 mW) and self-healing mesh capabilities. Conversely, long-range technologies like Sigfox and LoRaWAN offer massive network scalability, accommodating up to 1,000,000 and 10,000 nodes per base station, respectively, making them highly suited for expansive agricultural zones.
- Network Topologies: Network design plays a vital role in balancing latency and coverage. Star topologies excel at minimising routing delays by routing traffic directly to a server, whereas multi-sink, tree, or mesh configurations provide the structural resilience required to gather data across vast open fields without draining node batteries.

The Evolution of Intelligent Farming

A central finding of this review is that data collection is merely the catalyst; the true value of WSN-IoT frameworks lies in spatial visualisation and cognitive computation. Historically, yield monitoring relied on static data analysed using localised GIS software such as ArcInfo, MapInfo, or ESRI platforms. Today, the vanguard of precision agriculture has shifted toward context-aware intelligence optimised across edge-cloud boundaries. By unifying real-time IoT sensing with cloud-hosted Machine Learning (ML) models,

modern systems can dynamically process complex environmental parameters. This is explicitly demonstrated by advanced NPK mapping techniques, in which IoT telemetry closely aligns with traditional laboratory chemical analysis. When this data is fed into a predictive algorithm, such as a Gaussian Naïve Bayes classifier, it achieves 94% test accuracy for fertiliser recommendations. Therefore, the system can autonomously dictate optimal agricultural scheduling and actuation to maximise crop yields while minimising environmental degradation.

Challenges and Future Directions

Despite the undeniable potential of the synergy among WSN, IoT, and AI, widespread open-field deployment faces a critical bottleneck: market fragmentation. The current agricultural ecosystem is heavily constrained by proprietary solutions and unpredictable costs. This lack of standardised communication protocols and platforms builds compatibility and connectivity barriers between disparate equipment, isolating valuable data silos. Future research and industrial development must prioritise the creation of open-source, interoperable frameworks that allow plug-and-play compatibility across different hardware manufacturers. Additionally, future work should focus on enhancing edge computing capabilities to reduce reliance on constant cloud connectivity in remote farming regions. Resolving these interoperability and structural limitations is the definitive next step toward achieving global "Zero Hunger" strategies, securing food production lines, and building a sustainable, resilient agricultural future.

ACKNOWLEDGEMENT

This research is fully supported by Universiti Sains Malaysia, Short Term Grant, 304/PAERO/6315567. The authors fully acknowledged Universiti Sains Malaysia for the approved funding, which makes this important research viable and effective.

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