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COMPUTER ENGINEERING DEPARTMENT

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Literature & Technology Review

A Review on Internet of Things, Machine Learning, and Digital Twin Approaches in Smart Agriculture

ARDA KAHRAMAN - 202111002
HATİCE ELİF ARABACI - 202211008
ÖYKÜ EYLÜL BOZDAĞ - 202311410
MUSTAFA BERK KESKİN - 202211042

1. Introduction

Modern agriculture is increasingly affected by climate variability, declining freshwater resources, and sustainability challenges. Many farmers still make irrigation and crop-management decisions based on intuition rather than systematic measurements, which reduces decision accuracy and leads to inefficient water use [1]. Research also shows that improper irrigation practices can cause water loss and yield reduction, making data-driven decision support essential for future agricultural productivity [2], [3].

Recent advances in digital agriculture offer viable solutions. IoT-based sensing systems provide continuous measurements of soil and environmental conditions [4], while machine-learning algorithms can analyze these data to generate accurate irrigation recommendations [4]. Digital twin technologies enable virtual representations of agricultural fields for real-time simulation and visualization [5], and later studies show that digital twins can significantly enhance field monitoring under dynamic conditions [6]. In parallel, computer-vision models have demonstrated strong performance in diagnosing plant diseases directly from leaf images [7].

TARAS platform brings these technologies together into a unified, farmer-oriented system that offers real-time field monitoring, irrigation prediction, disease assessment, and digital-twin visualization. The project aligns with Türkiye's Twelfth Development Plan, which emphasizes AI-supported digital agriculture [8], and also contributes to global sustainability objectives such as SDG 12, SDG 13, and SDG 15 [9].

1.1 Background

Agriculture has progressed through four major transformations: the emergence of settled farming, the mechanization introduced during the Industrial Revolution, the productivity gains of the Green Revolution, and today's Agriculture 4.0 era driven by digital technologies. Precision Agriculture, a key component of this era, relies on monitoring and responding to spatial and temporal field variability to optimize resource use [4]. IoT sensors enable real-time environmental monitoring, digital twins provide interactive virtual models of fields for prediction and analysis [5], and computer-vision systems support early disease recognition through image-based diagnosis [7]. TARAS builds on this technological landscape to create a unified platform tailored for real agricultural environments.

1.2 Problem Definition

Traditional Farming Limitations: One of the major challenges in modern agriculture is that farmers struggle to make reliable, data-based decisions. Many still rely on intuition rather than systematic and evidence-based methods, which limits the accuracy of field management [1]. Although intuition has supported farming for generations, it is becoming less effective as climate patterns shift and soil conditions change. As a result, crops often fail to reach their full yield potential when decisions depend solely on historical experience.

Resource Scarcity: Water scarcity is one of the most critical constraints in agriculture today. Traditional irrigation methods frequently lead to over-watering, which wastes water and damages root systems, or under-watering, which stunts plant growth. Studies show that inefficient or poorly timed irrigation can cause significant water loss and reduce productivity [2], [3]. Because soil moisture varies across fields and changes over time, static rule-based irrigation schedules cannot meet crop-specific requirements, leading to substantial inefficiencies in both water and energy use.

Disease Management Challenges: Farmers commonly notice unusual visual changes in plants but cannot determine whether these differences indicate disease or harmless variation. This uncertainty can delay intervention or lead to unnecessary pesticide use. When early symptoms are subtle or unfamiliar, problems may be ignored until they become severe, or pesticides may be applied without need. Both outcomes increase production costs and negatively affect food safety and environmental health. Image-based decision-support systems can help address this uncertainty by allowing farmers to upload leaf images and receive automated analysis, improving early assessment and supporting timely, informed action [7].

Data Quality & System Reliability Issues: Even when farmers adopt technological tools, field data are often incomplete or inconsistent due to sensor drift, hardware faults, or communication failures. Soil-moisture probes may lose calibration over time, wireless connections may drop, and environmental fluctuations can distort sensor readings. Without proper validation, calibration, and anomaly-detection mechanisms, inaccurate data can mislead decision-making and become as harmful as intuition-based irrigation.

Lack of Accessible, Integrated Decision Support: Many farms rely on fragmented digital tools, such as separate systems for sensors, irrigation controllers, weather forecasts, and crop health information. Because these systems do not communicate with each other, farmers, especially small-scale producers, struggle to benefit from advanced analytics. This fragmentation highlights the need for an integrated platform that combines real-time field monitoring, intelligent recommendations, visual explanations, and sustainability metrics within a single accessible system.

1.3 Scope of the Study

The scope of TARAS covers the development of an end-to-end precision-agriculture platform. The system includes IoT-based soil-moisture and temperature sensing, long-range communication through LoRa, and a gateway for field-to-cloud data transfer. It incorporates a secure cloud database for storing real-time and historical records, machine-learning models for irrigation prediction, and computer-vision algorithms for disease identification.

The project further includes the design of a mobile application that provides farmers with moisture visualization through a digital twin, image-based disease assessment, and an AI-assisted decision interface. The system focuses on decision support rather than full automation, ensuring that farmers remain central to the decision-making process. It is intended to be low-cost, portable, and scalable across various field configurations.

1.4 Aim and Contributions

Aim

The aim of TARAS is to provide farmers with an intelligent, real-time agricultural assistant that can analyze environmental conditions, predict irrigation requirements, detect plant diseases from leaf images, and visualize moisture distribution through digital twin technology. By bringing together IoT, machine learning, computer vision, and cloud computing, the system offers a highly adaptive and user-centered approach that supports precision farming and sustainable resource management.

TARAS aims to:

- Optimize irrigation efficiency
- Reduce water and energy waste
- Enhance crop health monitoring
- Improve sustainability through carbon footprint tracking
- Provide farmers with actionable, explainable, and accessible insights

Contributions

Recent advancements in smart agriculture highlight the value of combining IoT-based sensing with machine-learning-driven decision systems to improve irrigation efficiency and field management. Studies show that ML algorithms using soil moisture, temperature, humidity, and soil-type data can generate highly precise irrigation recommendations and adapt to changing field and weather conditions. TARAS builds on these findings by pairing such predictive models with real-time digital-twin visualizations, enabling farmers to interpret moisture patterns through intuitive heatmaps, observe changes over time, and identify areas requiring intervention more clearly.

Beyond irrigation, TARAS incorporates computer-vision-based disease detection that allows farmers to upload leaf images through the mobile application. These images are processed using CNN models that classify diseases or stress symptoms and provide actionable assessments, reducing the need for expert diagnosis. The platform also addresses sustainability by integrating carbon-footprint metrics, estimating emissions based on pump energy usage, fertilizer inputs, and water savings.

By combining these capabilities into a single, cohesive platform, TARAS contributes to the development of intelligent, adaptive, and sustainability-focused digital farming systems that make advanced decision support accessible to farmers across different scales.

2. IoT Sensor Node Architecture

The foundation of any smart farming system is the ability to collect accurate environmental data from the field [10]. The literature emphasizes that hardware in agriculture must be low-power, durable, and cost-effective.

2.1 Microcontroller Selection: The Shift to ESP32-C6 and RISC-V

In the realm of agricultural IoT, the primary engineering challenge is maximizing the operational lifespan of battery-powered nodes. Zhang and Meng (2021) highlight that energy efficiency is the most critical factor for the economic viability of precision agriculture, as frequent battery replacements increase labor costs significantly [11].

While earlier projects successfully utilized standard ESP32 or ESP8266 modules, recent literature indicates a shift toward more specialized architectures. Recent studies in wireless sensor networks have begun favoring RISC-V based architectures for their superior power-to-performance ratio. For example, a study by Liu et al. (2023) implemented agricultural monitoring nodes using RISC-V processors, noting a significant reduction in standby power consumption compared to traditional ARM-based controllers [12].

Building on these findings, the TARAS project utilizes the **ESP32-C6**, which integrates this efficient RISC-V architecture. Similar projects focusing on energy-harvesting IoT—such as devices powered by small solar panels—have cited the ESP32-C series as a benchmark for minimizing energy drift. Nguyen and Kumar (2024) highlighted that the C-series chips allow nodes to survive distinct periods of low sunlight or winter months without going offline, a critical factor for continuous year-round field monitoring [13].

The decisive factor for selecting the ESP32-C6 is its dedicated **Low-Power (LP) Core**. Unlike standard microcontrollers where the entire system must wake up to perform a simple reading, the C6 allows the power-hungry main CPU to remain in deep sleep while the highly efficient LP core stays active to monitor sensor thresholds [14]. This architecture allows the system to perform essential tasks—such as checking if soil moisture has dropped below a critical level—while consuming micro-amps rather than milli-amps.

Another advantage of using ESP32 is its support of the I^2C (Inter-Integrated Circuit) Communication Interface, which is a widely used two-wire communication interface designed for low-power embedded systems. I^2C enables multiple digital sensors to communicate with the ESP32 microcontroller over a shared SDA (data) and SCL (clock) bus, reducing wiring complexity and supporting scalable node designs. Its address-based structure allows several sensors to operate simultaneously, making it particularly suitable for multi-parameter agricultural monitoring. The protocol's low latency and efficient power consumption make it ideal for continuous field measurements where reliability and simplicity are critical [14].

2.1 Sensing Technologies: Capacitive vs. Resistive

Accurate irrigation depends entirely on accurate soil moisture readings. Historic literature often cited "resistive" sensors, which measure moisture by passing an electric current through the soil [15]. However, engineering studies have extensively documented the failure of these sensors due to **electrolysis**, which causes the metal probes to corrode (rust) within weeks [16].

To solve this, modern research advocates for **Capacitive Soil Moisture Sensors**. These measure the dielectric permittivity of the soil, basically how much charge the soil can hold, without any exposed metal touching the soil. This prevents corrosion and ensures reliable data over long periods [17]. Similarly, for air metrics, digital sensors like the **SHT31** are preferred over analog thermistors because they provide calibrated digital output, eliminating errors caused by electrical noise in the wires [18].

3. Long-Range Communication Infrastructure

Once data is collected, it must be transmitted to a central point. This is one of the most difficult challenges in precision agriculture due to the size of fields and the lack of infrastructure [19].

3.1 LoRa vs Traditional Connectivity

Standard communication protocols often fail in agricultural settings. Wi-Fi, for example, is designed for indoor use and typically loses signal strength after 50–100 meters, making it useless for large crop fields. Cellular networks (4G/LTE) offer great range, but they are power-hungry and expensive, requiring a data plan for every single sensor node [20].

To bridge this gap, researchers have turned to **LoRa (Long Range)** technology. LoRa utilizes a radio technique called "Chirp Spread Spectrum," which allows it to send data over extremely long distances (10–15 km in rural areas) while using very little power [21]. Additionally, LoRa operates on Sub-GHz frequencies, which gives it better physical penetration properties than Wi-Fi; it can pass through dense crop canopies, trees, and uneven terrain that would block higher-frequency signals. These characteristics make LoRa the optimal choice for connecting scattered sensors in a rural environment.

4. Edge Computing and Gateway Strategy

While LoRa connects the sensors, the data still needs to get to the internet. This requires a "Gateway."

4.1 Role of Raspberry Pi

While it is possible to use a microcontroller as a simple bridge, literature suggests that a robust gateway should run a full operating system. A survey by Ray (2018) indicates that gateways running Linux (like the **Raspberry Pi**) offer superior security and protocol management compared to bare-metal microcontrollers [22]. Unlike a simple microcontroller, the Raspberry Pi can perform "Edge Computing." It can buffer data locally if the farm's internet connection goes down, a common occurrence in rural areas, and upload it later when connectivity returns [23]. This store-and-forward capability ensures that no critical environmental data is lost during network outages.

5. Cloud Computing and Data Management

Handling the influx of data from the field requires a scalable and organized backend system.

5.1 Structured Database Design (PostgreSQL)

Agricultural data is primarily "Time-Series Data" (e.g., specific moisture values recorded at specific times). While flexible NoSQL databases are popular for web apps, scientific applications usually prefer Relational Databases like **PostgreSQL** for their strict structure and reliability. PostgreSQL is ACID-compliant, meaning it guarantees data validity even in the event of errors or power failures [24]. Furthermore, the system utilizes a "Log-Based" architecture. As recommended in foundational database literature, this approach involves never deleting or overwriting old records, but simply appending new ones [24]. This creates an unchangeable history of the field, which is essential for training accurate machine learning models later.

6. Artificial Intelligence and Machine Learning

Collecting data is only useful if it leads to better decisions. **Artificial Intelligence (AI)** is used to process raw numbers into actionable advice [25].

6.1 Machine Learning for Irrigation

Determining when to water crops is fundamentally a prediction problem. Traditional irrigation controllers typically rely on static rules (e.g., "water every morning") or simple mathematical formulas (e.g., "if moisture < 30%, turn on"). However, literature argues that these static methods are inefficient because they fail to account for non-linear environmental factors, such as sudden weather changes or varying crop growth stages.

Research indicates that **Machine Learning (ML)** algorithms significantly outperform these static rules by learning complex patterns from historical data. For instance, **XGBoost (eXtreme Gradient Boosting)** is frequently cited as a top performer for tabular data, capable of adapting to changing climate conditions better than linear regression models [26].

Furthermore, ensemble methods like **Random Forest (RF)** have demonstrated superior robustness in irrigation scheduling. A review by Munir et al. (2021) highlights that RF consistently outperforms simpler models like Decision Trees (DT) in predicting irrigation volumes and Evapotranspiration

(ETo). The study notes that RF achieves the highest accuracy among comparative models for time-series environmental data, often competing with complex Artificial Neural Networks (ANN) while remaining computationally efficient [27]. Studies show these predictive models can reduce water consumption by 20–30% [28].

6.2 Computer Vision for Disease Detection (CNNs)

Identifying plant diseases early can save a harvest, but expert agronomists are not always available [7]. To automate this, we use **Convolutional Neural Networks (CNNs)**. These are deep learning models designed specifically to analyze images. By training a CNN on thousands of photos of sick and healthy leaves, the model learns to recognize specific patterns, like the texture of a fungal spore or the color of a bacterial spot. Using optimized architectures like **MobileNet**, these models can run efficiently on mobile devices, providing farmers with instant disease diagnosis with over 90% accuracy [7].

6.3 Large Language Models

To translate complex analytical outputs into actionable guidance for farmers, TARAS integrates a **Large Language Model (LLM)** within an interactive chatbot interface. This component acts as the system's communication layer, interpreting sensor data, historical irrigation records, and computer vision findings to generate clear, context-aware explanations.

Research by Wang et al. (2024) indicates that LLMs significantly bridge the gap between technical data and farmer understanding by providing natural language explanations for agronomic advice [29]. Instead of presenting users with raw numerical values, the LLM-equipped assistant provides meaningful insights, for example, why irrigation is recommended on a specific day or how a detected disease might impact the crop. Additionally, the LLM supports "what-if" scenario analysis by simulating alternative decisions (such as delaying irrigation or applying preventive treatments) and explaining their potential outcomes. Through domain-adapted fine-tuning or retrieval-augmented generation (RAG), the model ensures high accuracy, transforming TARAS into a transparent, reliable, and user-friendly agricultural advisor.

7. Visualization and Digital Twins

The interface between the human and the machine is just as important as the technology itself.

7.1 Reducing Cognitive Load with Digital Twins

"Cognitive Load" refers to how much mental effort is needed to understand information. Research indicates that standard spreadsheets impose a high cognitive load, whereas visual maps reduce this load significantly [30]. The concept of the **Digital Twin** involves creating a 3D virtual replica of the physical field. Research suggests that visualizing data spatially, such as a 3D heat map where dry areas glow red, allows farmers to identify problem zones much faster than reading lists of numbers [31]. To make this accessible, **React Native** is used to build a cross-platform mobile app, ensuring the tool works on the smartphones farmers already own.

8. Mobile Application

Mobile applications have emerged as one of the most widely adopted interfaces in smart agriculture systems. Studies highlight that mobile platforms make complex IoT and AI infrastructures accessible by presenting field information directly to farmers in real time. They support continuous monitoring, rapid decision making, and convenient data entry, which makes them a practical tool for field operations where desktop interfaces are rarely available [32].

8.1 Mobile Applications in Agriculture

Recent smart-agriculture research emphasizes the role of mobile applications as the primary interaction layer between farmers and digital farming systems. Mobile tools frequently act as gateways for sensor networks, cloud platforms, and machine-learning models. They are used for monitoring field conditions, visualizing environmental data, delivering agronomic recommendations, and providing remote diagnostic services. Literature also notes that mobile interfaces significantly increase technology adoption among farmers, especially when the design is simple and the recommendations are easy to interpret [32].

8.2 Mobile App in TARAS

Within this literature landscape, the TARAS mobile application follows the same principles identified in prior studies. It functions as the primary interface through which farmers receive sensor readings, irrigation recommendations, and disease analysis results. The app also includes a 3D digital-twin visualization that represents moisture distribution spatially, a feature that extends the capabilities of many existing mobile agricultural systems. By combining monitoring, prediction, disease assessment, and spatial visualization into a single platform, TARAS addresses the fragmentation noted in current literature and provides a unified decision-support tool aligned with modern precision-agriculture practices.

8.3 Technology Stack

The technological choices used in the TARAS mobile application reflect practices recommended in mobile and IoT literature. **React Native** is widely adopted for agricultural applications because it enables cross-platform deployment on Android and iOS, which is essential given the diversity of devices in rural areas [33]. Expo simplifies development and maintenance processes by managing native modules and supporting incremental updates, which is useful for systems deployed in field environments with limited technical infrastructure [33].

For visualization, **React Three Fiber** allows efficient rendering of 3D elements on mobile devices, supporting interactive digital-twin displays similar to those explored in recent spatial agriculture studies [31]. The data exchange between the mobile client and the cloud backend uses a simple request–response API model, which is frequently adopted in smart farming architectures for real-time synchronization.

9. Ecological Impact

Technology must also serve environmental goals. Modern agriculture is under pressure to reduce its environmental impact, in line with UN Sustainable Development Goals 12 and 13 [9]. Literature suggests that IoT systems are uniquely positioned to automate sustainability tracking. By monitoring exactly how long water pumps run and how much resource is consumed, the system can calculate a real-time **Carbon Footprint**. This moves sustainability from a vague concept to a measurable metric [34].

9.1 Water Consumption

The TARAS system promotes responsible resource use by ensuring that irrigation is conducted only when and where it is needed, directly supporting the principles of Goal 12. By replacing uniform, schedule-based watering with sensor-driven and ML-optimized recommendations, TARAS minimizes unnecessary water consumption, reduces nutrient runoff, and lowers the overall environmental footprint of agricultural production. This precision in irrigation not only conserves water but also decreases the energy required for pumping, thereby reducing operational emissions and contributing to Goal 13 on climate action. Through its Digital Twin visualizations and adaptive decision-support engine, the system enables farmers to monitor consumption patterns, identify inefficiencies, and implement more sustainable long-term practices. In doing so, TARAS strengthens both resource responsibility and climate resilience within modern agriculture.

9.2 Carbon Footprint

Agriculture is one of the most significant contributors to global greenhouse gas (GHG) emissions, accounting for approximately one-fifth of total anthropogenic emissions [35]. The main sources include fertilizer production and application, energy consumption for irrigation and machinery, livestock management, and soil-based emissions such as nitrous oxide (N_2O) from nitrogen fertilizers and methane (CH_4) from organic decomposition. These emissions, when expressed as carbon dioxide equivalents (CO_2e), constitute the carbon footprint of agricultural production. Understanding and reducing this footprint has become a major focus in achieving the United Nations Sustainable Development Goals (SDGs), particularly Goal 12 (Responsible Consumption and Production) and Goal 13 (Climate Action).

Recent studies indicate that digital and IoT-based farming systems can play a transformative role in mitigating agricultural greenhouse gas emissions. Precision irrigation systems that utilize real-time soil-moisture and climate sensing enable farmers to reduce unnecessary water use and the associated energy required for pumping, thereby decreasing CO_2 emissions [36]. Similarly, IoT-supported fertilization and nutrient-management approaches help align nitrogen application with actual crop demand, preventing overuse and limiting nitrous oxide (N_2O) emissions, one of the most potent agricultural greenhouse gases [37]. Overall, these digital and sensor-driven strategies improve resource efficiency and contribute to more sustainable agricultural production [38].

Machine learning and decision-support systems further enhance the ability to estimate and monitor carbon footprints dynamically. By combining environmental sensor data (soil moisture, temperature) with user-provided activity data (fertilizer use, diesel consumption, electricity usage), these systems can calculate real-time carbon emission scores at the farm or greenhouse level.

Integrating this functionality into a mobile application significantly increases accessibility and user engagement. Farmers can view their estimated emissions, identify the main contributing factors. Within the TARAS system, this allows users to enter their input data and instantly calculate their farm's carbon footprint. The module supports sustainability awareness and provides actionable insights for emission reduction strategies, reinforcing the system's contribution to climate action (Goal 13) and responsible production (Goal 12).

10. Related Work

To design the TARAS platform, we analyzed several existing systems and research projects. While many solutions exist, they typically solve only one part of the problem. This section discusses these related works and how they directly influenced our design choices.

10.1 Single-Purpose Smart Irrigation Systems

A significant amount of research focuses solely on automating water pumps.

- **The Study:** A prominent study by Nawandar & Satpute (2019) developed a low-cost IoT system using simple neural networks to schedule irrigation based on soil data [39].

- **Limitation:** While effective at saving water, this system operates in a vacuum. It assumes the plant is healthy. If a plant is attacked by a fungus, it might need less water or a chemical treatment, not just standard irrigation. The system had no way of "seeing" the plant's health.

- **Effect on TARAS:** This influenced us to build a **hybrid system**. TARAS combines soil sensors with camera-based disease detection so decisions are made based on the whole picture, not just the soil moisture level.

10.2 Standalone Disease Detection Applications

On the other side of the spectrum, there is extensive research on using AI to spot diseases.

- **The Study:** The most famous work in this field is by Mohanty et al. (2016), who trained Deep Learning models on the PlantVillage dataset [7].

- **Limitation:** While scientifically impressive, this approach was purely diagnostic. It tells the farmer "You have Apple Scab," but it doesn't link that information to the farm's environmental history. Was the disease caused by over-watering? The app couldn't say because it didn't have access to soil data.

- **Effect on TARAS:** This taught us that **context matters**. In TARAS, when a disease is detected, the system can cross-reference it with historical humidity logs to help explain why the outbreak happened.

10.3 High-End Digital Twins

Finally, we looked at existing "Digital Twin" concepts.

- **The Study:** Pylianidis et al. (2021) explored creating digital twins for high-tech greenhouses. These systems create incredible 3D simulations of crop growth and climate control [40].

- **Limitation:** These systems are extremely complex, expensive, and require powerful desktop computers. They are designed for industrial agronomists, not for a typical farmer standing in a field with a phone.

- **Effect on TARAS:** This defined our **Mobile-First strategy**. We chose technologies like **React Native** and **low-poly 3D rendering** to ensure our Digital Twin works smoothly on a standard smartphone, making the technology accessible to regular farmers.

11. Conclusion and Research Gap

The review of existing literature establishes that **LoRa** is the optimal communication protocol for rural fields, with data-driven irrigation prediction, and CNNs are effective for disease detection.

However, a significant gap remains. Most current solutions function in isolation, offering either irrigation control or disease detection, and often lack user-friendly visualization tools for small-scale farmers. Furthermore, few systems actively track sustainability metrics like carbon footprints alongside agronomic data. Consequently, there is a need for a unified, **low-cost platform** that combines **real-time sensing, AI-driven predictions**, and **visual analytics into a single accessible mobile system**. The proposed TARAS project aims to address this gap by developing an end-to-end solution tailored for these needs.

References

[1] A. Araujo-McCole, K. D. Ilyes, and J. M. S. da Silva, "Exploring Farmers' Decision-Making Practices in Precision Agriculture," *Agricultural Systems*, vol. 204, p. 103554, 2023.

[2] S. Ali et al., "Effects of Improper Irrigation Practices on Water Use Efficiency," *Irrigation Science*, vol. 42, no. 1, pp. 45–58, 2024.

[3] Y. An et al., "Impact of Irrigation Scheduling on Crop Productivity and Water Savings," *Agricultural Water Management*, vol. 265, p. 107530, 2022.

[4] A. Soussi, E. Zero, R. Sacile, D. Trinchero, and M. Fossa, "Smart Sensors and Smart Data for Precision Agriculture: A Review," *Sensors*, vol. 24, no. 8, p. 2647, 2024.

[5] R. Zhang, Y. Wang, and L. Chen, "A Comprehensive Review of Digital Twin Technology in Agriculture," *Agriculture*, vol. 15, no. 2, p. 301, 2025.

[6] T. Y. Melesse, J. Kang, and P. Nam, "Digital Twin-Based Applications in Crop Monitoring," *Computers and Electronics in Agriculture*, vol. 216, p. 108488, 2025.

[7] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," *Frontiers in Plant Science*, vol. 7, p. 1419, 2016.

[8] Republic of Türkiye, "Twelfth Development Plan (2024–2028)," Presidency of Strategy and Budget, Ankara, 2023.

[9] United Nations, "Transforming our world: the 2030 Agenda for Sustainable Development," A/RES/70/1, 2015.

[10] T. Ojha, S. Misra, and N. S. Raghuwanshi, "Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges," *Computers and Electronics in Agriculture*, vol. 118, pp. 66–84, 2015.

[11] B. Zhang and L. Meng, "Energy Efficiency Analysis of Wireless Sensor Networks in Precision Agriculture Economy," *Scientific Programming*, vol. 2021, Article ID 8346708, 2021.

[12] Y. Liu, Z. Zhang, and X. Wang, "Energy-Efficient RISC-V Architecture for Wireless Sensor Networks in Precision Agriculture," *IEEE Internet of Things Journal*, vol. 10, no. 4, pp. 3452–3460, 2023.

[13] T. Nguyen and A. Kumar, "Performance Evaluation of ESP32-C3 and C6 in Energy Harvesting IoT Applications," *Sensors and Actuators A: Physical*, vol. 360, p. 114502, 2024.

[14] Espressif Systems, "ESP32-C6 Technical Reference Manual: Ultra-Low-Power (ULP) Coprocessor," Version 1.0, Espressif Systems, Shanghai, China, 2023.

[15] E. T. Engman, "Soil Moisture," in *Remote Sensing in Hydrology and Water Management*, G. A. Schultz and E. T. Engman, Eds. Berlin, Heidelberg: Springer, 2000, pp. 197–216.

[16] R. Rowe, *Soil Moisture Measurement Lab Manual*, Biosystems Engineering, Auburn University, 2018.

[17] S. K. Sahoo, "Capacitive Soil Moisture Sensor for Smart Irrigation: A Review," *IEEE Sensors Journal*, vol. 19, no. 14, pp. 5374-5383, 2019.

[18] Sensirion AG, "Datasheet SHT3x-DIS: Humidity and Temperature Sensors," Version 6.0, Sensirion AG, Stäfa, Switzerland, 2023.

[19] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A Survey on Wireless Sensor Networks and IoT in Precision Agriculture," *IEEE Access*, vol. 7, pp. 117727–117759, 2019.

[20] X. Yang et al., "Choosing the Right Wireless Network Technologies for Agricultural Internet-Of-Things Applications," South Dakota State University Extension, Brookings, SD, USA, Technical Report, Oct. 2024.

[21] J. Haxhibeqiri et al., "A Survey of LoRaWAN for IoT: From Technology to Application," *Sensors*, vol. 18, no. 11, p. 3995, 2018.

[22] P. P. Ray, "A survey on Internet of Things architectures," *Journal of King Saud University - Computer and Information Sciences*, vol. 30, no. 3, pp. 291-319, 2018.

[23] P. Angin and M. Karam, "AgriLoRa: A Digital Twin Framework for Smart Agriculture," *IEEE International Workshop on Metrology for Agriculture and Forestry*, 2020.

[24] M. Stonebraker and L. A. Rowe, "The Design of Postgres," *ACM SIGMOD Record*, vol. 15, no. 2, pp. 340–355, 1986.

[25] T. S. L. V. Ayyarao et al., "A review on the use of AI for IoT based smart farming," *Measurement*, vol. 201, p. 111812, 2022.

[26] B. Mbunge et al., "Review of machine learning techniques for precision irrigation in agriculture," *Computers and Electronics in Agriculture*, vol. 184, p. 106081, 2021.

[27] M. S. Munir, I. S. Bajwa, A. Ashraf, W. Anwar, and R. Rashid, "Machine Learning Algorithms for Smart Irrigation System: A Review," *Applied System Innovation*, vol. 4, no. 1, p. 6, 2021.

[28] M. Goap et al., "An IoT based smart irrigation management system using Machine Learning," *Computers and Electronics in Agriculture*, vol. 155, pp. 41–49, 2018.

[29] Q. Wang, Y. Ma, K. Zhao, and Y. Tian, "A Comprehensive Survey of Large Language Models in Agriculture: Applications, Challenges, and Future Directions," *IEEE Access*, vol. 12, pp. 11200-11220, 2024.

[30] S. Kummar, F. S. Al-Aani, H. Kahtan, M. J. Darr, and H. Al-Bashiri, "Data Visualisation for Smart Farming Using Mobile Application," *International Journal of Computer Science and Network Security*, vol. 19, no. 11, pp. 174-180, 2019.

[31] C. Verdouw et al., "Digital twins in smart farming," *Agricultural Systems*, vol. 189, p. 103046, 2021.

[32] A. Sharma et al., "Mobile Apps for Farmers: Adoption and Usability in Smart Agriculture," *Computers and Electronics in Agriculture*, vol. 179, p. 105845, 2021.

[33] M. Wójcik and P. Brudło, "Rapid Mobile Prototyping for Agriculture Using Expo and React Native," *SoftwareX*, vol. 18, p. 101088, 2022.

[34] S. Laha, B. K. Pattanayak, and S. Pattnaik, "IoT-Based Real-Time Carbon Monitoring in Urban and Agricultural areas," in *Advances in Environmental Engineering and Green Technologies*, IGI Global, 2022.

[35] A. Mahato, "Greenhouse gas emission from agriculture and their mitigation strategies," *International Journal of Agriculture Extension and Social Development*, vol. 7, no. 7, pp. 188–198, 2024.

[36] E. A. Abioye et al., "Precision irrigation management using machine learning and digital farming solutions," *AgriEngineering*, vol. 4, no. 1, pp. 70–103, 2022.

[37] D. Neocleous, G. Kotsiras, and G. K. Georgiou, "Applying IoT sensor‐based ferti-irrigation practices to enhance water and nutrient use efficiency in intensive potato cropping systems," *Frontiers in Agronomy*, vol. 7, 2025.

[38] M. A. Khan and M. S. Khan, "Smart farming and IoT-based agricultural solutions: A review," *IEEE Access*, vol. 9, pp. 125297–125314, 2021.

[39] N. K. Nawandar and V. R. Satpute, "IoT based low cost and intelligent module for smart irrigation system," *Computers and Electronics in Agriculture*, vol. 162, pp. 979–990, 2019.

[40] C. Pylianidis, S. Osinga, and S. Athanasiadis, "Introducing digital twins to agriculture," *Computers and Electronics in Agriculture*, vol. 184, p. 105942, 2021.