Agriculture and Food

AIMS Agriculture and Food, 11(4): 1059–1083.
DOI: 10.3934/agrfood.2026052
Received: 20 December 2025
Revised: 12 June 2026
Accepted: 07 October 2026
Published: 10 November 2026

http://www.aimspress.com/journal/agriculture

Review

The Internet of Things as a tool for smart monitoring of fruit crops: A systematic review of the literature

Cinthia F. Chapoñan-Baldera[1], Julio A. Gutierrez-Ballona[1] and José A. Vásquez-Coronel[2,*]

[1] Ingeniería Industrial, Universidad Tecnológica del Perú, Esquina Hermann Guiner con Av. Augusto B. Leguía, Chiclayo, 14000, Perú
[2] Centro de Apoyo Logístico al Investigador (CALI), Universidad Tecnológica del Perú, Esquina Hermann Guiner con Av. Augusto B. Leguía, Chiclayo, 14000, Perú

* **Correspondence:** Email: C31374@utp.edu.pe; Tel: (+51)913802508.

Abstract: Climate variability constitutes a primary threat to fruit crop productivity. Specifically, severe volumetric water deficits, extreme thermal anomalies, and excessive solar irradiance disrupt essential physiological functions, directly reducing both total agricultural yield and the commercial quality of export-oriented fruit species. This systematic review analyzes the impact of these microclimatic stressors on crop physiology and evaluates how Internet of Things architectures optimize agricultural management. The methodology was structured using the PIOC framework in accordance with PRISMA 2020 guidelines to systematically retrieve and filter relevant scientific literature. The synthesized evidence demonstrates that prolonged exposure to these climatic extremes drastically reduces net photosynthesis and stomatal conductance. To counteract this physiological degradation, integrating distributed agro-environmental sensors, long-range communication networks, and machine learning algorithms can automate precision irrigation. This technological synergy significantly improves water-use efficiency, minimizes yield variability, and enables early prediction of physiological stress. Furthermore, these digital frameworks facilitate early productivity forecasting, the detection of tissue anomalies, and the dynamic adaptation of agronomic management across Mediterranean, semi-arid, and tropical microclimates. Ultimately, IoT-driven digitization strengthens agroecological resilience, promoting highly efficient and sustainable fruit cultivation under increasingly erratic global climate constraints.

Keywords: machine learning; fruit quality; internet of things; precision irrigation; climate variability

1. Introduction

Population growth and pressure on agricultural systems demand innovative solutions that enable more food to be produced using fewer resources [1,2]. In this context, the use of Internet of Things (IoT) technology facilitates the collection of real-time data on key parameters such as temperature, radiation, the physiological state of fruit crops, and soil moisture [3,4]. In recent years, several systems have described how the adoption of IoT solutions in agriculture has evolved from reactive models to integrated systems with technologies such as Big Data and artificial intelligence [5,6].

This continuous monitoring capability contributes to improved decision-making regarding irrigation, fertilization, and resource management, optimizing production efficiency and reducing losses [7,8]. Recent studies have shown that the Internet of Things applied to fruit crops improves irrigation management and yield prediction, highlighting significant differences between traditional irrigation and automated irrigation using IoT technology [9]. Smart irrigation, supported by IoT sensors and wireless communication, not only reduces excessive water consumption in areas with water constraints but also improves the quality of the fruit obtained, as has been demonstrated in tropical crops where water is the most critical input [7,8]. Furthermore, the integration of these technologies helps to address the extreme climate variations that affect yields, promoting more resilient and sustainable agriculture [2–4].

Climate change is one of the most significant global challenges, with direct effects on agriculture [10]. Changes in water patterns, such as temperature and soil fertility, create significant constraints on production, especially in rural areas and developing countries, where producers face greater difficulties in adapting. Water scarcity has evolved into a global challenge, affecting even regions where it was not previously recognized as a limiting factor. This scenario is especially critical in agriculture, a sector that accounts for approximately 70% of global freshwater withdrawals, according to reports by the Food and Agriculture Organization of the United Nations.

The use of IoT and new digital solutions offers concrete alternatives to overcome these limitations. Through sensors, remote sensing, and satellite image processing, it is possible to identify crop areas in greater detail, adjust planning, and support more accurate decisions in the field [10,11]. Methods such as object-based analysis have proven to be more effective than traditional methods, identifying orchards in detail and classifying crops in heterogeneous landscapes [12,13]. Likewise, soil management through the application of conditioners such as dolomitic rock contributes to optimized nutrient absorption [14], while drones equipped with spectral sensors allow for the early detection of pests, such as thrips [15]. Another key aspect is accurate yield prediction. Advances in computer vision and machine learning, integrated with vegetation indices and climate data, offer more reliable predictive models [6,8]. The ability of the Internet of Things to provide constant information is essential for optimizing resource management [3,4]. This makes this technology a fundamental tool for increasing productivity and strengthening the quality of export-oriented crops and fruits [7,16]. For this reason, the focus is on the fruit crop segment, whose high sensitivity to water variations and the need for export quality make intelligent monitoring indispensable.

The objective of this review is to evaluate the impact of implementing IoT systems on water use efficiency, yield prediction, and real-time data detection in fruit growth. To this end, the available evidence on the effects of heat stress, water deficit, and solar radiation was synthesized, as well as IoT applications linked to precision irrigation and predictive models used to improve yield and fruit quality.

The rest of the article is structured as follows: in Section 2, the study selection procedure using the PIOC approach is described. Section 3 presents the results, integrating evidence related to climate variability, IoT technologies, and agronomic performance. Section 4 provides a discussion of the findings, current trends, technical implications, and implementation challenges in different climate contexts. Section 5 summarizes the key contributions of the review and highlights future opportunities to strengthen digital management and the resilience of fruit crops.

2. Methodology

The study is a systematic literature review designed to identify, evaluate, and synthesize the available evidence on the topic of interest. The search strategy is based on the PICO tool, an approach used to formulate research questions, based on an acronym representing its main components [17]. In this case, a variant of this method was used, called PIOC (Problem, Intervention, Outcomes, Context). This adaptation omits the comparison component (C) because the study does not include comparative analyses, and incorporates the element "Context", which allows the research environment to be defined. The specific questions were defined based on each component of the PIOC model and serve to guide the search, selection, and categorization of the included studies. Based on these specific questions, the general question of the review was constructed: What impact does climate variability have on the productivity and quality of fruit crops, and how can IoT technologies optimize their management and monitoring in the face of the challenges facing the sector? The specific questions and respective keywords are presented in Table 1.

Table 1. Questions and keywords for the study.

Component	Question	Keywords
P	What is the impact of climate variability on the productivity and quality of fruit crops?	Climate variability, climate change, productivity, fruit quality
I	How does the application of IoT technologies influence the optimization of fruit crop management?	IoT, Internet of Things, precision irrigation
O	What are the benefits of applying IoT technologies to fruit cultivation?	Yield, sustainable production, production quality, sustainability
C	What is the importance of fruit cultivation, and what are the main challenges in its production?	Fruit

2.1. Search strategy and eligibility criteria

The search was conducted during November 2025 in the Scopus and Web of Science databases. The keywords associated with each PIOC component, detailed in Table 1, were combined using the Boolean operators OR and AND to filter the articles, where OR was utilized to broaden the search scope, and AND was applied to intersect the core topics. Additionally, the following basic filters were applied to the search: document type (article), year (2020–2026), access (open access), and language (English). The search equations used in each database are presented below:

- Scopus: (TITLE-ABS-KEY ("climate variability" OR "climate change" OR "productivity" OR "Fruit quality") AND TITLE-ABS-KEY (IoT OR "internet of things" OR "precision irrigation" OR "machine learning") AND TITLE-ABS-KEY (yield OR "sustainable production" OR

"production quality" OR sustainability) AND TITLE-ABS-KEY (fruit*)) AND PUBYEAR > 2019 AND PUBYEAR < 2027 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (OA , "all"));

- WoS: "climate variability" OR "climate change" OR productivity OR "fruit quality" (Topic) and IoT OR "internet of things" OR "precision irrigation" OR "machine learning" (Topic) and yield OR "sustainable production" OR "production quality" OR sustainability (Topic) and fruit* and 2026 or 2025 or 2024 or 2023 or 2022 or 2021 or 2020 (Publication Years) and Article (Document Types) and English (Languages) and All Open Access (Open Access).

The selection of documents was based on predefined inclusion criteria (IC) and exclusion criteria (EC) to ensure the relevance of the selected studies. These criteria are detailed in Table 2.

Table 2. Inclusion and exclusion criteria for the study.

Inclusion criteria	Exclusion criteria
CI1: Publications focused on fruit crop research	CE1: Studies not focused on irrigation conditions for fruit crops
CI2: Research on the use of IoT in the management and monitoring of fruit crops	CE2: Studies unrelated to IoT technologies
CI3: Studies evaluating yield, fruit quality, and efficient water management	CE3: Review articles

2.2. Selection process and PRISMA2020 tool

The selection process for the articles found followed the guidelines of the PRISMA2020 (Preferred Reporting Items for Systematic Reviews and Meta Analyses) tool [18], in order to ensure that the procedure was transparent and easily reproducible. Each stage, from the initial search to the final inclusion of studies, was systematically documented in an Excel spreadsheet, allowing for a clear and orderly record of all decisions made during the review. A total of 86 articles were obtained from the Scopus platform and 86 articles from WoS, for a total of 172 articles. From this set, 56 duplicate articles were identified and eliminated. Subsequently, an initial filter was applied based on reading the title and abstract, resulting in the exclusion of 50 articles. The remaining 66 articles were selected for full-text eligibility assessment, for which they were downloaded and managed in the Zotero bibliographic manager. Of these, 11 were excluded for not being related to the topic, 3 for not being linked to IoT technology, and 2 for corresponding to reviews, leaving a total of 50 selected articles. In addition to the primary database searches, a secondary review was conducted on the Google Scholar portal using the snowball strategy, which involves recursively identifying relevant references cited in the retrieved literature and incorporating them into the analysis [19]. To broaden the scope of the review beyond irrigation and fully align with the principles of precision agriculture, this snowball strategy specifically targeted supplementary crop operations aimed at spatially variable rate crop input applications. The search prioritized field-validated studies that addressed key concepts such as autonomous agricultural robotics and unmanned aerial vehicles, variable-rate application for precision spraying, chemical thinning, and artificial automated pollination in fruit crops. The PRISMA 2020 flow diagram, illustrated in Figure 1, visualizes the detailed process of document selection.

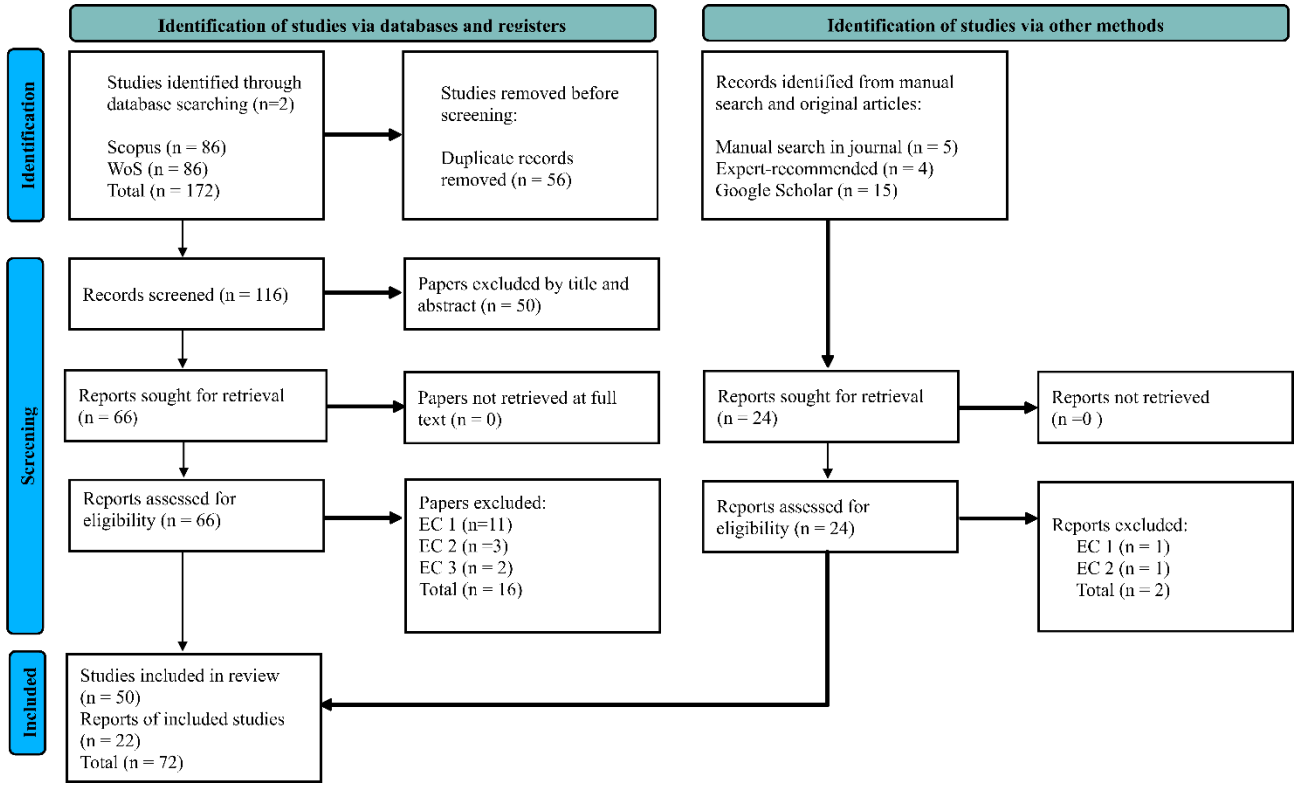


Figure 1. PRISMA2020 flow diagram of the study selection process.

3. Results

This section presents the findings from the 72 included scientific articles, synthesized to address the research questions formulated under the PIOC framework. Figure 2 illustrates the percentage of components present across the reviewed literature, as well as their level of agreement based on the number of components. It shows that the integration of all four components represents the highest frequency among multi-component groupings for the application of IoT technologies, sensors, and machine learning in fruit crops. This reflects the scientific community's sustained interest in deploying these technologies to optimize agricultural management in response to specific environmental stressors, primarily extreme air temperatures, high solar irradiation, and soil moisture deficits [12,20].

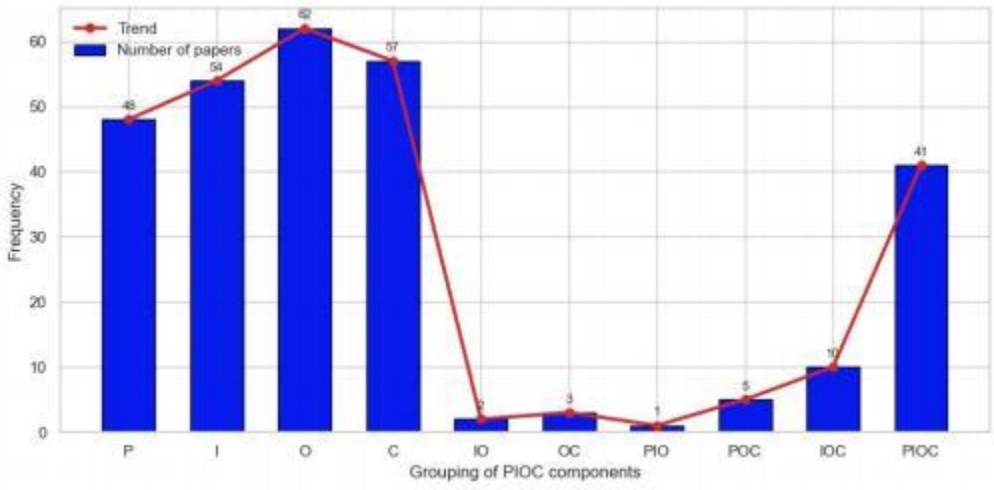


Figure 2. Distribution of studies according to research questions.

3.1. Influence of climate variability on fruit crops

Current research indicates that fruit tree systems respond to specific microclimatic and edaphic parameters rather than broad climatic factors. These primary parameters include low volumetric soil water content [21], extreme maximum air and canopy temperatures [22], high vapor pressure deficit, and excessive solar irradiance [23]. Variations in these environmental variables cause imbalances in crop physiology. They directly affect net photosynthesis [24], stomatal conductance to water vapor, and leaf gas exchange [25,26]. Prolonged periods of soil moisture depletion reduce fruit yield and commercial quality [13]. This production deterioration is also driven by thermal stress, particularly when air temperatures exceed the critical physiological threshold of 35 °C [27,28]. Thus, extreme air temperature anomalies and low soil water availability are established as the main determinants of yield loss in agricultural systems [12,28,29].

In addition to yield reductions, fluctuations in these microclimatic parameters compromise not only yield but also the fruit's internal and external quality. Extreme air temperatures disrupt the acid-base balance and degrade secondary metabolites. This process leads to reduced concentrations of anthocyanins, carotenoids, and vitamin C [30]. Additionally, abrupt changes in soil moisture and relative humidity are primary triggers for fruit cracking. This physiological disorder diminishes marketability and increases susceptibility to fungal infections. Relying solely on broad regional climatic data is insufficient to prevent these sudden shocks. Under such dynamic conditions, precision irrigation scheduling based on real-time soil moisture sensors becomes essential. This technology helps maintain stem water potential above the safe threshold of −1.2 MPa [31]. By doing so, it maintains crop water balance, cools the canopy through transpiration, and prevents irreversible tissue damage [32].

Table 3 shows the specific environmental stressors and their effects on fruit crop productivity. The analysis reveals that these abiotic factors rarely act in isolation [9]. Their synergistic interaction accelerates tissue damage more than their independent effects [23,33]. For instance, a critical reduction in volumetric soil water content, combined with a high vapor pressure deficit, induces osmotic stress and flower drop [34]. Moreover, prolonged exposure to excessive solar radiation accelerates senescence [4,20]. When this radiation is combined with air temperatures above

35 °C, it triggers physiological disorders, such as sunburn necrosis, berry shrivel, or surface burns [26,32]. These results underscore the need for technological strategies to mitigate the impacts of microclimatic extremes through precise environmental monitoring and automated control [7,35,36].

Table 3. Specific microclimatic parameters affecting fruit crop physiology, quality, and yield.

Parameter	Physiological problem	Reference
Low soil moisture and high vapor pressure deficit	Severe osmotic stress and altered plant water balance	[9,10,12,37,38]
	Reduced stomatal conductance and flower drop	[14,16,21–23]
	Altered gas exchange and reduced fruit yield under water deficit conditions.	[31,39–42]
	Decreased fruit size, yield, and commercial quality	[24,32–35]
Extreme air temperatures	Thermal stress, sunburn necrosis, and berry shrivel	[4,9,16]
	Altered gas exchange and reduced fruit yield under water-deficit conditions.	[25–27,33]
	Flower drop and poor pollination	[34,43,44]
Excessive solar irradiance	Degradation of secondary metabolites and vitamins	[30,45–48]
	Accelerated senescence and photo-oxidative damage	[13,15,25,26]
	Surface burns and superficial deterioration of the fruit	[32,38,49]
Abrupt moisture and humidity fluctuations	Severe osmotic shock and triggering of fruit cracking	[3,4,20,27]
	Climate related changes in fruit nutritional quality and increased fruit cracking.	[29,30]
	Susceptibility to fungal infections and elevated pest pressure	[38,45]
	Fruit yield variability and challenges in disease detection and quality assessment.	[50–53]
	Overall yield reduction	[54,55]

High-density agricultural systems with continuous water demand have negative physiological responses to extreme maximum air temperatures [36] and abrupt fluctuations in soil moisture availability [56]. These specific microclimatic stressors induce a decline in yield parameters [10], limit cultivar adaptability [13], and eventually reduce overall water productivity [26]. Along with these physiological disruptions, prolonged thermal stress and water deficits accelerate plant energy consumption [28], reduce fruit tissue firmness [43], and deplete volumetric soil water content [49]. Figure 3 illustrates the distribution of these contrasting physiological responses to microclimatic variations. In this visual representation, the blue area represents positive values associated with enhanced water-use efficiency, stable productivity, and post-stress physiological recovery. Conversely, the red area reflects the negative values linked to physiological deterioration, energy consumption, and structural damage.

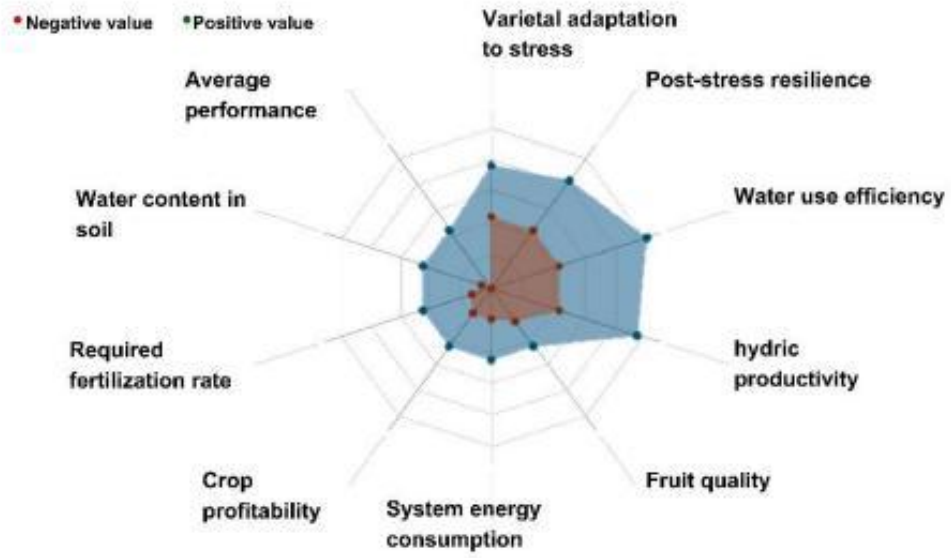


Figure 3. Impact of climate variability on agronomic indicators in fruit crops.

3.2. Application of IoT technologies for optimizing fruit crop management

Current agricultural interventions integrate networked sensors to measure specific microclimatic parameters. These parameters include air temperature, relative humidity, and volumetric soil water content [57]. Mobile applications interface with these networks to enable real-time monitoring [27] and automated remote control of irrigation schedules [58]. IoT architectures facilitate the mass acquisition of meteorological data using distributed sensor nodes connected via long-range communication protocols. This network supports automated decision-making across extensive orchards [16]. Beyond standard drip irrigation, these IoT frameworks now control advanced water-saving techniques such as automated subsurface irrigation and partial root-zone drying. These specific methods drastically reduce water consumption by up to 64% while enhancing fruit flesh firmness [43,49]. To optimize scheduling, precision irrigation strategies utilize dendrometers to continuously monitor maximum daily trunk shrinkage. These physiological diameter measurements serve as a direct criterion for regulating water application and preventing water stress [14,59]. To mitigate extreme climatic shocks, sensor-driven automated sheds have been implemented to physically protect crops from heavy rainfall and thermal stress exceeding 35 °C [44].

In addition to microclimatic control, recent IoT deployments incorporate deep learning and computer vision to optimize crop health and yield estimation. Unmanned aerial vehicles and ground-based optical sensors capture high-resolution multispectral imagery across orchards [1,56]. This visual data is processed using convolutional neural networks and instance segmentation algorithms to automatically detect individual fruits. As a result, these algorithms estimate fruit size and forecast total yield prior to harvest [1,60]. Moreover, IoT-based monitoring systems are increasingly utilized for real-time epidemiological forecasting. By continuously analyzing environmental data, these smart networks can predict outbreaks of severe fungal infections and pest infestations, such as powdery mildew and codling moth [61]. Deep learning architectures, including hybrid optimal attention capsule networks, classify these diseases with precision rates exceeding 99% [51]. Targeted

automated spraying interventions based on these predictions reduce overall pesticide and fungicide consumption by up to 50%. This reduction improves fruit quality and minimizes chemical residues.

Advanced agricultural frameworks integrate multiple sensors to continuously collect real-time data on volumetric soil moisture [2], maximum air temperature [26], and solar light intensity [27]. The collected data is communicated through the Message Queuing Telemetry Transport protocol to cloud platforms. Subsequently, various machine learning architectures process this sensory data to anticipate plant development, optimize irrigation decisions, and forecast crop yields [58]. These predictive algorithms include multiple linear regression and support vector machines [13]. Other applied models include partial least squares regression, support vector regression, and extreme gradient boost regression [20,58]. Additionally, multilayer perceptron, least absolute selection, and selection operator regression analyze these agricultural datasets [62]. These mathematical models provide robust estimates across different spatial scales. They process continuous environmental variables transmitted via long-range communication networks for precise water control. The specific technologies and computational methods used for this microclimatic anomaly detection and comprehensive environmental monitoring are synthesized in Table 4.

Table 4. IoT technologies and computational methods for fruit crop optimization.

Technologies	Application	Method	Reference
Sensors	Precision volumetric water control and irrigation scheduling	Multiple linear regression and ridge regression	[21,22]
		Support vector machine	[20,58,62]
		Random forest and least absolute shrinkage and selection operator	[13,58]
		Volumetric water content monitoring	[20,36]
		MeteoHelix IoT Pro micro-weather station	[11]
		Partial least squares regression	[13,63]
		Extreme gradient boosting	[23,58]
Hyperspectral IoT vision	Early detection of physiological stress and tissue anomalies	Support vector machine	[20,58]
		K-means clustering	[62]
		Partial least squares regression and support vector regression	[63]
		Extreme gradient boosting, random forest, and multilayer perceptron	[20,58,63]
Wireless IoT networks	Automated fertigation and distributed environmental monitoring	Long-range wide-area network, Wi-Fi, long-range communication, and comma-separated value retrieval on smartphones	[9,10,14,24,40]
	Integrated crop monitoring and precision irrigation management	IoT-based sensor data fusion, automated irrigation management, and digital dashboards for monitoring fruit yield and quality.	[46,55,64]
Cloud and edge platforms	Automated agricultural decision support and real-time data visualization	Perimeter computing systems, mobile applications for remote monitoring, Magellan cloud, ThingSpeak, and one-way analysis of variance	[2,12,45,47]

Threshold control methods and predictive machine learning models, including random forest, extreme gradient boosting, and support vector regression, optimize irrigation scheduling [11],

predict volumetric soil moisture [22], and improve overall water use efficiency [26]. On the other hand, hyperspectral imaging techniques combined with convolutional neural networks and mask region–based convolutional neural networks enable the early detection of fruit stress [13] and physiological ripeness [24]. This integration facilitates precise interventions in harvesting and fruit quality management [29]. The continuous application of these technologies, from Internet of Things devices to analytical methods, controls specific agronomic variables and establishes a functional link between digital tools and crop management [9,31,63]. In the long term, these technological integrations drive the transition toward automated, predictive, and resilient agricultural systems under climatic constraints [59]. Figure 4 illustrates this continuous intervention flow and the sequence of technology applications.

Agronomic models combined with decision support systems dynamically adjust precise water application [36] and nutrient distribution [42] in response to specific microclimatic fluctuations [65]. At the same time, the integration of cloud-based architectures and real-time data processing mitigates severe soil moisture depletion [2]. This continuous data processing optimizes volumetric water use [3] and reduces the electrical energy consumption of irrigation pumps [54]. These technological interventions establish a network of continuous environmental control [15]. Therefore, they sustain fruit-crop productivity [40] and enhance overall agricultural sustainability under resource constraints [46]. The specific connections between these digital tools, analytical methods, and controlled agronomic variables are illustrated in the Sankey diagram in Figure 4.

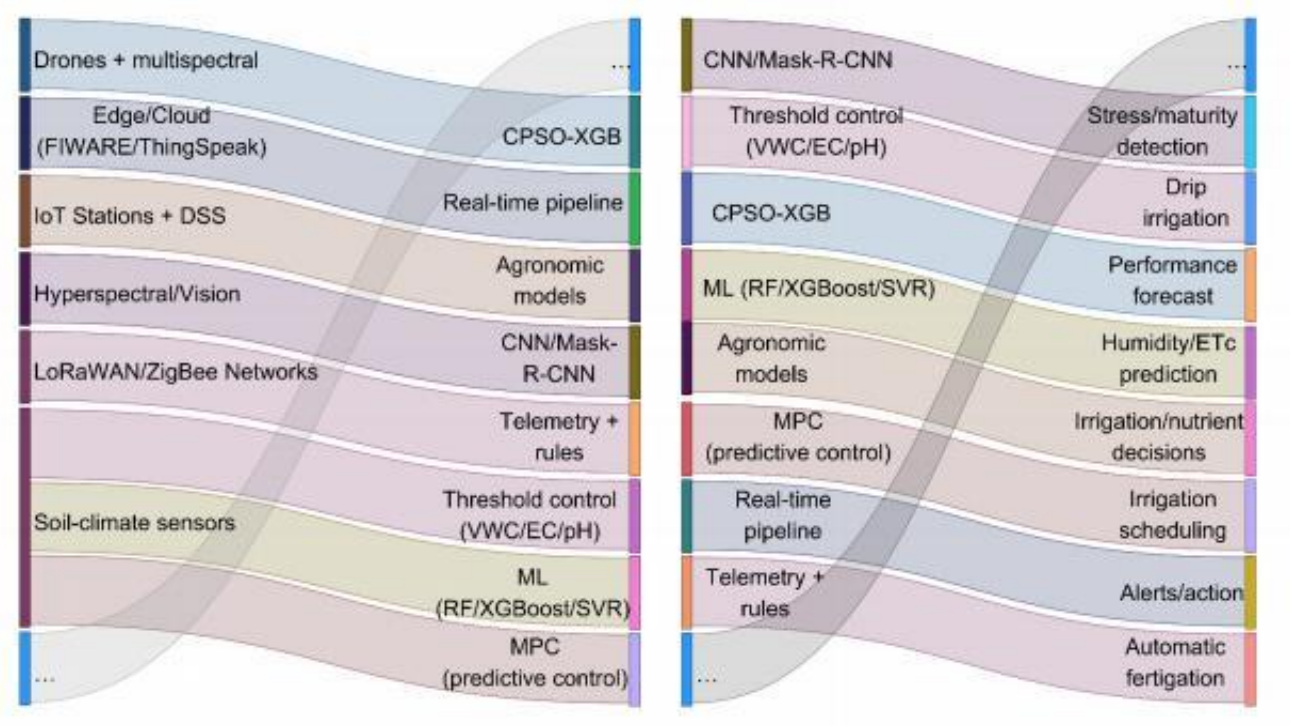


Figure 4. Technological intervention flow in precision fruit growth.

3.3. Impact and advantages of IoT in fruit growing

The implementation of Internet of Things architectures in fruit systems drives intelligent automation and data-driven management. These digital tools integrate specific microclimatic, physiological, and edaphic variables into predictive mathematical models [28]. By doing so, they optimize crop productivity and reduce uncertainty in agronomic decision-making [37]. Interconnected sensor networks transform traditional agriculture into an analytical and precise activity [9,41]. By continuously processing field data, these systems facilitate adaptive crop management under dynamic environmental constraints [35,56]. This technological integration establishes a foundation for sustainable agricultural practices [42,45].

Field evaluations demonstrate the direct quantitative benefits of these digital interventions. The deployment of cloud-based decision support systems in lemon orchards reduced irrigation water consumption by 50% while increasing total fruit yield by 35% [9]. Similarly, in semi-hydroponic strawberry cultivation, automated edge computing frameworks achieved a 20% reduction in water usage and a 15% increase in production [45]. These systems also enhance internal fruit quality, as evidenced by an 11.8% increase in the soluble solids content [45]. In arid regions, automated subsurface irrigation networks controlled by real-time soil moisture sensors reduced water application by 64.1% in date palm orchards compared to traditional surface methods [49]. To complement irrigation controls, computer vision and deep learning algorithms integrated into mobile platforms enable precise blossom detection and variable-rate chemical thinning in apple orchards. This machine vision application optimizes fruit load and minimizes chemical inputs [60].

Agricultural digitization optimizes precision irrigation and automated fertigation [24]. Moreover, it introduces advanced computational metrics to evaluate yield, fruit quality, and electrical energy efficiency [22,38]. Sensor-controlled irrigation systems optimize water application, leading to documented increases in water-use efficiency of up to 46% [11,66]. This structural shift toward integrated fruit system management is characterized by minimized resource losses and continuous environmental monitoring [28,36]. Conclusively, the synergy among control algorithms, cloud platforms, and in-field sensors ensures long-term agricultural sustainability and resource efficiency [63,65]. The main performance areas related to productivity, resource efficiency, and environmental sustainability are summarized in Table 5.

Automation and smart control strategies balance fruit-crop productivity and agroecological sustainability [28]. These specific technological interventions support total yield and resource-use efficiency [49]. From a systems perspective, adopting interconnected digital networks facilitates the stability of agricultural systems [10]. Implementing predictive computational processes reduces yield variability under specific microclimatic stressors [23,56]. These interventions serve to bolster orchard resilience to extreme thermal anomalies and severe soil moisture depletion [37,41,50]. Figure 5 plots the relationship between these crop yield increases and corresponding resource savings as discrete pairings extracted from independent studies. Because these data points represent separate field evaluations under diverse agronomic conditions rather than a single continuous trial, the resulting trends exhibit non-monotonic fluctuations across the 15%–20% yield increase range.

Table 5. Benefits of using IoT technologies in fruit cultivation.

Dimension	Indicators	Impact on fruit cultivation	Reference
Agricultural productivity	15%–20% total yield increase	Higher overall yield and optimized fruit set	[1,2,9,15,16]
	Improved fruit yield and quality through irrigation and crop management	More efficient production and better fruit development	[22,28,29,35]
	Artificial intelligence accuracy up to 99.7%	Enhanced fruit quality and precise disease detection	[31,34,38,40,42]
	Optimized irrigation scheduling and agricultural productivity	Improved agricultural monitoring and resource management	[43,44,47,49]
	Digital monitoring of fruit diseases and guality	Improved fruit classification and disease identification	[51,64]
	Real-time physiological data tracking	Precise harvest timing and post-stress recovery	[53,54,56,58,66]
Resource efficiency	Savings of 25%–50% of water and 46% higher water use efficiency	Precise irrigation scheduling and optimized crop water balance	[31,38,42–44]
	Smart irrigation control and monitoring	Improved water management and reduced unnecessary resource use	[34,40,47,49]
	Digital nutrient monitoring and resource optimization	Improved nutrient assessment and reduced agricultural resource footprints	[39,48,63,67,68]
	Savings of 38%–65% in applied nutrients	Automated fertigation and reduction in nutrient leaching	[33,36,41,45,46]
Environmental sustainability	Carbon footprint reduction of up to 40%	Mitigation of greenhouse gas emissions	[3,9,12,14,15]
	Remote sensing and sensor-based monitoring of orchard conditions, pest damage, crop nutrition, and growth	Improved orchard surveillance, targeted crop management, nutrient optimization, and fruit quality	[4,7,63,69]
	Reduction of deep percolation and leaching by 30%	Resilient cultivation with low environmental impact	[24,25,50,53,59]
Automation and digital monitoring	Microclimatic checks every 10–15 minutes with root mean square error below 0.002	High-precision environmental tracking	[9,10,11,15,16]
	Automated fruit detection and crop stress monitoring	Early identification of crop conditions and improved irrigation decisions	[1,27,28,36]
	Integrated sensor monitoring and predictive agricultural management	Improved yield estimation, nutrient assessment, and resource management	[46,56,65,66,67]
	Continuous operational automated cycles	Autonomous irrigation and significant electrical energy savings	[37,38,40,49,55]

Continued on the next page

Dimension	Indicators	Impact on fruit cultivation	Reference
Smart management and decision-making	Robust water forecasting and predictive microclimatic anomaly detection	Automated agronomic decision support	[12–14,20,21]
	Sensor-based irrigation and fruit quality monitoring	Better water management and optimized crop production	[22–24]
	Digital agricultural systems and climate-related productivity analysis	Improved crop monitoring and adaptation strategies	[39,47,48]
	Integrated crop growth and resource-use monitoring	Improved irrigation management and sustainable fruit production	[54,67,69]
	Real-time crop phenology and canopy monitoring	Optimal decisions for efficient harvesting	[26,29,34,43,45]
	Integration of cloud-based architecture and data analytics	Long-term orchard management and yield estimation	[52,55,57,62,65]

Note: The 100 citations listed represent 58 unique studies. Of these, 26 are counted once, 23 are double-counted, 8 are triple-counted, and 1 is quadruple-counted across dimensions, explaining the overlap.

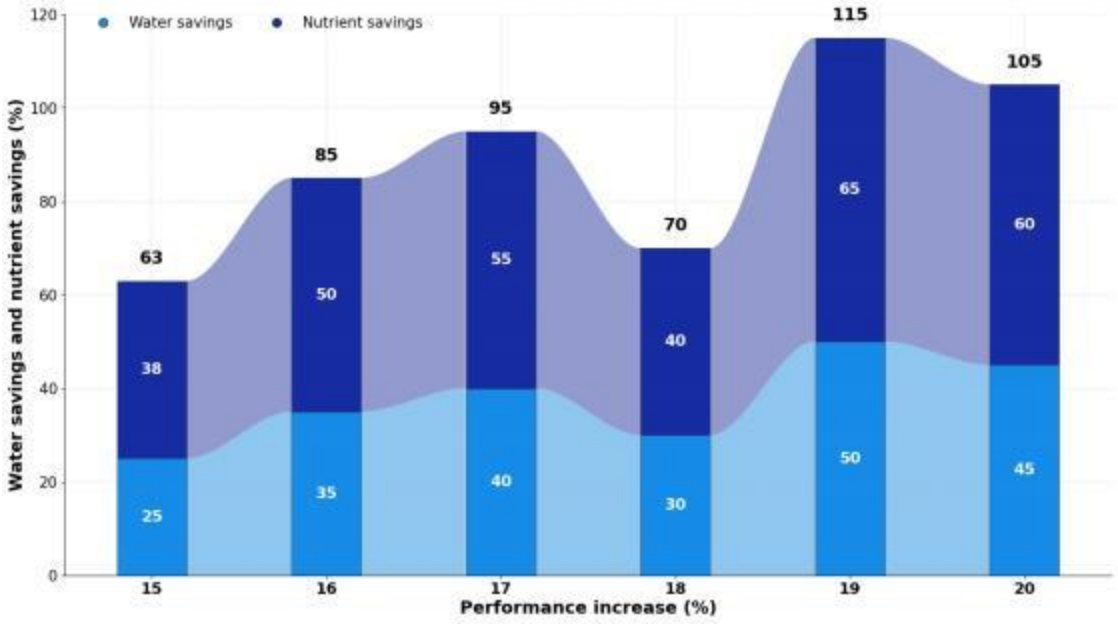


Figure 5. Increased yield with water and nutrient savings.

The deployment of IoT architectures establishes a precision agriculture model that integrates electrical energy efficiency [15], agroecological sustainability [34], and fruit yield optimization [40] into a unified operational framework. From a traceability perspective, the integration of distributed cloud platforms and blockchain protocols ensures immutable crop traceability throughout the agricultural supply chain [40,55]. Precise automated fertigation algorithms minimize agricultural input losses by reducing nutrient leaching and deep percolation [36,45]. As a direct result, this digital management strengthens orchard resilience, enabling rapid physiological

recovery from extreme thermal anomalies and severe soil moisture depletion [42]. These interconnected digital frameworks go beyond passive microclimatic monitoring [4]. In this manner, they serve as automated decision support systems [53] that sustain crop productivity and ensure long-term agricultural sustainability under severe environmental constraints [67].

3.4. Socioeconomic relevance and environmental challenges of fruit cultivation

The implementation of precision agricultural technologies in fruit orchards is strictly conditioned by specific geographical constraints and regional microclimates. Severe thermal anomalies [21], severe soil moisture depletion [33], and erratic precipitation patterns [37] directly compromise overall irrigation efficiency and fruit quality. To counteract these microclimatic fluctuations, regional agronomic strategies integrate IoT architectures and distributed sensor networks. This technological deployment establishes precise volumetric water control [25] and enhances the physiological recovery of plants post-stress [36,43]. To address these microclimatic fluctuations, localized management protocols prioritize automated irrigation scheduling [28], data-driven yield forecasting [31], and continuous real-time environmental monitoring [45].

Despite the proven agronomic benefits, the adoption of these digital frameworks in developing regions faces significant socioeconomic barriers. In regions across South Asia and Latin America, the transition toward automated agriculture is constrained by high initial deployment costs, limited access to stable wireless communication networks in rural areas, and a lack of specialized technical training among small-scale farmers [10]. Traditional farming practices in these areas frequently rely on surface-flood irrigation, which accelerates groundwater depletion and reduces overall crop profitability [44]. Nevertheless, the strategic implementation of low-cost, open-source microcontrollers and long-range wide-area network protocols provides a practical alternative to address these financial limitations [36]. The integration of these accessible digital tools minimizes manual labor costs, optimizes the use of expensive agricultural inputs, and ultimately aligns fruit production with global sustainable development goals [14,23].

Specific regional climates dictate the technological interventions required across global fruit-growing regions. Semi-arid and dry Mediterranean environments require advanced water conservation strategies due to severe volumetric water deficits [28] and prolonged exposure to high solar irradiance [43,49]. Within these regions, the application of regulated deficit irrigation is critical for sustaining crop productivity under prolonged thermal stress [10,31]. Conversely, intensive fruit production in East and South Asia faces extreme maximum air temperatures combined with low soil moisture retention. These specific edaphic and climatic conditions necessitate the integration of continuous soil moisture sensors and wireless communication networks to maximize irrigation efficiency [13,20]. In Latin America, tropical and semi-arid microclimates demand precise volumetric water management [3,23] to minimize radiation damage and sustain the commercial quality of export-oriented fruit crops [53]. The geographical distribution of these prevailing environmental conditions and their corresponding agricultural regions is synthesized in Table 6.

Table 6. Environmental and geographical conditions of fruit cultivation areas.

Region	Prevailing climate and environmental constraints	Reference
East and South Asia	Monsoon-influenced climates with seasonal rainfall variability and prolonged dry periods	[12–14,20]
	Arid and semi-arid conditions characterized by elevated summer temperatures and limited water availability	[24,26,53]
	Seasonal water deficits and soils with low water retention capacity	[28,29,33,37]
	High solar radiation and increased exposure to heat and water stress	[39,41,64,66]
Mediterranean basin	Mediterranean climate characterized by hot, dry summers and relatively mild winters	[10,25,28]
	Seasonal precipitation deficits and high atmospheric evaporative demand	[31,34,43]
	Intense solar radiation and elevated temperatures during critical crop development periods	[48,49,53]
	Heat stress and water scarcity requiring regulated deficit irrigation strategies.	[59,65]
Latin America	Semi-arid to tropical conditions with severe precipitation deficits and high temperatures	[3,4,23,52]
	High solar radiation and dependence on technical irrigation for fruit crops export	[53,54,55,59]
Oceania	Dry subtropical climate with sandy soils, low water retention, and high evapotranspiration	[14,15]
North and Central America	Mediterranean and warm temperate climates with severe water deficits and heat stress	[10,36,65]
Mainland Europe	Temperate to humid continental climate with irregular rainfall and precipitation variability	[1,9,46,47,48]

Note: The 44 citations listed represent 36 unique studies. Of these, 29 are counted once, 6 are double-counted, and 1 is triple-counted across regions, explaining the overlap.

In Oceania, dry subtropical climates characterized by sandy soils and high evapotranspiration rates require the implementation of automated fertigation frameworks to compensate for severe soil moisture depletion [15,40]. Similarly, perennial fruit crops in North America experience marked temperature variability and seasonal water deficits, necessitating continuous climate monitoring systems for precise irrigation scheduling [10,36]. Across mainland Europe, erratic precipitation patterns and the increasing risk of intermittent droughts drive the adoption of digital predictive models to sustain agricultural productivity [9,46,48]. Across all evaluated geographies, severe volumetric water deficits and extreme thermal anomalies remain the most restrictive microclimatic factors that determine the overall productivity of modern fruit orchards [3,28,43].

Specific fruit species exhibit varying degrees of vulnerability to microclimatic stressors, dictating the focus of technological research. Commercial crops such as apple [29], mango [31], and strawberry [56] demonstrate high sensitivity to extreme thermal anomalies and severe water deficits. Other intensive crops, including melon [7], tomato [35], and grape [16], frequently integrate

advanced irrigation-efficiency protocols, automated fertigation, and continuous climate control. Conversely, tropical fruits such as bananas, mandarins, and watermelons receive less technological intervention [3].

This lower representation is primarily attributed to their cultivation in humid environments with reduced exposure to prolonged drought [52]. As a result of this vulnerability, current digital agricultural research predominantly targets commercially valuable fruit species that are highly vulnerable to restrictive climatic conditions and water scarcity [10,23,28,36]. This direct correlation between specific environmental stressors and the level of applied digital innovation drives the deployment of IoT architectures [39]. These frameworks, integrated with artificial intelligence algorithms and advanced distributed sensor networks, dynamically adjust precision irrigation [12] and automated fertilization protocols based on real-time microclimatic data [34]. Digital fruit cultivation therefore functions as a direct adaptive response to global climate change [10]. In practice, regional geographical constraints and specific environmental conditions dictate the rate and methods by which producers adopt these advanced interconnected technologies [23,28]. The quantitative distribution of these most frequently studied fruit species is summarized in Figure 6.

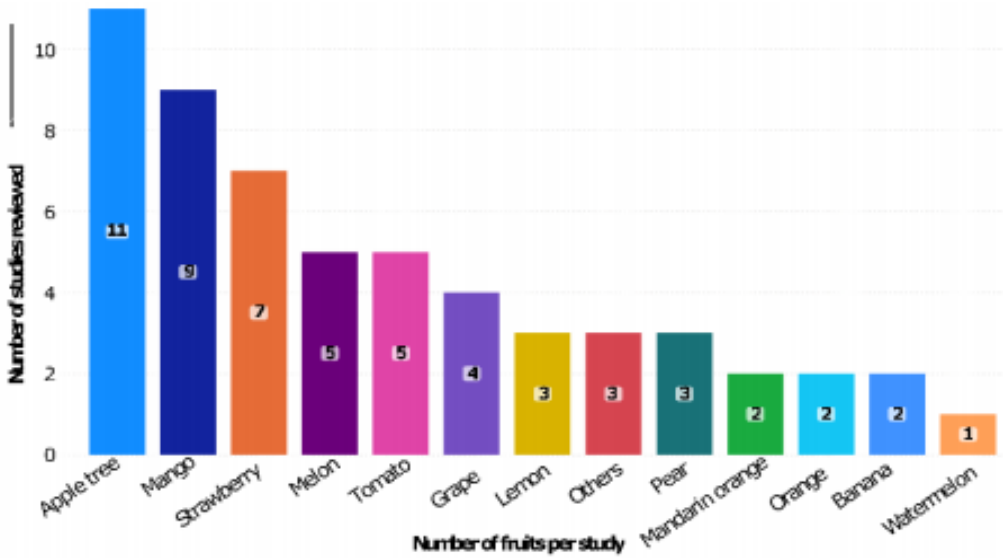


Figure 6. Frequency distribution of fruits in the studies analyzed.

3.5. Variable-rate applications beyond irrigation

Recent advancements in precision agriculture have expanded variable-rate application technologies beyond water management to encompass complex crop operations. These digital frameworks manage physical agricultural inputs through the Internet of Things [10] and autonomous machinery driven by artificial intelligence [47]. Specifically, variable-rate fertilization enhances nutrient use efficiency [3] by eliminating redundant, uniform applications [65]. The integration of sensor-based fertigation facilitates the delivery of fertilizers at site-specific rates strictly tailored to the active root uptake zone. This targeted spatial distribution improves overall fruit yield and commercial quality [11] while substantially reducing nutrient leaching into groundwater [21]. Despite these validated agronomic advantages, widespread commercial adoption remains constrained by high

initial deployment costs, sensor vulnerability to harsh field microclimates, and the need for specialized technical expertise among traditional producers [47].

The deployment of variable-rate applications for crop protection relies on continuous real-time disease detection protocols. Deep learning models deployed on edge computing devices successfully identify specific leaf diseases directly under field conditions [70]. Concurrently, unmanned aerial vehicles [4] integrated with single-stage object detection architectures localize specific pathogens [71] and facilitate highly targeted agrochemical interventions [72]. During the physical application of these chemicals, ground-based autonomous robots [47] and intelligent sprayers utilize advanced sensor fusion [73] to dynamically adjust nozzle outputs according to real-time canopy architecture [74]. This precision spraying method targets specific zoned canopy volumes to substantially decrease chemical waste [75] and minimize toxic air drift [76]. In complex or high-density orchards where ground machinery encounters severe operational constraints, unmanned aerial vehicles adaptively modulate spraying parameters using neural network–driven controllers to ensure optimal droplet distribution [24, 77]. In practice, the performance of these automated spraying systems is limited by dynamic field variables, including sudden wind disturbances, inconsistent solar lighting, and strict payload capacities [77]. Addressing these operational limitations requires the continued development of robust adaptive control algorithms and enhanced sensor fusion capabilities for consistent real-time execution [73].

Variable-rate application protocols are progressively adapted for highly specialized horticultural tasks involving physical inputs beyond conventional agrochemicals. Advanced computer vision [1] and hyperspectral imaging systems estimate total fruit load with high precision [13]. Within apple orchards, these computational systems generate georeferenced fruitlet maps to guide precision sprayers [62], continuously modulating chemical thinning agents on a localized per-tree basis [60]. Expanding beyond chemical treatments, unmanned aerial vehicles extend their agricultural utility into non-chemical interventions, including automated artificial pollination [24]. Artificial intelligence–driven drones optimize date palm pollination by delivering precisely targeted, variable-rate pollen loads directly to the inflorescence [78]. The successful transition of these technologies from controlled prototype validation to extensive commercialization requires addressing spatial mapping errors induced by global navigation satellite system inaccuracies [60]. Furthermore, these autonomous frameworks must continuously adapt to the inherent biological complexity and structural variability of diverse orchard architectures. These persistent technical challenges necessitate comprehensive lifecycle assessments prior to extensive commercial deployment [78].

4. Discussion

Climate variability remains a primary driver of yield and quality degradation in fruit crops. Extreme thermal anomalies and prolonged water deficits disrupt net photosynthesis and transpiration. High temperatures before flowering reduce pollen starch content and compromise fruit set [79]. Rather than viewing these abiotic factors in isolation, current research demonstrates their synergistic effects, where soil moisture fluctuations during ripening interact with ambient vapor pressure deficits to cause fruit cracking. To counteract these vulnerabilities, agronomic strategies are increasingly divided between genetic adaptation and digital intervention. Although thermally resilient or dwarfing rootstocks provide a passive, long-term defense against sunburn damage [80], they cannot dynamically

adjust to rapid microclimatic fluctuations. This limitation highlights the need for active IoT monitoring systems that continuously track in-field water status and trigger automated microclimate controls to preserve fruit quality under severe environmental stress.

IoT architecture addresses these monitoring needs by establishing structured, multi-layer frameworks that integrate real-time perception, low-latency transport, cloud-based processing, and decision-support applications. A critical challenge in these deployments is achieving seamless interoperability across diverse, multi-vendor agricultural systems. Integrating standardized open-source middleware and long-range wide-area networks resolves this compatibility barrier by providing unified data interfaces [81]. However, a critical comparison of the literature reveals a clear trade-off between architecture complexity and processing latency. While cloud-based middleware simplifies data aggregation across large geographical areas, it often suffers from communication delays that limit its effectiveness in high-frequency, closed-loop control tasks. In contrast, decentralized edge-computing solutions bypass these latencies, enabling immediate local decisions. To maximize overall agroecological resilience, these digital frameworks must evolve beyond isolated, single-parameter monitoring systems and transition toward comprehensive multi-sensor integrations [82]. A robust agricultural approach requires integrating microclimatic, edaphic, and physiological data to adapt dynamically to severe environmental constraints.

This architectural trade-off also extends to selecting predictive computational models. Integrating sensor networks with machine learning has shifted agronomic management from descriptive tracking to predictive optimization in smart farming [83]. Predictive platforms leverage multi-source data fusion to anticipate crop development, as illustrated in the AgriFusion model [84]. A comparative analysis of these predictive frameworks highlights a clear division between lightweight traditional models and advanced deep learning systems. Lightweight algorithms, such as support vector regression and random forest, are highly efficient for localized soil moisture prediction because they require minimal computational resources. However, these traditional models struggle to process high-dimensional spatial, visual, or spectral datasets. Conversely, advanced convolutional neural networks and hybrid attention models achieve superior accuracy in non-destructive quality management and defect detection. As critically synthesized in [85], harnessing artificial intelligence for fruit quality management enables automated sorting, internal defect tracking, and precise ripeness estimation. However, these deep learning architectures impose high computational demands that restrict direct edge deployment and require extensive annotated training datasets. Therefore, selecting the optimal algorithm depends on a careful balance between the available computational infrastructure and the required predictive precision.

Despite these technological advances, a critical synthesis of the literature reveals a significant geographic and economic divide in technology adoption. Most field-validated IoT deployments are concentrated in developed regions and focus on high-value, export-oriented commercial species, where the high initial costs of sensor networks and cloud infrastructure are economically viable. Conversely, small-scale producers in developing areas face severe financial and technical barriers, including unstable rural telecommunication networks and a lack of specialized training. To bridge this gap, future research must prioritize low-cost, open-source hardware and energy-efficient, long-range communication protocols. Developing highly durable, low-maintenance sensors that withstand harsh field conditions is essential to globally ensure the long-term viability and equitable distribution of digital agriculture.

5. Conclusions

Extreme thermal anomalies, severe volumetric water deficits, and excessive solar irradiance constitute the primary microclimatic stressors degrading fruit crop productivity. These restrictive environmental conditions disrupt essential physiological processes, including net photosynthesis and stomatal conductance, directly altering crop water balance. Under these circumstances, this continuous exposure induces severe osmotic stress, premature flower drop, and surface tissue necrosis, ultimately reducing total agricultural yield and compromising the commercial quality of export-oriented fruit species.

The strategic deployment of Internet of Things architectures establishes a robust framework to counteract these environmental constraints. Distributed agro-environmental sensors, integrated with artificial intelligence algorithms and advanced machine learning models like extreme gradient boosting and random forest, process real-time data transmitted through long-range wide-area networks. This technological synergy automates precision irrigation and facilitates the early detection of physiological stress. In practice, these digital interventions achieve predictive accuracies of up to 99.7%, increase water-use efficiency by saving 25%–50% of applied water, and drastically reduce nutrient leaching. In summary, this precision management reduces the agricultural carbon footprint by up to 40%, strengthening the overall agroecological resilience of fruit orchards.

The successful implementation of these digital frameworks is strictly conditioned by specific regional geographies. Semi-arid and Mediterranean environments facing severe water deficits prioritize precision agriculture research on high-value commercial species, including apple, strawberry, and mango. Within these regions, advanced agronomic strategies such as regulated deficit irrigation demonstrate that localized microclimates dictate the optimal deployment of digital networks. As global agricultural systems face increasingly erratic climatic shifts, the continued integration of accessible, data-driven technologies remains essential to sustain long-term crop profitability and ensure global food security.

Use of AI tools declaration

During the preparation of this work, the authors utilized artificial intelligence technologies to enhance the academic tone, stylistic flow, and overall readability of the English text. After applying these technological enhancements, the authors critically reviewed, revised, and validated the final manuscript, accepting complete intellectual and scientific responsibility for the published content.

Acknowledgments

The authors would like to thank the Center for Logistical Support for Researchers (CALI) and the Technological University of Peru (UTP) for their support during the preparation of the manuscript.

Conflict of interest

The authors declare that there are no conflicts of interest in this manuscript.

Author contributions

CF-B: Formal analysis, methodology, writing–original draft, investigation, conceptualization. JA-G: Writing–original draft, formal analysis, conceptualization, writing–review & editing, investigation, methodology. JV-C: Supervision, investigation, project administration, writing–original draft, writing–review & editing, visualization, methodology.

References

1. Ferrer-Ferrer J, Ruiz-Hidalgo E, Gregorio V, et al. (2023) Simultaneous fruit detection and size estimation using multitask deep neural networks. *Biosyst Eng* 233: 63–75. https://doi.org/10.1016/j.biosystemseng.2023.07.010
2. Sagheer A, Mohammed M, Riad K, et al. (2020) A cloud-based IoT platform for precision control of soilless greenhouse cultivation. *Sensors* 21: 223.https://doi.org/10.3390/s21010223
3. Pereira Souza CG, Sales Rodrigues M, Silva KAD, et al. (2022) Precision agriculture tools for liming management in mango orchards in the Brazilian semiarid region. *Comun Sci* 13: e3630. https://doi.org/10.14295/cs.v13.3630
4. Wang L, Tang Y, Liu Z, et al. (2024) Prediction of thrips damage distribution in mango orchards using a novel maximum likelihood classifier. *Agronomy* 14: 795. https://doi.org/10.3390/agronomy14040795
5. Postolache S, Sebastião P, Viegas V, et al. (2022) IoT-based systems for soil nutrients assessment in horticulture. *Sensors* 23: 403. https://doi.org/10.3390/s23010403
6. Salimath M, Kaliannan N, Prabhakar V, et al. (2025) IoT and sensor technologies: Increased water and nutrient savings and profit in Banana cv. Grand Nain (AAA) production. *Sci Hortic* 341: 113982. https://doi.org/10.1016/j.scienta.2025.113982
7. Pazhanivelan S, Shyam AT, Ragunath KP, et al. (2025) Advanced mapping of mango orchards in Chittoor district through object-based image analysis approach using Sentinel-2 imagery. *Plant Sci Today* 12: No.2. https://doi.org/10.14719/pst.6889
8. Verma HC, Ahmed T, Rajan S, et al. (2022) Development of LR-PCA based fusion approach to detect the changes in mango fruit crop by using Landsat 8 OLI images. *IEEE Access* 10: 85764–85776. https://doi.org/10.1109/ACCESS.2022.3194000
9. Zia H, Rehman A, Harris NR, et al. (2021) An experimental comparison of IoT-based and traditional irrigation scheduling on a flood-irrigated subtropical lemon farm. *Sensors* 21: 4175. https://doi.org/10.3390/s21124175
10. Mba PC, Njoku JN, Uyeh DD (2025) Enhancing resilience in specialty crop production in a changing climate through smart systems adoption. *Smart Agric Technol* 11: 100897. https://doi.org/10.1016/j.atech.2025.100897
11. Bonelli L, Incrocci L, Incrocci G, et al. (2024) Sensor-based fertigation management enhances resource utilization and crop performance in soilless strawberry cultivation. *Agronomy* 14: 465. https://doi.org/10.3390/agronomy14030465
12. Jaroensutasinee K, Jaroensutasinee M, Boonsanong P, et al. (2024) Mangosteen yield and fruit quality under regulated irrigation with sensors and IoT. *J Hum Earth Future* 5: 205–215. https://doi.org/10.28991/HEF-2024-05-02-05

13. Torgbor BA, Rahman MM, Brinkhoff J, et al. (2023) Integrating remote sensing and weather variables for mango yield prediction using a machine learning approach. *Remote Sens* 15: 3075. https://doi.org/10.3390/rs15123075
14. Arshad J, Aziz M, Al-Sumaiti AS, et al. (2022) Implementation of a LoRaWAN based smart agriculture decision support system for optimum crop yield. *Sustainability* 14: 827. https://doi.org/10.3390/su14020827
15. Jin J, Huang N, Huang Y, et al. (2022) Proximal remote sensing-based vegetation indices for monitoring mango tree stem sap flux density. *Remote Sens* 14: 1483. https://doi.org/10.3390/rs14061483
16. Šuljug J, Spišić J, Grgić K, et al. (2024) A comparative study of machine learning models for predicting meteorological data in agricultural applications. *Electronics* 13: 3284. https://doi.org/10.3390/electronics13163284
17. Cumpston MS, McKenzie JE, Thomas J, et al. (2021) The use of'PICO for synthesis' and methods for synthesis without meta-analysis: protocol for a survey of current practice in systematic reviews of health interventions. *F1000Res* 9: 678. https://doi.org/10.12688/f1000research.24469.2
18. Page MJ, McKenzie JE, Bossuyt PM, et al. (2021) The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* 372: n71. https://doi.org/10.1136/bmj.n71
19. Choong MK, Galgani F, Dunn AG, et al. (2014) Automatic evidence retrieval for systematic reviews. *J Med Internet Res 16*: e223. https://doi.org/10.2196/jmir.3369
20. Wu K, Jia Z, Duan Q (2023) The detection of kiwifruit sunscald using spectral reflectance data combined with machine learning and CNNs. *Agronomy* 13: 2137. https://doi.org/10.3390/agronomy13082137
21. Meshram D, Srivastava AK, Utkhede A, et al. (2025) Response to sensor-based fertigation of Nagpur Mandarin (Citrus reticulata Blanco) in Vertisol of Central India. *Horticulturae* 11: 508. https://doi.org/10.3390/horticulturae11050508
22. Raffaelli D, Qaderi R, Mazzoni L, et al. (2025) Yield and sensorial and nutritional quality of strawberry (Fragaria × ananassa Duch.) fruits from plants grown under different amounts of irrigation in soilless cultivation. *Plants* 14: 286. https://doi.org/10.3390/plants14020286
23. Zapata-García S, Temnani A, Berríos P, et al. (2023) Using soil water status sensors to optimize water and nutrient use in melon under semi-arid conditions. *Agronomy* 13: 2652. https://doi.org/10.3390/agronomy13102652
24. Swamidason ITJ, Pandiyarajan S, Velswamy K, et al. (2022) Futuristic IoT based smart precision agriculture: Brief analysis. *J Mob Multimed* 18: 1041–1058. https://doi.org/10.13052/jmm1550-4646.18323
25. Valentini G, Allegro G, Pastore C, et al. (2024) Use of an automatic fruit-zone cooling system to cope with multiple summer stresses in Sangiovese and Montepulciano grapes. *Front Plant Sci* 15: 1391963. https://doi.org/10.3389/fpls.2024.1391963
26. Allegro G, Valentini G, Pastore C, et al. (2025) Prediction of berry sunburn damage with machine learning: Results on grapevine (*Vitis vinifera* L.). *Biosyst Eng* 250: 62–67. https://doi.org/10.1016/j.biosystemseng.2024.12.006
27. Rahman MH, Zhang N, Sun D, et al. (2025) Transformer-based hyperspectral image analysis for phenotyping drought tolerance in blueberries. *Comput Electron Agric* 228: 109684. https://doi.org/10.1016/j.compag.2024.109684

28. Chen F, Liu Y, Zhang C, et al. (2023) Multi-objective deficit drip irrigation optimization of citrus yield, fruit quality and water use efficiency using NSGA-II in seasonal arid area of Southwest China. *Agric Water Manage* 287: 108440. https://doi.org/10.1016/j.agwat.2023.108440
29. Saruk BS, Rayalu GM (2024) Integrating machine learning for enhanced agricultural productivity: A focus on bananas and arecanut in the context of India's economic growth. *J Stat Theory Appl* 23: 408–426. https://doi.org/10.1007/s44199-024-00090-y
30. Manzoor MA, Sabir IA, Riaz MW, et al. (2024) Horticulture crop under pressure: Unraveling the impact of climate change on nutrition and fruit cracking. *J Environ Manage* 357: 120759. https://doi.org/10.1016/j.jenvman.2024.120759
31. Selahvarzi M, Ansari H, Ziaei AN, et al. (2025) Precision irrigation scheduling improves water productivity and economic indicators in young high-density apple orchards. *Sci Hortic* 354: 114264. https://doi.org/10.1016/j.scienta.2025.114264
32. Sugiura T (2025) Meteorological responses of fruit trees, impact of climate change on fruit production, and adaptation strategies. *Hortic J* 94: 285–295. https://doi.org/10.2503/hortj.SZD-R004
33. Zapata-García S, Berríos P, Temnani A, et al. (2025) Combined use of biostimulation and deficit irrigation improved the fruit quality in table grape. *Plants* 14: 485. https://doi.org/10.3390/plants14030485
34. López-Morales JA, Martínez JA, Caro M, et al. (2021) Climate-aware and IoT-enabled selection of the most suitable stone fruit tree variety. *Sensors* 21: 3867. https://doi.org/10.3390/s21113867
35. Avianto Y, Budianta D, Napoleon A, et al. (2024) Integrating automated drip irrigation and organic matter to improve enzymatic performance and yield of water efficient chilli in karst region. *J Ecol Eng* 25: 175–187. https://doi.org/10.12911/22998993/192820
36. De Oliveira HFE, Silva FL, Silva PC, et al. (2021) Horticultural performance of greenhouse cherry tomatoes irrigated automatically based on soil moisture sensor readings. *Water* 13: 2662. https://doi.org/10.3390/w13192662
37. Abioye AE, Hensel O, Esau T, et al. (2023) Model based predictive control strategy for water saving drip irrigation. *Smart Agric Technol* 4: 100179. https://doi.org/10.1016/j.atech.2023.100179
38. Martelli A, Rapinesi D, Verdi L, et al. (2024) Smart irrigation for management of processing tomato: A machine learning approach. *Irrig Sci* 42: 601–615. https://doi.org/10.1007/s00271-024-00993-9
39. FaghihKhorasani H, FaghihKhorasani A (2022) Predicting the impact of Internet of Things on the value added for the agriculture sector in Iran using mathematical methods. *Agris-line Pap Econ Inform* 14: 17–25. https://doi.org/10.7160/aol.2022.140302
40. Ahmed S, Reza MN, Karim MR, et al. (2025) Abnormal operation detection of automated orchard irrigation system actuators by power consumption level. *Sensors* 25: 331. https://doi.org/10.3390/s25020331
41. Mohammed M, Sallam A, Munir M, et al. (2021) Effects of deficit irrigation scheduling on water use, gas exchange, yield, and fruit quality of date palm. *Agronomy* 11: 2256. https://doi.org/10.3390/agronomy11112256
42. Bao L, Zhang SH, Ding Z, et al. (2023) Intelligent drip fertigation increases water and nutrient use efficiency of watermelon in greenhouse without compromising the yield. *Agric Water Manage* 282: 108278. https://doi.org/10.1016/j.agwat.2023.108278
43. Belkher S, Hammani A, Bouazzama B, et al. (2025) Effects of partial root-zone drying and deficit irrigation on yield, quality and water productivity of Washington Navel orange. *J Ecol Eng* 26: 12–27. https://doi.org/10.12911/22998993/200478

44. Sarker KK, Kamaruzzaman M, Alam MM, et al. (2025) Sensor-driven automated shed and irrigation for summer tomato (Solanum lycopersicum L.) production in Bangladesh under the changing climate. *Results Eng* 26: 104993. https://doi.org/10.1016/j.rineng.2025.104993
45. Abdo-Peralta P, Hernández-Hernández JL, Rodríguez-Reséndiz J, et al. (2024) Implementation of an enhanced edge computing system for the optimization of strawberry crop in greenhouses: A smart agriculture approach. *Agronomy* 14: 3030. https://doi.org/10.3390/agronomy14123030
46. Rezvani SM, Drueke J, Minaei S, et al. (2020) IoT-based sensor data fusion for determining optimality degrees of microclimate parameters in commercial greenhouse production of tomato. *Sensors* 20: 6474. https://doi.org/10.3390/s20226474
47. Zhang M, Han Y, Li D, et al. (2024) Smart horticulture as an emerging interdisciplinary field combining novel solutions: Past development, current challenges, and future perspectives. *Hortic Plant J* 10: 1257–1273. https://doi.org/10.1016/j.hpj.2023.03.015
48. Khan T, Qiu J, Banjar A, et al. (2021) Effect of climate change on fruit by co-integration and machine learning. *Int J Clim Change Strateg Manag* 13: 208–226. https://doi.org/10.1108/IJCCSM-09-2020-0097
49. Mohammed M, Riad K, Alqahtani N (2021) Efficient IoT-based control for a smart subsurface irrigation system to enhance irrigation management of date palm. *Sensors* 21: 3942. https://doi.org/10.3390/s21123942
50. Sakurai G, Ishitsuka N, Okabe N (2025) Evaluating the prediction ability and stability of data-driven methods for estimating the impact of climate change on fruit yields. *J Agric Meteorol* 81: 136–146. https://doi.org/10.2480/agrmet.D-24-00009
51. Sajitha P, Diana Andrushia A, Anand N, et al. (2024) A deep learning approach to detect diseases in pomegranate fruits via hybrid optimal attention capsule network. *Ecol Inform* 84: 102859. https://doi.org/10.1016/j.ecoinf.2024.102859
52. Mojumdar MU, Islam S, Mamun MA, et al. (2025) AFruitDB: A comprehensive dataset of six commonly used Asian fruits for advanced grading and biodiversity insights. *Data Brief* 59: 111380. https://doi.org/10.1016/j.dib.2025.111380
53. Yu F, Wang J, Zhang K, et al. (2025) Irrigation and planting density effects on apple–peanut intercropping system. *Agronomy* 15: 1798. https://doi.org/10.3390/agronomy15081798
54. Dzikiti S, Gush MB, Taylor NJ, et al. (2024) Fruit growth and water use of two pear cultivars grown in South Africa: implications for precision irrigation scheduling. *Water SA* 50: 4. https://doi.org/10.17159/wsa/2024.v50.i4.4109
55. Universidad Cooperativa de Colombia, Agudelo-Torres J, Martínez-Restrepo L, et al. (2024) Preliminary results of irrigation management for mango using LSTM neural networks and IoT. *Rev Fac Ing Univ Antioquia* 113: e20240725. https://doi.org/10.17533/udea.redin.20240725
56. Xu W, Zhang Y, Zhao X, et al. (2025) Improvement of citrus yield prediction using UAV multispectral images and the CPSO algorithm. *Agronomy* 15: 171. https://doi.org/10.3390/agronomy15010171
57. Ngoma DH, Ndabakurane I, Mwangama J, et al. (2025) Design and development of IoT smart drip irrigation and fertigation prototype for small and medium scale farmers. A case study of tomato farmers in Tanzania. *J Inst Eng India Ser A* 106: 373–395. https://doi.org/10.1007/s40030-024-00857-7

58. Wang Z, Li M, Zhou Y, et al. (2025) A machine learning-based irrigation prediction model for cherry tomatoes in greenhouses: Leveraging optimal growth data for precision irrigation. *Comput Electron Agric* 237: 110558. https://doi.org/10.1016/j.compag.2025.110558
59. Arbizu-Milagro J, Castillo-Ruiz FJ, Tascón A, et al. (2023) Effects of regulated, precision and continuous deficit irrigation on the growth and productivity of a young super high-density olive orchard. *Agric Water Manage* 286: 108393. https://doi.org/10.1016/j.agwat.2023.108393
60. Kang C, Kumar SK, He L (2025) Integrating computer vision and precision sprayers for targeted green fruit chemical thinning. *Precis Agric* 26: 86. https://doi.org/10.1007/s11119-025-10286-6
61. Jamshidi B, Ghasemi-Varnamkhasti M, Mohtasebi SS, et al. (2025) Internet of things-based smart system for apple orchards monitoring and management. *Smart Agric Technol* 10: 100715. https://doi.org/10.1016/j.atech.2024.100715
62. Khort DO, Kutyrev AI, Smirnov IG, et al. (2024) Enhancing sustainable automated fruit sorting: Hyperspectral analysis and machine learning algorithms. *Sustainability* 16: 10084. https://doi.org/10.3390/su162210084
63. Jang S, Park E, Lee H, et al. (2023) Estimation of apple leaf nitrogen concentration using hyperspectral imaging-based wavelength selection and machine learning. *Horticulturae* 10: 35. https://doi.org/10.3390/horticulturae10010035
64. González-González MG, Gómez-Sanchis J, Blasco J, et al. (2020) CitrusYield: A dashboard for mapping yield and fruit quality of citrus in precision agriculture. *Agronomy* 10: 128. https://doi.org/10.3390/agronomy10010128
65. Senapaty MK, Ray A, Padhy N (2023) IoT-enabled soil nutrient analysis and crop recommendation model for precision agriculture. *Computers* 12: 61. https://doi.org/10.3390/computers12030061
66. Bal F, Kayaalp F (2023) A novel deep learning-based hybrid method for the determination of productivity of agricultural products: Apple case study. *IEEE Access* 11: 7808–7821. https://doi.org/10.1109/ACCESS.2023.3238570
67. Santikari V, Shukla S, Sishodia RP, et al. (2024) Reducing water, nutrient, pesticide, and carbon footprints and costs for drip-irrigated vine crops with compact bed plasticulture. *J ASABE* 67: 501–515. https://doi.org/10.13031/ja.15813
68. Santos SE, Ribeiro-Neto JA, Silva DJH, et al. (2025) High-yield phenotyping in evaluating the productivity of a diallel with tomato plant. *Sci Hortic* 342: 114044. https://doi.org/10.1016/j.scienta.2025.114044
69. Rus RC, Adam NM, Ishak WIW, et al. (2023) Influence of composition of soilless substrates monitored with IoT sensor nodes on the growth, nutrient and fruit quality of rockmelons (Cucumis melo var. cantalupensis). *Indian J Agric Res* 57: 758–764. https://doi.org/10.18805/IJARe.AF-758
70. Sushma C, Veerappa BN (2026) A biologically inspired multi-scale CNN for edge-based grape leaf disease detection. *Eng Technol Appl Sci Res* 16: 34090–34096. https://doi.org/10.48084/etasr.16230
71. Poblete-Echeverría C, Hernández I, Iñiguez R, et al. (2025) Using artificial intelligence for automatic and fast detection of downy mildew symptoms in grapevine canopies. *Eur J Agron* 170: 127755. https://doi.org/10.1016/j.eja.2025.127755
72. Alzahrani AS, Iqbal A, Zafar W, et al. (2025) Swin-YOLO-SAM: a hybrid Transformer-based framework integrating Swin Transformer, YOLOv12, and SAM-2.1 for automated identification and segmentation of date palm leaf diseases. *Front Plant Sci* 16: 1666374. https://doi.org/10.3389/fpls.2025.1666374

73. Gerdan Koc D, Koc C, Comakli M (2025) AI-powered autonomous spraying robot for precision orchard applications. *J Agric Eng* 57: 1. https://doi.org/10.4081/jae.2025.1766
74. Partel V, Costa L, Ampatzidis Y (2021) Smart tree crop sprayer utilizing sensor fusion and artificial intelligence. *Comput Electron Agric* 191: 106556. https://doi.org/10.1016/j.compag.2021.106556
75. Wodzicki LM, Madden LV, Long EY, et al. (2023) Evaluation of a laser-guided intelligent sprayer for disease and insect management on grapes. *Am J Enol Vitic* 74: 0740024. https://doi.org/10.5344/ajev.2023.23013
76. Liu L, Liu Y, He X, et al. (2022) Precision variable-rate spraying robot by using single 3D LIDAR in orchards. *Agronomy* 12: 2509. https://doi.org/10.3390/agronomy12102509
77. Tang R, Tang J, Aridas NK, et al. (2026) Research on RBF-PID hybrid drive control models for drone pesticide applications in tropical orchards. *Geo-Spat Inf Sci* 29: 193–210. https://doi.org/10.1080/10095020.2025.2519374
78. AlRaeesi I, El-Khazali R (2026) AI-enabled drones for date palm pollination. *Sci Rep* 16: 10158. https://doi.org/10.1038/s41598-026-39739-2
79. Wang Q, Wu Y, Wu W, et al. (2025) Research progress on the physiological, biochemical and molecular regulatory mechanisms of fruit tree responses to high-temperature stress. *Hortic Plant J* 11: 1–14. https://doi.org/10.1016/j.hpj.2023.09.008
80. Xu H, Blatt S, Ediger D (2023) Tools for climate resilience in tree fruit I: large-dwarfing rootstocks can alleviate sunburn damage in "Buckeye Gala" apple. *Can J Plant Sci* 103: 128–132. https://doi.org/10.1139/cjps-2022-0080
81. Pagano A, Croce D, Tinnirello I, et al. (2023) A survey on LoRa for smart agriculture: Current trends and future perspectives. *IEEE Internet Things J* 10: 3664–3679. https://doi.org/10.1109/JIOT.2022.3230505
82. García L, Parra L, Jimenez JM, et al. (2020) IoT-based smart irrigation systems: An overview on the recent trends on sensors and IoT systems for irrigation in precision agriculture. *Sensors* 20: 1042. https://doi.org/10.3390/s20041042
83. Dhanaraju M, Chenniappan P, Ramalingam K, et al. (2022) Smart farming: Internet of Things (IoT)-based sustainable agriculture. *Agriculture* 12: 1745. https://doi.org/10.3390/agriculture12101745
84. Singh RK, Berkvens R, Weyn M (2021) AgriFusion: An architecture for IoT and emerging technologies based on a precision agriculture survey. *IEEE Access* 9: 136253–136283. https://doi.org/10.1109/ACCESS.2021.3116814
85. El-Beltagi HS, Gad M, Khedr N, et al. (2026) Harnessing artificial intelligence and machine learning for fruit quality management: A comprehensive review. *J Stored Prod Res* 116: 102920. https://doi.org/10.1016/j.jspr.2025.102920



© 2026 the Author(s), licensee AIMS Press. This is an open access article distributed under the terms of the Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0)