



## Systematic Review

# Information and Communication Technologies Used in Precision Agriculture: A Systematic Review

Jorge Díaz <sup>1,\*</sup>, Yadira Quiñonez <sup>2</sup> , Emiro De-la-Hoz-Franco <sup>1</sup> , Shariq Butt-Aziz <sup>3</sup>, Teobaldis Mercado <sup>4</sup> and Dixon Salcedo <sup>1</sup>

<sup>1</sup> Department of Computer Science and Electronics, University of the Coast, Barranquilla 080020, Colombia; edelahoz@cuc.edu.co (E.D.-I.-H.-F.); dsalcedo2@cuc.edu.co (D.S.)

<sup>2</sup> Facultad de Informática Mazatlán, Universidad Autónoma de Sinaloa, Culiacán Rosales 80020, Mexico; yadiraqui@uas.edu.mx

<sup>3</sup> School of Systems and Technology, Department of Computer Science, University of Management and Technology, Lahore 54000, Pakistan; shariq.aziz@umt.edu.pk

<sup>4</sup> Department of Agronomic Engineering, University of Cordoba, Moteria 230001, Colombia; tmercado@correo.unicordoba.edu.co

\* Correspondence: jdiaz5@cuc.edu.co

**Abstract:** This article presents a systematic literature review on Information and Communication Technologies (ICTs) applied to precision agriculture, focusing on their relevance to Colombia. It identifies key technical and administrative needs for digital transformation in the sector and proposes a conceptual roadmap for implementation. Findings highlight the potential of early warning systems (EWSs), the Internet of Things (IoT), and artificial intelligence (AI) to improve productivity, sustainability, and climate resilience. The study outlines current adoption barriers and proposes future empirical validation through field experiments.

**Keywords:** systematic; precision; agriculture international; underdeveloped; developing; technologies



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## 1. Introduction

Agriculture has been central to human development for over 12,500 years. This development had a profound impact on the evolution of Homo sapiens. It marked the process of plant and animal domestication, allowing for the settlement and formation of human groups [1]. Furthermore, agriculture has been instrumental in poverty and hunger alleviation in many parts of the world, as it is the primary source of food production.

Within the realm of agricultural products, corn holds paramount importance for Colombia, ranking as the third most cultivated crop after coffee and rice. Despite this, Colombia is the largest corn importer in South America and seventh globally. While national corn production has increased over the last 50 years, the demand for this product has grown even more. Corn is a dietary staple for millions of Colombians who consume items like arepas and mazamorra [2]. Therefore, innovative projects aimed at enhancing the productivity of the agricultural sector at a national level are necessary.

In the context of agricultural practices among most domestic producers, issues such as weed control through pasturing, indiscriminate irrigation, overexploitation of water resources, soil contamination due to excessive pesticide and chemical use, and land burning for cultivation preparation are prevalent [3]. Information and Communication Technologies (ICTs) have impacted all aspects of human life, from employment to entertainment, education, and other essential services like banking and healthcare [4–7]. As expected,

agriculture has not remained untouched by this process of technological advancement, resulting in what is now referred to as precision agriculture.

The integration of ICTs in agriculture has shown measurable impacts on productivity and knowledge transfer. For instance, Ali [8] explored the adoption of ICTs in agricultural decision-making, emphasizing the importance of policies promoting training and technology access to foster adoption. Das et al. [9] analyzed the effect of ICT services on food crop production in Bangladesh and found that areas with ICT-based services reported significantly higher yields than those without. He et al. [10] analyzed the factors influencing farmers' adoption of e-commerce in Wuchang, China. Factors with a positive impact include gender, the number of household members engaged in agricultural activities, favorable perceptions of government policies, and a subjective willingness to adopt digital technologies. In contrast, risk perception and certain infrastructural limitations may act as barriers, negatively affecting the adoption of e-commerce in agricultural settings. Marwa et al. [11] evaluated mobile-based extension services in Kenya and concluded that ICT use improves productivity and the economic well-being of smallholder farmers. Similarly, Newase et al. [12] found that ICTs play a crucial role in enhancing the economic and social development of rural communities in India. Kante et al. [13] proposed ICT-based models to support farming activities and facilitate informed agricultural decision-making, promoting more efficient and sustainable practices. Finally, Habanyati et al. [14] used statistical analysis to examine variables such as crop yield and the application of organic formulations, identifying key challenges such as high conversion costs, intensive labor requirements, knowledge gaps, and lower initial yields.

Despite the opportunities offered by the modernization of the agricultural sector, Colombia still lags in this regard [15,16]. Due to the low level of technological adoption in Colombian agriculture, there is a lack of historical data (dataset) for the region concerning the measurement of agricultural and climatic variables needed for phenological analyses of different crop types. Climatic variables are essential for phenology and climate's impact on the successful execution of field activities. For instance, early warning systems (EWSs), which announce the occurrence of floods, are currently nonexistent in regions of Colombia like the southern Atlantic despite known risks [17]. The south of the Atlantic region is significant as it is a major corn producer.

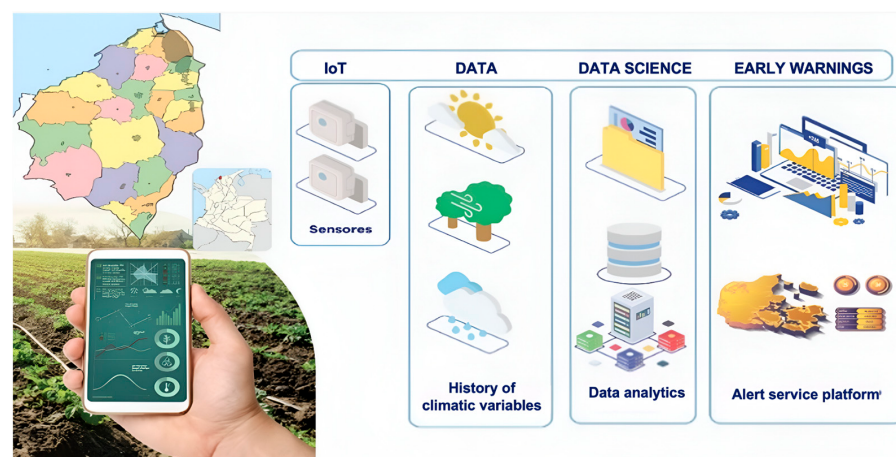
EWSs could be the first step toward technological advancement in the Colombian rural sector, especially in the Caribbean region. They could serve as the central axis around which other complementary precision agriculture systems related to crop monitoring and productive activities can be deployed. The country lacks the evaluation of ensemble data models and artificial intelligence techniques based on real-world data. Data are collected using low-cost devices, resulting in simplistic architectures with implementations based on limited technological availability in the market. While this provides some information, the data often lack georeferencing and microclimate considerations. There is a shortage of platforms for real-time visualization of variables of interest. Additionally, early warning systems are absent for agricultural producers in the southern Atlantic region. Advanced systems for predicting climate and atmospheric variables are also not in place.

When reviewing the literature globally, the following four categories of ICT applied to agriculture, leading to precision agriculture, can be identified: the Internet of Things (IoT) in precision agriculture [18], architectures and services [19], expert systems in decision-making [20], and crop monitoring and health [21]. These categories offer opportunities for research in various areas. The first area relates to datasets used in precision agriculture. Due to the heterogeneity of datasets, applying predictive techniques based on data analytics (Big Data) becomes necessary. Big Data techniques are most suitable for handling massive and unstructured data [22]. Data security in IoT-based agriculture systems requires novel

and robust protection strategies. Amanullah et al. [23] proposed using deep learning and Big Data techniques to enhance threat detection and response capabilities in IoT environments. Khan and Salah [24] explored blockchain-based frameworks to secure distributed agricultural data, analyzing key vulnerabilities such as weak authentication, lack of privacy, and inefficient data management. Mohamad Noor [25] introduced protection techniques centered on hardware-level security, including secure boot processes and advanced encryption standards. Additionally, Sidhu et al. [26] identified hardware vulnerabilities and highlighted the threat hardware Trojans pose to compromising the integrity of IoT agricultural devices. Finally, utilizing information collected in datasets to identify diseases and crop anomalies further extends the scope of precision agriculture [27].

The second area involves the evaluation of predictive model effectiveness. Evaluating predictive model performance in agriculture is essential to ensure accurate forecasting and informed decision-making. De la Casa et al. [28] used NDVI images with varying spatial resolutions to assess soybean yield variability, emphasizing the value of remote sensing in identifying productivity patterns within fields. Vahidi et al. [29] proposed estimating soil moisture at 10 cm and 30 cm depths in corn fields by integrating drone-mounted hyperspectral sensors with machine learning techniques. Miller et al. [30] employed 3D imaging and machine learning to predict live weight and carcass traits in beef cattle, illustrating the utility of advanced modeling in livestock productivity. Bwambale et al. [31] reviewed AI applications across crop management, soil monitoring, weather prediction, and pest and disease detection, noting that while AI offers significant potential for improving agricultural sustainability, overcoming data and infrastructure challenges is crucial. Vergara-Díaz et al. [32] introduced novel technological approaches for crop characterization under shifting environmental conditions to support sustainable food production. Finally, Flynn et al. [33] demonstrated that the combination of hyperspectral reflectance and machine learning algorithms can accurately estimate cotton crop traits, reinforcing the role of precision agriculture in optimizing resource use and crop performance.

This research is part of a project focused on EWSs applied to the rural sector, aimed at supporting the execution of climate change risk prevention and mitigation actions for farmers in southern Atlántico, especially corn producers. However, the literature analysis conducted below to identify the technological needs of the agricultural sector and implementation technologies is global. It should be noted that many of the variables measured to feed EWSs are also used in precision agriculture implementations for crop monitoring and control systems. Nonetheless, a separate section is dedicated to EWSs. Figure 1 outlines the desired architecture of a national precision agriculture system. Sections 4–6 discuss how components like sensing networks, DSS tools, and EWSs correspond to this framework.



**Figure 1.** Schemes follow the same formatting.

The article is organized as follows. Section 2 presents the methodology used for the literature review. Section 3 analyzes the results obtained from searches in the selected databases. Section 4 identifies the sector's needs regarding precision agriculture, establishing various opportunities for improvement and innovation. Section 5 provides an analysis of potential technological implementations that could be carried out in Colombia to achieve the state of precision agriculture. Section 6 focuses on early warning systems (EWSs). Finally, Section 7 presents the conclusions and future work.

## 2. Methodology

This article conducts a documentary review of the literature on the management needs in precision agriculture and the technologies to be implemented to meet those needs. A systematic literature search was performed on selected databases following a defined methodology to achieve this. The methodology includes four steps, beginning with the definition of search parameters. Initially, a research question was formulated: 'What are the needs and technological implementations demanded by the field of precision agriculture?'. To explore all technologies applicable to precision agriculture, three keywords were extracted from the research question: 'Needs', 'Technologies', and 'Precision Agriculture'. The search strings obtained were: 'Precision Agriculture', 'Needs' AND 'Precision Agriculture', and 'Technologies' AND 'Precision Agriculture'. English versions of the keywords were used for database searches.

The methodology's second step was defining the databases to be consulted. The criterion for database selection was the availability of full-text articles via institutional subscriptions. IEEE Xplore and ScienceDirect were chosen because they provided comprehensive access to the necessary content. Although databases like Scopus and Web of Science (WoS) are esteemed for their rigor and comprehensiveness, they were excluded from the search owing to subscription constraints that hindered full-text access. We recognize that this limitation may result in selection bias and expressly identify it as a constraint of this review. A focused Google search was used to supplement peer-reviewed literature and fulfill the requirement for policy and implementation studies pertinent to the Colombian context. These sources were included only when they originated from reputable institutions, such as ministries, national research centers, or international organizations. All sources acquired through Google underwent identical eligibility criteria and quality assessment. A detailed list of inclusion and exclusion criteria, along with the types of documents analyzed, is presented in Table 1.

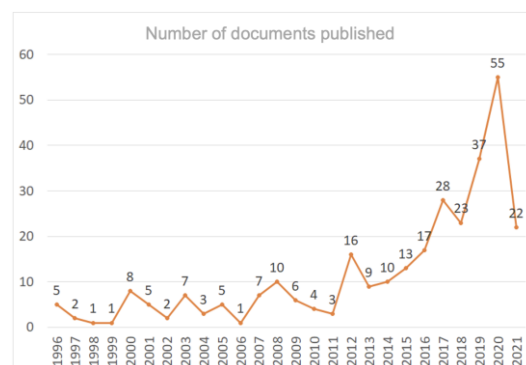
**Table 1.** Eligibility criteria applied to the selection of studies in the systematic review.

| Criterion            | Inclusion                                                                                                                        | Exclusion                                                               |
|----------------------|----------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|
| Language             | English and Spanish                                                                                                              | Other languages                                                         |
| Type of source       | Peer-reviewed journal articles, academic books, and technical reports from recognized institutions (e.g., ministries, FAO, CIAT) | Blogs, forums, news articles, non-peer-reviewed or unauthored documents |
| Accessibility        | Full-text availability (via institutional subscription or open access)                                                           | Documents with only abstract available                                  |
| Thematic focus       | ICT applications in precision agriculture                                                                                        | General ICT topics not related to agriculture                           |
| Geographic relevance | Global, with emphasis on Latin America and Colombia                                                                              | Regions not comparable to Colombia or without agricultural application  |
| Publication year     | 2000–2024                                                                                                                        | Publications prior to 2000                                              |

The third step involved searching the selected databases, identifying documents, verifying access, and refining articles according to the research's needs. Finally, the fourth step was to analyze the results obtained.

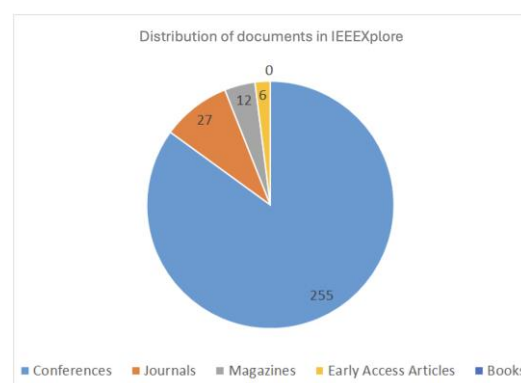
### 3. Analysis of the Obtained Results

The term 'Precision Farming' was searched in the IEEE Xplore database to track the temporal evolution of precision agriculture publications and highlight its growing impact in recent years. Figure 2 shows that for the specific case of IEEE, the topic has evolved slowly, with sustained growth only since 2013. This is a developing field that offers significant research and development opportunities.



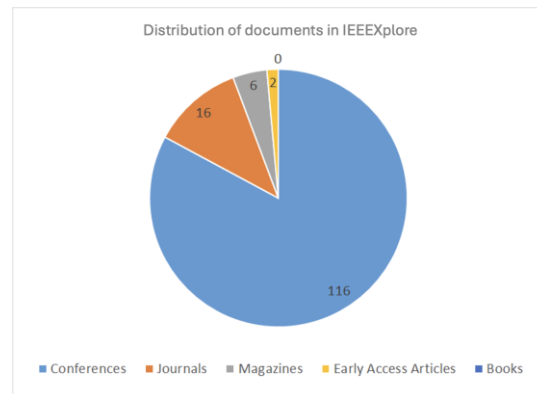
**Figure 2.** Number of documents published per year on 'Precision Farming' in IEEE Xplore.

It was interesting to determine the type of publication in which most documents in this database are concentrated. This distribution is presented in Figure 3. Most publications on the topic are in conference proceedings. The number of articles in journals is still limited. Interest in this topic is so recent that the number of documents published in magazines is still low. Books are typically written when topics become more established, which is why no books have been published on this specific subject.

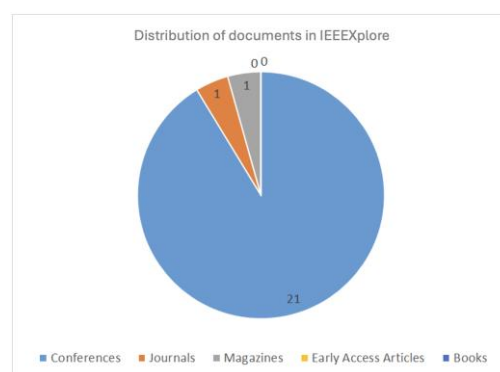


**Figure 3.** Distribution of documents in IEEE Xplore by publication type.

Further refining the search, inquiries were made for the strings 'Technology' AND 'Precision Farming' and 'Needs' AND 'Precision Farming'. These searches intended to determine how many documents among those found addressed the topic of technological implementations, how many discussed and studied the needs of the precision agriculture sector, and in what type of publication they were found. Figures 4 and 5 show these results.



**Figure 4.** Distribution of documents in IEEEExplore for the search string “Technology” AND “Precision Farming”.

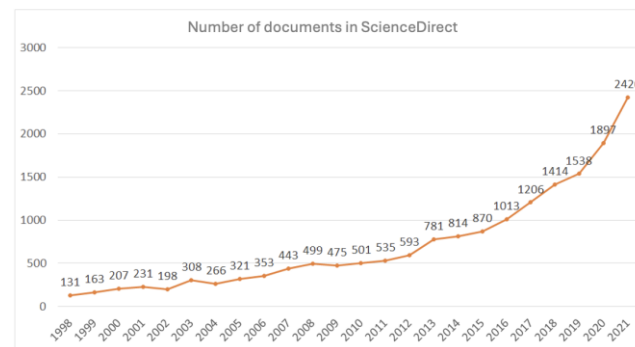


**Figure 5.** Distribution of documents in IEEEExplore for the search string “Needs” AND “Precision Farming”.

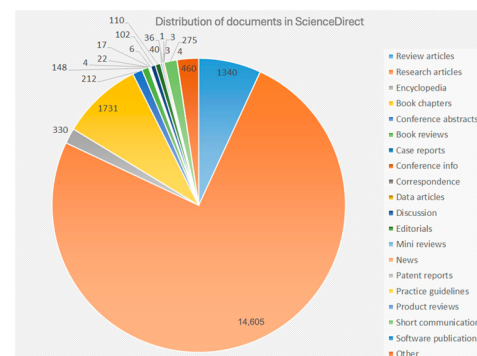
A significant portion of the published literature addresses the topic of precision agriculture technologies and implementations. A much smaller number of documents have been published related to the discussion of sector needs. As expected, the documents published in IEEEExplore are scattered across various journals and conferences affiliated with the institute. The journal that stood out the most was the IEEE Sensors Journal, which had five articles, followed by the 2012 IEEE International Geoscience and Remote Sensing Symposium, which had four documents. The most prominent author was Andrea Gasparri, who had seven articles. The country with the most notable publications on the topic in various conferences was the United States, with 28 articles.

The IEEEExplore database has a certain level of specialization, focusing on electronics, software, and electrical engineering. Due to this, its range of publications is more limited. It is different with ScienceDirect. This database is extensive and associated with many journals; therefore, the number of articles is significantly higher. While IEEEExplore reported 300 articles for the search string ‘Precision Farming’, ScienceDirect reported 19,449 documents. Figure 6 shows the number of articles published each year. Unlike IEEE, which did not experience significant growth in the early years, there is a noticeable increasing trend from the beginning. However, it is worth noting that the growth became more important around 2012–2013, like the case of IEEE.

Figure 7 shows the distribution of articles and documents according to their type. Most of the literature is concentrated on research articles, followed by a distant second, literature review articles on the topic, of which 1340 have been written. This distribution also shows that articles related to datasets have only been published six times. This represents a significant opportunity for future work, especially with data obtained in Latin American agricultural environments.



**Figure 6.** Number of documents published per year on “Precision Farming” in ScienceDirect.



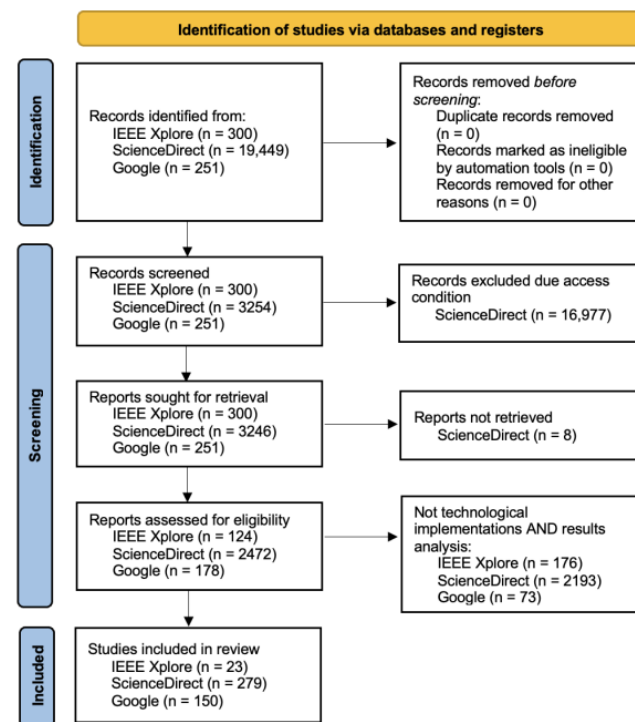
**Figure 7.** Distribution of documents in ScienceDirect by type.

Some additional findings from the ScienceDirect database are noteworthy. The journal with the most articles on the topic is *Computers and Electronics in Agriculture*, with 788 documents, followed by *Science of The Total Environment*, with 648. In the case of the former, the publication’s name suggests its specialization in precision agriculture. The study areas that stand out in publications related to precision agriculture are ‘Agricultural and Biological Sciences’ with 9445 documents and ‘Environmental Science’ with 5732 documents. It is striking that the computer science field is seventh, with only 1410 documents.

Due to the high number of documents resulting from searches in ScienceDirect, a primary filter that significantly reduced the searches was the criterion of full-text access. This reduced the number of records to 2472. To further refine the search, the search string was changed to ‘Technology’ AND ‘Precision Farming’, which reduced the results to 279 documents. A review was conducted for these latter documents, evaluating each for relevance and timeliness once the full text was read. In addition to the above articles, 150 documents obtained through Google searches were added and refined based on their strategic value as institutional information sources.

The process of identifying, selecting, and determining study eligibility is described according to the guidelines of the PRISMA 2020 Declaration. Figure 8 shows the flowchart with the study selection process.

Although the review presents a detailed mapping of technologies used in precision agriculture, there is limited statistical validation regarding their effectiveness across regions. To enhance the analysis, a comparative assessment was performed utilizing chosen case studies from Latin America (Brazil and Mexico) and Africa (Kenya). These regions share challenges like Colombia’s, such as limited access to digital infrastructure, climate vulnerability, and smallholder farming predominance.



**Figure 8.** PRISMA flowchart of the study selection process for the systematic review.

Table 2 compares the key technologies implemented, highlighting their adoption levels, and supporting infrastructure. This comparative framework identifies transferrable strategies and contextual constraints that must be addressed when adapting these technologies to the Colombian context.

**Table 2.** Comparative overview of precision agriculture technologies in developing regions.

| Region/Country | Technologies Used                                | Adoption Level | Supporting Infrastructure                        |
|----------------|--------------------------------------------------|----------------|--------------------------------------------------|
| Brazil [34]    | IoT sensors, GPS-guided tractors, drones         | Medium to high | 4G rural connectivity, national ag-tech programs |
| Mexico [35]    | Climate-smart irrigation systems, mobile apps    | Medium         | Government-supported rural innovation centers    |
| Kenya [11]     | SMS-based weather alerts, EWSs, mobile platforms | Low to medium  | Basic mobile coverage, NGO and donor support     |
| Colombia [16]  | EWSs (pilot), IoT (low-cost), basic data logging | Low            | Limited connectivity, high hardware costs        |

#### 4. Technical and Administrative Needs Related to Precision Agriculture

This section presents the technical and managerial needs identified in the sector, which are essential to enabling a farm to implement precision agriculture.

##### 4.1. Classification of Farms

Initially, it is possible to arbitrarily categorize farms based on the level of innovation they exhibit at a given moment. The classification is subjective and serves as a starting point for further development of technological concepts related to the topic. This classification is based on the work of Martin et al. (2016) [36], as detailed below.

- Farms Level 1: These farms lack computer systems for management and agricultural activities. Their operation relies on the experience gained by producers in previous

harvests. At this level, the producer cannot assess the process's financial sustainability, profitability, and productivity. There is a lack of information on whether the farm produces quality products and is financially profitable.

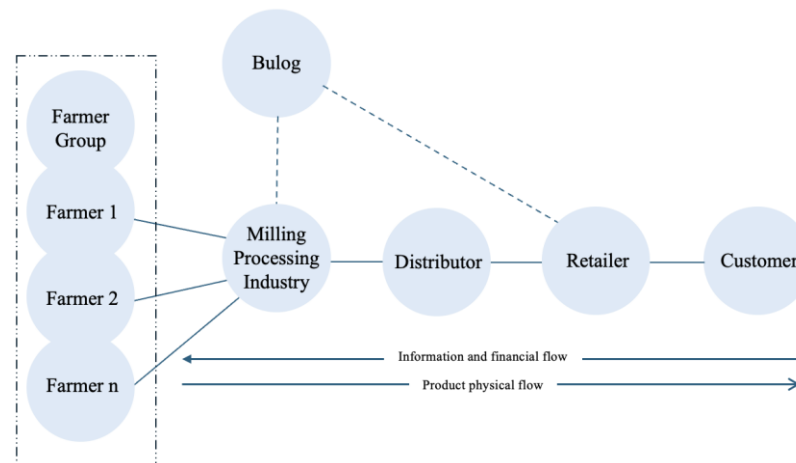
- Farms Level 2: These farms have a certain level of technical implementation using sensors to measure crop conditions. Examples of such devices include soil moisture probes. While there is now some information related to agricultural activities, overall management is still carried out in a traditional manner. The advantage is that there is now more precise data that slightly favors technical decisions related to cultivation.
- Farms Level 3: In these farms, producers have a basic information management system primarily aimed at financial management to determine the profitability of the process. It is common for some information management related to crops for phytosanitary purposes to also occur. This information system is a crucial step towards further advancing farm innovation until reaching what is known as precision agriculture.
- Farms Level 4: These farms continue Level 3 farms, as they complement the information management system with remote control systems for elements that perform processes in the cultivated field, such as water and fertilizer irrigation pumps and environmental variable control in greenhouses.
- Farms Level 5: These farms integrate all the above with a comprehensive monitoring and management system that supports the producer's decision-making for overall farm and crop management. Mobile applications have been developed for agricultural producers that assist them in monitoring, management, and decision-making. All of this adds value to the producer's management efforts.

These concepts provide a roadmap for the progressive adoption of precision agriculture practices, allowing farms to evolve from basic, traditional methods to advanced, data-driven, technology-enhanced management approaches.

#### 4.2. Traceability and Transparency

Traceability is a process that entails monitoring a crop from seed planting, overseeing plant development, and tracking the handling of the finished product across distribution chains until it reaches the ultimate consumer. This underscores the necessity to advance and invent technology that facilitates meticulous and thorough monitoring of the entire process, as previously said, to guarantee the end customer that the product has been managed appropriately. Consequently, pertinent health authorities can gather all information about consumer health protection [37]. It is important to emphasize that retrospective adoption requires engagement with pre-existing infrastructure, which poses both technical and economic challenges, particularly for smallholder farmers. The authors underscore the necessity of addressing these barriers through targeted public policies, agricultural training and extension services, and the development of robust value chains for agroforestry products [38]. Figure 9 illustrates a value chain for the agro-industry sector and its associated traceability system.

Producers and marketers, due to the current market demands, must control all this information and make it quickly and readily available to health authorities and consumers. This will translate into greater trust on the part of consumers in various target markets [40]. For example, using QR codes or BIDI codes can be suggested to provide consumers and marketers with information swiftly and straightforwardly [41–43]. Such information could encompass all processes, from seed handling and processing to the final product reaching the consumer.



**Figure 9.** Model of a value chain for the agro-industrial sector. Modifications from Purwandoko et al. [39].

#### 4.3. Environmental Impacts Metrics

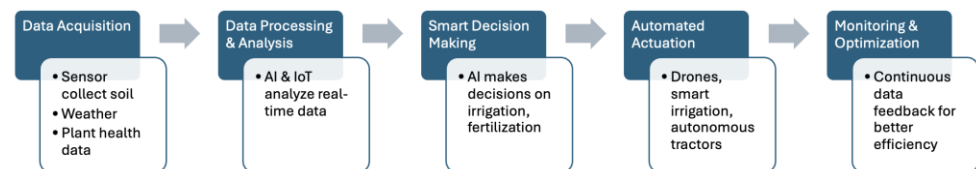
This involves measuring and quantifying the so-called environmental footprint that a product leaves throughout its entire life cycle [44–46]. It complements agricultural traceability. It is not enough to have confidence in the handling of products; the impact of the entire production process, including marketing, on the environment must also be considered. Both measurements and footprint calculations are expected to be automated throughout the process. Currently, three specific environmental footprints are of great interest: carbon [47–49], water [50–52], and ecological [53–55]. These footprints constitute specific numerical indicators that provide information about resource use in agricultural production processes. Calculating these footprints requires information related to energy consumption on farms, the use of fossil fuels in transportation, engines, tractors, and all agricultural machinery in general, water resource consumption in crops, and the use of fertilizers and phytosanitary products. These data should feed into an algorithm that calculates the environmental footprints of interest.

#### 4.4. Decision Support Tools

To assist producers in making decisions regarding the management of their crops, data must be collected from various sources, such as sensors placed on plants, weather sensors, and soil sensors. Additionally, data related to climate and its relationship with plant cycles (phenology) must be periodically measured. Remote sensing, crop imaging, and meteorological measurements in the farm's location are also necessary. Furthermore, studies related to crop development (plant and production) should be conducted to establish the corresponding indicators for the dashboard that the producer will use for decision-making and proper crop management [53,56,57]. These indicators will have corresponding threshold and optimal values. The indicators correspond to the following crop characteristics: smell, color, size, caliber, fruit composition, water, fertilization, and phytosanitary requirements. All of this would constitute a Decision Support System (DSS).

As you can see, the origin of the information is highly diverse, leading to unstructured data that necessitates advanced analysis and processing to make them more uniform and algorithmically combine them to provide the correct indicators needed by the producer [56]. Such necessary processing involves the use of Big Data techniques, as they allow for structuring an array of Key Performance Indicators (KPIs) that are made available to the producer/user of the system to support and assist in their crop management strategies [58–61].

On the other hand, the information presented to the user for decision-making is made available through various channels such as websites, text messages, mobile services, and emails, among others. These channels enable interaction, which establishes the possibility of automatically triggering various control actuators in the crops [62,63]. Examples of such interactions include remote control of crops through irrigation or ventilation systems, among others. Figure 10 illustrates a typical AI-driven precision agriculture workflow that integrates sensor data acquisition, real-time processing, automated decision-making, and actuation.



**Figure 10.** Implementation of a Decision Support System. Modifications from Cambra Baseca et al. [62].

#### 4.5. Remote Control of Crops

SCADA (Supervisory Control and Data Acquisition) systems can be implemented to remotely control agricultural production processes, allowing interactions with various electrical and mechanical control systems located in crop fields [64,65]. These systems include water tank filling/emptying pumps, irrigation and fertilization systems, climate control systems (in greenhouses), CO<sub>2</sub> level control, and other automated systems.

#### 4.6. Automatic Crop Monitoring

Each plantation is linked to a range of agronomic and environmental variables that must be monitored, managed, and regulated to guarantee that the growth and productivity of crops conform to the standards established by the producer or farmer, this being the objective of precision agriculture. To achieve this, it is necessary that information systems can be utilized to aid the producer in monitoring the relevant parameters. This necessitates the utilization of diverse probes and sensors for automated data collection alongside software applications for data processing. Thus, monitoring and control platforms for plantations can be established, enabling growers to track their crops continuously [66–68]. In this sense, the sensors must have frequent calibration, environmental protection, and remote diagnostics for agricultural electronics, as stipulated in ISO 12188 [69], to provide long-term stability and precision.

#### 4.7. Automation of Agricultural Processes

The automation of agricultural processes can be carried out in plantations established in controlled environments, where the situation of crops and their processes is well-established and structured [70–72]. Certain agricultural activities can be automated using robots [73,74]. Examples of such activities include fruit detection and determination of its ripeness, quality, and dimensions based on artificial vision, automatic fruit cutting and harvesting systems, and automatic product sorting and packaging systems. This implies the possibility of the product being prepared from the plantation and ready for the marketing system.

These automated systems, called robots, capture data from all production activities and transmit it through wireless networks for integration into the information system. This allows for the automatic management of the crop and provides the necessary information for developing Key Performance Indicators (KPIs) and tracking the entire crop production process.

#### 4.8. Remote Sensing

In addition to the variables mentioned in previous sections, the study and monitoring of crops can include data related to aerial photographs or videos that provide additional information about a specific plantation area. This activity is known as remote sensing. Devices for remote sensing can be drones [75–78] or specific satellites [79–81]. These devices detect the radiation naturally emitted by the objects and areas being observed. In the case of agriculture, radiation levels can provide information about the phenology of crops in the plantations.

#### 4.9. Geographic Information

As is well known, precision agriculture is about managing agricultural plantations, regardless of their variations. One way to make such variability transparent to management processes is through computer tools that define farming activities and their outcomes. Among such tools are geographic information systems [82–84]. These systems enable the geo-positioning of arbitrary elements associated with crops, such as the plants themselves, irrigation systems, electricity distribution systems, motor vehicles, and electrical and mechanical actuation systems. Geographic information systems can include descriptive data related to the elements, which can be valuable for decision-making.

#### 4.10. Monitoring of Machinery in Crops

The need to monitor the machinery used in crop cultivation is evident at this point, as it is the way to obtain data for calculating the costs associated with these resources in contrast to their associated productivity [85–87]. Whether a machine can be monitored, geo-referenced, and remotely controlled depends on the type of machine. This implies that by using information technology based on agricultural and biological criteria, machinery can be managed to maximize crop productivity concerning resource productivity maximization.

#### 4.11. Prediction and Prediction Systems

Disciplines related to crops and plantations, namely meteorology and agronomy, provide estimation models based on multiple parameters that can be automatically detected in the actual cultivation. These models serve as the foundation for prediction systems that anticipate information related to the productivity of production processes and optimize planning in commercial activities for products [88–90]. Prediction systems also enable better planning and optimization of resource usage based on costs in the crop production process. Such planning can consider the market demand for the product.

#### 4.12. Efficiency in the Use of Water and Energy Resources in Cultivation

Producers may be interested in analyzing how to improve the consumption of resources in the production process, with the principal resources being water and energy. The primary cost of any agricultural plantation is associated with using these resources. It is logical to consider that precision agriculture and its associated technologies can provide information that allows for decisions related to the efficiency of water and energy resource utilization [91,92]. Examples of such decisions could include when it is less costly to consume, what quantities to consume at different stages, and which energy sources to use at each stage of the production process, among others.

These decisions are not only oriented towards the producer's financial aspects but are also related to compliance with the environmental regulations currently required by governments.

#### 4.13. Fertilization and Irrigation of Crops

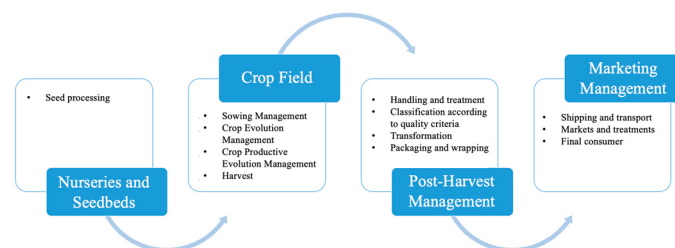
Every crop requires calculating the levels of irrigation and fertilizer usage it needs based on its specific situation. It is not just about using water and energy but also about applying chemicals that could potentially contaminate soils and water sources if used excessively [93]. This need aims to calculate the quantity and timing of fertilizer and irrigation application according to agronomic criteria so that the crop absorbs everything without contaminating residues. The necessary calculations involve determining the irrigation dosage and nutrient dosage.

### 5. Precision Agriculture Technologies Used in Implementations

The necessary technologies in precision agriculture contribute to the establishment of level 4 and 5 farms. This section will study these technologies, highlighting their objectives and contributions to improving crop management and sustainability based on the technical and administrative needs presented in the previous section.

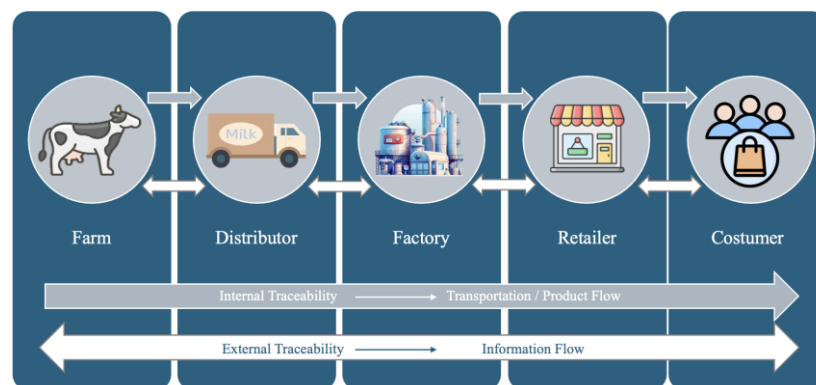
#### 5.1. Traceability

The technologies required to ensure food safety by ensuring the traceability of crops and products primarily consist of the automatic recording of field information about the crop, known as agronomic information, and its input into the information system, which also contains information about crop management. This allows the consumer of the final product to be informed about all activities carried out on the crop and the final product obtained. The associated technologies are detailed below. Figure 11 shows the operation scheme of an agricultural traceability system.



**Figure 11.** Scheme of operation of an agricultural traceability system.

Traceability in food supply chains has traditionally been implemented using RFID technologies. Recently, QR codes and blockchain technology have emerged as promising tools to enhance the transparency and legitimacy of recorded information. According to Patelli and Mandrioli [94] and Demestichas et al. [95], blockchain can significantly improve traceability by offering secure and immutable records; however, they also emphasize critical challenges, including the need for standardized processes, the creation of joint platforms, and the establishment of independent governance structures to ensure successful implementation. Further studies [96,97] highlight that blockchain-based traceability systems in agri-food supply chains enable the development of decentralized, immutable, transparent, and reliable infrastructures that support process automation and real-time monitoring. Cao et al. [98] identify additional limitations in current approaches, such as the absence of standardized architectural frameworks, the risk of information overload, and the prevalence of greenwashing practices. They propose a four-layer architectural model to enhance transparency, data integrity, and real-time traceability. In resource-constrained environments, lightweight blockchain solutions like IOTA and Hyperledger Fabric have been explored for agricultural traceability, offering offline functionality and reduced processing demands [99,100]. Figure 12 illustrates the execution of such a traceability system within the food agribusiness sector.



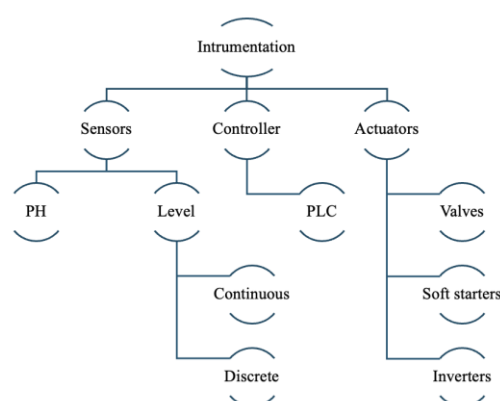
**Figure 12.** Implementation model of a traceability system in the food/agricultural sector. Modifications from Behnke et al. [96].

#### 5.1.1. Integration of Machinery into Cultivation

For this purpose, standard communication protocols are used, such as the ISOBUS field bus [101–104]. These integration architectures have allowed the Controller Area Network (CAN) concept to develop, defining interconnected machines for control and automation purposes. These protocols facilitate the integration of information management software with the real-time embedded operating system in the hardware that governs the diverse devices deployed in the field. These are onboard systems known as Electronic Control Units (ECUs). This integration method enables the detection of data generated by numerous machines in field operations into the farm management information system.

#### 5.1.2. Scada Systems in Fertilization and Irrigation Activities

SCADA systems implement the automated detection of variables and actions on the crop [105]. SCADA systems can exchange information with farm management information systems, such as the doses of fertilizer (nitrates, potassium, etc.) used in each irrigation process. Field communication protocols like Service-Oriented Architecture (SOA) are used to carry out this exchange process, providing service-oriented architectures. Figure 13 presents the elements necessary to implement a SCADA system at the agricultural level. It shows the presence of robust control systems such as industrial programmable logic controllers (PLC) and a series of valves and sensors that allow actions to be taken on the crop.



**Figure 13.** Elements required to implement a SCADA system on a farm. Modifications from Silva-Díaz et al. [105].

#### 5.1.3. Detection of Agricultural Information Through Mobile Equipment

Field laborers use mobile equipment to record information related to the activities they perform on crops. This information is provided to traceability systems offered to the

end consumers of the products obtained. Mobile equipment for this task includes smart-phones, tablets, and laptops [106,107]. These devices must have software for automatically detecting and transmitting data to information management systems. This software communicates with digital pens (smartpens) to capture data as it is written through detection and interpretation; some pens also integrate cameras for taking photos of observations.

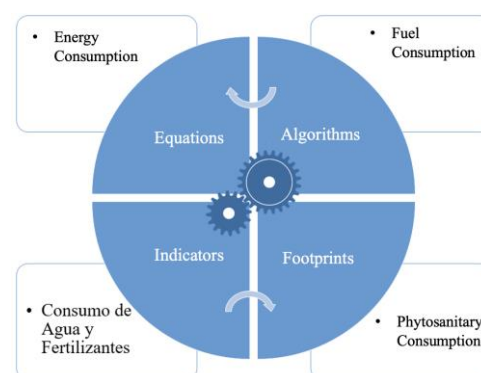
#### 5.1.4. Big Data for Advanced Data Analysis

Owing to the volume, variety, and disorganization of the data generated by a crop, sophisticated processing using Big Data analytical tools is requisite. These systems can organize and standardize the discovered data, rendering the information comprehensible for the end user or consumer of the product [108]. Colombia has initiated the exploration of emerging technologies, including the Internet of Things (IoT), artificial intelligence (AI), and Big Data in agriculture; nevertheless, their implementation is predominantly experimental or at the pilot stage. Many implementations depend on inexpensive sensors, fundamental data acquisition via mobile applications, and the discrete application of AI for crop diagnostics or image categorization. There is insufficient national coordination or interaction with governmental agriculture databases.

Conversely, nations like India and Israel [109–111] have developed cohesive digital agriculture platforms. India's "Digital Agriculture Mission" integrates IoT devices, AI analytics, and satellite imagery to assist millions of smallholder farmers. With a robust startup ecosystem, Israel has implemented AI-driven irrigation and fertilization systems that automatically adapt according to real-time climatic data and plant health indicators.

#### 5.1.5. Environmental Footprints

In this case, software applications implement algorithms to calculate the usage/consumption function of resources in the crop. This calculation can be performed globally for the entire farm or at the level of each crop or product obtained. The comprehensive farm management software records the use of various resources in different activities of the production process in the field. Figure 14 shows the interaction of indicators, equations, algorithms, and footprints based on resource consumption data such as fuel, energy, water, fertilizers, and phytosanitary inputs. This structure enables precise traceability and environmental impact quantification at various production levels.



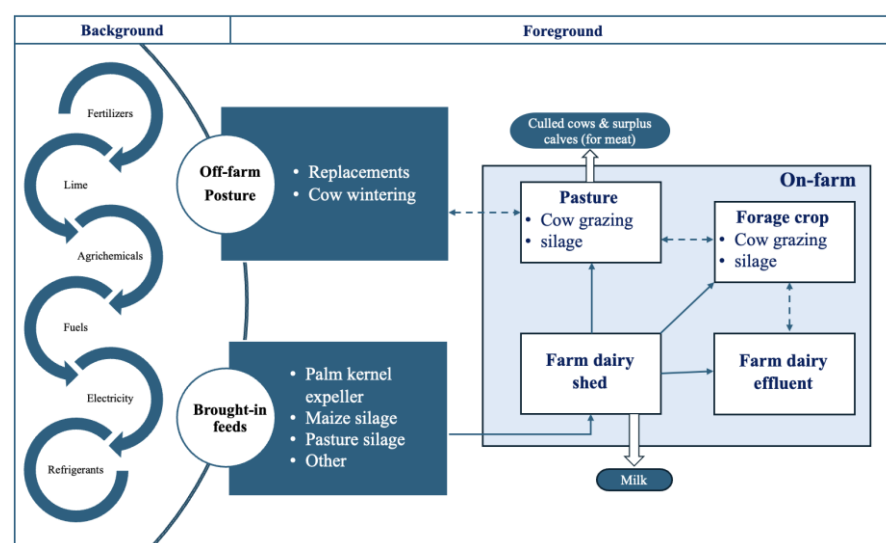
**Figure 14.** Diagram for the determination of environmental footprints.

#### 5.2. Scheme for Obtaining Environmental Footprints

The carbon footprint is defined as a kind of ecological label containing all the calculations of greenhouse gas emissions related to institutions, activities, and the life cycle of any product to establish its contribution to climate change [47]. This footprint is given in units of tons of CO<sub>2</sub> equivalents. This indicator helps establish and report the contribution each product manufactured in the world has to climate change. It is not just products but

also institutional processes and services. The importance of the carbon footprint lies in its contribution to the measurement and, hence, the minimization or elimination of CO<sub>2</sub> emissions in the production processes of business institutions to mitigate the consequences of climate change. This ecological label helps establish markets for products and services with minimal carbon emissions, thus responding to society's growing demand for the care of the planet and the environment.

On the other hand, it provides opportunities to save on costs such as environmental taxes. It also allows companies and institutions to show the public, environmental, and health authorities their commitment to social responsibility and comply with requirements and demands related to climate change mitigation. Figure 15 shows a system model that includes the calculation of the carbon footprint for a case study in New Zealand. You can see how the system is fed with information on the consumption of specific resources, including electricity and fuels.



**Figure 15.** A model of an information system that includes carbon footprint calculation. Modifications from Ledgard et al. [47].

### 5.2.1. Water Footprint

This indicator measures the amount of water consumed, evaporated, and contaminated over a specific period or per a certain mass amount. Essentially, it indicates the use of water, whether direct or indirect. The concept officially emerged in 2002 by UNESCO, with Arjen Hoekstra being one of its primary proponents. Today, water footprint is defined as the total volume of freshwater used to produce goods and services for an individual, institution, or community. This indicator is valuable for activities aimed at improving water consumption. The International Organization for Standardization (ISO) has developed a set of standards, ISO 14046 [112], concerning water footprint or water footprinting.

Greywater quantifies the volume of water that has become contaminated while producing goods and services. In the case of precision agriculture, it represents the volume of water that becomes contaminated in the processes and activities carried out on farms. Greenwater is the volume that evaporates. Precision agriculture includes the measured volume of water that evaporates during irrigation activities and the volume that evaporates through plant transpiration [113–115]. This calculation can be performed using Crop Evapotranspiration (ETC). Evapotranspiration is the process by which plants return some soil water to the atmosphere through transpiration. Finally, blue water is the volume of freshwater consumed from surface or groundwater sources. In precision agriculture, it represents the volume of water consumed in the irrigation process.

### 5.2.2. Decision Support Systems for Farm and Crop Management

To address this need, specific technologies should be incorporated for the implementation of software modules that present an array of data with PKI indicators [116]. At this point, thresholds and alarms can be defined for each PKI indicator. In this way, the farm producer or administrator can make decisions related to crop management. These decisions can be reactive or preventive, depending on what is most suitable for crop management. This means that this system allows for establishing activities and processes to be carried out in specific crops, as well as in the overall plantation, to achieve optimal development. The goal is to achieve a productive process that delivers high-quality products and maximum productivity.

### 5.2.3. Remote Crop Monitoring Systems

In the case of implementing remote control for crops, the next step is to place remote control centers at various points within the farm and crops for agricultural activities [117–119]. These tools/devices are designed to perform actions in the crops and can collect data related to the state of the plants. Once connected to the global information system, producers and farm workers can operate them and carry out activities remotely without physically being present in the crop. Remote control systems offer the advantage of optimizing farm labor while allowing activities and processes to be conducted simultaneously on multiple crops or farms. Achieving this optimal point in agricultural activities reduces crop costs since it reduces labor-related expenses, eliminating the need for numerous laborers in each crop to perform the same activities.

### 5.3. Pumps for Filling and Draining

These mechanisms fill and drain water repositories. Information systems enable the automation of filling and draining processes through remote control of the pumps used for this purpose. This control is carried out based on decisions made in advance, depending on energy criteria, indicator decision thresholds, and calculations of the water requirements for crops [120].

### 5.4. Fertilization and Irrigation Control

Based on agronomic criteria and according to levels of specific pre-established indicators analyzed automatically, automated irrigation and fertilization activities are planned at specific times and calculated doses. Algorithms controlling devices and tools in the field will be implemented in robust information systems [121].

### 5.5. Climate Control in Greenhouses

To perform this type of control, elements that can influence the climatic conditions of a greenhouse hosting a particular crop are used. Optimal climatic parameters can also be influenced to maximize production function. These systems can include greenhouse ventilation systems, heat injection systems, and humidification systems [122].

### 5.6. Carbon Dioxide Control

Actuator devices are controlled to regulate the injection of carbon dioxide to increase its presence in the greenhouse, favoring photosynthesis and crop productivity indicators [123,124].

### 5.7. Automatable Arbitrary Systems

Depending on the level of automation on the farm and in cultivation, a series of machines and tools capable of automation can be available, implying their integration with information systems through field communication protocols.

### 5.8. Automatic Crop Monitoring Systems

Regarding this aspect, the necessary technologies consist of probes and sensors that should be installed in farms and crops to automatically detect various types of data, including phenological and physiological data of plants and soil. These data are used to create indicators and alarms interpreted by the system operator, allowing for monitoring plant and crop conditions [66]. To implement such a system, a group of data loggers is required to centralize all the data from the sensors and probes located in various sample capture zones determined by producers on the farms. These are points for precise and detailed monitoring [68]. These points maintain a real-time connection with the farm's global information system. The probes or sensors that can be used are described below.

#### 5.8.1. Ambient Temperature Sensors

The temperature in the environment where plants will grow is one of the most significant phenological factors that will affect the growth and fruit development of plants in crops. It is necessary to electronically record ambient temperature data as an essential indicator in making decisions related to crop management [125]. This work presents the development of a passive, wireless temperature sensor based on radiofrequency oscillation. It can measure temperatures up to 125 °C.

#### 5.8.2. Ambient Humidity Sensors

This case concerns the relative humidity in which the plants of various crops are located. Like temperature, this variable is another significant phenological factor due to its impact on crop vegetative growth. It is necessary to electronically record it as another indicator in decision-making regarding crop management [126,127].

#### 5.8.3. Radiation Sensors

The importance of radiation lies in its impact on evaluating the photosynthetic capacity of plant leaves in crops. This indicator should be highlighted since the photosynthetic capacity of its leaves determines the plant's productivity. For this reason, the Photosynthetically Active Radiation (PAR) parameter, which indicates what percentage of the total radiation the plant receives directly participates in the photosynthesis process, constitutes another essential indicator for electronic recording. It is one of the indicators that guide the plant's development and productivity [128,129].

#### 5.8.4. Rain Gauges

These sensors detect the amount of precipitation in a specific area. These data should be electronically recorded because producers can make decisions related to irrigation and plan the dosing of water resources according to the area's needs based on the recorded rainfall [130–132].

#### 5.8.5. Wind Speed and Direction Sensors

The wind has multiple effects on crops and their phenology. Wind promotes pollination, which is beneficial, but it can also aid in the spread of pests, spores, and harmful pathogens for crops. Therefore, measuring wind speed and direction becomes crucial for planning suitable actions in the crop to favor its phenology [133].

#### 5.8.6. Plant Sensors

These are devices that are directly implanted in crop plants. Various types of plant sensors are presented below [134,135].

- **Dendrometers:** These continuously measure the growth values of the plant's trunk or stem over a specific period. These devices provide information related to the vegetative development of the plants. Keeping an electronic record of such values is convenient because it provides the producer with nutritional information about the plants in the crops.
- **Sap Flow Sensors:** These sensors continuously measure the sap flow levels along the plant's stem. The need to electronically record this data provides the producer with information regarding the plant's nutritional status. This value, combined with the data provided by the dendrometer, establishes an indicator of the level of plant development in the crops.

#### 5.8.7. Soil/Terrain Probes

These probes allow information to be obtained about the terrain/soil where the crop is grown. Below are several types of probes with different applications [136–138].

- **Suction:** These are instruments that allow solution extraction from the soil. This process provides information about the conditions of the terrain/soil in which the crop has been planted. Its computerized recording is essential because the producer can determine the most suitable area for their plantation to maximize crop yield.
- **Nutrition:** These instruments measure the levels of nitrate and potassium in the soil. They are usually located around the roots and record the availability of minerals and nutrients for the crop's plants. Their computerized recording is necessary due to their impact on the crop's indicators of plant nutrition levels.
- **Conductivity, temperature, and humidity:** These probes measure electrical conductivity and, thus, record the salinity level of the soil, as well as the moisture level (amount of water) and temperature. In summary, they record the compliance of conditions for plant roots to be nourished by the soil's conditions.

#### 5.9. Crop Automation Systems

These are technological implementations aimed at remote control of systems and technical tools that allow the automation of the activities that must be carried out in the field for cultivation. Automated devices are used to perform agricultural activities autonomously [139]. A clear example of this is field robots. Their implementation not only optimizes the processes carried out on the crop but also provides the infrastructure to capture data that are supplied to the information system. This improves farm management and enhances productivity yields.

#### 5.10. Remote Sensing Systems

These technological implementations allow the remote detection of information related to the crops on a farm and their variability. The NDVI (Normalized Difference Vegetation Index) can be mentioned at this point. It is an index that provides information about the differences and variations in the plants of a specific area, such as the different crops on a particular farm. In addition, such remote sensing devices detect differences in radiation from different surfaces within a plantation and data like relative humidity, among others [140]. Remote sensing and its connection to a farm's information system will lead to the development of algorithms that assess the degree of crop development and its potential productivity. Remote sensing can be implemented using two types of technology.

##### 5.10.1. Unmanned Aerial Vehicles (Drones)

These vehicles can fly at an appropriate altitude and incorporate cameras with remote sensing technology to capture such images. Images taken by these vehicles typically require

further processing to make the captured terrain data more uniform since a drone is not a fixed image capture device but is constantly in motion during flight, which affects the captured data [141].

#### 5.10.2. Satellite

Satellites capture images with consistent characteristics. They are geostationary devices located in a fixed position. This makes it possible to capture images at different times over the same location, maintaining consistent spatial criteria in each capture. The main disadvantage of satellites is that being outside the atmosphere, various meteorological events can affect their image capture process [142].

#### 5.11. Geographic Information Systems

Geographic Information Systems (GISs) are technologies utilized for managing geographic information, comprising software applications for the graphical depiction of maps, which furnish precise information about each object displayed, known as metadata. Metadata seeks to delineate the diverse things represented on the map, including farms, plantations, crops, water wells, canals, irrigation systems, pumping systems, and, broadly, any agricultural apparatus. These systems enhance agile and visual management. Numerous uses exist, but the primary implementation of GISs in precision agriculture is fundamental, as it allows farmers to gather, analyze, and visualize intricate geographical data regarding their crops. This enables individuals to make informed decisions and implement agricultural inputs locally, optimizing land productivity and sustainability. These methods enhance resource utilization, including water and fertilizers, improve production efficiency, and mitigate environmental effects [143].

#### 5.12. Systems for Monitoring Agricultural Machinery in the Field

These encompass all mechanisms and devices that enable remote and automated control of the systems and tools necessary for cultivating activities. Such tools include dispensers, shovels, and hoes, among others. These systems also allow for tracking and georeferencing the operation of machinery in the field. For example, they enable monitoring the status of an engine, the oil or fuel level of a tractor, the activity being performed by any of the machines, and the presentation of metadata about its activity in the GIS system, among other functions [144].

The integration of OnBoard systems in agricultural tractors is steadily increasing. These systems are embedded within the tractor and connect to all its components, enabling comprehensive monitoring and control through standardized communication protocols such as ISOBUS [145]. Authors such as Das et al. [146] and de Melo et al. [147] emphasize that incorporating electronic technologies, particularly wheel slip control, can significantly enhance fuel efficiency and operational performance in fieldwork. Furthermore, Pérez et al. [148] analyze the evolution and advantages of electrification in agricultural machinery, especially tractors, noting improvements in torque control, energy efficiency, and emission reductions. OnBoard systems can also record essential operational data to ensure precise and optimized machinery performance on crops. Leading manufacturers like New Holland, John Deere, and AGCorp have adopted these systems and protocols to enable seamless interaction and communication. These technologies allow real-time data acquisition and monitoring of field operations [34]. One notable example is the GreenStar 2 system, an embedded computer platform that uses ISOBUS and GIS technologies to control and document all tasks carried out by the tractor in the field [149].

### 5.13. Computerized Prediction Systems

These involve implementing algorithms for simulating crops' growth and productivity in software applications. To do this, models of the growth and development of each type and variety of crop are required. These models should start from the seed and reach the fruit production level. Such mathematical models, supported by knowledge bases, provide simulations of future states of crop plants based on their current phenological characteristics. An example of such mathematical models includes statistical regression models. These models also allow for modifying initial phenological conditions, thus evaluating multiple scenarios to determine the most favorable one. Producers can then make decisions and undertake activities in crop management that lead to the best of these scenarios. These systems offer evaluation and planning of harvests and planting to provide optimal control over production [150–152].

### 5.14. Systems for Efficient Use of Water and Energy Resources

This category focuses on all the techniques that can be applied to feed software tools by combining different sources of information and data. These tools allow decision-making to optimize resource use, especially energy and water [153]. An example of the data needed in these cases is the daily electricity price in a specific country, for which access to information from the electricity market, where indexed prices are determined, is required. This information is used to estimate the daily cost of energy used in planned crop activities. Using data analytics, short-term estimates can be made based on the historical behavior of the electricity price time series provided by the corresponding regulatory authority.

Another example of this data type could be provided by dose calculation models for irrigation and fertilization, which estimate the fertilizer and irrigation requirements for a specific crop [154]. Combining these two types of data would allow for planning irrigation and fertilization timings and durations during hours when energy is cheaper but adjusted to the crop's nutritional needs under given conditions. This way, the producer can reduce production costs, given the significant impact that energy costs have on the total cost of cultivation, estimated to be around 40%.

### 5.15. Systems for Fertilization and Irrigation of Crops

For this aspect, producers can apply software technologies that implement algorithms to estimate the required doses of fertilization and irrigation for a particular crop. This estimation is based on the soil's capabilities and the crop's water requirements, among other factors. These tools primarily calculate crop irrigation's volume, duration, and frequency. They also calculate the quantities of nutrients required per unit of volume, with the fundamental nutrients being nitrate and potassium.

### 5.16. Feasibility and Barriers to Implementation in Colombia

Notwithstanding the advantages of precision agriculture technology [155], their deployment in Colombia encounters many obstacles that must be recognized. These encompass economic, physical, institutional, and social obstacles that hinder such solutions' scalability and long-term viability. In this context, economic obstacles are especially pronounced in rural regions. Many smallholder farmers cannot afford expensive sensors, automated equipment, or subscriptions to digital platforms. Even inexpensive alternatives may be prohibitively costly without subsidies or governmental assistance.

Infrastructure constraints, like intermittent internet connectivity, inadequate road access, and restricted electrical supply in rural areas, impede the implementation of IoT systems, remote sensing platforms, and real-time monitoring networks. Institutional obstacles encompass the absence of national strategies for digital agriculture, disjointed

information systems, and insufficient incentives for public/private partnerships that may facilitate extensive technology adoption. Social and cultural impediments are also evident. The digital literacy of farmers is inadequate, and there is frequently mistrust over the adoption of unfamiliar technologies. Inadequate training, suboptimal user interfaces, and insufficient community engagement can hinder the effectiveness of even the most sophisticated solutions. In conclusion, overcoming these obstacles necessitates collaborative endeavors among state institutions, academic entities, business sector participants, and international development organizations.

## 6. Early Warning Systems for Precision Agriculture

Early warning systems (EWSs) represent planned and coordinated processes and activities designed to minimize the impact of certain natural phenomena on a community or a specific production system, particularly in agriculture [156]. EWSs must act preventively, not reactively, to mitigate impacts or adapt social and economic processes. In other words, the EWS should manifest itself before the occurrence of considered adverse events [157].

EWSs consist of four concrete phases for their operation. The first phase is monitoring and supervision. This phase involves measuring specific meteorological variables using climate sensors [158]. Examples of these sensors include humidity, precipitation, and temperature, among others. The data detected in this phase feed into the second phase. This second phase uses mathematical models and their algorithmic implementations to forecast future weather conditions based on the data detected in the first phase. The system automatically generates an alert based on its forecasted state. This alert issuance constitutes the third phase of the process, which leads to the fourth phase, corresponding to adaptation and mitigation measures.

Early warning systems have weather stations equipped with climate sensors, as mentioned earlier, but they also have databases with information on climatic variables from previous moments. These data constitute a dataset. Real-time measurement of atmospheric variables, combined with historical data, feeds software that implements an expert system. It is also essential to have information about the state of the crop provided by the producers through remote systems connected to the principal information system [35]. This system executes predictive algorithms based on previously developed mathematical climate models by experts. These algorithms have the primary function of deducing future weather conditions. This process results in issuing an alert informing producers of the potentially harmful future situation and advising them on the actions to minimize the impact.

These EWSs primarily analyze agricultural and climatic information in combination to determine the degree of vulnerability of producers at regional and local levels. Therefore, they predict possible agricultural and climatic scenarios, considering the variability and climate change experienced in these times. The EWS generates vulnerability indicators that indicate the impact of the climate on producers. Based on this information, producers manage land and water resources in crops comprehensively. It also enables the planning and execution of actions to mitigate pests and diseases related to climate. With a view of the future climate, producers can leverage agricultural biodiversity and use the genetic resources they already must meet the specific needs posed by each forecast. Finally, by combining all the above, producers can design and implement various technological options that help them adapt to and mitigate climate change.

The implementation of EWSs in Colombia, namely in the southern region of Atlántico, remains in the experimental phase; nonetheless, analogous systems have been effectively established in other developing nations encountering similar agricultural and climatic difficulties. Kenya has established SMS-based early warning systems to provide timely

weather notifications to smallholder farmers, markedly decreasing crop losses and enhancing preparation [11]. In Vietnam, the EWS is incorporated with national meteorological data and decision-support tools specifically designed for rice and coffee producers [159]. These systems deliver real-time notifications and suggest mitigation strategies based on predictive algorithms.

## 7. Conclusions and Future Work

The topic of precision agriculture, which is essential in developing countries to overcome conditions of poverty and increase agricultural productivity, is a relatively recent area of scientific and technological research. The first publications date back to the late 1990s, and it was only after 2010 that a significant increase in research related to the topic became evident. Throughout this review, we have seen the needs of the agricultural sector to integrate technology into its activities, allowing for better management of field production processes and supporting producers' decisions with more objective criteria than mere experience, as was the case until a few years ago. Information systems applied to agriculture improve resource efficiency, help mitigate environmental impact, and make agricultural activities more rational. It is a process of industrializing the field. This study area opens up opportunities for innovation and research in countries like Colombia, where the level of field technology is still low. This literature review has identified the needs and requirements that must be met for precision agriculture to become a reality in Colombia. It has also been possible to describe the technical implementations necessary to achieve this technological advancement. One technological system that has received particular attention is early warning systems (EWSs) due to the need for farmers to know the impact climate change will have on their agricultural work. EWSs are essential because they align with other requirements of precision agriculture, as they share standard variables that need to be measured. Therefore, EWSs represent a first step toward a more technologically advanced rural sector. Other complementary systems can be integrated with EWSs, achieving a more comprehensive solution.

As an opportunity for future work, the integration of EWSs with the actuating devices implemented in the field for crops and agricultural activities is envisioned. This integration would enable automated decision-making based on historical measurements and predictions made by the system. Thus, all agricultural planning would consider past climatic conditions and possible future scenarios. In addition, we intend to empirically validate certain precision agriculture technologies highlighted in this review, emphasizing early warning systems (EWSs) and economic IoT infrastructures.

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post-publication stages; visualization, J.D., Y.Q., E.D.-I.-H.-F., S.B.-A., T.M. and D.S. Preparation, creation and/or presentation of the published work, specifically visualization/data presentation; supervision, D.S. and Y.Q. Oversight and leadership responsibility for the research activity planning and execution, including mentorship external to the core team; project administration, J.D., Y.Q., E.D.-I.-H.-F., S.B.-A., T.M. and D.S. Management and coordination responsibility for the research activity planning and execution; funding acquisition, J.D., Y.Q., E.D.-I.-H.-F., S.B.-A., T.M. and D.S. All authors have read and agreed to the published version of the manuscript.

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