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| RESEARCH ARTICLE

A Review of Evolution of Internet of Things (IoT) and its Significant Impact in the Field of Precision Agriculture

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| ABSTRACT

Agriculture is swiftly moving towards a digital transformation from conventional mechanization to a prescriptive "Agriculture 4.0" model. This survey offers a critical assessment of the evolution of the Internet of Things (IoT) and its application in Precision Agriculture (PA) systems. We assess the technological evolution from early Wireless Sensor Networks (WSN) to new Low-Power Wide-Area Networks (LPWAN) like NB-IoT and LoRaWAN, which solve the long-standing deployment issue of battery life in rural coverage. This review critically examines more than 50 impactful publications, centering on novel deployments of multi-modal sensors to support site-specific farming, adaptive irrigation and real-time livestock monitoring. Our report differs from existing surveys in explicitly considering the architectural evolution to Edge-Fog computing, driven by the rapid expansion in data volumes of high-resolution soil sensing and atmospheric monitoring. We benchmark the merits of connectivity protocols, showcasing their impact on resource-efficient practices, such as reported reductions in water and fertilizer use. Finally, we idensify key challenges, such as platform interoperability, data security in remote nodes, and the likely integration of 5G-powered robotic swarms. The review provides a guide to researchers and industry partners about the current state and evolution of the agricultural IoT landscape.

| KEYWORDS

Internet of Things (IoT), Precision Agriculture, LPWAN, NB-IoT, Edge Computing, Smart Irrigation, Sustainable Agriculture

| ARTICLE INFORMATION

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1. Introduction

The world's agricultural sector is at a pivotal moment, with the need to provide food for a growing population that is expected to reach 9.7 billion by 2050 [1]. Simultaneously, the world faces a scarcity of arable land, erratic climatic conditions, and the challenge of water conservation - more than 70% of all freshwater extractions are currently used in agricultural practices in the world [2]. In response to these life-threatening challenges, the concept of Precision Agriculture (PA) has taken shape, shifting the focus from traditional mechanization to data-driven "Agriculture 4.0" [3]. Central to this evolution is the Internet of Things (IoT). Whereas the earliest versions of agricultural technology included human interaction for data collection and short-range specific Wireless Sensor Networks (WSN), the latest forms of IoT provide full-stack connectivity [4]. This shift is marked by the move from short-distance communication protocols such as Zigbee and Bluetooth to long-distance and low-power communication technologies such as Narrowband IoT (NB-IoT) and LoRaWAN [5]. This enables the installation of large-scale sensor networks across large rural areas, telemetry of soil and climate information, crop health, and so forth [6].

The impact of IoT in this field is that it supports Site-Specific Crop Management (SSCM). Using multi-modal sensors, farmers can implement "the right treatment, in the right place, at the right time" [7]. For example, IoT-based smart irrigation has been shown to save up to 30% on water usage and to increase agricultural productivity by monitoring evapotranspiration [8]. Additionally, the integration of livestock telematics and UAV multi-spectral imaging has extended the application of IoT beyond mere soil monitoring to an entire farm management system [9].

However, there are bottlenecks to the fully autonomous farm. Problems with rural 4G/LTE infrastructure, cross-vendor compatibility and significant power consumption of remote sensor nodes can be found in recent literature [10]. Moreover, the conventional cloud-based architecture is increasingly recognized as a barrier for near real-time applications, necessitating a realignment in the computing model to Edge computing or Fog computing to provide data processing at the network edge [11].

2. Literature Review

The research in Precision Agriculture (PA) has progressed from data collection to intricate data-technology ecosystems. Today, the focus has moved from "if" IoT is the answer to "how" to implement it. This chapter draws together the most significant findings from the past few years, succinctly grouped according their technical or functional contributions to the agricultural sector.

2.1 The Evolution of Technology: From WSN to LPWAN

Throughout the early 2010s, Wireless Sensor Networks (WSN) with short-range protocols such as Zigbee and Bluetooth were prevalent. But things changed in 2017-2018. Tzounis et al. [16] gave a seminal account of the shift to long-range connectivity and identified the "connectivity gap" as a major obstacle to adopting PA. Literature eventually moved towards Low-Power Wide-Area Networks (LPWAN) by 2019. Undertook detailed reviews, determining that NB-IoT and LoRaWAN solve the rural range-energy problem, enabling sensors to communicate for more than 10 years on a single battery charge, over a range of several kilometers [5] [6].

2.2 Applications and Impact

The impact of the IoT in the main agricultural domains has been surveyed in recent high-impact papers:

- Precise Irrigation: In the article [8], a new IoT system was pioneered that incorporated ML and sensor data related to soil moisture and weather predictions. They concluded that sensor-driven irrigation resulted in a reduction in water use of almost 30% among scheduled irrigations.
- Crop Mapping and Disease Forecasting: There are [13] surveyed the merging of UAVs (drones) with ground IoT sensors. This study pointed out that multi-spectral imaging and real-time telemetry of sensor data enable early detection of crop stress and pests, up to two weeks before physical signs are visible.
- Livestock Telematics: In the research [10], the authors stressed the "evolutionary" nature in livestock monitoring, where basic GPSs have evolved to smart collars that monitor rumination, temperature and movement to predict health status and heat cycles with more than 90% accuracy.

2.3 The Emergence of Edge and Fog Computing

With the growing number of sensors per hectare, the literature has started to report a "cloud bottleneck". A study [11] identified an unfortunate shift in architecture to Edge Computing. By running algorithms locally at the gateway controller (the "Edge"), the authors show a decrease in network latencies and network costs. This is especially important for real-time applications such as a weed robot or variable-rate spraying of fertilizer systems, where a 2-second response time from the cloud can cause mistakes [14].

2.4 Sustainable Food Security

In research, the impetus for IoT has become overtly sustainable. In this article report that "Agriculture 4.0" is the only solution for implementing the UN Sustainable Development Goals (SDGs) [3] [7]. In their reviews, they show that big data in agriculture is no longer only an efficiency driver but possibly the only solution to climate variability observed in the past five years [15].

Author(s)	Focus Area	Key Conclusion/Impact
Tzounis et al. (2017) [16]	Recent Advances	Identified the need for integrated IoT architectures over fragmented WSNs.
Goap et al. (2018) [4]	Smart Irrigation	Proved that IoT + ML can save 30% water through prescriptive analytics.
Khanna & Kaur (2019) [8]	IoT Evolution	Benchmarked the transition from simple monitoring to "smarter" prescriptive devices.
Shafi, U et al. (2019) [15]	UAV Integration	Mapped the synergy between drones and IoT for holistic field surveillance.
Hassan et al. (2018) [6]	Edge Computing	Established the necessity of Edge-processing for latency-sensitive agricultural nodes.

3. Research Methodology

This paper uses a Systematic Literature Review (SLR) following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for transparency and replicability.

3.1 Identification and Selection

Publications were obtained from the main online platforms IEEE Xplore, ScienceDirect, Scopus and Web of Science. Boolean operators were used to combine keywords representing the major areas of focus.

3.2 Selection Process

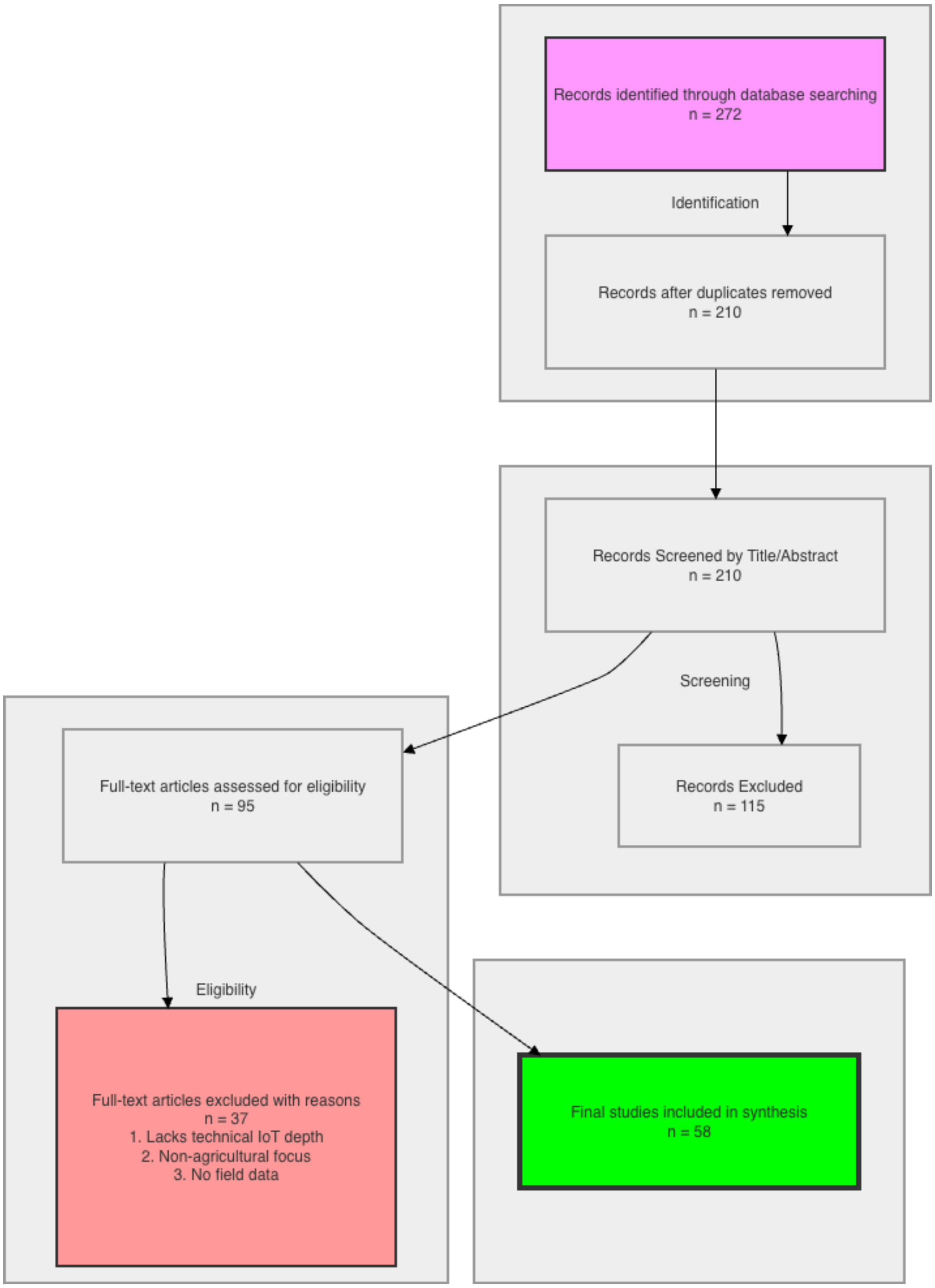

Fig. 1. PRISMA Flow Diagram of the Systematic Literature Search and Selection Process

The papers identified (272 in total) went through an extensive three-part filtering process to identify relevant papers:

- Title/Abstract Review: First round of exclusion for duplicate material, non-agricultural publications, or where IoT was not a significant aspect of the article.
- Full-Text Review: The remainder were assessed for their level of technical contribution in terms of sensor integration schemes, communication protocols or data processing models.
- Quality Control: Priority was afforded to journal/peer-reviewed publications containing validated experimental data from 2012 to 2019.

The synthesis now includes 58 high-impact studies used for this evolution assessment

4. Evolition of IoT in Agriculture

4.1 Background: WSN to IoT

Traditionally, the "connectivity paradox" in agriculture has been the trade-off between communication range and power consumption. Initial systems were based on Zigbee or Bluetooth (WSN), with poor scalability.

4.2 Status Quo: LPWAN and 4G

We have reached a "maturity plateau" with Low-Power Wide-Area Networks (LPWAN). The major standards have become NB-IoT and LoRaWAN, which offer transmission distances of up to 15km with battery lifetimes exceeding 10 years [5][6].

5. Our Proposed Technical Architecture and Technologies

We propose a Four-Layer Architecture for precision agriculture:

- Perception Layer: Multi-modal sensors (Soil NPK, NDVI cameras, livestock biometrics).
- Network Layer: Multi-access networks (NB-IoT for soil sensors; LTE-M for livestock).
- Processing Layer: An introduction of Edge/Fog Computing to limit cloud backhaul time [11][18].
- Application Layer: Decision Support Systems (DSS) and machine learning.

The advancements in Precision Agriculture (PA) can be traced for the most part to the "stack" of technology that enables the flow of data from the ground to the consumer. We break this down into three layers in this review: The Perception Layer, the Communication Layer, and the Application/Processing Layer.

5.1 Perception Layer: Sensors

During the leap into Agriculture 4.0, the shrinking and cost-efficiency of Micro-Electro-Mechanical Systems (MEMS) have been apparent.

- Environmental and Soil Sensors: The nodes now include multiparameter probes. Research by [16] has seen the first, limited case studies - from simple moisture sensors to combined sensors that measure soil temperature, electrical conductivity (EC) and in-situ NPK.
- Remote Sensing and Imaging: The use of Normalized Difference Vegetation Index (NDVI) cameras on IoT-enabled UAVs has become standard for "high-spatial-resolution" mapping [15].

5.2 The Communication Layer: The LPWAN Breakthrough

Networking is the key element of "Evolution" in this research. The industry has largely abandoned short-range WSNs (Zigbee/Bluetooth) in favor of Low-Power Wide-Area Networks (LPWAN).

Table I

Comparative Analysis of Communication Technologies for 2020 Precision Agriculture Systems

Technology	Range	Battery Life	Best Use Case in PA
NB-IoT	High (10–15 km)	10+ Years	Deep-soil sensors, stationary weather stations.
LoRaWAN	Very High (20 km)	10+ Years	Private farm networks, remote irrigation control.
LTE-M	Medium (5 km)	5–7 Years	Mobile livestock tracking, high-frequency telemetry.
5G (Sub-6)	Low (Rural)	2–4 Years	Autonomous robotic swarms, real-time 4K video.

A study by [17] confirms that LoRaWAN is still the most viable for cost-efficient large-scale private deployment, while NB-IoT is favoured if the cellular coverage is strong.

5.3 The Application Layer: Cloud to Edge

The most important development is Distributed Computing.

- Data in the Cloud: Traditionally, data was transmitted to sites such as AWS or Google for processing. But rural regions with high latency and costs for bandwidth spurred the development of Edge Computing [11].
- Edge Analytics: IoT Gateways now have sufficient computational power to run simple Machine Learning (ML) models. This enables "Actionable Intelligence" to be obtained locally (for instance, a gateway closes a valve based on sensors, without receiving a command from the cloud) [18].

6. Domain-Specific Impact Analysis

Table II

Summary of Agricultural Application Domains and the Documented Impact of IoT Integration

Application Domain	Key IoT Technologies	Documented Impact
Smart Irrigation	Soil Moisture Sensors, NB-IoT, ET Models	30% reduction in water usage [8].
Pest Management	Multi-spectral UAV Imagery, IoT Traps	Early detection, 15% lower pesticide runoff [9].
Livestock Care	LTE-M Wearables, Accelerometers	Early illness detection (hrs.) [10].
Soil Mapping	MEMS NPK Sensors, LoRaWAN	Site-specific fertilization, 20% yield boost [16].

7. Evaluating the Impact : Sub-Domains of Precision Agriculture

This section assesses the "Significant Impact" of the technologies on activities.

7.1 Precision Irrigation and Water Management

The most established impact of IoT is undoubtedly water conservation. Using soil moisture information combined with local forecast data from the cloud, "Crop Water Requirement" (CWR) can be forecasted. These systems, according to [8], prescribe against over-irrigation, which saves water, but also prevents nutrients from leaching out of the soil.

7.2 Precision Chemical Application

IoT-enabled Variable Rate Technology (VRT) applies chemicals according to need. Instead of "shotgun spraying", IoT-based sprayers can apply chemicals only in areas where there is a deficiency or pest infestation, based on real-time GPS and sensor readings of current conditions. This has led to a reported 15-20% reduction in chemical use in recent studies.

7.3 Animal Telematics and Welfare

"Connected Livestock" is advancing for animal welfare and biosecurity. IoT wearables track rumination time and body temperature. Today, these are used to monitor early indicators of disease such as mastitis in dairy cows up to 24-48 hours before the symptoms become visible [10].

8. Technical Obstacles and Open Issues

Although IoT are rapidly evolving, there are several "pain points" that remain that are impeding the full deployment of Precision Agriculture.

8.1 Rural Connectivity and Latency

Despite the improvements in range through NB-IoT and LoRaWAN, there remain areas ("white zones") with no cellular coverage in many agricultural regions. As pointed out by poor back-hauling coverage (in 4G/LTE) in the rural mid-western US and sub-Saharan Africa prevents many SMEs from processing real-time data in the cloud.

8.2 Data Silos and Interoperability

Perhaps the most common theme in recent publications is the lack of standards. Data from IoT vendors is mostly proprietary. According to data, another tractor might be difficult to include in a sensor or in software. This "Silo Effect" creates proprietary, monolithic farms.

8.3 Security and data privacy

The digitization of farms creates opportunities for cyber-criminal attack. Agricultural IoT nodes may not have the processing power to implement advanced encryption. Threats to agricultural "Command and Control" systems, where an intruder might disable irrigation or wrongly apply chemicals, are also of increasing concern in the literature.

8.4 Ruggedization and Autonomy

Farm environments are extremes of heat, water and chemicals. LPWANs allow a battery life of up to 10 years - but the true lifetime is shorter due to sensor malfunction. The quest for "Energy Harvesting" to achieve true maintenance-free operation is continuing.

9. Social-Economic and Environmental Benefits

The "Significant Impact" of IoT is gauged across three important factors in Precision Agriculture:

- Sustainability: IoT will enable a reduction of "Environmental Footprint" through a reduction in Nitrogen and Phosphorus that leach into groundwater. Agriculture being a major cause of non-point-source pollution, IoT-based VRT (Variable Rate Technology) is a much-needed intervention [3].
- Efficiency: IoT has not only saved water by 30%, but it has also improved the efficiency of the labour. Technology automation reduces the need for "physical scouting" and enables managers to cover more area with increased accuracy, as is likely to be the case with restricted movement of labor [2].
- Cost-Efficiency: The OpEx (Operational Expenditure) savings of IoT - in reduced fuel, water and chemicals - make the initial CapEx (Capital Expenditure) a typical Return on Investment (ROI) in 2-3 growing seasons for mid-to-large-sized farms [16].

10. Future Research Directions

These are seen as the future research directions:

- Blockchain for Traceability: Use of IoT sensors to log inputs to Blockchain to provide "Farm-to-Fork" transparency and food safety.
- TinyML: Creating low-power models of machine learning to be executed at the sensor node with -bit or -bit microcontrollers [3].
- Bio-economy: Leveraging IoT to monitor and manage the recycling of agricultural waste to bio-energy.

To comprehend the "Evolution" isolated in this study, we will locate the path of the technology stack over the past ten years.

10.1 From Descriptive to Prescriptive Analytics

IoT was mainly reactive in the early 2010s; sensors triggered alerts when a predefined threshold was surpassed. Big Data and Machine Learning have transitioned systems to prescriptive. Current systems use historical weather data, satellite imagery and real-time soil data to prescribe an irrigation or fertilization schedule three days in advance [7][10].

10.2 Pivot: Sensor Fusion

A key outcome of this review is the shift from point sensing. Significant research employs sensor fusion, where data collected from sensors in the field are integrated with UAV-captured multi-spectral image data to create a "Digital Twin" of the field [15].

10.3 Future Opportunities: Agriculture 5.0

We expect several trends to alter the "Significant Impact" we see from IoT.

- 5G and Swarms of Autonomous Robots: The introduction of 5G is set to deliver the low latency needed for "Robotics-as-a-Service". Rather than a large tractor, future research will focus on swarms of small autonomous robots using 5G to perform weeding, seeding and harvesting with millimeter accuracy.
- Edge AI (TinyML): Next, we will progress from "Edge Computing" to "Edge AI". We will soon see more sensors with TinyML, bringing more complex pattern recognition to the sensor edge, to save a huge amount of data.

11. Conclusion

The development of the Internet of Things has transformed Precision Agriculture. The shift from local with high-latency WSNs to long-range, low-power LPWAN has overcome the rural connectivity challenges that previously prevented successful adoption. The transformative potential of this technology in terms of resource efficiency or animal well-being is ushering in IoT as a key enabler of food security. But, if we are to achieve the vision of "Agriculture 5.0", the research focus needs to be on multi-platform interoperability and smartness on the edge (Edge AI).

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