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TOPICAL REVIEW

Agro-Technological Systems in Traditional Agriculture Assistance: A Systematic Review

NAYELI MONTALVO-ROMERO[1], **AARÓN MONTIEL-ROSALES**[1], **RUBÉN PURROY-VÁSQUEZ**[2], **AND POMPEYO QUECHULPA-PÉREZ**[3]

[1]Division of Postgraduate Studies and Research, National Technological of Mexico/HTI of Misantla, Misantla 93821, Mexico
[2]Academic Direction, National Technological of Mexico/HTI of Zongolica, Zongolica 95005, Mexico
[3]General Direction, National Technological of Mexico/HTI of Zongolica, Zongolica 95005, Mexico

Corresponding author: Aarón Montiel-Rosales (ar.chimedes@hotmail.com)

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ABSTRACT Guaranteeing food security from agriculture in an uncertain context, derived from the effects of multiple factors, is a challenge. Traditional agricultural production is the one that faces the greatest challenges, derived from the scarce evolution in agricultural practices, despite being the one that contributes the most to the availability of food, at 80%. This systematic review aims to identify and analyze agrotechnological systems belonging to precision agriculture, which may be potentially adaptable to traditional rural agriculture. Contributions that improved crop yields from scientific and technological studies were analyzed. The PRISMA statement was used as a formal outline to collect and analyze 114 studies from the period 2018-2023. From the review, it was identified that there is a growing trend in the adoption of intelligent systems that help producers in the management of crops, accentuated in the increase of crop yield, in the determination of product quality, and in the management of water resources, mainly. Likewise, it was identified that the preponderant approach is the monitoring and control of crop development. This is achieved through emerging technologies, such as the Internet of Things, artificial intelligence, and machine learning, with information mainly collected by sensors embedded in drones, algorithms, decision support systems, sensors, and Arduino technology systems. Finally, this review shows that there are five viable systems that can be adapted to traditional agriculture to strengthen agricultural production. Therefore, the adoption of scientific-technological contributions from precision agriculture contributes to ensuring food security.

INDEX TERMS Agricultural applications, food security, precision agriculture.

I. INTRODUCTION

Traditionally, agricultural food production is an activity humanity has been carried out since it has settled in a single place. *Homo sapiens* began to expand around the world less than 100,000 years ago, despite this it was not until 13,000 before the common era when the Agricultural Revolution began [1]; the post-ice age in *ad hoc* to Holocene climates in stationary tropical and temperate latitudes, mainly [2]. Since then, various agricultural practices have emerged worldwide in diverse cultures. Within this framework, natural resources have been exploited to meet the demands for food production. A situation that is capable of degrading the earth affect the environment and the connection between humanity and nature [3]. During the Neolithic, substantial changes occurred in food production, the management of natural resources, and settlement patterns, resulting in intensive agricultural systems [4]. Globally, food insecurity is growing, requiring an increasing food supply. We are seven years away from achieving the goals established by the United Nations in the "2030 Agenda for Sustainable Development", aligned with eradicating hunger, food insecurity, and all forms of malnutrition —targets 2.1 and 2.2 of the Sustainable Development Goals (SDGs)— and we are still far from achieving this. In this sense, considering that in 2022 the world population was more than 7,953 billion, while by 2050, a population

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of 9,700 billion inhabitants is estimated [5]; date, by which the FAO (Food and Agriculture Organization of the United Nations) estimates that at least 50% more food for humans and animals, as well as biofuels, will have to be produced than in 2012; using for this, a cultivation area of 1,732 million hectares [6].

In addition, in 2021the FAO estimated that about 8.9 and 10.5% of the world's population suffered from hunger [7]; in that same year, the total estimate of food insecurity of the world population reached 29.3% —representing 11.7% severe food insecurity, while the rest experienced moderate food insecurity— [8]. In 2022 in the Global Report on Food Crises, the alarming deterioration of food insecurity as a result of the intensification of conflicts, economic crises, extreme weather events, or a combination of these was highlighted; while the 2021 supply chain fractures related to the Covid-19 pandemic led to an increase in commodity prices [9], further exacerbated by the war in Ukraine, to such an extent that the increase in food prices affected 47% of countries by 2020 [10], which exacerbated access to food for the most vulnerable families, threatening to worsen food security.

According to World Bank data, from October 2022 to February 2023, in low-income and middle-income countries, inflation levels were above 5% —in 94.1% of low-income countries, 86% in lower-middle-income countries, and 87% in upper-middle-income countries—; while approximately 87.3% of high-income countries had an increase in food price inflation [11].

This situation is alarming since it represents that approximately 2.3 billion people went hungry, ran out of food, and went a day or more without eating. Likewise, despite a decrease from 33% in 2000 to 22% in 2020 in stunting in children under five, there is still a 50% child stunting in some countries [8]. In addition, it is estimated that by 2030 approximately 670 million people will be undernourished [7]. Thus, generating pressures on agricultural production with impacts on the environment is associated with a high demand for food by a growing population.

Therefore, ensuring food security from increased agricultural productivity through sustainable practices is crucial. However, this is complex due to the interaction of multiple factors compromising the achievement of targets 2.1 and 2.2 of SDG 2, "Zero Hunger". Concerning this, in the Agricultural Outlook 2022-2031, it is mentioned that population growth and food consumption are factors attributable to the degradation of natural resources and the increase in greenhouse gases [12]; while in The Sustainable Development Goals Report 2022, FAO is attributed to the degradation of global food security due to conflicts, Covid-19, climate change and growing inequalities, which have converged [10]. To this, agriculture faces the challenge of providing food without compromising the agroecosystem's long-term sustainability and resilience [13].

The challenges of meeting the food needs of the present and future generations are compromised. The primary sector faces the reality of satisfying a growing demand for food, conditions derived from climate change, degradation of natural resources due to indiscriminate overexploitation, loss of biodiversity, and inefficiency of the agri-food logistics system which has increased food waste. In addition, it is estimated that between 2020 and 2050, 53% of people living in urban areas will increase to 70% [14], further undermining agri-food systems.

The FAO estimated that between 2000 and 2020, primary crop production increased globally by 52%; this is attributable to a combination of factors, *e.g.*, a greater use of irrigation, pesticides, and fertilizers in the face of a smaller cultivated area; the latter factor, derived from the fact that population growth was faster than the area of farmland; therefore, the area of arable land per capita in 2020 on average was reduced by 18% [8]. Despite the growth in food supply, this is not enough. By 2050, the food supply should increase by 50% compared to that in 2012 [15].

The agricultural sector is the largest source of employment in the world, supporting 40% of the current population [16]. Representing, for rural households, the largest source of income. Given this situation, in the United Nations World Report on the Development of Water Resources 2019, it is mentioned that more than 80% of all farms around the world develop Traditional Agriculture (TA) with an area of less than two hectares; these small farmers contribute more than half of agricultural production in many countries [17]. Therefore, the TA provides up to 80% of the food consumed worldwide [16].

Considering the importance of the agricultural sector. Over time, multiple efforts have been developed and applied to increase the yield of agricultural production, with a greater boom —in recent times— focused on sustainability. Given this situation, incorporating scientific/technological approaches into agricultural practices has been presented as a valuable strategy capable of improving crop yields under an ecosystem approach. In [18], advancement in technological developments is considered to impact the development of the agricultural industry.

Agriculture has evolved hand in hand with science/ technology (Figure 1) through Agriculture 1.0 [19], [20], [21], [22], [23], Agriculture 2.0 [24], [25], [26], [27], [28], Agriculture 3.0 [29], [30], [31], [32], [33], Agriculture 4.0 [34], [35], [36], [37], [38], until today called Agriculture 5.0 [39], [40], [41], [42], [43]. In this sense, agricultural automation includes using machinery and equipment that improve agricultural activities —diagnosis, decision-making, and execution— thereby reducing the heavy workload while improving the accuracy of agricultural activities [44]. Adopting machinery and equipment as an intelligent strategy leads Precision Agriculture (PA).

In each stage of evolution, agricultural yield has been improved in tandem with agricultural scientific/technological development. In [45], it is established that the next phase of the evolution of agricultural technology is the autonomous management of the field; because the agricultural sector is

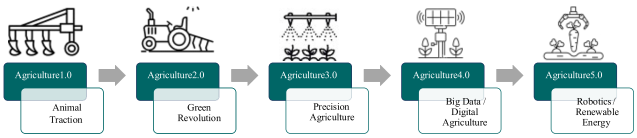


FIGURE 1. **Stages of the evolution of agriculture.**

transitioning towards "smart agriculture" from the adoption of emerging technologies [46]. In [47], it states that agri-food systems are being transformed in order to provide healthier, more affordable, and safer diets aligned with sustainable production. The new era of agriculture is characterized by (*i*) new concepts of cultivation and harvesting, (*ii*) robotics, (*iii*) renewable energies, (*iv*) interconnected intelligent systems, and (*v*) animal welfare through technological systems [48].

Agriculture has transformed the planet on which we all live [49]. It is a reality that agricultural practices have evolved. Current knowledge about good agricultural practices results from the knowledge and experience of ancestral generations, who, in an "empirical" way, *i.e.*, by trial and error, have perfected the practice of crops according to the relationship between the crop and the conditions of the ecosystem.

While it is true that the technification of modern intensive agro-production of crops has had a vertiginous exponential growth that has increased production volume, it is also true that, despite this, the demand for food cannot be fully supplied. This situation is attributable to the fact that Industrial Agriculture (IA), as a link in the Global Agri-Food Chain (GAFC), is a part of a long logistics chain. The GAFC is integrated by multiple interrelated activities that begin in the field of cultivation until its exhibition at fixed points of sale through multiple transports between the different links of the logistics chain —*e.g.*, field-packing, field-processing, imports-exports, distribution centers-marketing points—. In this regard, these situations show a long GAFC —in time and distance— and fragile, a situation that limits its ability to immediately supply food requirements, a situation that is exacerbated by atypical events.

In parallel, traditional agricultural production has limited development and growth; and this production system has stagnated. The modes and forms of the practices of the TA remain ancestral to such an extent that draught animals are still used for plowing the land and are used as rudimentary tillage utensils, where the producers provide the care and determination of crop requirements. Despite the limited evolution of the TA production system, the model has the strength of providing a variety of crops through environmentally sustainable practices — *e.g.*, from the use of organic fertilizer— allowing its proximity to quickly complements the requirements.

A. REVIEW STRATEGY

So, considering that there is an incomparable technological evolution between the production models of AI and TA and that there is a recent vertiginous growth of technologies applied to agriculture, this review study has been inspired by the objective of identifying and analyzing the scientific/technological contributions that have been successfully developed and applied in agriculture, and that can be adaptable and assimilated to the TA of small rural producers, considering their context and infrastructure, as well as identifying the existing knowledge gap. As far as we know, some studies evaluate the adoption of PA, but it is not analyzed from TA in small-scale crops [50]. This systematic review is aimed at researchers interested in developing projects that improve the yield of small-scale crops from their technification and aims to serve as a basis for developing social policies from political actors and social associations. In addition, this study may lead to more in-depth and detailed reviews of the technologies applied to other agricultural subsectors. This study adopts a strategy of regressive analysis of the secondary data of published contributions. The systematic review of the literature allows, as an analysis strategy, a deep understanding of this phenomenon. This approach guarantees a formal and structured review that allows to extraction reliable and reliable information from the features of the studies of agro-technologies reported in the articles and patents, which have the potential to be adaptable to traditional rural agriculture to increase its yield.

In addition, from Section I Introduction, the rest of the document is organized as follows: Section II describes the formal PRISMA methodology used to collect the studies; Section III presents the findings identified in the studies reviewed; Section IV describes the evidence and limitations of the study; finally, Section V concludes the systematic review study between the transition from modern production technology to traditional agricultural production.

II. MATERIALS AND METHODS

A formal systematic review was conducted following the Systematic Review of the Literature (SRL) [51] and adhered to the recommendations of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines (PRISMA) [52]. The protocol was registered in osf.io/acms7/ (accessed on August 3 2023) [53].

A. ELIGIBILITY CRITERIA

The PICO approach (P: population, I: intervention, C: comparator, O: outcome) was used to establish eligibility criteria and assess the effects of interventions and comparisons [54].

Studies that met the following inclusion criteria were considered for the review: (*a*) studies with agricultural scientific/technological applications/developments, (*b*) studies with cutting-edge/innovation approaches, (*c*) studies with strategies for viable uptake and adoption by smallholder farmers, and (*d*) studies that improve crop yields. Studies that met the following exclusion criteria were excluded from the review: (*a*) studies that are of complex adaptation to crop areas less than two hectares, (*b*) studies with applications to specific monocultures that are difficult to adapt to polycultures, (*c*) studies with empirical or theoretical results, obtained from simulated scenarios, and (*d*) biotechnologies that consider, *e.g.*, the use of bacteria and gene modification in increasing crop yield.

The literature search was not limited by discipline or subdiscipline. However, it was limited to English language studies and a 5-year search period (2018-2023), and original research studies and intellectual property registration, *i.e.*, literature review studies, book chapters, books, non-peer-reviewed articles and conference proceedings were not considered in this review.

B. INFORMATION SOURCES

The retrieval of scientific studies for the review was conducted using: Web of Science (WoS), Scopus, ScienceDirect, and SpringerLink; as which contain a large number of relevant peer-reviewed indexed journals. Meanwhile, technological studies were recovered from the World Intellectual Property Organization (WIPO) database, the world's primary source of intellectual property registration.

Given the rapid exponential growth of smart agriculture, a 5-year search period was established, *i.e.*, from January 2018 to May 2023; thus, it excluded outdated information that could be irrelevant. The databases were consulted during May 2023, as follows: on May 23, the search in WoS [55] was performed by N.M.-R. and A.M.-R.; on May 25, the search was conducted in Scopus [56] by N.M.-R. and R.P.-V.; on May 26 we searched ScienceDirect [57] by N.M.-R. and A.M.-R.; on May 27 the search was conducted on SpringerLink [58] by A.M.-R. and P.Q.-P.; and WIPO [59] was searched on May 28 by N.M.-R. and A.M.-R.

C. SEARCH STRATEGY

The key terms used in the search included words closely related to the main domains of the study. This study considers multiple electronic databases, which helps authors ensure that relevant studies are included in the systematic review. The authors selected the keywords for the bibliographic search in joint agreement. The search strategy for each type of database was designed by A.M.-R. and reviewed by N.M.-R. The search code defined for the keywords considered the use of the Boolean operators "OR", "AND", and "NOT": OR, was used for those concepts that shared similar notions and thus recovered a broad vision of studies; AND, was used to include other concepts; NOT, was used to exclude concepts that are not related to the object of study (see Table 1).

D. SELECTION PROCESS

The studies were individually reviewed to minimize the risk of missing important information. The study selection was based on the relevance of the results aligned with the purpose of this systematic review. Researchers N.M.-R., A.M.-R., and R.P.-V. conducted independent review and screening reviewed titles, abstracts, and keywords; we excluded those studies that did not meet the inclusion criteria. At the same time, those studies that met the inclusion criteria were considered for the review. Once the studies to be reviewed were defined, we proceeded to carefully read each complete article individually, extracting the information related to the objective of this review. The investigator P.Q.-P. intervened when the split decision of inclusion or exclusion of a study was presented. The Delphi method [60] resolved complex decision-making situations through consensus.

E. DATA COLLECTION PROCESS

After study selection, three investigators (A.M.-R., R.P.-V., and P.Q.-P.) independently extracted the information with triple verification, whereas a researcher (N.M.-R.) supervised. The data were aggregated into a knowledge matrix consisting of a structured and standardized form in Microsoft® Excel® for Microsoft 365 MSO (16.0.12827.20236) 64-bit [61]. Zotero 6.0.23 [62] was used to manage the bibliographic references of recovered studies.

F. DATA ITEMS

The four scientific studies databases were combined. Then, in this review, two final databases were integrated, one with the features of the studies of (*i*) scientific contributions —WoS, Scopus, ScienceDirect, and SpringerLink— and another based on the (*ii*) technological contributions —WIPO—. Duplicate studies were removed manually. The data extracted from the scientific studies were "Year", "Country", "Publishing", "Journal", "CiteScore", "Impact Factor", "Title", "Objective", "Sector", "Category", "Application", "Crop", "Cultivation System", "Conditions", "System", "Tool", "Objective Function", "Input Variable", "Output Variable", "Contrast System", "Performance (%)", and "Resource". While, a database was formed to concentrate the features of technological developments, being the data extracted from technological studies were "Office", "Application Number", "Application Date", "Publication Number", "Publication Date", "Applicants", "Inventors", "Title", "Objective", "Sector", "Application", "System", "Tool", "Input Variable", "Output Variable", and "Resource".

G. STUDY RISK OF BIAS ASSESSMENT

Risk of bias assessment allows the assessment of the effects of an intervention, which is a primary component of a systematic review [63]. In this review, we established strategies to limit this situation to avoid the risk of bias and random errors. The strategies involved an exhaustive search of the studies in various scientific/technological databases that are of quality —this, evidenced by its rigorous evaluation and publication process—, the inclusion and exclusion criteria were reproducible and explicit; likewise, the design and characteristics of the studies were valued; and finally, the results of the studies were synthesized and interpreted.

H. EFFECT MEASURES

For each study, the effect of the results was measured, *i.e.*, crop yield improvement.

TABLE 1. Database search strategy.

Type of Study	Database	Search Algorithm
Scientist	WoS	ABS-KEY (“Agriculture” OR “Crop” OR “Smart Agriculture” OR “Precision Agriculture” OR “Agrotechnology”) AND NOT TITLE (“Review”) AND ALL FIELDS (“Technology” AND “Performance”)
	Scopus	ABS-KEY (“Agriculture” OR “Crop” OR “Smart Agriculture” OR “Precision Agriculture” OR “Agrotechnology”) AND NOT TITLE (“Review”) AND ALL (“Technology” AND “Performance”) AND PUBYEAR AFT 2018
	ScienceDirect	ABS-KEY (“Agriculture” OR “Crop” OR “Smart Agriculture” OR “Precision Agriculture” OR “Agrotechnology”) AND NOT TITLE (“Review”) AND ALL FIELDS (“Technology” AND “Performance”)
	SpringerLink	(“Agriculture” OR “Crop” OR “Smart Agriculture” OR “Precision Agriculture” OR “Agrotechnology”) AND (“Technology” AND “Performance”) AND NOT (“Review” OR “Literature” OR “Bibliometric”) AND (“Low Cost”)
Technological	WIPO	(“Agriculture” OR “Crop”) AND (“Agriculture 5.0” OR “Precision Agriculture” OR “Technology”) AND (“Low cost” AND “Easy to use”)

TABLE 2. Search parameters.

Parameter	Specification	
	Science	Technology
Search period	January 2018 to May 2023	January 2018 to May 2023
Database	WoS, Scopus, ScienceDirect, and SpringerLink	WIPO
Search words	“Agriculture”; “Crop”; “Smart Agriculture”; “Precision Agriculture”; “Agrotechnology”; “Technology”; “Performance”; “Low Cost”	“Agriculture”; “Crop”; “Agriculture 5.0”; “Precision Agriculture”; “Technology”; “Low cost”; “Easy to use”
Search terms	TITLE-ABS-KEY / ALL FIELDS / PUBYEAR AFT	Not applicable
Search method	Boolean operators (AND – OR – NOT)	Boolean operators (AND – OR)
Type of study	Original articles	Patents
Discipline	No restriction	Not applicable
Subdiscipline	No restriction	Not applicable
Language	English	English
Country	No restriction	No restriction
Revision	Peer review	Not applicable
Selection of studies	Made by N.M.-R., A.M.-R. and R.P.-V., verified by P.Q.-P.	Made by N.M.-R., A.M.-R. and R.P.-V., verified by P.Q.-P.

I. SYNTHESIS METHODS

Hermeneutics was applied as a method of interpreting texts. Then, a narrative synthesis of the studies was performed following the guidelines of the PRIMA statement. The retrieved information was extracted and processed in sections of interest, and the information of the studies was analyzed independently and together, thus obtaining the findings of the review article. The findings of the studies were presented in the form of tables and graphical representations from the descriptive statistics developed in Microsoft® Excel® for Microsoft 365 MSO (16.0.12827.20236) 64-bit.

J. CERTAINTY ASSESSMENT

Two investigators (R.P.-V. and P.Q.-P.) independently assessed the certainty of evidence from the retrieved studies.

III. RESULTS

In this section: (*a*) the results of the search and selection process of the studies that make up the review, considering the inclusion and exclusion criteria; (*b*) the characteristics of the studies are described individually and analyzed in subgroups of interest, synthesizing the findings in tables and graphs; and (*c*) study quality is assessed.

A. STUDY SELECTION

1) SEARCH

The search parameters that define screening for the selection of the studies that make up the review are presented in Table 2. The search parameters were established in consensus by the research team, these being: ‘‘Search period’’, ‘‘Database’’, ‘‘Search words’’, ‘‘Search terms’’, ‘‘Search method’’, ‘‘Type of study’’, ‘‘Discipline’’, ‘‘Subdiscipline’’, ‘‘Language’’, ‘‘Country’’, ‘‘Review’’, and ‘‘Selection of studies’’.

2) ELIGIBILITY

The PICO strategy (Table 3) was implemented to define the inclusion and exclusion criteria for the studies under review. The screening of the studies was improved by considering these criteria; in this sense, the screening process was strengthened.

3) SELECTION

Figure 2 shows the selection process of the studies considering previously established search strategies and eligibility criteria.

The selection process began with 6,552 identified articles from science studies —2,170 from WoS, 1,723 from Scopus, 590 from ScienceDirect, and 2,069 from SpringerLink—. Of these studies, 94 were considered for the systematic review and meta-analysis —34 from WoS, 10 from Scopus, 7 from ScienceDirect, and 43 from SpringerLink—. When the four databases were combined, 3,473 were eliminated for duplication, and after a process of relevance analysis, 584 studies were eliminated. In addition, 1,946 studies were excluded because they did not align with the objectives of the study.

TABLE 3. Eligibility criteria.

PICO	Inclusion Criteria	Exclusion Criteria
Population	Low-cost, easily assimilated/adopted agricultural scientific/technological applications in small-scale polyculture production	Agricultural scientific/technological applications of intensive monoculture production complex to scale at a small scale, and in which they also contemplate studies of animal production and floriculture
Intervention	Studies with scientific/technological applications/developments aligned to Agriculture 5.0; that demonstrate improvement in agricultural crop yields	Studies with agricultural scientific applications derived from assumed, empirical or theoretical scenarios; and studies with biotechnology applications
Comparator	Performance of the application/scientific/technological development in crop yield	None
Outcome	Scientific/technological applications/developments, easily assimilated/adopted by rural agro-producers with basic or no knowledge of technology	Complex scientific/technological applications/developments to be assimilated/adopted by rural agro-producers with basic or no knowledge of technology

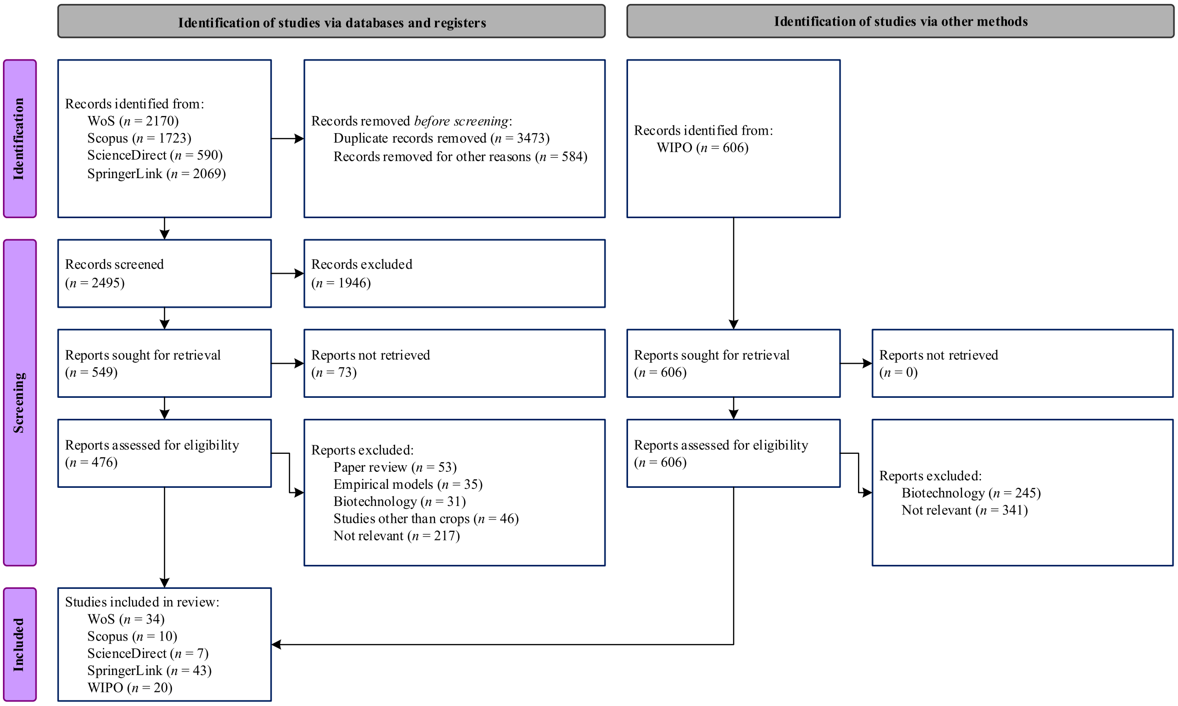


FIGURE 2. Flowchart of the selection of studies considered for review.

In addition, 73 studies could not be retrieved from their links. Ultimately, 382 science studies were not considered. We excluded review studies, articles considering empirical models, biotechnology use/development, studies other than crops, and non-relevant articles.

Meanwhile, 606 patents were identified as technology studies obtained from the WIPO consultation system. Of these studies, 20 were considered for a systematic review and meta-analysis for their relevance. Finally, 586 technology studies were not considered; patents focused on technological developments addressing the development/application of biotechnology, and studies that were irrelevant to the review, were excluded.

B. STUDY CHARACTERISTICS

Once the studies are selected, the following is integrated: (*a*) a scientific knowledge base with the records of: "Year", "Country", "Publishing", "Journal", "CiteScore", "Impact Factor", "Title", "Objective", "Sector", "Category", "Application", "Crop", "Cultivation System", "Conditions", "System", "Tool", "Objective Function", "Input Variable", "Output Variable", "Contrast System", "Performance (%)", and "Resource"; and, (*b*) a technological knowledge base with the records of "Office", "Application Number", "Application Date", "Publication Number", "Publication Date", "Applicants", "Inventors", "Title", "Objective", "Sector", "Application", "System", "Tool", "Input Variable", "Output Variable", and "Resource". In osf.io/acms7/ (accessed on 3 August 2023) [53] are "Database_Science" and "Database_Technological_Developments" for more information.

Thus, this section describes and analyzes the features of the studies collected, which allow the identification and analysis of scientific/technological contributions developed and applied in industrial agriculture, that can be scalable to small-scale production by rural agro-producers, being low-cost and easy assimilation/adoption.

1) GEOGRAPHICAL DISTRIBUTION OF STUDIES

The 114 studies retrieved in the review are distributed worldwide, with a significant presence in China, in article and patent publications. It was identified that 38.30% of the published articles come from China; 12.77% from India; 8.51% from the USA; while Italy, Pakistan, and Spain, has contributed 4.26%, individually; 3.20% of the studies correspond to Iran, and the UK, respectively; likewise, with 2.14% of contribution individually in Australia and Malaysia; finally, the countries of Belgium, Brazil, Canada, Chile, Colombia, Egypt, Ethiopia, France, Greece, Korea, Mexico, Morocco, New Zealand, Taiwan, Turkey, and Palestine, contributed 1.06%, independently (see Figure 3). Regarding registered patents, 45.00% have been registered with the China office, 40.00% in India; in Australia, Belgium, and Korea, 5.00% have been recorded (see Figure 4).

2) ARTICLES BY EDITORIAL

Scientific studies are published in journals that guarantee rigorous double-blind arbitration so that they contain CiteScore metrics and/or have an Impact Factor (Table 4). Of the 114 scientific studies retrieved: 54 were obtained from Springer Nature, 17 from Elsevier, 10 from the Institute of Electrical and Electronics Engineers (IEEE), 8 from the Multidisciplinary Digital Publishing Institute (MDPI), 3 from Frontiers, and 2 from Taylor & Francis. It is notorious that more than half of the recovered contributions (57.45%) have been published in Springer Nature; while in CiteScore, IEEE Journals are better positioned, and in Impact Factor, Elsevier Journals.

3) EVOLUTION OF STUDIES OVER TIME

In recent years, the scientific/technological contributions have become a topic of interest to the community, with increasing behavior (see Figure 5). Regarding scientific studies from 2018 to 2023, the year 2022 experienced the highest number of published articles with 27.66% (Figure 5a), while, in that same period, technological studies were greater in 2019, *i.e.*, 35.00% of technological developments were patented (Figure 5b).

4) SCOPE OF SCIENTIFIC STUDIES

It was identified that the scientific studies are aligned to 3 sectors, "Crop", "Soil", and "Environmental", in 88.30, 7.45, and 4.25%, respectively (Table 5). Being the "Crop" sector in which more contributions are identified. Then, when aligned by category, this sector derived five types, namely: "Yield" (33.73%), "Alterations" (21.69%), "Detection" (21.69%), "Irrigation" (19.28%), and "Integral" (3.61%).

5) CONTRIBUTIONS OF SCIENTIFIC STUDIES

The purpose of the 94 articles is described in this section, considering the type of sector identified.

a: SECTOR CROP

The 83 studies of the "Crop Sector" were aligned to five applications:

Yield: Studies that focus on increasing crop yield are presented for this application. Gée et al. [69] developed a device to estimate crop growth by considering the presence of weeds and if this influences crop growth. An approach capable of estimating crop parameters is presented by Zhu et al. [91]. Reference [78] described a methodology for predicting crop yield from images. The authors of [68] develop and implemented a wireless network of micro-climatic sensors at the field level to monitor phenological development in a vineyard. Herrero-Huerta et al. [70] predict crop yield from automated phenotyping.

A production system is designed by Mohmed et al. [80], From the modeling and intelligent prediction of crop growth to different factors (*e.g.*, temperature, humidity). Kaur et al. [74], present the design and construction of an intelligent agricultural system of controlled growth supported by Internet of Things (IoT). In [64], underground cultivation data is collected through an integrated system of sensors, aerial vehicles, and remote connections.

An algorithm that extracts crop growth characteristics from a short-term memory model predicts crop yield is described in [65]. Lee et al. [75] describe an algorithm that estimates the growth rate of hydroponic crops in the face of environmental factors. A model that predicts spatial performance is developed by Jiang et al. [73], with the intention of knowing more precisely the management of inputs for the field.

Reference [79] describes a temperature controller for plant growth in enclosed spaces. An intelligent model is used to predict crop yield from multispectral images by Selvaraj et al. [84]. Iniyan and Jebakumar [71] describe an intelligent strategy for predicting crop yields based on phenotypic factors. The authors of [67] present an approach that fuses data from multiple sensors based on Unmanned Aerial Vehicle (UAV) and that with the learning of sets, the accuracy of crop yield prediction is improved. Wang et al. [85] estimate the Leaf Nitrogen Concentration in the growth stages of the crop. A system that improves crop yield is developed that employs emerging technologies in monitoring environmental and agricultural conditions by Raju and Vijayaraghavan [82].

An approach to estimating crop yields using multispectral imaging is presented in [83]. The development of a UAV-LiDAR (Unmanned Aerial Vehicle - Light Detection And Ranging) system is presented, assisted by a novel algorithm used to estimate plant parameters in agricultural studies by Yuan et al. [89]. Lu et al. [77] propose a strategy to improve the accuracy of crop nutrition estimation based on UAVs. The authors of [88] have developed a crop spectral monitoring model based on a light source system. In [90], a model for predicting crop yield, and protein content, has been developed.

Wang et al. [86] estimate the best period to evaluate the nitrogen (N) status of the crop; and, thus, accurately apply nitrogen fertilizers. In [76], the estimation of the Aboveground Biomass of the crop is improved by improving

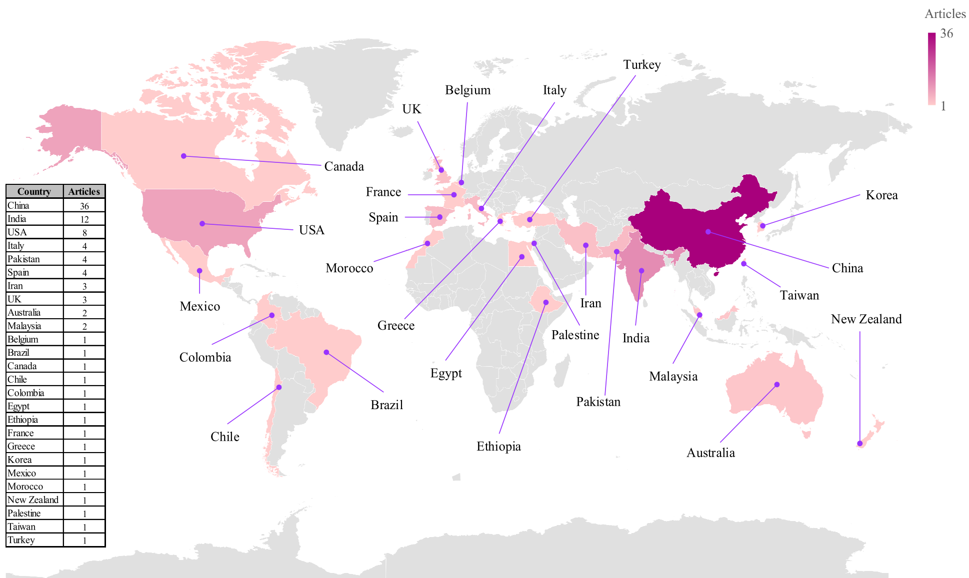


FIGURE 3. **Distribution of studies: articles; in the world.**

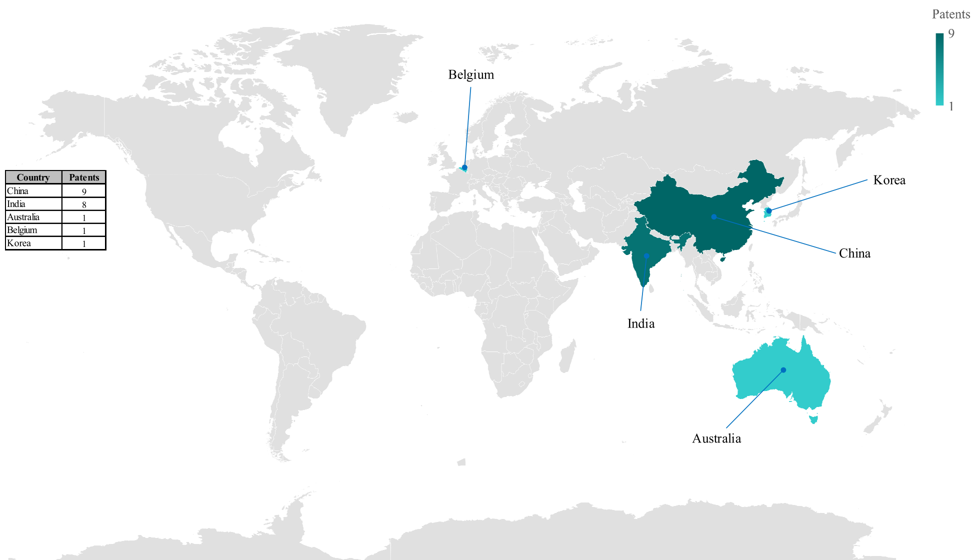


FIGURE 4. **Distribution of studies: patents; in the world.**

the UAV system. The authors of [72] optimize metabolites in leaves and fruits of *Momordica charantia L.* using elicitors. Using high-resolution imaging and information from multiple sensors, Wu et al. [87] estimate the Leaf Area Index, considering the influence of the soil background.

The CROPGRO-Cotton cultivation system model was developed by Rahman et al. [81] to predict, based on the simulation of flowering under suboptimal climatic conditions, the estimation of cotton production concerning the planting date. Whereas Fei et al. [66] propose an approach that improves crop yield prediction, considering hyperspectral data.

Alterations: Studies related to identifying and controlling phenomena that affect the crop are synthesized in this section. Li et al. [104] describe a methodology that detects crops from aerial images for the growth and detection of diseases and pests of the crop. In [96], the development of a system that detects, counts, and calculates the area covered by open and closed stomata of crop leaves is presented. Martinez-Guanter et al. [105] present the design and construction of a hydraulic spraying system of agrochemicals supported in a UAV with specific applications. The performance of the UAV is improved, with an intelligent focus that improves high-resolution multispectral images to detect stress symptoms and variations in their health in plants, by Farooque et al. [98].

In [95], An aerial system for crop pest control is described. Rezk et al. [106] present an intelligent system capable of detecting and predicting diseases in the crop. Whereas, Bao et al. [93], developed a system for the automatic detection of diseases in crops. Describes a system developed

TABLE 4. Journals by editorial.

Editorial	Journal	Metrics			
		CiteScore		Impact Factor	
		Min	Max	Min	Max
Springer Nature	Agricultural Research, Arabian Journal for Science and Engineering, Chinese Geographical Science, Cluster Computing, EURASIP Journal on Image and Video Processing, International Journal of Environmental Science and Technology, International Journal of Information Technology, Irrigation Science, Journal of Ambient Intelligence and Humanized Computing, Journal of Biosystems Engineering, Journal of Food Measurement and Characterization, Journal of the Indian Society of Remote Sensing, Mobile Networks and Applications, Multimedia Tools and Applications, Neural Computing and Applications, Plant Methods, Precision Agriculture, Proceedings of the National Academy of Sciences, India Section A: Physical Sciences, Scientific Reports, Soft Computing, and Wireless Personal Communications.	1.6	9.9	1.291	5.827
Elsevier	Biosystems Engineering, Computers and Electronics in Agriculture, Environmental Research, Field Crops Research, HardwareX, Industrial Crops and Products, Journal of Environmental Management, Journal of Hydrology, Postharvest Biology and Technology, Remote Sensing of Environment, Science of The Total Environment, Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, and Urban Forestry & Urban Greening.	4.2	20.7	4.831	13.85
IEEE	IEEE Access, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal on Emerging and Selected Topics in Circuits and Systems, IEEE Sensors Journal, and IEEE Transactions on Industrial Informatics.	6.1	21.3	3.476	11.648
MDPI	Agriculture, Agronomy, Applied Sciences, Electronics, Horticulturae, and Sustainability.	1.8	5	2.69	3.949
Frontiers	Frontiers in Plant Science, and Frontiers in Water.	8	1.2	6.627	6.627
Taylor & Francis	New Zealand Journal of Crop and Horticultural Science, and Plant Production Science	2.3	3.9	1.094	2.471

TABLE 5. Scientific studies identified by sector of the agricultural process.

Sector	Category	Application	Studies
Crop	Yield	Nitrogen concentration, controlled growth, phenological development, nutrition, and growth rate, among others	[64]–[91]
	Alterations	Diseases, pests, fumigation, fertilizer, and health, among others	[92]–[109]
	Detection	Counting (*e.g.*, bunches, mature crops, seeds), damage (*e.g.*, in harvest, mechanical), extraction of characteristics, crop recognition, and parameters (*e.g.*, environmental, phenology), among others	[110]–[127]
	Irrigation	Water stress, humidity, water monitoring, water requirements, and automatic water supply, among others	[128]–[143]
	Integral	Automatic irrigation, controlled fertilizer, yield alarm system; traceability; and disease detection, water irrigation, and fertilizers	[144]–[146]
Soil	-	Classification, current conditions, monitoring of indicators, soil properties, and salinity, among others	[147]–[153]
Environmental	-	Floods, droughts, weather, and evapotranspiration	[154]–[157]

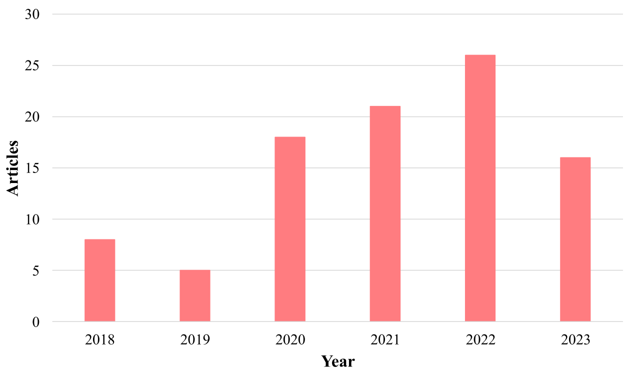
by Su et al. [108] that detects the disease of the crop, taking advantage of aerial visual perception. A feature extraction model, which learns and classifies crop disease status from images using visual models, is detailed in [109]. Costa et al. [97] have developed a methodology to determine nutrient concentrations in crop leaves. In [107], a system that monitors crop health is described.

An automated system that detects pests in orchards is described by Albanese et al. [92]. The authors of [102] develop a novel algorithm that identifies crop diseases. In [94], a tool is developed to detect diseases in the crop in a timely manner to guarantee the crop's healthy development. It is proposed by Hao et al. [100], a new IDSF model based on an enhanced heterogeneous care mechanism (AgHA-IDSF) considering an intent embedding matrix; as a knowledge management approach to pest and disease control. An automatic monitoring strategy based on images that track changes in crop vegetation in the face of changing environmental conditions is described by Larbi and Green [103].

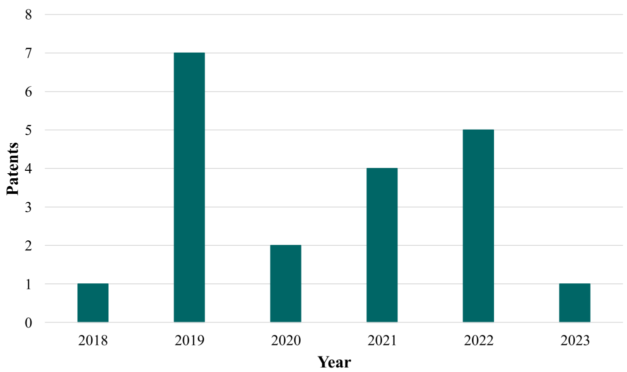
In addition, Gao et al. [99] have developed a weed detection system. At the same time, Hu et al. [101] present a method of detecting and monitoring crops for the robotic determination of spraying.

Detection: In this section, studies focused on the detection of factors related to the crop and its development are described. Shah et al. [125] describe the development of a pneumatic seed dosing machine for crops capable of sowing various types of seeds without changing discs or other parts. [121] describes a universal algorithm identifying various spherical or cylindrical fruits in natural environments. An approach that counts crops in the last stage of growth from images, such as assistance in crop management, is described by Che et al. [112]. A method that combines deep learning and aerial imagery is proposed by Li et al. [120] in the automatic recognition of freeze-tolerant crops.

The development of a comprehensive network system of portable and wireless sensors that monitors environmental parameters remotely, capable of providing crop managers with alerts and information on the current state of the field; finally, the data is stored in a database for future consultation, presented in [116]. Fu et al. [115] present an algorithm that detects crops. The authors of [123] developed a method that



(a) **Articles published per year.**



(b) **Patents registered per year.**

FIGURE 5. Study behaviors by year.

calculates the number of crop seedlings quickly and accurately. In addition, a model has been developed that detects aerial images, trees, and individual species [113]. It is presented by Zhang et al. [127], an approach that improves the time of obtaining images from UAVs. In [124], an approach is presented that detects and correctly segments crop clusters.

Wu et al. [126] monitor and estimate parameters of crop phenology using aerial images, considering defoliant fumigation. The design and development of a solar seeder are described by Javidan and Mohamadzamani [118], which detects crop rows. A system that extracts the main geometric parameters was developed in [114]. It describes a system that detects the maturity and 3D position of the crop by the authors of [117]; information that can be used as input for future robotic crop harvesting systems. Li et al. [119] have developed an approach that improves the UAV system by automating crop bunch counting.

A system that determines crop harvesting and thus assesses crop damage is developed by Biswal et al. [111]. Bai et al. [110] present a method that accurately counts the number of plants in the field from remote images. Whereas, Lin et al. [122] propose a strategy that integrates thermography and YOLOv5s in the detection of mechanical damage (*e.g.*, blows, bruises, cracks, perforations).

Irrigation: Those studies that address strategies for the efficient use of water resources are described in this section. Vivekanandan and Kanaga Suba Raja [143] have developed a management system through a control center that integrates technology in the water irrigation process. In [135], the development of a strategy that allows remote monitoring of water using a drone, which receives signals from miniaturized and biodegradable sensors placed in the crop's soil, is presented. An intelligent irrigation system, which estimates water needs based on climatic and environmental needs, was developed by Bülbül and Öztürk [130]. Kanan et al. [136] present an approach that improves the crop's water use efficiency through wireless communication and sensors.

The authors of [138] optimize irrigation by precisely activating the water valve, employing neural network-based prediction —and adjusted with Fuzzy Logic— of the soil water requirement one hour in advance; structural similarity (SSIM)-based to locate water-deficient regions. An agricultural decision support system is designed by Poonia and Bhatnagar [141] to indicate the crop's water needs and is sent to a smartphone. Camporese et al. [131] model sprinkler irrigation. An automatic irrigation system is developed with sprinklers by Saretta et al. [142]. Ferreira et al. [133] present the estimation of water requirements in crops. To quantify the water requirements of the crop and thereby design the irrigation program, Gong et al. [134] (*a*) develop two models to obtain accurate estimates of crop evapotranspiration and (*b*) evaluate the configuration performance of different models.

In [132], an automated drip irrigation system is described, integrated with real-time water content sensors in the soil. Bettelli et al. [129] have developed a model that characterizes, classifies, predicts the water stress of the crop, and from the above, irrigation is automated. A model of assistance is presented by Mohapatra et al. [140] that from the prediction of soil moisture content over periods with a Neural Network (NN), irrigation is controlled, and SMS notifications are generated for farmers using Fuzzy Logic, in addition to generating statistics; the system can compensate for the amount of water lost through evapotranspiration.

Abdullah et al. [128] describe a monitoring system that controls the switching time of the water pump based on the farmer's knowledge of the flow effect. Likewise, an intelligent irrigation system is proposed by Kashyap et al. [137] from the prediction of the moisture content in the crop's soil. In [139], the integral intelligent irrigation of water and fertilizer in crops improves growth and stable production by developing a system that determines the needs using Big Data.

Integral: Studies addressing comprehensive contributions, *i.e.*, that consider more than one application along the agri-food value chain, are described in this section. In this regard, the authors of [144] developed a system that provides for the crop: recommendations, automatic irrigation, and alarms for optimal performance. Li et al. [146] describe a code-based strategy that addresses crop traceability information along the logistics chain. While a wireless technology platform that monitors physical and environmental variables, detects diseases and automatically controls irrigation and fertilization is presented by Contreras-Castillo et al. [145].

b: SECTOR SOIL

The contributions of the 7 studies of the "Soil Sector" are:

Tziolas et al. [151] present a monitoring scheme for soil indicators. In [148] describes an approach to mapping agricultural soil salinity. Soil properties are predicted by Yu et al. [152], by a wavelength selection method, as an approach to measuring soil properties. A strategy to improve the processing of Visible and Near-infrared (Vis-NIR) spectroscopy in the determination of the content of Soil Organic Matter (SOM) of the soil is described by Zhang et al. [153].

In [150], a system is developed that provides automatic information on users' mobile phones about the current conditions of the crop soil. Abeje et al. [147] present a model that classifies agricultural land. Kisekka et al. [149], considering the space-time relationship, predicted the distribution of soil moisture in crops.

c: SECTOR ENVIRONMENTAL

Finally, the 4 studies of the "Environmental Sector" identified are described below:

An intelligent system that manages data and provides weather forecasts, and evapotranspiration, is developed by Hachimi et al. [157]. The surface heat and water vapor fluxes are estimated in [156], to understand the dynamics of water balance —surface flows allow us to know the relationship between vegetation transpiration and soil evapotranspiration—. Arabameri et al. [154] present four machine-learning techniques on flash flood susceptibility and thus reduce the effect of flooding. Finally, a forecasting model for drought prediction is developed by Dikshit et al. [155].

6) AGRO-TECHNOLOGICAL SYSTEMS REPORTED FROM SCIENTIFIC STUDIES

Of the 94 articles collected, five types of agro-technological systems were identified that group 87 studies, *i.e.*, 92.55% of the approaches of scientific studies are considered viable to be adopted and scaled at the level of the TA of rural agro-producers. These types of systems are: "Drone", "Algorithm", "Decision Support System (DSS)", "Sensors", and "Arduino Technology"; with contribution portions of 34.48, 32.18, 14.94, 11.49, and 6.91%, respectively (see Table 6).

The Drone comprises the Unmanned Aerial Vehicle (UAV), Unnamed Aircraft System (UAS), and Unmanned Aerial Base Stations (UABS). Whereas the Decision Support System (DSS) groups the Farm Management System for Decision-Making (FMSDM), Smart Agricultural System (SAS), and Agricultural Decision-Making Systems (ADMS).

It was identified as part of the agro-technological systems that there are tools that are used collaboratively between these systems and that are frequently used, *e.g.*, Neural Networks, Sensors, IoT, Machine Learning, Deep Learning, Computer Vision, Artificial Intelligence, Machine Vision, and You Only Look Once (YOLO). Finally, the recurring input variables are "images", "temperature", and "humidity"; while it was identified that the output variables follow a trend towards "yield", "water needs", and "diseases and pests".

7) SCOPE OF TECHNOLOGICAL STUDIES

It was identified that the technological studies are aligned to 3 sectors, "Agricultural Monitoring", "Agricultural Monitoring and Control", and "Others", in 55.00, 25.00, and 20.00%, respectively (Table 7).

8) CONTRIBUTIONS OF TECHNOLOGICAL STUDIES

The purpose of the 20 patents is described in this section, considering the sector type identified.

a: SECTOR AGRICULTURAL MONITORING

The contributions of the 11 studies of the "Sector Agricultural Monitoring", are:

Zhou et al. [168] describe a method and device of monitoring (air temperature and humidity) and climate prediction (temperature or humidity) for agriculture in closed facilities (greenhouse). A method and device that generates, reports, and stores agricultural and forestry operation activities, is presented by You [167]. In [164], it shows a method and system of agricultural assistance that receives information on the agricultural activity and the agricultural area where it will be carried out, selection of the robot or robots indicated for the activity, sending information and power for the development of the activity to the robots. Liu [165] developed an intelligent platform for storing and exchanging agricultural information in crop life cycle assistance.

In [160] describes a secure cloud service system for storing and disposing of crop information. A system of evaluation of the classification of the state of the agricultural product (quality) is developed by Ritesh and Saurabh [159] from image processing. An agricultural monitoring apparatus is described by Li [166]. Sourabh et al. [161] feature a real-time device that predicts and monitors water, temperature, and humidity requirements.

The authors of [163] have developed an agricultural monitoring and water irrigation system depending on the crop' s needs. Gopal et al. [162] have developed an intelligent expert system to assess the suitability of fertilizer, depending on the crop type. Narmada et al. [158] describes an expert system of assessing crop suitability that predicts diseases in the crop.

b: SECTOR AGRICULTURAL MONITORING AND CONTROL

The "Agricultural Monitoring and Control" sector focuses on 5 studies, which involve:

Tapaswi et al. [171] present an intelligent crop monitoring and control system; that detects diseases and supplies necessary inputs (nutrients, chemicals, and water). Likewise, Kyeung et al. [169] describe an intelligent pesticide control system; the method that diagnoses the pest inside a greenhouse and, depending on the results, determines the mixture and sprays the agricultural pesticide.

Dhirubhai and Vaghela [172] have developed an intelligent multi-parameter optimization system that improves the

TABLE 6. Agro-technological systems identified in the articles.

System	Tool	Input Variable	Output Variable	Studies
Drone	Capsule Network (CapsNet), Back-Propagation Neural Network (BPNN), Multi-Variable Linear Regression (LM), Random Forest (RF) model, Support Vector Machine (SVM), Aerial Treatment for a High Orchard System (ATHOS), Machine Vision (MV), Generative Adversarial Networks (GAN), Internet of Things (IoT); Machine Learning (ML): Deep Neural Network (DNN), Computer Vision (CV), Gradient Boosting Regression Tree, Adaptively Spatial Feature Fusion Network (ASFFNet), and Degradable Intelligent Radio Transmitting Sensor (DIRTS), among others	Images, Vegetation Indices (VIs), Volumetric Water Content (VWC), Multispectral Imaging (MI), and canopy height metrics, among others	Yield, Nitrogen Concentration (NC), plant height and Leaf Area Index (LAI), Aboveground Biomass (AGB), and plant numbers, among others	[64], [67], [70], [76], [77], [84]–[87], [89]–[91], [93], [95], [97], [98], [104], [105], [107]–[112], [119], [120], [123], [126], [127], [135]
Algorithm	Spiked bottom-up with modified Local Gaussian, Regression (LGR) method, OK_BP (Ordinary Kriging combined with Back-Propagation Network), Region Convolutional Neural Network (Mask R-CNN), and Masked Region Convolutional Neural Network (Mask R-CNN), SlypNet: Mask R-CNN (Region Convolutional Neural Network) and U-Net, Genetic Algorithm (GA) and Artificial Neural Network (ANN), Bayesian Neural Networks (BNNs), Bayesian optimization-based Long- and Short-Term Memory model (BO-LSTM), Deep YOLOv3-tiny (DY3TNet) model, and Inception ResNet v2, among others	Images, humidity, temperature, light radiation, and Normalized Difference Vegetation Index (NDVI), among others	Yield, biomass (dry and fresh weight), water needs, crop detection, and pest identification, among others	[65], [69], [72], [73], [75], [78], [80], [83], [92], [94], [96], [99], [102], [113], [115], [117], [121], [122], [124], [130], [134], [146]–[148], [151], [154]–[156]
Decision Support System (DSS)	LoRaWAN [Long Range (LoRa) using Serial Peripheral Interface (SPI)]; Android, GPS (Global Positioning System), FLA7A: Smart Weather Data Management System with Deep Learning: Feed Forward Neural Network (FFNN), Long Short-Term Memory (LSTM), real-time sensors, Internet of Things (IoT) devices, Big Data (MongoDB NoSQL), Internet of Things (IoT) and Artificial Intelligence (AI): Machine Learning (ML) and Deep Learning (DL) techniques, Virtex-II Pro FPGA (Field Programmable Gate Array), Radial Basis Function (RBF) based Neural Network, and Fuzzy Logic (FL), among others	Images, NPK, temperature, humidity, and pH, among others	Agricultural diseases and pests, yield, water needs, and crop growth, among others	[81], [82], [100], [106], [137], [139]–[141], [143]–[145], [150], [157]
Sensors	Sensors and Communication System, Wireless Sensor Network (WSN) framework with Internet of Things (IoT), Neural Network (NN) (Gradient descent, Variable Learning Rate Gradient Descent) and Fuzzy Logic (FL), Time Domain Reflectometry (TDR), Microcontroller, Automated System, Remote Sensing (RS), Automatic Agrometeorological Station, Automated Irrigation System - Management Allowed Depletion (MAD), and Bioristor, among others	Humidity, meteorological data, soil properties, vegetation index, and CO_2 level of air, among others	Irrigation water productivity, yield, Root Zone Soil Moisture (RZSM), evapotranspiration, and temperature, among others	[66], [103], [129], [131]–[133], [136], [138], [142], [149]
Arduino Technology	Thermo-hygrometers, considering the DHT22 sensor (temperature and relative humidity) – "SEN-GPV (Sensor - Parker model): phenology estimation made using the Parker model, in combination with a spatialized sensor [ATmega328-PU microcontroller with wireless network connection sensors (WSN) and Arduino (LiPo Power shield, XBee shield, SD-RTC shield)]", Internet of Things (IoT) enabled Automated System - Deep Flow Technique (DFT) hydroponics, sensors, and an automatic pH and Total Dissolved Solids (TDS) balancing system, Automated Control System: Internet of Things (IoT) - Microcontroller: Arduino Uno R3, with three sensors: an air temperature and humidity sensor, a light intensity sensor, and a soil moisture sensor, among others	Humidity, soil moisture content, temperature, ultrasonic waves, and plant height, among others	Yield, temperature, total dry biomass, row detection, and watering time, among others	[68], [74], [79], [116], [118], [128]

TABLE 7. Technological studies identified by sector of the agricultural process.

Sector	Application	Studies
Agricultural Monitoring	Operating parameters, agricultural activity, information storage, classification by quality, yield, and remote sensing, among others	[158]–[168]
Agricultural Monitoring and Control	Diseases, fertilizer, water, and fumigation	[169]–[173]
Other	Agricultural robot control, soil analysis, assistance with planting and marketing, agricultural activity, and assistance	[174]–[177]

efficiency of agricultural production. An intelligent irrigation assistance system with wireless sensors that detect and manage the irrigation rate is described in [170]. While in [173], an intelligent insect detection and control system is presented.

c: SECTOR OTHER

Finally, 4 studies that include diverse studies are grouped in the "Other" sector, these being:

In [174], a control system in real-time that monitors agricultural and forestry robots is described. An intelligent interconnection and intercommunication system, which improves the yield of cropland use, is presented by Chen [176], considering soil analysis, assistance in the planting process, monitoring, and marketing process. A method and system of using autonomous robots in agricultural mobile production are developed by Sinan et al. [175]. Whereas, Wen et al. [177]

describe a multifunctional control device to assist agricultural production.

9) AGRO-TECHNOLOGICAL SYSTEMS REPORTED FROM TECHNOLOGICAL STUDIES

Of the 20 patents recovered, five types of agro-technological systems were identified that group 13 studies, *i.e.*, 65.00% of the approaches of technological studies are considered viable to be adopted and scaled at the level of the TA of rural agro-producers. These types of systems are: "Decision Support System (DSS)", "Algorithm", "Arduino Technology", "Drone", and "Sensors"; with contribution shares of 46.16, 23.08, 15.38, 7.69, and 7.69%, respectively (see Table 8).

The Decision Support System (DSS) groups the Intelligent Systems (IS), Smart Farming System (SFM), Hybrid Smart Decision Support System (HSDSS), Expert System (ES), and Intelligent Control System (ICS). It was identified that, as part of agro-technological systems, tools are used collaboratively between these systems and frequently used, *e.g.*, IoT, Neural Networks, sensors, and Machine Learning. Finally, the recurring input variables are "soil", "temperature", and "humidity"; while it was identified that the output variables follow a trend towards "water requirements", "temperature", and "humidity".

C. EVALUATION OF THE QUALITY OF THE STUDIES

N.M.-R. analyzed the quality and relevance of all the articles included in this review, and two authors (R.P.-V. and P.Q.-P.), in a second check, analyzed 50% of the articles each. Multiple studies deposited in various high-quality databases with rigorous selection and publication processes are analyzed to avoid the risk of bias and random errors.

1) MAP OF CO-OCCURRENCES

A co-occurrence analysis is performed to identify the relevant terms of the studies that make up the review. Analysis was performed using VOSviewer version 1.6.19 [178].

Figure 6 shows the co-occurrence map of the scientific studies. The terms of the extracted articles were analyzed, omitting the structure of the abstracts and the copyright statements. The complete counting method was used. With a minimum occurrence threshold of 4 —of the 2610 terms, 93 reach the threshold—. A relevance score was calculated to select the most relevant terms. In total, 52 relevant terms were selected and analyzed, with the main terms being "computers", "electronics", "applications", "internet", "season", and "IoT", with the relevance of 4.21, 2.40, 2.00, 1.50, 1.43, and 1.41, respectively.

Figure 7 shows the co-occurrence map of the technological studies. The terms of the extracted patents were analyzed, omitting the structure of the abstracts and copyright statements. The complete counting method was used. With a minimum occurrence threshold of 4 —of the 829 terms, 63 reach the threshold—. A relevance score was calculated to select the most relevant terms. In total, 46 relevant terms were selected and analyzed, the main terms being "image", "agriculture produce grade assessment system", "agriculture produce", "stationary robot system", "agriculture pod", and "agriculture land", with the relevance of 3.78, 3.56, 3.47, 2.11, 1.95, and 1.61, respectively.

IV. DISCUSSION

Over time and as a consequence of industrialization and growth in population density, there was a need to increase the availability of crops through industrialization —industrial agriculture— using large areas of land, specialized machinery, and technological advances —*e.g.*, Big Data, Artificial Intelligence, Internet of Things, Virtual or Augmented Reality, robots—. Despite this, industrial agriculture has not fully covered the world population' s food requirements because it is part of a long logistics chain, where there are multiple processes from sowing to disposal at points of sale. A situation that has been more than evidenced by the Covid-19 pandemic.

However, from its beginnings to the present, traditional agriculture continues to be the fundamental agricultural practice that continues to be the main source of food production despite having little or no technification in its processes.

The two agricultural production patterns were unbalanced. On the one hand, industrial agriculture is intensive. It uses agrochemicals, employs little labor, focuses on large tracts of land in which a large volume is planted but little variety, uses cutting-edge equipment and machinery, and generate unsustainable levels of pollution and waste due to its characteristic of belonging to a long logistics chain. Traditional agriculture is not so intensive but has a wide variety of products and employs a workforce with little or no technification. Despite the significant differences between these schemes, both contribute to ensuring food security.

However, given the current context of supply-demand behavior, the question arises as: how to produce twice as much food by 2050? To achieve this, it is necessary to improve the performance of agro-productive systems and increase the food supply with the maximum use of resources. Specifically, it is necessary to make the productive system of traditional agriculture more efficient, as it is the system that contributes most to food production and the development of small producers but one that lags furthest behind, being a "forgotten" sector.

The FAO (2022c) [6] emphasizes that human beings are putting agricultural production at risk, resulting land degradation, water scarcity, and climate change. Therefore, the option of expanding the cultivation area is limited; and farmland is being lost to urbanization.

From this systematic review, it has been identified that scientific/technological contributions as tools aligned to precision agriculture contribute to improving the yield and quality of agricultural products from the management of the information generated in the agri-food production process. It coincides with Charania and Li [179], whereas technological advances have enabled the achievement of automated data-driven agriculture, giving rise to this last assistance

TABLE 8. Agro-technological systems identified in patents.

System	Tool	Input Variable	Output Variable	Studies
Decision Support System (DSS)	Deep Learning: Support Vector Machine (SVM), U-NET model; IoT (Internet of Things), and Artificial Intelligent, Cloud Computing and Wireless Sensor Network; AAGA (Agro ANN_ Genetic Algorithm), a hybrid of the Artificial Neural Network (ANN) and the Genetic Algorithm; A PLSR (Partial Least Square Regression) and Fuzzy Logic, Artificial Intelligence System: Artificial Neural Networks, and Multi-Layer Perceptron (MLP), among others.	Land use, image, air temperature, soil moisture and soil type, water, crop data, fertilizers, geographic information, temperature, and humidity, among others	Accuracy of agricultural product size, color and defect detection, evapotranspiration and precipitation, irrigation requirements, NPK (nitrogen-phosphorus-potassium) content, and recommendation of fertilizers according to the type of crop (most suitable, suitable, moderately adequate, and inadequate), among others	[159], [162], [170], [172], [173], [176]
Algorithm	Artificial Intelligence - Big Data, and IoT (Internet of Things), Deep Learning: Neural Network; sensors; and cloud storage with encryption.	Data on land, water, climate, soil nutrients, heavy metals, fertility of cultivated land, air temperature and humidity, soil temperature and moisture, carbon dioxide, illuminance, meteorological data, parameters of the crop, soil, and environment throughout the life cycle of the crop, among others	Data on land, water, climate, population, agricultural economy and agricultural resources, soil nutrients, heavy metals, fertility of cultivated land, and disease recognition, among others	[158], [160], [165]
Arduino Technology	IoT (Internet of Things), ML (Machine Learning), Big Data, and wireless sensors	Temperature, soil moisture, humidity and water level	Water, temperature and humidity requirements	[161], [163]
Drone	Smart Farm Environmental Control Device	Environmental information inside and outside a greenhouse and a thermal image/image of the crop inside the greenhouse	Occurrence of pests and pesticide mixture according to the pest	[169]
Sensors	IoT (Internet of Things)	Temperature, humidity	Multifunctional parameter control	[177]

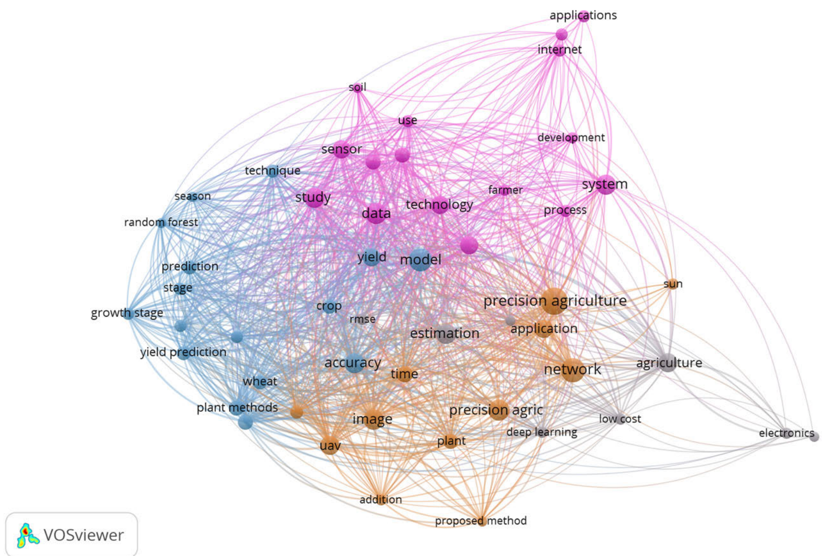


FIGURE 6. Map of co-occurrences of terms of the articles under review.

to a counterpart of precision agriculture, smart agriculture. Technology can improve communication and the relationship between farmers and stakeholders, as well as cited by Ehsan et al. [180]. Smart and efficient agricultural techniques can increase agricultural productivity, coinciding with Gopal et al. [162].

From this systematic review, it appears that the 114 studies collected belong to Asian countries of China and India, which represent more than 50% of the contributions recovered. This situation coincides with Arrubla-Hoyos et al. [181], where these two countries have been applying precision agriculture to increase crop yields. However, for Radočaj et al. [182], the country that leads research in precision agriculture is the United States, followed by China, India, and Brazil. This situation can be attributed to the economy of the United States, which is a world power where mainly developed agro-technologies are focused on intensive production; whereas, the results of this review are based on agro-technologies that are considered to be easy assimilation and adoption to small rural agro-producers. The results presented in this review are based on the established search and selection parameters; so, studies that broaden the landscape and explore other criteria, search periods, and document types are welcome.

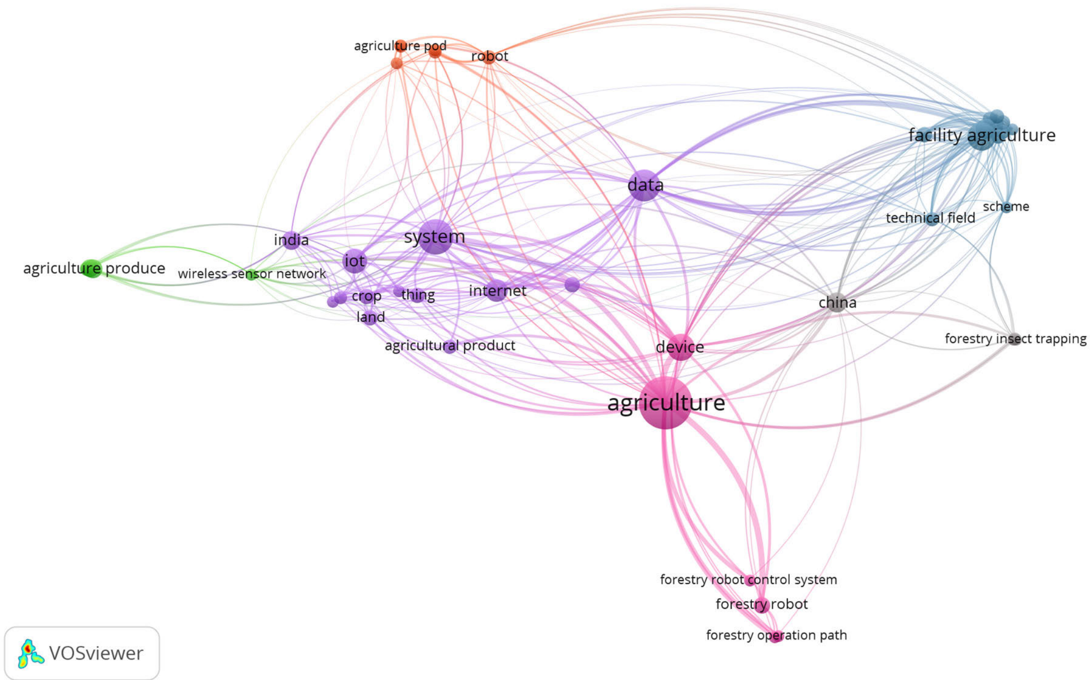


FIGURE 7. Map of co-occurrences of terms of patents under review.

Studies on precision agriculture technologies are present in several countries; despite this, not all agro-technologies are adaptable and easy to use, so when performing the search under this inclusion criterion, it is denoted that China and India are leaders in the development of technology capable of being adaptable in traditional agriculture. It is a reality that there are multiple studies reported in formats other than the studies that have been presented in this review. There are contributions reported not necessarily as original articles, with JCR and/or Scopus factor, published as book chapters, conference proceedings, dissemination, and dissemination articles.

Some agro-technologies reported in other formats consider, *e.g.*, he developed an online crop management system employing IoT, by Dasig [183] in the Philippines to provide the farm with environmental conditions. In the Netherlands, Cobbenhagen et al. [184] describe a framework for scheduling time, location, and amount of resources at the same time that farm revenue is optimized using multi-agent. In [185], Bakken et al. through a Deep Convolutional Neural Network (DCNN) and an end-to-end learning strategy, predict the steering angles of an autonomous agricultural robot, in Norway.

Likewise, López-Leyva et al. [186] in Mexico have developed a system that monitors environmental variables in a vineyard, using ZigBee technology. An automated irrigation system based on crop water needs is proposed in India by Meeradevi et al. [187], using wireless sensors. In Mashongedza and Beem [188] present a crop fumigation device with automatic operation.

A network of wireless sensors that through an IoT application, collects environmental and soil information to assist in making informed decisions, is described by Fathallah et al. [189] in Tunisia. In [190], Prasetya et al. in Indonesia they monitor water flow in IoT using a water flow sensor. Meanwhile, orchards are monitored using drones equipped with thermal cameras, and red, green, and blue, by Yusof et al. in Malaysia [191].

Therefore, the number of contributions that exist around the world published and stored in various repositories is vast. In this sense, it would be interesting for this study to be the basis for future contributions that expand the panorama of agro-technologies that allow the agro-productive systems of traditional agriculture to be more efficient. This study is considered relevant when analyzing scientific/technological agro-technologies that can be scalable and adaptable to traditional agriculture.

While it is true that there is agricultural technology developed and applied and that it has managed to increase the yield and quality of crops, it is also true that this technology has not been aligned and adjusted to the requirements of traditional agriculture where small farmers are located in rural areas with limited resources, and who are in geographical areas with difficult access. Then, these producers require technology at their disposal that allows them to increase their agricultural yield to improve their quality of life.

This systematic review is considered a pioneering study that offer a new contribution by conducting a review in which it has been identified and analyzed that there is a technically viable technology for its scope of being adopted by traditional agriculture to improve its performance. Systems identified include "Drone", "Algorithm", "Decision Support System (DSS)", "Sensors", and "Arduino Technology". Adapted and adequately aligned to traditional agriculture, these technologies are easy and inexpensive to use. Matches Narmada et al. [158], where the rapid growth of remote technologies —such as IoT— and the development of *in-situ* parameter measurement systems —such as sensors—, make feasible, low-cost methods for agricultural automation and decision-making.

Modern precision agriculture systems are rarely implemented on small, low-mechanization farms, as mentioned by Erickson and Fausti [192], however there is no indication of its application in traditional agriculture. The FAO [44] mentions that if agricultural automation remains inaccessible, inequality can be exacerbated for those marginalized groups —small producers, youth, and women—. Since rural peoples are complex systems, and their growth requires ecosystem development, as mentioned by Sgroi [193].

However, the current context of traditional agriculture is framed by a ''forgetfulness'' in its technification and migration of its young members and a part of men towards urbanization in search of a better ''quality of life''; so, the reality is that arable farmland is running out of labor to work it, the labor force is falling on women and the elderly. Traditional agricultural practice is valuable for the vast knowledge developed over generations and offers schemes for adequately managing and using resources, as cited by Melash et al. [194]. Also, one of the strengths of traditional agriculture is that it is a low-cost production system and therefore provides economic products. Coupled with this, the surpluses of traditional agriculture are generally marketed at nearby points of influence, which represents a rapid availability of fresh, healthy, and healthy products at a low price.

On the other hand, a change in people's consumption habits is being marked. Healthier and healthier foods are being preferred, *i.e.*, there is a trend towards consuming organic products. Then, it coincides with what was stated by Reganold and Wachter [195], in that it must be produced organically since it is a profitable and environmentally friendly system capable of offering equally or more nutritious food with less —or none— pesticide residue compared to the conventional production system. In this sense, traditional agriculture encourages organic production by employing non-invasive, environmentally friendly practices. In this aspect, sustainability improvement is possible by applying digitalization in agriculture, coinciding with Mohr and Höhler [196].

However, this review identified that the contributions are mainly focused on increasing agricultural yields, improving crop quality, identifying and controlling pests and diseases, and optimizing the use of resources such as water and soil. Therefore, it coincides with what was raised by Seppelt et al. [197], that pathways to eradicate global hunger must be performance-driven through ecological principles focused on improving stress resilience and yield while minimizing crop losses and food waste by adopting emerging technologies.

This review also identified a trend in developing and applying technology focused on monitoring and controlling factors remotely through IoT and sensors to keep parameters under control; this is associated with crops being ''living beings'' that require care. So, knowing the state of crop parameters is fundamental to their development. This situation is a priority since there is less and less availability of labor in traditional agriculture due to migration, as discussed above. Therefore, knowing and controlling agricultural parameters through remote technology is fundamental in traditional agriculture.

Another strategy that is being well adopted is the development and application of computational algorithms, which optimize the performance of crops and the quality of agricultural products, collecting information *in-situ* through sensors and/or Arduino Technology and transmitting it in real-time through IoT and cloud storage. In addition, generational agricultural knowledge management should be considered in technology-assisted agricultural systems since ancestral experiences are a valuable source of knowledge of functional agricultural practices. In this sense, the development of Decision Support Systems are systems that recommend farmers in more than one sector. Therefore, they turn out to be robust and complete systems in agricultural assistance, designed with the purpose of efficient global management of the productive system, which maximizes the use of resources in quality agricultural production.

Aligning precision agriculture technology with traditional agriculture is not an easy task. Given this situation, challenges and challenges arise; it is necessary to consider the current context of the actors and conditions of traditional agriculture; and a technological and generational gap must be filled. In agreements with Melash et al. [194], sociodemographic factors —educational level, marital status, and agricultural experience— influence the use of traditional agricultural knowledge.

Although individual technological solutions exist, they have not yet been integrated autonomously; for the achievement of this, it is agreed with Gackstetter et al. [45] that synergy is required in the face of societal commitment, public acceptance, legal frameworks, and the development of the crucial role as a success factor for farmers. In developing countries, access to technology is limited due to the digital divide, as cited by Engås et al. [18]; this coincides with Siddharth et al. [198], in which the foundations of future sustainable agriculture are laid in artificial intelligence strategies that integrate agricultural data. However, the heterogeneity of agricultural technologies should not be underestimated, as mentioned by Stræte et al. [46].

The increase in the efficiency of the production system of traditional agriculture supported in precision agriculture from the findings of the present review is feasible and feasible. Therefore, the adoption of precision agriculture strategies will be paid to ensure food security, thus contributing to meeting the objectives of SDG 2 by 2030. However, for the proper adoption and assimilation of technology into traditional agriculture, the support of young producers is necessary; since these are growing in a digitized world, they are knowledgeable and possess skills in the use of technology. While women, by taking control of crop production

—due to the exponentially increasing migration of men to the cities— position themselves as the system's administrators; this coincides with the figures provided by the World Water Assessment Programme (2019) [17], which states that women in developing countries account for about 43 percent of the agricultural labor force. That, with adequate access to productive resources, agricultural yields could increase agricultural yields by 2.5 to 4 percent, which in general terms would represent a reduction of 12 to 17% worldwide. Therefore, women and youth must be agents of changes in traditional agriculture.

The development of strong, sustainable, and inclusive food systems is fundamental to achieving the development goals at the global level, coinciding with the FAO (2022a) [14], in which the Scientific Group advising the UN Food Systems Summit, in 2021 recognized that the management and governance systems of rural peoples allow a high level of self-sufficiency to be achieve, at the same time that they make efficient use of resources under a resilient and sustainable scheme. However, this transformation must be implemented in the global context of the main challenges facing the food and agriculture sectors, with factors such as climate change, population growth, urbanization, and the depletion of natural resources.

Finally, it coincides with FAO (2022a) [14], where technological innovations are part of the agricultural solution. The proper use of technology in traditional agriculture can improve the efficiency of production systems and their components. Considering the growing conditions, experience, and desired results, farmers make decisions in agricultural management, which can be supplemented by recommendations derived from agricultural information systems as well as cited by Gangwar et al. [199]. Matches Nery et al. [200], in that the transformation of the agricultural production system must be aligned to sustainable production, respectable to the components of the ecosystem.

V. CONCLUSION

This study presents a systematic review supported by the PRISMA statement, which addresses identifies and analyzes existing technologies that are viable for adoption and assimilation by traditional agriculture to improve the performance of the agricultural production system, thus improving agricultural yield and quality of agro-products. This review considered the evaluation of scientific/technological studies, original articles, and patents. The review was conducted during the last five years (2018-2023).

From the review, 114 studies —94 articles and 20 patents— were retrieved and analyzed. From these studies, it was identified that five systems are viable for adoption by traditional agriculture after the adaptation and assimilation of small producers, according to their agricultural context.

These systems identified from science and technology are: ''Drone'', ''Algorithm'', ''Decision Support System (DSS)'', ''Sensors'', and ''Arduino Technology''. The identified systems are mainly focused on increasing agricultural yields, improving crop quality, and identifying and controlling pests and diseases.

For this, it was identified that Precision Agriculture strategies are used, such as IoT, Artificial Intelligence, and Machine Learning, with the information collected by sensors. The systems identified are considered low cost and, when developed appropriately to the needs of small farmers, are considered viable for use and adoption. This adoption of technological tools can be even easier with the support of young people who are aware of the use of technology today.

This review lays the foundation for developing research projects that improve the efficiency of traditional agricultural production through emerging technologies. This study did not review bio-technologies as an improvement strategy, it would be interesting to identify and evaluate bio-technologies that are adaptable to traditional agriculture, as well as extend the study to other agricultural sectors.

Finally, increasing the efficiency of the traditional agricultural system supported by Precision Agriculture is a strategy that contributes to guaranteeing food security by promoting environmentally friendly practices. Therefore, it is necessary to make the productive system of traditional agriculture more efficient to increase food security, nutrition of the most vulnerable sectors, and food availability for local and global markets.

DATA AVAILABILITY STATEMENT

The data analyzed are available in the protocol registry at (osf.io, accessed on August 3, 2023) and available to the public.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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NAYELI MONTALVO-ROMERO received the master's degree in industrial engineering from the National Technological of Mexico, Campus Orizaba. She is currently pursuing the Ph.D. degree in engineering sciences with the National Technological of Mexico, Campus Misantla. Her research interests include developing new products with a sustainable approach, process simulation, and artificial intelligence.

AARÓN MONTIEL-ROSALES received the master's degree in industrial engineering from the National Technological of Mexico, Campus Orizaba. He is currently pursuing the Ph.D. degree in engineering sciences with the National Technological of Mexico, Campus Misantla. His research interests include the development of decision support systems using artificial intelligence and multi-criteria optimization.

RUBÉN PURROY-VÁSQUEZ received the Doctor of Science degree in tropical agroecosystems from Colegio de Postgraduados. He is the author of at least 30 articles on agroecosystems and has registered software for the evaluation of cattle carcasses. He is a National System of Researchers in Mexico Level 1 Member. His research interests include the agricultural sector, observing the factors and interrelation of agroecosystems and society.

POMPEYO QUECHULPA-PÉREZ received the Doctor of Materials Sciences degree in chemical engineering and M.Sc. degree in mechanical engineering with a specialty in thermal. His research interests include bio-organic materials, specifically in using agricultural products and by-products for energy generation through biodigesters.