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Theme Mapping and Bibliometric Analysis of Two Decades of Smart Farming

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Abstract: The estimated global population for 2050 is 9 billion, which implies an increase in food demand. Agriculture is the primary source of food production worldwide, and improving its efficiency and productivity through an integration with information and communication technology system, so-called "smart farming", is a promising approach to optimizing food supply. This research employed bibliometric analysis techniques to investigate smart farming trends, identify their potential benefits, and analyze their research insight. Data were collected from 1141 publications in the Scopus database in the period 1997–2021 and were extracted using VOS Viewer, which quantified the connections between the articles using the co-citation unit, resulting in a mapping of 10 clusters, ranging from agriculture to soil moisture. Finally, the analysis further focuses on the three major themes of smart farming, namely the IoT; blockchain and agricultural robots; and smart agriculture, crops, and irrigation.

Keywords: bibliometric; smart farming; clustering; machine learning; text mining

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1. Introduction

In the 21st century, the challenge of food production has become an increasingly pressing issue due to the steady growth of the world's population. It is estimated that by 2050, the global population will reach between 9.4 and 10.1 billion, placing a significant demand on the world's biodiversity due to dedicated land for food production, particularly for crops and livestock [1]. Anthropogenic changes in the environment may make it impossible to develop new crops. Similarly, the trend towards urbanization has reduced the availability of local labor, with an increase in costs and decrease in the sector's production capacity [2].

According to the research by Van Der Mesnbrugghe et al. from the World Bank, the growth of the world's population and food saturation will likely moderate the increase in food demand. Additionally, health and environmental concerns could lead to a shift in tastes that further tempers demand. The projected global population for 2050 is estimated to be around 9 billion people, representing a 12.82% increase from 2022, in which the population was 7.977 billion people [3]. Van Dijk et al. reported that total world food demand will increase by 35% to 56% between 2010 and 2050, representing a 20% increase [4]. The United Nations General Assembly (UNGA) formulated the Sustainable Development Goals (SDGs) as part of the Post-2015 Development Agenda, which aimed to create a global development plan to succeed the millennium development goals. One of the SDGs focuses on the issue of food security and sustainability [5]. Agriculture is the crucial factor in the world's food supply, as it involves the science, art, or practice of cultivating the soil, producing crops, and raising livestock. This is in addition to preparing and marketing the resulting products to varying degrees, as defined the by Merriam-Webster dictionary [6].

In response to the challenge of food production, numerous studies are being conducted on the potential of information and communication technology to support agriculture and drive innovation in farming, including the transition from traditional to smart farming.

This trend is becoming increasingly important as farming practices evolve. According to Balafoutis et al., precision agriculture involves the collection, analysis, and evaluation of data from the field, followed by targeted action in specific areas that need improvement. By implementing precision agriculture, productivity can be optimized, and farming can become more efficient [7].

The agriculture sector has experienced significant influence from the development of the IoT in recent years. This influence has resulted in the emergence of the theme "Smart Farming", which involves the application of intelligent information and ICT systems such as Artificial Intelligence (AI) to optimize the production of farm products [8]. With the integration of ICT into agriculture, the development of technology to support the potential benefits of smart farming systems has become a motivating factor for numerous studies, practitioners, and both private and public companies [9]. Based on research findings from [6,7], smart farming systems present numerous areas for exploration, such as smart systems for monitoring and controlling agricultural parameters, automated smart systems to enhance efficiency and reduce human interactions, and smart systems for green urban environments. The primary objective is to integrate ICT technology with existing agricultural systems to enable broad connectivity across the globe. In recent years, IoT solutions for smart farming have been reviewed in a number of publications, indicating constant contributions and improvement. A review paper by Villa Henriksen et al. [10] investigates smart farming research from 2008 to 2018; examines communication technologies and protocols, data analysis, and collection, IoT architecture and applications; and highlights the future prospects pertaining to the use of IoT technology in agriculture. A review paper by Ray [11] presents the technology used for data collection and communication within IoT solutions for smart farming, as well as several cloud-based IoT solutions for smart farming. Several cases were also presented for the identified applications of the IoT in smart farming. The review [12] presents a systematic review of papers published from 2006 to 2016, which are classified by application domains, such as prediction, logistic, monitoring, and controlling. Within these domains, the data visualization strategies and the technology used for edge computing and communication were also identified. A study by Tzounis et al. [13] examined the papers published from 2010 to 2016, which relied on an IoT architecture with three layers, namely application, perception, and network. The papers were further reviewed in terms of applications, network technologies, and perception devices. These studies identified embedded communication technology and platforms used in providing solutions to IoT applications. Unmanned aerial (UAV) devices, network technologies, embedded systems platforms, network topologies and protocols, and supporting cloud platforms were frequently covered in previous studies. Finally, the authors of [14] analyzed the reviewed papers published from 2010 to 2015 to show the state of the art of IoT in smart farming. The studies referred to IoT architecture with three layers (application, network, and perception) to analyze the application of actuators, sensors, technology with several farming domains, food consumption, livestock farming, and agriculture.

Several studies have been conducted on the topic of smart farming, utilizing various approaches such as surveys [15,16], bibliometric analysis [17–19], systematic mapping [20], text mining [21], and comparation methods [22,23]. These studies aimed to improve the quality of farm production through the implementation of these techniques. One major area of concern is the impact of farming activities on soil carbon emissions and subsequent implications for climate change [24]. Furthermore, practices are being developed in alignment with the concept of food security, which is used to increase farm productivity [25].

A transition of agriculture from traditional to modern methods is currently taking place, and the IOT is a tool that can assist this transition. Considering this, bibliometric analysis is a useful tool for identifying emerging trends, evaluating journal performance, and exploring the intellectual structure of a specific field based on the existing literature to clarify what the trend is throughout this modernization phase. The data used in bibliometric analysis are typically objective and massive, such as the number of publications, topics, occurrences of keywords, and citations. However, the interpretations can include both objective (performance analysis) and subjective (thematic analysis) assessments, using informed procedures and techniques. Well-conducted bibliometric research can provide a solid foundation for advancing a field in novel and meaningful ways, enabling scholars to gain a comprehensive overview of the field, identify knowledge gaps, derive novel ideas for investigation, and position their intended contributions.

This paper aims to investigate smart farming trends, identify their potential benefits, and analyze their research insight. It examines global research trends in smart farming and related data, with potential interest for students, academic practitioners, science policymakers, and research development management. It explores the major themes in a present key term cluster analysis, captures the major themes in smart farming, provides a descriptive analysis of the research structure based on the growth of the number of publications; text collections; cited papers; and most productive countries, institutions, and authors.

We used the VOS Viewer application to present a bibliometric analysis from the Scopus database in the publication period 1997–2021. VOS Viewer is a meta-analytical tool which can provide information regarding interconnections between research articles in specific terms and their topics. The use of VOS Viewer in bibliometrics studies of smart farming can provide information regarding the most cited articles regarding specific terms and topics and visualize them with a graph of citations related to smart farming. VOS Viewer can assist researchers in analyzing a broad range of bibliometric networks with its keyword analysis in terms of interconnection for each specific topic [26,27].

The remainder of this paper is as follows: Section 2 outlines the methods and data of analysis used in this research; Section 3 shows the bibliometric analysis; Section 4 shows the thematic analysis; Section 5 provides a discussion; and Section 6 is the conclusion.

2. An Overview of Smart Farming System

The use of smart farming systems is gaining more attention due to their potential to meet the increasing demand and achieve global food supply needs. Smart farming technology utilizes new technology to monitor, increase productivity, improve cost efficiency, and predict crop diseases. Smart farming involves collecting more data and utilizing information technology in the farm, extracting relevant knowledge for stakeholders, or acting intelligently on that knowledge. It aims to increase productive activity and enable strategic decision-making by farmers [28]. Over the last decade, the availability of low-cost devices such as Arduino and Raspberry Pi boards has made it possible to build and program sensor networks on a non-industrial scale. Meanwhile, advances in data gathering, storage, and processing techniques have led to an increase in the amount of data, models, and resources accessible for use in agriculture. This includes low-cost computers with interfaces, cloud-based mass storage servers, high-resolution digital cameras first seen in smartphones and later in drones and other flying objects, and improved satellite image resolution and accessibility [29].

There is research implementing various technologies in smart farming systems, such as sensors, UAV, IoT, Artificial Intelligence (AI), etc. The authors of propose a survey for smart farming technologies by describing and evaluating their challenges and issues. Smart farming technologies have improved in many ways, but there is still room for improvement. Further potential reviews should be carried out on topics such as the privacy, security, and involvement of machine learning methods, such as unsupervised learning, to enhance the user experience of the technology used in smart farming systems. Another area that has been discussed recently is the smart IoT devices that can enhance the effectiveness of smart farming systems and have a high impact on the success of smart farming systems. The study [30] also encompasses the results of surveys, comparisons, and research challenges of IoT application protocols for smart farming systems. An IoT application layer protocol has been studied and further developed based on each characteristic, performance, and agricultural application. Further research is expected to be in progress to enhance the availability of smart farming systems and their reliability in order to improve and implement them for future generations.

Smart devices are utilized to monitor farm data, which are transmitted to the cloud through an edge gateway to facilitate real-time access, as shown in Figure 1. This system enables farmers and users to easily analyze the data and respond quickly in case of any activity, thereby enhancing the overall quality of smart farming. The evolution of Industry 4.0, IoT, and other communication models has led to the automation of smart farming in a collaborative and intelligent manner. Instead of relying solely on farmers, sensors, communication devices, control units, and smart machines are now being used to handle tasks such as planting, sowing, reaping, crop trimming, irrigation, weed cropping, and cultivation in accordance with climate and greenhouse effects. These smart features of the deployed devices ensure that the farm is operating efficiently and optimally [31]. The use of ICT (Information and Communication Technology) and IoT (Internet of Things) technologies in smart farming can have significant quantitative impacts on productivity and resource consumption. By integrating these technologies into agricultural practices, farmers can achieve various benefits:

(a) Improved productivity: ICT and IoT enable real-time monitoring of crops, soil conditions, weather patterns, and pests, allowing farmers to make informed decisions and take action in a timely manner. This optimization can lead to increased crop yields and overall productivity.
(b) Resource efficiency: Smart farming technologies enable precise monitoring and control of resources such as water, fertilizers, and pesticides. By employing sensors, data analytics, and automation, farmers can optimize resource usage, reducing wastage and environmental impact.
(c) Water conservation: IoT-based smart irrigation systems can measure soil moisture levels and weather conditions, ensuring that crops receive adequate water without unnecessary over-irrigation. This targeted approach minimizes water wastage and promotes sustainable water management.
(d) Reduced environmental impact: ICT and IoT technologies facilitate the implementation of precision agriculture techniques, such as variable-rate application of inputs. This targeted approach minimizes the use of chemicals, reducing the environmental footprint associated with farming.

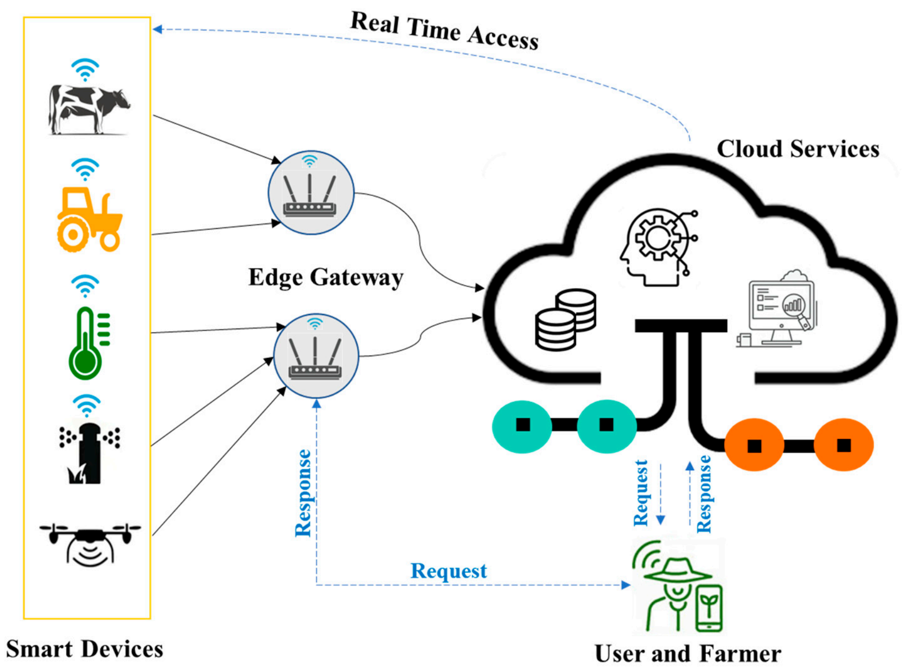

Figure 1. Model of end-to-end interaction between various stakeholders in smart farming.

It is worth noting that the exact quantitative impact may vary depending on factors such as the specific technologies implemented, the scale of adoption, and the local agricultural conditions. Nonetheless, numerous studies have demonstrated the potential of ICT and IoT in smart farming to improve productivity, resource efficiency, and sustainability in agriculture.

3. Methods and Data

3.1. Data Analysis Framework

Our scientific research utilized a variety of tools for its analytical framework, as shown in Figure 2. Scopus was used to analyze publication quantities, authorship, university affiliations, and author countries. Microsoft Excel facilitated data recapitulation and processing through its sorting and filtering features and enabled the creation of an S-curve from data extrapolation. VOS Viewer was used to extract keywords and generate bibliometric networks [32], while Desmos provided an interactive and user-friendly platform for plotting data [33].

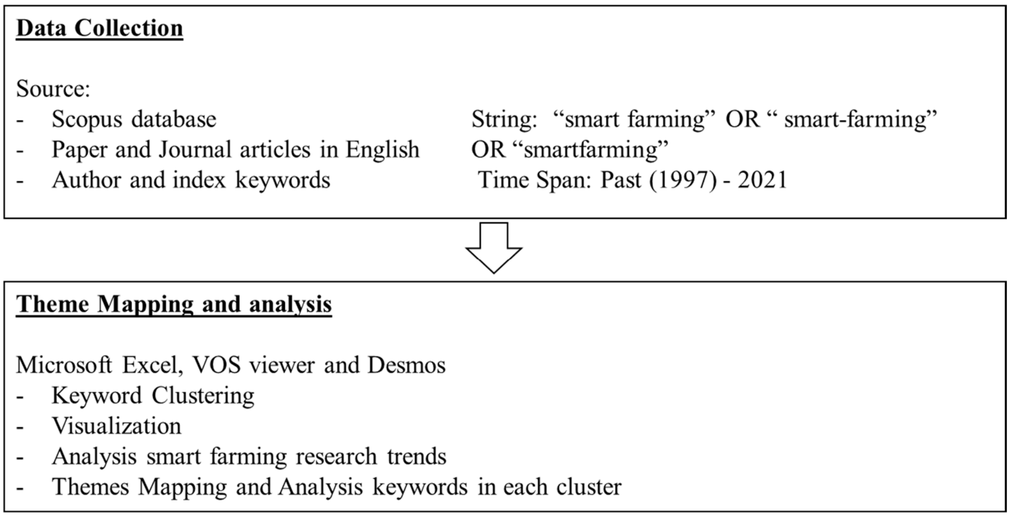

Figure 2. Analysis framework.

3.2. Data Collection

The initial stage of this research involved gathering data on author and index keywords from journal and conference articles pertaining to "smart farming", "smart-farming", and "smartfarming". The Scopus database was selected as the data source due to its claim of being the largest abstract database and citation of peer-reviewed scientific literature [34]. To identify relevant publications, the search query "smart farming" was used in the Scopus database search interfaces, which includes many types of documents. A total of 1141 articles published between 1997–2021 were collected, and those with duplicate or incomplete required data were excluded. This resulted in the formation of a corpus of articles relevant to this research.

3.3. General Analysis and Thematic Mapping

Bibliometric methods were used to evaluate and measure the academic output [35]. Performance analysis and scientific mapping were the two main bibliometric techniques used to assess and evaluate a research area. Performance analysis aimed to evaluate research actor groups, including research, nations, and institutions, along with the impact of their activities. On the other hand, scientific mapping was utilized to gather knowledge and data on a particular research field's conceptual or social structure [29]. This research used general analysis to show the rise in the key journals and publications, and the most prolific nations, organizations, and authors. Furthermore, the theme progression of smart farming research was investigated by thematically categorizing the basic context in the corpora, where basic contexts referred to words and sentences.

Correspondence analysis [36] can be used to visualize and explore the relationship between clusters in two-dimensional space. Graphs generated from this analysis can be utilized to propose cluster labels automatically using a specific VOS viewer.

4. Bibliometric Results

A total of 1141 journal and conference proceeding articles within the scope of smart farming were analyzed in terms of their publication years, as shown in Figure 3. Prior to 2013, only a few articles had been published. However, the number of articles published on smart farming has steadily increased since 2013, as shown in Figure 3 and detailed in Table 1. This trend suggests that this research topic has received increasing attention in recent years. Using the publication data per year and extrapolating it using the formula from Lee's research [37], the results suggest that smart farming research will continue to increase before eventually saturating in the next few years. Based on the information provided by the researchers Venston and Hodges [38], it is suggested that the developmental phase of a technology can be estimated using an S-curve, starting from its inception until saturation occurs. This concept can be applied to smart farming technology, which may eventually reach a saturation point and be replaced by more advanced alternatives. The expectation of saturation in smart farming research can be attributed to various factors. As the global population continues to grow, there is an increasing demand for efficient agricultural practices to meet the rising food requirements. Smart farming, incorporating advanced technologies such as IoT, AI, and data analytics, holds the potential for optimizing resource utilization, enhancing crop yields, and improving overall agricultural productivity.

The saturation point signifies a theoretical threshold at which the widespread adoption and implementation of smart farming practices result in diminishing returns in terms of further productivity gains. This point is expected to be reached when a significant portion of the agricultural industry has already embraced smart farming technologies and practices. However, determining the exact timeline for saturation is challenging due to factors like technological advancements, economic considerations, regulatory frameworks, and the global adoption rate among farmers. Ongoing research in this area will likely provide more insights into the anticipated timeline for saturation in smart farming.

Based on the yearly cumulative document, the keyword count and current beginning phase increased. Using the formula, the extrapolation data of each keyword is shown in Table 1.

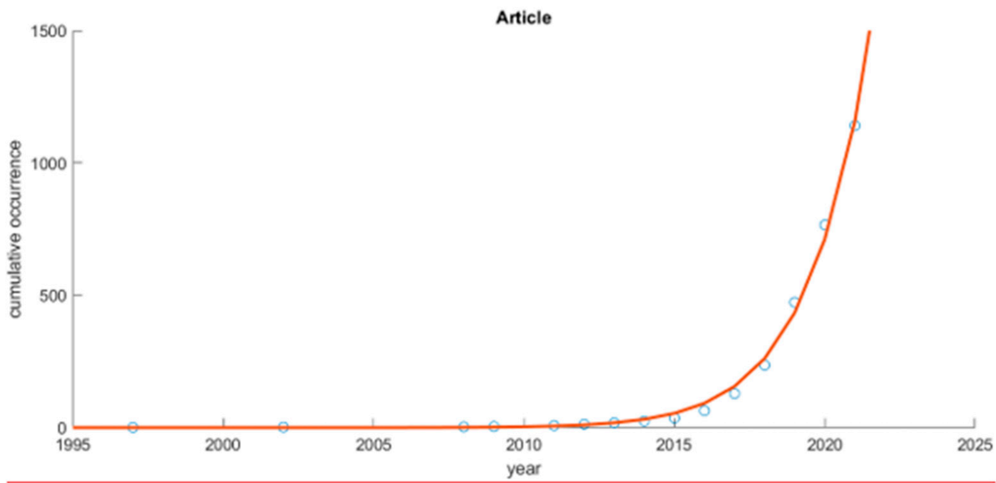

Figure 3. Cumulative occurrence of journals and conference proceeding publications of smart farming.

Table 1. Journal and conference proceeding publications of smart farming research yearly published.

Year	Article	Cum. Article
1997	1	1
2002	1	2
2008	1	3
2009	1	4
2011	4	8
2012	5	13
2013	5	18
2014	7	25
2015	11	36
2016	28	64
2017	65	129
2018	107	236
2019	238	474
2020	292	766
2021	375	1141

Further, we may continue the extrapolation to depict the continuous trend until it reaches the saturation phase. There are variant reparametrized forms of the Richards curve in the literature [39–42], and it is calculated using the following formula:

$$f(t;\theta_1;\theta_2;\theta_3;\xi) = \frac{\theta_1}{\left[1+\xi e^{(-\theta_2(t-\theta_3))}\right]^{\frac{1}{\xi}}} \tag{1}$$

where θ_1, θ_2, and θ_3 are real numbers, and ξ is a positive real number. The utility of the Richards curve is its ability to describe a variety of growing processes, endowed with strong flexibility due to the shape parameter ξ [39]. Analytically, the Richard curve (i) becomes the logistic growth curve [43] when $\xi = 1$, and (ii) converges to the Gompertz growth curve [44] as the ξ converges to zero from the positive side of real numbers. The Gompertz curve is g $(t;\theta_1;\theta_2;\theta_3) = \left[1+\xi e^{(-\theta_2(t-\theta_3))}\right]^{\frac{1}{\xi}}$, but it is also known that the estimation of ξ is a complicated problem [45], and we resorted to the use of a modern sampling scheme, the elliptical slice sampler [46], to estimate the ξ.

θ_1	θ_2	θ_3	ξ	R^2
9,897,000	0.1005	2051	0.1603	0.9956

Figure 4 examines the publication of articles on smart farming from 2013–2021 and their indexing in the Scopus database; there were 129 papers published in the top eight journals in this field. None of these journals were used in the research prior to 2013. The top four journals, in terms of number of papers published, were *Computers and Electronics in Agriculture* (29 papers), *IEEE Access* (20 papers), *Sensors Switzerland* (15 papers), and *Sustainability Switzerland* (15 papers). Table 2 provides further details, including the total number of articles published, the name of each journal, and the number of articles published per year in each journal.

According to the data, 82 countries have contributed to the publication of journal articles on smart farming. The top 10 most productive countries in smart farming research are shown in Figure 5, with India having the highest number of publications, followed by the United States and Germany. India alone accounts for more than one-fifth (23.6%) of worldwide publications on the topic. The total number of journal articles related to smart farming published by these three countries was more than four-fifths (76.4%) of world productivity.

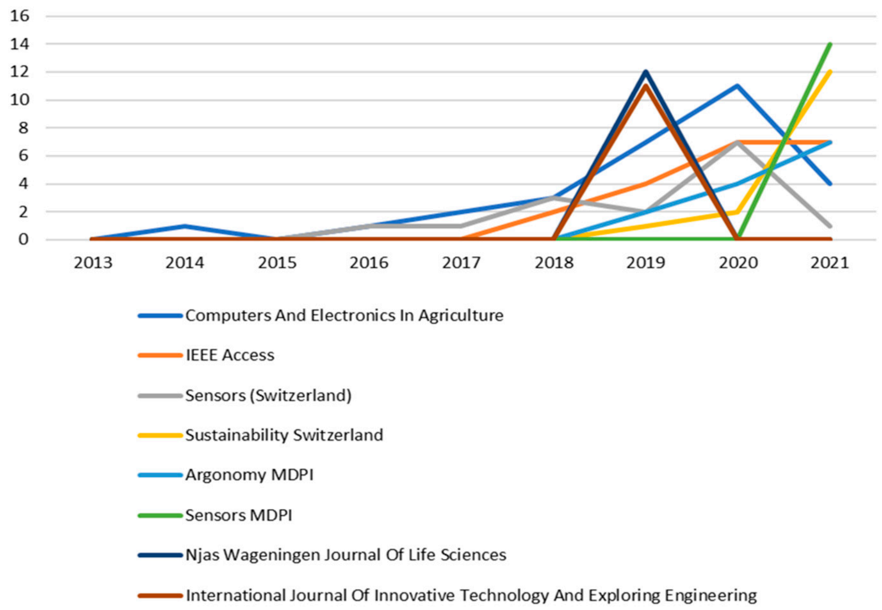

Figure 4. Top eight journals in which the highest numbers of documents regarding smart farming research were published.

Table 2. Top eight journals in which the number of documents regarding smart farming research were published yearly and in total.

Journal	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Computers And Electronics in Agriculture	0	1	0	1	2	3	7	11	4	29
IEEE Access	0	0	0	0	0	2	4	7	7	20
Sensors (Switzerland)	0	0	0	1	1	3	2	7	1	15
Sustainability Switzerland	0	0	0	0	0	0	1	2	12	15
Agronomy MDPI	0	0	0	0	0	0	2	4	7	13
Sensors MDPI	0	0	0	0	0	0	0	0	14	14
Njas Wagenigen Journal Of Life Sciences	0	0	0	0	0	0	12	0	0	12
International Journal Of Innovative Technology And Exploring Engineering	0	0	0	0	0	0	11	0	0	11
										129

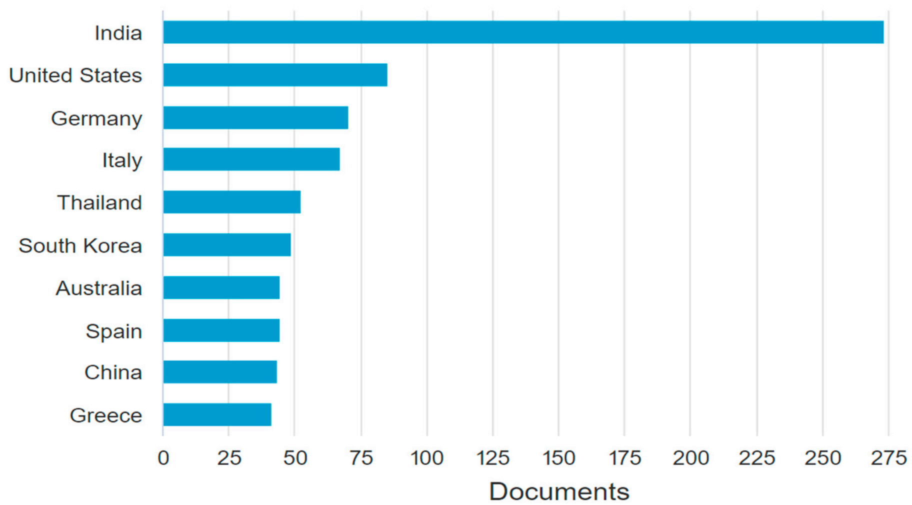

Figure 5. The top 10 most productive countries in smart farming research.

Figure 6 reveals the most productive institutions in smart farming research publications based on Pub data, led by Wagenigen University and Research, with 24 articles published in this field. The second and third most active institutions are Vellore Institute of Technology and De La Salle University, both with 12 articles published. Figure 7 shows that the majority of these top 10 institutions are from Europe (62.9%), while the remaining institutions are from Asia (37.1%). The characteristics of smart farming publications released by the 10 most active institutions are summarized in Table 3. Institutions from The Netherlands dominate the research activity in this field, while those located in India, the world's most productive nation, did not make it to the top 10 list. This is because research on smart farming is distributed more evenly in India, which may explain why there are not as many well-known institutes in this sector compared to The Netherlands.

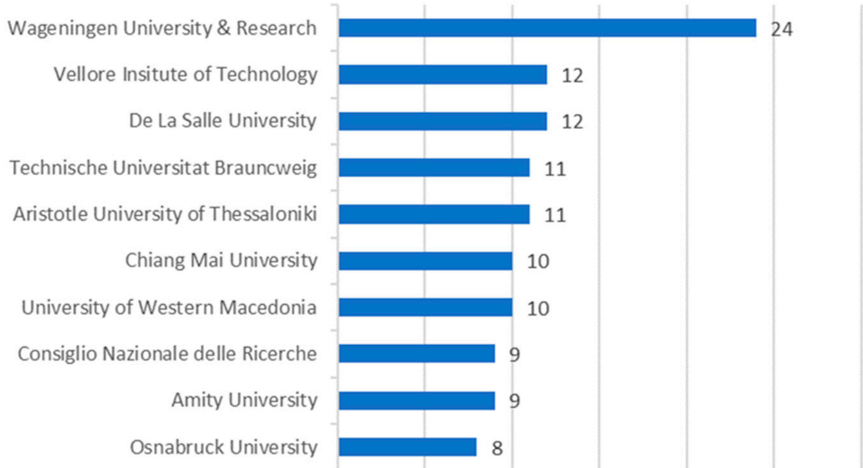

Figure 6. Top 10 most productive institutions in smart farming research.

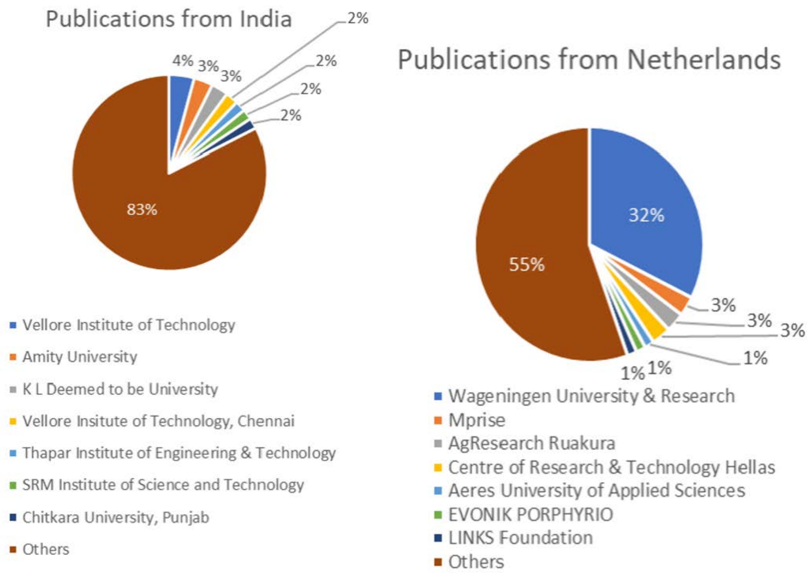

Figure 7. Publication information for India and The Netherlands.

Figure 8 dis plays the top 10 most productive authors in smart farming research. Among them, Mahmoudi, S.; Dadios, E.P.; Sarigianidis, P.; and Wolf, L. had the highest number of publications, with eight articles each. The remaining authors ranked second and have published six journal articles each. Table 4 summarizes the number of articles and citations from these authors across four different periods. Interestingly, the authors with the most publications are not necessarily the ones with the most citations. These top authors started their research in the field of smart farming in 2017.

Table 3. Top 10 most productive institutions in smart farming research.

Institution	Country	1997–2015	2016	2017	2018	2019	2020	2021	Total	Citation	Cit/Pub
Wagenigen University and Research	The Netherlands	4	1	4	3	8	1	3	24	2390	99.56
Velore Institute of Technology	India	0	0	1	1	3	3	4	12	208	17.34
De LaSalle University	Philippines	0	2	1	1	4	3	1	12	149	12.42
Technische Universitat Brauncweig	Germany	0	1	4	2	2	1	1	11	68	6.18
Aristotle University of Thessaloniki	Greece	0	0	0	1	4	4	2	11	185	16.82
Chiang Mai University	Thailand	0	0	3	2	1	1	3	10	120	12
University of Western Macedonia	Greece	0	0	0	0	4	5	1	10	357	35.7
Consiglo Nazionale delle Ricerche	Italy	0	0	0	2	2	3	2	9	268	29.78
Amity University	India	0	0	0	1	2	4	2	9	160	17.78
Osnabruck University	Germany	0	0	0	2	1	4	1	8	80	10

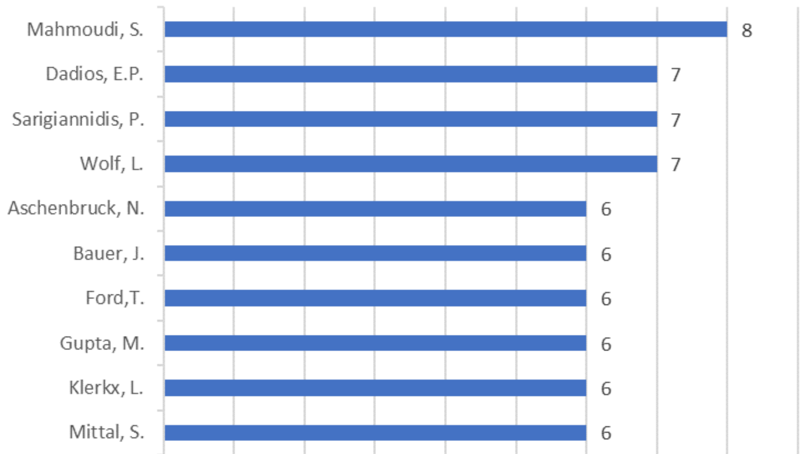

Figure 8. Top 10 most productive authors.

Table 4. The number of publications (Pub.) and citations (Cit.) of the top 10 most productive authors in four periods.

Author	1997–2015		2017		2018		2019		2020		2021		Total		
	Pub.	Cit.	Pub.	Cit.	Pub.	Cit.	Pub.	Cit.	Pub.	Cit.	Pub.	Cit.	Pub.	Cit.	Cit/Pub
Mahmoudi, S	0	0	0	0	1	28	0	0	5	20	2	14	8	62	7.75
Dadios, E.P.	1	28	1	15	1	0	2	41	1	4	1	10	7	98	14
Sarigiannidis, P.	0	0	0	0	0	0	2	61	4	44	1	35	7	140	20
Wolf, L.	1	20	3	17	0	0	2	5	1	0	0	0	7	42	6
Aschenbruck, N.	0	0	2	23	1	40	3	16	0	0	0	0	6	79	13.17
Bauer, J.	0	0	2	23	1	4-	3	16	0	0	0	0	6	79	13.17
Ford, T.	0	0	0	0	1	4	2	2	1	1	2	0	6	7	1.17
Gupta, M.	0	0	0	0	0	0	0	0	4	212	2	2	6	214	35.67
Klerkx, L.	0	0	0	0	1	41	1	156	3	424	1	0	6	621	103.5
Mittal, S.	0	0	0	0	0	0	0	0	4	212	2	2	6	214	35.67

Table 5 presents the top 10 most cited journal articles in the field of smart farming publications. The number of citations reflects the level of popularity of each study in this area. The majority of these articles are surveys that focus on smart farming analytics, deep learning, AI, unmanned aerial vehicles (UAV), and IoT. The highest-ranked article, entitled "Deep Learning in Agriculture: A Survey", was written by Kamilaris et al. This paper provides an overview of the use of deep learning in agriculture, which is directly relevant to smart farming research. Field data were collected and reviewed with deep learning techniques to optimize farm operations based on the results [15].

Table 5. Top 10 most highly cited articles.

No	Title	Author(s)	Year	Cited by
1	Deep learning in agriculture: A survey	Kamilaris, A. et al.	2018	1402
2	Big data in Smart Farming—A review	Wolfert, S. et al.	2017	1063
3	A review on the practice of big data analysis in agriculture	Kamilaris, A. et al.	2017	380
4	A review of social science on digital agriculture, smart farming, and agriculture 4.0: New contributions and a future research agenda	Klerkx, L. er al.	2019	273
5	Cropping practices manipulate abundance patterns of root and soil microbiome members paving the way to smart farming	Hartman, K. et al.	2018	247
6	A survey on the role of IOT in Agriculture for the implementation of smart farming	Farooq, M.S. et al.	2019	235
7	Internet of Things (IoT) for Smart Precision Agriculture and Farming in Rural Areas	Ahmed, N. et al.	2018	230
8	A review on UAV-based applications for precision agriculture	Tsourus, D.C et al.	2019	229
9	UAV-based crop and weed classification for smart farming	Lottes, P. et al.	2017	224
10	Design of Secure Authenticated key Management Protocol for Generic IoT Networks	Wazid, M. et al.	2018	219

5. Analysis

Figure 9 displays the co-occurrence network cluster visualization generated using the VOS Viewer tool. The largest bubble represents IoT, agricultural robots, and smart agriculture, with each cluster showing the relationships between the cited documents based on the frequency of their co-occurrence, as shown in Table 6. The research on IoT in the context of smart farming is a major area of investigation. The left and right bubbles relate to technology to support smart farming and biotechnology. The big bubbles for IoT and agricultural robots indicate their prominence in the field, while the lack of connections between some keywords suggests opportunities for further research.

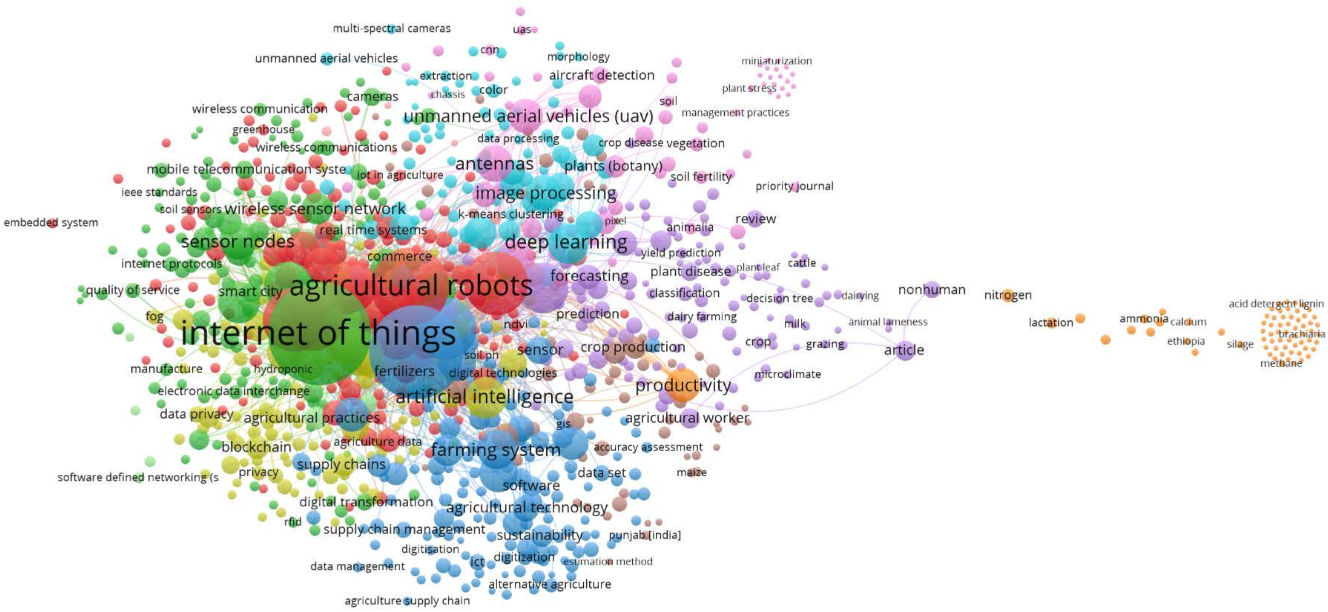

Figure 9. Key terms cluster visualization using VOS Viewer.

Authors' keywords and index keywords from bibliographic records were grouped in order to fully capture the topic map of smart farming research. Table 6 presents the total number of key terms, as well as the quantity and proportion of categorized key terms for eight periods (1997–2015, 2016, 2017, 2018, 2019, 2020, 2021, and 1997–2021). Figure 9 shows the number and percentage of key terms classified in each cluster for the data period 2009–2018. IoT emerged as the most prominent key term in smart farming research, aligning with the concept of Industry 4.0. Additionally, specific key terms related to plant-based smart farming research, such as soybeans, show potential for further investigation. Term such as “cloud computing”, “middleware”, “big data”, “decision support systems”, “communication protocols”, “wireless sensor and actuator networks—WSANs”, and “integrated farm management” had a number of occurrences less than 90. Artificial intelligence was ranked 10 with a percentage of 3%, and had a number of occurrences of 90.

Table 6. The number and percentage of key terms classified in the thematic analysis process for each period.

Period	Total Key Terms	Number of Key Terms Classified	Percentage
1997–2015	246	31	13%
2016	107	49	46%
2017	286	137	48%
2018	372	204	55%
2019	1013	402	40%
2020	1077	630	58%
2021	1367	703	51%
1997–2021	4468	2156	48%

5.1. Major Themes in Smart Farming Research

As seen in Figure 10, the clustering process of the entire data period (1997–2021) resulted in 10 clusters of key terms. These key-term clusters can be considered as the dominant topics or themes in smart farming research and can be further grouped into three major themes as follows:

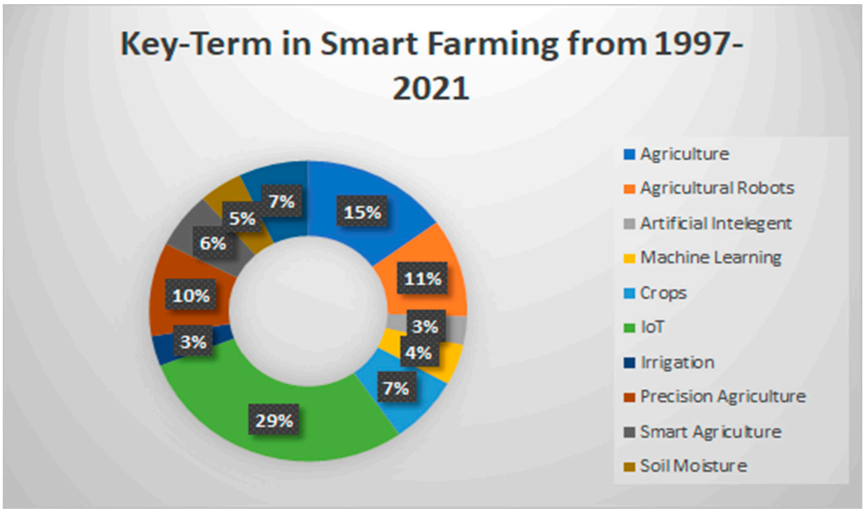

Figure 10. The number of key terms in each cluster for the periods 1997–2021.

5.1.1. Internet of Things (IoT)

IoT infrastructure in smart farming starts with sensors placed in various locations on the farm, such as in the soil, for irrigation, on crops/plants, and on livestock. The data are transmitted wirelessly through communication layers, such as Wi-Fi, Radio Frequency Identification (RFID), Long-Range Radio (LoRa), and Narrowband Internet of Things (NB-IoT), to a cloud-based server. The server stores the collected data and shares it with applications and users such as farmers, owners, investors, and end-users for monitoring and decision-making purposes [47–50]. Figure 11 shows IoT infrastructure in smart farming. The analysis of key terms reveals the cluster’s labels and the terms related to IoT. An IoT system continuously monitors and collects data in the field, which is then analyzed by machine learning algorithms to provide effective and cost-efficient farm management solutions.

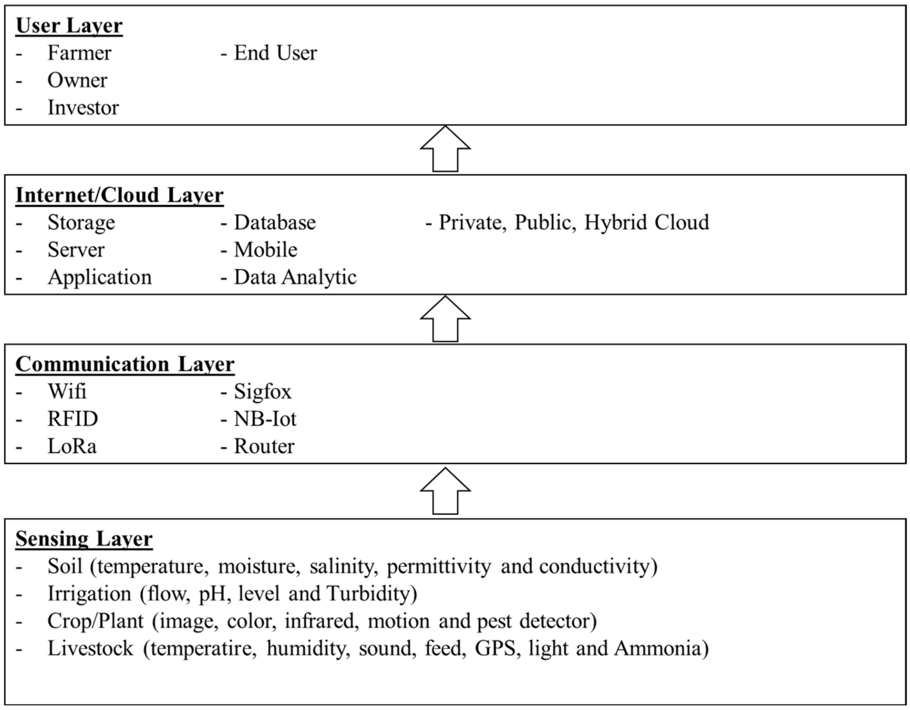

Figure 11. IoT infrastructure.

5.1.2. Blockchain and Agricultural Robots

Blockchain technology is a type of ledger that can store important information for different applications. Its potential use in precision agriculture has been extensively discussed in [51], where it is highlighted that blockchains can be used to record and verify data related to agriculture products, track and monitor movables, and share information. Selecting the right type of blockchain for smart farming depends on several criteria, and a tool to evaluate the most suitable one has been proposed in [52]. Using blockchains in smart farming provides authentication and supports the persistence and auditability of stored data, ensuring the correctness of the data when needed later, and adding transparency, anonymity, and traceability. Smart contracts can also be used in blockchain-based smart farming [53]. Agricultural robots have become increasingly popular on farms as they help to improve agricultural efficiency. These robots can perform operations such as harvesting, weeding, and land preparation [54]. In some cases, tractors are controlled by a low-cost brain–computer interface (BCI) to monitor the electroencephalographic (EEG) signal, resulting in high control accuracy (93.5%) and low time consumption (0.48 ms) [55]. Agricultural robots have also been used for harvesting strawberries, potatoes, and mushrooms [56–58].

5.1.3. Smart Agriculture, Crops, and Irrigation

Smart farming has seen widespread adoption across countries, with numerous applications and services available for improving farming practices in crop cultivation and livestock management. Many Asian countries, for example, are promoting farm automation using data analytics, robotics, and sensor technology. These tools can have a significant impact on crop yield, crop quality, and overall profitability for farmers and investors. Japan, for instance, is using robots to automate fruit picking on farms. Farmers can monitor their fields using technology that provides access to temperature, carbon dioxide levels, light sources, and sterilizing water through their smartphones. The robots can pick fruits automatically and at a faster pace than farmers [59]. Meanwhile, Australia is using UAV technology to control rural farms, with the livestock industry utilizing UAV to monitor and manage livestock in open areas. Cows are identified and their health monitored using dongles or tags, with data managed on websites that are easily accessible through iPads [60,61].

5.2. Future Smart Farming Research Trends

The challenges, new trends and opportunities in the future research of smart farming are discussed below.

- The increasing prevalence of Industry 4.0 has made it challenging to analyze smart farming using traditional tools, as the vast number of interconnected devices generates large amounts of data. To effectively visualize and integrate this data in real time, more advanced data processing techniques are required. Based on the results of existing research in this area, it can be inferred that smart farming will continue to be a growing research topic in the coming decades. This trend is reflected in the interpolation patterns displayed in Appendix B, showing that the research topics related to smart farming are still evolving and considered immature.
- The keywords identified from this research—such as agriculture robots, sensor networks, IoT, and blockchain—are still under development. These findings are in line with the statements made during the observations.
- India has been found to be the most productive country when it comes to conducting research related to smart farming. However, the institution that has been deemed the most effective in conducting smart farming research is Wageningen University and Research in The Netherlands.
- The most frequently occurring keyword in the research was 'Internet of Things', followed by 'Agriculture Robot' and 'Blockchain'. The combination of IoT with Agriculture Robot and Blockchain for agricultural security is currently the best solution and is in line with the principles of Industry 4.0.

5.3. Limitations

This research relied on data obtained from Scopus, an international scientific database. However, it was restricted to four specific areas: computers, engineering, agriculture, and mathematics. Additionally, the analysis only considered journal articles to exclude research still in progress. The second limitation was on the use of keywords as clustering input. Although the keywords selected could be considered to represent the contents of a document, they might not adequately reflect the contents of an article. Future research should consider more in-depth content analysis to address these limitations.

Figures A1 and A2 show the top 10 characteristic key terms for each cluster, while the relationships between the clusters are visualized in Figure 8, where each circle represents a key-term cluster or topic. The numbers and percentages of authors and index keywords classified in each cluster are presented in Table 1, and Figure A3 displays the cluster relationships for four different periods (1998–2021, 2019, 2020, and 2021).

6. Conclusions

This research employed bibliometric analysis to investigate smart farming trends, identify their potential benefits, and analyze their research insights. A total of 1141 publications were collected from the Scopus database in the period 1997–2021 (accessed in October 2022). The VOS Viewer tool was utilized to quantify the connections between the articles using the co-citation unit. It resulted in 10 clusters of smart farming research topics, i.e., agriculture, agricultural robots, artificial intelligence, machine learning, crops, IoT, irrigation, precision agriculture, smart agriculture, and soil moisture. The main trend observed in smart farming related to the adoption of new technology in line with Industry 4.0. However, the limitations of this research included only presenting research trends and failing to compare them with previous bibliometric research on smart farming. To address this, future research should include improved statistical analysis to confirm the observed relationships.

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Data Availability Statement: All the data used for this research are publicly available and provided by Scopus at https://www.scopus.com, accessed on 15 October 2022.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

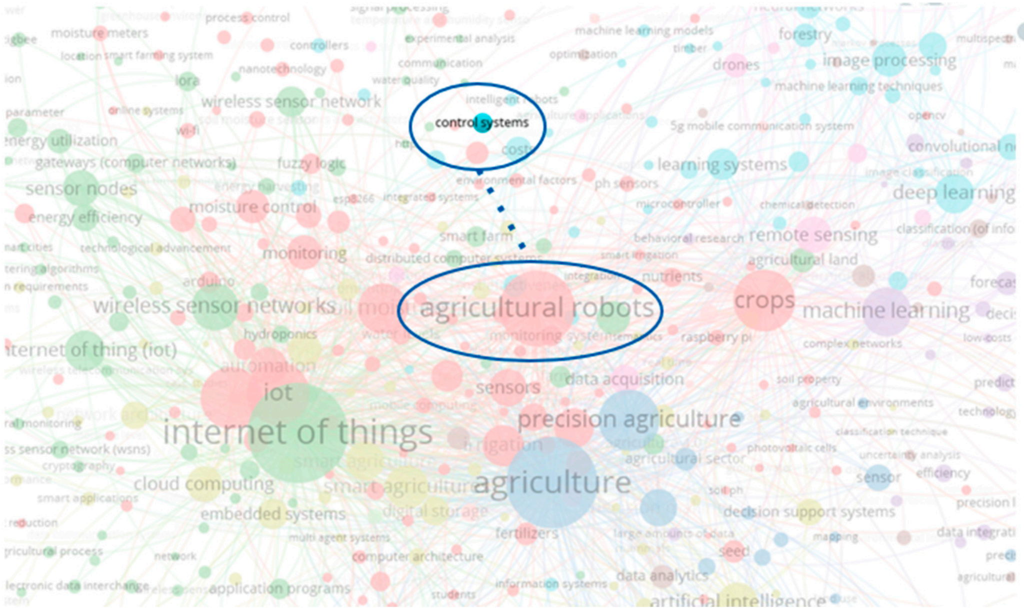

Figure A1. Potential Growth Control System Issue to support Agricultural Robot.

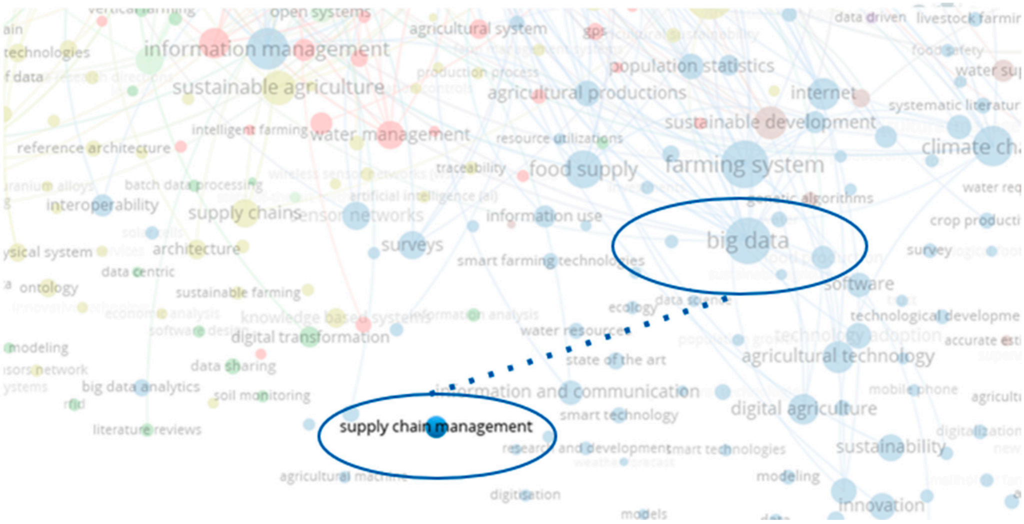

Figure A2. Relation between Supply Chain Management and Big Data.

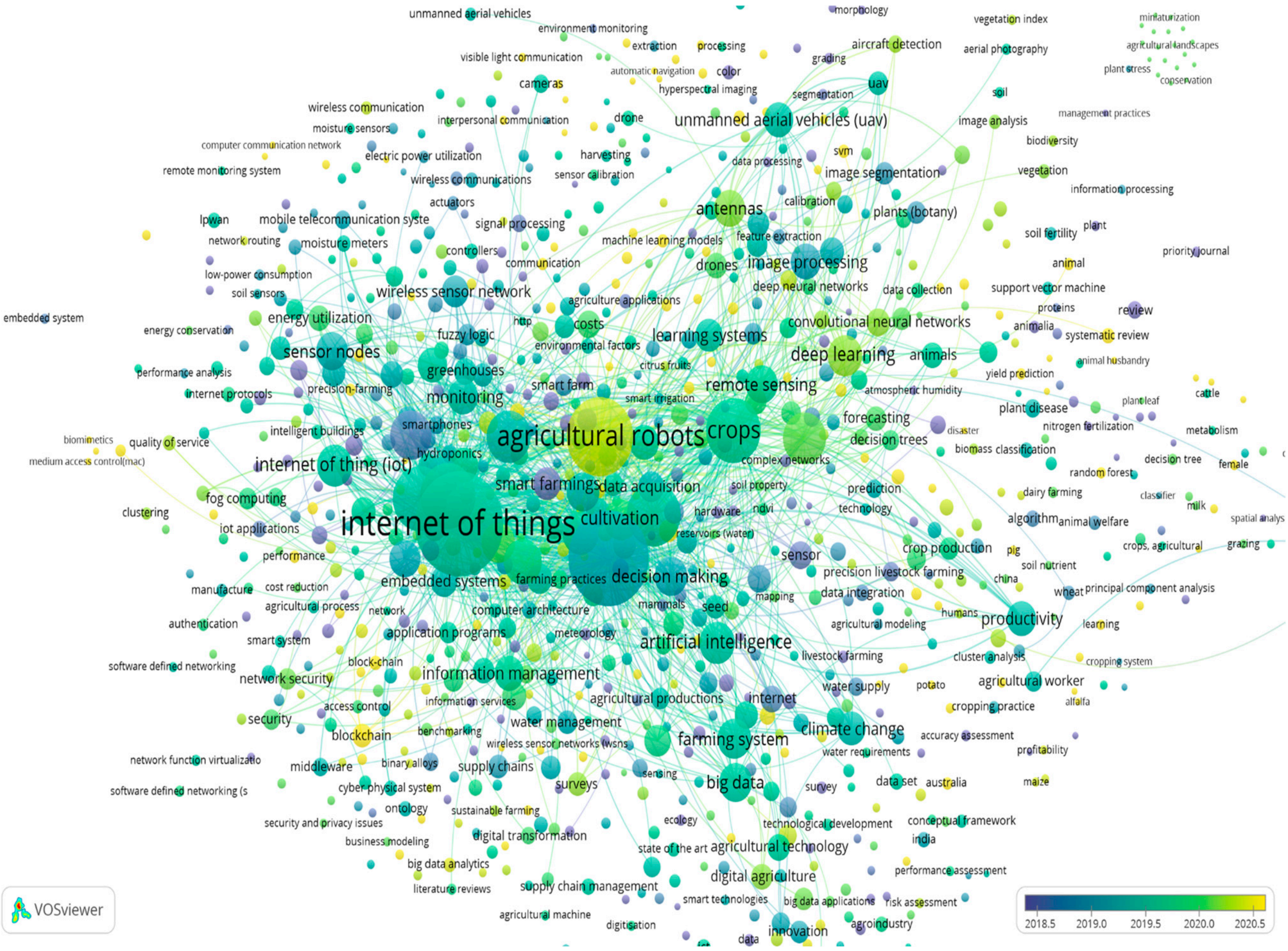

Figure A3. Potential Growth Internet of things, Agricultural Robot and Blockchain.

Appendix B

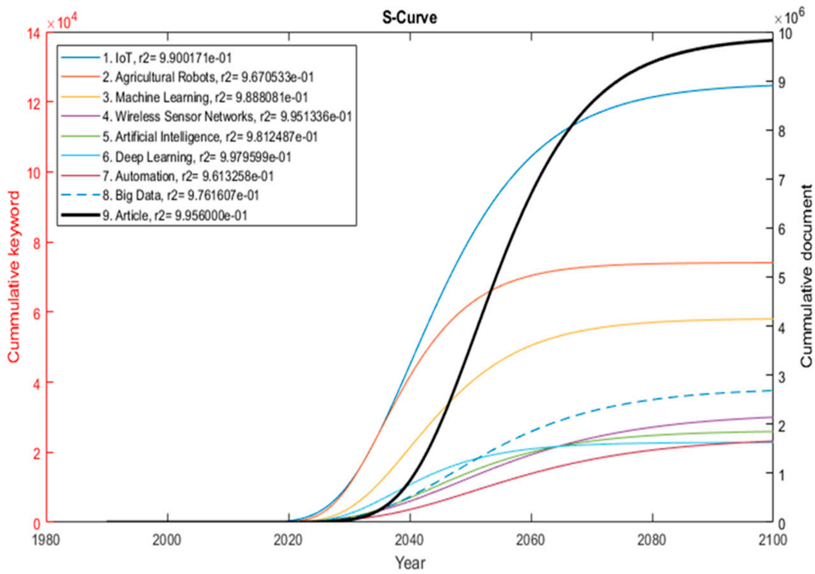

Figure A4. Smart Farming Technological Agenda S-Curve for document.

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