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Review

Bibliometric Analysis of Trends in Smart Irrigation for Smart Agriculture

Yiyuan Pang [1,2], Francesco Marinello [2,*], Pan Tang [1], Hong Li [1] and Qi Liang [1]

[1] Research Centre of Fluid Machinery Engineering and Technology, Jiangsu University, Zhenjiang 212013, China; 2111911010@stmail.ujs.edu.cn (Y.P.)
[2] Department of Land, Environment, Agriculture and Forestry, University of Padua, 35020 Legnaro, Italy
* Correspondence: francesco.marinello@unipd.it

Abstract: Agriculture is considered one of the most critical sectors that play a strategic role in ensuring food security. It is directly related to human development and social stability. The agricultural sector is currently incorporating new technologies from other areas. These phenomena are smart agriculture and smart irrigation. However, a challenge to research is the integration of technologies from different knowledge fields, which has caused theoretical and practical difficulties. Thus, our purpose in this study has been to understand the core of these two themes. We extracted publications in Scopus and used bibliometric methods for high-frequency word and phrase analysis. Research shows that current research on smart agriculture mainly focuses on the Internet of Things, climate change, machine learning, precision agriculture and wireless sensor networks. Simultaneously, the Internet of Things, irrigation systems, soil moisture, wireless sensor networks and climate change have received the most scholarly attention in smart irrigation. This study used cluster analysis to find that the IoT has the most apparent growth rate in smart agriculture and smart irrigation, with five-year growth rates of 1617% and 2285%, respectively. In addition, machine learning, deep learning and neural networks have enormous potential in smart irrigation compared with smart agriculture.

Keywords: cluster analysis; high-frequency phrase; Scopus; Internet of Things; irrigation system

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1. Introduction

The world's population is increasing and is expected to reach 10 billion by 2050 and food security has become one of the main issues of concern to the world [1]. Simultaneously, due to the acceleration of urbanization, the land area available for agricultural cultivation is gradually decreasing [2]. Labour shortages, frequent extreme weather, and declining soil fertility have further brought tremendous obstacles to improving productivity [3]. COVID-19 and the ongoing Russia-Ukraine conflict have also significantly increased global hunger levels [4]. All of these will exacerbate risks to food security. Currently, two ways to solve food shortages are to increase arable land or use modern technology to increase productivity. The latter is the most straightforward and effective way to address the current predicament.

Agriculture is considered one of the most critical sectors that play a strategic role in ensuring food security [3]. It is directly related to human development and social stability [5]. The development of agriculture can be roughly divided into four stages: (1) Traditional agriculture (Agriculture 1.0) mainly focuses on human and animal operations. (2) Mechanized agriculture (Agriculture 2.0) converts an agricultural activity that requires days of human sweat and draft animal labor into a few hours [6]. (3) "Agriculture 3.0" was sensor-based and designed to tailor treatments and inputs to the right place and time by accounting for variability at increasingly finer scales [7,8]. (4) The fourth is "Agriculture 4.0 (smart agriculture)", which extends the "Agriculture 3.0" approach to include sensors and robotics, and also the Internet of Things (IoT), cloud computing, data analytics, and decision support systems into an integrated "smart" approach to production [9–11].

Modern technology represented by artificial intelligence (AI) began to be explored in agriculture in the last century. However, due to the limited technical level at that time, it brought little substantial progress [12]. After entering the 21st century, the considerable effectiveness of AI in the industrial area has given agriculture new opportunities for change [13,14]. Intelligent technology has gradually intervened in agricultural production, and promoting intelligence has become the mainstream agriculture trend [15]. Smart agriculture (SA) uses modern industrial organizational methods, management concepts and advanced technologies to develop new concepts of modern agriculture, transforming traditional agriculture characterized by "land + machinery" into modern agriculture with "equipment + information + AI" as its core [16,17]. The SA market was estimated at USD 13.8 billion in 2020 and is projected to reach USD 22 billion by 2025 at a compound annual growth rate of 9.8% [18].

To comprehensively understand SA, we first need to understand which topics belong to this research area. In this sense, Chander emphasized in his systematic literature review that precision agriculture, IoT, and human health assessment are the development directions of agriculture, and systematically discussed and summarized advanced emerging technologies, smart sensor clouds, big data analysis and ubiquitous computing are new ground-breaking applications anticipated in recent years [19]. Angelita proposed that smart agriculture is modern agriculture that integrates technology, equipment, and protocols to improve agricultural processes. It is also proposed that intelligent systems include more computing capabilities, such as edge computing, processing massive data, artificial intelligence resources, and security functions [20]. Hassina proposed that SA is a unified application based on different technologies such as automation, data collection, data transmission, data processing and decision-making [21]. Subeesh provides an overview of the latest research in agriculture driven by digital technologies and identifies the most prominent applications of AI and IoT in agricultural engineering [13]. The above results show that SA is a research field with comprehensive coverage, mainly involving topics such as the Internet of Things, artificial intelligence, and data processing. However, many reviews only introduce a particular hot spot in detail and do not provide an overview of SA, which is not conducive to readers' quick understanding of the study's popularity in each field. This paper uses bibliometric analysis methods to conduct cluster analysis on various topics in agriculture, aiming to digitize the research popularity of each topic.

As an essential part of SA, smart irrigation (SI) has a more detailed focus, focusing on the relationship between agricultural water use and crop growth, including information on water quantity and quality, soil characteristics, weather conditions, and fertilizer use parameters [22]. The Food and Agriculture Organization of the United Nations (FAO) predicts that food production will increase by more than 50% by 2050, leading to a 10% increase in agricultural water demand [23]. SI can minimize water waste based on plants' actual water and nutrient needs, which can alleviate the contradiction between the growing food needs of the growing population and agricultural water needs [24], while minimizing environmental impacts such as greenhouse gases and fuel consumption [25].

Many papers have analyzed trends in SI. Simona conducted a bibliometric on SI and divided it into 10 clusters: internet, uncrewed aerial vehicles, crop coefficient, precision irrigation, lawn turf, irrigation system, cost-effective, machine vision, wireless sensors network, sprinkler irrigation, and energy saving, and using the most prominent techniques in cluster analysis are the IoT and machine learning [26]. Ahmed made a detailed analysis of SI management under climate change in drylands. He proposed that artificial intelligence, deep learning, model predicting, variable rate irrigation technology, and uncrewed aerial vehicles could ensure high water use efficiency in water-scarce regions [27]. The above research results comprehensively analyze smart irrigation and propose current main research topics. This paper aims to obtain research popularity in various fields to facilitate readers to understand the current research status more quickly. In addition, given the high correlation between SA and SI, the current research hotspots of SA are used to predict the research direction of SI.

The purpose of this article makes sense because there is no consensus among different papers on SA and SI. The preceding paragraphs briefly overview the entire section of SA and SI and show how broad the subject is and how it relates to several other topics, such as AI, IoT and data processing. However, there still needs to be a gap between the above research and the topics involved in smart agriculture or smart irrigation, especially the relationship between the two.

Due to the massive workload of publication bibliometric, in this complex framework, a text-mining analysis, as proposed by Giora and Ferrari, seems to be appropriate to appreciate the interconnection among the hotspots of the research [28,29]. This kind of analysis allows to objectively identify and weigh the most critical topics in a specific research field and study how they interact.

The present analysis aims to provide a general and comprehensive review of smart agriculture and smart irrigation. The specific objectives of this work were to: (1) Describe the temporal trend of publications over this century; (2) identify the most important topics to which the research of SA and SI area has been mainly directed; (3) analyze the essential links among topics. To obtain such results, this paper decided to perform a bibliometric analysis, as it would be the most effective, and determine the focus of future work.

The remainder of this paper is organized as follows [30]. Section 2 presents the extraction method and results of publications related to the topic and defines clusters. Section 3 presents the analysis and results. It mainly analyzes the development trends of smart irrigation and smart agriculture and compares their high-frequency words and phrases, focusing on crops and the most common phrases. Section 4 discusses the differences and connections between different topics, future research trends of these two topics, and seven high-frequency phrases in smart agriculture and irrigation. Finally, Section 5 concludes this study and gives some limitations and future research directions.

2. Materials and Methods

Scopus is an internationally renowned academic literature database and citation index server operated by Elsevier. It covers journals, conference papers, patents, and other literature resources in multiple subject areas. Scopus encompasses a more significant number of journals and articles than Web of Science [31,32]. It is widely recognized in the academic community and has an authority. Therefore, this paper uses Scopus to extract publications.

The key to using bibliometric analysis is to use advanced searches to limit areas of interest, extract documents from databases, and conduct a systematic quantitative review. It enables presenting the key topics raised by the scientific community and performing cluster analysis. The analytical approach allows us to map the gaps from a statistical point of view and a research hotspot perspective. For example, Giora used the method to analyze mulberry and silkworm [28]. Ferrari conducts a bibliometric analysis of trends in biomass for bioenergy research [29].

This paper uses the below analysis method to conduct a bibliometric analysis of SA and SI [28,29]. The flow chart is shown in Figure 1. First, download the titles and abstracts of publications related to the topic in Scopus, then extract high-frequency words and phrases from the database and obtain the research trends of the topic through cluster analysis. Among them, it is worth noting that this paper differs from the traditional bibliometric analysis. In order to obtain the research direction more accurately, this paper not only extracts high-frequency words, but also analyzes high-frequency phrases. At the same time, a script was designed to achieve an efficient and accurate extraction of high-frequency phrases.

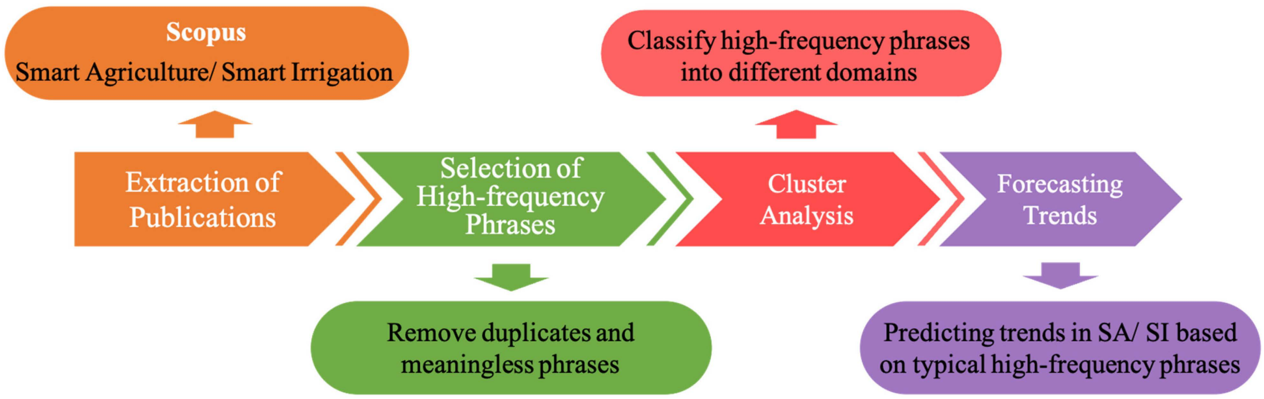


Figure 1. Flow chart for bibliometric analysis of trends in smart agriculture and smart irrigation.

2.1. Article Selection

This study selected publications in Scopus that contain the string "smart agriculture" and "smart irrigation" and their derived terms in the title, abstract, or keywords. To better understand the progress of the latest research, a time filter was used to constrain the search period to this century. The present review limits document types to articles and conference papers, excluding reviews, editorials, books, and notes [33].

This study used the script "TITLE-ABS-KEY (smart AND agriculture) AND PUBYEAR > 1999 AND PUBYEAR < 2023 AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar"))" to conduct an advanced search in Scopus and obtained 7260 publications on "smart agriculture". In contrast, the number of publications obtained by the "smart irrigation" search was 2033. Further, a search for smart irrigation in smart agriculture was extracted, and 1148 publications were obtained (Table 1).

Table 1. Scripts for extracting publications in Scopus.

Topic	Script	Number of Publications
SA	*TITLE-ABS-KEY (smart AND agriculture) AND PUBYEAR > 1999 AND PUBYEAR < 2023 AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar"))*	7260
SI	*TITLE-ABS-KEY (smart AND irrigation) AND PUBYEAR > 1999 AND PUBYEAR < 2023 AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar"))*	2033
SA & SI	*TITLE-ABS-KEY (smart AND agriculture*) AND TITLE-ABS-KEY (smart AND irrigation*) AND PUBYEAR > 1999 AND PUBYEAR < 2023 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp")*	1148
SA (Year—2022)	*TITLE-ABS-KEY (smart AND agriculture) AND (LIMIT-TO (PUBYEAR, 2022)) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp"))*	316

In addition, in order to analyze the annual research hotspots, this study uses the script "*TITLE-ABS-KEY (smart AND agriculture) AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (PUBYEAR, 2022))*" for extracting, different years can be modified through scripts, and the values of PUBYEAR are replaced accordingly to obtain data from different years [29].

2.2. Article Elaboration

According to the method in Section 2.1, the search results are converted and saved into easy-to-process .txt files [28], and Python is used to extract high-frequency words and phrases in the saved files. It is worth noting that phrases consist of 2–4 nouns, such as machine learning (two words), convolutional neural network (three words), and crop water stress index (four words).

The first step of the data pre-processing was tokenization. This paper designed a Python script for text analysis and high-frequency phrase identification. The script utilizes regular expressions and the counter class from the collections module to process a given text file. It begins by defining a function called *tokenize_text* that tokenizes the text into *n-grams*, allowing the user to specify the desired *n-gram size*. To enhance the accuracy of the analysis, a set of common words is defined and excluded from consideration (for example: "of", "to", "for", "show", "on", "in", "can", "the", "by", "with", "use", "are", "based", "used", "but", "also", etc.). The primary function, *count_and_display_high_frequency_phrases*, counts and displays high-frequency phrases in the text, excluding *n-grams* containing common words or digits. Users can customize the n-gram size and the number of top phrases to display by adjusting the *n* and *top-k* values.

Although the Python script can exclude a large number of invalid phrases, different files need to be filtered further, for example, merging "wireless sensor" and "wireless sensors", deleting "case study", and integrating synonymous phrases like "smart agricultural" and "smart agriculture".

Finally, the results are imported into Gephi 0.10.1 for analysis [29]. Gephi is a tool for data analysts and scientists passionate about exploring and understanding graphs. The goal is to help data analysts make assumptions, visually discover patterns, and isolate structural singularities or failures in data source processes. It is a complementary tool to traditional statistics, as visual thinking with interactive interfaces is now thought to facilitate reasoning. To create connectivity diagrams in Gephi, users must import data files into the software. This study uses the most concise .csv format to import the retrieved data into Gephi and sets the source, target, weight and other information. The weights are treated as vectors, which is the quantity of occurrence of each phrase.

2.3. Cluster Definition

Cluster analysis is classifying data into different classes or clusters [32]. From the perspective of practical applications, cluster analysis is one of the main tasks of data mining. Moreover, clustering can be used as an independent tool to obtain data distribution, observe each data cluster's characteristics, and focus on specific clusters for further analysis.

When the main topic can be subdivided into several interrelated parts, cluster analysis allows us to study and characterize the relationship among the different sections of the main topic: how the IoT connects to machine learning and deep learning [34].

As this analysis is only qualitative, no fixed rules exist for defining clusters [33]. Taking Scopus as an example, the website defaults to many clustering methods, such as publication years, document types, databases, research areas, source titles, affiliations, countries, languages, open access, etc.

The paper follows Scopus's clustering method and divides the extracted high-frequency phrases into four clusters according to different engineering fields: "Agricu-ltural and Crop", "Technology and Algorithm", "Environmental and Climate", and "Social and Economic". The "Agriculture and Crop" cluster collects words or phrases related to efficient production, environmental protection, and crops (e.g., smart agriculture, smart irrigation, soil moisture, and crops) [35]. The "Technology and Algorithm" cluster collects phrases related to computers and AI, such as the Internet of Things and wireless sensor networks. The "Environmental and Climate" cluster includes climate change, climate-smart agriculture, forestry, environmental technology, and ecosystem. The "Social and Economic" cluster includes food supply, efficiency, productivity, and energy utilization.

As shown in Table 2, this subject-based clustering method is broad and direct and does not reflect the specific research direction of a specific topic. Therefore, this article will conduct a more detailed cluster analysis on this basis.

Table 2. Name of the considered clusters and phrases that compose them.

Cluster	Phrases
Agricultural and Crop	Agriculture, Agricultural Robots, Crop, Smart Farming, Irrigation, Soil Moisture, Cultivation, Automation, Food Security, Agricultural Technology, Irrigation System, Soil, Moisture Control, Crop Yield, Fertilizer, Greenhouse, Farming System, Animal
Technology and Algorithm	Internet of Things, Machine Learning, Deep Learning, Artificial Intelligence, Wireless Sensor Network, Sensor, Blockchain, Big Data, Remote Sensing, Cloud Computing, Information Management, Image Processing, Digital Storage, Smartphone, Data Handling, Convolutional Neural Network, Gateways, Convolution
Environment and Climate	Climate Change, Sustainable, Climate-smart Agriculture, Water Management, Forestry, Environmental Technology, Ecosystem
Social and Economic	Food Supply, Smart City, Efficiency, Productivity, Human, Cost Effectiveness, Economic, Energy Utilization, Developing Country, Commerce, Environmental Impact

3. Results

3.1. Analysis of the Trends

As a preliminary analysis, this article uses the annual quantity and the annual growth quantity of publications as indicators to evaluate research trends on smart agriculture and smart irrigation in this century. The annual growth quantity is used instead of the growth rate here because these topics are an entirely new concept, and using the growth quantity for analysis will make it clear to readers [29]. For example, the number of publications on smart agriculture increased from only one in 2000 to three in 2001, a growth rate of 200%, while the quantity increased by 351 articles from 2020 to 2021, a growth rate of only 31%. If growth rates are used to analyze this, the results can be seriously skewed from reality.

As shown in Figure 2, the number of publications containing "smart agriculture" in this century can be roughly divided into four stages. The first is that between 2000 and 2014, the number of publications remained relatively the same, not exceeding 100 per year. The second is that between 2015 and 2018, the number of publications on "smart agriculture" increased significantly, from 155 in 2015 to 936 in 2019, an average annual growth of approximately 200; this may be because, with the emergence of digitalization, the Industry 4.0 model has been extended to the agricultural sector, significantly promoting the development of smart agriculture [34,35]. The third is 2020 and 2021. Although the quantity of publications at this stage is still rising, the growth trend has slowed down (the curve in Figure 2) [36,37]. The fourth is 2022: the number and the growth number return to ap-parent growth. Therefore, judging from the number and growth of publications this century, scholars have developed a strong interest in smart agriculture. Especially in the past ten years, scholars' research results in smart agriculture have shown an apparent growth trend.

The same method was used as when searching for "smart agriculture" to search for "smart irrigation". As shown in Figure 2, their growth trends are almost in sync. Between 2000 and 2012, there was no significant growth in the number of publications. Starting in 2013, the number of publications began to grow, but growth slowed significantly in 2020 and 2021 before returning to 2019 growth in 2022.

On the other hand, using the number of publications in 2022 for analysis, the number of publications on smart agriculture and smart irrigation is 2019 and 476, respectively. Smart irrigation accounts for up to 23.6% of smart agriculture. Therefore, it shows that smart irrigation is an important research area in smart agriculture, and scholars have paid high attention to it.

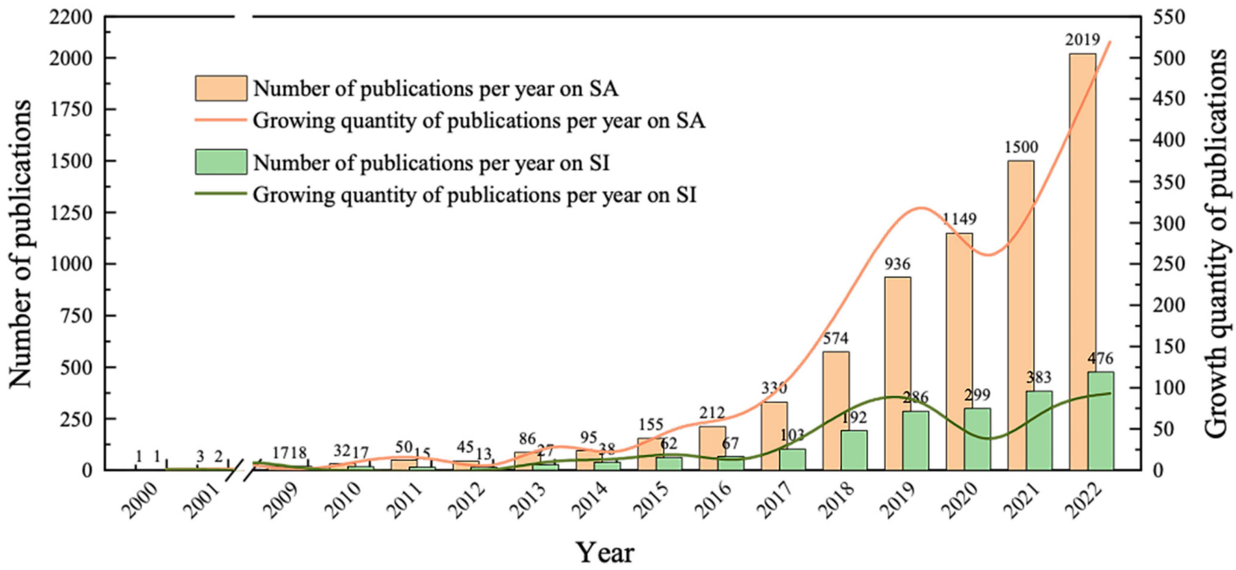


Figure 2. Annual number and annual growth of publications on SA and SI.

In addition to the number of publications, the country attributes of publications can also positively reflect the research trends of the topic [28]. An analog analysis was performed, considering the number of publications per country to characterize the geographic distribution of the research on smart agriculture and smart irrigation. Figure 3 shows the top five countries for the quantity of publications in 2000–2022.

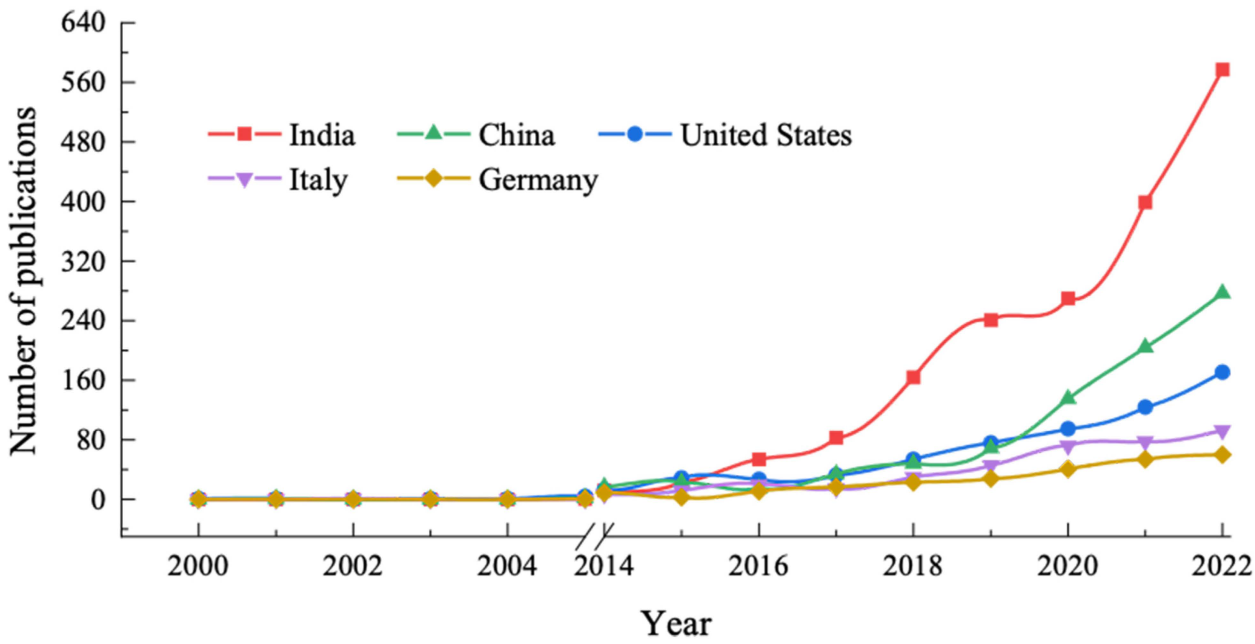


Figure 3. Number of publications by the top five countries this century.

As can be seen from the ranking, the top five are India, China, the United States, Italy and Germany. This result is not unexpected because India and China have huge populations, reaching 1.4 billion, directly affecting the number of publications. Simultaneously, rapid population growth and resource depletion have put pressure on ecological and socioeconomic systems. These developing countries must develop smart agriculture to alleviate this pressure [38]. On the other hand, traditional agricultural powers such as the United States, Italy and Germany have been conducting in-depth research on smart agriculture, and it is reasonable to publish many publications. Among them, Italy has a population of only 60 million and has the most publications per capita among these countries.

A more specific analysis of the geographical extent of the research focuses on collaborations among universities from different countries that aim to determine how the chosen topic can generate collaborations in the scientific community. Figure 4 shows in a graphic way how the web of collaborations for the smart agriculture topic is well distributed in the world among different countries.

Figure 4. Geographic extent of collaborations for research in smart agriculture and darker colored lines indicate a more significant number of connections.

As shown in Figure 4, the countries that cooperate with India the most are the United States (57 publications), Saudi Arabia (43), Ethiopia (20), Australia (18), and China (17). The countries that cooperate with China the most are the United States (90), Pakistan (86), the UK (36), Australia (21), and Canada (18). The countries that cooperate with the United States the most are China (90), India (57), the UK (30), Canada (29), and Italy (28). The countries cooperating with Italy the most are the United States (28), Spain (21), France (20), Netherlands (15), and Brazil (14). The countries cooperating with Germany the most are the UK (19), the United States (17), China (17), The Netherlands (13), and France (13).

More detailed information about collaborations among different countries is presented in Table 3, where data about the first five countries for the total number of collaborations that led to articles publication between 2000 and 2022 are summarized; data on collaborations were derived from the affiliation metadata in Scopus.

Table 3. Collaborations among countries.

Country	Total Number of Collaborations	Number of Partner Countries	Average Number of Collaborations per Country
India	662	83	8.0
China	525	74	6.3
USA	756	90	9.1
Italy	365	79	4.4
Germany	343	81	4.1

As seen in Figure 3 and Table 3, India is the first country in terms of many publications. It has 662 co-authored publications, collaborating with 83 different countries. However, even though the United States has fewer publications than India and China, it ranks first in the total number of collaborations, partner countries, and average number of collaborations per country. The total number of publications in collaboration with the US is 756, and the number of partner countries is 90, which is significantly higher than other countries.

3.2. Compare High-Frequency Words

3.2.1. Smart Agriculture

This study uses the method described in Section 2.2 to extract the 100 most frequent words. The paper used the weight assigned to each term to define the relative weight of the cluster to which that specific word belongs [28]. As shown in Equation (1), the overall score of a term was obtained by the weighted mean of the values over the years, giving higher weight to the most recent years to better focus the attention on the current situation [29]:

$$S_T = \frac{\sum_{i=1}^{k} \omega_i \cdot \frac{O_i}{B_i}}{\sum_{i-1}^{k} \omega_i} \quad (1)$$

where k is the time frame for extracting publications, which is 22 years for this paper, w_i is the weight of the ith year, O_i is the number of occurrences of the given term in the ith year, and B_i is the number of articles in the topic in the ith year.

Therefore, the relative weight of each cluster was calculated based on the total sum of the relative weights of all the n-words contained in the cluster itself. Table 4 shows the constitution of each cluster, with the relative weights of all the considered words.

Table 4. Clusters composition with the relative weight of each word and the overall relative weight of each cluster.

Cluster	Words	Cluster Relative Weight/%
Agriculture and Crop	System 5.0%, Water 2.9%, Soil 2.6%, Farmer 2.4%, Crop 2.3%, Irrigation 2.0%, Food 1.7%, Production 1.7%, Plant 1.3%, Machine 1.0%, Device 1.0%, Quality 1.0%, Growth 0.9%, Moisture 0.9%, Land 0.8%, Greenhouse 0.7%, Disease 0.7%, Parameter 0.7%, Factor 0.6%, Rice 0.5%, Humidity 0.5%, Livestock 0.5%, Leaf 0.4%, Fertilizer 0.4%, Cultivation 0.3%, Organic 0.3%, Maize 0.3%, Storage 0.3%	31.1
Technology and Algorithm	Data 4.9%, IoT 4.6%, Sensor 2.3%, Technology 2.1%, Monitoring 1.9%, Management 1.9%, Network 1.8%, Information 1.7%, Application 1.5%, Control 1.4%, Precision 1.2%, Wireless 1.1%, Design 0.9%, Intelligent 0.8%, Computing 0.7%, Digital 0.7%, Method 0.7%, Framework 0.7%, Decision 0.7%, Algorithm 0.7%, Accuracy 0.7%, Image 0.7%, Sensing 0.6%, Processing 0.6%, Intelligence 0.5%, Neural 0.5%, Automation 0.4%, Strategy 0.3%	34.6
Environment and Climate	Climate 2.8%, Change 1.3%, Temperature 1.0%, Environment 1.0%, Cloud 0.9%, Challenge 0.7%, Potential 0.7%, Increase 0.7%, Nature 0.5%, Weather 0.5%, Global 0.5%, Carbon 0.4%, Emissions 0.4%, Range 0.4%, Social 0.4%, Modern 0.3%	15.8
Social and Economic	Development 1.7%, Energy 1.6%, Sustainable 1.0%, Cost 0.9%, Efficiency 0.7%, Productivity 0.7%, Developed 0.7%, Blockchain 0.7%, Efficient 0.7%, Resource 0.6%, Industry 0.6%, Health 0.6%, Artificial 0.6%, Supply 0.6%, Economic 0.6%, Remote 0.6%, Consumption 0.5%, Human 0.5%, Population 0.4%, Further 0.4%, User 0.4%, Urban 0.4%, Innovation 0.4%, Policy 0.4%, Economy 0.3%, Business 0.3%, Green 0.3%	18.5

As can be seen in Table 4, the relative weight of the "Agriculture and Crop" cluster is 31.1%. The top 3 most frequently used words are "System", "Water", and "Soil ", with weights of 5.0%, 2.9%, and 2.6%, respectively; the weight of "Crop" directly related to agriculture is 2.3%. The "Technology and Algorithm" cluster has the highest relative weight, reaching 34.6%, of which the weights of "Data" and "IoT" are 4.9% and 4.6%, respectively. In contrast, "Environment and Climate" and "Society and Economy" have lower weights.

"Climate" and "Change" appear most frequently in the "Environment and Climate" cluster, at 2.8% and 1.3%, respectively. "Development" and "Energy" appear most frequently in the "Society and Economy" cluster, 1.7% and 1.6%, respectively.

From the weight perspective, it can be seen that "Technology and Algorithm" is the current research hotspot, among which the IoT and data processing are the main research directions of current agriculture. On the other hand, system, soil, farmer, climate, and energy, which are more relevant to traditional agriculture, are also the primary research hotspots of smart agriculture.

3.2.2. Smart Irrigation

The same method is used to search for high-frequency words in smart irrigation. In order to compare with smart agriculture more conveniently, this article divides these words into the same Clusters as smart agriculture: "Agriculture and Crop", "Technology and Algorithm", "Environment and Climate" and "Social and Economic", as shown in Table 5.

Table 5. Clusters composition with the relative weight of each word and the overall relative weight of each cluster.

Cluster	Words	Cluster Relative Weight/%
Agriculture and Crop	Water 9.0%, System 6.7%, Soil 3.6%, Agricultural 2.0%, Moisture 2.3%, Crop 2.2%, Farming 1.6%, Farmer 1.5%, Plant 1.0%, Production 1.0%, Humidity 0.8%, Food 0.8%, Machine 0.8%, Farm 0.7%, Growth 0.7%, Quality 0.7%, Parameters 0.6%, Land 0.5%, Greenhouse 0.5%, Rice 0.5%, Scheduling 0.4%, Evapotranspiration 0.4%, Drip 0.4%, Factor 0.4%, Watering 0.4%, Pump 0.3%, Controller 0.3%, Fertilizer 0.3%, Wheat 0.2%	39.2
Technology and Algorithm	Smart 6.6%, IoT 3.4%, Data 3.1%, Sensor 2.5%, Management 1.7%, Control 1.7%, Monitoring 1.5%, Technology 1.2%, Model 1.2%, Application 1.1%, Network 1.1%, Technologies 1.2%, Information 1.2%, Wireless 1.0%, Learning 1.0%, Precision 1.0%, Analysis 0.8%, Research 0.8%, Design 0.8%, Automated 0.6%, Approach 0.5%, Intelligent 0.5%, Automation 0.5%, Mobile 0.5%, Monitor 0.5%, Platform 0.5%, Technique 0.5%, Controller 0.4%, Sensing 0.4%, Fuzzy 0.4%, Microcontroller 0.3%, WSN 0.3%, Neural 0.3%, Software 0.3%	39.5
Environment and Climate	Climate 1.4%, Temperature 1.4%, Cloud 0.7%, Resource 0.7%, Change 0.7%, Weather 0.6%, Solar 0.6%, Environmental 0.6%, Performance 0.5%, Amount 0.5%, Increase 0.5%, Potential 0.5%, Effective 0.4%, Reduce 0.4%, Prediction 0.4%, Rainfall 0.3%, Nature 0.3%, Groundwater 0.3%, Drought 0.2%	12.5
Social and Economic	Energy 1.3%, Development 0.9%, Cost 0.8%, Efficiency 0.7%, Power 0.7%, Developed 0.7%, Sustainable 0.6%, Consumption 0.6%, Productivity 0.6%, Supply 0.5%, Remote 0.5%, Artificial 0.4%, Resource 0.4%, Significant 0.4%, Human 0.4%, Urban 0.3%, Economic 0.3%, Population 0.3%	8.8

As can be seen from Table 5, the relative weight of the "Agriculture and Crop" cluster is 39.2%. The most frequently used word is "Water", accounting for 9.0%; "System" has a weight of 6.7%, and "Soil" has a weight of 3.6%. The "Technology and Algorithm" cluster has the highest relative weight, reaching 39.5%, of which the weights of "Smart" and "IoT" are 6.6% and 3.4%, respectively. "Environment and Climate" and "Society and Economy" have lower weights. "Climate" and "Temperature" appear most frequently in the "Environment and Climate" group, both at 1.4%. "Energy" and "Development" appear most frequently in the "Society and Economy" group, at 1.3% and 1.0%, respectively.

Compared with smart agriculture, the relative weight of the "Agriculture and Crop" cluster of smart irrigation is higher, while the relative weight of the "Social and Economic" cluster is lower. Data shows that smart agriculture pays more attention to society and climate, while smart irrigation focuses more on soil and crops.

3.3. Compare High-Frequency Phrases

3.3.1. Smart Agriculture

Although high-frequency words can reflect the current agricultural research direction, high-frequency phrases can make the research direction more specific. For example, “cloud computing” can move the high-frequency word “cloud” from “Environment and Climate” cluster to “Technology and Algorithm” cluster; “big data” can make “Data” more specific; and “machine learning” can thoroughly combine “Machine” and “Learning”, two words that are not highly related. Therefore, this study conducted high-frequency phrase searches for “smart agriculture” in Scopus, and the top 24 high-frequency phrases obtained are shown in Table 6.

Table 6. The top 24 high-frequency phrases related to smart agriculture and the number of times they were extracted.

Phrases	Quantity	Phrases	Quantity	Phrases	Quantity
internet of things	10,047	big data	923	agricultural production	595
climate change	2306	food security	918	smart city	595
machine learning	1750	smart irrigation	914	cloud computing	595
precision agriculture	1676	irrigation system	895	crop yield	484
wireless sensor network	1420	low cost	735	remote sensing	463
soil moisture	1321	neural network	729	energy consumption	455
deep learning	1273	monitoring system	655	unmanned aerial	447
artificial intelligence	966	supply chain	649	image processing	434

It can be seen from the number of times the phrases are extracted: (1) The current research hotspots of smart agriculture are the IoT, climate change, machine learning, precision agriculture, wireless sensor networks, soil moisture, deep learning, artificial intelligence, big data and food security. (2) Classic research areas such as agricultural production and crop yield are receiving less attention [39]. (3) New research areas similar to unmanned aerial and image processing have received less attention from scholars than expected [38,39].

Further, as shown in Table 7, cluster analysis was performed on high-frequency phrases. The “Agriculture and Crop” cluster includes all agricultural characteristics-related phrases. In descending order within this cluster are precision agriculture (5.4%), soil moisture (4.2%), smart irrigation (2.9%), etc. The “Technology and Algorithms” cluster consists mainly of phrases related to the characteristics of modern technology. In descending order within this cluster are the Internet of Things (32.2%), machine learning (5.6%), wireless sensor network (4.5%), etc. The “Environment and Climate” cluster consists of phrases directly related to the environment. Although this cluster has only one phrase, this does not mean the other phrases are irrelevant to the cluster. The “Social and Economic “cluster mainly consists of phrases related to characteristics of human activities. In descending order within this cluster are food security (2.9%), low cost (2.4%), supply chain (2.1%), etc.

The results show that the cluster “Technology and Algorithm” accounts for the most significant proportion in smart agriculture, even higher than the other clusters combined. This demonstrates that the current research direction is more focused on high-tech applications, and agriculture is enjoying the convenience brought by modern technology.

3.3.2. Smart Irrigation

In addition, this study extracted high-frequency phrases in smart irrigation and obtained 24 phrases as shown in Table 8.

Table 7. The relative weight of each cluster and all phrases in smart agriculture.

Cluster	Phrases	Cluster Relative Weight/%
Agriculture and Crop	precision agriculture (5.4%), soil moisture (4.2%), smart irrigation (2.9%), irrigation system (2.9%), crop yield (1.5%)	16.9
Technology and Algorithm	internet of things (32.2%), machine learning (5.6%), wireless sensor network (4.5%), deep learning (4.1%), artificial intelligence (3.1%), big data (3.0%), neural network (2.3%), monitoring system (2.1%), cloud computing (1.9%), remote sensing (1.5%), unmanned aerial (1.4%), image processing (1.2%)	62.9
Environment and Climate	climate change (7.4%)	7.4
Social and Economic	food security (2.9%), low cost (2.4%), supply chain (2.1%), smart city (1.9%), agricultural production (1.9%), energy consumption (1.6%)	12.8

Table 8. The top 24 high-frequency phrases related to smart irrigation and the number of times they were extracted.

Phrases	Quantity	Phrases	Quantity	Phrases	Quantity
internet of things	2668	water management	336	neural network	191
irrigation system	1638	low cost	281	water level	190
soil moisture	1286	drip irrigation	267	crop yield	181
smart agriculture	808	water resources	265	automated irrigation	181
wireless sensor network	782	irrigation scheduling	237	monitoring system	174
climate change	446	irrigation management	232	moisture content	170
machine learning	431	artificial intelligence	218	deep learning	166
precision agriculture	419	water consumption	192	control system	166

As shown in Table 9, based on the number of times high-frequency phrases are extracted, this study defines smart agriculture using the same clusters as high-frequency words: "Agriculture and Crop", "Technology and Algorithm", "Environment and Climate", and "Social and Economic". As shown in Table 9, the "Agriculture and Crop" cluster includes irrigation system (13.7%), soil moisture (10.8%), etc.; the "Technology and Algorithm" cluster includes the Internet of Things (22.4%), wireless sensor network (6.6%), etc.; the "Environment and Climate" cluster includes: climate change (3.7%), water resources (2.2%); the "Social and Economic" cluster includes: water management (2.8%), low cost (2.4%), and water consumption (1.6%).

Table 9. The relative weight of each cluster and all phrases in smart irrigation.

Cluster	Phrases	Cluster Relative Weight/%
Agriculture and Crop	irrigation system (13.7%), soil moisture (10.8%), smart agriculture (6.8%), precision agriculture (3.5%), drip irrigation (2.2%), irrigation scheduling (2.0%), irrigation management (1.9%), water level (1.6%), crop yield (1.5%), automated irrigation (1.5%), moisture content (1.4%), control system (1.4%)	48.3%
Technology and Algorithm	internet of things (22.4%), wireless sensor network (6.6%), machine learning (3.6%), artificial intelligence (1.8%), neural network (1.6%), monitoring system (1.5%), deep learning (1.4%)	38.9%
Environment and Climate	climate change (3.7%), water resources (2.2%)	5.9%
Social and Economic	water management (2.8%), low cost (2.4%), water consumption (1.6%),	6.8%

The weights of the clusters show that "Agriculture and Environment" have the most significant relative weight, followed by "Technology and Algorithm", which is the same as SA, and "Environment and Climate" has the lowest relative weight.

"Agriculture and Crop" has the highest relative weight because this cluster has many high-frequency phrases, accounting for half of all high-frequency phrases. This shows that SI pays more attention to managing production and water resources. However, there is another point worthy of attention. The phrase with the highest weight (IoT) appears in "Technology and Algorithm", which shows that modern technology has begun to participate in smart irrigation [27]. Still, judging from the weight of machine learning (3.6%), AI (1.8%), neural network (1.6%) and deep learning (1.4%) have yet to be popularized in SI.

3.4. Compare Smart Agriculture and Smart Irrigation

As a sub-field of smart agriculture, smart irrigation must be closely related to it [40]. As shown in Section 3.1, the quantity of publications on smart irrigation is only 23.6% of that on smart agriculture. Therefore, the development direction of smart irrigation can be further explored by integrating high-frequency phrases from the two.

The present analysis sorted out common high-frequency phrases about smart agriculture and smart irrigation, conducted a comparative analysis and found that (Figure 5): (1) The same high-frequency phrases in both are IoT, climate change, machine learning, precision agriculture, wireless sensor network, soil moisture, deep learning, artificial intelligence, irrigation system, low cost, neural network. At the same time, most of these phrases use thicker colored lines (Figure 5), which show that these areas are highly concerned in SA and SI. (2) High-frequency phrases that do not include smart agriculture in smart irrigation are big data, food security, supply chain, agricultural production, smart city, cloud computing, and energy consumption. These research hotspots may be the next research direction of smart irrigation [10,26].

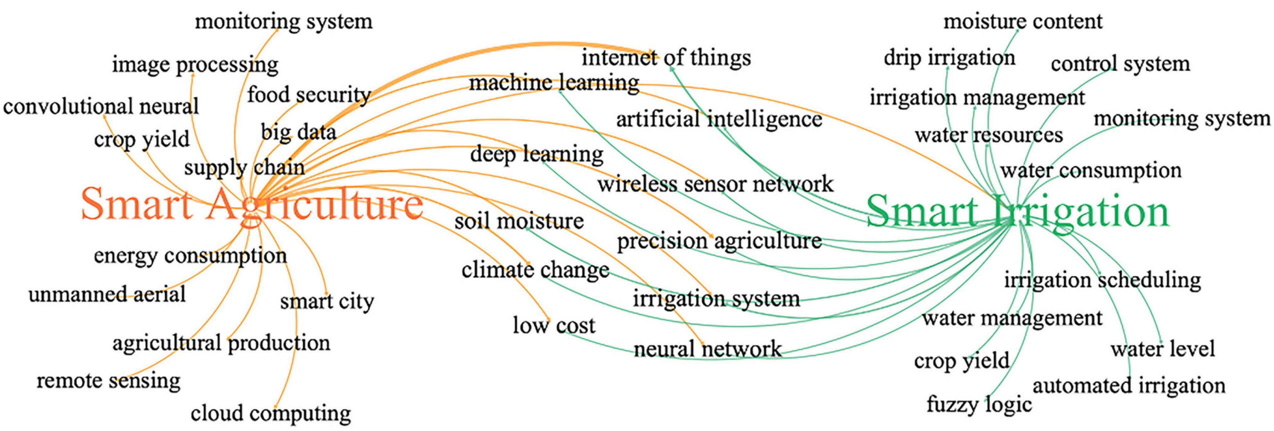


Figure 5. Compare high-frequency phrases in smart agriculture and smart irrigation.

3.5. Research on Crops

The relationship between smart agriculture and crops is crucial. The study classified crops into four categories based on their use: food crops, fruits, vegetables and oil crops [16]. Food crops mainly include maize/corn, rice, wheat, potato, cassava, and peas. Fruits include grape, apple, strawberry, mango, peach, cherry, lemon, watermelon, pineapple, olives, sugar cane, kiwi, and avocado. Vegetables: tomato, lettuce, chili, mushroom, cucumber, cabbage, carrot, onion, garlic. Oil crops: soybeans, cottonseed, peanut, sunflower (Figure 6).

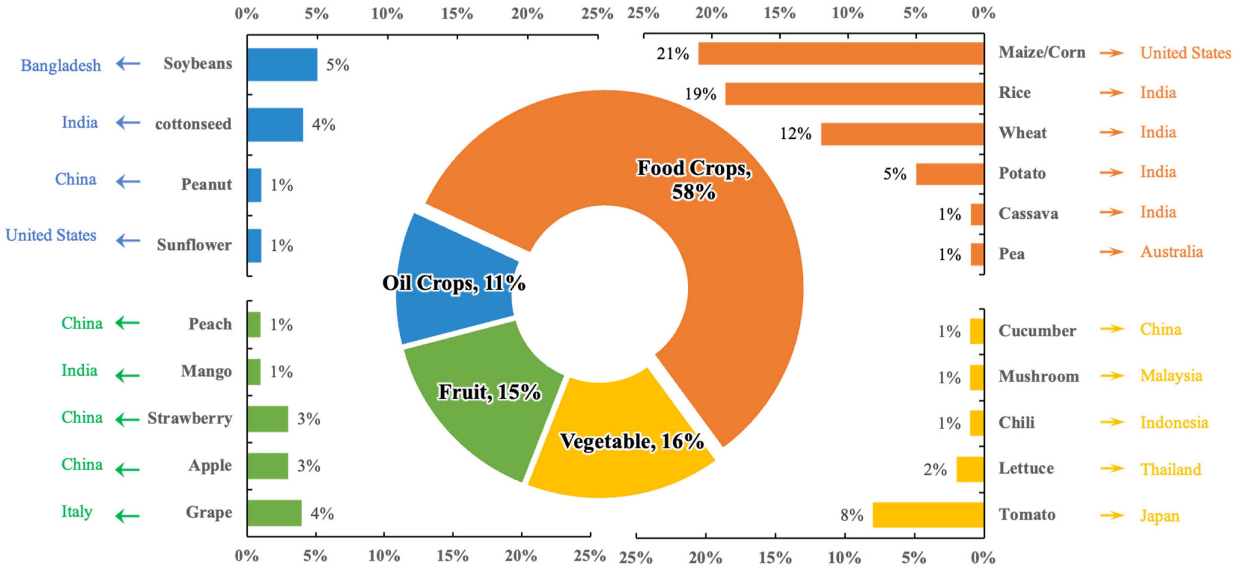


Figure 6. Classification, relative weight, and countries with the most publications on major crops.

As shown in the figure above, the highest weight among crops is "Food Crops", accounting for 58%. Among them, "Maize/Corn" has the highest weight, reaching 21%. The primary source of publications is the United States. The other three major food crops are Rice (19%), Wheat (12%) and Potato (5%), and the primary sources of publications are India. It can be seen from the "Vegetable" cluster that tomato has the highest weight, and related publications are mainly from Japan. It can be seen from the "Fruit" cluster that grape has the highest weight, and related publications are mainly from Italy. It can be seen from the "Oil Crops" cluster that soybeans have the highest weight, and related publications mainly come from Bangladesh.

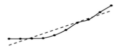
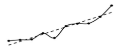
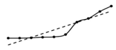
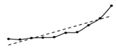
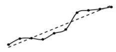
3.6. Research on Most High-Frequency Phrases

The paper conduct a detailed analysis of the top five high-frequency phrases in smart agriculture and smart irrigation, considering their evolution over time [28]. This study was conducted to describe the research findings of this century better.

3.6.1. Smart Agriculture

This study selected three parameters commonly used in statistics to characterize phrases' evolution over time objectively [34]. The first parameter is the average slope of fitting the number of publications per year; this parameter represents the efficiency of first-order linear fitting of the curve between the number of high-frequency phrases and years. This parameter can clearly show the trend of high-frequency phrases changing over time. The larger the value, the faster the scholar's attention to the phrase increases. The second parameter is the dimensionless Pearson correlation coefficient, which represents the linearity of the trend. When this coefficient is 1, a straight-line equation can describe the number of high-frequency phrases retrieved and time, and the quantity of retrievals increases with time. At the same time, 0 means no linear relationship between the two variables. The third parameter is the relative change over the past five years, calculated as the ratio between the average number of occurrences of each phrase in searches from 2013 to 2017 and the average number of events from 2018 to 2022. Table 10 lists some of the most cited phrases and their associated parameters.

Table 10. Analysis of clusters considering their slope, Pearson regression coefficient, and their relative increment in the past five years.

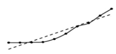
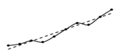
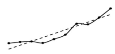
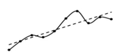
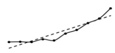
Phrase	Slope	Pearson Correlation Coefficient	Five Years Relative Changing	Graph	Fitting Formula
internet of things	285.5	0.98	1617%		Y = 285.5x + 737.1
climate change	30.7	0.99	497%		Y = 30.7x − 36.3
machine learning	44.8	0.98	4203%		Y = 44.8x − 126.5
precision agriculture	49.4	0.96	813%		Y = 49.4x − 123.9
wireless sensor network	24.6	0.85	304%		Y = 24.6x − 3.8

It can be seen from the slope that in the past ten years, the IoT has developed the fastest in smart agriculture, followed by machine learning, precision agriculture, climate change, and wireless sensor networks. According to the Pearson correlation coefficient, it can be found that other primary high-frequency phrases have developed steadily except for the apparent fluctuations in the wireless sensor network. Within five years of relative change, machine learning has developed the fastest, especially in Scopus, reaching an astonishing 4203%.

3.6.2. Smart Irrigation

The same parameters were used to analyze the top five high-frequency phrases of smart irrigation, and the results are shown in Table 11. Similar to smart agriculture, it can be seen from the slope that the Internet of Things has developed the fastest in smart agriculture in the past decade. According to the Pearson correlation coefficient, it can be found that wireless sensor networks exhibit more obvious fluctuations than smart agriculture. In addition, judging from the relative changes in five years, unlike smart agriculture, the growth rate of machine learning is 984%, significantly lower than smart agriculture 4203%; this shows that there is still a lot of research space for machine learning in smart irrigation.

Table 11. The most high-frequency phrases considering their slope, Pearson correlation coefficient and their relative increment in the past five years.

Phrase	Slope	Pearson Correlation Coefficient	Five Years Relative Changing	Graph	Fitting Formula
internet of things	74.9	0.99	2285%		Y = 74.9x − 200.1
irrigation system	35.7	0.94	443%		Y = 35.7x − 47.1
soil moisture	27.8	0.96	642%		Y = 27.8x − 53.6
wireless sensor network	5.4	0.54	211%		Y = 5.4x + 14.5
climate change	21.0	0.92	984%		Y = 21.0x − 55.8

3.7. Interrelationships among High-Frequency Phrases

The analysis aims to obtain reliable information about the interrelationships between the analyzed phrases [28]. In this study, the high-frequency phrases of smart agriculture and smart irrigation were further simplified, and seven were extracted to form a new list containing smart agriculture and smart irrigation. These nine phrases generated 36 mutual relationships ($C_9^2 = 36$), and their connections were analyzed based on these relationships.

To achieve this goal, the paper used the method described in Section 2.1 to extract publications related to IoT, climate change, machine learning, wireless sensor networks, and precision agriculture and save them as .txt files. The results show that the number of publications on IoT is 85,163; the number of publications on climate change is 288,081; machine learning is 320,426; wireless sensor network is 85,823; irrigation system is 29,433; soil moisture is 68,945; and precision agriculture is 8677. Furthermore, the occurrence times of eight other high-frequency phrases were searched from nine .txt files, and Gephi was used for correlation analysis.

As reported in Figure 7, there is a powerful connection between the IoT, wireless sensor networks and machine learning, which shows that the IoT needs to use wireless sensor networks and machine learning to complete hardware and software construction. At the same time, many publications on climate change include the IoT, which shows that many climate change studies need to use the Internet of Things. In addition, the interrelationship diagram clearly illustrates the need for further improvement in the relevance of smart irrigation and smart agriculture to modern technologies such as machine learning.

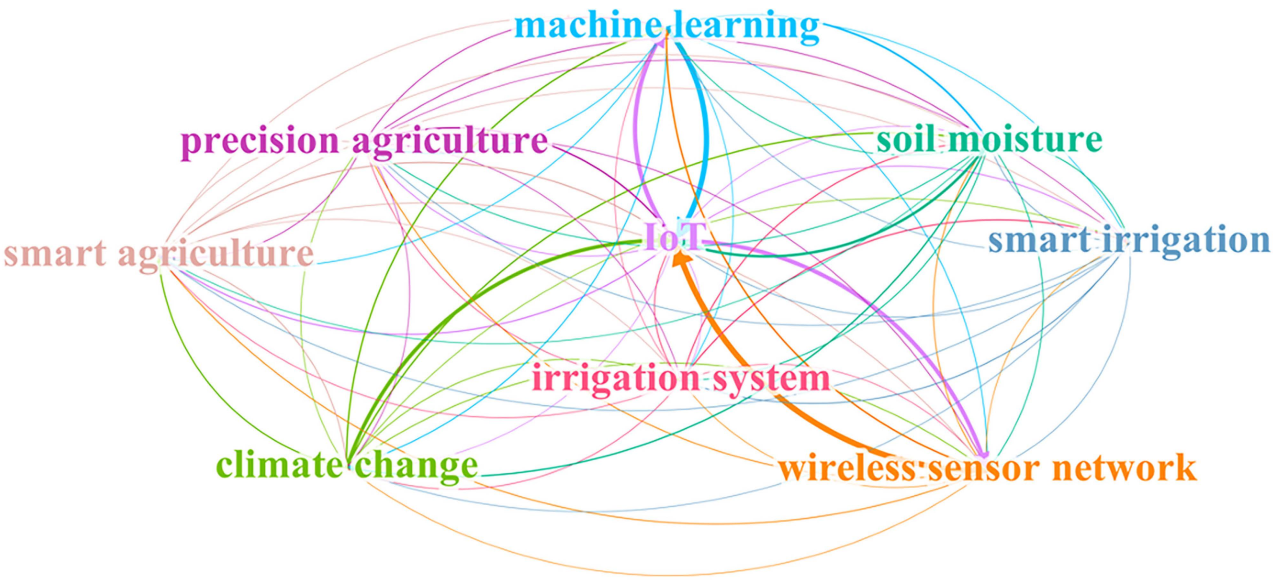


Figure 7. Interrelationships among the nine topics.

4. Discussion

The results of bibliometric analysis show that smart agriculture is an agricultural development model that uses advanced technology and information technology [2]. Smart irrigation is a method that uses advanced information technology and automation equipment to improve agricultural irrigation systems [41]. They have similar purposes, namely improving agricultural production efficiency, reducing resource consumption, optimizing farmland management, and improving the quality of agricultural products. As other papers have already observed, there needs to be more consistency or clarity among topics from different areas of knowledge [36]. Nonetheless, there is no doubt that any innovation in agriculture is welcome, especially when making farming more efficient.

Based on the two topics of smart agriculture and smart irrigation, this paper extracted 7260 and 2033 publications, respectively, and compared the high-frequency phrases between the two. The results show that smart agriculture's top five research popularity are the Internet of Things, climate change, machine learning, precision agriculture, and wireless sensor networks. The top five hot spots for smart irrigation are the Internet of Things, irrigation systems, soil moisture, smart agriculture, and wireless sensor networks. In addition, the Internet of Things, climate change, machine learning, precision agriculture, wireless sensor networks, soil moisture, deep learning, artificial intelligence, irrigation systems, low cost, and neural networks are joint research focuses of both parties.

By analyzing the limitations of current research and future research directions, the results show that although smart agriculture and smart irrigation show great promise in many aspects, they still have certain limitations. (1) Construction costs are too high, making adopting these technologies economically challenging for small-scale farmers or developing countries [15]. Future research should focus on developing more cost-effective solutions that make these technologies more accessible to farmers. (2) A high technology dependence, especially in areas with poor network connectivity or unreliable power supply [42]. Future research should explore technologies such as low power consumption and convenient operation. (3) There are security risks in data and privacy [14]. This is because collecting and utilizing large amounts of data have raised concerns about security and privacy. Future research should focus on creating standards and ethical guidelines for data governance. (4) Lack of standardization of equipment, leading to compatibility issues between different systems and vendors [13]. Future research should be devoted to developing industry standards for communication protocols, data formats, and interfaces. In conclusion, addressing these limitations through targeted research efforts can increase the effectiveness of smart agriculture and smart irrigation technologies, ultimately contributing to sustainable and efficient agricultural practices.

As shown in the above results, the most fundamental relationship between high-frequency phrases is shown in Figure 8. To better understand the relationship between popular research areas, the following paragraphs provide a detailed analysis of this relationship and a discussion of crops. These concepts are interrelated, and the IoT and machine learning as overarching technologies can be applied in various fields, including agriculture, to address challenges related to climate change, precision agriculture, and efficient resource management.

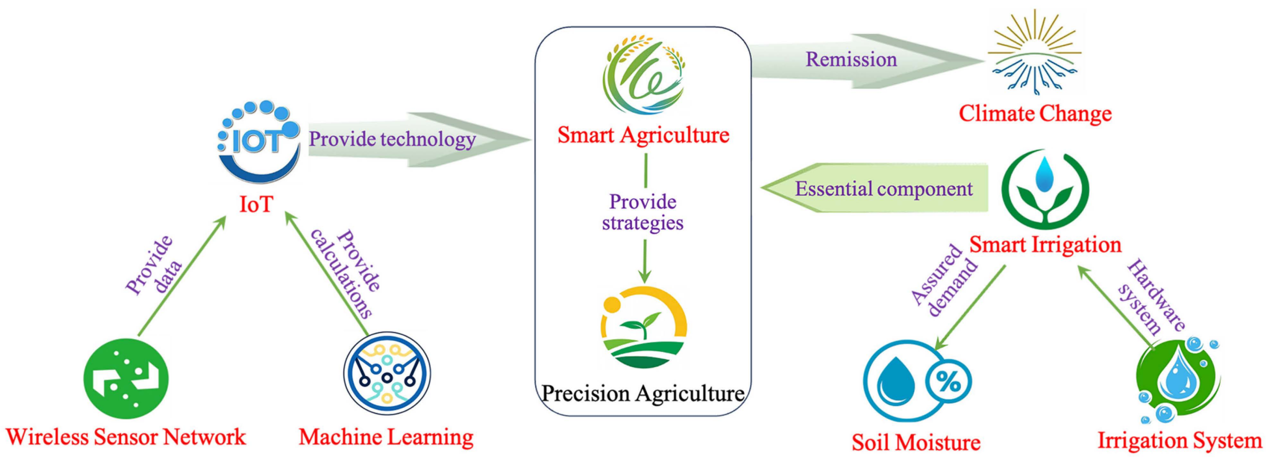


Figure 8. The most basic relationship between high-frequency phrases.

4.1. Internet of Things

The relationship between the IoT, SA and SI is closely related. The IoT can provide necessary support and help to agriculture, making agricultural production more scientific and intelligent. The IoT can combine sensors, monitoring equipment, and actuators with cloud computing, big data, AI and other technologies, bringing many benefits to agriculture [19]. For example, it can realize automated planting, fertilizing, and watering, reduce labor costs and water consumption, and improve the quality of agricultural production.

The IoT has injected new vitality and power into traditional agriculture. Through agricultural informatization and refined management, sustainable development of agricultural production is achieved and brings more opportunities and benefits to farmers [30].

Especially for farmers in developing countries, smart agricultural can help them improve agricultural production efficiency.

The IoT also brings significant improvements and benefits to traditional irrigation. By monitoring soil moisture, meteorological conditions, crop water demand and other data in real-time, farmers can accurately control the distribution and dosage of water and fertilizer, avoiding the problem of over-irrigation or under-irrigation, thus improving the efficiency of water resource utilization [8]. In addition, the Internet of Things can also help farmers optimize the energy use of irrigation systems, automatically perform irrigation tasks, and reduce energy consumption and operating costs. The IoT also supports predictive maintenance to avoid equipment damage [6].

The IoT is a broader concept that encompasses various applications, including agriculture. It involves the integration of sensors, actuators, and communication technologies for efficient data collection and decision-making.

4.2. Climate Change

The Sixth Assessment Report of the United Nations Intergovernmental Panel on Climate Change (IPCC) points out that climate change has caused colossal damage and increasingly irreversible losses to terrestrial, freshwater, coastal and pelagic marine ecosystems and is affecting the world [38]. Therefore, how to actively respond to climate change is a common issue the international community faces.

According to the definition of the Food and Agriculture Organization of the United Nations, smart agriculture is a new agricultural development model that can not only maintain agricultural production capacity but also achieve carbon sequestration, emission reduction and climate change mitigation in the context of responding to global climate change [34]. Currently, some countries are accelerating agricultural scientific and technological innovation and the transformation of production methods, vigorously developing biotechnology water-saving irrigation technology, and actively exploring the development of climate-smart agriculture and achieving good results. The future research trend in SA and SI is alleviating the food crisis by responding to climate change.

While climate change affects agriculture, it is a broader environmental issue. The IoT and machine learning are tools that can be employed to mitigate and adapt to the effects of climate change in agriculture.

4.3. Machine Learning

With the assistance of machine learning, smart agriculture and smart irrigation continue to develop, improving agricultural efficiency and productivity. Machine learning is a branch of science that allows machines to learn without being explicitly programmed, which is the mechanism behind it. Machine learning has evolved alongside big data technologies and powerful computers to open new possibilities for unraveling, analyzing and understanding data-intensive processes in agricultural organizational settings [43].

Smart agriculture and smart irrigation development always take data, algorithms and computing power as the core elements. It uses algorithm innovation to effectively combine the “massive data” brought by modern information technology with the “amount of computing” supported by physical computing hardware platforms, forming information perception, quantitative decision-making, and intelligent control of agricultural production [25]. Machine learning brings a more standardized and sustainable management method to traditional agriculture and is expected to achieve tremendous success in the farming field.

Machine learning is a subset of artificial intelligence that involves the development of algorithms that can learn from data. It can be applied in various fields, including agriculture, to improve efficiency and decision-making.

4.4. Precision Agriculture

Precision agriculture is based on modern technical means, such as 3S technology (remote sensing, geographic information systems, and global navigation satellite systems), sensor technology, and the Internet of Things, to achieve precise control of the farming process, accurate monitoring of crop growth, disasters, and other aspects, and achieve precision farming, precision irrigation, specific fertilization, pesticide application, precise sowing, precise harvesting, earning the same or higher income with the minor investment [12]. Smart agriculture relies on modern technical means such as 3S technology and is deeply integrated with new technologies such as cloud computing, the Internet of Things, and mobile Internet. It is an all-around introduction of intelligent ideas and technology applications into agricultural production to achieve precision in farming operations, infrastructure intelligence, and modernization of industrial development [2].

Compared with precision agriculture, smart agriculture covers a broader scope. In a narrow sense, it includes commonly understood agricultural fields such as field agriculture, facility agriculture, safety traceability, and agricultural e-commerce; broadly, it uses information means represented by the Internet to analyze agriculture. It performs full-process information services and guidance, adopts innovative business operation models, and extends them to the agricultural economy. Developing smart agriculture can promote precision agriculture development and improve crop products.

Precision agriculture is a specific application of technology in farming, while IoT and machine learning are broader concepts that can be applied in various domains.

4.5. Wireless Sensor Network

The wireless sensor network is widely used in smart agricultural systems to manage and monitor the productivity and sustainability of agricultural yields. Wireless sensor technology plays a vital role in smart agriculture and smart irrigation, bringing significant benefits. First, farmers can use wireless sensor networks to optimize agriculture by monitoring multiple vital parameters such as soil moisture, temperature, antennas, and meteorological conditions in real time [44]. This helps improve the growth quality and yield of epidemics, reduce resource waste, and reduce reliance on chemical fertilizers and pesticides, making sustainable agriculture possible.

Secondly, wireless sensors also provide early detection and warning of pests and diseases. In addition, wireless sensor technology can be integrated with automation systems to automate agricultural production, including automatic irrigation, fertilization, agricultural machinery operations, etc., improving labor efficiency and reducing labor costs. Wireless sensor technology brings opportunities for informatization, automation and sustainable development to smart agriculture and is expected to promote more innovation and progress in the agricultural field [26].

Wireless sensor networks are a specific technology within the broader framework of the IoT. They play a crucial role in collecting data for various applications, including precision agriculture.

4.6. Irrigation System

The irrigation system is an engineered system widely used in agriculture and gardening fields to provide plant growth water. This can range from simple irrigation methods such as drip, sprinkler and subsurface irrigation to complex canals and pumping stations. Smart irrigation combines advanced sensors, data analysis, and automated control to achieve efficient, precise, and sustainable plant irrigation. Whether it is an irrigation system or a smart one, their primary purpose is to provide plants with the necessary water to support their growth and development. In contrast, smart irrigation is a modern, highly automated, data-driven irrigation system designed to improve efficiency and resource utilization [8].

An irrigation system is a specific agricultural technology, and when combined with the IoT and sensor networks, it becomes a part of precision agriculture.

4.7. Soil Moisture

The development of smart agriculture and smart irrigation has brought considerable benefits to agricultural production, among which precise control of soil humidity is one of the keys. First, for smart agriculture, soil moisture control optimizes agricultural growth [7]. Using sensor networks and data analysis, farmers can understand soil moisture levels in real-time to take timely measures, such as adjusting irrigation volume and frequency to ensure the soil in their fields is always within the closest moisture range. This improves immediate yield and quality, reduces water waste, and is conducive to realizing sustainable agriculture.

Secondly, soil moisture control in smart irrigation is crucial for water resources management. By monitoring soil moisture in real-time, the smart irrigation system can accurately calculate plants' water needs and adjust irrigation as needed, avoiding over- or under-irrigation. This saves water resources, reduces irrigation costs and helps reduce the risk of salinization. Therefore, effective control of soil moisture not only improves the water utilization efficiency of farmland but also helps maintain soil health and ecological balance, providing a foundation for the realization of sustainable agriculture.

Soil moisture is a specific parameter monitored in agriculture, and the technologies mentioned, such as the IoT and wireless sensor networks, are tools used to gather and analyze data related to soil moisture.

4.8. Crop Topic

As mentioned in Section 3.5, this paper divides crops into food crops, fruits, vegetables, and oil crops for analysis. As seen in Figure 6, food crops account for the highest proportion, indicating that these crops are the main focus of smart agriculture. At the same time, it can be seen from the research results that smart agriculture plays a positive role in promoting food security.

Additionally, the main source countries of crop publications show that most publications about corn and rice come from the United States and India, while most publications about tomatoes and grapes come from Japan and Italy [16]. This is highly consistent with the major producing countries of these crops, indicating that most studies have focused on the major crops in their countries.

5. Conclusions

Smart agriculture and smart irrigation are multidisciplinary and broad topics involving knowledge in different fields. In our bibliometric analysis, we have shown an integrated vision approach. This study has limitations related to its themes' diversity. Only articles and conference papers were considered, although we extracted 7260 and 2033 publications, respectively. Thus, with the inclusion of all documents in the research field, the results could be different.

This study used cluster analysis and found that the growth rate of the Internet of Things in smart agriculture and smart irrigation is the most obvious, with five-year growth rates of 1617% and 2285%, respectively. Moreover, another prominent phrase that appears in the list of high-frequency phrases is machine learning. In smart agriculture, its growth rate is 4203%, and in smart irrigation, its growth rate is 984%. This shows that machine learning has an enormous potential in smart irrigation compared with smart agriculture.

The bibliometric analysis gave evidence that the Internet of Things, machine learning, precision agriculture, and wireless sensor networks are all high-frequency phrases in smart agriculture and smart irrigation. These emerging technologies can bring about earth-shaking changes in agriculture, achieving a smooth transition to smart agriculture. IoT can provide necessary support and help for agriculture, making agricultural production more scientific and intelligent. Machine learning has evolved alongside big data technologies and powerful computers to open up new possibilities for unraveling, analyzing and understanding data-intensive processes in agricultural organizational settings. Precision agriculture methods are being utilized to improve the accuracy of fertilizer, pesticide, and herbicide applications. Wireless sensor technology brings opportunities for informatization, automation and sustainable development to smart agriculture and is expected to promote more innovation and progress in the agricultural field.

In terms of water resource management, smart agriculture enables more effective management of water resources. In terms of reducing greenhouse gas emissions, smart agriculture can reduce the negative impact of agriculture on climate change by optimizing production processes and reducing the use of energy and chemical fertilizers. In terms of renewable energy applications, smart agriculture can integrate renewable energy and reduce dependence on traditional energy, thereby reducing greenhouse gas emissions. In terms of food security, smart agriculture can improve efficiency, reduce production costs, and increase disaster resistance, thus promoting the development of sustainable agriculture. In short, almost every part of agriculture and irrigation, from planting to sowing and harvesting, stands to profit from the effect of smart technology.

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