

Review

A Review of Smart Crop Technologies for Resource Constrained Environments: Leveraging Multimodal Data Fusion, Edge-to-Cloud Computing, and IoT Virtualization

Damilola D. Olatinwo¹, Herman C. Myburgh¹ , Allan De Freitas¹  and Adnan M. Abu-Mahfouz^{1,2,*} 

¹ Department of Electrical, Electronic and Computer Engineering, University of Pretoria, Pretoria 0002, South Africa; damibaola@gmail.com (D.D.O.); herman.myburgh@up.ac.za (H.C.M.); allan.defreitas@up.ac.za (A.D.F.)

² Council for Scientific and Industrial Research (CSIR), Pretoria 0184, South Africa

* Correspondence: aabumahfouz@csir.co.za

Abstract

Smart crop technologies offer promising solutions for enhancing agricultural productivity and sustainability, particularly in the face of global challenges such as resource scarcity and climate variability. However, their deployment in infrastructure-limited regions, especially across Africa, faces persistent barriers, including unreliable power supply, intermittent internet connectivity, and limited access to technical expertise. This study presents a PRISMA-guided systematic review of literature published between 2015 and 2025, sourced from the Scopus database including indexed content from ScienceDirect and IEEE Xplore. It focuses on key technological components including multimodal sensing, data fusion, IoT resource management, edge-cloud integration, and adaptive network design. The analysis of these references reveals a clear trend of increasing research volume and a major shift in focus from foundational unimodal sensing and cloud computing to more complex solutions involving machine learning post-2019. This review identifies critical gaps in existing research, particularly the lack of integrated frameworks for effective multimodal sensing, data fusion, and real-time decision support in low-resource agricultural contexts. To address this, we categorize multimodal sensing approaches and then provide a structured taxonomy of multimodal data fusion approaches for real-time monitoring and decision support. The review also evaluates the role of IoT virtualization as a pathway to scalable, adaptive sensing systems, and analyzes strategies for overcoming infrastructure constraints. This study contributes a comprehensive overview of smart crop technologies suited to infrastructure-limited agricultural contexts and offers strategic recommendations for deploying resilient smart agriculture solutions under connectivity and power constraints. These findings provide actionable insights for researchers, technologists, and policymakers aiming to develop sustainable and context-aware agricultural innovations in underserved regions.

Keywords: cloud computing; edge computing; farm management; food security; machine learning; multimodal data fusion; smart agriculture



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1. Introduction

Agriculture is a cornerstone of global food security and economic development, playing a pivotal role in achieving the Sustainable Development Goals (SDGs) such as poverty alleviation and hunger reduction [1]. With the global population projected to

reach nearly 10 billion by 2050 [2], innovative strategies are essential to meet rising food demands sustainably.

Smart crop technologies, including IoT sensors, weather monitoring stations, and machine learning models, have emerged as modern tools for enhancing agricultural productivity and decision-making. These systems enable precise irrigation, predictive yield modeling, and efficient resource management [3] through integrated platforms that combine edge computing, cloud services, and data analytics.

While promising, the deployment of such technologies in infrastructure-limited regions faces significant barriers. In many African countries, unreliable electricity, intermittent internet connectivity, and limited access to technical training hinder the scalability of smart agriculture solutions. Addressing these constraints is critical to ensuring equitable access to innovation.

Several reviews have attempted to identify trends in the application of technology to smart agriculture; however, existing studies often present a fragmented view and fail to comprehensively address the integrated nature of modern smart crop systems, particularly concerning multimodal sensing and real-time data integration for informed decision-making. For instance, the authors of [4] reviewed IoT sensors and control technologies for smart irrigation agriculture but limited their scope to soil condition monitoring, overlooking broader applications such as weather patterns and smart crop management, which necessitate the integration of diverse sensor modalities. The study by [5] examined the use of machine learning-driven data fusion algorithms for multimodal fusion in smart agriculture systems, yet it often overlooked the effectiveness of these algorithms in facilitating real-time monitoring and actionable insights for farmers dealing with immediate challenges. Similarly, the authors of [6] focused on the implementation of digital twin technologies for virtual farm representation but did not adequately address the crucial aspect of data integration from diverse, real-time sources or the adaptability of such systems within the constraints of low-resource contexts. The authors of [7] explored smart crop management through technologies such as IoT, remote sensing, and AI. However, they did not consider the aspect of multimodal sensing and real-time data fusion for informed decision-making, nor consider the adaptability of these systems in low-resource agricultural contexts. The author of [8] presents a broad review of IoT applications in agriculture, covering areas such as smart irrigation, precision farming, supply chain management, and pest control. While the paper outlines both advantages and challenges, including connectivity, cost, and data privacy, it did not consider the aspect of real-time data fusion to support informed decision-making and adaptability of these systems in low-resource agricultural environments.

Despite these contributions (e.g., [4–8]), a critical gap remains in the literature regarding a holistic understanding of smart crop systems that effectively integrate multi-sensors and multimodal data for real-time monitoring and decision support, especially within resource-constrained environments. The existing reviews have not comprehensively explored the virtualization of IoT infrastructure as a means to create adaptive sensor networks capable of seamless data integration from diverse sources, thereby enabling timely responses to critical agricultural challenges. Furthermore, a consolidated analysis of data fusion technologies specifically aimed at creating cohesive, real-time monitoring systems that address the immediate needs of farmers facing issues like adverse weather, pests, and diseases is lacking. This systematic review aims to address these gaps by providing a comprehensive analysis of smart crop system components, the application of multi-sensors, effective multimodal data fusion approaches, and the potential of IoT virtualization in enabling real-time monitoring and integrated systems within low-resource contexts. Ultimately, this review seeks to offer valuable insights for researchers and agri-

cultural stakeholders, particularly in regions like Africa, to facilitate the development and deployment of sustainable and impactful technological solutions.

This systematic review analyzes research published between 2015 and 2025 on smart crop technologies for enhanced monitoring, efficient data processing, and advanced analytics. It focuses on challenges related to resource utilization and the need for real-time data integration in diverse agricultural operations, particularly in regions with limited infrastructure and connectivity. Specifically, this review seeks to address key aspects of these technologies by answering the following research questions:

RQ1: What are the fundamental components of smart crop systems and how are they applied to monitor soil health, crops, and environmental conditions across diverse farming operations?

RQ2: What are the available data fusion approaches for effectively integrating multi-modal data to create a cohesive and comprehensive understanding of the agricultural environment?

RQ3: How can IoT virtualization be leveraged within smart crop systems to facilitate real-time monitoring and seamless integration of multimodal data for timely and informed decision-making in low-resource environments with intermittent internet connectivity?

RQ4: How can the resource constraints in low-resource environments (e.g., African countries) be managed to ensure the reliable operation and data flow of adaptive smart crop systems?

The contributions of this study are summarized as follows:

- This study presents a systematic literature review that examines smart crop technologies specifically within the context of resource-constrained African agriculture.
- This review identifies and quantifies key trends in technology adoption for advancing smart crop systems, highlighting a major shift towards integrated solutions. It then provides an in-depth analysis of these emerging integrated frameworks, exploring the pivotal roles of multimodal sensing, edge-to-cloud computing, IoT virtualization, and machine learning in enabling the development of adaptive sensor networks.
- This study analyzes and categorizes the available data fusion approaches (data-level, feature-level, and decision-level) for effectively integrating multimodal agricultural data (soil, crop, weather), crucial for creating a cohesive and comprehensive understanding of complex farm environments.
- The paper provides a detailed analysis of strategies for managing resource constraints, particularly concerning power supply and internet connectivity, in low-resource agricultural settings.
- This review provides insightful recommendations for future research and development. These recommendations are specifically designed to guide the creation and deployment of more efficient, sustainable, and resilient smart crop technologies that are practical and impactful for farmers in resource-constrained regions.

Next, the research methods adopted in this study are discussed in Section 2. The research findings are presented in Section 3. Section 4 provides the trends in technology adoption in smart crop systems. Section 5 discusses the challenges or limitations in current research, Section 6 provides recommendations and future direction, and the paper is concluded in Section 7.

2. Methods

The research questions defined in Section 1 guided the systematic review process, which was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Figure 1) [9].

Literature Search and Inclusion Criteria

A structured search was performed using the Scopus database as the primary source due to its extensive coverage of peer-reviewed literature, including indexed content from ScienceDirect, IEEE Xplore, Web of Science, and other major repositories. The literature search process was used to identify articles published within the last ten years, from 1 January 2015, to 24 March 2025 (search conducted on 24 March 2025). This timeframe was chosen to capture recent trends in smart crop technologies. Keywords were developed based on preliminary scoping searches and a review of existing literature in the field.

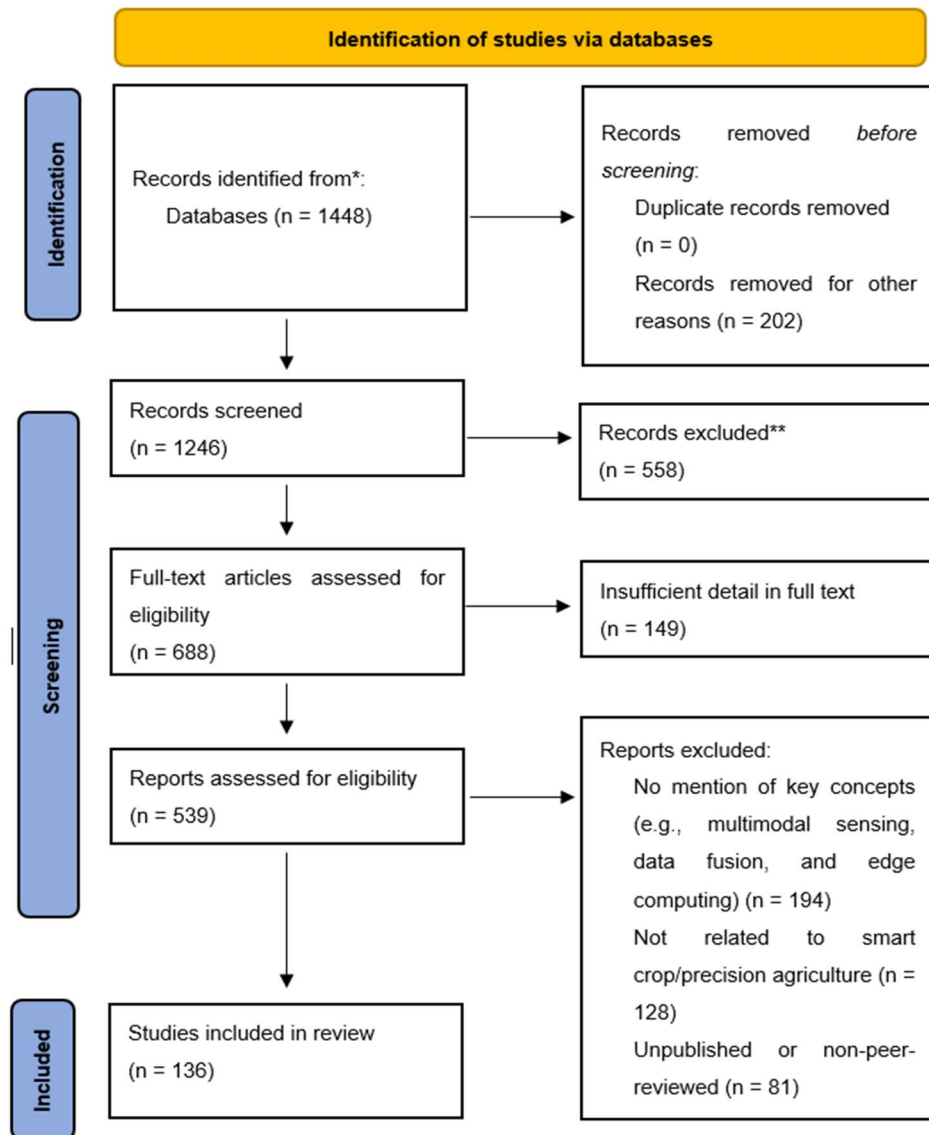


Figure 1. PRISMA flow diagram detailing the systematic process of study identification, screening, inclusion, and exclusion criteria for the review. The asterisks (*, **) are used to point to note the number of databases used and the excluded records.

The Scopus database was searched within the Title, Abstract, and Keywords fields using a search string, employing Boolean operators (OR within concepts, AND to combine concepts) and truncation (* to capture variations), such as (“agricultural sensor*” OR “farm sensor*” OR “crop sensor*” OR “environmental sensor*”) AND (“data fusion” OR “sensor integration” OR “information fusion”) AND (“agriculture” OR “farming” OR “precision agriculture” OR “smart agriculture” OR “environmental monitoring” OR “crop monitoring” OR “soil monitoring” OR “weather monitoring”). The keyword combinations

were developed through preliminary scoping searches, manual review of highly cited articles, and iterative refinement based on thematic relevance to the research questions. We focused on core domains such as crop sensing, data fusion/integration, smart farming applications, and IoT virtualization. Terms like “crop sensor”, “agricultural sensor”, “farm sensor”, and “environmental sensor” captured a broad range of sensing technologies. Integration-related terms (“data fusion”, “sensor integration”, “information fusion”) and application-level terms (“precision agriculture”, “smart agriculture”, “crop monitoring”) ensured comprehensive coverage of system architectures and use cases. For example, the phrase “integrated systems” was implicitly covered by our broader search for “data fusion” and “sensor integration,” as these are the core technical processes that enable system-level integration. We rigorously refined our search string to balance a broad scope with the need for precision, ensuring our results were directly relevant to the review’s focus on multimodal sensing and IoT-enabled smart crop systems. The final string was optimized for precision and alignment with the review’s focus on multimodal sensing and IoT-enabled smart crop systems.

To reduce unrelated studies, pre-defined inclusion and exclusion criteria were applied. **The inclusion criteria consisted of:** (1) Peer-reviewed journal articles and conferences to ensure a baseline level of quality. (2) Publications written in the English language to facilitate comprehensive analysis. (3) Studies focused on the application or development of smart crop technologies, including but not limited to sensor networks, data fusion, IoT, and machine learning in agricultural settings. (4) Articles providing sufficient technical details regarding the technologies or approaches investigated. **Exclusion criteria included:** (1) Review papers, as the focus of this study was on primary research. (2) Publications not written in English due to resource limitations for translation. (3) Studies with a primary focus outside of smart agriculture, agricultural policy without technological focus or unrelated environmental monitoring. (4) Conceptual or theoretical papers that did not present empirical data or specific technological implementations. (5) Conference abstracts or posters without accompanying full-text publications. Following the screening of the records using the pre-defined inclusion and exclusion criteria, 1448 records were retrieved from the Scopus database.

Following the retrieved publications, an initial step involved the removal of 202 records for other reasons prior to formal screening. This resulted in 1246 records that proceeded to the screening phase. First, the titles and abstracts of the 1246 records were screened against the pre-defined inclusion and exclusion criteria. Following this stage, 558 records were excluded, leaving 688 publications that were retrieved for full-text assessment. The full texts of these 688 articles were then assessed for eligibility based on the inclusion and exclusion criteria. During this process, 149 articles were excluded due to insufficient detail in the full text. This resulted in 539 reports that underwent a final assessment for eligibility.

The assessment of these 539 reports led to the exclusion of 403 additional records for the following reasons: 194 records did not mention key concepts relevant to this review (e.g., multimodal sensing, data fusion, and edge computing), 128 records were not related to smart agriculture, smart crop, or precision agriculture as defined by the scope of this review, and 81 records were identified as unpublished or non-peer-reviewed sources. Consequently, 136 publications met all inclusion criteria and were included in the present review. Within these studies, 30 were from Springer, 16 from IEEE Xplore, 31 from Web of Science, 41 from ScienceDirect, 10 from Wiley Online Library, 3 from Taylor & Francis Online, and 5 from Directory of Open Access Journals. Each included study was reviewed to extract metadata on publication year, technology domain, and application context.

Figure 2 illustrates the distribution of the 136 included publications across the ten-year study period (2015–2024, as the search concluded in early 2025). As shown in Figure 2, there is a clear trend of increasing publications in the later years, with the highest number of selected papers published between 2023 and 2024, potentially reflecting the growing research interest and advancements in smart crop technologies during this period.

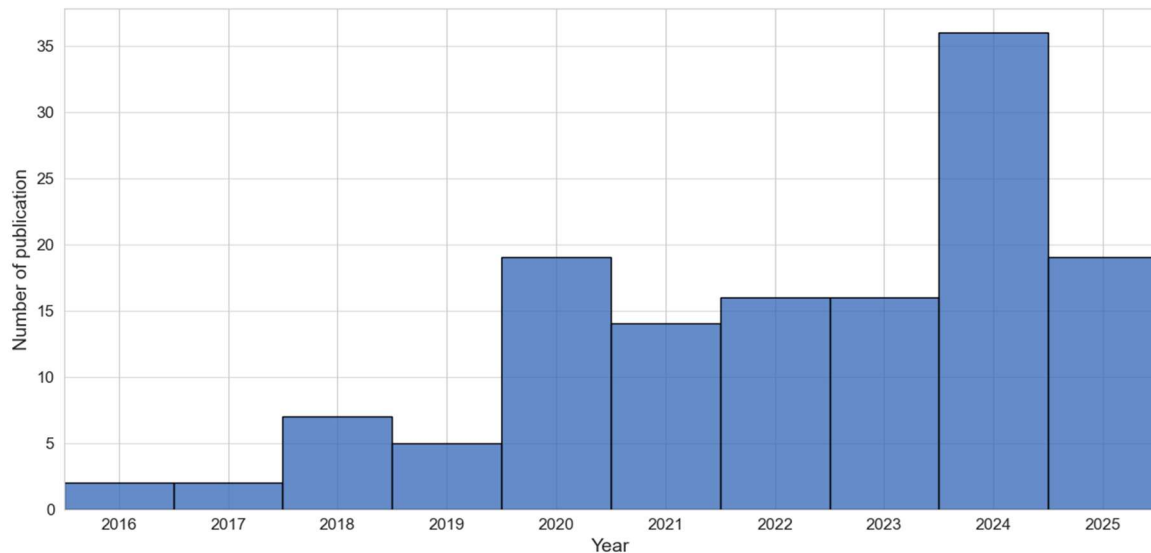


Figure 2. Number of publications distributed by year, highlighting the yearly growth in research output from the past 10 years. Data for this figure was sourced from Scopus database search results spanning 2015–2025.

3. Research Questions

This section outlines the four RQs that this study aims to address. These questions are designed to provide a structured framework for the review, guiding the analysis of relevant literature and the synthesis of key findings. RQ1 aims to establish a foundational understanding of smart crop systems by identifying their fundamental components and how they are applied to monitor key agricultural parameters, specifically soil health, crop status, and environmental conditions across various farming operations. RQ2 explores the methodologies and techniques employed to integrate data from multiple sensors, potentially of different types (multimodal), to create a holistic and comprehensive understanding of the agricultural environment. This question addresses the challenge of data heterogeneity and the need for cohesive information. Also, RQ3 investigates the potential of IoT virtualization in addressing the challenges of real-time monitoring and data integration, particularly in resource-constrained environments with intermittent internet connectivity. This question seeks to identify how IoT virtualization can be leveraged to develop adaptive sensor networks that enable timely and informed decision-making.

3.1. What Are the Fundamental Components of Smart Crop Systems and How They Are Used to Monitor Soil Health, Crops, and Environmental Conditions Across Diverse Farming Operations?

This research question aims to dissect the architecture of smart crop systems and understand how their constituent parts are utilized for monitoring key agricultural parameters. Based on the literature, smart crop systems can be broadly categorized into three fundamental layers: (i) data acquisition (sensing), (ii) data processing and communication (gateway/edge/fog), and (iii) data analysis and application (cloud server). The components within these layers and their applications in monitoring soil health, crops, and environmental conditions are elaborated in the following subsections. Figure 3 shows the architecture of a smart crop involving several components such as the agricultural

sensors, edge computing, WiFi/LoRa/5G wireless communication, cloud computing, and the stakeholders.

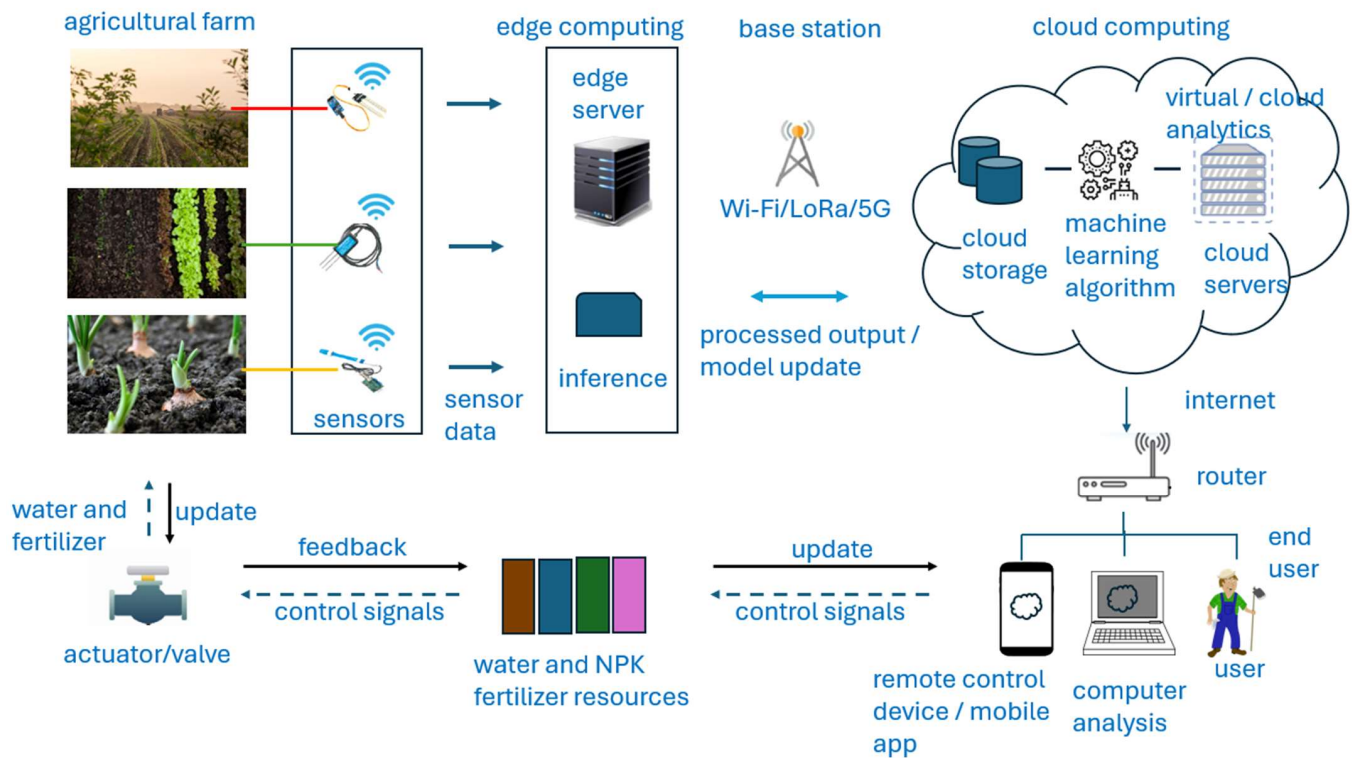


Figure 3. Architecture of an end-to-end smart crop system for precision farming. This diagram illustrates the full data lifecycle, beginning with the sensing layer (e.g., soil moisture, temperature, nutrient levels) and progressing through secure wireless protocols (e.g., BLE, ZigBee) to edge gateways for localized preprocessing and inference. Processed outputs and model updates are transmitted to a centralized cloud platform for big data analytics, machine learning model execution, and decision support. The system enables real-time monitoring, predictive analysis, and automated control of irrigation and fertilization via actuators. Arrows indicate bidirectional data flow, highlighting feedback loops between cloud analytics, user interfaces, and field-level actuators. The figure also distinguishes between physical components (e.g., sensors, crops, actuators) and virtual/cloud analytics, emphasizing the cyber-physical interface. Note: This figure was drafted by the authors to conceptually represent the integrated architecture described in Section 3.1.

3.1.1. Smart Crop System Components

Smart crop leverages a variety of interconnected technologies to enhance the monitoring and control of agricultural environments and decision-making [7,8,10,11]. Smart crop systems can be broadly categorized into two main functions: monitoring and controlling. Monitoring systems use sensors to collect data about various agricultural parameters, while controlling systems use that data to automate and optimize agricultural processes. Both monitoring and controlling functions rely on the fundamental architecture of IoT systems, which comprises three primary functional elements: data acquisition, a processing and communication layer (often involving gateways, edge, or fog computing), and a data analysis and application layer (typically residing in the cloud or on local servers) [12–15]. These layers work synergistically to collect, process, analyze, and act upon agricultural data.

1. Data Acquisition (Sensing)

Data acquisition forms the foundation of smart agriculture, involving the collection of crucial information about the agricultural environment. This is achieved through a diverse array of sensors deployed across farming operations. These sensors can be broadly

categorized into three types based on their technology and deployment. This includes crop sensors, soil health sensors, and environmental sensors, and they are discussed in this section.

a. Crop Sensors

These types of sensors are used to directly monitor plant status and health, providing crucial data for precision agriculture. Examples include normalized difference vegetation index (NDVI) sensors, which assess plant vigor and biomass by quantifying the differential reflectance of red and near-infrared light, commonly deployed on aerial platforms like drones and satellites [16–20]. Multispectral and hyperspectral cameras are advanced imaging systems that capture detailed spectral signatures of plants, enabling the detection of subtle variations indicative of diseases, nutrient deficiencies, and growth stages [21–25]. Leaf wetness sensors detect the presence and duration of moisture on leaf surfaces, a critical microclimatic factor influencing the development and spread of plant diseases [26–30]. Furthermore, plant growth sensors quantify various plant biometrics, such as stem diameter and plant height, providing insights into growth rates and development [31–35].

b. Soil Sensors

Soil health sensors are employed to assess vital soil properties beyond just moisture and temperature. Key examples include soil nutrient sensors, which measure the levels of essential macronutrients like nitrogen, phosphorus, and potassium (NPK) [36–41]. Soil pH sensors determine the acidity or alkalinity of the soil, a critical factor influencing nutrient availability and microbial activity [42–46]. Moreover, soil electrical conductivity sensors are utilized for assessing soil salinity levels and providing insights into soil texture and water-holding capacity [47–52].

c. Environmental Sensors

Environmental sensors play a crucial role in monitoring various parameters vital for plant growth and overall health. Examples include weather stations, which measure a suite of atmospheric conditions such as temperature, humidity, rainfall, wind speed, and solar radiation, providing essential data for irrigation scheduling, disease prediction, and comprehensive crop management [53–64]. Soil moisture sensors are deployed to measure the volumetric water content within the soil profile at different depths, a critical metric for optimizing irrigation practices and mitigating water stress [58–63]. Soil temperature sensors monitor the thermal conditions of the soil, influencing key processes like seed germination, root development, and nutrient uptake [64–68]. Light sensors quantify photosynthetically active radiation (PAR) and other relevant light intensities that directly impact plant growth and development [69–74]. Also, air quality sensors detect the presence and concentration of pollutants and gases in the atmosphere that can potentially affect plant health and productivity [75–79].

2. IoT Gateway or Edge/Fog Computing Layer

In smart crop systems, IoT gateways and edge/fog computing layers serve as intermediaries between distributed sensors and central data processing systems [80–85]. Gateways aggregate sensor data, filter redundant information, and provide temporary storage in areas with intermittent network connectivity [86–89]. Edge and fog nodes, equipped with computational capabilities, are positioned near agricultural sensors to minimize cloud dependency. Since sensors generate vast amounts of data, edge nodes perform preliminary raw data processing such as averaging values, detecting anomalies, and triggering immediate actions before forwarding only essential information (processed data) to the cloud layer. This optimizes bandwidth usage, alleviates cloud load, and accelerates response times. Ad-

ditionally, the proximity of edge servers to sensors significantly reduces latency, ensuring timely data processing and enhancing operational efficiency in agricultural applications.

a. Cloud Server Layer

The cloud server layer serves as the central hub for data storage, advanced analytics, and application delivery in smart crop systems. This layer typically handles data storage, big data analysis, data fusion, and predictive modeling for comprehensive data processing of the entire system. The cloud or dedicated server infrastructure provides scalable and durable storage solutions, capable of accommodating the voluminous and heterogeneous datasets originating from various sensor modalities (e.g., time-series environmental data, spatial imagery, spectral information). Data lakes are often employed to handle the variety and velocity of incoming data.

Data fusion algorithms are critical for integrating data from disparate sources (e.g., combining soil moisture data with weather forecasts and crop growth stage information) to derive more comprehensive and contextually relevant insights. Big data analytics techniques, leveraging distributed computing frameworks (e.g., Spark, Hadoop), are applied to identify patterns, trends, and correlations within these large datasets. Furthermore, predictive modeling algorithms, including machine learning models (e.g., regression and classification), are employed for forecasting key agricultural outcomes such as crop yield, disease outbreaks, pest infestations, and resource demand. Anomaly detection algorithms are also crucial for identifying unusual patterns that may indicate equipment malfunction, environmental stress, or other critical events.

The insights derived from the advanced analytics are then translated into user-friendly formats and delivered through various applications. Web-based dashboards and mobile applications serve as decision support systems, providing farmers, agronomists, and other stakeholders with interactive visualizations (e.g., maps, charts, time-series plots), actionable recommendations (e.g., optimal irrigation schedules, variable rate fertilization prescriptions), and timely alerts. Furthermore, the server/cloud layer facilitates the integration of data with other relevant agricultural information systems, such as farm management software (FMS) for task planning and record-keeping, weather APIs for real-time and forecast data [77], and geographical information systems (GIS) for spatial analysis and visualization. This interconnected ecosystem aims to provide a holistic and data-driven view of the entire agricultural operation, enabling more efficient and sustainable management practices.

3.1.2. Smart Crop Applications

Smart crop systems are increasingly employed across a broad spectrum of crucial agricultural activities to address specific challenges and enhance overall efficiency, ultimately aiming for improved crop productivity and sustainability. This section outlines four key application areas where data-driven insights are transforming farming practices: precision irrigation systems, crop and soil monitoring systems, pest and disease management systems, and crop yield estimation systems. Leveraging fundamental smart crop system components—sensors, data processing, and communication technologies—these applications rely to varying extents on the integration of soil, crop, and weather data to optimize the use of resources like water, fertilizers, and pesticides, thereby minimizing environmental impact and reducing operational costs. The following subsections will explore the data requirements, technological underpinnings, and existing solutions within these key application areas, examining how each contributes to sustainable and profitable farming practices in crop monitoring, pest and disease identification, and resource optimization. Figure 4 shows the concepts of smart crop applications discussed in this section.

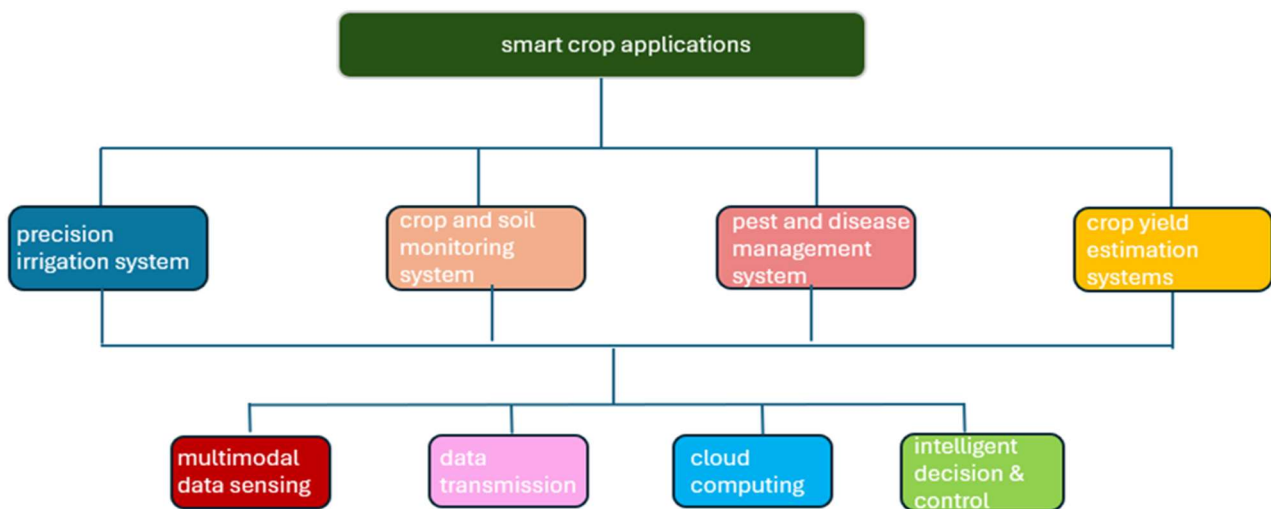


Figure 4. This figure, drafted by the authors, describes the concept of various smart crop application domains and their underlying technological components.

1. Precision Irrigation Systems

Precision irrigation systems are designed to optimize water use by applying water precisely when and where needed. These systems employ various sensors to monitor and collect data on soil conditions, crop health, and weather patterns, enabling data-driven irrigation and nutrient management decisions.

Soil sensors provide real-time data on moisture levels, nutrient concentrations, and pH, which are essential for determining immediate irrigation needs and fertilizer applications. Weather data such as rainfall forecasts, evapotranspiration rates, temperature, humidity, and solar radiation are gathered from meteorological stations to predict future water requirements and optimize irrigation schedules. Crop-related data, including plant water stress indicators and nutrient uptake, can be obtained from plant-based sensors or remote sensing technologies, further refining water and fertilizer management strategies [90–92].

The collected sensor data is transmitted via communication technologies to a gateway device and then relayed to a cloud-based system. In the cloud, advanced data analytics algorithms process and interpret the information, generating actionable insights. The central system analyzes crop-specific water requirements by considering factors such as growth stage, soil properties, and prevailing weather conditions. Based on these insights, smart irrigation systems can autonomously regulate water distribution, fertilizer application, and pesticide deployment, ensuring optimal crop health and resource utilization [92–95].

By enhancing the precision of water, precision irrigation systems reduce input costs for farmers, conserve water resources, minimize environmental impact (e.g., by decreasing nutrient leaching and runoff), and improve overall crop yield and quality.

Several researchers have proposed IoT-based precision irrigation systems incorporating diverse sensor technologies to optimize resource management [90–95]. For instance, the authors of [90] implemented soil moisture sensors and meteorological stations to monitor soil parameters and environmental conditions, including temperature, humidity, wind speed, solar radiation, evapotranspiration, and precipitation, to determine crop water requirements. In [91], dendrometer sensors were utilized to measure trunk diameter variations, enabling optimized irrigation schedules and improved tree health management. The researchers in [92] integrated soil moisture, pH, temperature, and nitrogen-phosphorus-potassium (NPK) sensors to regulate water and fertilizer usage. The authors of [93] leveraged weather station data, including precipitation levels, solar radiation, humidity, air pressure, wind speed and direction, and temperature, to optimize irrigation efficiency.

In [94], watermark and soil temperature sensors were deployed to monitor soil conditions and enhance irrigation efficiency. The authors of [95] focused on soil moisture sensors to regulate irrigation water usage.

2. Crop and Soil Monitoring Systems

These systems are designed for continuous assessment of the health and status of the soil and crops [96–98]. This involves assessing key agricultural parameters, including soil properties, crop development, and environmental conditions, providing essential data for informed decision-making and optimized input management. They fundamentally rely on soil data (e.g., nutrient levels, pH, moisture content, electrical conductivity, salinity, temperature) acquired from various in situ soil sensors; crop data (e.g., growth stage, biomass, spectral indices reflecting plant health, canopy temperature) obtained from optical, proximal, and remote sensing technologies; and weather data (e.g., temperature, humidity, precipitation, solar radiation, wind speed) sourced from on-site weather stations or meteorological services [97–99]. Farmers utilize this integrated data to gain comprehensive insights into soil fertility dynamics, plant health status, and prevailing environmental conditions, enabling proactive interventions for disease prevention, pest management, and optimized crop rotation strategies [96–100]. This detailed monitoring facilitates the precise determination of the correct quantity and timing for fertilizer application, ensuring crops receive the necessary nutrition for healthy growth and high-quality food production without the risks of over- or under-fertilization.

Data from the deployed IoT sensors is transmitted via communication technologies to a cloud-based central system, where advanced analytics are applied to generate actionable recommendations for input applications and overall crop management. Several IoT-based soil and crop monitoring systems have been proposed in the literature, leveraging diverse sensing technologies to optimize inputs like fertilizers based on real-time soil conditions, crop health status, and prevailing weather conditions, ultimately aiming to maximize crop yields [96–100]. For instance, the authors of [96] employed a suite of soil sensors (NPK, pH, moisture, salinity, electrical conductivity, and temperature) to provide a comprehensive understanding of soil conditions. In [97], the research focused specifically on the dynamic assessment of key soil nutrients critical for plant growth. The work by the authors of [98] utilized soil humidity, temperature, moisture, and pH sensors to monitor overall soil health and its impact on crop yields. In [99], the system monitored soil nutrient levels and subsequently used this data to prescribe precise fertilizer application tailored to specific crop requirements and existing soil nutrient concentrations. The study in [100] integrated soil humidity, soil temperature, air humidity, and air temperature data to optimize fertilization and irrigation regimes for citrus cultivation.

3. Pest and Disease Management Systems

These systems leverage a range of IoT technologies, including smart traps, cameras, and specialized sensors, to proactively detect, identify, and manage pest infestations and disease outbreaks, thereby minimizing crop losses [101–103]. Early detection is heavily reliant on crop data obtained from various sensors, such as imaging systems capturing visual anomalies, spectral sensors identifying early signs of plant stress or disease-related spectral changes, and smart traps monitoring pest presence and population dynamics [102,103]. Weather data (e.g., temperature, humidity, rainfall) gathered from weather stations and forecasts is crucial for predicting the development and spread patterns of pests and diseases, often through the application of sophisticated predictive models. While its influence is often indirect, soil data can also play a role in affecting overall plant health and resilience to biotic stresses.

The operational workflow of these systems involves continuous field monitoring through deployed IoT devices. Smart traps can be programmed to target specific pests, while cameras equipped with computer vision algorithms can automatically detect visual symptoms of diseases or the presence of pests [101–103]. The collected information is then analyzed using advanced data analytics and machine learning algorithms to determine the severity and spatial spread of infestations or outbreaks. Farmers receive immediate notifications about identified threats, enabling timely intervention. Based on the analyzed insights, informed control measures can be planned and executed, such as the targeted release of beneficial insects or the application of biological control agents. This early and precise intervention significantly reduces the need for broad-spectrum chemical pesticides, leading to more sustainable and environmentally friendly pest and disease control practices [101–103]. By optimizing pesticide use, farmers can protect their crops while minimizing the negative impact on beneficial organisms like bees and other non-target species. Furthermore, these systems often provide farmers with access to historical data and trend analysis, aiding in the informed selection of appropriate crop rotations, planting schedules, and resistant crop varieties, fostering a proactive approach to pest and disease management that safeguards farmers' returns, minimizes losses, and ensures long-term crop health.

To support farming practices, researchers have proposed IoT-based pest and disease management systems to optimize the application of interventions, such as pesticides, based on real-time crop health and prevailing weather conditions, ultimately aiming to maximize crop yields [101–103]. For instance, the authors of [101] employed a suite of weather sensors (humidity, CO₂, and temperature) to monitor environmental conditions conducive to specific pest development. In [102], the authors combined soil data (likely influencing plant vigor) with weather data to model and manage pest populations. The authors of [103] utilized crop data, specifically visual imagery, processed with machine learning to detect the presence of pest fruit flies.

4. Crop Yield Estimation Systems

Crop yield estimation systems, often powered by IoT infrastructure, are designed to predict the quantity of agricultural produce harvested from a specific area, providing crucial insights for resource allocation, market planning, and sustainable farming practices [104–106]. These systems leverage various data sources collected by IoT-enabled sensors and platforms, including imagery from satellite, aerial platforms, and ground-based camera systems, environmental data from weather stations, dynamic soil data from in situ sensors, and potentially historical yield records stored in cloud platforms, to forecast potential harvest outcomes [105,106]. IoT-enabled sensors play a significant role in data acquisition for yield estimation. Satellite and aerial imagery, often analyzed using vegetation indices (VIs), provides a non-destructive means of assessing crop vigor, biomass, and overall health over large areas. Additionally, ground-based camera systems, including those mounted on IoT-connected robots, drones operating at lower altitudes and transmitting data wirelessly, or fixed monitoring stations with network connectivity, capture high-resolution images of crops at closer ranges [104–106]. These close-range images can be analyzed using computer vision techniques, often processed on edge devices or cloud platforms, to assess plant health, count fruits or ears, and monitor development stages, all of which contribute to more precise yield predictions at a field or even plant level.

IoT-enabled weather stations provide real-time and historical weather data, including precipitation, temperature patterns, and solar radiation, which are critical as these environmental factors directly influence crop growth and development, and consequently, final yield. In situ IoT soil sensors primarily monitor dynamic soil data such as nutrient availability, moisture retention capacity, and temperature, providing crucial real-time information to refine yield predictions by understanding the dynamic resources available to the plants.

While soil type is an important static factor influencing yield potential, it is often integrated as geospatial data rather than directly sensed in real-time by typical in situ IoT sensors. The data collected from these diverse IoT sensors and platforms is transmitted via various communication technologies to a central processing system, frequently cloud-based, where advanced data analytics and machine learning models are employed. These models analyze the complex relationships between various input parameters (VIs from different imagery sources, weather variables from IoT stations, soil characteristics from IoT sensors, historical data, and features extracted from camera images processed on edge or cloud) to generate accurate yield forecasts [104–106].

Different machine learning algorithms can be utilized, ranging from regression models to more complex deep learning architectures, to learn patterns and predict future yields with increasing accuracy. The insights generated by crop yield estimation systems empower various stakeholders. Farmers can make informed decisions regarding harvesting schedules, storage planning, and market strategies, often receiving real-time updates and predictions on their connected devices. Policymakers gain valuable data aggregated from various IoT deployments for regional and national agricultural planning, supply chain management, and food security assessments. By providing timely and accurate yield predictions based on data from interconnected devices, these systems contribute significantly to improved agricultural productivity, reduced risks associated with market fluctuations, and more efficient resource management across the agricultural sector.

To support farming practices, researchers have proposed IoT-based crop yield estimation systems to forecast the quantity of agricultural produce [104–106]. Specifically, the authors of [104] demonstrated this approach by employing a suite of crop camera sensors not only to monitor crop disease but also to predict eventual crop yield based on visual analysis. In a different approach, the work by the authors of [105] focused on leveraging soil data as a key input, utilizing this information to guide crop type selection and subsequently predict the anticipated yield. Building upon the integration of multiple data streams, the authors of [106] adopted a more holistic perspective, combining soil, crop, and weather data to achieve a more comprehensive and potentially accurate estimation of crop yield.

Table 1 provides a comprehensive overview of smart crop systems, analyzing their strengths and limitations based on applications and monitored data from recent literature.

Table 1. A comprehensive overview of smart crop systems by crop type, application, and monitored parameters from recent literature based on RQ1.

Ref.	Crop Type	Applications	Monitored Parameters	Connectivity	Strengths	Limitations
[90]	Not provided	Precision irrigation	Soil and weather conditions	WiFi	Multi-parameter data fusion	Crop data not considered
[91]	Christmas trees	Smart irrigation	Crop (trunk diameter, water stress), weather (air temperature)	4G LTE	Crop and weather integration	Soil data not considered
[92]	Tomato	Precision irrigation	Soil (pH, NPK level), weather (air temperature, humidity)	Not specified	Integrated soil and weather data	Limited data

Table 1. Cont.

Ref.	Crop Type	Applications	Monitored Parameters	Connectivity	Strengths	Limitations
[93]	Not provided	Precision irrigation	Weather (air temperature, humidity, wind speed)	LoRa	General monitoring	Soil/crop data not considered
[94]	Wheat	Smart irrigation	Crop water, soil temperature, soil water, NPK	LoRa	Soil/crop integration	Weather data not considered
[95]	Sweet corn	Precision irrigation	Soil moisture levels	ZigBee, WiFi	Sweet corn-specific monitoring	Lacks crop and weather data
[96]	Rice	Crop & soil monitoring	Soil (NPK, pH, moisture, salinity)	WiFi	Rice-specific monitoring	Lacks weather and crop data
[97]	Diverse crops	Crop & soil monitoring	Soil	WiFi/LoRa	General crop monitoring	Lacks crop and weather data
[98]	Not provided	Crop & soil monitoring	Soil (humidity, temperature, moisture,)	ZigBee	Crop/soil focus	Lacks weather and crop data
[99]	Apple, beans, coffee, grapes, banana	Crop & soil monitoring	Soil nutrient levels	LoRa	Multi-crop monitoring	Limited data
[100]	Citrus	Crop & soil monitoring	Soil & weather	ZigBee	Citrus-specific monitoring	Lacks crop data
[101]	Not provided	Pest & disease management	Weather	ZigBee	Pest/disease focus	Lacks multimodal data
[102]	Not provided	Pest & disease management	Soil & weather	ZigBee	Soil/ weather integration	Lacks crop data
[103]	Guava	Pest & disease management	Crop	Not provided	Crop yield specific	Lacks soil/ weather data
[104]	Cherry, citrus, guava, mango	Crop yield estimation	Crop	Not provided	Multi-crop yield estimation	Limited data
[105]	Maize, cotton, rice, wheat	Crop yield estimation	Soil (pH, humidity, temperature)	Not provided	Multi-crop yield estimation	Limited data
[106]	Cotton, banana, coffee	Crop yield estimation	Soil	Not provided	Multi-crop yield estimation	Limited data

3.2. What Are the Available Data Fusion Approaches for Effectively Integrating Multimodal Data to Create a Cohesive and Comprehensive Understanding of the Agricultural Environment?

Data fusion is the process of integrating information from multiple sensor sources to construct a unified and comprehensive representation, leveraging the strengths of each individual source [100–107]. In agriculture, such comprehensive fusion significantly enhances the accuracy of critical practices, including pest control, irrigation management,

and yield prediction. Because of this, advanced data fusion approaches are indispensable for developing a holistic understanding of the agricultural environment, synthesizing disparate information streams from various sensors that collect soil, crops, and weather data. These techniques can be broadly categorized into three distinct levels: data-level fusion, feature-level fusion, and decision-level fusion as presented in Figure 5. This section systematically examines these data fusion methodologies employed in agricultural applications, analyzing their inherent strengths and limitations to identify existing research gaps and delineate future research directions.

3.2.1. Data-Level Fusion

Data-level fusion is the combination of raw data or signals provided by heterogeneous (different) IoT sensors, prior to any feature extraction or pattern recognition [107–109]. In an agricultural context, this approach could entail the synchronization of readings from multiple soil sensors, crop sensors, and weather sensors strategically positioned across a field. Crucially, preprocessing steps at this level are paramount for data integrity and include a suite of tasks such as temporal alignment of disparate sensor readings, data buffering to manage varying sampling rates, noise reduction techniques to enhance data quality, basic calibration to correct systematic errors and biases inherent to individual sensors. These preprocessing operations are often performed on microcontrollers or at the edge, on local gateways, before transmitting the data for further fusion in a centralized system. For instance, raw voltage readings from multiple soil data probes might be averaged or statistically combined at the edge, subsequently being transmitted to a cloud platform for integration with other data types, such as weather station readings. Examples of fusion techniques at the data level include the use of the Kalman filter to integrate various sensor data. This integrated data provides a more robust and potentially more accurate representation of the current state of the agricultural environment. It can then be further preprocessed (e.g., feature extraction) and utilized for advanced analytical tasks such as yield prediction, early detection of plant stress conditions, or forecasting resource requirements.

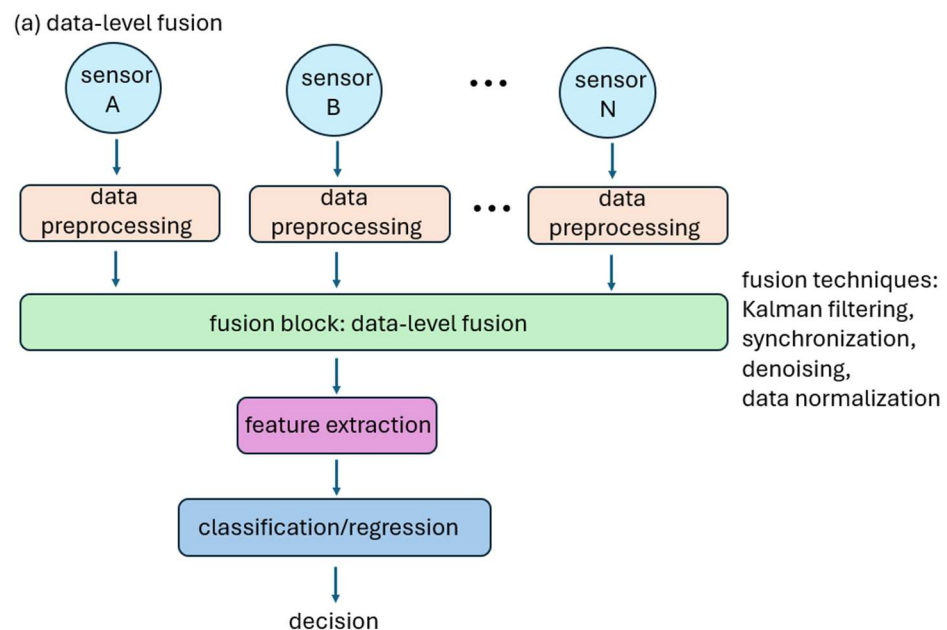


Figure 5. Cont.

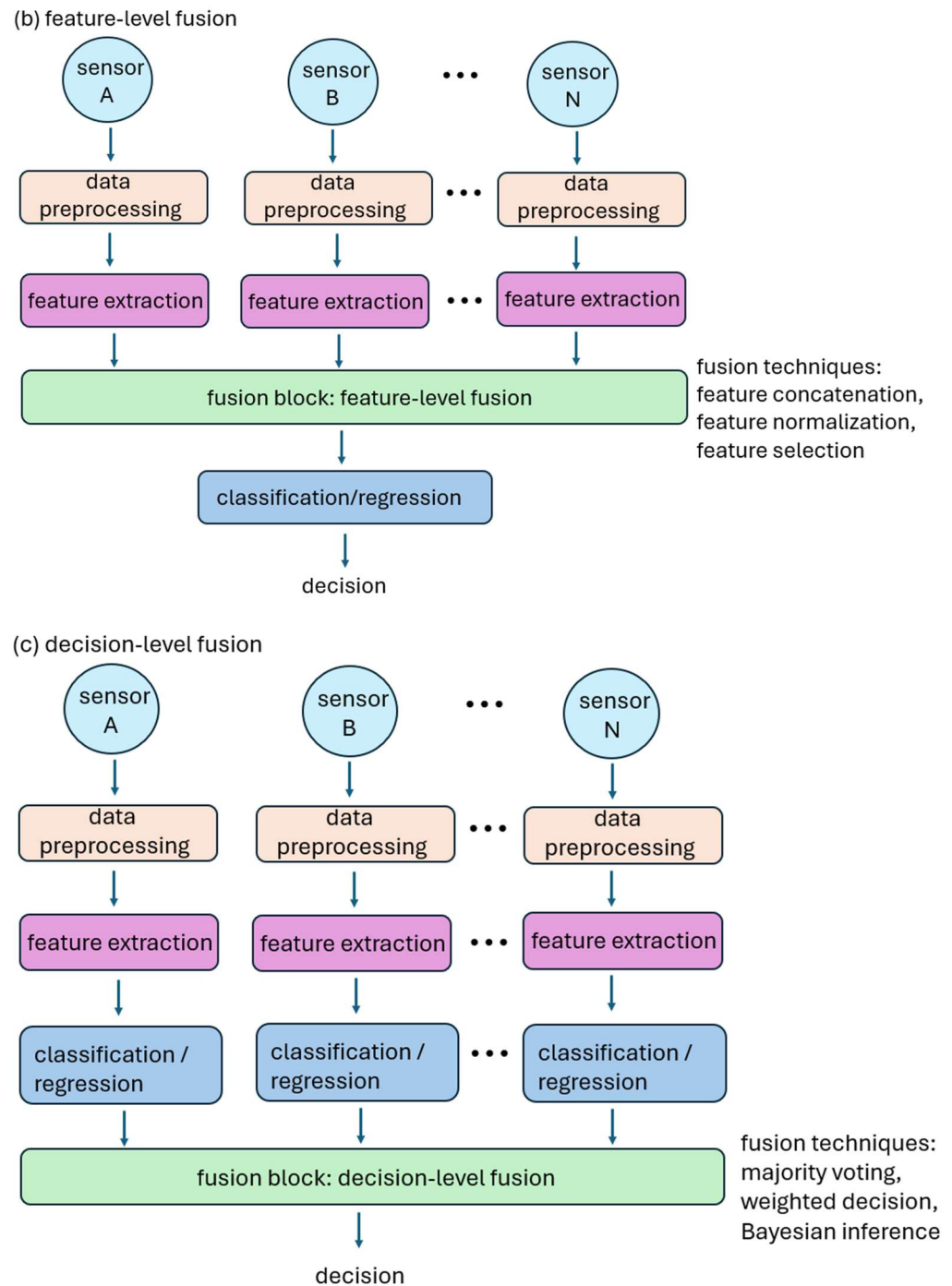


Figure 5. Conceptual overview of data, feature, and decision-level fusion architectures. This diagram illustrates three hierarchical fusion strategies used in multi-sensor systems: (a) Data-level fusion merges raw sensor inputs immediately after preprocessing to maximize data utility. Techniques such as Kalman filtering, denoising, and synchronization are commonly applied. (b) Feature-level fusion combines extracted features from multiple sensors using methods like feature concatenation, normalization, and selection, enabling compact and informative representations. (c) Decision-level fusion aggregates independent sensor decisions, typically via majority voting, Bayesian inference, or weighted decision rules, when raw data or features are inaccessible. This figure is conceptual and was drafted by the authors to support the discussion in Section 3.2. Note: No external data sources were used in the creation of this figure.

Some studies have employed data-level fusion approaches to integrate sensor data from multiple sources [110–112]. For example, the authors of [110] utilized a data-level

fusion method such as Kalman filter algorithm to estimate and fuse soil and weather data to optimize irrigation water use. Likewise, in [111], a data-level fusion method was employed for a single-source data fusion of current season weather data and historical weather data to forecast crop growth. Similarly, the authors of [112] used a data-level fusion method and current season weather data for irrigation scheduling for maize crops.

3.2.2. Feature-Level Fusion

Feature-level fusion is the combination of features extracted from individual IoT sensors (raw data) before classification or prediction. This approach capitalizes on the ability to distill meaningful information from raw sensor outputs. For soil data, extracted features might encompass parameters such as average moisture content, variability in nutrient levels, or temperature gradients across different soil depths. In the context of crop data, relevant features could include various vegetation indices, like the normalized difference vegetation index (NDVI) derived from spectral sensors, direct measurements of plant height, or calculations of leaf area index (LAI). For weather data, pertinent features might include daily temperature ranges, cumulative rainfall, average wind speed, or humidity fluctuations. Examples of fusion techniques used at this level include simple concatenation of the feature vectors from different sources, weighted averaging based on the reliability or importance of the contributing sensor, or dimensionality reduction methods like principal component analysis to create a unified and more compact feature vector. This unified feature vector provides a comprehensive representation of the current state of the agricultural environment and can then be utilized for advanced analytical tasks such as yield prediction, early detection of plant stress conditions, or forecasting resource requirements.

Examples of studies that employed a feature-level data fusion approach to integrate multi-sensor data are [110,113]. The authors of [110] utilized the Penman-Monteith method to derive an evapotranspiration feature from weather sensor data. This evapotranspiration feature was then fused at the feature level with other crop variables to determine optimal irrigation timing. Also, the authors of [113] utilized a long short-term memory (LSTM) neural network to perform feature-level data fusion of soil and weather data to determine the optimal watering adjustment needed for a smart irrigation system.

3.2.3. Decision-Level Fusion

Decision-level fusion is the combination of decisions or outputs from multiple models. It involves data preprocessing (e.g., feature extraction, standardization, normalization) and pattern recognition where independent inferences, predictions, or decisions are generated based on the data from each individual IoT sensor or group of sensors. This approach leverages the strengths of specialized models or algorithms tailored to specific data types. For example, a dedicated model might predict irrigation needs solely based on soil moisture data, while another might assess crop stress levels using only spectral data from imaging sensors. Concurrently, a third model could forecast pest risk probabilities by analyzing historical and real-time weather patterns. The ultimate decision regarding complex agricultural interventions, such as irrigation scheduling, the implementation of specific intervention strategies, or an overall risk assessment, is then formulated by intelligently combining these individual outputs. Examples of techniques employed for this final decision aggregation include machine learning algorithms, weighted voting, assigning different weights to the outputs of individual models based on their estimated confidence or accuracy, and rule-based systems that implement expert-defined rules considering multiple indicators and their interrelationships. Some studies have employed decision-level fusion [110,114]. For example, in a study by [110], a decision-level fusion involving independent models

were first used to derive distinct predictions, such as a localized irrigation recommendation based on soil and weather data. These individual predictions were then fused using a linear regression model to generate a final, integrated decision, such as an overall irrigation scheduling recommendation that balanced water needs with pest control considerations. The authors of [105] employed a decision-level fusion approach for multi-sensor data fusion of soil and crop data for crop yield estimation. They used individual models such as partial least squares regression, backpropagation neural network, and extreme learning machine, each trained on the soil and crop data (or features derived from them), and then combined the yield predictions from these different models using a decision-level fusion method (e.g., voting).

3.2.4. Tiny Machine Learning (TinyML) Algorithms for Edge AI

To circumvent the inherent challenges posed by centralized cloud computing in smart crop systems, particularly concerning latency, intermittent connectivity, and power consumption, alternative computing paradigms that bring processing closer to the data source are highly advantageous. Edge computing is a primary example of such a paradigm, necessitating the application and development of lightweight machine learning models suitable for deployment directly on resource-constrained edge devices. For this reason, TinyML has emerged as a particularly promising solution [115]. TinyML are lightweight machine learning techniques deployed on resource-constrained devices like microcontrollers, enabling on-device inference with minimal memory, power, and computational resources. This capability holds significant potential advantages for smart crop systems, especially in low-resource regions like Africa, where the integration of advanced AI with embedded systems is currently underutilized [116]. The core advantages of TinyML for these environments include reduced memory consumption, minimal power consumption, and the ability to operate autonomously without continuous internet connectivity.

TinyML algorithms can be deployed through frameworks like TensorFlow Lite (TFLite), which optimizes models for embedded platforms. Examples of TinyML-based solutions in smart crop systems include [117–119]. The study in [117] introduced a TinyML-based approach for identifying drought stress in soybean crops. This system is integrated with a Raspberry Pi Zero W (a low-cost, low-power single-board computer) and a Sony IMX219 camera module. After capturing images, the Raspberry Pi executed a convolutional neural network (CNN) to analyze signs of drought stress in the plants. The resulting predictions were then transmitted to an online platform. Crucially, to ensure compatibility with the resource-constrained hardware, the CNN model was converted into TFLite format. Researchers in [118] developed a machine learning pipeline specifically tailored for embedded systems to support the real-time monitoring of crop growth. They trained CNNs for two primary objectives: (a) estimating the Leaf Area Index (LAI), and (b) determining the plant's growth phase. Upon completion of training, the models were optimized and converted into TFLite format to suit deployment on microcontroller units (MCUs). The Sony Spsense platform was selected as the prototype hardware for validation, demonstrating the feasibility of complex image analysis on embedded systems.

Another study in [119] implemented a TinyML-based CNN to distinguish between healthy and diseased coffee plants. The system was designed to facilitate real-time crop health monitoring directly at the source, aiming to reduce the risk of disease transmission across plantations. To accommodate limited-resource hardware, the model was compressed using the Q_{m,n} format via the X-CUBE-AI framework, highlighting model quantization techniques. For deployment, the solution utilized a STMicroelectronics STM32F746G-DISCO board connected to an STM32F4DISCAM camera module. These components were

housed in a unit outfitted with LED lighting to illuminate coffee leaves during image capture, showcasing practical deployment considerations.

While TinyML offers benefits in terms of power efficiency and real-time inference at the edge, it is important to note that TinyML often involves trade-offs in model complexity (reduced model size) and accuracy (accuracy loss) compared to larger cloud-based models. Nevertheless, its ability to enable localized, autonomous decision-making makes it a cornerstone technology for developing adaptive smart crop systems in environments where continuous cloud connectivity is not guaranteed.

The various data fusion techniques, their applications, and their corresponding strengths and limitations in smart crop systems are summarized in Table 2.

Table 2. A summary of data fusion approaches in smart crop systems based on RQ2.

Ref.	Crop Type	Application	Data Fusion Type	Data Fusion Approach	Strength	Limitation
[105]	Rice, maize, jute, cotton	Crop yield estimation	Data-level fusion	Concatenation	Simplicity, low computation cost	Data redundancy
[110]	Coconut tree and cashew	Precision Irrigation	Data-, feature-, and decision-level fusion	Kalman filter algorithm, voting	Improved accuracy, flexibility	High computation complexity, integration challenges
[111]	Maize	Smart Irrigation	Data-level fusion	Concatenation	Lightweight computation	Poor results
[112]	Maize	Precision irrigation	Data-level fusion	Concatenation	Low computation cost	Data redundancy
[113]	Not specified	Smart irrigation	Feature-level fusion	LSTM deep fusion	Richer representation, better performance	Near-optimal results

3.3. How Can IoT Virtualization Be Leveraged Within Smart Crop Systems to Facilitate Real-Time Monitoring and Seamless Integration of Multimodal Data for Timely and Informed Decision-Making in Low-Resource Environments with Intermittent Internet Connectivity?

Farming operations increasingly face continuous environmental changes and resource pressures, necessitating the deployment of highly adaptive smart crop systems. These systems empower farmers with real-time decision-making capabilities, enabling timely responses to critical issues such as disease outbreaks, pest infestations, and adverse weather conditions [120]. By reacting swiftly to dynamic environmental shifts, farmers can optimize intervention windows, thereby mitigating risks associated with climatic variations and improving crop yields [121].

The development and management of these adaptive smart crop systems can be enhanced through IoT virtualization technologies, particularly via digital twin concepts. A digital twin is a dynamic virtual replica of a physical farm, enabling real-time simulation and decision-making [122,123]. As detailed by [121] the digital twin is not merely a model but a continuously evolving, multi-domain system that integrates heterogeneous data sources, from the molecular scale to the macro-level of entire fields. This virtual model continuously integrates real-time data from IoT sensors—such as soil sensors, crop monitors, and weather stations for simulation, predictive analytics, and optimized control of farming processes.

In smart crop systems, digital twins facilitate virtual representations of farming operations, encompassing key tasks such as pest control, crop yield estimation, fertilization, and irrigation management [124]. This virtualization enables seamless interaction between various system components, ensuring an integrated and cohesive agricultural management approach [125]. A conceptual architecture of a digital twin concept in smart crop systems is provided in Figure 6.

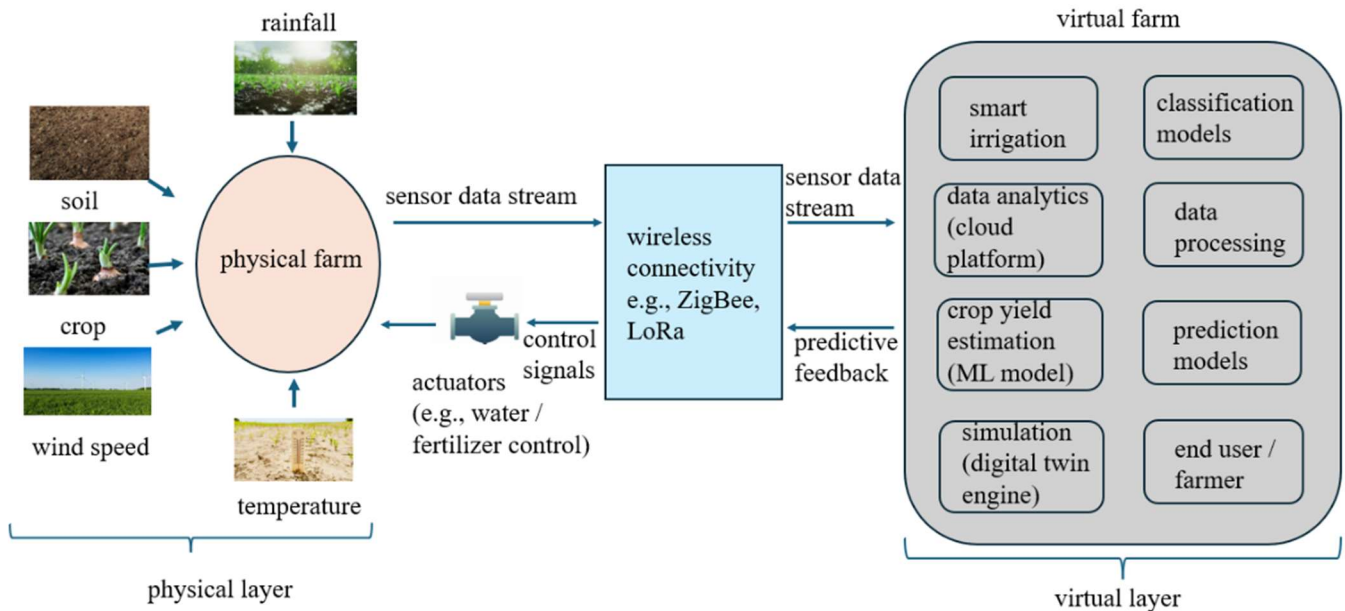


Figure 6. Conceptual architecture of a smart crop digital twin (virtual farm). This diagram illustrates the dynamic interaction between the physical farm environment—including real-time data from soil, crops, and weather sensors—and its virtual replica, enabled via wireless connectivity (e.g., ZigBee, LoRa). Bidirectional data flow is shown between the physical and virtual layers, supporting real-time monitoring, predictive feedback, and automated control. The virtual farm integrates modules for smart irrigation, crop yield estimation, data analytics, simulation, and machine learning-based classification and prediction, forming a closed-loop system for optimized agricultural decision-making. Note: This figure is conceptual and was drafted by the authors to support the discussion in Section 3.3. No external data sources were used.

Digital twins have demonstrated notable success across various industries, including manufacturing [126], energy [127], and aerospace [128]. In smart crop system, their application has yielded promising results, supporting precision farming efforts such as irrigation optimization [129], pest management enhancement [130], real-time crop monitoring [131], and improved yield prediction [132]. For instance, the authors of [129] developed a digital twin model for a smart irrigation system, utilizing sensor-driven analytics to optimize water usage and mitigate excessive applications. Similarly, in [132], machine learning was integrated with digital twin models to enhance crop yield estimation, demonstrating the potential of IoT virtualization in predictive agricultural analytics.

Leveraging IoT virtualization directly contributes to the development of adaptive sensor networks by enabling them to dynamically adjust their data collection strategies and operational parameters in response to evolving environmental conditions. This adaptability is particularly crucial since many existing smart crop solutions, despite their technological advancements, often lack the flexibility required for diverse farming contexts [133]. As highlighted by [134,135], the success of integrated systems is highly dependent on factors such as organizational readiness and the seamless flow of information between disparate components. Traditional systems are frequently tailored for specific, large-scale operations, limiting their adaptability for smaller farms or low-resource environments [136].

IoT virtualization inherently addresses this challenge by facilitating the seamless integration of multimodal data from heterogeneous sensors—including soil, crops, and weather monitoring devices—into a unified, virtualized platform. This integration eliminates the fragmented data approaches commonly observed in current systems [137], providing a more holistic and actionable view of agricultural ecosystems.

Table 3 provides a summary of recent literature on the application of IoT virtualization, specifically digital twins, in smart crop systems.

Table 3. Summary of RQ 3 based on IoT virtualization applications in smart crops.

Ref.	Crop Type	Application	IoT Virtualization
[129]	Maize, banana, beans	Smart irrigation system	Digital twin
[130]	Vegetables	Pest management enhancement	Digital twin
[131]	Not specified	Crop monitoring	Digital twin
[132]	Not specified	Crop yield estimation	Digital twin

3.4. How Can the Resource Constraints in Low-Resource Environments Be Managed to Ensure the Reliable Operation and Data Flow of Adaptive Smart Crop Systems?

The reliable operation and sustained data flow of adaptive smart crop systems in low-resource agricultural environments are profoundly challenged by constraints in power supply and internet connectivity. These limitations directly impact the system's ability to perform continuous monitoring, real-time data processing, and timely decision-making, which are critical for optimizing crop management and enhancing yields. This section delves into the peculiar challenges posed by these resource limitations and explores robust mitigation strategies essential for the successful deployment of adaptive smart crop technologies.

3.4.1. Power Resource Management

The power module within smart crop systems is responsible for supplying electrical energy to all active components, including the sensing elements (e.g., NPK, moisture, temperature, spectral sensors), data processing units (microcontrollers, edge devices), and transceiver components (e.g., Wi-Fi, LoRa, cellular modules). In resource-constrained settings, the pervasive lack of constant and reliable grid electricity presents a significant hurdle for ensuring continuous system operation. While many existing smart crop systems in the literature often rely on a stable electrical grid or AC outlets [96,100,104,106], only a few applied solar energy harvestings [97,101,138]. The reliance on an electric grid is impractical for remote, off-grid agricultural deployments. Furthermore, the inherent limitations of battery-only power sources, such as finite capacity, degradation over time, and the need for periodic manual replacement or recharging, impede long-term autonomous operation.

3.4.2. Internet Connectivity Management

The internet resource is fundamental for smart crop systems to forward collected data to cloud environments for extensive processing, analysis, and the derivation of actionable insights into farm conditions. However, in low-resource rural areas, inadequate and intermittent internet connectivity poses a formidable challenge, leading to data loss, delayed insights, and the inability of farmers to respond promptly to critical events. The predominant reliance of many existing smart crop systems on cloud computing [96,100,101,104,106,138] exacerbates this issue, as continuous, strong internet connectivity is a prerequisite for seamless data flow to and from the cloud.

Table 4 summarizes the system architecture used in smart crop systems, focusing on the roles of cloud and edge computing, power resource management, and their respective strengths and limitations.

Table 4. Summary of RQ 4 based on power resource management and internet connectivity management.

Ref.	Power Resource Management	Cloud Computing for Data Analysis	Edge Computing for Internet Connectivity Management	Strength	Limitation
[96]	Not considered	Yes	No	Scalable and flexible	Internet dependency and system instability
[97]	Solar energy harvesting	Yes	No	Energy efficient and remote accessibility	Requires stable connectivity
[100]	Not considered	Yes	No	Remote accessibility	Energy inefficient and requires stable connectivity
[101]	Solar energy harvesting	Yes	No	Sustainable system and remote accessibility	Internet dependency
[104]	Not considered	Yes	No	Flexible and cost efficient	Requires stable internet and not energy efficient
[106]	Not considered	Yes	Yes	Allowing local data processing	Energy efficient
[138]	Solar energy harvesting	Yes	No	Prolonged operation	Strong internet connection required

4. Trends in Technology Adoption in Smart Crop Systems

To contextualize our proposed research, we analyzed the key technological trends in smart crop systems. The findings of this analysis are summarized in Figure 7, which presents the adoption of core technologies in smart crop systems from 2015 to 2025.

The data revealed an increase in technological complexity and integration over the past decade, with a surge in publications beginning in 2020 and peaking in 2024. This reflects growing interest in scalable, intelligent agricultural solutions.

From 2015 to 2019, research was sparse and largely focused on unimodal sensing, cloud computing, and machine learning for tasks like yield prediction and disease classification. However, beginning in 2020, the literature expanded significantly in both volume and scope. Notably, references to unimodal sensing, cloud computing, and machine learning increased, signaling a transition toward distributed, interconnected systems.

The most prominent trend is the rapid rise in unimodal sensing, cloud computing, and machine learning, which collectively dominate recent publications. Their prevalence underscores a shift from isolated tools to integrated, data-driven frameworks. This evolution directly supports our proposed approach, which combines multimodal sensing, edge-to-cloud computing, IoT virtualization, and machine learning to meet the emerging demand for holistic smart farming solutions.

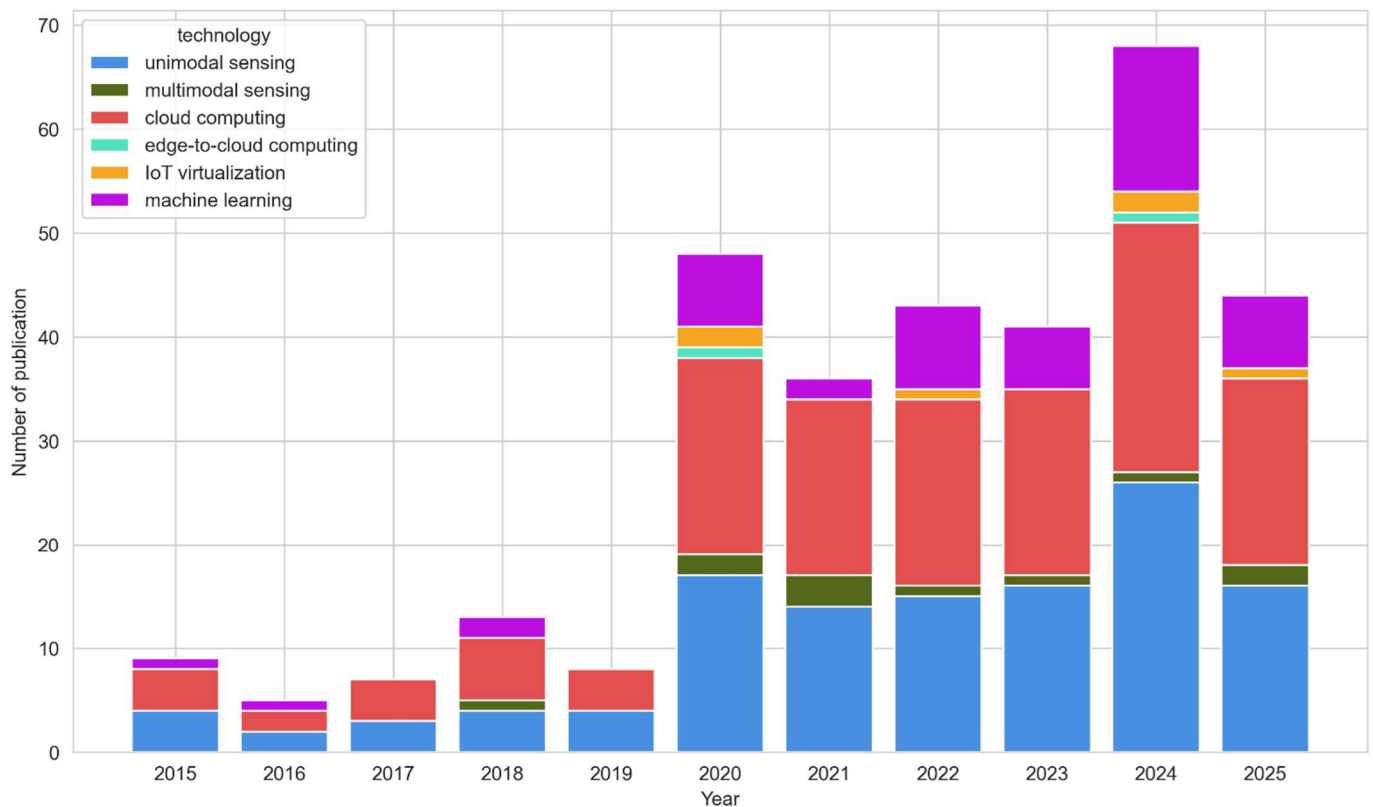


Figure 7. Trends in technology adoption based on the reviewed literature. This stacked bar chart illustrates a clear upward trajectory in research output and a shift in technological focus. Early studies were dominated by foundational technologies such as unimodal sensing and cloud computing. Post-2019, the growth accelerates, with machine learning emerging as a central component of increasingly data-rich, integrated systems for smart crop management.

5. Challenges in Existing Research on Smart Crop Systems

This section examines the limitations identified in the study, highlighting key challenges in smart crop applications, data fusion methodologies, and system virtualization. By analyzing gaps in data integration, computational efficiency, and infrastructure adaptability, the discussion provides insights into areas requiring further research and technological advancements to enhance precision, resilience, and scalability in smart crop systems.

5.1. Challenges Associated with Smart Crop Systems

The analysis of existing smart crop system applications reveals that the effectiveness of smart crop systems is often constrained by limited integration of diverse data streams. Many precision irrigation studies rely predominantly on soil data [92–95], with fewer incorporating crop [91] or weather data [93], and only a handful combining multiple sources [90]. This narrow focus can lead to suboptimal resource use. For example, irrigation decisions based solely on soil moisture may overlook plant water stress or upcoming rainfall.

Similar limitations are evident in IoT-enabled monitoring systems, where soil data dominates [96–99], and integrated approaches remain rare [100]. Fertilization strategies based on static soil nutrient levels may ignore plant uptake dynamics and weather-driven nutrient leaching, reducing efficiency and sustainability.

In pest and disease management, reliance on isolated data streams—weather [101], soil and weather [102], or crop imagery [103]—can delay or misguide interventions. Without accounting for crop susceptibility or environmental triggers, predictive models may miss early warning signs or apply treatments unnecessarily.

Yield estimation systems also tend to prioritize crop data [104,105], with limited use of integrated soil and weather inputs [106]. This can result in inaccurate forecasts, especially when vegetation indices are interpreted without context from soil nutrient availability or seasonal climate conditions.

Across these domains, the recurring challenge is the lack of cohesive, real-time integration of soil, crop, and weather data. Addressing this gap is essential for enabling dynamic, context-aware decisions that improve resource efficiency and system resilience.

5.2. Challenges Associated with Data Fusion

The reviewed literature reveals a tendency towards the utilization of data-level fusion [107–109], which, while potentially offering a more direct integration of sensor readings, can present challenges in managing data heterogeneity and potential redundancies arising from diverse sensor characteristics. While cited as potentially straightforward, the computational cost can vary depending on the required preprocessing steps for alignment and noise reduction. Feature-level fusion [107,110], involving the extraction and subsequent combination of salient features from individual sensors, appears less prevalent in the examined studies. This approach offers the advantage of integrating semantically richer information and can be effective in handling disparate data types before feeding into analytical models. Decision-level fusion [107,111], where independent models generate predictions based on individual data sources, and these predictions are then combined, is also less common but holds the potential for improved performance [122–124]. This advantage often stems from the ability to leverage specialized models tailored to each sensor modality and to integrate higher-level insights, potentially leading to more robust and context-aware decisions.

5.3. Challenges Associated with Smart Crop System Virtualization

IoT virtualization enables adaptive sensor networks that support real-time monitoring and multimodal data integration, even in connectivity-constrained environments. By leveraging digital twins and localized computation, smart crop systems can maintain functionality during network disruptions and respond dynamically to environmental changes. These capabilities enhance the accessibility, resilience, and operational efficiency of smart agriculture, particularly in underserved regions.

5.4. Challenges Associated with Resource Management

The analysis of existing smart crop systems reveals that they often overlook the resource constraints prevalent in low-income agricultural settings. As highlighted in Section 3.4, many reviewed deployments [96,100,101,104,106] assume constant access to electrical power—typically via grid connectivity or frequent battery replacement. This assumption clashes with the realities of off-grid farms, where power supply is unreliable and infrastructure is limited. The absence of integrated energy harvesting and low-power design strategies restricts scalability and long-term autonomy in precisely the regions that stand to benefit most.

In parallel, most systems depend on stable internet connectivity for cloud-based data processing [96,100,101,104,106,138]. While cloud computing enables scalable analytics, it introduces latency and vulnerability in areas with intermittent or no network access. This limits farmers' ability to receive timely insights, delaying critical interventions and reducing system responsiveness.

Together, these infrastructure mismatches undermine the practical viability of smart agriculture in resource-constrained contexts. Addressing them requires future research to prioritize energy-efficient hardware, adaptive communication protocols, and edge comput-

ing architectures that support local autonomy and buffered data flow, ensuring reliable operation despite environmental and infrastructural limitations.

6. Recommendation and Future Direction

This section outlines key research and technological advancements needed to enhance smart crop systems.

6.1. Enhanced Multi-Source Data Integration for Smart Crop Applications

The effectiveness of smart crop systems hinges on their ability to comprehensively integrate real-time and historical data from multiple sources, including soil, crops, and weather conditions. Existing systems predominantly rely on isolated data streams, which limit the accuracy and adaptability of precision irrigation, fertilization management, pest/disease control, and crop yield estimation. Addressing this fragmentation requires a holistic, multi-modal data fusion framework that dynamically integrates diverse data sources to improve predictive accuracy and operational efficiency.

6.1.1. Precision Irrigation Optimization

A multi-source fusion model that integrates real-time soil moisture data with crop physiology and weather forecasts can significantly enhance irrigation scheduling. Unlike traditional approaches that rely solely on soil parameters, this integrated framework enables adaptive irrigation strategies that consider plant water stress levels and anticipated weather-induced fluctuations, preventing both under- and over-irrigation.

6.1.2. Sustainable Fertilization Management

Implementing a data-driven fertilization system that combines soil nutrient profiles, crop nutrient uptake rates, and meteorological data can reduce environmental losses and improve efficiency. This approach ensures fertilization applications are dynamically adjusted based on growth-stage-specific nutrient demands, minimizing risks such as nutrient leaching due to unexpected rainfall while optimizing overall yield potential.

6.1.3. Advanced Pest and Disease Prediction

To enhance proactive intervention strategies, a real-time fusion of soil conditions, crop stress indicators, and environmental factors is essential for pest and disease management. Predictive models that integrate high-resolution imagery, soil microbiome analysis, and seasonal weather trends offer more precise risk assessments, allowing for targeted pesticide applications rather than broad-spectrum treatments, reducing chemical overuse and environmental impact.

6.1.4. Accurate Crop Yield Estimation

A multi-factor predictive modeling framework leveraging historical yield data, current crop health indicators, and soil/water availability trends can improve forecasting accuracy. Incorporating AI-driven context-aware analysis, which aligns environmental variables with real-time crop stress measurements, ensures highly adaptive yield predictions that can inform better resource allocation decisions.

6.2. Leveraging Advanced Data Fusion Level

High-level data fusion offers significant potential in achieving robust analytical results; however, it remains the least commonly applied among the three fusion levels. This limited adoption can be attributed to two primary challenges. First, the computational demands associated with high-level fusion, particularly during the training phase, can be substantial—this is especially evident when incorporating classifiers built on deep neural

networks, which require extensive processing resources. Second, selecting optimal variables for a single model is already a complex task, and extending this selection process across multiple models can introduce additional layers of difficulty. Despite these constraints, the integration of high-level fusion techniques is expected to increase as computational limitations diminish, advancements in data fusion research accelerate, and the unique attributes of various models and classifiers become more comprehensively understood.

6.3. Resource Management Solutions

The analysis of existing smart crop systems has revealed a critical deficiency in addressing the pervasive power and internet connectivity constraints prevalent in low-resource agricultural environments. To ensure the reliable operation and sustained data flow of adaptive smart crop systems in these challenging contexts, future research and development must prioritize robust resource management strategies.

6.3.1. Sustainable Power Resource Management

Current reliance on grid power or limited battery solutions is impractical for remote, off-grid deployments. Future work should focus on developing and integrating self-sustaining and efficient power solutions.

1. **Advanced Energy Harvesting Systems:** Research should emphasize the development of more efficient and cost-effective solar power systems tailored for agricultural IoT nodes, including optimized panel sizing, maximum power point tracking (MPPT) algorithms for varying light conditions, and robust battery management systems suitable for extreme temperatures. Exploration of hybrid energy harvesting approaches (e.g., combining solar with micro-wind or thermal gradients) for enhanced reliability in diverse climatic conditions is also crucial.
2. **Ultra-Low Power Hardware and Software Design:** Further advancements are needed in designing ultra-low-power microcontrollers (ULP-MCUs) and specialized System-on-Chips (SoCs) that minimize power consumption during active states and enable aggressive deep sleep modes. Complementary research into optimized embedded software architectures that facilitate efficient task scheduling, data aggregation at the node level, and intelligent sensor duty cycling will significantly extend battery life and reduce maintenance requirements.
3. **Low Power Communication Protocols:** While existing low-power wide-area network (LPWAN) protocols like LoRaWAN and NB-IoT are promising, future work should explore their further optimization for agricultural data patterns and the development of adaptive medium access control (MAC) protocols that dynamically adjust transmission parameters (e.g., data rate, transmit power, sleep cycles) based on real-time power availability and network conditions, thereby maximizing energy efficiency.

6.3.2. Resilient Internet Connectivity Management

The widespread dependence on continuous, high-bandwidth internet connectivity for cloud-centric processing severely limits smart crop system deployment in areas with intermittent or poor network infrastructure. Future research should focus on enhancing connectivity resilience by investigating and implementing.

1. **Optimized Edge-to-Cloud Architectures for Intermittent Connectivity:** Building upon the principles of edge computing, future work must develop intelligent edge nodes capable of extensive local data preprocessing, filtering, and aggregation. These nodes should incorporate robust data buffering mechanisms with sophisticated store-and-forward capabilities, ensuring data integrity and eventual transmission even during prolonged network outages. Research into adaptive data synchronization algorithms

that prioritize critical data and optimize transmission schedules based on available bandwidth is also essential.

2. Hybrid and Adaptive Communication Strategies: Investigating seamless integration and dynamic switching between multiple communication technologies (e.g., LoRaWAN for long-range sensor data, Wi-Fi for local gateway-to-edge communication, and satellite IoT for remote backhaul when terrestrial options are unavailable) is vital. Research should focus on self-organizing mesh networks among sensor nodes to improve local connectivity and data routing in challenging terrains, reducing reliance on single points of failure.

6.4. Network Security and Data Privacy

The increasing interconnectedness of smart crop systems, while offering immense benefits, simultaneously introduces critical vulnerabilities related to network security and data privacy. In a multi-stakeholder ecosystem, particularly where data aggregation and sharing might occur (e.g., for regional yield forecasting or pest outbreak alerts), the risk of unauthorized access, data breaches, or misuse of sensitive information becomes paramount. For instance, if individual farmers' specific data on crop health, soil nutrient profiles, or precise yield predictions were inadvertently or maliciously exposed to competitors, it could lead to significant economic disadvantages and erode trust in the entire system. To address this, future research and development must prioritize the implementation of robust security and privacy by design.

6.4.1. End-to-End Network Security

Implementing strong encryption protocols for data in transit (from sensors to edge, edge to cloud) and at rest (in databases). This also encompasses secure authentication mechanisms for all devices and users, and intrusion detection systems to monitor network integrity.

6.4.2. Specific Access Control, Data Segregation, and Privacy-Preserving Data

Developing sophisticated access control policies that allow farmers to define precisely who can access their data, to what extent, and for what purpose. This necessitates robust data segregation techniques to ensure that individual farm data remains isolated unless explicit sharing permissions are granted. Additionally, advanced privacy-enhancing technologies for scenarios requiring aggregated or shared data could be employed. Techniques such as differential privacy, homomorphic encryption, or secure multi-party computation can enable collaborative analytics (e.g., for regional trends) without exposing sensitive individual farm data. Research into blockchain for immutable data logging and transparent access management could also be considered.

6.4.3. Edge Computing for Enhanced Data Security and Privacy

Edge computing nodes, by processing data closer to the source, offer a significant opportunity to bolster data security and privacy in smart crop systems. Future research should leverage edge capabilities to investigate and implement.

1. Local Data Anonymization and Aggregation: Implement privacy-preserving techniques directly at the edge, allowing sensitive raw data to be anonymized or aggregated into less identifiable forms before being transmitted to the cloud. This minimizes the exposure of individual farm or sensor-level details while still providing valuable insights for broader analysis.
2. Decentralized Access Control Enforcement: Edge nodes can act as local policy enforcement points, verifying access credentials and permissions before data leaves the farm

- perimeter. This creates a more distributed security architecture, reducing reliance on a single, centralized control point.
3. **Secure Device Management and Firmware Updates:** Edge gateways can serve as secure conduits for managing and pushing authenticated firmware updates to sensor nodes, mitigating the risk of malicious code injection. They can also perform local integrity checks on connected devices.
 4. **Reduced Attack Surface for Raw Data:** By performing initial processing and filtering at the edge, the volume of raw, potentially sensitive data exposed to the wider internet is significantly reduced, thereby shrinking the attack surface for data in transit to the cloud.
 5. **Offline Security Resilience:** Edge nodes can maintain basic security operations and data buffering even during intermittent connectivity, providing a layer of security resilience when cloud-based security services are temporarily unavailable.

7. Conclusions

Smart crop systems hold immense potential to revolutionize agricultural practices, significantly enhancing productivity and sustainability in the face of escalating global challenges. This systematic review addressed four key research questions to clarify the architecture, integration strategies, and deployment challenges of smart crop technologies in resource-constrained environments.

First, we found that smart crop systems typically follow a three-layered architecture, comprising data acquisition, edge-based processing, and cloud-level analytics, supported by diverse sensors monitoring soil, crop, and environmental parameters. Second, data fusion techniques were categorized into data-level, feature-level, and decision-level approaches, each offering distinct advantages for integrating multimodal agricultural data. Third, IoT virtualization, particularly through digital twin technologies, emerged as a promising strategy for enabling adaptive sensor networks and real-time monitoring, even under intermittent connectivity. Fourth, resource constraints such as unreliable power and internet access can be mitigated through solar energy harvesting and edge computing frameworks like TinyML, which support localized decision-making without continuous cloud dependence.

Our findings reveal that current smart crop systems often suffer from fragmented sensor deployments, limited data integration, and overreliance on centralized cloud infrastructure—factors that hinder responsiveness and scalability in low-resource settings. To empower farmers and harness the full potential of these technologies, a paradigm shift is needed toward resilient, context-aware system design.

Future research should prioritize the development of unified frameworks that integrate multimodal sensing with robust data fusion pipelines tailored to heterogeneous farm environments. Emphasis should be placed on lightweight, energy-efficient architectures that balance edge and cloud computing to reduce latency and improve autonomy. Additionally, expanding the use of IoT virtualization and digital twins can facilitate predictive analytics and adaptive control, especially in regions with infrastructure limitations. Addressing these gaps will be critical to ensuring that smart crop technologies are not only technically advanced but also practically deployable and impactful for farmers in underserved agricultural regions.

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