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Integration of IoT and Artificial Intelligence in Ecuadorian Agriculture: A Systematic Literature Review (2020–2025)

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***Abstract* — The Internet of Things (IoT) and Artificial Intelligence (AI) have become key technologies for advancing precision agriculture. This systematic literature review explores their integration in Ecuadorian agriculture, addressing four main aspects: AI techniques applied for pest detection and crop monitoring, types of agricultural data utilized, the most commonly implemented IoT platforms, and sensors employed in monitoring systems. The review encompasses 40 studies published between 2020 and 2025, revealing a predominance of machine learning approaches, with notable applications of Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN), achieving accuracy levels between 0,80 and 0,95. Environmental and agricultural production data were the most frequently used, while platforms such as ThingSpeak and ThingsBoard, together with local solutions, were commonly employed for real-time management. The findings highlight current technological trends and challenges related to connectivity, costs, and data quality, emphasizing the need for future research to enhance productivity and sustainability in strategic Ecuadorian crops such as banana, cacao, mango, and rice.**

Keywords: **Internet of Things; Artificial Intelligence; smart farming; precision agriculture; Ecuador.**

***Resumen* — El Internet de las Cosas (IoT) y la Inteligencia Artificial (IA) se han consolidado como tecnologías clave para impulsar la agricultura de precisión. Esta revisión sistemática de la literatura explora su integración en el contexto ecuatoriano, considerando cuatro ejes principales: las técnicas de IA aplicadas en la detección de plagas y el monitoreo de cultivos, los tipos de datos agrícolas utilizados, las plataformas IoT más implementadas y los sensores empleados en los sistemas de monitoreo. La revisión abarca 40 estudios publicados entre 2020 y 2025, revelando un predominio de enfoques de *machine learning*, con aplicaciones destacadas de Redes Neuronales Convolucionales (CNN) y Redes Neuronales Artificiales (ANN), que alcanzaron niveles de precisión entre 0,80 y 0,95. Los datos ambientales y de producción agrícola fueron los más empleados, mientras que plataformas como ThingSpeak y ThingsBoard, junto con soluciones locales, se consolidaron como herramientas frecuentes de gestión en tiempo real. Los hallazgos evidencian tendencias tecnológicas en expansión y desafíos vinculados a la conectividad, los costos y la calidad de los datos, resaltando la necesidad de investigaciones futuras que fortalezcan la productividad y sostenibilidad en cultivos estratégicos del Ecuador como banano, cacao, mango y arroz.**

Palabras Clave: **Internet de las Cosas; Inteligencia Artificial; agricultura inteligente; agricultura de precisión; Ecuador.**

I. INTRODUCTION

AGRICULTURE is a pillar of the Ecuadorian economy, but it faces challenges of productivity, sustainability, and adaptation to a changing environment. The Fourth Industrial Revolution has introduced technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI), which transform agricultural systems through data collection, processing, and analysis. These tools optimize processes such as crop monitoring, pest detection, and efficient resource management, enabling precision agriculture that increases yield and reduces environmental impact.

IoT, through sensors and platforms, captures environmental, soil, and production data in real time, while AI models patterns and predicts critical events in the agricultural cycle. In Ecuador, these technologies are mainly applied in strategic crops such as banana, cocoa, and rice, although adoption is limited by gaps in infrastructure and digital capacities. Only 28,2 % of cultivated land has technical irrigation [1], which restricts automation dependent on controlled water.

In the digital sphere, setbacks persist: in 2024, digital illiteracy reaches 19,2 % among Indigenous peoples and 17,0 % in Montubio communities (ages 15-49), reflecting barriers to incorporating IoT and AI across wide rural areas. Added to this are unequal connectivity and limited technical training, which explain why many initiatives remain isolated projects and why available information is scattered. In Latin America, limitations are similar: only 37 % of the rural population has meaningful connectivity and 17 % has 4G coverage. More than 35 % do not know how to use the internet, and fewer than 10 % possess

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the basic digital skills needed to take advantage of agricultural platforms, sensors, and predictive models [2], [3]. The lack of trained personnel and low investment in rural research further restrict the integration of these technologies [4].

This study provides a structured view of the integration of IoT and AI in Ecuadorian agriculture. Through a systematic literature review, it organizes and analyzes existing findings based on research questions that identify trends, predominant approaches, and areas of development [7], [8].

Research questions (RQ)

- RQ1: What AI techniques have been applied in pest detection and monitoring of crop growth, and what have been their results in terms of accuracy or effectiveness?
- RQ2: What types of agricultural data are commonly used in studies that integrate IoT and AI for pest detection?
- RQ3: Which IoT integration platforms are most frequently employed in agricultural monitoring systems in Ecuador?
- RQ4: Which specific sensors are most used in precision agriculture to improve yield and sustainability in Ecuador?

The structure of the document is as follows: the Materials and Methods section presents the SALSA approach and the procedures of search, evaluation, synthesis, and analysis. The Results section presents the findings regarding the research questions. The Discussion contrasts them with previous studies, highlighting trends and challenges. Finally, the Conclusions summarize contributions, practical implications, and recommendations for future research on IoT and AI in Ecuadorian agriculture.

II. MATERIALS AND METHODS

This study was developed using the SALSA approach (Search, Appraisal, Synthesis, Analysis), which provides a rigorous and transparent structure for systematic literature reviews. The methodology was chosen for its relevance in organizing, evaluating, and critically interpreting academic production on IoT and AI applied to Ecuadorian agriculture [4], [5].

The review identified patterns, advances, limitations, and gaps in the use of digital tools in agriculture, offering an updated view of the state of the art. The SALSA approach guided the entire process, from the initial search to the thematic analysis of the findings [6]. Fig. 1 shows the methodological flow followed, illustrating the four stages of the SALSA approach: Search, Appraisal, Synthesis, and Analysis.

To guide the development of the review, the following research questions were formulated (RQ1-RQ4) —as listed in the Introduction— and search strategies were designed in Spanish and English. These strategies combined key terms related to AI, IoT, precision agriculture, and the Ecuadorian context using Boolean operators. Google Scholar, IEEE Xplore, and ScienceDirect were consulted, prioritizing publications from 2020 to 2025 with full access and written in Spanish or English.

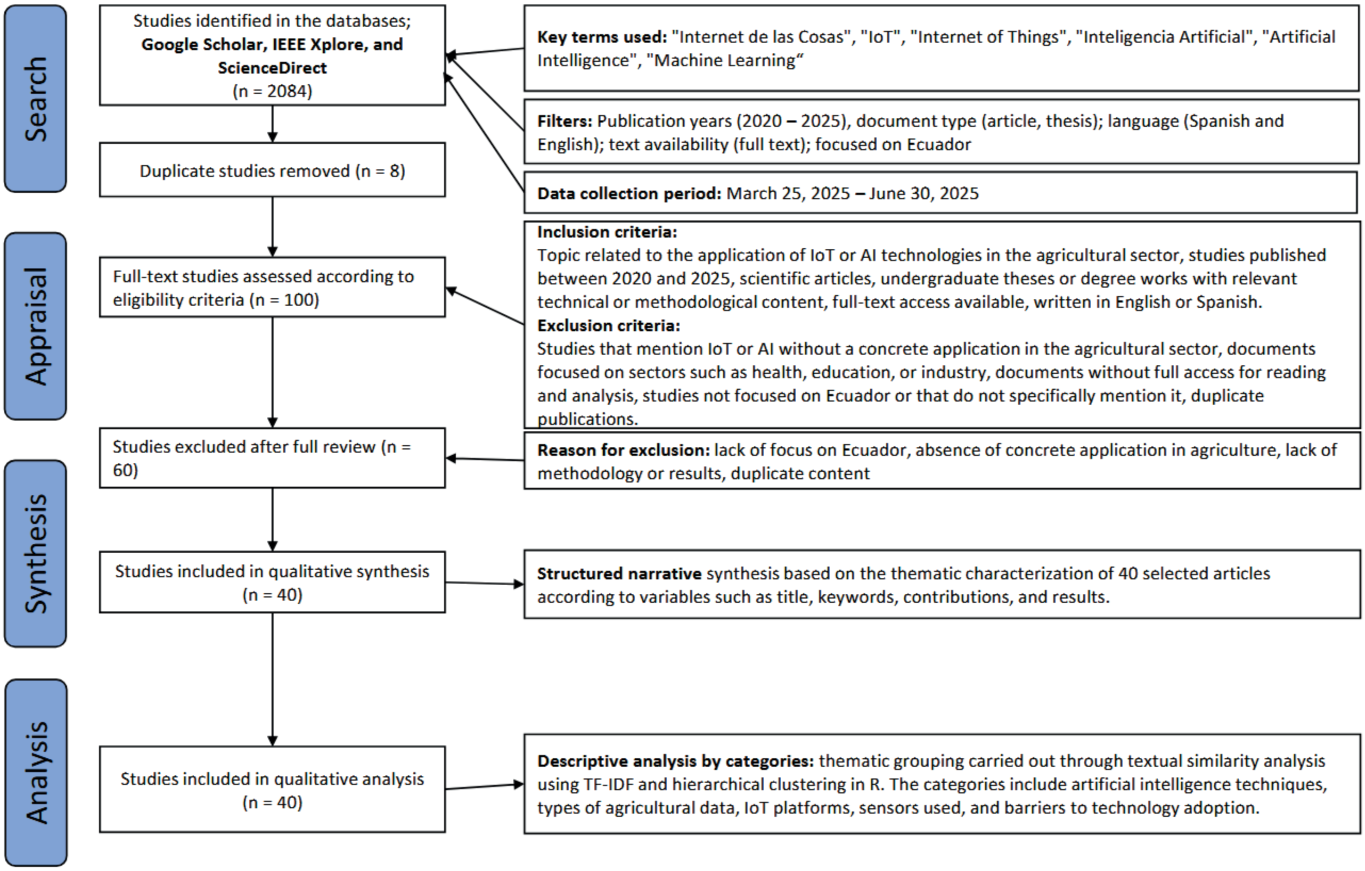

Fig. 1. SALSA flow diagram.

A. Search

The identification phase consisted of retrieving relevant literature on IoT and AI in Ecuadorian agriculture. Keywords were defined in both languages, for example: Internet de las Cosas, IoT, Internet of Things, Inteligencia Artificial, Artificial Intelligence, Machine Learning, Deep Learning, Computer Vision, Modelling, Smart farming, Precision agriculture, Crop monitoring, Banana, Cacao, Mango, Rice, and Ecuador. These terms were combined with Boolean operators ("AND", "OR") and adapted to each database consulted. The sources used are shown in Table I.

TABLE I
SEARCH STRATEGY AND INFORMATION SOURCE

Database	Search string
Google Scholar	("Internet de las Cosas" OR "IoT" OR "Internet of Things" AND "Inteligencia Artificial" OR "Artificial Intelligence") AND ("Agricultura de precisión" OR "Monitoreo agrícola" OR "Smart farming" OR "Precision agriculture" OR "Crop monitoring") AND ("Ecuador")
IEEE Xplore	("Machine Learning" OR "Deep Learning" OR "IoT" OR "Computer Vision") AND ("Agriculture" OR "Farming" OR "Precision agriculture") AND ("Banana" OR "Cacao" OR "Mango" OR "Rice") AND ("Ecuador")
ScienceDirect	("IoT" OR "Artificial Intelligence" OR "Modelling") AND ("Agriculture" OR "Irrigation") AND ("Ecuador")

Each search was adjusted to retrieve documents published between 2020 and 2025, in Spanish and English, with full-text access. The search strings were optimized to capture studies applied to Ecuadorian agricultural contexts, both general and crop-specific.

B. Appraisal

In this stage, inclusion and exclusion criteria adapted to the Ecuadorian agricultural context were applied according to the PICOS (Population, Intervention, Comparison, Outcomes, Study design) framework. The review was carried out in two phases: first, titles and abstracts were screened to discard non-relevant studies; second, the full texts of preselected documents were read to confirm their coherence with the objectives and PICOS criteria.

The PICOS criteria considered were:

P (Population): Studies focused on Ecuadorian agriculture, including crops, pest management, and agricultural monitoring.

I (Intervention): Application IoT and AI technologies.

C (Comparison): Studies presenting comparative results with traditional methods, alternative approaches, or conceptual analyses that provide contrast.

O (Outcomes): Quantitative metrics (accuracy and precision) and qualitative results that demonstrate the effectiveness and benefits of the applied technologies.

S (Study design): Scientific articles, theses, and academic works with technical or methodological content, published between 2020 and 2025, in English or Spanish, with full-text access.

Documents without concrete agricultural application, without mention of Ecuador, without full access, duplicates, or focused on other sectors were excluded. Table II summarizes the inclusion and exclusion criteria applied.

TABLE II
SELECTION CRITERIA

Inclusion Criteria	Exclusion Criteria
Topic related to the application of IoT or AI technologies in the agricultural sector. Studies published between 2020 and 2025. Scientific articles, undergraduate theses, or academic works with relevant technical or methodological content. Full text available. Written in English or Spanish.	Topics that mention IoT or AI without a concrete application in agriculture. Documents focused on sectors such as health, education, or industry without a link to agriculture. Documents without full-text access. Studies not focused on Ecuador or not mentioning it specifically. Duplicate publications.

From the total articles retrieved (n = 2 084), approximately 100 studies were preselected after applying the initial filters, and finally 40 studies were included that met all the criteria for the systematic review.

C. Synthesis

To synthesize the information from the selected studies, a matrix was built including title, keywords, problem description, approach, contribution, and results; this matrix was used for textual similarity analysis. The TF-IDF (Term Frequency-Inverse Document Frequency) model [9], [10], [11] was applied to numerically represent the content and highlight the most relevant terms. Subsequently, hierarchical clustering with cosine distance and the Ward.D2 method was performed to form homogeneous thematic groups [12], [13], [16].

The result was a dendrogram that identified five main thematic groups: (1) AI applications for agricultural diagnosis; (2) IoT implementations for agricultural monitoring; (3) spectral remote sensing in Andean crops; (4) computer vision, sensors, and UAVs for agricultural monitoring; and (5) strategic and socioeconomic evaluation of digital technologies in Ecuadorian agriculture. Each group was characterized according to technologies used, crops studied, performance metrics, and regions of implementation.

D. Analysis

The qualitative analysis was organized into five stages:

1. **Initial content coding:** Each study was read to extract key fragments related to the research objectives (AI techniques, types of agricultural data, IoT platforms, sensors, and adoption barriers). Coding was manual, using thematic labels based on the research questions (RQ1–RQ4).
2. **Grouping by thematic categories:** The coded fragments were organized in matrices according to common axes: type of AI technique, type of agricultural data, technological platform, and sensor. Technical, social, and operational barriers were also recorded, allowing the establishment of frequencies and relationships between variables.
3. **Classification by frequency and recurrence:** For each category, the number of studies addressing that aspect was counted (e.g., neural networks, image data, DHT22 sensors, infrastructure limitations), prioritizing the most representative trends.
4. **Cross-study comparison:** Cross-references between categories were performed, such as AI technique vs. type of data or IoT platform vs. reported barriers, to identify methodological and operational correlations and observe which techniques were used with certain sensors or in rural contexts.
5. **Interpretative synthesis:** The data were organized into a synthesis table with the grouped findings, without making judgments, serving as input for the conclusions stage. This process allowed characterization of emerging groups and provided a structured view of the state of the art, establishing the basis for the discussion and conclusions of the study.

This process made it possible to characterize emerging groups and provide a structured vision of the state of the art, establishing the foundations for the discussion and conclusions of the study.

III. RESULTS

A. Search

During this phase, 40 relevant studies on the application of IoT and AI technologies in Ecuadorian agriculture were initially identified. These studies were selected after applying search criteria in scientific databases such as IEEE Xplore and ScienceDirect.

B. Appraisal

Once the articles were collected, a refinement and preliminary analysis of the full texts was carried out. It was verified that the documents met the inclusion criteria defined in the methodology (geographic focus on Ecuador, application of IoT or AI in agriculture, and full-text availability).

This phase confirmed the validity of the 40 selected studies for synthesis and analysis.

A general visualization of the most frequent words extracted from the texts can be seen in Fig. 2, where key terms such as “iot,” “system,” “ndvi,” “blockchain,” “artificial,” “pests,” and “cacao” stand out [14], [15].

Fig. 2. Word count from the 40 selected studies

C. Synthesis

The information extracted from each study was organized and coded according to key variables: technologies used, types of agricultural data, IoT platforms, sensors employed, performance metrics, reported impacts, and identified barriers. This coding made it possible to build a comparative matrix based on the research questions.

As part of the synthesis process, a textual similarity analysis was used to explore common patterns in the studies. The result of this analysis is shown in Fig. 3, which presents a dendrogram generated from the TF-IDF matrix and the Ward.D2 hierarchical clustering method.

Additionally, a heat map was developed that cross-references the applied AI techniques with the types of crops analyzed in the studies, in order to visualize the frequency and relationship between these variables (Fig. 4). This representation makes it possible to identify the most recurrent combinations and facilitates the interpretation of technological trends according to the agricultural context.

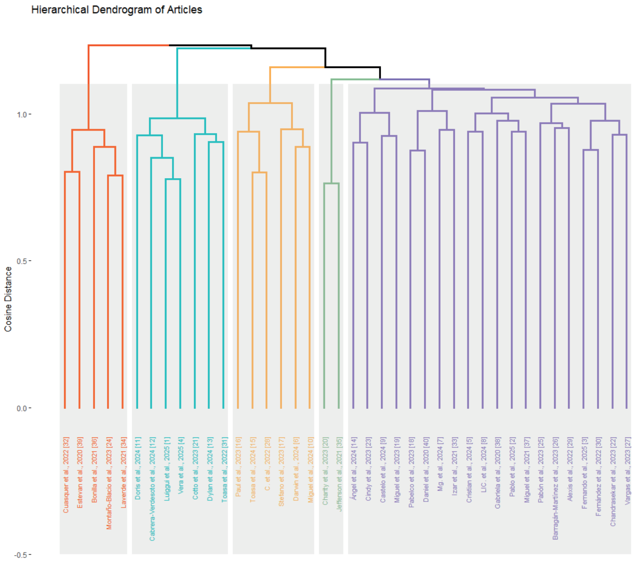

Fig. 3. Clustering dendrogram of the 40 articles.

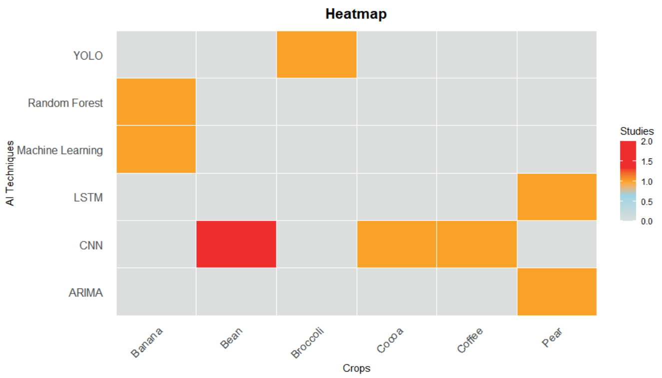

Fig. 4. Frequency of AI algorithm applications by crop type.

D. Analysis

A textual similarity analysis was applied to the titles, keywords, and descriptions of the studies. Using TF-IDF and a hierarchical clustering algorithm (Ward.D2 method), five main thematic groups were identified. For each group, specific word clouds were generated, and their content was characterized based on the analyzed variables.

RQ1: What AI techniques have been applied in pest detection and monitoring of crop growth, and what have been their results in terms of accuracy or effectiveness?

- A review of 40 studies reveals diverse AI techniques applied to pest detection, crop growth monitoring, and agroclimatic variable prediction in Ecuadorian agriculture.
- ANN were the most common, used in 11 studies (27,5 %), with accuracies of 0,89-0,95 for plant growth modeling and environmental analysis [17], [18], [20], [21], [22], [23], [24], [25], [26], [27], [36].
- CNN, a subtype of ANN, appeared in 6 studies (15,0 %) with accuracies of 0,82-0,95 for image classification of crops such as corn, tomato, and broccoli [17], [18], [20], [22], [26], [27].
- General Machine Learning techniques, reported in 8 studies (20,0 %), achieved accuracies of 0,95-0,99, while Random Forest, used in 3 studies (7,5 %), ranged from 0,80-0,99 [18], [20], [21].
- Long Short-Term Memory (LSTM) models, found in 2 studies (5,0 %), reported R² values of 0,76-0,78 [26], [36].
- Models such as YOLO (You Only Look Once) and ARIMA/SARIMA (AutoRegressive Integrated Moving Average / Seasonal ARIMA) were reported in 1 study each (2,5 %), reaching accuracy levels of 0,91-0,93 and R² values of 0,89-0,97, respectively [20], [36].
- Single-study techniques included YOLO (accuracy 0,91-0,93), ARIMA/SARIMA (R² 0,89-0,97), KNN (K-Nearest Neighbors), a distance-based classification method (accuracy 0.91), SVM (Support Vector Machine), a margin-based classifier (accuracy 0,83–0,96), and Decision Tree (accuracy 0,91-0,95) [20], [22], [27].

Table III presents a summary of the identified techniques, their frequency of use, the metrics used and the reported effectiveness ranges.

TABLE III
AI TECHNIQUES APPLIED
IN AGRICULTURAL STUDIES IN ECUADOR

Algorithm / Model	Number of studies	Metric used	Reported effectiveness range
ANN	11	Accuracy	0,89-0,95
Machine Learning	8	Accuracy	0,95-0,99
CNN	6	Accuracy	0,82-0,95
Random Forest	3	Accuracy	0,80-0,99
LSTM	2	R²	0,76-0,78
YOLO	1	Accuracy	0,91-0,93
ARIMA /SARIMA	1	R²	0,89-0,97
KNN	1	Accuracy	0,91
SVM	1	Accuracy	0,83-0,96
Decision Tree	1	Accuracy	0,91-0,95

Note: Reported performance metrics reflect each study's conditions. A higher accuracy or R² does not inherently indicate a superior model, as results depend on the dataset, task type, and evaluation methodology.

RQ2: What types of agricultural data are commonly used in studies that integrate IoT and AI for pest detection?

- The analysis of the selected studies shows diversity in agricultural data used in AI and IoT solutions, mainly for pest detection, environmental monitoring, and crop-development analysis.
- Environmental data were the most frequent, present in 16 studies (40 %), including temperature, humidity, pH, electrical conductivity, and ultraviolet radiation, generally captured by sensors and recorded as time series [30], [33], [35].
- Agricultural production data appeared in 9 studies (22,5 %), containing quantitative information on weight, size, and number of bunches or boxes [31], [39], [43].
- Geospatial sources were reported in 5 studies (12,5 %), with GPS coordinates and digital terrain or crop models [42].
- Declarative or survey data were used in 3 studies (7,5 %), with Likert-type responses and local testimonies [37].
- Digital images appeared in 2 studies (5 %), in RGB or multispectral formats from public and local sources, for visual classification [47].
- Time-series and historical data were identified in 2 studies (5 %), including univariate or multivariate records such as temperature, precipitation, wind, and SPEI [30], [35].
- Spectral or multispectral data were reported in 1 study (2,5 %) for physiological crop analysis [33].
- Other data (bibliographic or non-agricultural metadata) appeared in 2 studies (5 %) [31], [43].

Table IV summarizes data types, frequencies, characteristics and representative examples.

TABLE IV
TYPES OF AGRICULTURAL DATA
USED IN AI STUDIES IN ECUADOR

Data source	Number of studies	Source or repository	Characteristics
Environmental data	16	Not specified	Quantitative, numeric format, multivariate time series (temperature, humidity, pH, electrical conductivity, UV radiation).
Agricultural production data	9	Not specified	Quantitative, numeric format (weight, size, number of bunches/ boxes).
Geospatial data	5	Local dataset	Quantitative, GPS coordinates and digital models (terrain/ crop).
Declarative / Survey data	3	Local surveys	Qualitative, textual format (Likert survey responses, testimonies).
Digital images	2	PlantVillage, Kaggle, LeLePhid, Dataset local	Quantitative, RGB format (JPG/PNG) or multispectral, no time series.
Time series and historical data	2	NASA, Local dataset	Quantitative, numeric format, univariate (e.g., temperature) or multivariate time series (temperature, precipitation, wind, SPEI).
Spectral / Multispectral data	1	Multispectral datasets	Quantitative, multispectral image format.
Others (metadata, non-agricultural data)	2	Bibliographic datasets	Mixed (qualitative/quantitative), textual/numeric format (metadata, water data, buildings), no time series.

RQ3: Which IoT integration platforms are most frequently employed in agricultural monitoring systems in Ecuador?

- The analysis of the reviewed studies shows diversity in IoT platform implementation, depending on the level of integration, technological maturity, and specificity [19], [38], [46]. Of 40 studies, 16 (40 %) implemented platforms in practice, 17 (42,5 %) did not specify any platform, and 7 (17,5 %) did not integrate IoT [40], [44].
- Among practical applications, local/edge platforms (ThingsBoard, SQL Server, and local dashboards) were used in 10 studies (25 %), enabling data collection, edge processing, and visualization through LAN networks, web servers, or local databases, accessible via browser or mobile apps [48], [50], [46], [44]. Cloud platforms (ThingSpeak, AWS IoT Core, Power BI Cloud) were employed in 4 studies (10 %) for remote visualization, automatic alerts, and monitoring [19], [45], with ThingSpeak highlighted in 2 studies for its integration with microcontrollers [34]. Two studies combined SQL Server and Power BI for data storage and analysis [44]. Overall, most implementations were practical, with some analytical applications.

Finally, 17 studies (42,5 %) proposed architectures or conceptual models without specifying platforms or concrete strategies, indicating that much of the literature remains exploratory [51], [55]. Table V summarizes IoT platforms according to category, number of studies, type of implementation, and key characteristics, providing an overview of the Ecuadorian agricultural context.

TABLE V
IOT PLATAFORMS USED IN AGRICULTURAL
MONITORING IN ECUADOR

Category / Deployment	Plataforma IoT	Number of studies	Implementation type	Description
Local / Edge	ThingsBoard, SQL Server, Local dashboards	15	Mostly practical	Platforms for local data collection and edge processing; dashboards accessed via browser or app; local storage and processing of agricultural data.
Cloud	ThingSpeak, AWS IoT Core, Power BI Cloud	8	Mostly Practical	Cloud platforms for remote monitoring, real-time visualization, alerting, and data analysis; integration with local or cloud databases.
Unspecified	-	17	-	Proposed architectures or conceptual models without specifying platforms. No concrete implementation detailed.

RQ4: Which specific sensors are most used in precision agriculture to improve yield and sustainability in Ecuador?

- The analysis of the reviewed studies shows that precision agriculture in Ecuador uses various sensors and devices for environmental monitoring, irrigation automation, visual analysis, and soil control [28], [32], [41]. However, 30 studies (75 %) did not specify models or brands, mentioning only general sensors such as pH, electrical conductivity, thermal cameras, barometric pressure, and CO_2 sensors [52], [53], applied to nutritional management, environmental control, and soil assessment.
- Among the sensors with specific models, RGB cameras were reported in 3 studies (7,5 %) for fruit classification and disease detection [29], [54]; the DHT22 appeared in 2 studies (5 %), used for temperature and humidity monitoring, enabling irrigation automation

and climate control [49]; and NDVI, in 1 study (2,5 %), focused on plant health and biomass assessment [56]. Other devices include DFROBOT SEN0114 and HC-SR04 (1 study each, 2,5 %) for soil moisture and robot navigation [41], and Davis 6466M and 6830 weather stations (1 study each, 2,5 %) for climate variable monitoring [28].

Table VI summarizes these sensors, their applications, and their frequency of occurrence.

TABLE VI
SENSORS AND AGRICULTURAL DEVICES
USED IN STUDIES IN ECUADOR

Sensor / Device	Number of studies	Agricultural application	Contribution to yield
RGB cameras	3	Fruit classification, disease identification	Quality and productivity improvement, loss reduction
DHT22	2	Temperature and humidity monitoring	Water savings, climate control, irrigation optimization
Davis 6466M	1	Weather stations (climate, rainfall, temperature)	Climate prediction, more accurate agronomic planning
Davis 6830	1	Weather stations (climate, rainfall, temperature)	Climate prediction, more accurate agronomic planning
NDVI	1	Plant health and biomass analysis	Input reduction, precise fertilization, efficient monitoring
DFROBOT SEN0114	1	Soil moisture measurement	Automatic irrigation activation, resource-use precision
HC-SR04	1	Navigation and obstacle detection in robots	Labor automation, precision in movement.
Not specified / Not used	30	Generic mention of EC meters, thermal cameras, barometric and CO_2 sensors.	Support for nutritional management, environmental control, soil condition assessment.

IV. DISCUSSION

This study analyzes 40 investigations on the integration of IoT and AI in Ecuadorian agriculture. Four questions were addressed: AI techniques and their accuracies, types of data employed, IoT platforms used, and the most frequent sensors. The findings show the use of ANN and CNN, supported by environmental data and digital images, along with a diversity of platforms and sensors covering both practical applications and conceptual proposals [57], [60], [78].

Regarding AI techniques, ANN were the most frequent, applied to plant growth modeling and environmental conditions, with accuracies ranging from 0,89 to 0,95 [57], [63], [75]. CNN achieved between 0,82 and 0,95 in image classification of crops such as maize, tomato, and broccoli [63], [83], [85]. Other approaches included YOLO, LSTM, ARIMA/SARIMA, KNN, SVM, and Decision Tree, with metrics above 0,9 but lower frequency [83], [84]. Some studies reported accuracies between 0,95 and 0,99 under the general label of machine learning, without specifying the technique [78], [83]. Additional works confirm these trends, reporting values of 0,9948 in EfficientNetB0, 0,99 in ResNet50, 0,98 in InceptionV3, and 0,95 in custom CNN, and 0,89 in ANN for temperature prediction [63], [83], [85]. Efficiencies of 0,92 in computer vision with OpenCV and hybrid models between 0,79 and 0,95 were also documented [79], [85]. However, the generalized use of the term machine learning without specifying techniques or metrics persists [78], [83].

In terms of data, quantitative environmental variables predominated, such as temperature, humidity, pH, electrical conductivity, and radiation in multivariate series, followed by production data and RGB images for leaf and fruit classification [57], [70], [86]. To a lesser extent, qualitative, geospatial, spectral, and metadata sources were used, indicating an incipient integration of heterogeneous data [57], [73]. Other studies confirm the importance of environmental variables and RGB images and include acoustic data for insect monitoring, vegetative indices such as NDVI, and administrative records [58], [79]. Social or livestock variables did not appear in our results [58], [65].

Concerning IoT platforms, conceptual proposals predominated over real implementations. Solutions such as ThingSpeak, ThingsBoard, SQL Server with Power BI, and local web platforms for monitoring and visualization were identified [59], [70], [71], although most lacked clear integration [60], [61], [68]. Other studies also highlight ThingSpeak and mention AWS IoT Core, Blynk IoT, and custom architectures with LoRa or MQTT [61], [67], [74]. The abundance of proposals without practical validation limits the ability to assess the effectiveness of these solutions [60], [68], [78].

Regarding sensors, devices such as DHT22, RGB cameras, NDVI, DFROBOT SEN0114, and HC-SR04 were identified, associated with irrigation, water savings, and crop improvement [66], [70], [71], [74]. Comparative studies are usually less specific, mentioning temperature, humidity, pH sensors, RGB cameras, CO_2, multispectral, thermal, and LIDAR sensors without detailing models [58], [79]. Only in a few cases were DHT11, HC-SR04, ESP32, or Arduino UNO reported [71], [74]. Both groups coincide in monitoring environmental and soil variables, although external studies include advanced sensors absent in Ecuador, highlighting a technological gap [77], [79], [81].

In Latin America, greater diversity is observed. In Brazil, random forests are applied for agricultural prediction [88]; in Colombia and Argentina, LoRa, IoT platforms, and optimized classification models are used [87], [91]. Overall, varied sensors, classical and deep learning techniques, and platforms ranging from prototypes to field systems are combined [90], [92]. In Ecuador, ANN and CNN predominate, with devices such as Raspberry Pi for local processing [69], [70], although exploratory studies and limited technical detail prevail [68], [78]. Thus, the region shows greater maturity and diversity, while Ecuador progresses with preliminary proposals but with significant potential for development [88], [91], [92].

V. CONCLUSION

This review on IoT and AI in Ecuadorian agriculture highlights significant potential, though still at an early stage. These technologies, applied to crops such as banana, cocoa, mango, and rice, promise more precise and sustainable agriculture through neural networks and environmental sensors. However, adoption remains centered on local solutions and theoretical proposals, with few practical implementations in the field.

Structural challenges include limited rural connectivity, insufficient irrigation infrastructure, and low digital literacy —particularly in indigenous communities— combined with insecurity and political instability that hinder investment and technological development. Recent studies reflect exploratory research, with proposals often lacking technical details on sensors or platforms.

Compared with Brazil or Colombia —countries in the region where more advanced technologies are employed— Ecuador relies on low-cost IoT platforms and basic neural networks. This opens opportunities to learn from regional experiences and strengthen local solutions through infrastructure improvements, farmer training, and political stability. Collaborations that integrate local and regional knowledge can transform these proposals into practical implementations, consolidating an efficient, inclusive, and resilient agriculture in the face of a changing world.

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