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Internet of Things and Green Computing for Sustainable Agricultural Management in Rural Small-Scale Farming: A Systematic Review †

Kerlyn Mejia Garces [1], Andrea Ordonez [1], Mabel Ruiz [2], Emily Cayambe [2], Christian Lopez [2] and Priscila Cedillo [1,*]

[1] Department of Computer Science, University of Cuenca, Cuenca 010150, Ecuador; kerlyn.mejiag@ucuenca.edu.ec (K.M.G.); alizzeth.ordonezl@ucuenca.edu.ec (A.O.)
[2] Faculty of Engineering, University of Cuenca, Cuenca 010150, Ecuador; mabel.ruiz@ucuenca.edu.ec (M.R.); emily.cayambe@ucuenca.edu.ec (E.C.); fabian.lopez1@ucuenca.edu.ec (C.L.)
* Correspondence: priscila.cedillo@ucuenca.edu.ec
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Abstract

The integration of the Internet of Things (IoT) in agriculture has advanced precision farming; however, most solutions target large-scale operations with stable electricity and internet connectivity. This limits their applicability in rural communities and among smallholder farmers, where energy and connectivity constraints remain critical. This article presents a systematic literature review of 32 primary studies identified through searches conducted in IEEE Xplore, Scopus, and ScienceDirect. The search covered studies published from 1 January 2016 to 9 May 2026. Although no studies published between 2016 and 2018 met the eligibility criteria, the final evidence base comprised 32 primary studies published between 2019 and 2026. Data were extracted on agricultural infrastructure, productivity effects, and adoption barriers. The study shows a shift toward edge computing, low-power communication protocols such as Long-Range (LoRa) communication, and solar-powered sensor nodes to enable off-grid autonomy. However, adoption remains limited by high hardware costs, unreliable cellular coverage, and gaps in farmers' digital literacy. The review identifies Tiny Machine Learning (TinyML) for local data processing and community-shared IoT networks as promising directions to address technical and socioeconomic barriers and enable sustainable smart agriculture for smallholder farmers.

Keywords: Internet of Things; green computing; smart agriculture; rural communities; smallholder farming; edge computing; sustainability

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1. Introduction

Current agriculture faces the challenge of adapting to an increasingly demanding environment, in which food security, environmental sustainability, and resource efficiency are fundamental pillars of resilient agricultural systems [1]. In this context, rural communities and smallholder farmers play a vital role in global agricultural production; however, they often operate under limited access to electricity, internet connectivity, economic resources, and technologies [2,3]. Therefore, it is necessary to analyze how digital technologies can contribute to strengthening more sustainable, accessible, and efficient agriculture in small-scale rural contexts [4]. In recent years, the integration of Information and Communication Technology (ICT) has driven the smart agriculture paradigm. In particular, the IoT has

enabled new capabilities for precision irrigation, crop health monitoring, and data-driven agronomic management [5,6]. These applications are linked to the Sustainable Development Goals (SDGs), especially SDG 2, Zero Hunger, and SDG 12, Responsible Consumption and Production, by promoting more efficient, sustainable, and inclusive production systems [7]. However, many agricultural IoT solutions have been designed for large-scale environments, limiting their direct applicability in rural areas with less infrastructure.

In this regard, green computing emerges as a relevant approach for adapting agricultural IoT to more constrained operating conditions. This paradigm promotes architectures, devices, and strategies that reduce energy consumption while improving the operational efficiency of computing systems [5]. In the agricultural context, it includes technologies such as energy harvesting, duty cycles, low-power sensors, low-power wide-area networks, and edge computing [8]. These alternatives help reduce dependence on the power grid and permanent internet connections, which are key factors for the sustainability of IoT systems in rural areas [9,10]. Among the most widely used technologies in this field are edge computing, Low-Power Wide-Area Networks (LPWANs), solar-powered nodes, and energy-saving mechanisms [11]. Edge computing enables data processing close to where it is generated, reducing the need to continuously transmit data to remote servers [12]. Meanwhile, technologies such as LoRa facilitate long-distance communication with low energy consumption [13]. Furthermore, models such as TinyML [14] and community-shared IoT networks [15] open up new possibilities for reducing costs, improving operational autonomy, and adapting technological solutions to the socioeconomic conditions of small-scale producers.

Although previous reviews of smart agriculture, agricultural IoT, and sustainability exist, they mainly focus on crop monitoring, resource optimization, or data-driven agricultural management from a general perspective. Many address large-scale agricultural settings or those with sufficient technological infrastructure, while others analyze socioeconomic barriers to adoption without examining the technical architectures required for autonomous and energy-efficient systems. Likewise, some reviews incorporate environmental, social, and governance (ESG) criteria but do not examine in detail the hardware, low-power communication protocols, or local processing strategies required for rural IoT networks. This Systematic Literature Review (SLR) aims to identify, evaluate, and synthesize the current state of knowledge regarding the application of these technologies in small-scale agriculture. To this end, the search covered literature published from 1 January 2016 to 9 May 2026, with a focus on agricultural infrastructure, productivity, energy efficiency, connectivity, adoption barriers, and technological sustainability. Although the search window began in 2016, no studies published between 2016 and 2018 met the eligibility criteria. Consequently, the final evidence base consisted of studies published from 2019 onward. Therefore, a research gap remains in secondary studies that link the needs of small-scale rural agriculture with IoT architectures based on green computing. This review aims to synthesize available knowledge, identify relevant technologies, recognize technical and socioeconomic barriers, and generate a comprehensive vision to guide future developments in sustainable smart agriculture. Consequently, the research question guiding this study is: How do IoT and green computing contribute to the development of sustainable systems for rural communities engaged in small-scale agriculture?

The remainder of this article is organized as follows. Section 2 describes the systematic review methodology, including the PICOC framework, research questions, search strategy, selection criteria, data extraction, and quality assessment. Section 3 presents the results of the selected studies, focusing on IoT technologies, green computing approaches, impacts, barriers, and future trends. Section 4 discusses the main findings and implications. Finally, Section 5 presents the conclusions and future research directions.

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2. Materials and Methods

This SLR followed the guidelines proposed by Kitchenham and Charters [16] for evidence-based reviews in software engineering and computer science. The process was organized into three stages: planning (Section 2.1), conducting the review (Section 2.2) and reporting (Section 3). The planning stage defined the scope, research questions, and protocol using the Population, Intervention, Comparison, Outcomes, and Context (PICOC) framework [17]. The conducting stage included the database search, application of inclusion and exclusion criteria, Quality Assessment (QA), and data extraction strategy. The reporting stage presents and interprets the extracted evidence, combining quantitative and qualitative analyses to discuss the main findings, identify research trends and gaps, and outline limitations and future research directions.

2.1. Planning the Review

The PICOC framework was used to define the research scope in a structured and reproducible manner. It helped align the search strategy with the objective of analyzing how IoT and green computing contribute to sustainable agricultural systems in rural and small-scale contexts. The PICOC elements are summarized in Table 1.

Table 1. PICOC framework used to define the research questions and search string.

PICOC Element	Description
Population	Primary studies addressing the application of IoT technologies and green computing approaches for sustainable agricultural management in rural communities engaged in small-scale farming.
Intervention	Implementation of IoT solutions incorporating green computing approaches to improve sustainability, energy efficiency, and agricultural management.
Comparison	Traditional agricultural practices without IoT technologies or green computing approaches.
Outcome	Technological trends, green computing approaches, impacts on agricultural management, adoption barriers, and future research directions.
Context	Academic.

Based on this framework, the central research question was: How do IoT and green computing contribute to the development of sustainable systems for rural communities engaged in small-scale agriculture? Three sub-research questions (SRQs) guided data extraction and synthesis:

- SRQ1: What sustainable IoT technologies and green computing approaches are applied in agricultural management in rural communities engaged in small-scale agriculture?
- SRQ2: How do sustainable IoT systems impact the productivity, efficiency, and autonomy of rural farmers?
- SRQ3: What are the main barriers to the adoption of IoT and green computing in rural agricultural communities, and what future trends may support their implementation?

2.2. Conducting the Review

2.2.1. Search Strategy

The PICOC framework also guided the search string. Four main concepts were defined: IoT, green computing, sustainable agricultural management, and rural context. For each concept, synonyms and equivalent terms were combined using the boolean operators AND and OR to ensure a comprehensive and focused search. The search terms are summarized in Table 2.

The final search string was: (“Internet of Things” OR IoT) AND (“green computing” OR “energy efficiency”) AND (agriculture OR farming) AND (rural OR “small scale farm-

ing"). Searches were conducted in IEEE Xplore Digital Library, Scopus, and ScienceDirect, applying the string to titles, abstracts, and keywords through each database's advanced search options.

Table 2. Search terms.

Concept	Main Term	Operator	Alternative Terms
Internet of Things	Internet of Things	OR	IoT
Green computing	Green computing	OR	Energy efficiency
Agriculture	Agriculture	OR	Farming
Rural context	Rural	OR	Small-scale farming

The eligibility window covered studies published from 1 January 2016 to 9 May 2026. The lower boundary was selected because it follows the adoption of the United Nations 2030 Agenda for Sustainable Development, which promoted sustainable agricultural production, resource efficiency, technological innovation, and the reduction in inequalities affecting vulnerable communities [7]. The upper boundary corresponds to the date on which the database searches were last executed and updated, ensuring that the review reflects the literature available at the time of manuscript preparation. Because the search covered only part of 2026, publication counts for that year represent partial-year evidence and should not be interpreted as complete annual output. No studies published between 2016 and 2018 met all inclusion criteria; consequently, the final evidence base comprised studies published from 2019 onward.

The identification, screening, eligibility assessment, and inclusion process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [18]. The PRISMA 2020 Checklist and the detailed flow diagram are available in the Supplementary Materials.

The initial search yielded 124 records: 60 from Scopus, 59 from IEEE Xplore, and 5 from ScienceDirect. After removing 24 duplicate records, 100 records remained for screening. These studies were screened by title, abstract, and keywords using the inclusion and exclusion criteria in Table 3. During screening, 68 articles were excluded because they were outside the review scope. The remaining 32 studies were retrieved and assessed in full text; no additional studies were excluded at this stage. Thus, the final sample comprised 32 primary studies. The complete selection process is shown in Figure 1.

Table 3. Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Studies that address IoT in agriculture, especially in rural contexts.	Studies that are not related to IoT, agriculture, or sustainability.
Studies that include green computing approaches or technological sustainability.	Studies focused exclusively on urban or industrial environments without connection to the rural context.
Studies written in English.	Studies not written in the selected language.
Studies focused on small-scale agriculture or rural communities with limited resources.	Studies without technical content, impact assessment, or analysis relevant to the adoption of sustainable IoT.
Studies that describe IoT technologies, such as sensors, networks, platforms, or energy-efficiency approaches.	Studies with insufficient information.
Studies that analyze at least one of the following aspects: impact, barriers, or future trends.	Secondary studies.

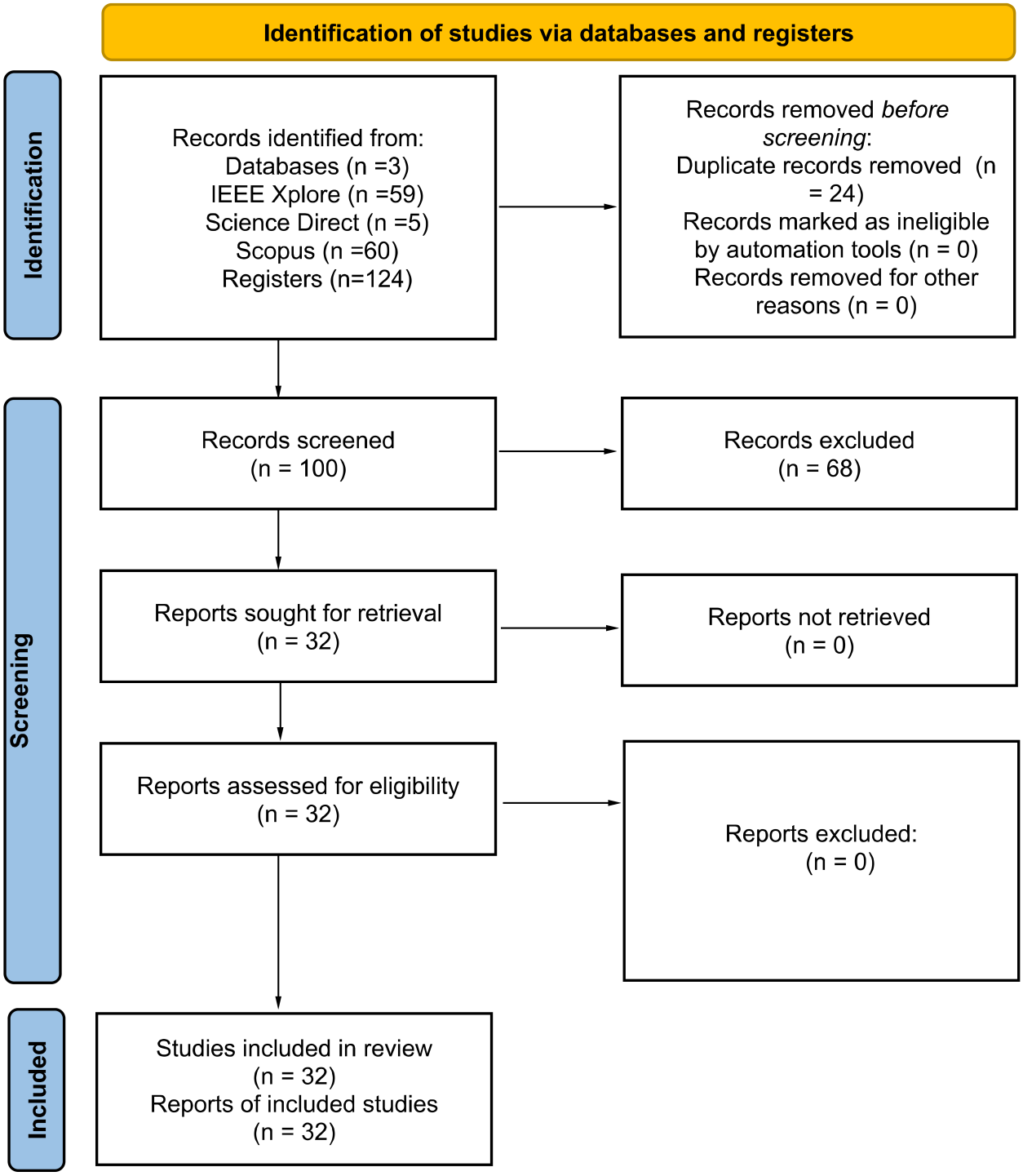


Figure 1. PRISMA 2020 flow diagram illustrating the literature screening and study selection process.

2.2.2. Data Extraction Criteria

Data Extraction Criteria (EC) were defined according to the sub-research questions to ensure a structured and consistent analysis of the 32 selected primary studies. The extraction focused on six categories: main IoT technology, green computing approach, productivity and efficiency outcomes, farmer autonomy, adoption barriers, and future trends. Each criterion was divided into specific sub-items to support the systematic recording and comparison of the evidence, as shown in Table 4.

Table 4. Data extraction criteria (EC).

Sub-Research Question	Criterion	Extraction Criterion	Category
SRQ1: What sustainable IoT and green computing technologies are applied in rural small-scale agricultural communities?	EC1	Main IoT technology	WSN
			Edge/fog computing nodes
			LPWANs
			Physical control systems
	EC2	Green computing approach	Energy harvesting
			Duty cycling and sleep scheduling
			Adaptive data rate
			Edge data aggregation
SRQ2: How do sustainable IoT systems impact productivity, efficiency, and autonomy among rural farmers?	EC3	Productivity and efficiency	Operational energy efficiency
			Precision irrigation
			Proactive crop health monitoring
	EC4	Farmer autonomy	Off-grid operational capability
			Independent, data-driven decision making
SRQ3: What are the main barriers to adopting IoT and green computing in rural agricultural communities, and what future trends can support their implementation?	EC5	Adoption barriers	High hardware and infrastructure costs
			Poor rural internet connectivity
			Low levels of digital literacy
	EC6	Future trends	TinyML
			Community-shared IoT networks

2.2.3. Quality Assessment and Validation Procedures

The QA process assessed the methodological relevance and empirical contribution of the selected studies following Kitchenham and Charters [16]. Although the search period began in 2016, the final sample included only studies published from 2019 onward, suggesting that the specific integration of IoT, green computing, and sustainable rural agriculture has become more explicit in recent years.

Recent QA tools for systematic reviews in software engineering recommend two- or three-level scales to capture the degree of compliance with each criterion [19,20]. This review used three criteria, summarized in Table 5. QA1 and QA2 assessed thematic relevance and methodological soundness, whereas QA3 assessed publication relevance.

Table 5. Quality assessment questions and scoring criteria.

ID	Question	Assessment Scores		
		Does Not Include	Partially Includes	Includes
QA1	The study clearly describes the application of IoT technologies in rural or small-scale agriculture.	0	0.5	1
QA2	The study addresses sustainability aspects, such as green computing, energy efficiency, or environmental impact.	0	0.5	1
QA3	The study was published in a relevant journal or conference.	0	0.5	1

Each criterion was scored using a three-level ordinal scale: 1 when the study fully met the criterion, 0.5 when compliance was partial or ambiguous, and 0 when the criterion was not met, or evidence was insufficient. Three reviewers independently evaluated each study. Inter-rater reliability was estimated using Fleiss's Kappa coefficient (κ), which measures agreement among more than two raters for discrete categories [21]. The obtained value was $\kappa = 0.817$, which indicates almost perfect agreement according to Landis and Koch [22]. This result supports the consistency and reliability of the QA process.

For QA3, journal articles were assessed using the SCImago Journal Rank (SJR), which estimates journal prestige based on weighted citations and the relevance of citing sources indexed in Scopus [23]. Conference papers were assessed according to venue-specific reputation, international scope, indexing, and publication visibility. Publication by an internationally recognized organization did not automatically determine the highest score, because the relevance and visibility of the specific conference venue were also considered. As shown in Table 6, the average QA3 score was 0.703, indicating that most selected studies were published in sources with moderate or high academic relevance.

For each study, the final score for each QA criterion was calculated as the arithmetic mean of the three reviewers' ratings. Then, the overall average for each criterion was calculated across the 32 studies to identify the most and least frequently satisfied aspects. These scores were not used as exclusion criteria; instead, they characterized the quality of the evidence and supported the interpretation of findings. The QA results are presented in Table 6.

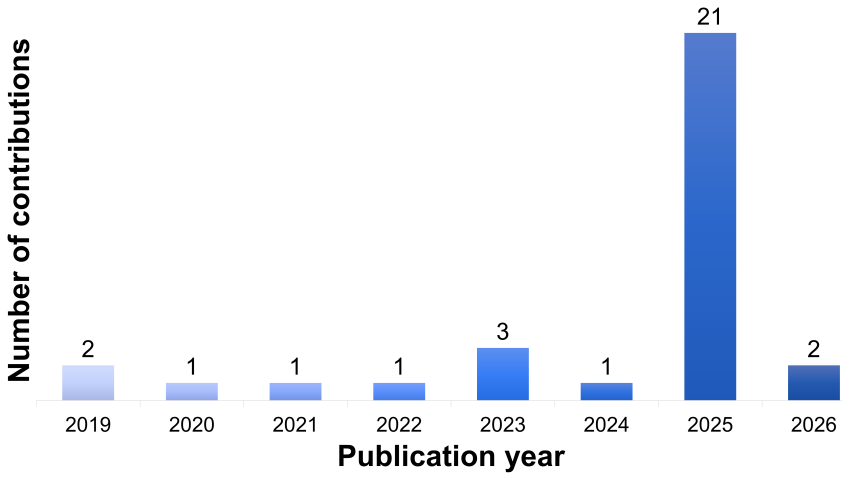
Table 6. Quality assessment results.

Article	QA1	QA2	QA3
Babaghayou and Zaoui (2025) [24]	0.833	1	0.667
Fonseca et al. (2023) [25]	1	1	1
Khandaker et al. (2025) [26]	1	1	0.5
Lu et al. (2025) [27]	1	1	1
Mani et al. (2025) [28]	1	1	0.833
Manurung et al. (2025) [29]	1	1	1
Mirsadri et al. (2025) [30]	1	1	1
Ntawuzumunsi et al. (2025) [31]	1	0.5	0.5
Ogbodo and Mendes (2025) [32]	1	0.833	1
Prathyusha et al. (2025) [33]	1	1	0.5
Rajakumar and V. K. (2025) [34]	1	1	0
Sharma and Sharma (2025) [35]	1	1	0
Bajpai and Yadav (2025) [36]	1	0.667	1
Mateen et al. (2025) [37]	1	0.333	1
Abu et al. (2024) [38]	1	1	0.5
Ali et al. (2025) [39]	1	1	1
Ammad Uddin et al. (2019) [40]	1	1	1
Bao (2022) [41]	1	0.833	0
Ellouze et al. (2025) [42]	1	1	1
Suman and Kumar (2025) [43]	1	1	0.5
Guillén et al. (2021) [44]	1	0.667	1
Hazarika et al. (2025) [45]	1	1	1
He and Chen (2026) [46]	1	0.833	0.5
Kourtis et al. (2023) [47]	1	1	1
Natrayan et al. (2025) [48]	1	0.833	0.5
Nurhasanah et al. (2025) [49]	1	1	0
Ragavee et al. (2025) [50]	1	1	0
Rodríguez-Robles et al. (2020) [51]	1	1	1
Shrestha and Drozdenko (2019) [52]	0.5	1	1
Teleron et al. (2025) [53]	1	1	0.5
Toke et al. (2023) [54]	1	1	1
Trînc et al. (2026) [55]	1	1	1
Total average	0.979	0.922	0.703

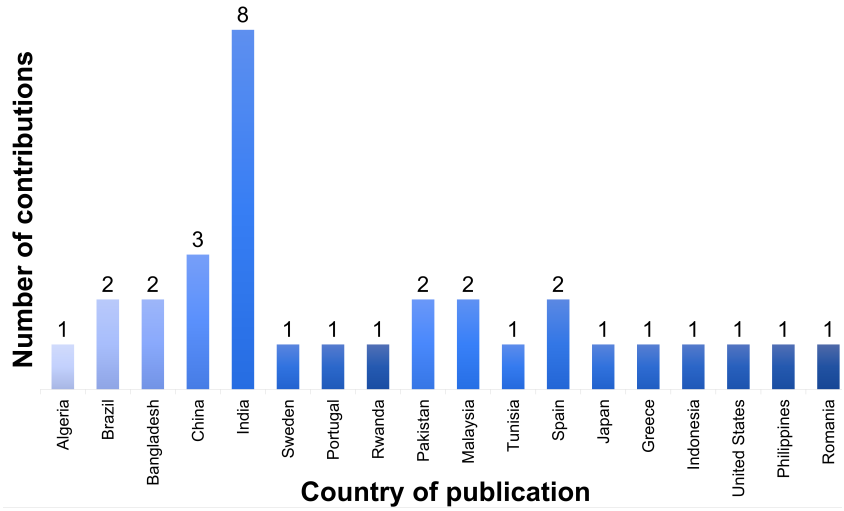
3. Results

This section synthesizes the 32 primary studies included in the systematic review. The search covered publications from 1 January 2016 to 9 May 2026; however, no studies published between 2016 and 2018 met the eligibility criteria. Consequently, the final evidence base comprised studies published between 2019 and 2026. Because the search was completed before the end of 2026, the number of studies reported for that year represents partial-year coverage and should not be directly compared with publication counts from complete calendar years.

As shown in Figure 2, scientific production was limited between 2019 and 2024 but increased sharply in 2025, with 21 studies identified, suggesting growing academic interest in the integration of IoT, green computing, and sustainable agriculture in rural contexts. Figure 2 also presents the geographical distribution of the selected studies, with contributions from 18 countries. India accounted for the largest share, with 8 studies, followed by China with 3. Brazil, Bangladesh, Pakistan, Malaysia, and Spain contributed 2 studies each, while the remaining countries were represented by one publication. Overall, the evidence indicates that research on sustainable IoT and green computing in rural agriculture has a global scope, although it is more concentrated in emerging Asian economies.



(**a**) Distribution of studies by year of publication.



(**b**) Geographic distribution of the studies.

Figure 2. General description of the selected studies.

3.1. Overview of the Selected Studies

The selected studies showed an uneven distribution across the extraction categories defined for this review. A single study could satisfy several extraction criteria; therefore, all category percentages were calculated independently using the complete sample of 32 studies as the denominator and are not expected to sum to 100%. As shown in Table 7, the most frequently identified categories were independent, data-driven decision-making, reported in 30 studies (93.8%), and operational energy efficiency, reported in 29 studies (90.6%). This indicates that most studies frame IoT not only as a monitoring tool but also as a mechanism for optimizing agricultural processes, reducing energy consumption, and supporting autonomous decision-making. Edge/fog computing nodes and poor rural Internet connectivity were each identified in 20 studies (62.5%), reflecting the relevance of local processing in areas with limited or unstable connectivity. Wireless Sensor Networks (WSNs) and proactive crop health monitoring were each identified in 19 studies (59.4%), confirming the importance of sensor networks for environmental data collection and timely crop monitoring. By contrast, adaptive data rate was identified in one study (3.1%), community-shared IoT networks in two studies (6.3%), low levels of digital literacy in four studies (12.5%), and TinyML in five studies (15.6%). These results suggest that current research prioritizes operational efficiency, connectivity, sensing, and data-driven decision-making, whereas social adoption, community collaboration, adaptive communication, and emerging edge intelligence remain underexplored.

Table 7. Extraction criteria and distribution of articles.

Research Question	EC	Extraction Category	Total Studies, *n*	Percentage [1]
SRQ1: What sustainable IoT and green computing technologies are applied in rural small-scale agricultural communities?	EC1	WSN	19	59.4%
		Edge/fog computing nodes	20	62.5%
		LPWANs	9	28.1%
		Physical control systems	18	56.3%
	EC2	Energy harvesting	12	37.5%
		Duty cycling and sleep scheduling	10	31.3%
		Adaptive data rate	1	3.1%
		Edge data aggregation	13	40.6%
SRQ2: How do sustainable IoT systems impact productivity, efficiency, and autonomy among rural farmers?	EC3	Operational energy efficiency	29	90.6%
		Precision irrigation	13	40.6%
		Proactive crop health monitoring	19	59.4%
	EC4	Off-grid operational capability	18	56.3%
		Independent, data-driven decision-making	30	93.8%
SRQ3: What are the main barriers to adopting IoT and green computing in rural agricultural communities, and what future trends can support their implementation?	EC5	High hardware and infrastructure costs	12	37.5%
		Poor rural internet connectivity	20	62.5%
		Low levels of digital literacy	4	12.5%
	EC6	TinyML	5	15.6%
		Community-shared IoT networks	2	6.3%

[1] Percentages were calculated as $(n/32) \times 100$ and rounded to one decimal place. A single study could satisfy several extraction criteria and could therefore contribute to more than one category. Consequently, percentages within an extraction criterion or sub-research question are not expected to sum to 100%.

Cross-tabulations were used to examine relationships among the extraction criteria. These relationships were represented through bubble charts, where each bubble indicates the number of studies addressing two criteria simultaneously, and its size reflects the frequency of that association. This visualization helped identify dominant technological combinations and gaps in the reviewed literature.

Figures 3–5 present the most frequently reported combinations as well as underexplored intersections. Table 8 subsequently complements this frequency-based analysis with a structured horizontal comparison of solution characteristics.

Figure 3 shows that operational energy efficiency was the most frequent application, particularly in WSNs and edge/fog computing nodes, with 18 studies each, followed by physical control systems, with 16 studies. Proactive crop health monitoring was also strongly associated with WSNs and edge/fog computing nodes, confirming their role in continuous crop monitoring. In contrast, adaptive data rate appeared only marginally, suggesting a gap in dynamic data transmission strategies.

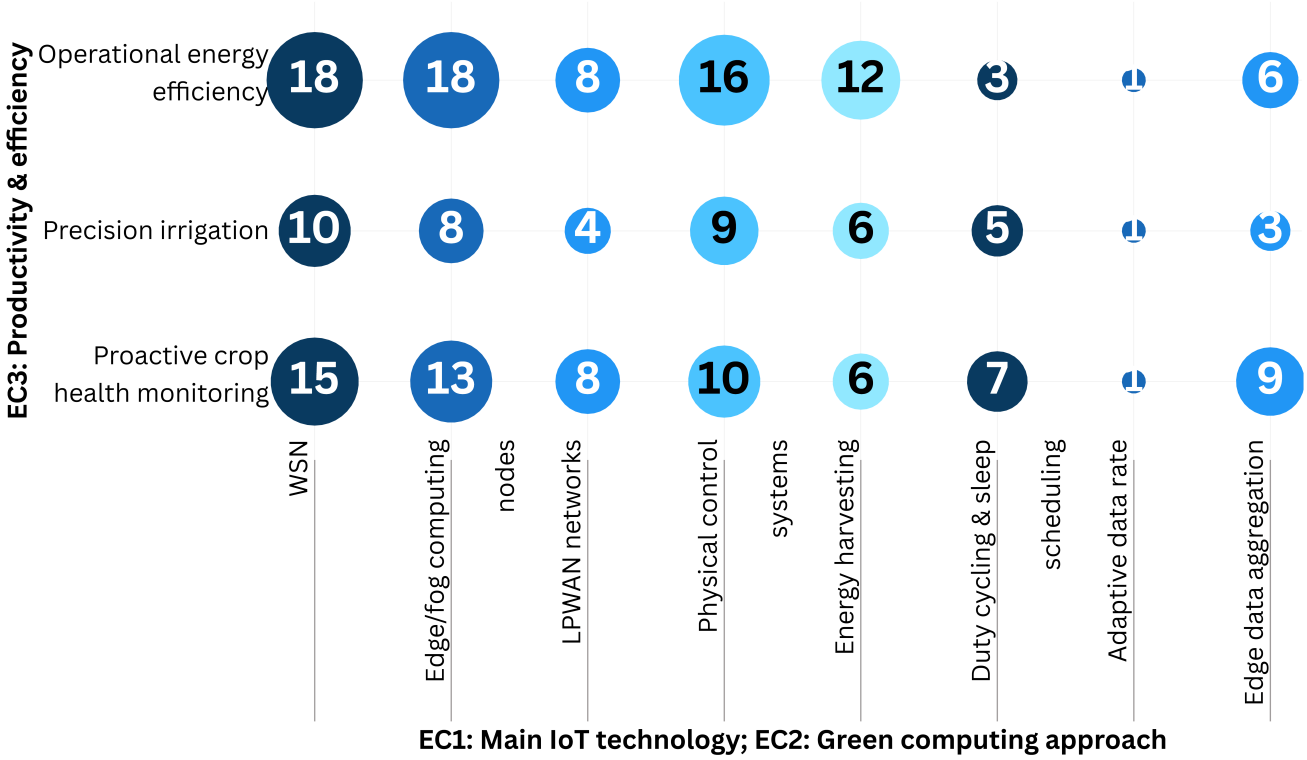


Figure 3. Relationship between IoT technologies, green computing approaches, and applications related to agricultural productivity and efficiency.

Figure 4 shows the relationship between IoT and green computing technologies and farmer autonomy. The highest concentration appeared in independent, data-driven decision-making, where WSNs, edge/fog computing nodes, and physical control systems each reached 18 studies. This suggests that the reviewed solutions support farmers through field data collection, local processing, and automated actions. Edge data aggregation and energy harvesting also appeared as relevant strategies for improving local information management and energy autonomy.

Figure 5 identifies adoption barriers. The most prominent barrier was poor rural internet connectivity, mainly associated with WSNs and edge/fog computing nodes, with 15 and 14 studies, respectively. This shows that, although these technologies are widely used, their deployment remains constrained by rural communication infrastructure. Edge data aggregation, LPWANs, and duty cycling and sleep scheduling appeared as possible

strategies for addressing connectivity and energy constraints. Conversely, low digital literacy showed low frequencies across all technologies, indicating limited attention to social and user-related barriers. Overall, the reviewed studies are mainly concentrated on sensing technologies, edge/fog processing, and physical control. However, adaptive data rate, digital literacy, community-shared infrastructure, and TinyML remain less developed and represent relevant directions for future research.

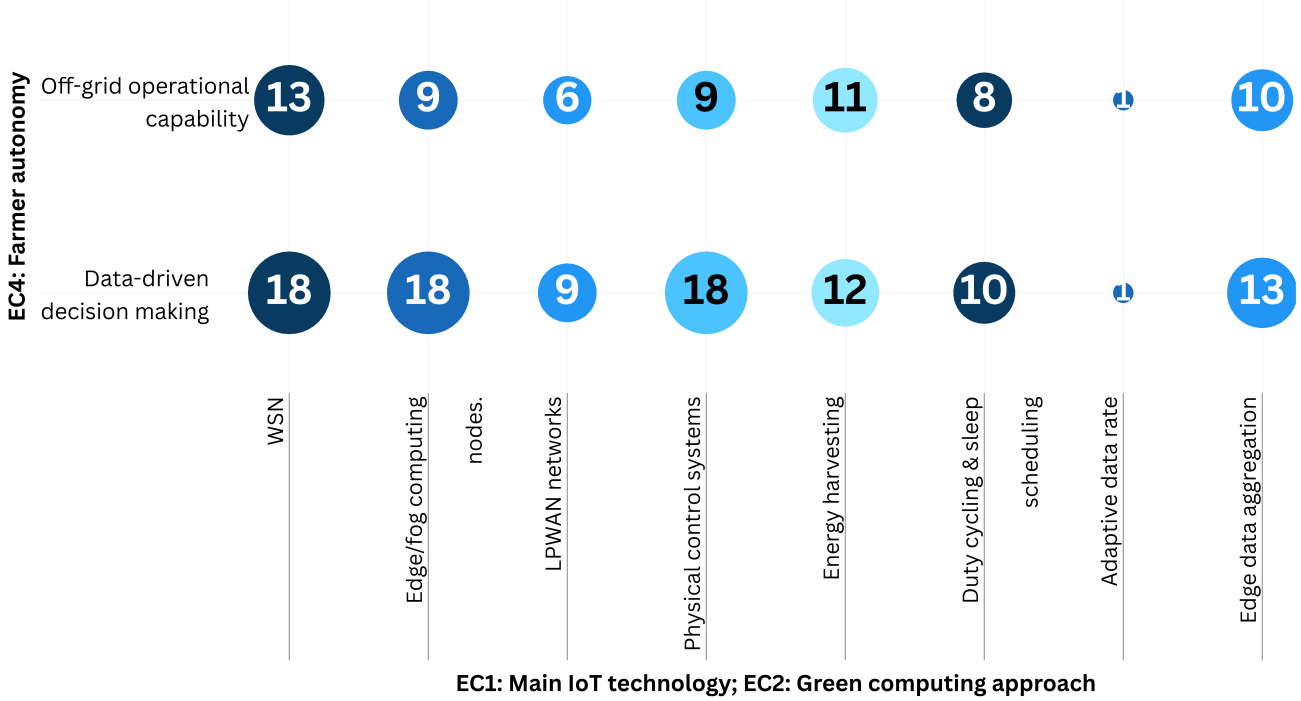


Figure 4. Relationship between IoT technologies, green computing approaches, and farmer autonomy.

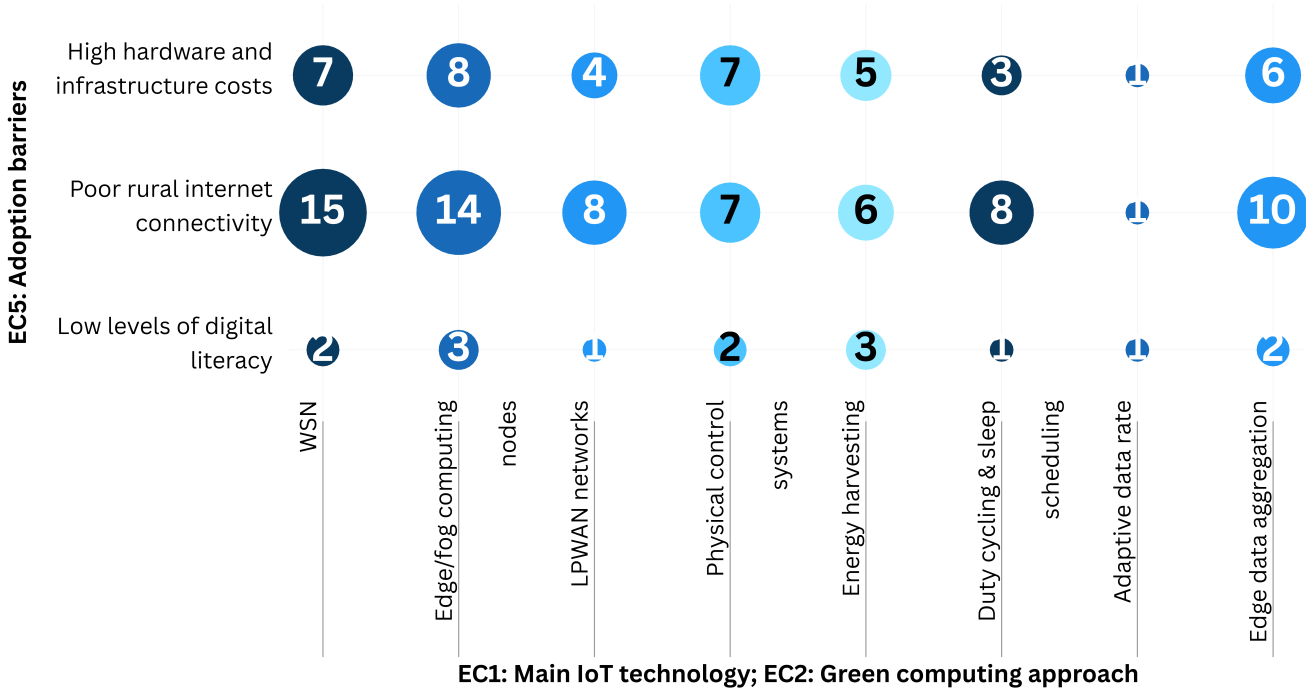


Figure 5. Relationship between IoT technologies, green computing approaches, and adoption barriers.

Table 8. Comparative synthesis of the advantages, limitations, and applicable rural scenarios of the IoT solution families and green computing strategies identified in the reviewed studies.

Solution Family or Strategy	Evidence Coverage	Primary Role or Sustainability Contribution	Reported Advantages	Main Limitations and Trade-Offs	Applicable Rural Agricultural Scenarios
Core IoT solution families					
WSN-based monitoring	19 studies (59.4%)	Distributed sensing of soil, crop, water, and environmental variables, including moisture, temperature, humidity, pH, soil nutrients, and crop-health indicators.	Enables continuous or near-real-time observation, early detection of adverse conditions, and data-driven irrigation, fertigation, and crop-management decisions.	Specialized sensors, weather-resistant enclosures, batteries, and communication modules may increase acquisition and maintenance costs. Remote deployments also require effective power management and reliable gateway access.	Soil and crop monitoring; precision irrigation and fertigation; greenhouse supervision; crop-health assessment; remote agricultural land monitoring.
Edge/fog computing architectures	20 studies (62.5%)	Local filtering, aggregation, analysis, and execution of lightweight machine-learning models at gateways or nearby processing nodes.	Reduces latency, unnecessary cloud transmission, and communication-related energy use; supports local operation under intermittent connectivity; enables faster detection and response.	Requires gateway or edge-processing hardware, appropriate software configuration, and local maintenance capacity. Comparable evidence on long-term field reliability remains limited.	Isolated or poorly connected farms; local crop-disease detection; frost prediction; environmental analysis; applications requiring timely local decisions.
LPWAN-based communication	9 studies (28.1%)	Long-range, low-power communication through LoRa, LoRaWAN, NB-IoT, Sigfox, LTE-M, or hybrid communication schemes.	Extends communication coverage while limiting radio energy use and supports battery- or renewable-powered devices across dispersed agricultural areas.	Field-level LPWAN connectivity does not eliminate dependence on cellular, Internet, or satellite backhaul when cloud services are required. Hybrid schemes may be necessary for higher latency or bandwidth requirements.	Dispersed fields, orchards, greenhouses, and remote monitoring sites where short-range connectivity is insufficient.

Table 8. *Cont.*

Solution Family or Strategy	Evidence Coverage	Primary Role or Sustainability Contribution	Reported Advantages	Main Limitations and Trade-Offs	Applicable Rural Agricultural Scenarios
Core IoT solution families					
IoT-enabled physical control systems	18 studies (56.3%)	Translation of monitored conditions into physical actions through valves, pumps, aerators, fans, irrigation and fertigation equipment, greenhouse controllers, drying systems, or agricultural robots.	Links sensing and decision-making to direct agricultural intervention; supports automated irrigation, ventilation, aeration, and environmental regulation; can improve resource use.	Actuators, controllers, power electronics, and supporting infrastructure increase installation and maintenance requirements, potentially constraining affordability and sustained operation.	Precision irrigation and fertigation; greenhouse environmental control; aquaculture aeration; crop-drying systems; applications requiring rapid or repeated physical intervention.
Green computing and deployment-enabling strategies					
Energy harvesting and off-grid photovoltaic power	12 studies (37.5%)	Supplies renewable energy to sensor nodes, gateways, control equipment, telemetry systems, greenhouses, aquaculture modules, and agricultural dryers.	Reduces dependence on unreliable or unavailable electricity grids; supports autonomous operation in remote locations; can be combined with batteries, MPPT controllers, and energy-management circuits.	Photovoltaic panels, storage batteries, controllers, and protection systems increase initial costs. Operational autonomy depends on solar irradiance, storage capacity, load demand, and appropriate system sizing.	Remote farms without stable grid access; autonomous environmental stations; greenhouse telemetry; aquaculture; crop-drying or dehydration systems.
Duty cycling and sleep scheduling	10 studies (31.3%)	Reduces the active time of sensors, radios, and microcontrollers when measurement or transmission is unnecessary.	Extends battery lifetime, decreases energy consumption, and can reduce maintenance frequency in isolated deployments.	Lower sampling or transmission frequencies can reduce real-time information availability during rapid environmental changes, including short-term microclimatic variations.	Battery-powered monitoring nodes; remote soil and environmental sensing; applications in which most monitored variables change gradually.
Edge data aggregation	13 studies (40.6%)	Filters, summarizes, or combines information locally before cloud or remote transmission.	Reduces redundant communication, network traffic, and transmission-related energy use; improves operation when connectivity is intermittent or costly.	Requires sufficient local processing capacity and appropriate aggregation logic. The reviewed studies do not provide standardized long-term comparisons of energy savings or downstream decision performance.	Farms with intermittent cellular or Internet connectivity; satellite- or cellular-assisted architectures; multisensor deployments generating repetitive data.

Table 8. *Cont.*

Solution Family or Strategy	Evidence Coverage	Primary Role or Sustainability Contribution	Reported Advantages	Main Limitations and Trade-Offs	Applicable Rural Agricultural Scenarios
Green computing and deployment-enabling strategies					
Adaptive data rate	1 study (3.1%)	Dynamically adjusts transmission parameters according to environmental or network conditions.	Can balance communication reliability and energy consumption more effectively than fixed transmission configurations.	The evidence base is limited to one coded study; robust conclusions on scalability, long-term reliability, or comparative energy performance cannot yet be drawn.	LPWAN deployments exposed to changing link quality, distance, interference, or environmental conditions.
TinyML	5 studies (15.6%)	Executes compact machine-learning models directly on microcontrollers or edge nodes.	Supports local event detection, alerts, or predictions while reducing cloud transmission, connectivity dependence, and communication-related energy use.	The small evidence base is concentrated in emerging or prototype implementations and does not yet support firm conclusions on long-term field performance or scalability.	Low-connectivity crop-health monitoring; local disease or anomaly detection; autonomous sensing nodes with limited computing and energy resources.
Community-shared IoT networks and infrastructure	2 studies (6.3%)	Allows farmers or cooperatives to share gateways, communication infrastructure, data platforms, and monitoring resources.	Distributes initial costs, improves infrastructure utilization, and may reduce the investment required from individual smallholders.	Only two studies addressed this model; the evidence is insufficient to assess long-term operation, maintenance, scalability, and financial sustainability.	Cooperatives, clustered farms, or rural communities where individual acquisition of gateways, networks, and monitoring platforms is financially restrictive.

3.2. Sustainable IoT Technologies and Green Computing Approaches Applied to Agricultural Management in Rural Communities with Small-Scale Farming

The reviewed evidence indicates that sustainable agricultural IoT is deployed as an integrated architecture rather than as a collection of isolated sensing devices [40,51,52]. These architectures combine sensing, low-power communication, local processing, automation, and energy-management strategies to operate under rural constraints related to connectivity, electricity, and infrastructure [26,29,38,42,45]. The most recurrent technological components were WSNs, edge/fog computing, LPWAN technologies, and physical control systems [41,55], while the principal green computing mechanisms were energy harvesting, duty cycling and sleep scheduling, and edge data aggregation. Adaptive data rate was identified in only one coded study (3.1%), making it the least represented strategy [43].

Table 8 shows that the reviewed approaches address distinct but frequently complementary rural constraints rather than representing mutually exclusive alternatives. WSNs provide the sensing layer; edge/fog nodes and local aggregation reduce cloud dependence and communication overhead; LPWAN technologies extend field-level coverage; and physical control systems translate monitored conditions into agricultural action. Energy harvesting and duty-cycled operation primarily address electricity availability and node lifetime.

At the sensing and processing layers, WSNs collected variables such as soil moisture, temperature, humidity, pH, soil nutrients, and crop-health indicators for soil monitoring, irrigation, greenhouse control, and crop assessment [26,28,41,51]. Edge and fog nodes were used or proposed to process these data near their source, reducing latency and unnecessary cloud transmission while supporting local filtering, lightweight machine learning, disease detection, frost prediction, and environmental analysis [24,30,34,44,47,48].

For field connectivity, LoRa, LoRaWAN, Narrowband Internet of Things (NB-IoT), Sigfox, and Long-Term Evolution for Machines (LTE-M) provided long-range, low-power communication for devices deployed across fields, orchards, greenhouses, and remote sites [26,38,55]. Hybrid configurations combining LPWANs with 4G or 5G were also proposed to balance distance, latency, and bandwidth requirements [32,39,47]. Physical control systems including valves, pumps, aerators, fans, irrigation and fertigation equipment, greenhouse controllers, drying systems, and agricultural robots—linked digital monitoring to direct intervention [25,33,37,53].

At the energy-management layer, photovoltaic generation was the dominant harvesting mechanism for sensor nodes, gateways, aquaculture modules, greenhouses, drying equipment, and autonomous monitoring networks [25,49,50,53]. Several systems combined solar generation with lithium or lithium iron phosphate storage, Maximum Power Point Tracking controllers, and battery-management circuits to support off-grid operation [49,51,55]. Duty cycling and sleep scheduling reduced the active time of sensors, radios, and microcontrollers, while edge data aggregation limited redundant transmission by filtering or summarizing information locally [24,29,35,36,38,44].

3.3. Impact of Sustainable IoT Systems on the Productivity, Efficiency, and Autonomy of Rural Farmers

The reviewed evidence shows that sustainable IoT systems affect rural agriculture through operational efficiency, productivity support, and farmer autonomy [26,40,51]. These impacts are observed in systems that combine energy-saving mechanisms, local processing, real-time monitoring, automation, and renewable energy to operate under rural constraints in connectivity, energy, and infrastructure [24,29,38,43,50,55].

In terms of efficiency, sleep scheduling, duty cycling, and edge data processing reduce transmission frequency and communication overhead in wireless nodes [29,35,36]. This

extends battery life and reduces maintenance needs in rural or isolated areas [29,38,51]. However, lower transmission frequency may reduce real-time data availability during rapid environmental changes, such as microclimatic variations [35,38].

Some studies reported measurable energy reductions. In aquaculture, an intelligent aeration system based on dissolved oxygen probes reduced electricity consumption by up to 64% through dynamic power regulation [25]. Similarly, in satellite-assisted edge architectures, the IsoLink algorithm evaluates the energy cost of processing and transmission before sending data, helping preserve the energy of isolated rural nodes [24].

Regarding productivity, sustainable IoT systems support proactive agricultural management [28,43,54]. Multisensor networks enable early detection of soil degradation, pests, water stress, and crop diseases [26,28,41]. This is particularly relevant for precision irrigation and fertigation, where decisions are adjusted to field conditions instead of fixed schedules or manual criteria [43,54].

Several examples illustrate this contribution. In cassava crops in Rwanda, Convolutional Neural Network (CNN) based deep learning models achieved accuracy above 90% for diagnosing Cassava Brown Streak Disease (CBSD) and Cassava Mosaic Disease (CMD) from local leaf images [31]. In mandarin orchards in Punjab, the AgriMon system monitored soil electrical conductivity and root-zone moisture to detect nutrient leaching and water stress before visible foliage symptoms appeared [43]. Field data therefore supported better use of water and nutrients, lower operating costs, and earlier responses to yield-related risks [26,28,43].

In terms of autonomy, several architectures used energy harvesting, mainly photovoltaic panels, to support off-grid operation in remote regions [49,51,53]. This allowed monitoring, telemetry, and automation systems to function where electrical infrastructure is limited, unstable, or costly [40,51,55]. For example, in solar-assisted copra dehydration, an ESP32 microcontroller regulated thermal and ventilation parameters inside a drying chamber, while a 48 V battery provided up to eight hours of autonomy under optimal irradiance conditions [53]. Photovoltaic configurations were also reported for greenhouse telemetry and sunflower seed dehydration [49,50].

Farmer autonomy does not imply replacing farmers, but changing how they interact with agricultural systems [40,52]. Web dashboards, edge processing, and monitoring platforms allow farmers to consult crop data, review alerts, and make decisions based on field information [44,52,54]. This can reduce dependence on constant manual inspections and external technical support for basic crop management decisions [26,43,54].

3.4. Main Barriers to the Adoption of IoT and Green Computing in Rural Agricultural Communities and Future Trends for Their Implementation

The adoption of IoT and green computing in rural agricultural communities is limited by technical, economic, and social barriers [31,40]. The first barrier is the high initial cost of infrastructure. Although microcontrollers and basic processing units have become more affordable, specialized components remain costly for smallholder farmers, including Nitrogen, Phosphorus, and Potassium (NPK) sensors, moisture sensors, weather stations, weather-resistant enclosures, solar charge controllers, batteries, and communication modules [26,28,40,43,55]. These components are necessary for robust systems but may be difficult to acquire in resource-constrained rural settings [28,31].

To address this limitation, some studies proposed low-cost designs and open-source tools [40,51,54]. Examples include environmental stations produced at lower costs than commercial systems and automated greenhouse kits developed with reduced budgets [51,54,55]. These cases show that IoT solutions can be adapted through modular, accessible designs tailored to local needs instead of depending exclusively on commercial infrastructure [40,54].

A second barrier is limited rural connectivity. Many agricultural communities are located in areas with weak, unstable, or unavailable cellular signal [24,26,40]. This affects cloud-dependent architectures, which may experience packet loss, delays, or monitoring interruptions [24,38]. The literature therefore highlights low-power, long-range communication technologies, such as LoRa, LoRaWAN, and LTE-M, which allow field data transmission to local gateways without permanent Internet connectivity [26,38,55].

A third barrier is limited digital literacy among some rural users [31,40]. Configuring wireless networks, interpreting dashboards, and using digital platforms can be difficult for farmers without technical training, generating resistance or dependence on third parties [31,52]. To reduce this barrier, some studies incorporated simple interfaces, visual cues, color-coded system status, local languages, and intuitive dashboards [43,54]. For example, AgriMon used a minimalist interface with color coding and localization in Punjabi and Hindi [43], while some greenhouse systems used Node-RED to build visual dashboards without advanced programming requirements [54].

Regarding future trends, TinyML is one of the most relevant directions [48,55]. It enables machine learning models to run directly on microcontrollers or edge nodes, reducing the need to send large data volumes to the cloud [36,55]. This allows systems to detect events, generate alerts, or perform local predictions with lower energy consumption and less dependence on connectivity [28,48,55]. This trend is especially relevant for rural areas where continuous transmission may be costly, slow, or unreliable [26,36].

Another relevant trend is community-shared IoT infrastructure [40,52]. Instead of each farmer individually acquiring sensors, gateways, communication modules, and energy systems, rural communities or cooperatives can share LoRaWAN gateways, local networks, data platforms, and monitoring systems [38,52]. This model can distribute initial costs, improve infrastructure use, and facilitate adoption where individual investment capacity is limited [40,52].

4. Discussion

This analysis shows that the adoption of IoT and green computing technologies in rural agricultural communities has increased, particularly since 2025, reflecting growing interest in technological solutions that support efficient and sustainable agriculture despite challenges related to connectivity, energy availability, and infrastructure. In addition to crop monitoring, these technologies facilitate local decision-making, enhance energy autonomy, reduce resource consumption, and enable automated agricultural management [25,28,43,51]. Although most studies demonstrate that a given system, protocol, or algorithm can perform specific technical functions, considerably less evidence is available regarding the reliability, affordability, maintainability, comprehensibility, and usefulness of these solutions during prolonged operation in real agricultural environments [6,8,12].

4.1. Contextualizing the Findings Within the Existing Review Literature

Previous reviews have investigated digital technologies in small-scale and rural agriculture from different perspectives, often concentrating on specific technological domains rather than providing a comprehensive view of sustainable IoT solutions. Antony et al. reviewed IoT practices and implementation in smallholder agriculture, emphasizing that successful adoption depends on factors beyond sensing and communication technologies, including affordability, data transmission, user feedback, project support, and the ability to convert collected data into actionable agricultural decisions [6]. Similarly, Bayih et al. analyzed the use of IoT and WSNs for farm-specific data acquisition in smallholder agriculture, identifying persistent social, economic, infrastructural, and technological barriers. Their

review also noted that much of the available evidence remains experimental, with limited implementation in actual smallholder farm plots [8].

Dhillon and Moncur adopted a broader perspective on small-scale farming by reviewing economic, educational, environmental, infrastructural, and technological challenges, as well as the opportunities presented by IoT, irrigation automation, smartphones, Uncrewed Aerial Vehicles (UAVs), robotics, artificial intelligence, and traceability systems [10].

Other reviews have concentrated on technological architectures and computational efficiency. Majumdar et al. examined green IoT in the context of Agriculture 4.0, addressing energy-conserving processing strategies, LPWANs, 5G, UAV-based systems, and the development of cost-effective and environmentally sustainable precision-agriculture architectures [11]. Yu et al. analyzed cloud-edge-device collaboration as a distributed computing paradigm for smart agriculture, highlighting its potential to reduce latency and bandwidth dependence while also identifying unresolved challenges related to device heterogeneity, resource constraints, interoperability, data consistency, and integration into real-world systems [12].

4.2. From Prototype Performance to Sustained Rural Deployment

A central finding is the gap between the performance demonstrated by prototypes or short-term pilots and the outcomes that can be expected from sustained rural deployment. The reviewed literature includes application-specific evaluations of aquaculture aeration, greenhouse automation, crop drying, environmental monitoring, and other agricultural systems [25,49,53,54]. These studies are significant because they establish technical feasibility and demonstrate potential improvements in energy use, automation, or agricultural management. However, evidence from controlled prototypes or limited field trials should not be regarded as equivalent to evidence of long-term operational sustainability. Although some studies have progressed to field-oriented deployment under rural connectivity and energy constraints [43,51,55], the available evidence remains dominated by short-term and researcher-supported evaluations.

The distinction among controlled prototypes, field pilots, and long-term deployments is methodologically significant. Controlled prototypes primarily assess whether sensors, algorithms, protocols, or control mechanisms function as intended under predefined conditions, typically using indicators such as prediction accuracy, latency, packet delivery, energy consumption, and response time. Field pilots provide greater ecological validity by exposing systems to real crops, environmental variability, communication constraints, and user interaction. However, these pilots are often limited to a single location, one agricultural application, or a brief evaluation period. Sustained deployment requires consistent performance across seasons, climatic variations, equipment degradation, network interruptions, maintenance events, changes in farming practices, and fluctuations in the availability of technical support. The reviewed evidence is strongest for controlled prototypes and field pilots, but considerably weaker for long-term deployments.

LPWAN technologies and energy-efficient routing approaches are appropriate for long-distance and resource-constrained agricultural networks [26,35,38]. However, operational reliability may decline because of terrain conditions, vegetation growth, weather, interference, signal fading, gateway unavailability, or unstable cellular and satellite backhaul [24,39]. Edge processing and local data aggregation can reduce reliance on remote platforms, but they do not eliminate the need for reliable local hardware, software maintenance, storage management, or recovery procedures [34,36]. Consequently, long-term evaluations should address system availability, fault recovery, and performance degradation rather than focusing solely on nominal range, throughput, or energy consumption.

Three recurrent methodological limitations were observed across the reviewed evidence. First, multi-site and multi-season evaluations under contrasting climatic, connectivity, infrastructural, and farm-management conditions remain scarce. Most studies evaluated a single farm, experimental station, or crop, or a limited number of deployment sites, which restricts the transferability of findings across different rural environments [25,43,53–55].

Second, economic assessments generally emphasized initial hardware or prototype costs rather than the total cost of ownership over the system lifetime. Although several studies presented their solutions as low-cost or affordable, recurring expenses associated with installation, sensor calibration, battery replacement, connectivity, software maintenance, repairs, spare parts, training, and technical support were rarely quantified [26,28,40,51].

Third, few studies reported whether farmers or local organizations continued using the systems after investigator or project support had ended. Measures such as continued use, maintenance continuity, system abandonment, user dropout, and reasons for discontinuation were generally absent. This reporting gap is consistent with previous reviews that identified limited implementation in actual smallholder settings and insufficient evidence regarding sustained adoption beyond supported pilot projects [6,8].

Therefore, the existing evidence provides only limited support for assessing the long-term scalability, economic viability, and sustained adoption of sustainable IoT systems under real rural conditions.

4.3. Theoretical Contributions

The findings of this study support a socio-technical interpretation of sustainable rural IoT in which operational continuity depends on four interdependent dimensions: field sensing and physical control, communication and local processing, energy management, and human or institutional capacity. These dimensions constrain one another. For example, renewable energy alone does not guarantee sustainability if communication remains unreliable. Similarly, edge processing does not ensure adoption if farmers are unable to interpret system outputs or maintain the equipment. Technically accurate recommendations do not foster autonomy if the system requires continuous external configuration or repair.

This perspective extends beyond analyses that isolate technical performance from adoption barriers. It proposes that sustainability is not an inherent characteristic of a low-power device, communication protocol, or edge architecture, but rather an emergent property of the entire deployment configuration. A system becomes sustainable only when its technical design aligns with local infrastructure, financial resources, maintenance capabilities, agricultural practices, and user competencies. This theoretical interpretation also explains why short-term technical success may coexist with limited long-term adoption, because optimization in one domain can be offset by unresolved constraints in another.

The progression from prototype success to sustained adoption is also influenced by economic and organizational factors. Although affordable and modular systems can reduce initial entry costs [26,28,40,54], acquisition expenses represent only one component of the total cost of ownership. Long-term operation may require sensor calibration, battery replacement, weather protection, software updates, connectivity fees, technical support, and access to spare parts. Systems that function effectively during researcher-supported pilots may become unsustainable after external support is withdrawn. Furthermore, monitoring platforms enhance farmer autonomy only when users can interpret the information, perform routine tasks, and obtain timely assistance when failures occur. Otherwise, digitalization risks replacing one form of dependency with reliance on external technical specialists.

4.4. Practical Implications for Technology Design and Rural Deployment

The findings of this study indicate the need for a context-sensitive approach to technology selection. In regions with intermittent Internet connectivity, integrating WSNs, LPWAN communication, edge or fog processing, and local data aggregation can reduce reliance on continuous cloud access [24,26,34,36,38]. In off-grid environments, photovoltaic energy generation, battery storage, duty cycling, and low-power communication are essential for maintaining service continuity [29,35,49,51,53,55]. For agricultural processes that require rapid intervention, local processing connected to irrigation, aeration, ventilation, storage, crop-processing, or robotic equipment enables a more direct transition from sensing to action [25,33,37,51,53,54]. These configurations represent context-sensitive alternatives rather than a universal hierarchy of technologies.

Shared infrastructure may reduce the burden of acquiring gateways, platforms, communication services, and technical support on an individual basis. However, this approach introduces governance requirements that are frequently overlooked in technical assessments. Sustainable shared systems require explicit agreements regarding ownership, maintenance responsibilities, data access, privacy, cost allocation, and dispute resolution [15]. Therefore, practical guidance must address not only technology selection, but also operational responsibilities, the financing of recurring costs, mechanisms for resolving failures, and the distribution of benefits and responsibilities within the community.

4.5. Contextual Priorities for Future Research and Practice

Future research should focus on evaluating sustainable IoT systems within real-world rural environments, rather than emphasizing general technological improvements. Assessment should address energy efficiency, connectivity, usability, maintenance, and affordability, as these factors critically influence long-term adoption in diverse contexts. Special consideration is warranted for smallholder farming in developing regions and remote, off-grid agricultural settings. Although the technologies discussed below were identified in the reviewed literature, their long-term suitability and transferability across rural regions have not yet been sufficiently established [6,8].

Future evaluations should therefore report performance across multiple sites, stations, seasons, and complete agricultural production cycles, together with life-cycle total cost of ownership and post-support indicators such as continued use, user dropout, system abandonment, and operational continuity after investigator involvement ends.

4.5.1. Smallholders in Developing Regions

For smallholders in developing regions, future research should emphasize low-cost, modular, and locally maintainable system configurations. Comparative studies are needed to evaluate combinations of affordable WSNs, LoRa or LoRaWAN communication, open-source gateways, and straightforward local dashboards. The primary objective is to determine whether these configurations deliver adequate monitoring and decision support while minimizing acquisition, connectivity, and maintenance costs [26,43].

Edge or fog gateways should be evaluated as shared local resources for producer associations or neighboring farms. Instead of requiring each farmer to invest in a complete computing and communication infrastructure, future pilot studies could assess shared gateways that aggregate data from multiple farms, provide local storage and basic analytics, and enable intermittent cloud synchronization. These studies should measure cost per participating farm, gateway utilization, maintenance workload, service continuity, and equitable access [12].

Research should further investigate user-oriented technologies identified in the review, such as visual dashboards, color-coded alerts, localized interfaces, and low-complexity

monitoring platforms. These technologies should be evaluated through participatory studies to determine whether farmers can interpret alerts, perform routine operations, and sustain system use without ongoing external assistance [43,54].

4.5.2. Remote and Off-Grid Farming

For remote and off-grid farming, future studies should evaluate fully autonomous system architectures rather than isolated components. Priority configurations should integrate photovoltaic generation, battery storage, low-power WSNs, duty cycling, LPWAN communication, edge data aggregation, and local control. Performance should be assessed across varying climatic seasons and entire agricultural production cycles [51,55].

Adaptive communication strategies warrant particular attention. Future experiments should compare fixed transmission schedules with adaptive data-rate and event-driven approaches that adjust transmission frequency according to battery level, network quality, and agricultural urgency. Key indicators for evaluation include energy autonomy, packet delivery, data completeness, gateway availability, retransmission costs, and recovery following communication failures [38,39].

TinyML should also be evaluated within off-grid system architectures. Future systems may employ on-device inference for the local detection of crop stress, environmental anomalies, equipment failures, or irrigation requirements [14]. Studies should report inference accuracy, energy consumption per inference, latency, memory usage, model drift, update procedures, and performance across seasons and deployment sites. Such evaluations would distinguish TinyML-ready hardware from systems capable of sustaining reliable local intelligence under prolonged field conditions [55].

Hybrid connectivity is another research priority. LPWANs can support intra-farm communication, while intermittent cellular or satellite links may enable external synchronization when available [24,26]. Future research should investigate how edge gateways can prioritize critical information, store non-urgent data locally, and synchronize selectively according to energy and backhaul availability.

For applications that require immediate intervention, future studies should integrate local processing with physical control systems, such as irrigation valves, pumps, aerators, ventilation systems, or crop-processing equipment [25,51,53]. These configurations should be evaluated in terms of response time, energy consumption, fail-safe operation, manual override capability, maintenance requirements, and agricultural outcomes.

5. Conclusions

This systematic review shows that integrating IoT and green computing is a relevant pathway toward more efficient, autonomous, and sustainable rural agriculture. The analyzed studies indicate that these technologies can support decision-making, reduce dependence on conventional energy infrastructure, and improve resource management in small-scale agricultural communities. However, their technical potential does not guarantee effective adoption. Successful implementation depends on systems that are affordable, usable, robust under rural conditions, and sustainable over time. The main limitations are therefore not only technological, but also social and operational, particularly regarding costs, connectivity, and users' digital capabilities.

Future research should focus on solutions better aligned with the real conditions of rural farmers. This includes strengthening user-centered design, conducting long-term field validation, promoting community-based shared infrastructure, and incorporating emerging technologies such as TinyML to reduce dependence on cloud connectivity. In this way, sustainable IoT can progress from promising prototypes to applicable, accessible, and useful solutions for rural agriculture.

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