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Agriculture 4.0 and Smart Sensors. The Scientific Evolution of Digital Agriculture: Challenges and Opportunities

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Abstract: The agriculture sector is one of the backbones of many countries' economies and its processes have been changing in order to enable technological adoption to increase productivity, quality, and sustainable development. In this research, we present a theoretical reflection through a scientific mapping of the adoption of precision techniques and breakthrough technologies in agriculture, the so-called Precision Agriculture (PA) and Agriculture 4.0 (A4.0). To do this, we used 4,694 documents from the Web of Science database to perform a Bibliometric Performance and Network Analysis (BPNA) of the literature with the support of the PICOC protocol and the SciMAT software. Our findings present 22 strategic themes related to Digital Agriculture (DA) such as Internet of Things (IoT) and Climate-smart Agriculture (CSA) among others, and the thematic network structures of the motor themes and the thematic evolution structure of the field of the study over time. In addition, our results discuss the main challenges and opportunities of DA. Our findings have the potential to provide insights for practitioners and researchers in decision-making and pave the way for future works.

Keywords: precision agriculture; agriculture 4.0; digital agriculture; smart farming; industry 4.0; sustainability; innovation; bibliometrics; science mapping.

1. Introduction

Agriculture has been revolutionized over time, reaching the concepts of Precision Agriculture (PA) and Agriculture 4.0 (A4.0) that give face to Digital Agriculture (DA). Around 10,000 years ago, humans began to dedicate efforts to domesticating plants and animals, spreading seeds, planting seedlings, and using animal force to plow the land [1]. This revolution that changed human life and transformed hunter-gatherers into farmers is called the Neolithic Revolution or the First Agricultural Revolution [2]. Although this revolution was a great leap for mankind, as it allowed the cultivation of plants and guaranteed food for the population, the new activities demanded more hours of work, and this dedication to agriculture generated a surplus of food that allowed the population to multiply, and created elites who owned land and food [2]. Between the First Agricultural Revolution and the prosperous and abundant society that we have today, thousands of years have passed, several transformations in the way of production, and several difficulties related to economic niches, malnutrition and wars over fields and cultures [2]. These significant disadvantages have led to new transformations and revolutions in the field of agriculture [3].

In the 19th century, Agriculture 2.0, also called Second Agricultural Revolution, changed farming by adding machinery, selective breeding, animal fertilizer, crop rotation, reapers and tractors that

shaped the first steps of modern agriculture [1]. In this frame, food started to be produced faster, but farmers were hindered by rust, pests, and soil depletion. New techniques and technologies have increased food surplus and reduced the need for labor in agriculture, forcing the migration of workers and the urbanization and the growth of cities [4,5]. This allocation of the workforce in cities was part of the industrial revolution, which stimulated the rise of manufacturing industries [4].

To deal with the challenges of the Second Agricultural Revolution, the Agriculture 3.0 or the Third Agricultural Revolution emerged in the 20th and early 21st centuries. In a frame of this period, between 1966 and 1985 the concept of Green Revolution emerged, especially in terms of the high use of technology such as biotechnology and genetic engineering to generate genetically varieties, hybrid plants and animals [6,7], and providing a breakthrough in agriculture. The third revolution was characterized by adding new technologies such as GNSS (Global Navigation Satellite System) to monitor animals and crops, computers and devices for data management and analysis of agricultural production information, robots, chemicals, fertilizers, and irrigation systems to increase productivity and production quality [1]. These transformations had a great impact on the quality of agricultural production and on the societal, economic, and environmental pillars of sustainability [8].

The concept of PA emerged in 1980 and represents the use of precision techniques and technologies used singly or in combination [9] to control the field variability [10,11]. Despite the concept of PA appeared in the Third Agricultural Revolution, its techniques and technologies are used in the context of the Fourth Agricultural Revolution. A4.0 emerged with the new technologies of the Fourth Industrial Revolution, also called Industry 4.0, in 2011 [11] and represents the use of technologies such as Internet of Things (IoT), Artificial Intelligence (AI), Big data (BD), Cloud Computing and other smart systems and devices for managing crops and farms [11,12]. In this sense, both terms are related to DA, which can be perceived as a driver for change and evolution in both sustainability and food security as well as efficiency and productivity. Economies of scope and scale may take on a new dimension with DA. Drones, IoT and BD, for instance, are to be as attached to individual firm strategic goals as to collective sustainable and inclusive agriculture objectives.

Even so, despite the revolutions have solved countless problems related to food production and security, the increase in population and the scarcity of resources are worrisome challenges for modern agriculture. Nowadays, almost one billion people go to sleep hungry every day [13]. The human population is expected to reach 9 billion by 2050 [11] increasing food demand by up to 50% [14]. Most of these people are expected to live in the regions of South Asia and sub-Saharan Africa, where more than 20% of the current population are food insecure [15]. In addition, agriculture is responsible for the consumption of 70% of the world's drinking water [11], human consumption has tripled in the last 50 years, and the exploitation of resources is 30% greater than nature's ability to regenerate [16]. In this perspective, the challenges of producing more food with less environmental impact are evident [17]. Given this backdrop, emerging technologies can be enablers for sustainable agricultural production, and the main challenges and opportunities of technological adoption need to be explored.

Several studies have revised the field of agriculture to understand the effects of technology adoption and its potential to deal with challenges related to food production for the current and future generations. Kim et al. (2019) and Raparelli and Bajocco (2019) [18,19] presented bibliometric analyzes on the use of Unmanned Aerial Vehicles (UAV) in agriculture, and Terence and Purushothaman (2020) and Navarro et al. (2020) [20,21] systematically reviewed the use of IoT in smart farms. In addition, previous studies explored the use of Machine Learning (ML) techniques [22–24], geospatial technology [25], and BD for smart farming [26,27]. Extensive reviews show the state of the art of PA technologies [28] and the main factors that influence technological adoption [29]. Although some reviews have already been carried out, no study has presented the complete evolution of the field of study over time or discussed the process of digitalization of agriculture. The present paper addresses precisely this literature gap, by highlighting the main challenges and opportunities related to DA.

Due to the transformational potential of emerging technologies for agriculture presented in the aforementioned reviews, the present paper is devoted to presenting a scientific mapping to identify strategic themes, the thematic evolution structure and the main challenges and opportunities of DA. For this, the PICOC protocol (Population, Intervention, Comparison, Outcome, and Context) was

used to guide and ensure the quality of this study, and the SciMAT (Science Mapping Analysis Software Tool) software developed by Cobo et al. (2012) [30] was used for data treatment and generation of the strategic diagram and the evolutionary map of the field of study.

The paper is organized as follows: Section 2 presents the research background. Section 3 contains materials and methods. Results and discussions are presented in Section 4. The main challenges and opportunities are presented in Section 5, and Section 6 presents the conclusions, limitations, and suggestions for further research.

2. Research background

Different terms and many contradictions exist related to PA and A4.0 [31]. Although some authors associate them, in this work we present a distinction between PA and A4.0. While PA is often associated with issues of field variability and specific analyzes and technologies, such as application of agricultural inputs in areas with the greatest productive potential (e.g., the use of georeferenced data for the application of chemicals according to the needs of each area), A4.0 goes beyond the analysis of field variability and aims to manage farms with awareness of context and situation, and to create a value chain that integrates stakeholders, technologies and agricultural processes [11,31,32]. Due to the variety of concepts and interpretations related to technological adoption in agriculture, in this research the term Digital Agriculture is used to describe both concepts associated with digital transformation in agriculture without considering the technological level.

2.1. Precision Agriculture

The PA concept represents the use of techniques and emerging technologies for crop management, pest control and field improvement [11,33], with PA was possible to increase crop quality and crop productivity. Since 1980, with the appearance of the concept, there has been a considerable increase in the use of technology in agriculture. For instance, the global soybean production could be 32 million tons higher if the PA were massively adopted [34]. Progressively, new techniques and technologies were related to the term, which was gradually being explored by researchers and practitioners to provide a range of advantages for the primary sector [11].

In addition, to increase crop productivity and farm profitability, PA is a key factor for reducing environmental impact. This occurs due to the more cost-effect use of agricultural productive inputs (e.g., chemical and fuel). Therefore, several studies have been showing the importance of the adoption of PA for reducing environmental impacts [35–37], for instance, the efficient use of phosphorus (P) and potassium (K) through PA technologies contributes to agriculture more sustainable [34]. PA research is also related to the identification of management zones [38,39], analysis and management of soil and plant nutrients [40–42], UAV applications for capture and analysis of plantation data [43,44], farmers' perception [45] and others.

2.2. Agriculture 4.0

The concept of A4.0 emerged after the development of Industry 4.0 in 2011, and seeks to make use of the same technologies used by factories of the future to create a new level of agricultural production for the sake of food safety and protection of the environment [11]. A4.0 represents the use of emerging technologies to create a value chain to integrate organizations, farmers, customers, and all stakeholders in favor of economic, social, and environmental sustainability. Therefore, A4.0 is important for mitigating several global concerns related to productivity, profitability, cost reduction and efficiency [11], and including mitigating climate changes effects and allocating agricultural resources reasonably [35]. Given this, there is an evident growing interest in the subject of digital agriculture [46].

Unlike the PA, A4.0 is broader and more comprehensive, as it seeks to integrate all actors in agri-food production through a technological value chain. In this perspective, A4.0 goes beyond local and specific analyzes to include all agricultural processes. Studies related to A4.0 address the development of decision support systems to integrate all members of the production chain [1], responsible innovation [47], real-time integration of IoT for agriculture [48], and the potential of A4.0 to address issues associated with environmental sustainability (e.g., carbon emissions and

exploitation of natural resources), social (e.g., impact on labor and food security) and economic sustainability (e.g., productivity, costs and agriculture as a subsistence economy) [11,32,49–52], among others.

3. Materials and Methods

To achieve our goal, we use the PICOC protocol and SciMAT software to perform a Bibliometric Performance and Network Analysis (BPNA). PICOC ensured the robustness and definition of the research criteria, while SciMAT helped identify the strategic themes, the thematic evolution structure and the main challenges and opportunities in the field of study.

3.1. PICOC protocol

The PICOC protocol was used to define the research questions [53], the key terms and variants [54], and inclusion and exclusion criteria for the selection of papers related to the field of study [55]. This method ensures the quality and reproducibility of the research with the lowest bias from the researchers. In this study, the process of the PICOC protocol was adapted by the steps presented by Bruzza et al. (2017) and Silva et al. (2020) [55,56]. Table 1 present the attributes according to the PICOC protocol.

Table 1. Steps according to the PICOC protocol.

Attributes	Description
Population (P)	Define keywords, search terms and variants related to DA.
Intervention (I)	Define the documents inclusion and exclusion criteria.
Comparison (C)	The approach was a bibliometric performance and network analysis.
Outcome (O)	The outcomes are the strategic diagram, and the evolution map of DA.
Context (C)	The future of DA is discussed through the main challenges and opportunities.

With the support of the PICOC protocol we defined three research questions (RQ1-3):

RQ1: What are the strategic themes related to digital agriculture?

RQ2: How is the thematic evolution of digital agriculture over time?

*RQ3: What are the main challenges and opportunities of DA?*

3.2. Network Analysis and Dataset

After defining the RQ, the criteria for assessing quality were defined. The search string, database, inclusion and exclusion criteria and bibliometric software used are present in Table 2. Then, the documents identified through the execution of the PICOC protocol were inserted in the SciMAT software for BPNA. The search terms used were mentioned in previous research [11,57,58] to represent DA, and were used to cover more related studies

Table 2. Quality assessment criteria.

Quality assessment	Description
Search string	("agriculture 4.0" OR "digital agriculture" OR "digital farming" OR "smart agriculture" OR "smart farming" OR "precision agriculture" OR "precision farming" OR "agri-food 4.0")
Database	Web of Science
Inclusion and exclusion criteria	Only documents with the search terms present in the title, abstract or keywords
	Related or applicable to digital agriculture
	Only documents in English
	Articles published over all time
Bibliometric software	Science Mapping Analysis Software Tool (SciMAT)

For bibliometric analysis and identification of strategic themes and the evolutionary map of the field, we used the SciMAT software developed by Cobo et al. (2012) [30]. We chose the SciMAT because it assists all stages of scientific mapping, bibliometric performance and network analysis, from data preprocessing to the generation of maps of the field of study [30,52,59,60]. With the support of the SciMAT, we plotted a strategic diagram and the intellectual network structure of the most important themes [61–63]. Also, it was possible to generate an evolutionary diagram that presents the most important themes of the field of study distributed over time. Figure 1 presents an example of the strategic diagram (a), thematic network structure (b), and thematic evolution structure (c), where the size of the clusters represents the number of associated documents and the importance of the theme for the research field, and the thickness of the lines represents the strength of the relationship between clusters [30,59,60]. The evolutionary map was created based on the equivalence index, where the solid lines (Figure 1 (c)) indicates that the clusters share the main theme (main theme ∈ {thematic nexuses}), while dashed lines represent a connection between non-main elements (main theme ∉ {thematic nexuses}), and the absence of lines means that the theme was discontinued from one period to the next [64].
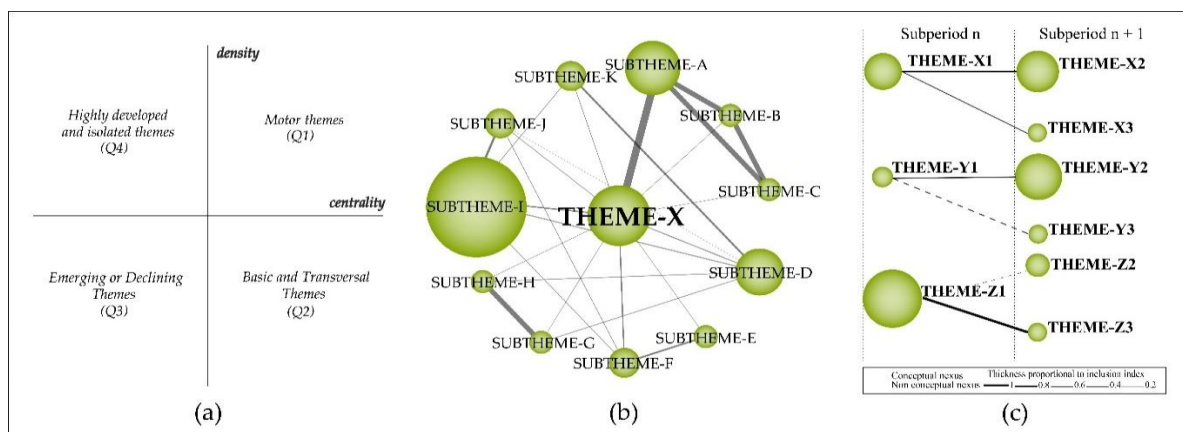
Figure 1. (a) Strategic diagram; (b) Thematic network structure; (c) Thematic evolution structure.

For analysis, we used the Web of Science as it is an indexed database with a greater quality of research available [65]. The data were extracted from the database on September 21, 2020. Altogether, 4,701 documents were exported from the Web of Science and 7 duplicate documents were removed. Using SciMAT software, 14,700 keywords related to the documents were identified and inserted into preprocessing step. Then, keywords with the same meaning were grouped, such as 'GEOSTATISTIC' and 'GEOSTATISTICS', and 'INTERNET OF THINGS' and 'IOT', and meaningless or generic words have been removed, totaling 13,935 clusters of words. After preprocessing the data, they were inserted in a period to generate the strategic diagram of the field of study, and later divided into three subperiods (1994 - 2011; 2012 - 2017; 2018 - 2020) to generate the evolutionary map. In this way, it was possible to identify from the first document published in Web of Science that discusses PA and the evolution of the field until the emergence of A4.0 in 2011 (1994 - 2011). The second subperiod (2012 -

2017) presents the evolution of DA after the emergence of the A4.0 concept, and the use of new technologies in agriculture. Finally, the third subperiod (2018 - 2020) presents the most relevant themes today and provides valuable insights about the future of the research field.

After defining the subperiods, we generate the diagrams based on the keyword co-occurrence matrix with the SciMAT to identify the most important themes and their nodes with other clusters [66–68]. Then, to identify the similarity between themes, the data were normalized using the Equivalence Index [69], and then clustered based on the Simple Centers Algorithm to create a network of relationships [70]. To create the diagrams, we reduced the data on a frequency reduction of eight times and defined a maximum and minimum network of 12 and 3, respectively, in order to plot only the most important clusters of the field of study. The clusters were plotted on a two-dimensional diagram with four quadrants (Q1-4) (e.g., Figure 1 (a)) whose horizontal axis represents the centrality of the themes and their number of connections with other themes, and the vertical axis represents the density of the connections between clusters [11,13,59,60]. The four quadrants are defined as that:

- Motor themes (Q1): the upper right clusters are highly developed themes. The strong centrality and density represent the high number of associated documents and the great number of links between these themes with others.
- Basic and transversal themes (Q2): clusters in the lower right quadrant are themes that have many relationships with other themes, but whose relationships are weak.
- Emerging or declining themes (Q3): represents clusters with few and weak links with other themes, and which may be appearing or disappearing in the field of study.
- Highly developed and isolated themes (Q4): the upper left quadrant are composed of clusters with low centrality and high density. These clusters have few but strong links with other themes.

The motor themes of the strategic diagram (Figure 1 (a), Q1) were explored to identify the relationships with other themes. In this way, it was possible to identify technologies, techniques and other subjects widely discussed, as well as the main challenges, opportunities and enablers of DA.

4. Results

To explore in-depth the DA field, we present a BPNA, which includes the performance in terms of productivity overtime and journal, the strategic themes (Figure 3), the thematic network structures of the motor themes (Figure 4), and the evolutionary map of the field (Figure 5). This analysis allows us to understand the transformations in agricultural production techniques, and the impact on sustainability, organizations, and society.

4.1 Bibliometric performance analysis of DA

In 1994 the term PA started to be widely discussed in studies that evaluated the rate of application of inputs in crops [71], the spatial and temporal variability of crops [72–74] and the potential of precision techniques for conserving natural resources [75]. After the initial fuse, the field of study has continued to grow and new concepts have emerged over time. In 2011, with the emergence of Industry 4.0, the term A4.0 came up with wide scope for the adoption of digital technology in agriculture and to represent the creation of a value chain [11,32].

Figure 2 shows the number of studies published over time, and highlights the importance and expansion of the field of research. In 1994, only 5 articles related to DA were published, in 2017 the number reached 374 articles, and 762 studies were published in 2019. In 2020, the decrease in publications is justified by the date of data collection (September 21, 2020).
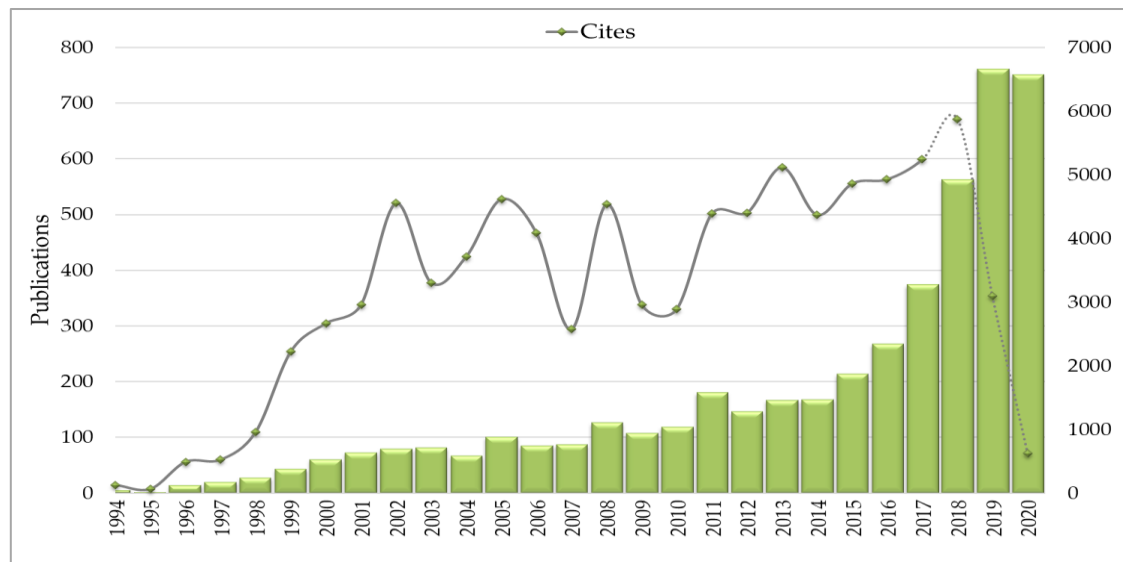
Figure 2. Publications over time (1994 - September 21, 2020).

Table 3 presents the Journals and authors that most published studies related to DA indexed in Web of Science in the period from 1994 to September 21, 2020 and based on the search string used. The most productive journal is the Computers and Electronics in Agriculture with 407 documents, followed by Precision Agriculture (231) and Sensors (187). The authors with the greatest number of studies related to the theme are Sudduth, K. A. with 46 documents, Lopez-Granados, F. (36) and Shearer S.A. (31).

Table 3. Most productive Journals and authors.

Most productive Journals	Doc	Most productive authors	Doc.
Computers and Electronics in Agriculture	407	Sudduth, K. A.	46
Precision Agriculture	231	Lopez-Granados, F.	36
Sensors	187	Shearer, S.A.	31
Remote Sensing	171	Schmidhalter, U.	21
Applied Engineering in Agriculture	101	Ribeiro, A.	21
Transactions of Asabe	87	Bareth, G.	17
Biosystems Engineering	71	Miao, Y.X.	16
Geoderma	70	He, Y.	15

4.2 Strategic Diagram

The Strategic Diagram (Figure 3) present 22 clusters distributed in four quadrants of the two-dimensional diagram, of which 9 are motor themes (Q1), 2 are basic and transversal themes (Q2), 8 are emerging or declining themes (Q3), and 3 are highly developed and isolated themes (Q4). The size of each cluster is proportional to the number of associated documents, the horizontal axis represents the links from one cluster to others (centrality), and the vertical axis demonstrates the strength of these links (density). The table in Figure 3 shows the core documents, h-index, cites, centrality (C), and density (D) of each theme.
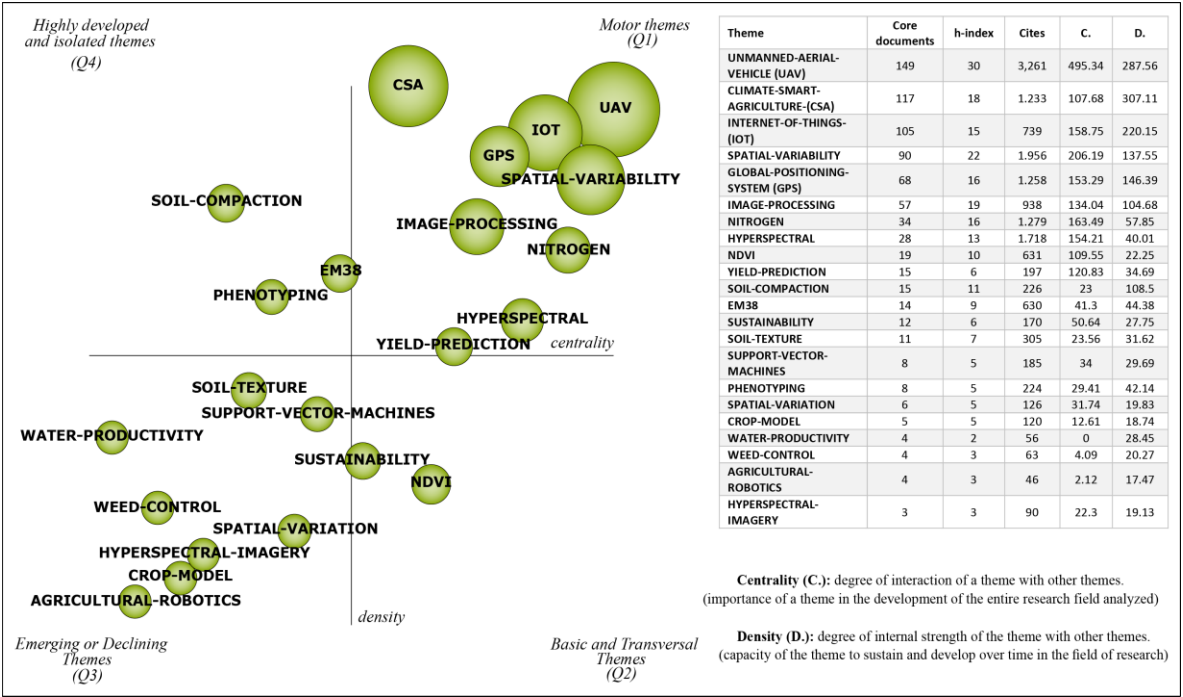
Theme	Core documents	h-index	Cites	C.	D.
UNMANNED-AERIAL-VEHICLE (UAV)	149	30	3,261	495.34	287.56
CLIMATE-SMART-AGRICULTURE-(CSA)	117	18	1.233	107.68	307.11
INTERNET-OF-THINGS-(IOT)	105	15	739	158.75	220.15
SPATIAL-VARIABILITY	90	22	1.956	206.19	137.55
GLOBAL-POSITIONING-SYSTEM (GPS)	68	16	1.258	153.29	146.39
IMAGE-PROCESSING	57	19	938	134.04	104.68
NITROGEN	34	16	1.279	163.49	57.85
HYPERSPECTRAL	28	13	1.718	154.21	40.01
NDVI	19	10	631	109.55	22.25
YIELD-PREDICTION	15	6	197	120.83	34.69
SOIL-COMPACTION	15	11	226	23	108.5
EM38	14	9	630	41.3	44.38
SUSTAINABILITY	12	6	170	50.64	27.75
SOIL-TEXTURE	11	7	305	23.56	31.62
SUPPORT-VECTOR-MACHINES	8	5	185	34	29.69
PHENOTYPING	8	5	224	29.41	42.14
SPATIAL-VARIATION	6	5	126	31.74	19.83
CROP-MODEL	5	5	120	12.61	18.74
WATER-PRODUCTIVITY	4	2	56	0	28.45
WEED-CONTROL	4	3	63	4.09	20.27
AGRICULTURAL-ROBOTICS	4	3	46	2.12	17.47
HYPERSPECTRAL-IMAGERY	3	3	90	22.3	19.13

Centrality (C.): degree of interaction of a theme with other themes.
(importance of a theme in the development of the entire research field analyzed)

Density (D.): degree of internal strength of the theme with other themes.
(capacity of the theme to sustain and develop over time in the field of research)

**Figure 3.** Strategic diagram ad performance analyzes.

The 'UAV' (Unmanned Aerial Vehicle) cluster contains the largest number of associated documents, and it is the most expressive theme in terms of h-index, cites and centrality, highlighting this cluster as one of the most discussed theme in the literature. The cluster 'CSA' (Climate-smart Agriculture) also have an expressive core documents, and is the first ranked in terms of density, but its low centrality shows that the relationship between CSA and other themes is still underexplored. Other clusters that stand out are 'IOT' (Internet of Things), 'SPATIAL-VARIABILITY', 'GPS' (Global Positioning System), 'IMAGE-PROCESSING', 'NITROGEN', 'HYPERSPECTRAL' and 'YIELD-PREDICTION' (Figure 3). These motor themes (Q1) are explored in depth through the thematic network structures in the next subsection.

Besides, 'NDVI' (Normalized Difference Vegetation Index) and 'SUSTAINABILITY' appear like basic and transversal themes (Figure 3), and represent the concern for the sustainable development of agriculture. Other techniques appears related to crop management such as 'WEED-CONTROL', 'CROP-MODEL', 'SOIL-TEXTURE', 'PHENOTYPING', 'SOIL-COMPACTION' and 'WATER-PRODUCTIVITY', and others related to technologies such as 'AGRICULTURAL-ROBOTICS', 'HYPERSPECTRAL-IMAGERY', 'SUPPORT-VECTOR-MACHINES' and 'EM38'. Although some clusters represent specific analyzes and techniques related to productivity and quality of agricultural production, the motor themes highlight the way of agriculture and the transformation expected for food production in the coming years.

4.3 Motor themes related to DA

We explore the thematic network structure (Figure 4) of the motor themes presented in the strategic diagram (Figure 3). This analysis highlights the relationships of a cluster with others and provides an in-depth view of the field of research. The size of each cluster is proportional to the number of associated documents, and the thickness of the lines denotes the binding force between clusters.
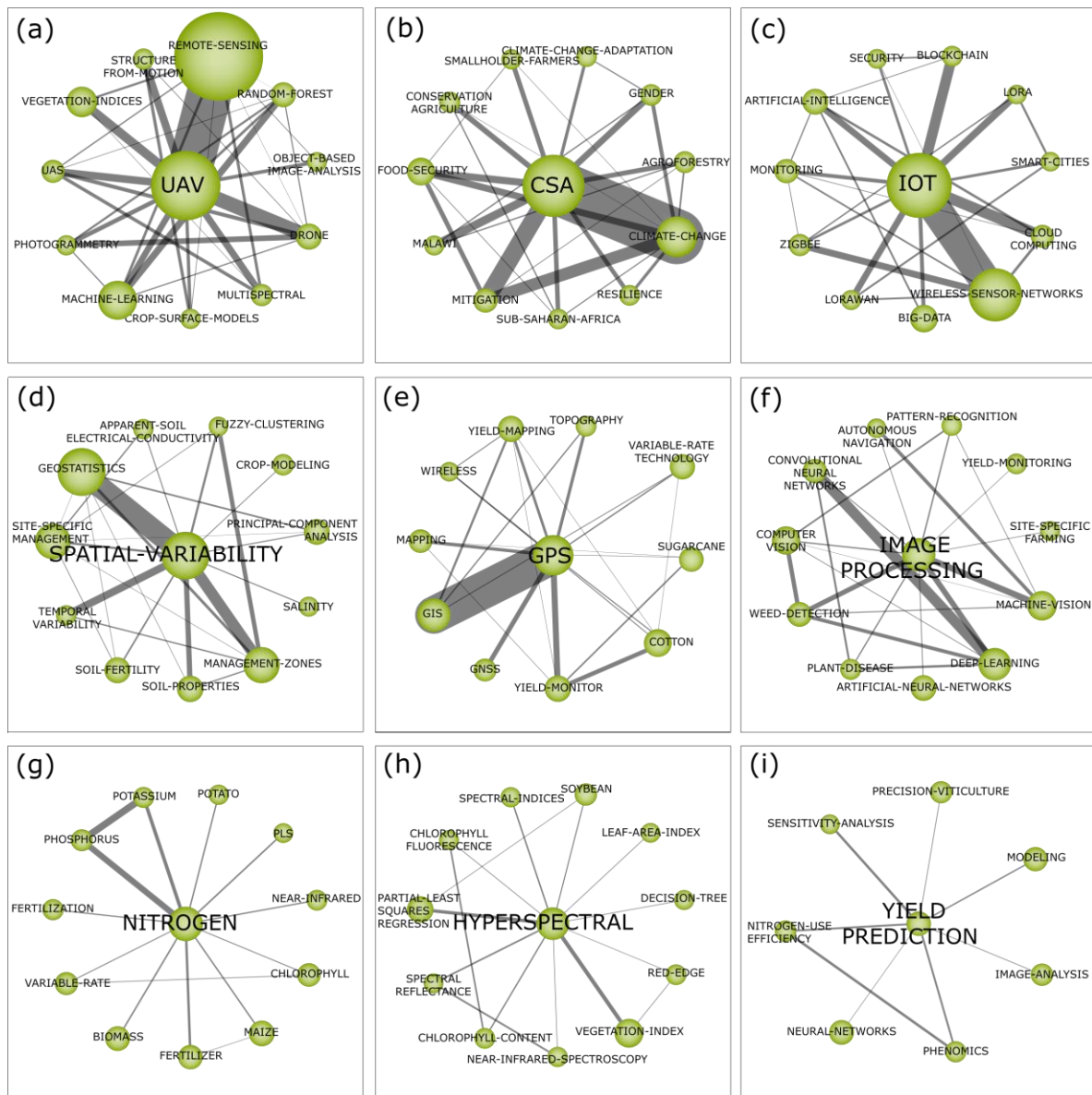
Figure 4. Thematic network structures. (a) UAV; (b) CSA; (c) IoT; (d) Spatial Variability; (e) GPS; (f) Image Processing; (g) Nitrogen; (h) Hyperspectral; (i) Yield Prediction.

4.3.1 Unmanned Aerial Vehicle (UAV)

The cluster 'UAV' (Figure 4 (a)) presents prominent importance in the strategic diagram (Figure 3) due to its high degree of interaction with the other motor themes. The UAV, commonly known as a drone [76], corresponds to a pilotless aircraft, i.e. a flying machine operated with no humans (passenger/pilot) onboard [77]. UAVs are low-cost and easy-to-operate technologies in agriculture [78] that can be adopted for spraying in fields [79], such as water precision irrigation. Given the technological advancement emerging in different countries, UAVs have been gaining more and more space and importance for smart farming [76,78]. Different sensors can be coupled to UAVs [76], which demonstrates the strong relationship between UAV and the subtheme 'REMOTE-SENSING', followed by the subthemes 'MACHINE-LEARNING', 'VEGETATION-INDICES' and 'DRONE', among others (Figure 4 (a)).

The sensors in the drones can generate vegetation indices, helping to monitor crop growth diagnosis and grain yield prediction [80]; disaster detection in environmental areas [81]; the existence of pests and pathogens in the crop; the analysis of the health and stress status of the vegetation; and the assessment of soil fertility for appropriate remote management and precise and reduced

application of agrochemicals, driving sustainable agriculture [76] and increased productivity. On this, machine learning improves decision-making on precision and digital agriculture, such as the prediction of nitrogen index of the crop through remote sensing from UAV [78,82]. Thus, farm's data and information easily collected through drones, such as images [83], can generate knowledge from machine learning techniques to make agriculture precise and digital. Zhang and Zhao (2019) [84] used images of coastal soils captured through UAV to identify salinization levels, and then proposed a method to improve the monitoring and management of the soil for avoiding the negative impacts of salinization on crop growth and production. Hence, this cluster highlights the central role of UAV, which, together with other emerging technologies, generates precision in agriculture and enables the interconnection among technologies for better decision-making, allowing farms to be smart.

4.3.2 Climate-smart Agriculture (CSA)

CSA (Figure 4 (b)) is a concept related to the adoption of best agricultural production practices and methods for reorienting agriculture for environmental protection, food security and climate change issues [15,85]. The population increase, land and environmental degradation, and the negative impacts of the food system on the climate require new agricultural practices. In this frame, CSA is an extremely necessary approach to find win-win solutions for the sustainable development of agriculture [86]. Climate change and the degradation of the planet's biodiversity cause risks to food supply, and the vulnerability of people who have agriculture as their main source of subsistence [15]. To deal with this, the resilient agriculture proposed by CSA seeks to create adaptive coherence between climate and agricultural practices [86]. To assist in the development of CSA, farmers embrace technological innovations that could make agriculture more sustainable. However, great governmental and academic incentives need to be dedicated to this area to assist the agricultural sector in sustainable development [85,86].

This high-density motor theme is related to sustainable agriculture, which shows its strong relationship with climate-related themes (e.g., 'CLIMATE-CHANGE', 'CLIMATE-CHANGE-ADAPTATION'), environmental preservation (e.g., 'AGROFORESTRY', 'CONSERVATION-AGRICULTURE'), organizations (e.g., 'SMALLHOLDER FARMERS') and discussions related to agricultural resilience, food security and the main challenges for organizations, especially for smallholders. Related research discusses technological adoption [87], farmers' adaptation to resilient agriculture [88], economic models [89], ways to increase the resilience of smallholder farmers [90], and the impact of CSA on food security [91], among other issues associated with resilient agriculture.

4.3.3 Internet of Things (IoT)

The cluster 'INTERNET-OF-THINGS (IoT)' (Figure 4 (c)) has a high degree of interaction with the subtheme 'WIRELESS-SENSOR-NETWORKS', followed by 'BIG-DATA', 'ARTIFICIAL-INTELLIGENCE', 'CLOUD-COMPUTING' and others. IoT can be defined as a grouping of technologies and infrastructures that, wirelessly connected, enables data mining from interconnected objects, as well as the monitoring and correct management of data [11,92]. It allows remote access and control of objects [93]. Thus, IoT has been achieving a prominent role in agriculture. Both the quality and quantity of production in the agricultural industry have been maximized through IoT [94], such as crop yield and efficiency [95]. IoT technologies, such as smart sensor networks, cameras, weather stations and smartphone applications can improve data collection from crops and decision-making for smart farm management [96].

There are many ways of adopting IoT in agriculture. Jin et al. (2020) [97] proposed a predictor for weather based on IoT to an accurate prediction of temperature and humidity in fields, allowing anticipated planning and control for sustainable precision agriculture. Jayaraman et al. (2016) [96] proposed an IoT platform capable of expanding the collection of data on soil, irrigation, fertilization and environmental conditions, generating relationships among data for forecasting crop performance and boost smart farming. Relating IoT to blockchain, Hussain (2019) [98] developed a model capable of helping in the migration from traditional to smart agriculture. Tekinerdogan (2018) [3] used IoT to develop a portable agricultural sensor network system, which collects data (temperature, light intensity, and soil moisture content) using sensors and a microcontroller to generate databases that can be used through Big Data for better crop management. These IoT actions can be maximized when

combined with artificial intelligence technologies, which facilitate the management of data collected from different objects in the field [93]. Besides, connectivity on DA through IoT becomes efficient and effective when based on cloud computing [99]. Thus, regardless of the application, IoT actions in agriculture require investments in cloud computing to facilitate the collection, storage, access, and management of integrated data. Therefore, this cluster emphasizes the importance of IoT as a link among different technologies, tools, equipment, and machines that jointly improve precision agriculture and, consequently, lead to digital agriculture. This technological transformation also highlights the need for digital innovation ecosystems, capable of integrating government, companies and universities for the development of digital, profitable and sustainable solutions.

4.3.4 Spatial Variability

The cluster 'SPATIAL VARIABILITY' (Figure 4 (d)), is a motor theme that presents strong interaction with the subthemes 'GEOSTATISTICS', 'MANAGEMENT ZONES', 'SITE SPECIFIC MANAGEMENT', 'SOIL PROPERTIES' among others. Therefore, this cluster in linked with the increase efficiency and crop productivity. The information obtained through 'MANAGEMENT ZONES', for instance, contributes for monitoring soil properties at agricultural sites. This is a key factor for increase food production [100] and farmers' economic returns [101]. The mapping of soil heterogeneity have been contributing for the use of 'MANAGEMENT ZONES' and 'GEOSTATISTICS' as tools in agricultural management [102]. Some studies shows that farmers, through GPS, visualize the information of DA made by georeferenced analysis [103].

4.3.5 Global Positioning System (GPS)

Through georeferencing, GPS was one of the first big steps towards DA. The cluster 'GPS' (Figure 4 (e)) is a motor theme that presents strong interaction with the subtheme Geographic Information Systems (GIS). Other subthemes, such as 'YIELD-MONITOR', 'YIELD-MAPPING' and 'VARIABLE-RATE TECHNOLOGY' also have prominence link with this cluster. Thus, the integration of GPS with other smart technologies such as GIS and remote sensing can boost farming productivity and cost efficiency [104]. GPS corresponds to a navigation system that, using satellites, identifies the exact position and velocity of an object around the world and can guide directions [105]. Agricultural activities, such as seeding and ploughing, can only be precisely by means of vehicle navigation accuracy [106].

In previous research, Si et al. [106] proposed a method to improve the accuracy of the steering angle of agricultural vehicles by combining GPS with the low-cost Micro-electromechanical System (MEMS), which improves DA. Palaniswami et al. [107] argue that the joint adoption of GPS and GIS technologies can improve the cultivation of sugarcane in coastal lowland ecosystems, making production precise and sustainable. Khosro (2018) [108] developed a strawberry yield-monitoring picking cart, equipped with a real-time kinematic global positioning system (RTK GPS), different types of sensors, a microcontroller, and an inertial measurement unit to improve the synchronization of the carts with robots in harvesting and creating yield mapping of strawberry productivity. Commonly, yield mapping on farms is performed using GPS and variable rate technology for boosting planters' performance [109]. Also, Thrikawakaa et al. [110] demonstrate that the application of variable rate technology through GPS in agricultural vehicles improves the water content in fields and reduces the application of fertilizers. Thus, this cluster highlights the role of GPS as a leading technology capable of improving the effectiveness of DA through its capacity of interconnection with other smart technologies. Emerging technologies combined with scientific knowledge make it possible to use the strategic geographical location of agricultural production, helping to make precise and targeted decisions.

4.3.6 Image Processing

The cluster 'IMAGE PROCESSING' (Figure 4 (f)) presents strong linkages with agricultural management tools (e.g., 'MACHINE VISION' and 'COMPUTER VISION') that provide data for the farmer's decision-making. Zhao et al. [111] used machine vision for providing color images for the detection of immature green citrus. The use of video processing (i.e., machine vision) also was

analyzed by Sabzi et al. [112] to classify potato plant and three types of weed. In this regard, machine vision also was revised by Wang et al. [113], combined with image processing as relevant tools for 'WEED DETECTION'.

Machine learning algorithms also are linked with image processing and provide 'DEEP LEARNING' in agriculture [114]. The use of 'ARTIFICIAL NEURAL NETWORKS' is an example of AI method [115] to create new forms to solve agricultural complex problems that are based in big data. Through image processing, several outputs provide by machine learning are showed in apps for smartphones and computers [116].

4.3.7 Nitrogen

The cluster 'NITROGEN' (Figure 4 (g)) likewise the 'HYPERSPECTRAL' and 'YIELD PREDICTION' clusters have no stronger relation with some themes as the others clusters. As an important nutrient for agricultural production, this cluster is related to crop management (e.g., 'MAIZE' and 'POTATO'), and fertilizers (e.g., 'PHOSPHORUS' and 'POTASSIUM'). The link between 'NITROGEN' and these themes comprise several fields of studies such as nitrogen deficiency [117], nutrient management [118,119], nutrient loses [120], nutrient efficiency [121], and nutrient monitoring [122]. Therefore, the technical agronomic backdrop is preeminent in this cluster. In addition, this theme is strongly linked to efficiency (such as application in variable-rate) in the application of nitrogen [118,119,123].

4.3.8 Hyperspectral

Several technologies are being developed and tested to analyze plants, soil and crop variables, such as optical sensors, three-dimensional (3D) imaging, fluorescence imaging, thermography, multispectral and hyperspectral imaging [124]. The 'HYPERSPECTRAL' cluster (Figure 4 (h)) shows that these analyzes are standing out in agriculture, mainly because hyperspectral imaging is a more advanced technique than traditional multispectral imaging, and allows the identification of more details of the target features [125]. Hyperspectral images are used as an efficient alternative for collecting and processing data and creating an electromagnetic spectrum of agricultural fields, being a useful tool for monitoring, analyzing, and more accurate detection of spatio-temporal variations of crop physiological and morphological characteristics [125,126] such as soil attributes and soil degradation.

Despite its great potential, hyperspectral images is still little used outside the academic context, but this is changing through low-cost and mini-sized airborne hyperspectral technologies that are being used by farmers [125]. This difficulty occurs due to the complexity of technologies and algorithms, and the need to store and transfer data collected by hyperspectral analysis devices [127]. The significance of the 'HYPERSPECTRAL' cluster shows the volume of analyzes performed using maps and images of crops. The clusters associated with this theme demonstrate analyzes related to vegetation indexes and characteristics (e.g., 'VEGETATION-INDEX', 'CHLOROPHYLL-CONTEXT', 'CHLOROPHYLL-FLUORESCENCE' and 'LEAF-AREA-INDEX'). Previous research used hyperspectral remote sensing to measure grapevine drought stress [128], identification of pests and diseases [129], and for assessing seed germination [130].

4.3.9 Yield prediction

Yield prediction is historically used in agriculture for farmers to plan inputs, labor, profitability and other issues related to agricultural productivity. The cluster 'YIELD-PREDICTION' (Figure 4 (i)) in DA represents the evolution of predictive analysis on crop yields, which in the past was carried out by the knowledge of farmers, and is now carried out with emerging technologies [89]. In this way, preharvest crop yield prediction helps farmers to make better and faster decisions related to planting, fertilization, irrigation, pruning and harvesting plantations [131], also contributes to the entire supply and consumption chain, and allows the projection of future scenarios for food production [132].

This cluster appears related to few themes, but among it we can highlight 'MODELING', 'IMAGE-ANALYSIS' and 'NEURAL-NETWORKS' used to map and model crop data and

information for future predictions. Previous research related to crop yield prediction used different techniques and technologies to collect and analyze data, such as Neural Network Techniques [91], Unmanned Aerial System Imagery [133], Airborne Optical Sensors [134], Artificial Neural Networks [135], Machine Learning [136–138], Hyperspectral Imagery and Ensemble Learning [139], among other.

4.4 Thematic evolution structure

The evolutionary map presents the themes that have stood out over time. The map was divided into three subperiods to show the most important themes according to the evolution of the field of study. The first subperiod presents the main themes studied since the first mention of the term PA in 1994 in Web of Science until the emergence of the Industry 4.0 concept in 2011 and, consequently, the emergence of the A4.0 concept. The second subperiod covers the years 2012 to 2017 and highlights the terms widely discussed since the appearance of A4.0. The last subperiod (2018 - 2020) highlights the most current and relevant terms in the literature in the last years. Figure 5 shows the evolutionary map of the field of study, the size of the clusters is proportional to the number of associated documents, while the thickness of the lines represents the relationship between the themes. Continuous lines represent conceptual nexus and dashed lines have non-conceptual nexus.
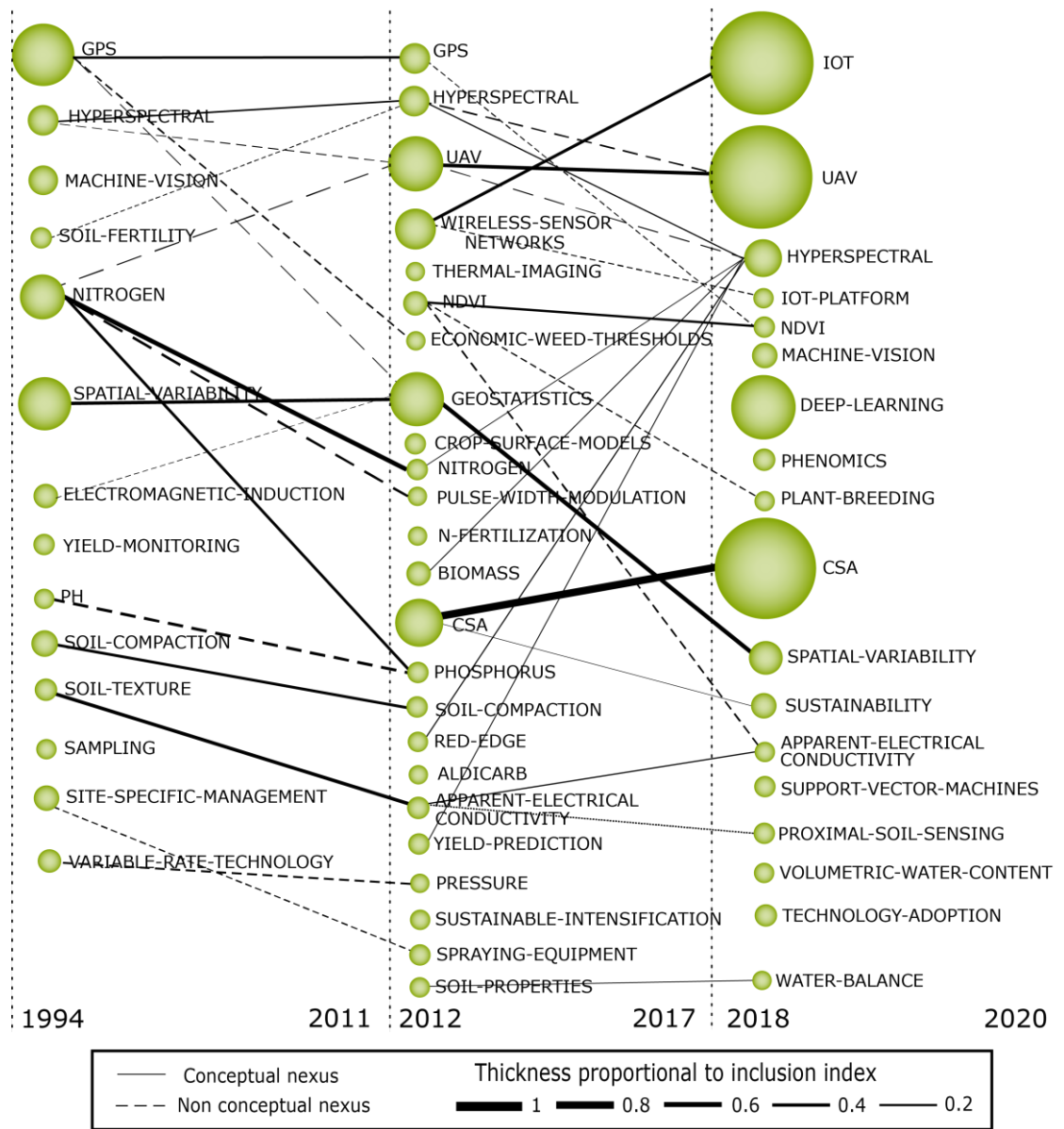

Figure 5. Thematic evolution structure.

4.4.1 First subperiod (1994 – 2011)

In this subperiod (1994 - 2011) (Figure 5), we identified the first studies that mentioned DA through discussions about the use of technologies to increase productivity, deal with environmental variability and environmental conservation of agribusiness [71–75]. This subperiod contains studies that used hyperspectral maps to analyze vegetation indices [140,141], imaging techniques [142] and geostatistical analysis [143]. Besides, Figure 5 shows that technologies started to be explored at this time such as 'GPS', 'HYPERSPECTRAL' images, and specific analyzes of soil and plants such as 'SOIL-FERTILITY', 'NITROGEN', 'ELECTROMAGNETIC-INDUCTION', 'PH', 'SOIL-COMPACTION' and 'SOIL-TEXTURE'. In general, these themes show that few technologies were discussed and most of the themes were associated with crop variability. These themes prove that the discussions associated with DA mainly represent the use of technologies such as georeferencing to analyze variability associated with soil and plants.

In this subperiod, the first discussions on agroecosystems were developed [144] to create strategies to mitigate damage to the environment. It is important to note that this subperiod was one of the most important for discussions related to sustainability, as the research was guiding for other in-depth studies aimed at the development of resilient agriculture and the sustainable development of agribusiness. In addition, many studies in this subperiod predicted that DA would be the future of agribusiness [145–150].

4.4.2 Second subperiod (2012 – 2017)

The second subperiod (2012 - 2017) (Figure 5) was characterized by a greater number of documents associated with the consolidated PA motor themes and with emerging A4.0 ones, as new technologies started to be discussed as the application of UAV [151], 'WIRELESS-SENSOR-NETWORKS' and 'NDVI'. Clusters still related to the first subperiod such as 'NITROGEN', 'HYPERSPECTRAL' and 'GPS' demonstrate that some themes have remained strong over time. In addition, new themes emerged such as 'GEOSTATISTICS' with a significant number of documents, and 'SUSTAINABLE-INTENSIFICATION' and 'CSA' associated with the development of resilient and sustainable agriculture, demonstrating the expansion of the field of study [152–154].

Between 2012 and 2017 the term A4.0 gained space and came to be widely discussed in the literature to portray the creation of a digital value chain in agriculture. Although many terms are discussed in this subperiod, few of them stand out in the volume of associated documents and interrelationships with themes from other subperiods. Only the 'GEOSTATISTICS' theme has a strong relationship with the 'SPATIAL-VARIABILITY' clusters of the first and third subperiods, highlighting the potential of geostatistics for analyzing crop variability. Also, 'CSA' evolves to become one of the main themes of the third subperiod. It is important to note that some themes have evolved over time, however, the small size of most clusters shows that the field of study was still under development.

4.4.3 Third subperiod (2018 – 2020)

The third subperiod (2018 - 2020) (Figure 5) presents the most recent themes related to DA. Three clusters stand out with a large volume of associated documents, they are 'IoT', 'UAV' and 'CSA', which indicates that the use of emerging technologies and sustainable development is currently the most important concerns of researchers in the primary sector. The 'IoT' and 'UAV' clusters show the potential and adaptability of small sensors for any agricultural scenario, whether in large crops or in mountainous areas that are difficult to cultivate [11], while the 'CSA' cluster shows that concern for the sustainable development of agriculture continues to grow and is characterized as one of the most important discussions for smart agriculture [88,91]. In addition, discussions related to 'DEEP-LEARNING' and 'MACHINE-VISION' represent technological adoption in agriculture, and themes like 'APPARENT-ELECTRICAL-CONDUCTIVITY' [155], 'WATER-BALANCE' [156] and 'PROXIMAL-SOIL-SENSING' [157] show that the concern with analyzes of plants and soil remains extremely important for the digital transformation of agriculture.

A broad look allows us to see the evolution of the field of study and the main themes discussed over time. The third subperiod also produces insights into future trends, because some themes stand out from the others and should remain important. Besides, other themes emerged only in the last subperiod, and may represent emerging themes that can be further explored in depth in the coming

years. The growth in the number of documents in the field of study (Figure 2) and discussions associated with technological adoption (Figure 4) demonstrate the commitment of researchers to the development of the primary sector and its importance for the sustainable development of society and organizations.

5. Challenges and Opportunities

5.1 Main challenges

There are many challenges related to the adoption of emerging technologies in agriculture, such as variations in soil, climate, cultivated species and producer size. Government investments, export volume, agricultural and consumer culture are also factors that directly impact the way food is grown, and the efforts and investments dedicated to production. Developed and emerging countries have different types of government investment for agricultural production and some are developing projects aimed at the digital transformation of agriculture in countries like China [158], Brazil [159], Mexico [160], Thailand [161,162] and others.

Among the main challenges of digital technology adoption are the characteristics and peculiarities of emerging technologies, which are often complex for the little technological knowledge of farmers [45]. The largest volume of agricultural production is from developing countries, and most of its farmers are small producers with low education. Under these circumstances, even the language can become a barrier to technological innovation, since most technologies are developed in English, a language not spoken by small producers in emerging countries [31]. This barrier for small producers favors large agribusiness companies that have workers trained to use technologies and apply them to increase the quality of large-scale production. In addition, there is a major digital infrastructure problem in many developing countries, which are gradually developing ways to bring digital devices and applications at low cost to small producers to increase profitability and production quality.

Technological advances bring complex issues related to data security and privacy. Concerns about information, confidentiality and data integrity are major challenges that concern farmers [163]. In highly technological scenarios, these concerns increase the efforts of researchers and practitioners in the search for better encryption and security techniques to reduce the risks of cyber-attacks and ensure data security and privacy [164]. According to Zhang et al. (2020) [165] farmers are insecure about data security, as well as the physical requirements for equipment and effective tools for data protection and distributed systems for agricultural management. Hussein (2019) [164] reinforces the care with the computational structure necessary for cloud storage to be effective and secure. These surveys highlight the concern with data security, confidentiality and reliability to guarantee fair competition and economic development. In this sense, two strands of challenges can be considered: the first is about technical challenges, such as the mastery and the adaptation of technological tools in order to direct them in the best possible way for optimal gains. The second aspect is related to sustainability issues such as the continuous world population growth and global warming (be it due to the greenhouse effect, gas emissions, etc.) and its harmful effects to agriculture [166].

Although many authors discuss the technological potential for promoting sustainable development, other authors discuss the paradox of sustainability [167] by raising questions about the contradictions between economic growth and sustainability that mainly affect the low-income population [168]. In the same perspective, the technological paradox discusses the lack of evidence about technological benefits in the productivity and sustainability of organizations and society [169]. These controversies between authors show that discussions about these paradoxes in agriculture are not yet sufficiently developed and future research could explore this topic in-depth [52].

5.2 Opportunities

The primary sector is crucial for human survival and full of challenges, and in this scenario, the technological potential can be exploited to meet the food needs of the human population without damaging the environment [52]. The number of studies associated with sustainable agriculture shows that technological adoption has great potential to assist in the development of a resilient agriculture that integrates the economic, environmental and social pillars of sustainable development. Previous

research on CSA explored the adaptation of agricultural methods to develop adaptive agriculture for plantations, landscapes and forests, while addressing climate issues and food security [85,86]. Regenerative and circular agriculture explores ways to avoid the use of chemicals, and ways to develop natural processes to protect the soil, the environment and people through the production of healthier foods [170]. According to Ofori and El-Gayar (2020) [31] the main drivers for technological adoption in agribusiness are related to governance, policies, trade opportunities, effects on human capital, employment opportunities and environmental protection. In this perspective, traditional agriculture is no longer sufficient to meet the demand for food, quality, sustainability and protection of the environment, and a new paradigm is needed, the technological paradigm [171].

Advances in agricultural production are crucial for increasing production and improving logistics performance and traceability of agricultural data in the coming years [52]. Although big machines favor agricultural monopolies, small technologies such as sensors, actuators and drones can be developed at a lower cost and with features to assist small farmers in the collection and analysis of crop variability data [11]. Other technologies such as smart grid can assist in the development of integrated energy networks that facilitate the management of crops at lower costs [172]. DA depends on technological progress, and a viable path for future research concerns strategic forecasting [173] and analysis of innovation capabilities [174,175] to develop technological innovations in smart agriculture. The DA can promote changes, evolution and gains, both for society and sustainability, as well as for economic agents through the gains in scale and efficiency of the digitization of agriculture. In this frame, if drones and IoT are more connected to companies and businesses, CSA has an important impact on inclusive and sustainable agriculture. The literature presents several technological solutions aimed at environmental protection and economic and social sustainability, which represent both technological and sustainable revolutions in the primary sector. It may motivate the development of a cycle of sustainable production and consumption to transform the planet and society.

To create a technological and sustainable culture, agriculture depends on the engagement of various members of society, such as universities, farmers, companies, the community and the government. The participation of universities is crucial for the development of technologies and research aimed at modeling and developing methods and techniques that assist farmers in the management of agricultural processes and technologies. Government programs and financing can assist in the digital transformation of agriculture in developing countries, instigating the production and consumption of sustainable products, less waste and awareness of recycling. In this perspective, innovation ecosystems can be explored in-depth for the digital and sustainable transformation of the primary sector. The adoption of new technologies enables the transformation of value chains into digital ecosystems, with the potential to integrate organizations and stakeholders, benefiting each participant in the ecosystem [176]. As in industries, in agriculture, value ecosystems can directly impact economic performance and business agility. To do this, national innovation systems can assist in the transfer of knowledge between industry and universities [177,178], facilitating the development of a digital innovation ecosystem.

Besides, the number of startups focused on agribusiness is growing, and they are developing technologies at a lower cost and that meet the needs of small and medium farmers. These enablers assist the development of small producers, who are responsible for a large portion of the world's population's food production, and who suffer from the challenges of agricultural revolutions. Lean agriculture techniques can be used to optimize agricultural processes and facilitate the adoption of emerging technologies in crops. Technologies such as Big Data facilitate the collection and analysis of large volumes of data, and IoT through its small sensors and actuators can be used in any type of environment. Besides, cyber security can be exploited to address farmers' fear of data protection and security. Together these approaches can facilitate the digital transformation of agriculture in different scenarios and for different sizes of agricultural producers.

6. Conclusions

In this research, we present the strategic themes and the scientific evolution structure of digital agriculture. With the support of the PICOC protocol and the SciMAT software was possible to map

and identify the strategic themes of the field of study, which are mainly associated with technologies and sustainable development such as IoT, UAV, GPS, spatial variability, CSA, and others. Besides, the evolution map divides the literature into three subperiods of time, listing the most important themes at each stage of development of digital transformation in agriculture. The main challenges associated with digital technological adoption were identified, which are mainly related to the complexity of technologies, agricultural culture and adaptation, data security and environmental issues. Also, we identified the main opportunities of technological adoption in agribusiness, that are strongly related to the creation of a technological and smart value chain to increase the productivity, quality and profitability of agricultural production, while promoting economic, social and environmental sustainability. Thus, we cover a gap in the literature related to the evolution of the digitalization of agriculture and its strategic themes over time.

6.1 Limitations and further research

Despite its contributions, this research has limitations. This study explored only documents from the Web of Science database and we explore only the thematic structures of the motor themes, and other themes could be addressed in future works. It is important to keep in mind that agriculture directly impacts socioeconomic conditions and environmental sustainability, thus a more comprehensive qualitative analysis could be realized in terms of the implications of DA for sustainability and social development. The role of emerging technologies to promote food security, and the impact of food production on society and organizations need to be explored. Future research can explore in-depth agricultural management practices focused on CSA, sustainable and lean agriculture to identify and analyze sustainable production paths, in addition scenarios and frameworks for smart agriculture implementation could be explored. Future research could yet explore specific research string based on emerging technologies such as Big Data, Artificial Intelligence, blockchain, Internet of Things, autonomous robots and others. Innovation ecosystems need to be explored as a means of integrating organizations, government and universities to integrate and digitize processes. Future works can also explore technological and sustainability paradoxes to identify the real potential of technologies in agriculture and the challenges related to the paradoxes, in order to understand whether human decisions about food production are in the right direction or are causing a collapse ecological and unrecoverable on the planet.

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